NBER WORKING PAPER SERIES

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Working Paper 25040
http://www.nber.org/papers/w25040

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
September 2018

We are grateful to Li An, Markus Brunnermeier, Hui Chen, Will Cong, Zhi Da, Itamar Drechsler, Darrell Duffie, Larry Harris, John Heaton, Dong Lou, Guangchuan Li, Roger Loh, Gordon Phillips, Dimitris Papanikolaou, Nick Roussanov, Sheridan Titman, Heather Tookes, and Pietro Veronesi, Liyan Yang for helpful discussions and insightful comments. Xiao Zhang, and especially Yiran Fan, provided excellent research assistance. We are grateful to seminar participants at AQR, BFI Macro Financial Modeling Conference, China Financial Research Conference, China International Conference in Finance, University of Chicago, Imperial College London, LBS Academic Symposium, NBER Asset Pricing 2018 Chicago Meeting, NY Federal Reserve, 2018 Rising Stars Conference at Fordham, Rotterdam, SITE 2018 Financial Regulation, Tilburg, University of Minnesota, Wharton, and Yale SOM. Zhiguo He acknowledges financial support from the Center for Research in Security Price at the University of Chicago Booth School of Business. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 25040
September 2018
JEL No. G01,G11,G18,G23

ABSTRACT

We provide direct evidence of leverage-induced fire sales contributing to a market crash using account-level trading data for brokerage- and shadow-financed margin accounts during the Chinese stock market crash of 2015. Margin investors heavily sell their holdings when their account-level leverage edges toward their maximum leverage limits, controlling for stock-date and account fixed effects. Stocks that are disproportionately held by accounts close to leverage limits experience high selling pressure and abnormal price declines which subsequently reverse. Unregulated shadow-financed margin accounts, facilitated by FinTech lending platforms, contributed more to the crash despite their smaller asset holdings relative to regulated brokerage accounts.

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1 Introduction

Excessive leverage and the subsequent leverage-induced fire sales are considered to be major contributing factors to many past financial crises. A prominent example is the US stock market crash of 1929. At the time, leverage for stock market margin trading was unregulated. Margin credit, i.e., debt that individual investors borrow to purchase stocks, rose from around 12% of NYSE market value in 1917 to around 20% in 1929 (Schwert, 1989). In October 1929, investors began facing margin calls. As investors quickly sold assets to deleverage their positions, the Dow Jones Industrial Average experienced a record loss of 13% in a single day, later known as "Black Monday" on October 28, 1929.[1] Other significant examples of deleveraging and market crashes include the US housing crisis which led to the 2007/08 global financial crisis (see e.g., Mian et al. (2013)) and the Chinese stock market crash in the summer of 2015. The latter market crash will be the focus of this paper.

As the worst economic disaster since the Great Depression, the 2007/08 global financial crisis greatly revived the interest of academics and policy makers in understanding and measuring the costs and benefits of financial leverage. In terms of academic research, the theory has arguably advanced ahead of the empirics. For instance, in a general equilibrium framework, Brunnermeier and Pedersen (2009) and Geanakoplos (2010) carefully model a "downward leverage spiral" in which tightened leverage constraints trigger fire sales, which then depress asset prices, leading to even tighter leverage constraints. This general equilibrium theory features a devastating positive feedback loop that is able to match various pieces of anecdotal evidence, and is widely considered to be one of the leading mechanisms behind the meltdown of the financial system during the 2007/08 crisis. Despite its widespread acceptance, there is little direct empirical evidence of leverage-induced fire sales contributing to stock market crashes. Empirical tests of the theory are challenging because of the limited availability of detailed account-level data on leverage and trading activities. This paper contributes to the literature on leverage and financial crashes by providing direct evidence of leverage-induced fire sales.

We use unique account-level data in China that track hundreds of thousands of margin investors' borrowing and trading activities. The Chinese stock market has become increasingly important in the global economy; for an informative reading, see Carpenter and Whitelaw (2017). With market value equal to approximately one-third that of the US market, it is now the second largest stock market in the world. Our data covers the Chinese stock market crash of 2015, an extraordinary

[1] For a detailed description of the 1929 stock market crash, see Galbraith (2009).

period that is ideal for examining the asset pricing implications of leverage-induced fire sales. The Chinese stock market experienced a dramatic run-up in the first half of 2015, followed by an unprecedented crash in the middle of 2015 which wiped out about 30% of the market's value by the end of July 2015.

Individual retail investors are the dominant players in the Chinese stock market and were the main users of leveraged margin trading systems.[2] Our data covers two types of margin accounts, brokerage-financed and shadow-financed margin accounts, for the three-month span of May to July, 2015. 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 firm, 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 asset sales.[3]

In contrast, the shadow-financed margin system, aided by the burgeoning FinTech industry, falls in a regulatory gray area. Shadow-financing was not initially regulated by the CSRC, and lenders do not require borrowers to have a minimum level of wealth or trading history to qualify for borrowing. There is no regulated Pingcang Line for shadow-financed margin trades. Instead, the maximum leverage limits are individually negotiated between borrowers and shadow lenders. Not surprisingly, shadow accounts have significantly higher leverage than their brokerage counterparts.[4]

On June 12, 2015, the CSRC released a set of draft rules that would tighten regulations on shadow-financed margin trading in the future; a month-long stock market crash started on the next trading day, wiping out almost 40% of the market index. The shadow-financed margin accounts data is particularly interesting for our study of the market crash, because it is widely believed that excessive leverage taken by unregulated shadow-financed margin accounts and the subsequent fire sales induced by the deleveraging process were the main driving forces behind the collapse of the Chinese stock market in the summer of 2015.[5] From this perspective, one of our main contributions

[2]Trading volume from retail traders covers 85% of the total volume, according to Shanghai Stock Exchange Annual Statistics 2015, http://www.sse.com.cn/aboutus/publication/yearly/documents/c/tjnj_2015.pdf. It is well known that retail traders play significant roles even in more developed financial markets; see, e.g., Foucault et al. (2011).

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

[4]This is confirmed in our sample. The equal-weighted average leverage (measured as assets/equity) is 6.6 for shadow accounts and only 1.4 for brokerage accounts.

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

is to show how fire sales can result when new financial innovations (FinTech in our case) advance ahead of regulation, much like unregulated margin trading during the US stock market crash in 1929.

We begin our empirical analysis by identifying how leverage and leverage constraints affect individual investor trading behavior. For each account-date, we first construct a Distance-to-Margin-Call measure based on the account's leverage (defined as the ratio of asset value to equity value), its Pingcang Line, and the volatility of the assets held by the account. In the spirit of the Distance-to-Default measure in Merton-style models, Distance-to-Margin-Call captures the risk that a margin account will hit its leverage constraint and consequently be taken over by creditors. When Distance-to-Margin-Call hits zero, the leverage hits the Pingcang Line and the creditor takes over the account.

In theories such as Brunnermeier and Pedersen (2009) and Garleanu and Pedersen (2011), costly forced sales occur if leverage exceeds the account's Pingcang Line and the account is taken over by the creditor. Forward-looking investors will sell as the account's leverage approaches its Pingcang Line due to precautionary motives.[6] We find strong empirical support for these theories in the data. After controlling for account fixed effects and stock-date fixed effects, we find that the selling intensities of all stocks are negatively related to the account's Distance-to-Margin-Call. The effect is non-linear, and increases sharply when the Distance-to-Margin-Call edges toward zero.

The significant negative relationship between selling intensity and Distance-to-Margin-Call identifies leverage-induced fire sales in our paper. We further note that this negative relationship can be driven by (1) leverage constraints, i.e. forced and preemptive sales that occur when leverage nears the maximum leverage limit and (2) a portfolio rebalancing motive in which risk-averse investors actively delever after a drop in asset values induces an increase in leverage. Thus, leverage-induced fire sales in our setting should be viewed as a combination of these two widely-accepted economic forces: one consists of pre-emptive and forced sales due to leverage constraints and the other is a rebalancing motive that could occur even in the absence of leverage constraints. We provide several tests that "rule in" a strong leverage constraint effect, although we do not rule out an additional leverage effect. First, we show that the ratio of leverage to the Pingcang line matters for

Chinese is available at http://opinion.caixin.com/2016-06-21/100957000.html.

[6]In static models such as Brunnermeier and Pedersen (2009) and Geanakoplos (2010), fire sales only occur when accounts hit the leverage constraint (the Pingcang Line). However, in a dynamic setting such as Garleanu and Pedersen (2011), forward looking investors will start to sell before hitting the constraint, knowing that the controlling creditors who only aim to recover their debt claims will dump the stock holdings by ignoring price impact. Investors' precautionary selling prior to hitting the leverage constraint can also be explained by runs in financial markets, as illustrated by Bernardo and Welch (2004), which is similar in spirit to the bank-run mechanism in Diamond and Dybvig (1983), Goldstein and Pauzner (2005), and recently He and Xiong (2012)).

selling behavior, even after we flexibly control for the account's level of leverage, and proxy for the Pingcang Line (which may be endogenously determined) using the average Pingcang Line for all accounts opened on the same day as the account in question. We also find that the announcement of regulations that would tighten leverage constraints for shadow-financed margin accounts led to large upward jumps in selling intensities for shadow accounts (and not for brokerage accounts), with especially large jumps for accounts with Distance-to-Margin-Calls closer to zero.

We find evidence of strong interactions between leverage-induced selling, market movements, and stock market trading restrictions. The relation between Distance-to-Margin-Call and net selling is two to three times stronger on days when the market is down rather than up. This result underscores how leverage-induced fire sales in specific stocks feed into and are fed by broad market crashes. As more margin accounts face leverage constraints, investors will seek to deleverage their holdings, which will contribute to a market decline. As the market declines, leverage constraints tighten further, causing investors to intensify their selling activities. We also find that government announcements aimed at curbing excessive leverage may have intensified leverage-induced selling in the short run, triggering market-wide crashes. Further, government-mandated price limits that restricted trading for individual stocks beyond a within-day price change of 10% had the unintended consequence of exacerbating fire sales crashes in other stocks that were not protected by the price limits. We find that investors seeking to deleverage significantly intensify their selling of unprotected stocks if other stocks in their portfolios cannot be sold due to stock-specific price limits.

We then show that stocks that are disproportionately held by margin accounts with low Distance-to-Margin-Calls experience high selling pressure. We classify accounts whose Distance-to-Margin-Call is below a threshold as "fire sale accounts." We then construct a stock-date level measure of fire sale exposure, which measures the fraction of shares outstanding held by fire sale accounts within our sample of margin accounts. We find that stocks with higher fire sale exposure experience significantly more net selling volume from fire sale accounts.

Next, we explore the asset pricing implications of leverage-induced fire sales. Following Coval and Stafford (2007), we test the prediction that fire sales should cause price drops that revert in the long run. In our setting, selling pressure from margin accounts close to their Pingcang Lines can cause fire sales if there is insufficient liquidity to absorb the selling pressure. Prices should then revert back when liquidity returns to the market. To test this prediction, we do not use the actual trading choices of fire sale accounts, as investors may exercise endogenous discretion in the choice of which stocks within their portfolios to sell. Following Edmans et al. (2012), we instead look at the pricing patterns for stocks with high fire sale exposure, i.e., stocks that are disproportionately held by margin accounts with leverage close to their Pingcang Lines. We find that stocks with high fire sale exposure significantly underperform stocks with low fire sale exposure, but these differences approach zero in the long run. Stocks in the top decile of fire sale exposure underperform stocks in the bottom decile by approximately 5 percentage points within 10 to 15 trading days, and the difference in performance reverts toward zero within 30 to 40 trading days. To better identify a causal effect of fire sales on asset prices, we also conduct an event study showing that the relation between FSE and stock returns became significantly stronger immediately after a regulatory tightening announcement aimed at curbing shadow margin trading. We further show that the long-run reversal should not be attributed solely to a large-scale government bailout which began on July 6, 2015. While the government bailout may have helped stem the aggregate decline in the market, the government did not disproportionately purchase stocks with high fire sale exposure; we find the correlations between government purchases and stocks' fire sale exposures at different lags are economically small (below 4%) and sometimes even negative.

Finally, our unique data allows us to perform the following forensic-style analysis: Which margin trading system, brokerage or shadow, played a more important role in the stock market crash? The answer to this question is important from a policy perspective because it can shape the focus of future regulatory oversight. Although practitioners, the media, and regulators have mainly pointed their fingers at shadow-financed margin accounts, the answer to this question is not obvious. First, according to many estimates, total market assets held within the regulated brokerage-financed system greatly exceeded that in the unregulated shadow-financed system. Second, brokerage-financed margin accounts have a lower Pingcang Line that is uniformly imposed by the CSRC. Thus, even though brokerage accounts have lower leverage on average, these accounts may also be closer to hitting leverage constraints.

We find that the data supports the view that shadow-financed margin accounts contributed more to the market crash. The leverage of brokerage accounts remained low, even relative to their tighter Pingcang Lines. There were also far fewer stock holdings in fire sale accounts within the brokerage-financed system than within the shadow-financed system. Further, a measure of fire sale exposure constructed from the shadow accounts data sample predicts price declines and subsequent reversals much more strongly than a similar fire sale exposure measure constructed from the brokerage accounts data sample.

Overall, we find strong empirical evidence that leverage-induced fire sales, originating primarily in the FinTech-fueled shadow sector and participated mainly by retail investors, contributed to the Chinese stock market crash of 2015. We caution that our results do not imply that fire sales were the ultimate cause of the large and persistent drop in the value of the Chinese stock market (the SSE index fell from a high of over 5000 in early June of 2015 to below 3000, and has stagnated in the low 3000s in the subsequent three years). The lack of a full recovery in the years after the crash is consistent with Chinese markets being fundamentally overvalued in the first half of 2015. While we cannot know the counterfactual with certainty, it is possible that the Chinese stock market would have experienced an eventual correction, even without the trigger of leverage-induced fire sales. Our evidence does suggest that fire sales contributed to the correction taking the form of a rapid crash in the days immediately following a regulatory announcement aimed at curbing shadow-financed margin trading.[7] Our cross-sectional evidence also shows that stocks disproportionately held by highly-leveraged margin accounts experienced larger percentage declines relative to other stocks, and that the *gap* between stocks with high versus low fire sale exposure closed once liquidity returned to the market. Our findings parallel common narratives concerning the US 1929 stock market crash (e.g., Schwert (1989)).[8] Like the Chinese 2015 crash, the US 1929 crash was followed by many years of market stagnation, consistent with a story of fundamental overvaluation and eventual correction. However, deleveraging and fire sales by margin traders contributed to the correction taking the form of dramatic single-day point drops during the summer of 1929.

Related Literature Our paper is related to the 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). In a seminal paper by Shleifer and Vishny (1992), the authors argue that asset fire sales are possible when financial distress clusters at the industry level, as the natural buyers of the asset are financially constrained as well. Pulvino (1998) tests this theory by studying commercial aircraft transactions initiated by (capital) constrained versus unconstrained airlines, and Campbell et al. (2011) documents 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.

[7] Indeed, an earlier Chinese stock market boom in 2007/08 which ended with a much slower downward correction is consistent with the view that margin trading contributes to rapid crashes, as margin trading was introduced in the Chinese stock market only after 2010 (Andrade et al., 2013).

[8] The Introduction of Schwert (1989) discusses the similarity between the 1987 and 1929 crashes in the US stock market, noting that regulators "feared that cheap credit allowed over-enthusiatic speculators to bid up stock prices, creating the potential for a crash as prices reverted down to lower (presumably more rational) levels. Similar fears were expressed in the Congressional hearings that followed the 1929 crash."

(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)).

It is worth emphasizing that, although fire sales can be triggered by many economic forces, the seminal paper by Shleifer and Vishny (1992) and the subsequent theory literature focus on the force of deleveraging. Meanwhile, the existing empirical evidence has not focused on *leverage-induced* fire sales, which have the additional feature of a downward leverage spiral. In this regard, our paper differs from the previous empirical literature by documenting a direct link between leverage, selling behavior, and fire sales, with the aid of account-level leverage and trading data. Our paper also differs from previous empirical work on financial markets which has mostly focused on fire sales in specific subsets of financial securities. We show how leverage-induced fire sales play a role in a broad stock market crash.

Our paper also contributes to the literature on the role of funding constraints, specifically margin and leverage, in asset pricing. Theoretical contributions such as Kyle and Xiong (2001), Gromb and Vayanos (2002), Danielsson et al. (2002), Brunnermeier and Pedersen (2009), and Garleanu and Pedersen (2011) help academics and policymakers understand these linkages in the aftermath of the recent global financial crisis.[9] There is also an empirical literature that connects various funding constraints to asset prices. Our paper follows a similar vein of investigating funding constraints tied to the market making industry (e.g., Comerton-Forde et al. (2010) and Hameed et al. (2010), among others).

Our paper is most closely related to the empirical literature which explores the asset pricing implications of stock margins and related regulations. Margin requirements were first imposed by Congress through the Securities and Exchange Act of 1934. Congress's rationale at the time was that credit-financed speculation in the stock market may lead to excessive price volatility through a "pyramiding-depyramiding" process. Indeed, 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 also seems to fit unsophisticated retail investors

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

in the Chinese stock market). Hardouvelis and Theodossiou (2002) further show that the relation between margin requirements and volatility only holds in bull and normal markets. This finding points to the potential benefit of margin credit, in that it essentially relaxes funding constraints. This trade-off is cleanly tested in a recent paper by Tookes and Kahraman (2016), which shows the causal impact of margin on stock liquidity using a regression discontinuity design comparing stocks on either side of a margin eligibility regulatory threshold.

There are several concurrent academic articles investigating the Chinese stock market boom and subsequent crash in the summer of 2015. In contrast with our analysis, most of the other studies use stock-level data rather than account-level brokerage and shadow margin trading data, e.g., Huang et al. (2016) and Chen et al. (2017). Using account-level data, but without a focus on margin trading or shadow financing, Huang et al. (2018) study trading suspensions that are discretionally chosen by the listed companies themselves. Focusing on the staggered liberalization of stock-margin lending and the associated market boom before 2015, Hansman et al. (2018) quantify the price impact due to the expectations of future margin-driven price increases. Our analysis and conclusions are complementary to a companion paper by Bian et al. (2018a), which uses the same dataset on margin traders in the Chinese stock market in 2015. Bian et al. (2018a) focus on contagion among stocks held in the same leveraged margin accounts and how the magnitude of the contagion can be amplified through increased account leverage. Bian et al. (2018a) also show that this within-account contagion can be further transmitted across account networks, again amplified by leverage. In contrast, this paper aims to provide direct evidence of leverage-induced fire sales, which itself does not require contagion (although contagion can, of course, feed and be fed by fire sales). This paper also differs from Bian et al. (2018a), because our analysis centers on the difference between the two types of margin accounts, regulated brokerage accounts and unregulated shadow accounts. Our findings concerning the unique nature of shadow-financing may help researchers and policymakers understand the role of regulation in the informal finance sector.

2 Institutional Background

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

2.1 Margin Trading during the Chinese Stock Market Crash of 2015

The Chinese stock market experienced a dramatic increase in the first half of 2015, followed by an unprecedented crash in the middle of 2015. The Shanghai Stock Exchange (SSE) composite index started from around 3100 in January 2015, peaked at 5166 in mid-June, and then free-fell to 3663 at the end of July 2015. It is widely believed that high levels of margin trading and the subsequent fire sales induced by the de-leveraging process were the main driving forces of the market crash.

There were two kinds of margin trading accounts active in the Chinese stock market during this time period. One is brokerage-financed and the other is shadow-financed, as shown in Figure 1, which depicts the structure and funding sources for the two margin trading systems.[10] Both accounts were nonexistent prior to 2010, but thrived after 2014 alongside the surge in the Chinese stock market. In what follows, we describe these two types of margin accounts in detail. Throughout the paper, whenever there is no risk of confusion, we use brokerage (shadow) accounts to refer to brokerage-financed (shadow-financed) margin accounts.

2.2 Brokerage-Financed Margin Accounts

Margin trading through brokerage firms was first introduced to the Chinese stock market in 2010. After its introduction, margin trading remained unpopular until around June 2014 when brokerage-financed debt began to grow exponentially. According to public data on exchanges, the total debt held by brokerage-financed margin accounts sat at 0.4 trillion Yuan in June 2014, but more than quintupled to around 2.2 trillion Yuan within one year. This amounted to approximately 3-4% of the total market capitalization of China's stock market in mid-June 2015, similar to the relative size of margin financing in the US and other developed markets.

Brokerage-financed margin trades represented a highly profitable business for brokerage firms. Brokers usually provide margin financing by issuing short-term bonds in China's interbank market or borrowing from the China Securities Finance Corporation (CSFC) at a rate slightly higher than the interbank rate.[11] Brokers then lend these funds to margin borrowers at an annual rate of approximately 8-9%, who then combine their own equity funds to purchase stocks (the left side of

[10] In Chinese, they are called "Chang-Nei fund matching" and "Chang-Wai fund matching," which literally means "on-site" and "off-site" financing. In a companion paper by Bian et al. (2018a), whose analysis is based on the same data set as our paper, "shadow-financed" is called "peer-financed," which emphasizes that margin credit can be supplied via either formal institutions like brokerage firms or informal lending providers like wealthy individuals.

[11] For a brief explanation of the China Securities Finance Corporation (CSFC), see https://www.ft.com/content/c1666694-248b-11e5-9c4e-a775d2b173ca.

Figure 1 Panel A).[12] With a risk-free rate of around 4% during our sample period, this business offered brokers higher profits than commissions, which were only about 4 basis points (or 0.04%) of trading volumes.

Almost all brokerage-financed margin account holders in China are retail investors.[13] Due to concerns of potential trading frenzies from household investors, the regulatory body of the Chinese securities market, the China Securities Regulatory Commission (CSRC), sets high qualification standards for investors to engage in 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 (cash and stockholdings combined) exceeding 0.5 million Yuan.

The minimum initial margin set by the CSRC is 50%, implying that investors can borrow at most 50% of asset value when they open their brokerage accounts. More importantly for our analysis, the CSRC also imposes a minimum margin, which requires that every brokerage account maintains its debt below 1/1.3 of its current total asset value (cash + stock holdings). Once the debt-to-asset ratio of a margin account increases above 1/1.3, and if borrowers fail to inject equity to reduce the account's debt-to-asset ratio the next day, the account will be taken over by the brokerage firm.

In China, practitioners call this maximum allowable leverage ratio, which equals $Asset/Equity = 1.3/(1.3-1) = 4.33$, the "Pingcang Line," which means "forced settlement line." Brokerage firms have discretion to set different Pingcang Lines for their customers, as long as the line lies below this regulatory maximum of 4.33. However, we do not observe any instances of a lowered maximum allowable leverage limit in our sample, which is from one of the leading brokerage firms in China. This suggests that the CSRC has been quite stringent in regulating the brokerage-financing business.[14]

Once the account leverage exceeds the Pingcang Line, control of the account reverts to the lender (the brokerage firm). The lender then has discretion to sell assets without borrower permission,

[12] For the rate at which the CSFC lent to security firms, see http://www.csf.com.cn/publish/main/1022/1023/1028/index.html. For the rate at which security firms lent to margin borrowers, see http://m.10jqka.com.cn/20170726/c599327374.shtml.

[13] The regulatory body CSRC banned professional institutional investors from conducting margin trades through brokers in China.

[14] Besides regulating leverage, the CSRC also mandated that only the most liquid stocks (usually blue-chips) were marginable, i.e., eligible for investors to obtain margin financing. However, this regulation only affected margin buying when the accounts were first opened. Investors were able to use cash from previous sales to buy other non-marginable stocks, as long as their accounts remained below the Pingcang Line. In our data, 23% of stock holdings in brokerage accounts are non-marginable stocks during the week of June 8-12, 2015 (the week leading up to the crash). When the prices of stock holdings in a leveraged brokerage account fell, the leverage rose, and the account engaged in either preemptive sales to avoid approaching the Pingcang Line or forced sales after it was taken over after crossing the Pingcang Line. Regardless of the situation, investors sold both marginable and non-marginable stocks, rendering the initial margin eligibility of the stocks largely irrelevant when we study the role of leverage-induced fire sales in the stock market crash. Moreover, shadow-financed margin accounts were not regulated and could always buy non-marginable stocks on margin.

and generally sells all assets very aggressively without regard for price impact or execution costs (see Footnote 32 for a detailed discussion of creditor incentives to liquidate assets). This aggressive selling may help the lender recover debt at the expense of the remaining equity value of the borrower. Therefore, borrowers may actively delever before hitting the Pingcang Line to avoid potential equity losses once the lender seizes control.

2.3 Shadow-Financed Margin Accounts

During the first half of 2015, aided by the burgeoning FinTech industry in China, many Chinese retail investors engaged in margin trading via the shadow-financing system, in addition to, or instead of, the brokerage-financing system. Shadow-financed margin trading started attracting investors in 2014, alongside the rapid growth of the FinTech industry in China. The shadow-financing system, similar to many financial innovations in history, 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 asset wealth or trading history to qualify for borrowing. In turn, shadow-financed borrowers paid higher interest rates of around 11-14%, which are 3-5 percentage points higher than their counterparts in the brokerage-financed market.

Shadow-financing usually operated through a web-based trading platform which provided various service functions that facilitated trading and borrowing.[15] The typical platform featured a "mother-child" dual account structure, with each mother account offering trading access to many (in most cases, hundreds of) child accounts. 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 creditor, 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, albeit with unusually large asset holdings and trading volume. In reality, these large brokerage accounts were mother accounts, which used a FinTech software program to transmit the orders submitted by associated child accounts in real time to stock exchanges. As shown, the professional financing company which manages the mother account provides margin credit to child accounts; its funding

[15] HOMS, MECRT, and Royal Flush were the three leading electronic margin trading platforms in China during 2015.

sources include its own capital as mezzanine financing as well as borrowing from China's shadow banking sector. Through this umbrella-style structure, a creditor can lend funds to multiple margin traders, while maintaining different leverage limits for each trader (child account).

Similar to brokerage-financed margin accounts, a child account in the shadow-financed margin system had a maximum allowable leverage limit—i.e., the Pingcang Line—beyond which the child account would be taken over by the mother account (the creditor), triggering forced sales. Often, this switch of ownership was automated through the software system, by simply triggering 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/investor negotiated the maximum allowable leverage limit for each account, resulting in account-specific Pingcang Lines for shadow accounts. The Pingcang Line never changes during the life of an account. In our sample, unregulated shadow accounts have much higher Pingcang Lines on average than their regulated brokerage peers (see Table 1). Just as with brokerage-financed market accounts, control of the account reverts to the creditor (the mother account) once leverage exceeds the Pingcang Line. The mother account generally sells assets aggressively without regard for price impact or execution costs. As a result, foresighted borrowers may delever in a precautionary way, by actively selling before hitting the Pingcang Line to avoid potential losses once the lender seizes control.

Whereas funding for brokerage accounts came from either the brokerage firm's own borrowed funds or from borrowing through the CSFC, 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 these sources of credit. Besides the capital injection by financing companies who were running the shadow-financed margin business and equity from shadow margin traders, the three major funding sources were 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. According to a research report issued by Huatai Securities, just before the stock market collapse in June 2015, borrowing from WMP peaked at around 600 billion Yuan and P2P informal lending peaked at about 200 billion Yuan.[16] For pledged stock rights, there is much less agreement on how much borrowing through pledged stock rights flowed back to the stock market; we gauge 250-500 billion Yuan to be a reasonable estimate.[17] Summing up, the estimated total debt held by shadow-financed margin accounts was about 1.0-1.4 trillion Yuan at its peak, consistent with the estimates provided by China Securities Daily on June 12, 2015.[18]

2.4 Lack of Regulation over Shadow-Financed Margin Accounts

The Chinese stock market stagnated for several years after the crisis of 2008 and began rapidly rising around the middle of 2014. Recent research has argued that a major cause of the market boom without corresponding real sector growth was leverage-fueled margin trading.[19] Although the government and professional traders warned that the stock market run-up may represent a bubble, new investors continued to rush into the market and the index grew by 60% from the beginning to the mid of 2015.

As explained in the previous section, the shadow-financing market was unregulated during our sample period. Shadow-financed margin investors could purchase any stock using margin as long as the total account leverage did not exceed the account-specific Pingcang Line, without any regulation on the Pingcang Line itself. While the shadow-financing market remained unregulated in the first half of 2015, many investors and media outlets believed that the CSRC would release regulatory guidelines in the near future. For instance, on May 22, 2015, newspapers reported that the government had asked several leading broker/securities firms to engage in self-examinations of services provided to shadow-financed margin accounts, and that providers of these "illegal" activities had received warnings from the CSRC as early as March 13, 2015.[20] On June 12, 2015, the CSRC released a set of draft rules that would strength the self-examinations of services provided

[16]These estimates are given in Figure 1 of the report issued by Huatai Securities on July 5th, 2015, which is available at https://wenku.baidu.com/view/565390bd43323968001c9234?pcf=2.

[17]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, for real investment. It is illegal to use borrowed funds to invest in the stock market, though, 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 10-20% of the borrowing flowed back to the stock market.

[18]http://news.xinhuanet.com/fortune/2015-06/12/c_127907477.htm.

[19]Huang et al. (2016) show that the Chinese government's regulatory and monetary policies supported the growth of the stock market; Liao and Peng (2017) explore price and volume dynamics during the market boom using a model with extrapolative beliefs and the disposition effect; and Bian et al. (2018a) show that the outstanding debt of brokerage-financed margin trades closely tracks the Shanghai composite index level.

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

to shadow-financed margin accounts and explicitly ban new shadow-financed margin accounts.[21] A month-long stock market crash started the next trading day on Monday, June 15, 2015, wiping out almost 40% of the market index. In response, the Chinese government began to aggressively purchase stocks to support prices around July 6, 2015, and the market stabilized in mid-September 2015. In this paper, we show that leverage-induced selling pressure by margin investors, especially shadow-financed margin investors, led to widespread fire sales that contributed to the crash in the interim period of June and July 2015.

2.5 Trading Regulations

Chinese regulators had several trading regulation policies in place during our sample period of May-July 2015, generally with the goal of reducing market turbulence. First, while there were no stock-specific or market-wide automatic trading suspension triggers,[22] listed firms could apply for trading suspensions with a typical length of days or weeks. These applications were actively used by firms that were concerned about continuously dropping market values, and the CSRC often approved these applications.[23] In the main analysis, we impute stock returns for days in which a stock experienced trading suspensions, based on the stock's previous closing price and next opening price; our results are robust to this treatment as shown in Section 5.3.

Second, Chinese regulators enforced a daily 10-percent rule (see e.g., Chen et al. (2018b) for a detailed analysis). Under this rule, each individual stock was allowed to move a daily maximum of 10 percent from the previous closing level in either direction, before triggering a price limit. Once triggered, all trades at prices beyond the limit was prohibited. For example, if the previous day's closing price was $10, and today's price dropped to $9, the price limit would be triggered, and the stock could not trade at less than $9. While the stock could technically continue trading within the 10 percent range, the de factco consequence of a triggered price limit was often a near-complete halt in trading for the affected stock. In later analysis, we explore whether these price limits may have had the unintended consequence of exacerbating fire sales crashes in other stocks that were not protected by the price limits.

[21] See the Chinese version available at http://www.sac.net.cn/flgz/zlgz/201507/t20150713_124222.html.

[22] The CSRC 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).

[23] For a thorough analysis for trading suspensions during the Chinese stock market crash in the summer of 2015, see Huang et al. (2018).

3 Data and Summary Statistics

In this section, we start by describing our data samples. We then define account leverage, and show that, during our sample period, leverage is highly countercyclical with the market index, with significant cross-account heterogeneity. We then define each account's Distance-to-Margin-Call, which measures the tightness of the leverage constraint that each account faces at the start of each day. Finally, we discuss summary statistics for our data sample.

3.1 Data

We use a mixture of proprietary and public data from several sources. The first dataset contains the complete equity holdings, cash balances, and trading records of all accounts from a leading brokerage firm in China. This brokerage firm is one of the largest brokers in China, with 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 180,000 of these accounts are eligible for brokerage-financed margin trading, hereafter referred to as "brokerage-financed margin accounts" or "brokerage accounts." After the data cleaning, 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. The remaining accounts are unleveraged, non-margin brokerage accounts, which we use in some analyses to form a control group.

The second dataset contains all trading and holding records of more than 300,000 investor accounts from a large web-based trading platform in China, i.e., "shadow-financed margin accounts" or "shadow accounts." After applying filters to focus on active accounts (with details provided in Appendix A), we retain a final sample of a little over 150,000 shadow accounts, with total debt reaching 56 billion Yuan in June 2015. For comparison, recall that Section 2.3 estimates that the debt associated with shadow accounts peaked at around 1-1.4 trillion Yuan, implying that our sample covers approximately 5% of the shadow-financed margin system.

As discussed previously, a key advantage of these two datasets is that we observe the assets and debt of each margin account, and hence its leverage on each trading day.[24] 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

[24] We observe end-of-day debt levels for all brokerage-financed margin accounts and about half of shadow-financed margin accounts. For the remaining shadow-financed margin accounts, we infer daily debt levels from their initial debt and subsequent cash flows between these shadow "child" accounts and their associated lending "mother" accounts. See Appendix A for details.

margin accounts (we are among the first to analyze detailed shadow-financed margin trading data), we can verify the representativeness of our brokerage sample. We find that the cross-sectional correlation in trading volume between our brokerage sample and the entire market is about 94%, suggesting the high representativeness of our brokerage sample.[25] In addition to the two proprietary account-level datasets, we obtain daily closing prices, trading volume, stock returns and other stock characteristics from the WIND database, which is widely regarded as the leading vendor for Chinese market data.

3.2 Leverage

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

$$Lev_{jt} = \frac{total\,assets_{jt}}{equity_{jt}}. \tag{1}$$

$Total\,assets_{jt}$ is the total market value of assets held by account j at the start of day t, including stock and cash holdings in Yuan value. $Equity_{jt}$ is equity value held by account j at the start of day t, equal to total assets minus total debt. Under this definition, an account with zero debt has leverage equal to 1.

As explained previously, the Pingcang Line is the maximum leverage the investor can hold before control of the account is transferred to the creditor (either the brokerage firm or the mother account). When leverage nears the Pingcang Line, the investor will receive a margin call, requiring her to either add more equity or liquidate her portfolio holdings to repay the debt. If the investor does not lower the account leverage after receiving a margin call, her account will be taken over by the creditor. The creditor then has discretion over all the trading decisions of the account.[26] To reduce the influence of these outliers, we cap leverage 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 for the brokerage- and shadow-

[25] For each trading day, we calculate the cross-sectional correlation in each stock's trading volume between the brokerage sample and the entire market; we then average across all trading days from May to July in 2015.

[26] Although the creditor generally liquidates stock holdings aggressively for debt repayment after gaining control, the creditor may be unable to sell due to daily 10% price limits or trading suspensions, leading to cases in which the account leverage increases far beyond the Pingcang Line. More specifically, stock prices may continue to drop by -10% every day before the sell orders can be executed (simply because there are no buyers at these price limits). There were also trading suspensions for many stocks during our sample period. In these situations, the market prices of these stocks are "frozen," leaving the leverage of the holding account unchanged. We exclude these latter observations with trading suspensions in identifying fire sale accounts in Section 4.1.

financed margin account samples, together with the SSE composite index, which is widely used as the representative market index in China. By weighting each account's leverage by equity in each account, the resulting average leverage is equal to total brokerage- or shadow-financed margin account assets scaled by total brokerage- or shadow-financed margin account equity, respectively. We observe that during the three-month period from May to July 2015, the leverage of shadow accounts fluctuates more dramatically than that of brokerage accounts. But the figure does not imply that brokerage leverage did not move; the correlation between these two leverage series is 91%. Further, there is a strong negative correlation between both leverage series and the SSE index (-84% for shadow and -68% for brokerage). When the stock index began to plummet in the middle of June, shadow leverage grew and hit its peak at around July 10th, when SSE index reached its lowest point. Overall, Panel A of Figure 2 shows that leverage displays significant counter-cyclical trends and across-account-type heterogeneity.[27]

We can also contrast the equity-weighted average level of leverage (shown in the previous figure) with the asset-weighted average level of leverage in the market. Highly leveraged accounts, by definition, have very little equity but can control a substantial amount of assets. Panel B of Figure 2 shows that, relative to the equity-weighted average, asset-weighted levels of leverage were much higher throughout our sample period and sharply increased toward a high of almost 7-to-1 when the market crashed. This contrast illustrates the fact that highly leveraged accounts with very little equity controlled a growing portion of market assets during the market crash.

3.3 Distance-to-Margin-Call (DMC)

Our analysis will be based on an account-date-level measure that captures the fire-sale risk of each margin-financed account at the start of each trading day. In the spirit of the Distance-to-Default measure in the Merton (1974) credit risk model, we calculate the size of the negative shock to the asset value of the stock portfolio held by each account that would be enough to push the account leverage to its Pingcang Line and trigger the control shift from margin investors to creditors

[27] There are two forces that drives the dynamics of leverage when asset prices fluctuate. The first is the passive valuation effect, which drives leverage up when asset prices fall, by the definition of leverage (assets/(assets-debt)); this leads leverage to be counter-cyclical (e.g., He and Krishnamurthy (2013); Brunnermeier and Sannikov (2014)). The second is the active deleveraging effect, in which investors respond to the negative fundamental shock by selling more assets, which contributes to pro-cyclical leverage. Clearly, 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 (2013)). He et al. (2017) discuss these two forces in various asset pricing models in detail, and explains why the first valuation effect often dominates in general equilibrium and hence counter-cyclical leverage ensues. In our sample, the first valuation effect is empirically stronger, which explains the counter-cyclical leverage pattern in Panel A of Figure 2.

(brokerage firms or mother accounts).

Specifically, we first calculate σ^A_{jt}, which is the volatility of the stock portfolio currently held in the account j at date t.[28] For each account-date observation with total asset value A_{jt}, equity value E_{jt}, and Pingcang Line $\overline{Lev_j}$, we then define the account's Distance-to-Margin-Call, denoted by Z, such that

$$\frac{A_{jt} - A_{jt}\sigma^A_{jt}Z}{E_{jt} - A_{jt}\sigma^A_{jt}Z} = \overline{Lev_j}. \tag{2}$$

In words, the account's Distance-to-Margin-Call (DMC) equals the number of standard deviations of downward movements in asset values (of the assets currently held in the account's portfolio) necessary to push the current level of leverage up to its Pingcang Line. The Pingcang Line never changes over the life of account. Hence $\overline{Lev_j}$ has no date-t subscript, and an account's DMC varies over time due to changes in its leverage and asset volatility.

From Eq. (2), we can calculate Z_{jt} as an explicit function of current leverage $Lev_{jt} = A_{jt}/E_{jt}$, Pingcang Line $\overline{Lev_j}$, and asset volatility σ^A_{jt}:

$$Z_{jt} = \underbrace{\frac{\overline{Lev_j} - Lev_{jt}}{\overline{Lev_j} - 1}}_{\text{Leverage-to-Pingcang}} \cdot \underbrace{\frac{1}{\sigma^A_{jt}}}_{\text{Volatility}} \cdot \underbrace{\frac{1}{Lev_{jt}}}_{\text{Amplification}}. \tag{3}$$

We further define "Leverage-to-Pingcang" LP_{jt} as

$$LP_{jt} \equiv \frac{\overline{Lev_j} - Lev_{jt}}{\overline{Lev_j} - 1}. \tag{4}$$

The DMC measure Z depends on the account's Leverage-to-Pingcang (the first term), the volatility of the asset holdings (the second term), and finally the amplification due to the account's current leverage (the third term). An account has a low DMC and hence is more likely to receive a margin call, if this account has a lower Leverage-to-Pingcang, greater asset volatility σ^A_{jt}, or higher leverage.

For account-days with no debt (so leverage is 1), we let Z_{jt} take on the value of an arbitrary large number (100); this treatment does not affect our analysis because we only use bins for Z_{jt} in our regressions. For any account-day observation with strictly positive leverage but below the Pingcang Line, $Z_{jt} > 0$, and a smaller Z implies a greater risk of the account being taken over. We also observe some accounts with leverage exceeding their respective Pingcang Lines, i.e., $Lev_{jt} > \overline{Lev_j}$ so $Z_{jt} < 0$. As explained in Section 3.2, these accounts have been taken over by creditors who may

[28] We calculate σ^A_{jt} for account j at date t based on the account holdings and estimated covariance matrix of these holdings. The covariance matrix is estimated using data from 5/1/2014 to 4/30/2015.

be unable to sell due to price limits and trading suspensions.

Figure 3 shows the distribution of DMC for each day, pooling together the brokerage and shadow samples; for ease of illustration, we plot the log of DMC, i.e., $\ln Z$. A key advantage of our analysis is that we can exploit the within-day heterogeneity in DMC across leveraged margin accounts. We observe a qualitatively similar pattern for the severity of leverage constraints: the upper percentile lines (50th and 80th) remain relatively flat throughout the sample period, whereas the 10th and 20th percentile lines dropped dramatically when the market index plummeted.

3.4 Summary Statistics

Table 1 reports summary statistics for our data sample. We separately report statistics for observations at the account-day, account-stock-day, and stock-day levels, where each day is a trading day. In addition, we report statistics separately for the brokerage- and shadow-financed margin account samples. Consistent with Panel A of Figure 2, we find average leverage in shadow accounts is more than four times larger than that in brokerage accounts. Shadow accounts also display substantially greater dispersion in leverage, with a standard deviation of 12.8 compared to a standard deviation of 0.5 for brokerage accounts.

In terms of of leverage constraints, the Pingcang Lines of shadow accounts are, on average, three times larger than the Pingcang Line of 4.3 that applies to all brokerage accounts. However, shadow accounts are also more likely to face leverage constraints despite their higher leverage limits. This point is evident from the difference in DMCs across the two margin-financed accounts: on average, the DMC of shadow accounts are about one-fourth of that of brokerage accounts.

We also use data from non-margin brokerage accounts as a benchmark for the trading activity of unlevered accounts. These accounts have zero debt and hence their leverage is equal to 1. While these accounts are part of our brokerage dataset, they are not included when we refer to "brokerage accounts" which always refer to brokerage-financed margin accounts.

4 Empirical Results

In this section, we empirically test how account-level leverage relates to selling pressure, fire sales, and asset prices. We begin by presenting analysis that pools the brokerage- and shadow-financed margin account samples. In later analysis, we will show that the main effects are driven by the relatively small pool of shadow-financed margin accounts that faced severe leverage constraints.

4.1 Account-Stock-Level Evidence: Leverage-Induced Fire Sales

We expect that the selling intensity of each trading account increases as its Distance-to-Margin-Call nears zero. A general feature of a portfolio choice problem with financial constraints is that forward-looking agents who are averse to losing control of their trading accounts will start selling their risky holdings in a precautionary way before hitting the leverage constraint. Margin investors may be averse to hitting the Pingcang Line because creditors will sell stocks aggressively to recover their debt claims, ignoring execution costs and without regard to potential temporary price declines. For a more detailed explanation, see footnote 32. As Z approaches zero, the investor's risk of losing control of the account increases, so we expect net selling to increase.

4.1.1 Selling Intensity

We first show that accounts with tighter leverage constraints, proxied by lower Distance-to-Margin-Call (DMC) Z_{jt} defined in Eq. (3) as of the start of each trading day, tend to sell more of their holdings over the course of the day. We sort Z_{jt} in decreasing order into 10 bins (one bin for $Z > 20$, two equally spaced bins for $Z \in (10, 20]$ and $Z \in (5, 10]$, and five equally spaced bins for $Z \in [0, 5]$) indexed by k, and construct dummy variables $I^j_{kt} = 1$ if Z_{jt} falls in the k^{th} bin. We also create two additional bins: bin 0 for unlevered accounts, and bin 11 for accounts with $Z_{jt} < 0$, which occurs if Lev_{jt} exceeds $\overline{Lev_j}$.

We then examine how the account DMC at the beginning of each day t relates to investor selling during that day. We estimate the following regression

$$\delta^j_{it} = \sum_{k=1}^{11} \lambda_k I^j_{kt} + \nu_{it} + \alpha_j + \varepsilon^j_{it}, \tag{5}$$

where δ^j_{it} is account j's net selling of stock i, defined as

$$\delta^j_{it} \equiv \frac{\text{net shares sold of stock } i \text{ by account } j \text{ during day } t}{\text{shares of stock } i \text{ held by account } j \text{ at the beginning of day } t}.$$

Because we are interested in selling behavior, the sample is restricted to stocks held by account j at the start of day t.[29] The sample is also restricted to stock-days during which the stock did not experience a trading suspension (note, this differs from the incidence of hitting the stock's daily

[29]Net buying of stock i by account j on date t results in negative values for δ^j_{it}, and the value is unbounded since some accounts may purchase stock i without much holding of stock i to start with. To avoid these outliers, we truncate the observations from below by -1.2. Results are insensitive to this treatment.

price limit under which trading is still allowed subject to a price limit). We regress net selling δ^j_{it} on dummy variables for each bin representing different DMCs. The omitted category is bin 0, representing unlevered brokerage accounts (which include all non-margin accounts and margin accounts that hold zero debt).

The main coefficients of interest are the selling intensities λ_k's, which measure the difference in selling intensity within each bin relative to the omitted category of unlevered accounts. It is worth emphasizing that Eq. (5) includes stock-date fixed effects ν_{it} and account fixed effects α_j. The stock-date fixed effects control for the possibility that all accounts in our sample may be more likely to sell a stock on a particular day; essentially, we compare the selling intensities for the same stock on the same day but sitting in accounts with different DMCs. The account fixed effects capture the account-specific unobservable effect–e.g., some accounts may be more likely to sell than others on average during our sample period.

The theory in Brunnermeier and Pedersen (2009), Geanakoplos (2010), and Garleanu and Pedersen (2011) implies that closeness to margin calls triggers net selling by leveraged accounts. As a result, we expect the selling intensity λ_k to increase with k, i.e., a higher selling intensity for accounts with lower DMCs, in regression (5). Our empirical results strongly support this theoretical prediction, as shown in Figure 4 which plots selling intensity λ_k for each bin representing DMC. The regression analogue for the figure is presented in Column 1 of Table 2. Relative to unlevered accounts, accounts in bin 11 with $Z < 0$ (these are accounts that have hit the leverage constraint and have been taken over by lenders) increase net selling by 0.19. This additional selling intensity of 0.19 is equivalent to 60% of a standard deviation in the level of net selling activity across accounts. Further, these coefficients may underestimate the extent to which investors desire to sell, as we include observations corresponding to stocks with partially limited daily trading due to the daily 10-percent rule.

Fire Sale Accounts In Figure 4, λ_k is close to zero for accounts that are far away from margin calls (Z is large), and increases sharply when the DMC edges toward 3. In other words, for the same stock on the same day, investors begin to intensify their selling (by selling an extra 6.4% of initial asset holdings relative to unlevered accounts) when a two-to-three standard deviation return movement would lead to loss of control of their accounts. For this reason, from now on, we refer to accounts with $Z \leq 3$ as "fire sale accounts." These accounts are significantly more likely to face margin calls and to contribute to fire sales of assets. In later tests, we also show that our results are not sensitive to the exact cutoff of $Z = 3$.

4.1.2 Asymmetry with Respect to Market Conditions

One important prediction of models with leverage-financed agents is downward leverage spirals (e.g., Brunnermeier and Pedersen (2009)). That is, the magnitude of leverage-induced selling should vary asymmetrically with market downturns and upturns. Asymmetric behavior with respect to market performance has been documented by Hameed et al. (2010) and Tookes and Kahraman (2016) in various related contexts.

The theory predicts that precautionary motives should lead investors that are close to receiving margin calls to exhibit high selling intensity, even when the aggregate market does well. However, conditional on a given DMC at the start of day t, leverage constraints will tighten further on average if the market return over day t is negative. Thus, we expect that the relation between DMC and selling intensity will be stronger if the market return on that day is negative.

Figure 5 and Appendix Table B.1 show how DMC at the start of day t affects selling intensity, conditional on whether the market return is positive or negative on day t. Consistent with the predictions above, we find that lower DMC leads to higher selling intensity even when market returns are positive; but the relation between DMC and net selling is two to three times stronger on days when the market is down. These results underscore how leverage-induced fire sales in specific stocks feed into and are fed by broad market crashes. As more margin accounts face leverage constraints, investors will seek to deleverage their holdings, which will contribute to a market decline. As the market declines, leverage constraints tighten further, causing investors to intensify their selling activities, conditional on each level of DMC.

4.1.3 Leverage and Leverage-to-Pingcang

Recall that we construct the DMC measure as a proxy for the risk of an account being taken over by the creditor. This risk measure depends on the account leverage, how close the leverage is to the Pingcang Line, and the asset volatility of its holdings. Eq. (3) essentially combines these three inputs in a particular structural way. Do our fire sale results hold without imposing this structure?

For ease of illustration, we focus on two terms in Eq. (3): leverage and Leverage-to-Pingcang. Focusing on these two measures also has the advantage of shedding light on the role of leverage versus leverage constraints (represented by the Pingcang Line), which we discuss further in the next subsection.

Following the format of regression (5), in Table 3 we regress net selling on bins for Leverage-to-Pingcang LP_{jt} defined in Eq. (4), five bins for the account's level of leverage, and interactions between the leverage bins and an indicator for accounts with $LP_{jt} \leq 0.4$ (we choose 0.4 because selling intensity increases sharply after this cutoff); as before, stock-date fixed effects and account fixed effects are included. We focus this analysis on shadow-financed margin accounts only. This is because Pingcang Lines vary across accounts in the shadow sample, allowing us to separately identify the effects of Leverage-to-Pingcang, leverage, and potential interactions. In contrast, the brokerage sample has the same Pingcang Line across accounts, so there is a one-to-one mapping between leverage and Leverage-to-Pingcang.

First, we find that Leverage-to-Pingcang, as a proxy for the leverage constraint, predicts higher selling intensity, after controlling for leverage. Moreover, the coefficients for the interaction between leverage bins and the leverage constraint (the indicator for accounts with $LP \leq 0.4$) are generally increasing in leverage. This positive interaction term lends support to the theoretical reasoning underlying the construction of the DMC in Eq. (3).[30]

4.1.4 Economic Mechanisms

This section investigates complementary mechanisms for the negative empirical relation between DMC and account selling intensity in Figure 4. It is worth emphasizing again that, since we control for stock-date and account fixed effects in our baseline specification, this strong negative relation cannot be explained by any mechanisms that only varies at the stock-date or account level.

Leverage and/or Leverage Constraint? We define the negative relation between DMC and net selling as leverage-induced fire sales. These fire sales can result from two related forces. First, leverage constraints could lead to both forced sales when control shifts from investors to creditors once leverage exceeds the Pingcang Line, as well as precautionary sales in which investors delever to avoid hitting the Pingcang Line. Second, leverage itself, even in the absence of financing constraints, may lead risk-averse investors to sell risky stocks for rebalancing purposes (e.g., Merton (1971)). Because the reciprocal of account leverage enters the DMC measure in Eq. (3), this simple leverage-based rebalancing force in Merton (1971) can also contribute to the negative relation between selling

[30]While very high leverage predicts increased net selling, the relation between leverage and net selling seems to be reversed for the range with low leverage. This empirical pattern is consistent with the view that investors choose to take on more leverage when they are feeling more bullish and/or speculative and therefore are more likely to buy rather than sell assets, holding leverage constraints (Leverage-to-Pingcang) constant. However, as leverage constraints begin to bind, investors become more likely to sell assets if the level of leverage is also high.

intensity and DMC documented in Figure 4. Note, a handful of general equilibrium asset pricing papers, such as Kyle and Xiong (2001) and He and Krishnamurthy (2013), have shown that leverage itself can play an important role in downturns in financial markets without leverage constraints.

In our sample, we can "rule in" the role of leverage constraints by looking at the net selling activity of accounts with negative DMC (i.e., $Z < 0$), which have been taken over by creditors and are engaged in forced sales.[31] Once the creditor gains the control over the trading account, he generally dumps the stock holdings as soon as possible (subject to daily trading limits) to recover his debt claims, ignoring any price impact or execution cost triggered by his aggressive selling.[32] In Section 4.3, we also show that our results are robust to the more conservative treatment in which we only classify account-date observations with $Z < 0$ as fire sale accounts.

We can further isolate the role of leverage constraints from leverage for accounts in which the investor remains in control (accounts with $Z > 0$). In other words, we can distinguish precautionary sales due to fear of hitting a leverage constraint from a simple deleveraging motive. First, Section 4.1.3 takes advantage of the fact that shadow accounts vary in their Leverage-to-Pingcang, holding the level of leverage constant; in that section, we showed that higher Leverage-to-Pingcang (a tighter leverage constraint) leads to higher selling intensity after controlling for account-level leverage. This evidence lends support to the leverage constraint mechanism.

However, a potential concern with the evidence in Section 4.1.3 is that the Pingcang Line is not randomly assigned to margin investors. There could be endogenous matching of creditors offering higher or lower Pingcang Lines with investors with heterogeneous risk aversion when opening their accounts, and this unobserved risk aversion could directly impact selling behavior as accounts near their leverage constraints. To address this concern, we use each account's "predicted" Pingcang Line, which is more likely to be an exogenous proxy for the account's leverage constraint. Instead

[31] Some margin accounts in our sample have leverage significantly above their Pingcang Lines. These observations likely correspond to cases in which creditors have gained control, but are unable to immediately sell their holdings due to daily price limits (the 10-percent-rule). Creditors can sell the stock holdings the next day (within the $\pm10\%$ return range), and can also exercise discretion in terms of whether and what to sell.

[32] While a creditor will generally prefer to sell aggressively upon gaining control over a trading account, this intuition may not hold in extreme cases. Suppose that the creditor has a debt claim D over the stock held by the account. In the context of fire sales, it is important to distinguish between the market value A and the (immediate) post-sale price $A - \Delta$, where Δ captures the price impact of immediate selling. For example, suppose the Pingcang Line equals 10, a common value in our shadow account sample. When leverage just hits 10 (implying that $A/E = 10$, so $D = 0.9 \cdot A$), the creditor who just gained control is eager to sell the stock and willing to accept any price impact $\Delta < 0.1 \cdot A$. This is because the creditor only needs to recover $D = 0.9 \cdot A$ for his debt claim, and the loss due to price impact is borne by the investor (who holds an equity claim). This logic also implies that the creditor will become more cautious in selling if the account leverage rises further, say 20 (in this situation, the creditor is only willing to accept a price impact $\Delta < 0.05 \cdot A$). Hence, for the very small portion of our sample with leverage far above the Pingcang Line, selling should become less aggressive, even after the creditor gains control. This empirical prediction is supported in our data (available upon request).

of using each account's actual Pingcang Line (which could result from endogenous matching), we proxy for the account's leverage constraint using the average Pingcang Line for all accounts opened on the same day as the account in question. Variation in average Pingcang Lines over time are likely to be driven by aggregate funding conditions rather than individual preferences. As shown in Table 4 which reports the updated regression estimates using this proxy for leverage constraints, we find that higher Leverage-to-Predicted-Pingcang bins strongly predict net selling average controlling flexibly for the level of leverage. Consistent with a leverage constraints channel, the basic monotone pattern with respect to leverage constraints persists even after controlling for account-level leverage.

While the aforementioned tests rule in a leverage constraints channel, we do not rule out the existence of a leverage channel. The exact distinction between the two channels is less crucial for the purpose of understanding the role of leverage (margin) and associated fire sales during the Chinese stock market crash. Recall that we refer to the negative relation between selling intensity and DMC in Figure 4 as leverage-induced fire sales. This overall effect can be viewed as the combination of two economic forces: rebalancing due to leverage, and precautionary and forced sales due to the leverage constraint. Both forces are rooted in leverage. Because in later sections we are only interested in the implications of leverage taken by margin accounts and resulting sales as a whole, we leave the detailed quantitative distinction between the leverage effect and the leverage constraint effect for future, more structural-based, research.

Regulatory Shocks Another important economic force that could impact leverage-induced fire sales is regulatory shocks. We now investigate how the selling intensities of brokerage and shadow accounts differ in their responses to regulatory shocks that occurred before the onset of the market crash. As mentioned in Section 2.4, two regulatory tightening announcements were made which had the potential to trigger spikes in the selling intensities of shadow-financed margin accounts: the May 22 event, in which some brokerage firms were required to self-examine their provision of services toward shadow-financed margin accounts, and the June 12 event, in which the CSRC released a set of draft rules that would explicitly ban new shadow accounts.

For both events, we estimate λ_k's for the five trading days before and after the regulatory announcements, which were released after-hours on Fridays. The results are plotted in Figure 6, and detailed regression results are presented in Appendix Table B.2. We find that the two regulatory announcements led to small and inconsistent changes in the selling intensities for brokerage accounts.[33] In contrast, news of regulatory tightening significantly increased the selling intensities of shadow accounts within each DMC bin. The June 12 announcement, in particular, led to dramatically higher selling intensities for shadow accounts with DMC below 3. This evidence is consistent with the widely-held view that news of potential future regulatory tightening triggered fire sales by shadow accounts.

These event studies also help establish a causal link between leverage constraints and selling pressure from shadow accounts close to margin calls. The sharp increase in selling intensity by shadow accounts immediately following these regulatory announcements (and the concurrent muted reaction by brokerage margin investors) points to the working of leverage constraints because shadow account investors feared increased constraints due to regulatory oversight. As with the previous account-level evidence presented in Figure 4, the regressions for these event studies control for stock-date and account fixed effects, so the empirical patterns cannot be explained by the fact that low DMC shadow accounts held an unobservably different set of stocks or engaged in different selling behaviors on average during the event study sample period.

The Disposition Effect and Leverage: Stabilization vs. Amplification We also explore another, more behavioral, explanation. Margin accounts that have recently experienced poor account-level returns will tend to be accounts with low DMC. Poor account-level returns may directly lead investors to sell, if, for example, investors extrapolate and believe that poor past returns will persist. This channel is not fully accounted for by the stock-date and account fixed effects in Equation (5), because it operates within an account over time. In supplementary results, shown in Appendix Table B.3, we find a similar and slightly stronger relation between DMC and net selling after also controlling for account-level returns in the past ten days. This occurs because lower past account-level returns actually predicts lower, not higher, net selling, consistent with the well-known disposition effect in which investors tend to sell to realize gains and hold on to losers to avoid realizing losses.

It is interesting to note that this disposition effect tends to stabilize any negative fundamental shocks, because investors are reluctant to sell to realize losses. Thus, the disposition effect channel can partly offset the amplification effect due to leverage. These two effects coexist in the Chinese stock market, although we find that the latter leverage-amplification effect dominates during our sample period.

[33] There are very few brokerage account observations corresponding to the far right bins representing DMC close to zero. As a result, the estimated selling intensities for those bins are insignificantly different from zero.

4.2 Stock-Level Evidence: Fire Sale Exposure and Selling Pressure

Selling pressure occurs when more investors wish to sell a stock than can quickly be absorbed by investors on the other side, leading to short-term price declines and long-run reversals. We hypothesize that stocks that are disproportionately held by margin accounts that have high risk of hitting their Pingcang Lines, i.e., fire sale accounts with DMC $Z_{jt} \leq 3$, are more exposed to fire sale risk. To test this hypothesis, we define stock i's fire sale exposure (FSE) on day t as:

$$FSE_{it} = \frac{\text{total shares of stock } i \text{ held in fire sale accounts at the start of day } t}{\text{outstanding shares of stock } i \text{ on day } t}. \tag{6}$$

In the numerator, we only count the number of shares held by margin accounts that are classified as fire sale accounts as of the start of day t. Table 1 presents summary statistics of our FSE measure.

4.2.1 FSE and Actual Net Selling

In the following analysis, we purposely do not use the actual trading choices of fire sale accounts, as investors may exercise endogenous discretion in the choice of which stocks within their portfolios to sell. We instead look at the pricing patterns for stocks with high fire sale exposure (i.e., stocks that are disproportionately held by margin accounts with leverage close to their Pingcang Lines); see Edmans et al. (2012) for a similar treatment.

One necessary step of this approach is to check whether higher-FSE stocks indeed experience greater selling by fire sale accounts. To check this, we estimate the following regression to examine the effect of FSE on stock-level selling pressure:

$$\delta_{it} = \beta \cdot FSE_{it} + controls_{it} + s_i + \tau_t + \varepsilon_{it}. \tag{7}$$

Here, we construct the stock-level selling pressure from fire sale accounts, δ_{it}, by

$$\delta_{it} = \frac{\text{net shares of stock } i \text{ on day } t \text{ sold by fire sale accounts}}{\text{outstanding shares of stock } i \text{ on day } t}.$$

In regression (7), $controls_{it}$ is a vector of control variables including the stock's volatility and turnover in the past 60 days, market capitalization measured in $t-3$, and 10 variables for the stock's daily returns in the past 10 days. We also control the stock fixed effects s_i and date fixed effects τ_t.

Table 5 presents the regression results. Across all specifications, we find that fire sale exposure significantly increases stock-level selling pressure. The estimates in Column 4 of Panel A imply that a one standard deviation rise in FSE increases the selling pressure of each stock by 40% of a standard deviation. We also find that FSE_{it} can explain a substantial amount of the variation in our measure of selling pressure δ_{it}. A regression of selling pressure on FSE_{it} alone, with no other control variables, yields an R-squared of 15%. This R-squared is large relative to the R-squared of 23.5% obtained from a more saturated regression in which we also control for stock and date fixed effects, past returns, and a large set of other time-varying stock characteristics. Thus, FSE_{it} can explain a substantial percentage of the variation in selling pressure from highly-leveraged accounts, and controlling for additional stock characteristics only marginally adds to the explanatory power of the regression.

In Figure 7, we plot the net selling by fire sale accounts in our sample of margin accounts, as a percentage of total volume on each calendar day. The sample is restricted stocks in the top decile of FSE_{it}, calculated as of the start of each day. As expected, we find that average net selling by fire sale accounts is positive over time. Net selling by fire sale accounts also negatively covaries with the market index, consistent with the idea that poor market returns amplify selling pressure from fire sale accounts. Finally, the figure shows that fire sale accounts represent a disproportionately large percentage of trading volume relative to the amount of assets held within these accounts (shown later in Figure 10),[34] which motivates our next set of tests which examines the asset pricing implications of selling pressure from fire sale accounts.

4.2.2 Attributes of High-FSE Stocks

What types of stocks have high FSE in our data? Table 6 reports the results when we regress FSE on various stock characteristics. First, not surprisingly, stocks that experience negative past returns (in the past 10 days) are associated with higher FSE. Second, higher volatility, which can push the account closer to its Pingcang Line, also contributes to greater FSE; this is consistent with the prediction of Eq. (3). We also find that larger firms in terms of market capitalization tend to have lower FSE, although this relation reverses once we introduce stock and date fixed effects. This positive relation between market capitalization and FSE could occur because, holding the stock constant, growing stocks are heavily covered in the media and therefore more salient to margin traders. Finally, investors may be more willing to take highly-levered positions in more

[34]Our sample of margin accounts represents approximately 5% of the margin market, so the total net selling pressure from fire sale accounts is likely to be approximately twenty times larger (see Section 4.4 for details).

liquid stocks, explaining the finding that higher FSE stocks tend to have greater turnover.

These results suggest that fire sale exposure is not randomly assigned across stocks. In the next section, we will account for non-random assignment when we examine how fire sale exposure affects stock prices.

4.3 Stock-Level Evidence: Fire Sale Exposure and Stock Prices

In this section, we show how fire sale exposure affects stock prices. If there is insufficient liquidity in the market to absorb the selling pressure from margin accounts that are close to margin calls, fire sales should cause stock prices to decline in the short run. In the long run, prices should revert to fundamental value once liquidity returns to the market. Thus, we expect stocks with high FSE to underperform stocks with low FSE over the short-run and to revert to similar levels in the long-run, a pattern that is hard to reconcile with standard frictionless rational settings.

We present two empirical strategies to test this conjecture. For both empirical strategies, we impute stock returns for days in which the stock experienced an outright trading suspension using prices before and after, assuming equally-compounded daily returns during the suspension period. For days in which stocks experienced binding daily price limits of $\pm 10\%$, we use the actual return on that day.[35]

A potential concern with our tests of how FSE affects stock-level returns is that stocks with high FSE may decline in value during our sample period for fundamental reasons unrelated to fire sales. After all, FSE is not randomly assigned across stocks; as shown in the previous section, high FSE stocks tend to have negative past returns, higher volatility, and higher turnover. We address this concern in three ways. First, we directly control for each stock's past returns and observable characteristics (and exploit within-stock variation in FSE over time in the regression analysis). Second, we focus on documenting a long run reversal, which is consistent with a fire sale channel and inconsistent with a negative fundamental shock. The long run reversal is also difficult to reconcile with a standard frictionless rational model of asset prices. Third, we show that the relation between FSE and price drops is substantially stronger immediately following regulatory tightening announcements. These regulatory tightening announcements are unlikely to coincide exactly with negative stock fundamental shocks; rather the announcements likely changed investor expectations of future leverage constraints, which led to increased fire sales for high FSE stocks.

[35]In previous regression analysis in which we used past returns as a control variable, we computed returns using the same methodology.

Another potential concern is that our findings of a long-run return reversal for high FSE stocks may be dependent on a large-scale government bailout of Chinese financial markets that began in early July. Specifically, we will present evidence of a strong long-run reversal of high FSE stocks *relative* to low-FSE stocks. This pattern might be driven by the possibility that Chinese regulators knew of the details of the brokerage and shadow margin systems and therefore targeted the bailout at high FSE stocks. However, this conjecture contradicts most post-bailout narratives of the government response to the crisis, which characterize the government as being severely underinformed about the details of the shadow-financed margin system and lacking a coherent trading strategy (Bian et al. (2018a), Bian et al. (2018b)). Moreover, using stock-day-level government net purchasing data in July 2015, we can calculate the correlation between FSE and government purchases at various lags. We find that the correlation between government purchases and individual stock FSE is close to zero, and sometimes even negative. This evidence shows that, while the bailout may have helped stem the aggregate decline in the market, the government did not disproportionately purchase stocks with high fire sale exposure. Therefore, the government bailout cannot explain the cross-sectional evidence of a long-run return reversal of high FSE stocks relative to low FSE stocks.[36]

4.3.1 Double Sorts

We begin by exploring abnormal returns to a double-sorted long-short portfolio. On each trading day t, we sort all stocks held by fire sale accounts into four quartiles according to their return over the period $[t-10, t-1]$. Within each quartile, we then sort stocks into 10 bins according to their FSE at the start of each day t. For each quartile of previous period returns, we construct a long-short strategy that longs the bin with the highest FSE and shorts the bin with the lowest FSE.

In Figure 8, we plot the cumulative returns for this long-short strategy in event time, averaged across all calendar trading days t. For all four quartiles of past 10-day returns, we find a distinct U-shape for the cumulative abnormal returns of the long-short portfolio. The figures show that, controlling for past returns, stocks in the top decile of FSE underperform stocks in the bottom decile of FSE by approximately 5 percentage points within 10 to 15 trading days after the date in

[36] The government purchase data was shared with us for the purposes of conducting this test by Bian et al. (2018b). The government engaged in secondary market purchases on July 6-9, July 15-17, and July 28-31, 2015. For each stock, we compute the stock-day government purchase $GP_{i,t}$ as a fraction of the outstanding market cap, and calculate the correlation between $GP_{i,t}$ and $FSE_{i,t-h}$ at various lags h. The correlations are 4%, 1%, -0.5%, -2%, -2%, and 0.07% for $h = 0, 3, 5, 10, 20,$ and 40.

which FSE is measured. The difference in performance reverts toward zero within 30 to 40 trading days.

4.3.2 Regression Analysis

To better account for other factors that could lead to differential return patterns for high and low FSE stocks, we turn to regression analysis. We estimate the following regression:

$$CAR_{i,t+h} = \gamma_h \cdot FSE_{it} + controls_{it} + s_i + \tau_t + \varepsilon_{it}, \tag{8}$$

where $CAR_{i,t+h}$ is the cumulative abnormal return (relative to the CAPM with beta estimated using 2014 data) for stock i from day t to $t+h$. We control for stock and day fixed effects. We also control for each stock's return volatility and turnover over the past 60 trading days, market value in $t-3$, and cumulative and daily returns over the past 10 trading days. If FSE has a negative short-run effect on stock returns that reverts in the long run, we expect $\gamma_h < 0$ for small h and $\gamma_h = 0$ for large h.

Table 7 presents regression results for return windows $h = 1, 3, 5, 10, 20,$ and 40 trading days. We find that FSE measured at the start of trading day t leads to significant price declines in the first 10 trading days after day t, but the price declines revert toward zero by approximately 40 trading days after day t. In Appendix Table B.5, we repeat this exercise, but calculate FSE only using accounts with $Z < 0$, i.e,. accounts that are engaged in forced sales because control has transferred to the lender. We continue to find the same U-shaped pattern in which stocks with high fire sale exposure experience abnormal negative returns that reverse in the long run.

4.3.3 Regulatory Announcement Event Study

To better identify a causal effect of fire sales, we conduct an event study examining how the relation between FSE and stock returns changes after a regulatory tightening announcement. This event study helps address the concern that an omitted factor, such as bad fundamentals, may spuriously drive the negative relation between high FSE and returns. Recall that on June 12 (after hours on a Friday), the CSRC released draft rules that would ban new shadow-financed margin accounts. As shown earlier in Section 4.1.4, the regulatory announcement led to a sharp increase in selling intensity, especially by highly-leveraged shadow accounts. The regulatory tightening announcement is unlikely to coincide exactly with negative stock fundamental shocks; rather the announcement likely changed investor expectations of future leverage constraints, which led to increased fire sales for high FSE stocks.

In Table 8, we show the relation between FSE and returns separately for each of the two weeks prior to the announcement as well as for the week immediately after the announcement. We find that the relation is insignificantly different from zero before the announcement and significantly negative immediately after the announcement. Further, the negative effect of FSE on returns right after the announcement may be understated, because the daily -10% limit protected high FSE stocks from larger price declines. In Columns 7-9, we regress an indicator for whether a stock's -10% price limit was triggered on the stock's fire sale exposure. We find a small relation between the triggered price limit indicator and FSE prior to the regulatory announcement, and a very strong positive relation immediately after.

4.4 Brokerage- vs. Shadow-Financed Margin Accounts

As explained in Section 2, two types of leveraged margin accounts were active during the Chinese stock market crash of 2015. In short, brokerage-financed margin accounts were managed by certified brokerage firms, and were heavily regulated with lower maximum allowable leverage (lower Pingcang Lines) and lower leverage on average. Meanwhile, shadow-financed margin accounts that conducted trading and borrowing on web-based platforms were free from regulation, and had much higher Pingcang Lines and leverage.

Since the onset of the stock market crash in early June 2015, practitioners, the media, and regulators have alleged that shadow-financed margin accounts were the driving force behind the market collapse. However, this accusation has largely been untested using concrete evidence. Whether shadow accounts were more to blame than brokerage accounts is also not obvious. As we will discuss in Section 4.4.2, many estimates suggest that total market assets held within the regulated brokerage-financed system greatly exceeded that in the unregulated shadow-financed system. Furthermore, because brokerage accounts have a lower (and uniformly imposed) Pingcang Line, brokerage accounts may have been closer to their Pingcang Lines (and closer to leverage constraints), despite their lower average levels of leverage.

However, we show in Panel A of Table 1 that, in addition to having low absolute levels of leverage, brokerage margin accounts also maintained lower leverage as a fraction of the Pingcang Lines. Equivalently, shadow margin accounts have lower Distance-to-Margin-Calls, implying that shadow accounts are more likely to become fire sale accounts. With the aid of detailed account-level data, we investigate differences between shadow and brokerage margin accounts in detail in this subsection. Our findings shed light on the consequences of regulation (or lack thereof).

4.4.1 Selling Intensities for Brokerage and Shadow Accounts

In Section 4.1.1, we showed that accounts tend to sell more of their stock holdings when they are closer to their account-specific Pingcang Lines, and we classified fire sale accounts as those with DMC below the cutoff of 3 (i.e., $Z_{jt} \leq 3$ as in Eq. (4)). We now repeat the exercise separately for the brokerage- and shadow-finance margin account samples. The estimated selling intensities (λ_k's) for each account type are plotted in Figure 9 and the corresponding regression coefficients are presented in Table 2, Columns 2 and 3. We find that the estimated selling intensities decrease as DMC increases for both samples, consistent with the leverage-induced fire sales mechanism.

There are several features in Figure 9 worth discussing. First, for fire sale accounts with DMC below 3 but above zero, selling intensities conditional on a DMC bin are comparable across the two types of accounts, with slightly larger magnitudes for the shadow margin sample. The similarity in selling intensities within a DMC bin lends support to our DMC measure in Eq. (3) as a comprehensive measure of account-level risk capturing leverage-induced fire sales. We also observe that the selling intensity of brokerage accounts relative to shadow accounts rises dramatically once the accounts have reverted to creditor control ($Z < 0$). Although our data does not allow us to investigate this issue fully, one plausible explanation is that some creditors of shadow accounts may be wealthy individual investors who exercise discretionary selling once they gain control of defaulted shadow accounts. In contrast, lenders of brokerage accounts are brokerage firms who may have more stringent automated risk management systems.

4.4.2 Contribution of Brokerage and Shadow Accounts to Fire Sales

As discussed in Section 2, brokerage-financed margin accounts dominate their shadow peers in terms of asset size. This point is vividly shown in Figure 10, which plots the asset holdings over time for each account type. The relative asset sizes of the two account types shown in Panel A roughly reflect their relative asset holdings in the entire market.[37]

[37] 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 2.3 (about 1.2 trillion in its peak time) and the asset-to-debt ratio in the shadow account sample

However, Panel A in Figure 10 offers a misleading picture of how these two types of accounts relate to fire sales. Relative to shadow accounts, brokerage accounts are, on average, less leveraged and farther from their Pingcang Lines. In Panel B, we instead plot total assets held in fire sale accounts, i.e., accounts with $Z_{jt} \leq 3$. These fire sale accounts are much more likely to receive margin calls and to exhibit greater selling intensity, as shown earlier in Figure 4.

Once we focus on the asset holdings of fire sale accounts in Panel B, we see a quite different picture. In general, shadow accounts have more total assets held in fire sale accounts than do brokerage accounts. Before the week of June 24, 2015, the stock holdings in shadow fire sale accounts exceed assets in brokerage fire sale accounts by more than 10 to 1. It is not until the week of July 1, 2015, when the SSE index had dropped by about 30% from its peak, that the asset holdings of brokerage fire sale accounts increased to be approximately on par with those of shadow fire sale accounts.

Next, we show that shadow accounts matter more for fire sales and reversals, i.e., the U-shaped pattern in cumulative abnormal returns for high FSE stocks relative to low FSE stocks. We develop a a measure of Fire Sale Exposure FSE in (6) using data for each of the brokerage and shadow data samples separately. The relation between returns and FSE measured within each sample are reported in Panels B and C of Table 7. FSEs from both brokerage and shadow accounts cause prices of exposed stocks to decline and then revert within approximately 40 trading days. However, the magnitude of the dip is more than twice as large for FSE based on shadow accounts. Because the distribution of the FSE measure can differ across the brokerage and shadow samples, we also present results with standardized coefficients in Appendix Table B.6. We find that a one standard deviation change in FSE as measured in the shadow sample leads to a five-times larger dip in returns than a one standard deviation change in FSE as measured in the brokerage sample. Overall, the differences in magnitudes support the view that shadow trading played a relatively more important role in driving fire sales during the Chinese stock market crash in the summer of 2015.

5 Discussion, Extensions, and Robustness

In this section, we first discuss how shadow-financed margin system and fire sales played a role in the 2015 Chinese stock market crash. We then explore the interaction between leverage-induced fire

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%.

sales and regulated price limits, which is an interesting institutional feature of the Chinese stock market. Finally, we show that our findings are robust to alternative weighting schemes, cutoffs, sample splits, and imputation procedures.

5.1 Discussion: The Role of the Shadow-Financed Margin System and Fire Sales

We have demonstrated that shadow-financed margin accounts contributed more than brokerage accounts to the Chinese stock market crash in 2015. Panel B of Figure 10 suggests the following narrative for the evolution of the market crash. In the first half of 2015, shadow accounts maintained higher absolute leverage and higher leverage relative their Pingcang Lines. However, the potential selling pressure from these fire sale shadow accounts were absorbed by the continuous inflow of retail investors who opened new shadow accounts: in our data, the net inflow of funding from shadow accounts peaked at 8.7 trillion Yuan during the week of June 1, 2015.[38] The news about potential regulatory tightening for shadow-financing released on June 12, 2015 not only halted the inflow of new investors (the net inflow of funding dropped to 4.6 trillion Yuan) but also increased the selling by existing shadow accounts, causing the stock market index to fall. The market decline after June 17 triggered a leverage spiral, turning more and more shadow accounts into fire sale accounts (as shown in Panel B of Figure 10), whose selling further depressed stock prices. The beaten stock prices in late June 2015 pushed the leverage of brokerage-financed margin accounts closer to their Pingcang Lines. As shown in Panel B of Figure 10, brokerage fire sale account assets rose sharply around July 1, and their fire sales contributed to the continued market collapse in early July 2015. The leverage-induced fire sale spiral finally stemmed around July 6th, when the Chinese government started to intervene using large-scale market purchases.

By presenting a battery of empirical evidence, including analysis of account-level selling behavior, reactions to regulatory shocks, and the reversal of high-FSE stocks, this paper shows the existence of fire sales during the 2015 Chinese market crash. However, we emphasize that our evidence, which is primarily cross-sectional in nature coupled with event studies around regulatory tightening announcements, does not imply that fire sales caused the entire Chinese market crash in 2015. The existing literature suggests that the Chinese stock market was overvalued in mid-2015 due to unleashed margin credit starting in 2010 (Hansman et al., 2018). Presumably, the market in-

[38]The net inflow of funding is calculated as the asset holdings of newly opened shadow accounts minus the asset holdings of closed shadow accounts over a given period.

dex would have reverted to its fundamental level even without leverage-induced fire sales. Leverage likely shortened the correction phase, causing a rapid crash in the days immediately following a regulatory announcement aimed at curbing shadow-financed margin trading. Our findings parallel the common narratives concerning the US 1929 stock market crash (Schwert, 1989). While deleveraging is unlikely to be the ultimate cause of the large and persistent drop in the value of the US stock market in the years following 1929, many scholars believe that deleveraging contributed to the correction taking the form of dramatic and destabilizing single-day crashes.

5.2 Price Limits and Selling Intensity

During our sample period of May to July 2015, each individual stock was allowed to move a daily maximum of 10 percent from the previous closing level in either direction, before triggering a price limit, as explained in Section 2.4. These price limits were introduced with the goal of suppressing excessive trading and controlling market volatility. However, the price limits may have had the unintended consequence of exacerbating fire sales crashes in other stocks. As shown in Table 2, margin investors are significantly more likely to sell assets when their account-level leverage nears their Pingcang Line limits. We hypothesize that an investor seeking to deleverage may further intensify the selling of a particular stock if other stocks in her portfolio cannot be sold due to stock-specific price limits.

For each account-day, we define "price limit fraction" as the fractional value of account j's assets as of the start of day t that consist of stocks that hit price limits at some later point on day t. Price limit fraction measures the extent to which margin investors are constrained in their ability to sell a subset of their holdings. We then regress net selling at the account-stock-day level on the set of DMC bins defined earlier, the price limit fraction, and the interaction between the price limit fraction and the DMC bins. We restrict the regression sample to stocks that do not face trading suspensions or price limits on day t. The results for the full sample of brokerage and shadow margin accounts are reported in Table 9 Column 1. As expected, we find that accounts with lower DMC are significantly more likely to sell. Moreover, the interaction between DMC and price limit is significant and positive for all DMC bins, with greater magnitudes for lower bins corresponding to lower DMC. This is consistent with investors being more likely to sell any particular stock in their portfolio if other holdings cannot be sold due to government-regulated price limits, with the effect being larger for investors with stronger deleveraging motives (i.e., those with lower DMC).

We also structured the analysis to account for a key alternative explanation. Accounts with a higher level of "price limit fraction" are likely to be accounts that hold stocks that experience low returns over the course of day t. Poor returns are correlated with the probability that stocks hit price limits. Poor portfolio returns may also directly increase the probability that investors sell assets. To control for this alternative channel, all specifications in Table 9 control for each account's day t counterfactual returns assuming no stocks are bought or sold on day t, interacted with the set of DMC bins. As in the previous regressions examining net selling, we also control for stock-day and account fixed effects. Thus, our estimated effects cannot be explained by high selling due to poor portfolio returns or by mechanisms that vary only at the stock-day or account level. Instead, we find that deleveraging motives combined with price limits intensify the selling pressure for stocks that are not yet protected by price limits.

5.3 Other Robustness Checks

Appendix Table B.4 shows that the results in Table 7 are robust to the choice of $Z_{jt} \leq 3$ as the cutoff for margin accounts to be classified as fire sale accounts. Instead of calculating each stock's fire sale exposure as the fraction of shares held by fire sale accounts, we estimate fire sale exposure as the fraction of shares held in any margin account, with each account's holdings weighted by the corresponding selling intensities λ_k associated with the account's DMC at the start of each day. We find that this alternative λ_k-weighted measure of fire sale exposure predicts a similar U-shaped return pattern. As another robustness check, we adopt a conservative treatment that only classifies account-date observations with $Z < 0$ (these accounts have been taken over by creditors) as fire sale accounts; this amounts to setting $\lambda_{Z<0} = 1$ while all other $\lambda_k = 0$. The results are qualitatively similar, as shown in Appendix Table B.5.

Appendix Table B.6 presents standardized coefficients, as discussed earlier in Section 4.4, which allow for comparison of magnitudes across the brokerage and shadow samples. Finally, Appendix Table B.7 shows that our results are unlikely to be driven by the imputation of stock returns. Some stocks in our sample experienced trading suspensions for one or more trading days. In our baseline analysis, we impute the returns for days in which trading was suspended using the most recent traded prices before and after the suspension. In this robustness test, we exclude stock-day observations from the regression sample if the stock ever experiences a full day of suspended trading during the event period $[t, t + 40]$, and find a similar U-shaped pattern in returns.

6 Conclusion

Using unique account-level data for brokerage-financed and shadow-financed margin traders in the Chinese stock market, we study the role of deleveraging and fire sales in the Chinese stock market crash in the summer of 2015, during which the SSE index fell by more than 30%. As direct evidence for leverage-induced fire sales, we show that margin investors heavily sell their holdings when their account-level leverage edges toward their maximum leverage limits (the Pingcang Line), controlling for stock-date and account fixed effects. This selling pressure leads stocks that are disproportionately held by investors who are close to receiving margin calls to be exposed to fire sale risk, especially during periods when the market is in rapid decline. Consistent with this view, we show that stocks with greater fire sale risk exposure experience larger abnormal price declines and subsequent reversals, relative to stocks with lower fire sale risk.

We would like to highlight that the leveraged-induced 2015 Chinese stock market crash studied in this paper closely resembles the US stock market crash of 1929. According to Galbraith (2009), margin trading thrived in the period leading up to the 1929 crash, with outstanding margin credit rising from about 1 billion dollars in the beginning of 1920s to 17 billion dollars in the summer of 1929. Moreover, the US margin trading system in 1929 was very similar to China's shadow-financed margin system in 2015, in that both systems lacked market-wide regulations of initial margins and minimum margins (these regulations were later introduced by the Securities and Exchange Act of 1934 in the US). In response to the regulatory void, individual traders took on excessive leverage both in the US in 1929 and in China in 2015, leading to fire sale externalities (e.g., Lorenzoni (2008), Stein (2012), He and Kondor (2016), and Davila and Korinek (2017)). This view is consistent with another major finding of this paper: although regulated brokerage-financed margin accounts held a much larger fraction of market assets, unregulated shadow-financed margin accounts played a more significant role in the 2015 Chinese market crash.

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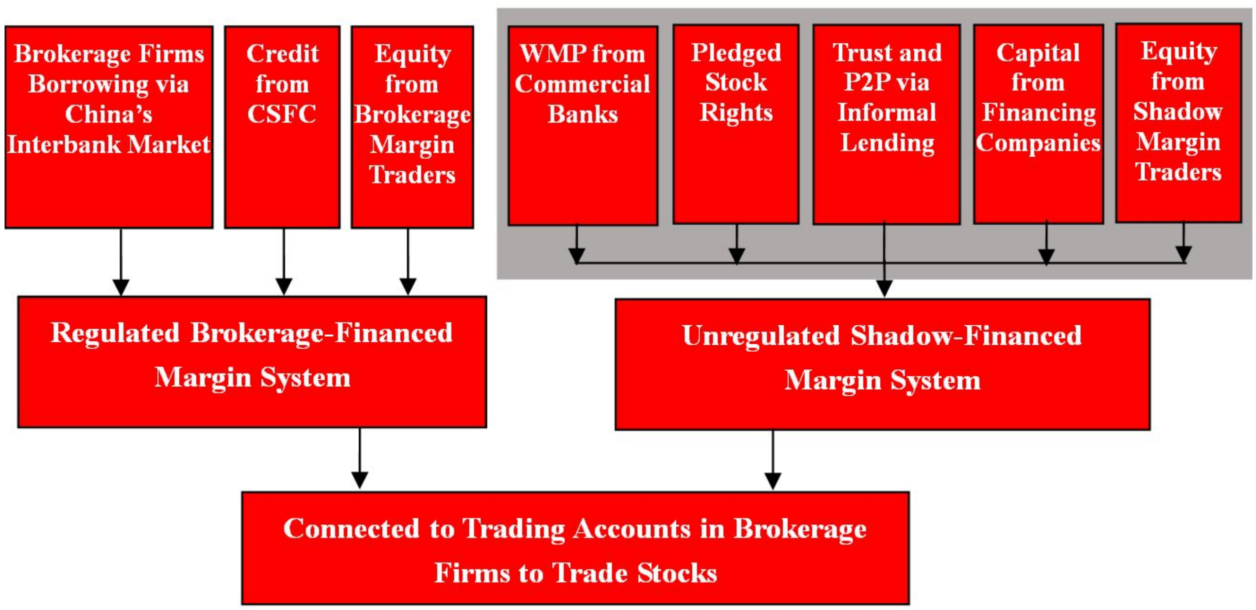
Figure 1
Structure and Funding Sources of Margin Systems in the Chinese Stock Market

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

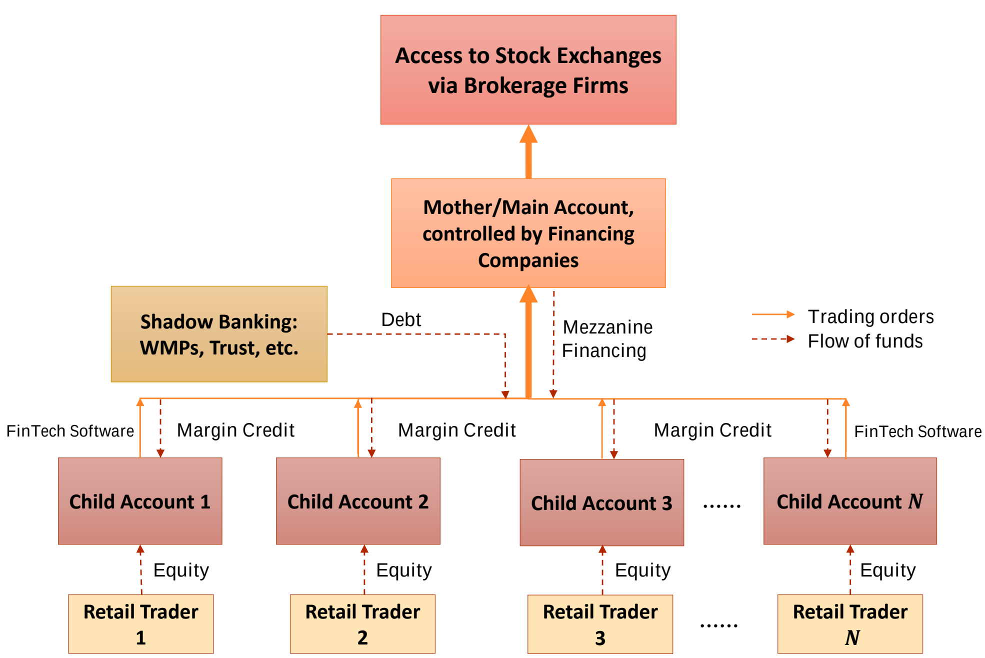
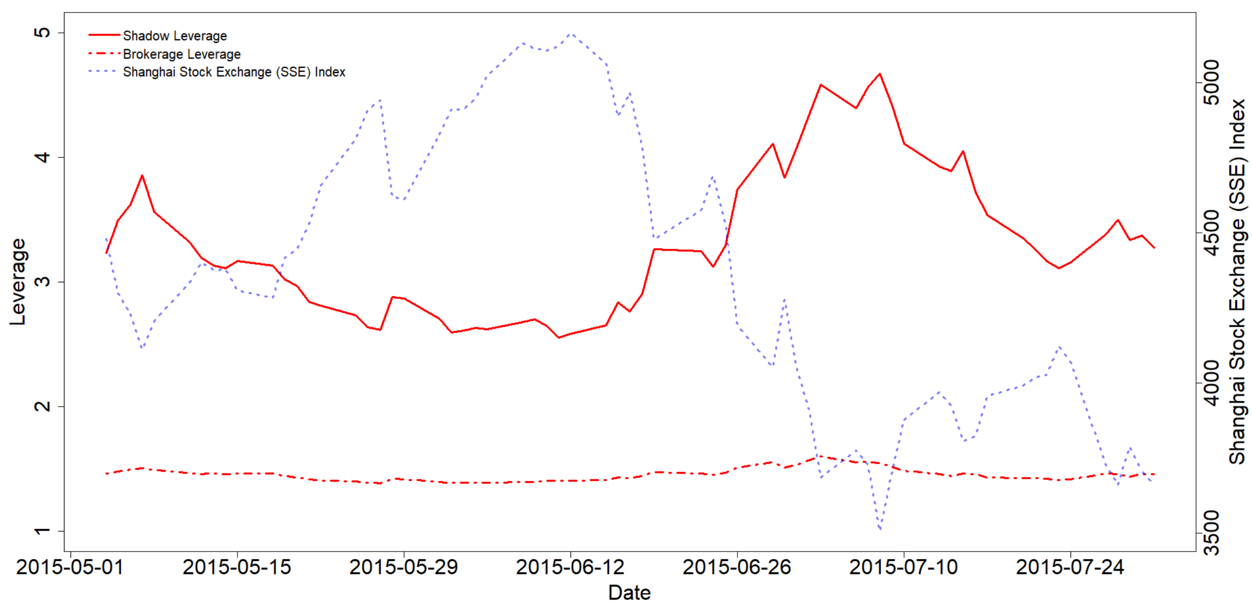


Figure 2
Leverage in Brokerage and Shadow Margin Accounts

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 average leverage for the combined sample of all brokerage and shadow margin accounts (the solid red line), and the equity-weighted average leverage for all margin accounts (the dashed-dotted red line), at the start of each day from May to July, 2015. To compute the averages, we weight each account's leverage by the assets or equity in each account.

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



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

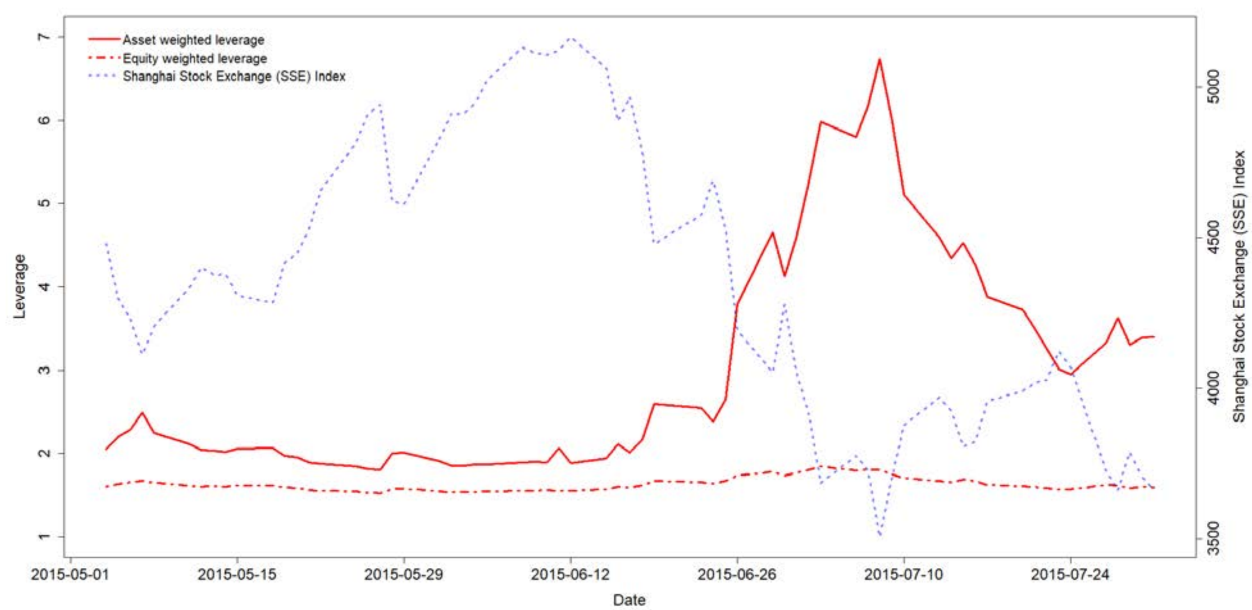


Figure 3

Distance-to-Margin-Call (DMC) Dispersion

This figure depicts the Shanghai Stock Exchange (SSE) composite index (the dashed blue line) and various percentiles of the log of the Distance-to-Margin-Call measure for each account at the start of each day. For each account at the start of each day, let $lev_{jt} = A_{jt}/E_{jt}$. Let σ_{jt}^{A} be the volatility of the assets currently held in the account (calculated as the weighted average of the annualized return volatilities of the stocks held in the account, measured using each asset's daily returns over the previous year 2014). We define the Distance-to-Margin-Call as the value Z such that $\frac{A_{jt}-A_{jt}\sigma_{jt}^{A}Z}{E_{jt}-A_{jt}\sigma_{jt}^{A}Z} = \overline{Lev}_j$. In other words, Z equals the number of standard deviations of downward movements in asset values necessary for the current level of leverage to meet the Pingcang Line; when Z drops below zero, the investor loses control of the account to the creditor because account level leverage has exceeded the account's Pingcang Line. We plot the 15th (solid red line), 20th (dashed-dotted red line), 50th (dashed red line), and 80th (dotted red line) percentiles of the full sample including both brokerage- and shadow-financed margin accounts, at the start of each day from May to July, 2015.

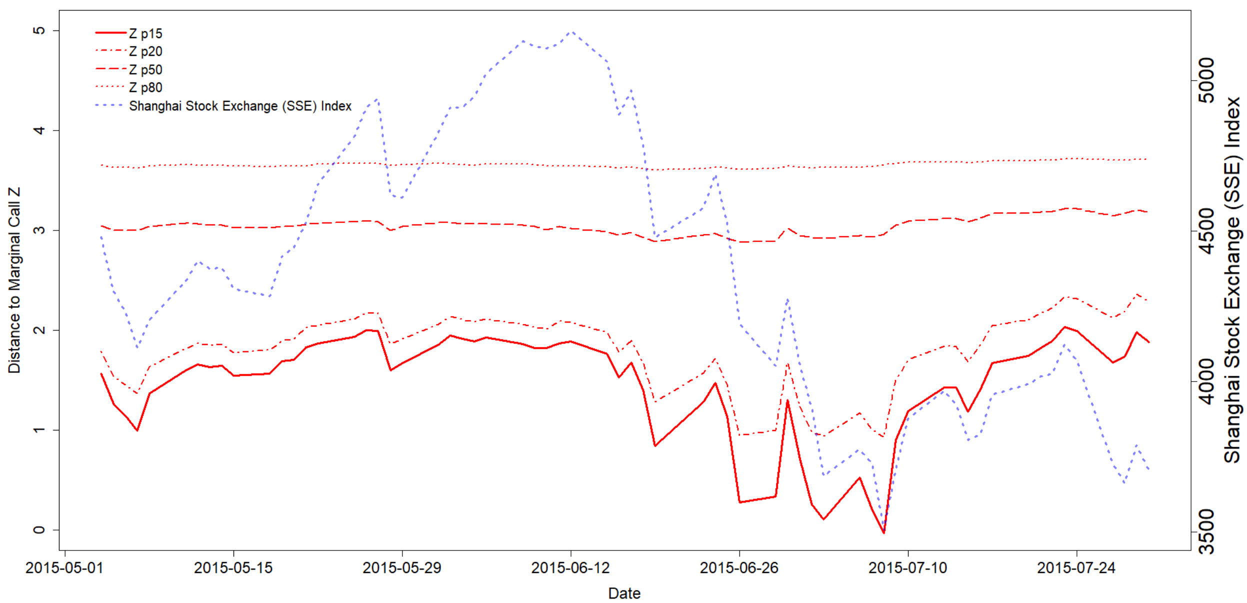


Figure 4
Distance-to-Margin-Call and Investor Selling Intensity

This figure plots the coefficients λ_k from the regression:

$$\delta_{it}^{j} = \sum_{k=1}^{11} \lambda_k I_{k,t-1}^{j} + \nu_{it} + \alpha_j + \varepsilon_{it}^{j},$$

where δ_{jt}^{j} is account j's net selling volume of stock i on day t, normalized by account j's initial holding of stock i at the beginning of day t. ν_{it} is the stock-date fixed effect and α_j is the account fixed effect. $I_{k,t-1}^{j}$ represents 10 bins for each account's Distance-to-Margin-Call, with higher bins corresponding to accounts that are closer to their leverage limit (the Pingcang Line). Accounts with leverage exceeding the Pingcang Line are assigned to bin 11. Unleveraged accounts are the omitted category. The sample includes all brokerage- and shadow-financed margin accounts, as well as brokerage non-margin accounts which aid in the estimation of the omitted category. The sample is restricted to stock-days in which a stock is not suspended from trading at any point during day t, and is also restricted to stocks i held by account j as of the start of day t. The time period is from May to July, 2015.

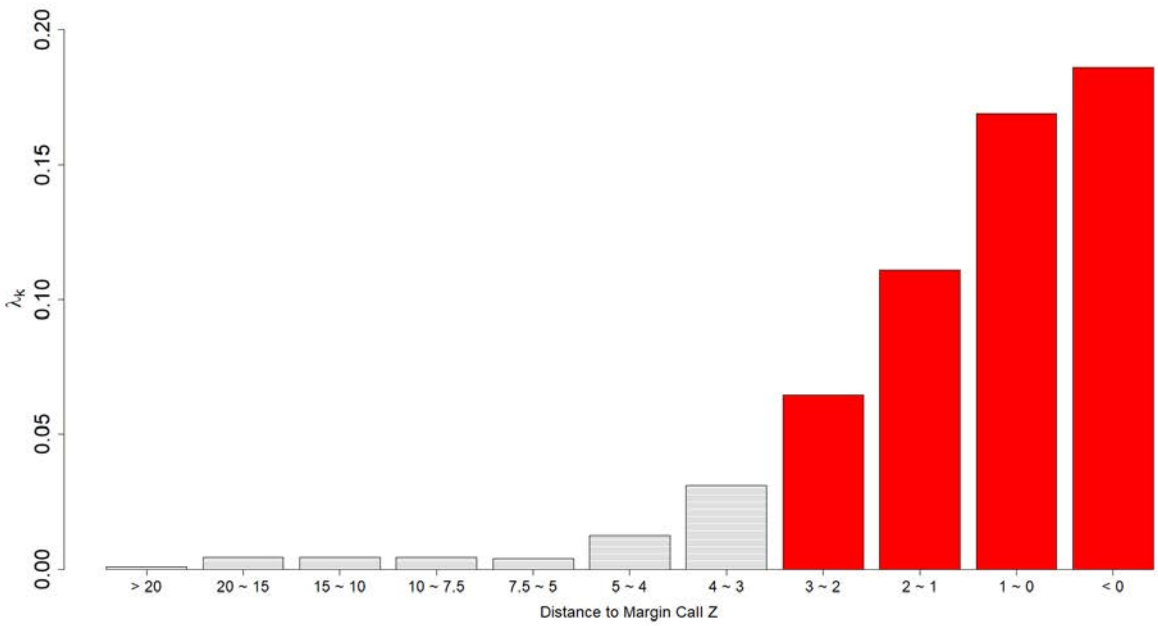


Figure 5
Distance-to-Margin-Call and Investor Selling Intensity: Market Returns

This figure plots the coefficients λ_k from the regression defined in Figure 4, estimated separately for the samples in which the market return on day t is positive and negative.

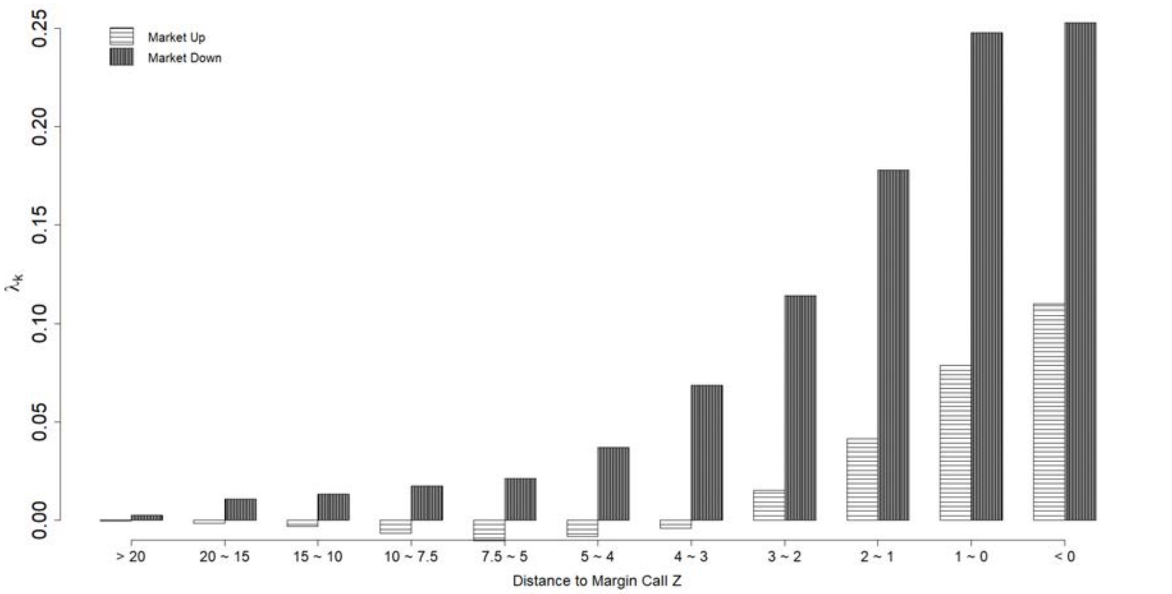


Figure 6
Regulatory Tightening

Regulatory tightening announcements occurred after hours on Friday May 22, 2015 and Friday June 12, 2015. This figure plots the coefficients λ_k from the regression defined in Figure 4, separately for the brokerage and shadow samples for the five trading days immediately before and after the announcements events. There are very few brokerage observations corresponding to the far right bins representing DMC close to zero if the left two panel; the λ_k's for those bins are insignificantly different from zero.

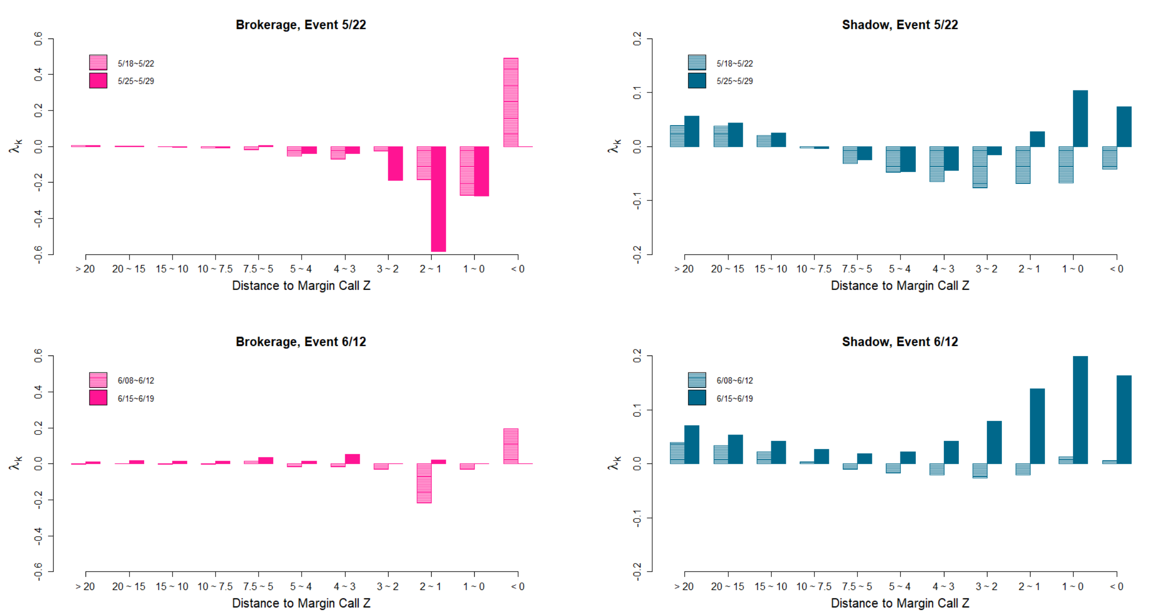


Figure 7
Net Selling by Fire Sale Accounts

This figure plots net selling of high fire sale exposure stocks by fire sale accounts as a percentage of total volume traded. To compute the series, we first restrict the sample to stocks in the top decile of fire sale exposure, calculated as of the start of each trading day. For each stock-day, we compute total net selling by fire sale accounts as a percentage of total trading volume for the same set of stocks on that day (in monetary units), and aggregate at the weekly level.

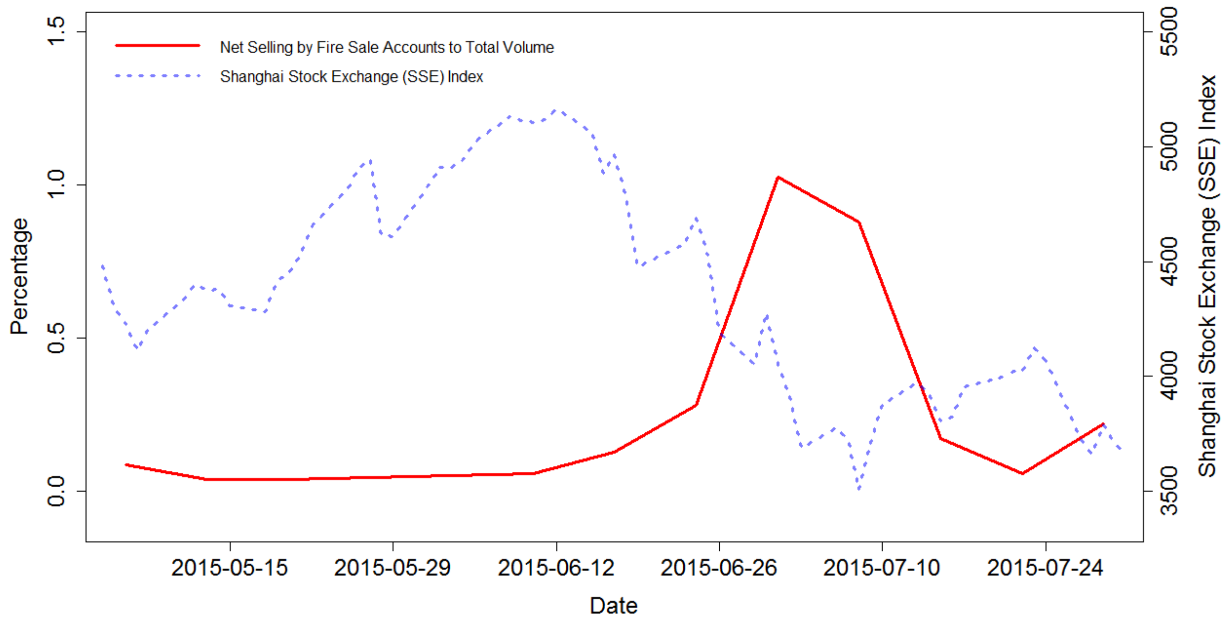


Figure 8
Returns Following Fire Sales: Long-Short Portfolio

This figure plots the average long-short portfolio cumulative abnormal return after double sorts based on each stock's previous period return and fire sale exposure (FSE). On each day t, we sort all stocks held by fire sale accounts into four quartiles according to their return over the period $[t-10, t-1]$. Within each quartile, we then sort stocks into 10 bins according to their FSE at the start of each day t. For each quartile of previous period returns, we construct a long-short strategy that longs the bin with the highest FSE and shorts the bin with the lowest FSE. The sample includes all stocks held by brokerage- and shadow-financed margin accounts. The time period is from May to July, 2015. The dotted lines represent 90% confidence intervals. Standard errors and confidence bands are estimated from a stock by event-day level regression using a sample restricted to the top and bottom deciles in terms of FSE at the start of day t and for the relevant return quartile over the period $[t-10, t-1]$. We regress cumulative returns on indicators for event dates t, t+1, ... , t+40 as well as the interaction between the event date indicators and an indicator for whether the observation is in the top decile for FSE. The graph plots the coefficients on the interaction terms, which represent the difference in average cumulative returns between the two decile portfolios for each event date. Standard errors are allowed to be double-clustered by calendar day and stock. The sample is restricted to stocks that do not experience suspended trading on day t.

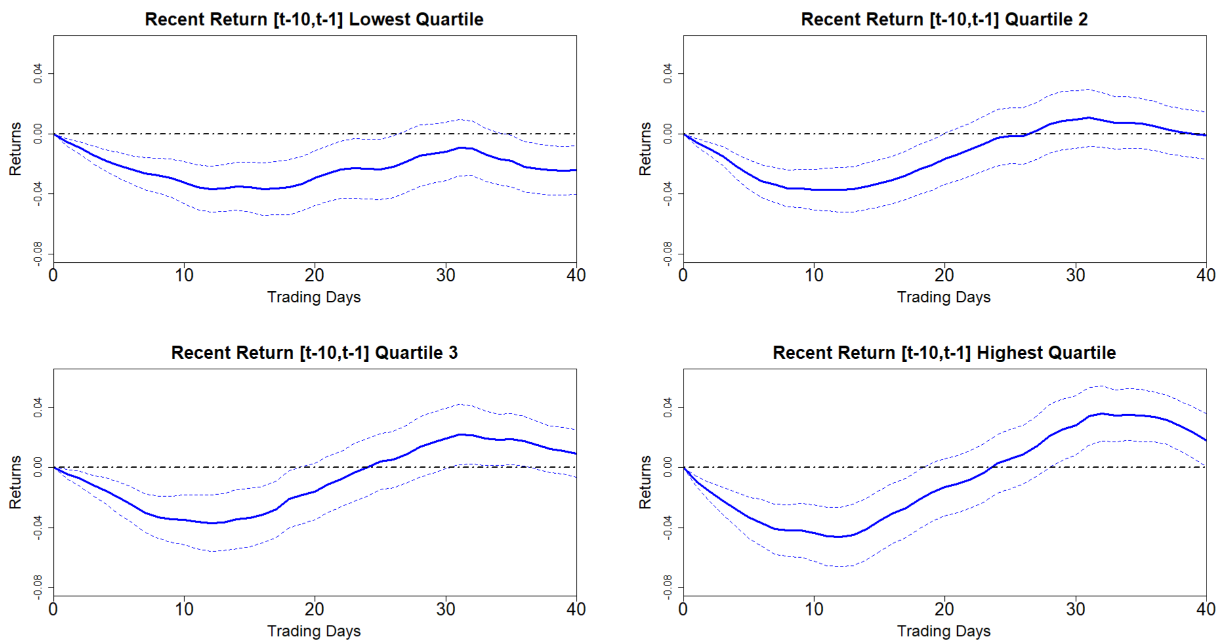


Figure 9
Distance-to-Margin-Call and Investor Selling Intensity: Brokerage and Shadow Accounts

This figure plots the coefficients λ_k from the regression defined in Figure 4, estimated separately for the brokerage- and shadow-financed margin account samples. The time period is from May to July, 2015.

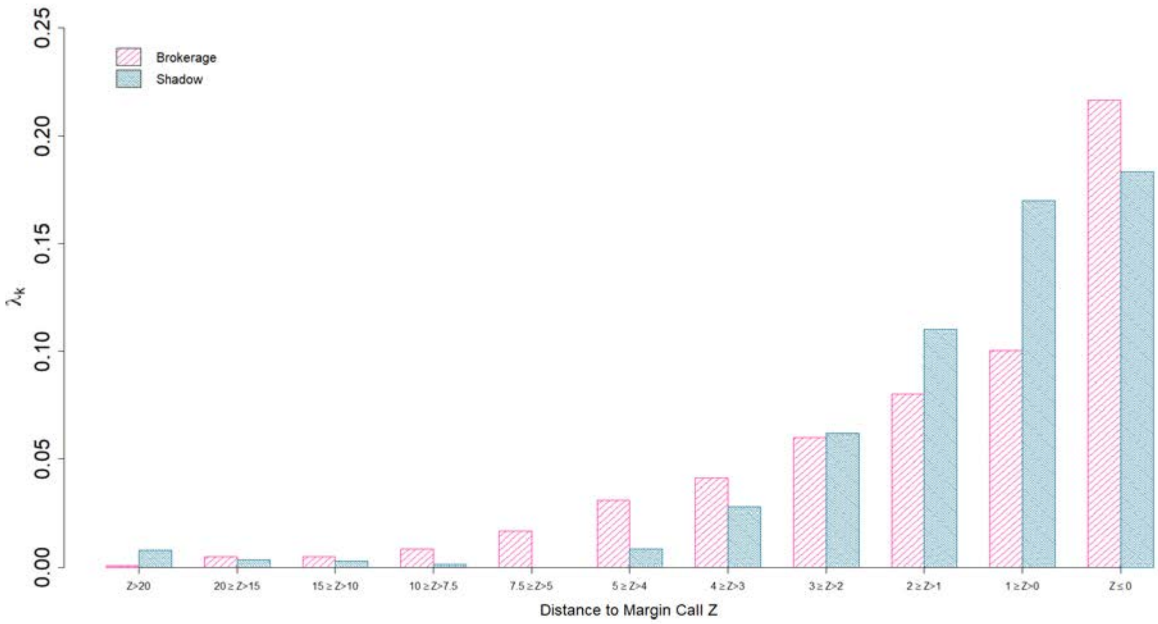


Figure 10
Market Capitalization of Brokerage and Shadow Accounts

Panel A shows the total market capitalization held in brokerage- and shadow-financed margin accounts over time. Panel B shows the total market capitalization held in fire sale accounts, i.e., accounts with Z less than 3. The solid black line depicts the Shanghai Stock Exchange (SSE) composite index.

Panel A: All Accounts

Panel B: Fire Sale Accounts

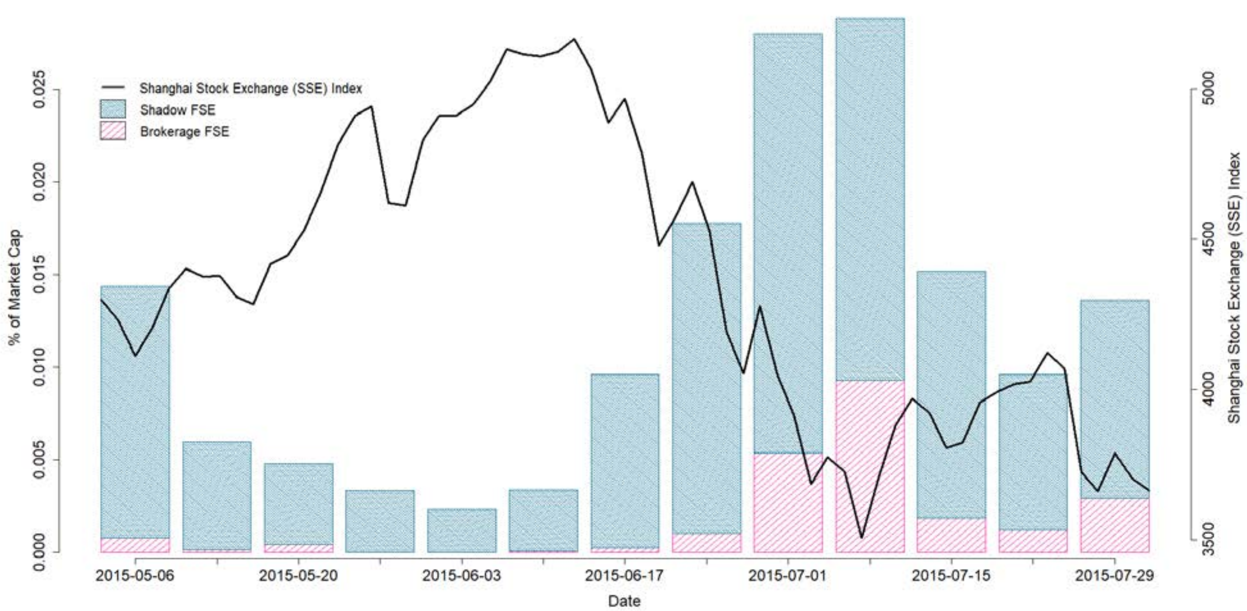


Table 1
Summary Statistics

This table presents summary statistics for account activity and stocks characteristics from May to July 2015. Leverage is the ratio of assets to equity at the start of each account-day, where equity is equal to assets minus debt. The Pingcang Line is the account-level maximum allowable level of leverage. Z is the Distance-to-Margin-Call. An account is classified as a fire sale account on day t if Z is less than or equal to 3. Net selling is account j's net selling volume of stock i on day t, normalized by account j's shares held of stock i at the beginning of day t. Selling pressure is the total net selling volume of stock i on day t from all fire sale accounts that hold stock i at the start of day t, scaled by the number of outstanding shares of stock i at the beginning of day t. Fire sale exposure is the ratio of the total shares of stock i held in fire sale accounts at the start of day t to the number of outstanding shares of stock i on day t. CAR is the cumulative abnormal return estimated relative to the CAPM, with beta calculated for each stock using year 2014 data. Return volatility is the standard deviation of returns during the prior 60 days. Log market value is the log of the product of each stock's daily close price and total number of shares outstanding, measured in $t-3$. Avg turnover is the average of the ratio of trading volume in shares to the total shares outstanding in the prior 60 days.

Panel A: Account-Day Level

	Mean	S.D.	Min	p25	p50	p75	Max	Obs
Leverage, full sample	1.1264	1.9923	1	1	1	1	100	114670045
Leverage, shadow accounts	6.6019	12.757	1	3.0254	4.2867	5.9794	100	2308872
Leverage, brokerage accounts	1.4372	0.476	1	1	1.3636	1.7042	100	3108015
Leverage, non-margin accounts	1	0	1	1	1	1	1	109253158
Pingcang Line, full sample	1.303	1.7409	1	1	1	1	100	114670045
Pingcang Line, shadow accounts	11.4846	5.3237	2	10	10	11.0011	100	2308872
Pingcang Line, brokerage accounts	4.3	0	4.3	4.3	4.3	4.3	4.3	3108015
Pingcang Line, non-margin accounts	1	0	1	1	1	1	1	109253158
Z, full sample	96.7684	16.2511	-48.8201	100	100	100	100	5416887
Z, shadow accounts	11.508	18.6731	-48.8201	3.4944	6.7863	11.7619	100	2308872
Z, brokerage accounts	46.9811	34.4584	-13.7431	21.0018	30.722	100	100	3108015
Z, non-margin accounts	100	0	100	100	100	100	100	109253158
Account assets, full accounts	2848592	24290699	0.02	165112	581690	1708483	4.5E+09	5416887
Account assets, shadow accounts	1522783	6233854	0.02	58967	211190	746180	5.1E+08	2308872
Account assets, brokerage accounts	3862068	31764740	3.85	412780	955315	2369806	4.5E+09	3108015

Panel B: Account-Stock-Day Level

	Mean	S.D.	Min	p25	p50	p75	Max	Obs
Net selling, full sample	0.0737	0.3145	-1.2	0	0	0	1	300003600
Net selling, shadow accounts	0.2184	0.4508	-1.2	0	0	0.439	1	5696005
Net selling, brokerage accounts	0.0849	0.3336	-1.2	0	0	0	1	14465239
Net selling, non-margin accounts	0.0702	0.3094	-1.2	0	0	0	1	279842356

Table 1
Summary Statistics (Continued)

Panel C: Stock-Day Level

	Mean	S.D.	Min	p25	p50	p75	Max	Obs
Selling pressure, all margin accounts	0.000017	0.000190	-0.01685	0.00000	0.00000	0.00001	0.02112	116749
Selling pressure, shadow accounts	0.000014	0.000170	-0.01687	0.00000	0.00000	0.00001	0.02112	116749
Selling pressure, brokerage accounts	0.000003	0.000083	-0.00201	0.00000	0.00000	0.00000	0.01955	116749
FSE, all margin accounts	0.000167	0.000624	0.00000	0.00001	0.00003	0.00012	0.04904	116749
FSE, shadow accounts	0.000151	0.000569	0.00000	0.00001	0.00003	0.00011	0.04904	116749
FSE, brokerage accounts	0.000016	0.000243	0.00000	0.00000	0.00000	0.00000	0.04226	116749
CAR [t]	-0.0003	0.0417	-0.1824	-0.0270	-0.0036	0.0245	0.2164	109675
CAR [t,t+3]	-0.0007	0.0817	-0.3971	-0.0489	-0.0034	0.0460	0.5344	109675
CAR [t,t+5]	-0.0006	0.1095	-0.5303	-0.0626	-0.0005	0.0641	0.5425	109675
CAR [t,t+10]	0.0034	0.1576	-0.7929	-0.0827	0.0107	0.0985	0.7455	109675
CAR [t,t+20]	0.0080	0.2048	-1.0486	-0.1159	0.0186	0.1374	1.1256	109675
CAR [t,t+40]	-0.0021	0.2071	-1.2508	-0.1299	-0.0033	0.1200	1.1301	109675
Cumulative return [t-10,t-1]	1.0312	0.2377	0.3487	0.8962	1.0371	1.1707	2.6017	116749
Return volatility [t-60,t-1]	0.0442	0.0128	0.0000	0.0344	0.0425	0.0532	0.1016	116749
Log market value [t-3]	9.47	0.98	7.36	8.79	9.29	9.97	14.78	116749
Average turnover [t-60,t-1]	0.0494	0.0257	0.0002	0.0314	0.0449	0.0624	0.2446	116749

Table 2
Distance-to-Margin-Call and Investor Selling Intensity

This table shows the coefficients λ_k of the regression:

$$\delta_{it}^j = \sum_{k=1}^{11} \lambda_k I_{k,t-1}^j + \nu_{it} + \alpha_j + \varepsilon_{it}^j,$$

where δ_{jt}^j is account j's net selling volume of stock i on day t, normalized by account j's initial holding of stock i at the beginning of day t. ν_{it} is the stock-date fixed effect and α_j is the account fixed effect. $I_{k,t-1}^j$ represents 10 bins for each account's Distance-to-Margin-Call, with higher bins corresponding to accounts that are closer to their leverage limit (the Pingcang Line). Accounts with leverage exceeding the Pingcang Line are assigned to bin 11. Unleveraged accounts are the omitted category. The sample includes brokerage- and shadow-financed margin accounts, as well as brokerage non-margin accounts which comprise the omitted category. The sample is restricted to stock-days in which a stock is not suspended from trading at any point during day t, and is also restricted to stocks i held by account j as of the start of day t. The time period is from May to July, 2015. Standard errors are allowed to be clustered at the account-date level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Net selling	Full	Broker	Shadow
	(1)	(2)	(3)
Distance to Margin Call Z > 20	0.000804***	0.000594**	0.00773***
	(0.000279)	(0.000282)	(0.0029)
Distance to Margin Call Z in (15,20]	0.00428***	0.00485***	0.0031
	(0.000443)	(0.000465)	(0.003)
Distance to Margin Call Z in (10,15]	0.00430***	0.00484***	0.00252
	(0.000539)	(0.000598)	(0.00297)
Distance to Margin Call Z in (7.5,10]	0.00435***	0.00838***	0.00116
	(0.000763)	(0.00121)	(0.00299)
Distance to Margin Call Z in (5,7.5]	0.00377***	0.0167***	-6.28E-05
	(0.000828)	(0.00175)	(0.00299)
Distance to Margin Call Z in (4,5]	0.0122***	0.0311***	0.00846***
	(0.0011)	(0.00299)	(0.00307)
Distance to Margin Call Z in (3,4]	0.0310***	0.0414***	0.0279***
	(0.00118)	(0.00316)	(0.0031)
Distance to Margin Call Z in (2,3]	0.0644***	0.0601***	0.0621***
	(0.00134)	(0.00436)	(0.00316)
Distance to Margin Call Z in (1,2]	0.111***	0.0801***	0.110***
	(0.00155)	(0.00607)	(0.00325)
Distance to Margin Call Z in (0,1]	0.169***	0.100***	0.170***
	(0.00187)	(0.00628)	(0.00343)
Distance to Margin Call Z <= 0	0.186***	0.217***	0.183***
	(0.0016)	(0.0106)	(0.00326)
Account FE	Yes	Yes	Yes
Stock-Date FE	Yes	Yes	Yes
R-squared	0.136	0.131	0.137
Observations, margin accounts	20,161,244	14,465,239	5,696,005
Observations, total	299,988,054	294,297,933	285,522,202

Table 3
Leverage-to-Pingcang and Leverage Interactions

This table examines how leverage levels and the Leverage-to-Pingcang ratio impact net selling. The sample is restricted to shadow-financed margin accounts, for which we can separately identify leverage and Leverage-to-Pingcang, due to variation in Pingcang Lines across accounts. Other sample restrictions are the same as in Table 2. Column 1 replicates Column 3 of Table 2, substituting DMC with ten equally spaced bins for Leverage-to-Pingcang. Column 2 adds controls for five bins representing leverage at the start of of each account-day and the interaction between the leverage bins and an indicator for whether the account has a Leverage-to-Pingcang below 4. The leverage bins are spaced so that the number of observations in the Leverage-to-Pingcang bins b and $b+1$ are equal to the number of observations in leverage bin $b/2$, for $b = 2, 4, ..., 10$. Standard errors are allowed to be clustered at the account-date level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Net selling	(1)	(2)
Leverage to Pingcang in (0.9, 1)	0.00403	0.00672**
	(0.00292)	(0.00293)
Leverage to Pingcang in (0.8, 0.9]	0.00188	0.00252
	(0.00298)	(0.00330)
Leverage to Pingcang in (0.7, 0.8]	0.00280	0.00167
	(0.00300)	(0.00338)
Leverage to Pingcang in (0.6. 0.7]	0.00538*	0.00319
	(0.00302)	(0.00350)
Leverage to Pingcang in (0.5, 0.6]	0.0157***	0.00909**
	(0.00305)	(0.00360)
Leverage to Pingcang in (0.4, 0.5]	0.0460***	0.0269***
	(0.00312)	(0.00378)
Leverage to Pingcang in (0.3, 0.4]	0.0866***	0.00579
	(0.00323)	(0.0175)
Leverage to Pingcang in (0.2, 0.3]	0.129***	0.0292*
	(0.00341)	(0.0176)
Leverage to Pingcang in (0.1, 0.2]	0.167***	0.0493***
	(0.00369)	(0.0177)
Leverage to Pingcang in (0, 0.1]	0.197***	0.0647***
	(0.00401)	(0.0179)
Leverage to Pingcang <= 0	0.195***	0.0340*
	(0.00328)	(0.0179)
Lev Bin 1		0.00111
		(0.00188)
Lev Bin 2		-0.00339
		(0.00218)
Lev Bin 3		0.0157***
		(0.00260)
Lev Bin 4		0.0641***
		(0.00377)
Lev Bin 5		0.0870***
		(0.00559)
Lev Bin 1 * 1{Leverage to Pingcang <= 0.4}		0.0326*
		(0.0177)
Lev Bin 2 * 1{Leverage to Pingcang <= 0.4}		0.0348**
		(0.0174)
Lev Bin 3 * 1{Leverage to Pingcang <= 0.4}		0.0540***
		(0.0173)
Lev Bin 4 * 1{Leverage to Pingcang <= 0.4}		0.0482***
		(0.0175)
Lev Bin 5 * 1{Leverage to Pingcang <= 0.4}		0.0735***
		(0.0181)
Account FE	Yes	Yes
Stock-Date FE	Yes	Yes
R-squared	0.137	0.137
Observations, margin accounts	5,696,005	5,696,005
Observations, total	285,522,202	285,522,202

Table 4
Leverage-to–*Predicted*-Pingcang and Leverage

This table examines how leverage levels and the Leverage-to-Predicted-Pingcang ratio impact net selling. The sample is restricted to shadow-financed margin accounts. Predicted Pingcang is calculated as the average Pingcang Line across all shadow accounts opened on the same day as the account in question. Other sample restrictions are the same as in Table 2. The leverage bins are spaced so that the number of observations in each Leverage-to-Predicted-Pingcang bins equals that number of observations in the corresponding leverage bin. Standard errors are allowed to be clustered at the account-date level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Net selling	(1)
Leverage to predicted Pingcang in (0.9, 1)	0.00638**
	(0.00292)
Leverage to predicted Pingcang in (0.8, 0.9]	-0.000617
	(0.00384)
Leverage to predicted Pingcang in (0.7, 0.8]	-0.000800
	(0.00413)
Leverage to predicted Pingcang in (0.6. 0.7]	-0.00532
	(0.00435)
Leverage to predicted Pingcang in (0.5, 0.6]	-0.00677
	(0.00462)
Leverage to predicted Pingcang in (0.4, 0.5]	0.00507
	(0.00500)
Leverage to predicted Pingcang in (0.3, 0.4]	0.0271***
	(0.00554)
Leverage to predicted Pingcang in (0.2, 0.3]	0.0479***
	(0.00626)
Leverage to predicted Pingcang in (0.1, 0.2]	0.0688***
	(0.00714)
Leverage to predicted Pingcang in (0, 0.1]	0.0841***
	(0.00817)
Leverage to predicted Pingcang <= 0	0.0986***
	(0.00913)
Lev Bin 1	0.00589**
	(0.00268)
Lev Bin 2	0.00551*
	(0.00311)
Lev Bin 3	0.00899***
	(0.00339)
Lev Bin 4	0.0224***
	(0.00372)
Lev Bin 5	0.0469***
	(0.00418)
Lev Bin 6	0.0695***
	(0.00482)
Lev Bin 7	0.0936***
	(0.00562)
Lev Bin 8	0.110***
	(0.00657)
Lev Bin 9	0.118***
	(0.00765)
Lev Bin 10	0.0995***
	(0.00866)
Account FE	Yes
Stock-Date FE	Yes
R-squared	0.137
Observations, margin accounts	5,696,005
Observations, total	285,522,202

Table 5
Stock-Level Fire Sale Exposure and Selling Pressure

This table presents the regression $\delta_{it} = \beta \cdot FSE_{it} + controls_{it} + s_i + \tau_t + \varepsilon_{it}$. δ_{it} measures stock-level selling pressure from fire sale accounts. FSE_{it} is the fire sale exposure for stock i on day t. δ_{it} and FSE_{it} are calculated using the combined brokerage and shadow account samples. The sample is restricted to stocks that did not face any trading suspensions on day t. All variables are as defined in Table 1. Standard errors are allowed to be clustered at the date level.

	Selling pressure			
	(1)	(2)	(3)	(4)
Fire sale exposure	0.104***	0.0935***	0.0927***	0.0913***
	(0.0111)	(0.00862)	(0.00859)	(0.00858)
Return volatility [t-60, t-1]			-0.000120	-5.25e-05
			(8.41e-05)	(9.05e-05)
Log market value [t-3]			1.48e-05***	6.30e-06*
			(3.61e-06)	(3.65e-06)
Avg turnover [t-60, t-1]			0.000158**	0.000176**
			(6.75e-05)	(6.76e-05)
Cumulative return [t-10, t-1]			-1.16e-05***	2.03e-05
			(2.61e-06)	(1.51e-05)
Stock FE	No	Yes	Yes	Yes
Date FE	No	Yes	Yes	Yes
Past 10-day daily returns	No	No	No	Yes
R-squared	0.149	0.231	0.232	0.235
Observations	115,168	115,167	115,167	115,167

Table 6
Fire Sale Exposure and Stock Characteristics

Column 1 shows a regression of fire sale exposure (multiplied by 100 for ease of exposition) on stock-level characteristics. Column 2 adds controls for stock and date fixed effects, so the reported coefficients represent within-stock and date relations. Standard errors are allowed to be clustered at the stock level.

Fire sale exposure	(1)	(2)
Return volatility [t-60, t-1]	0.173***	0.112**
	(0.0483)	(0.0464)
Log market value [t-3]	-0.00376***	0.0146***
	(0.000469)	(0.00336)
Avg turnover [t-60, t-1]	0.0824***	0.0426
	(0.0143)	(0.0292)
Cumulative return [t-10, t-1]	-0.000442***	-0.000182***
	(0.00548)	(0.00259)
Stock FE	No	Yes
Date FE	No	Yes
Observations	109,675	109,675
R-squared	0.048	0.272

Table 7
Fire Sales and Reversals

The table presents the regression

$$CAR_{i,t+h} = \gamma_h \cdot FSE_{it} + controls_{it} + s_i + \tau_t + \varepsilon_{it}.$$

All variables are as defined in Table 1. FSE_{it} is calculated using the combined brokerage and shadow account samples in Panel A, the brokerage account sample in Panel B, and the shadow account sample in Panel C. Standard errors are allowed to be clustered at the date level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: FSE Calculated Using All Margin Accounts

CAR:	[t]	[t, t+3]	[t, t+5]	[t, t+10]	[t, t+20]	[t, t+40]
	(1)	(2)	(3)	(4)	(5)	(6)
Fire sale exposure	-1.830***	-4.527***	-7.075***	-9.005***	-2.875*	0.778
	(0.499)	(0.985)	(1.372)	(1.907)	(1.5)	(0.992)
Return volatility [t-60, t-1]	-0.246	-0.423	-0.44	-0.204	0.531	0.23
	(0.164)	(0.352)	(0.457)	(0.575)	(0.646)	(0.409)
Log market value [t-3]	-0.0661***	-0.203***	-0.322***	-0.564***	-0.820***	-0.741***
	(0.00766)	(0.0147)	(0.0198)	(0.028)	(0.0305)	(0.0202)
Avg turnover [t-60, t-1]	-0.0928	-0.303**	-0.497***	-0.959***	-2.169***	-1.151***
	(0.0679)	(0.128)	(0.161)	(0.171)	(0.176)	(0.173)
Cumulative return [t-10, t-1]	-0.0552**	-0.0913*	-0.0748	0.0428	-0.0982	0.167***
	(0.0236)	(0.0523)	(0.0704)	(0.0836)	(0.0778)	(0.0491)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Past 10-day daily return	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.255	0.335	0.391	0.512	0.627	0.705
Observations	109,675	109,675	109,675	109,675	109,675	109,675

Table 7
Fire Sales and Reversals (Continued)

Panel B: FSE Calculated Using Brokerage Margin Accounts

CAR:	[t]	[t, t+3]	[t, t+5]	[t, t+10]	[t, t+20]	[t, t+40]
	(1)	(2)	(3)	(4)	(5)	(6)
Fire sale exposure	-0.753**	-1.775***	-3.155***	-4.249***	-4.754***	1.313
	(0.346)	(0.567)	(0.916)	(0.85)	(1.363)	(1.864)
Return volatility [t-60, t-1]	-0.25	-0.432	-0.454	-0.222	0.53	0.231
	(0.165)	(0.353)	(0.458)	(0.578)	(0.647)	(0.41)
Log market value [t-3]	-0.0664***	-0.203***	-0.323***	-0.566***	-0.820***	-0.741***
	(0.00769)	(0.0148)	(0.0199)	(0.0282)	(0.0303)	(0.0202)
Avg turnover [t-60, t-1]	-0.0942	-0.306**	-0.502***	-0.965***	-2.170***	-1.151***
	(0.068)	(0.129)	(0.162)	(0.171)	(0.176)	(0.173)
Cumulative return [t-10, t-1]	-0.0561**	-0.0936*	-0.0784	0.0384	-0.0984	0.167***
	(0.0237)	(0.0527)	(0.0707)	(0.084)	(0.078)	(0.0491)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Past 10-day daily return	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.255	0.334	0.39	0.512	0.627	0.705
Observations	109,675	109,675	109,675	109,675	109,675	109,675

Panel C: FSE Calculated Using Shadow Margin Accounts

CAR:	[t]	[t, t+3]	[t, t+5]	[t, t+10]	[t, t+20]	[t, t+40]
	(1)	(2)	(3)	(4)	(5)	(6)
Fire sale exposure	-2.170***	-5.397***	-8.313***	-10.50***	-2.256	0.602
	(0.618)	(1.309)	(1.758)	(2.425)	(1.985)	(0.9)
Return volatility [t-60, t-1]	-0.248	-0.428	-0.448	-0.215	0.527	0.232
	(0.164)	(0.352)	(0.457)	(0.576)	(0.647)	(0.41)
Log market value [t-3]	-0.0660***	-0.203***	-0.322***	-0.564***	-0.820***	-0.741***
	(0.00765)	(0.0147)	(0.0197)	(0.028)	(0.0306)	(0.0202)
Avg turnover [t-60, t-1]	-0.0927	-0.302**	-0.496***	-0.958***	-2.169***	-1.151***
	(0.0678)	(0.128)	(0.161)	(0.171)	(0.176)	(0.173)
Cumulative return [t-10, t-1]	-0.0558**	-0.0927*	-0.0771	0.0399	-0.0995	0.167***
	(0.0236)	(0.0524)	(0.0705)	(0.0836)	(0.0779)	(0.0494)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Past 10-day daily return	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.255	0.335	0.391	0.513	0.627	0.705
Observations	109,675	109,675	109,675	109,675	109,675	109,675

Table 8
Fire Sales: Regulatory Announcement Event Study

This table shows the relation between FSE and returns separately for each of the two weeks prior to the June 12, 2015 regulatory tightening announcement as well as for the week immediately after the announcement. In Columns 7-9, we regress an indicator for whether a stock's -10% price limit was triggered on the stock's fire sale exposure. Standard errors are allowed to be clustered at the date level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	CAR [t]			CAR [t,t+10]			Triggered price limit		
Week:	June 1	June 8	June 15	June 1	June 8	June 15	June 1	June 8	June 15
Fire sale exposure	4.281	-0.248	-3.446**	-1.747	1.317	-13.91**	-6.173	-2.153	34.42**
	(2.076)	(1.620)	(0.761)	(2.362)	(1.727)	(4.432)	(9.509)	(9.586)	(10.66)
Return volatility [t-60, t-1]	-0.0292	2.356	2.164	-0.180	-1.278	3.709*	-8.009	-34.44**	-22.87
	(0.996)	(1.587)	(1.375)	(0.672)	(1.092)	(1.521)	(6.685)	(7.754)	(11.79)
Log market value [t-3]	-0.623**	-0.309**	-0.154**	-1.117***	-0.624***	-0.331**	1.247	0.646***	0.675**
	(0.181)	(0.0893)	(0.0469)	(0.0450)	(0.130)	(0.102)	(0.986)	(0.0712)	(0.180)
Avg turnover [t-60, t-1]	0.936	-2.468**	-3.017**	-1.494**	-0.811	-4.088**	1.536	8.719**	4.247
	(1.504)	(0.841)	(1.033)	(0.440)	(0.668)	(1.426)	(3.017)	(2.752)	(2.470)
Cumulative return [t-10, t-1]	-0.00625	0.187	0.451***	-0.103	0.138	1.004**	-0.196	0.0333	-2.202**
	(0.0934)	(0.164)	(0.0216)	(0.0572)	(0.259)	(0.316)	(0.613)	(0.220)	(0.756)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Past 10-day daily return	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	9,452	9,329	9,266	9,452	9,329	9,266	9,452	9,329	9,266
Observations	0.447	0.532	0.460	0.924	0.916	0.919	0.393	0.348	0.501

Table 9
Price Limits

This table tests whether an investor is more likely to sell a stock if other stocks in her portfolio cannot be sold due to stock-specific price limits that limit trading if a stock's within-day absolute return exceeds 10%. Price limit fraction equals the fractional value of account j's total stock holdings as of the start of day t that consist of stocks that hit price floors at some later point on day t or experienced suspended trading for any reason on day t. All specifications control for each account's day t counterfactual returns assuming no stocks are bought or sold on day t, interacted with the set of bins for Distance-to-Margin-Call. All other variables are as defined in Table 2. The sample is restricted to stocks that do not face trading restrictions or price limits on day t. The sample includes brokerage- and shadow-financed margin accounts, as well as brokerage non-margin accounts which comprise the omitted category. Standard errors are allowed to be clustered at the stock-date level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Net selling	Full	Broker	Shadow
	(1)	(2)	(3)
Distance to margin call Z > 20	0.00817***	0.00782***	0.0154***
	(0.000676)	(0.000693)	(0.00299)
Distance to margin call Z in (15,20]	0.00646***	0.00919***	0.0131***
	(0.000802)	(0.000837)	(0.00311)
Distance to margin call Z in (10,15]	0.00113	0.00666***	0.00841***
	(0.000906)	(0.00101)	(0.00307)
Distance to margin call Z in (7.5,10]	-0.00480***	0.00496***	0.00254
	(0.00109)	(0.00174)	(0.0031)
Distance to margin call Z in (5,7.5]	-0.00990***	0.0113***	-0.00324
	(0.00115)	(0.00266)	(0.0031)
Distance to margin call Z in (4,5]	-0.00865***	0.0194***	-0.00237
	(0.00139)	(0.0042)	(0.0032)
Distance to margin call Z in (3,4]	0.000193	0.0381***	0.00581*
	(0.00148)	(0.00499)	(0.00323)
Distance to margin call Z in (2,3]	0.0240***	0.0408***	0.0293***
	(0.00163)	(0.00662)	(0.0033)
Distance to margin call Z in (1,2]	0.0638***	0.0803***	0.0679***
	(0.00189)	(0.00929)	(0.00342)
Distance to margin call Z in (0,1]	0.117***	0.132***	0.119***
	(0.00225)	(0.011)	(0.00364)
Distance to margin call Z <= 0	0.129***	0.274***	0.130***
	(0.00205)	(0.0183)	(0.0035)
Price limit fraction	0.0104***	0.0222***	0.00432***
	(0.000933)	(0.000939)	(0.00104)
Price limit fraction * distance to margin call Z > 20	0.0143***	0.0131***	0.0632***
	(0.00171)	(0.00175)	(0.00638)
Price limit fraction * distance to margin call Z in (15,20]	0.0174***	0.0124***	0.0326***
	(0.00258)	(0.00279)	(0.00629)
Price limit fraction * distance to margin call Z in (10,15]	0.0297***	0.00882**	0.0528***
	(0.00283)	(0.00343)	(0.00464)
Price limit fraction * distance to margin call Z in (7.5,10]	0.0589***	0.0250***	0.0704***
	(0.00411)	(0.00711)	(0.00503)
Price limit fraction * distance to margin call Z in (5,7.5]	0.0799***	0.0348***	0.0843***
	(0.00406)	(0.00852)	(0.00461)
Price limit fraction * distance to margin call Z in (4,5]	0.109***	0.0518***	0.114***
	(0.00649)	(0.0166)	(0.00708)
Price limit fraction * distance to margin call Z in (3,4]	0.168***	0.0404**	0.180***
	(0.00677)	(0.0188)	(0.00726)
Price limit fraction * distance to margin call Z in (2,3]	0.172***	0.0732***	0.184***
	(0.00729)	(0.0234)	(0.00767)
Price limit fraction * distance to margin call Z in (1,2]	0.132***	-0.0225	0.157***
	(0.0105)	(0.0287)	(0.00818)
Price limit fraction * distance to margin call Z in (0,1]	0.0862***	-0.0782**	0.108***
	(0.00987)	(0.0305)	(0.00956)
Price limit fraction * distance to margin call Z <= 0	0.0743***	-0.137*	0.0798***
	(0.0073)	(0.0792)	(0.00665)
Counterfactual portfolio returns x distance to margin call bins	Yes	Yes	Yes
Account FE	Yes	Yes	Yes
Stock-date FE	Yes	Yes	Yes
R-squared	0.176	0.148	0.194
Observations, margin accounts	14,902,413	9,873,701	5,028,712
Observations, total	25,305,234	20,283,178	15,431,383

A Internet Data Appendix

The shadow-financed margin account data is organized in a umbrella-style structure. There are 153,331 child accounts, each of which is connected to a mother accounts maintained by the trading platform. For each child account, we observe the initial *lending ratio* of the borrower, defined as the amount of borrowing divided by the investor's margin deposit (equity). We also observe the *minimum coverage ratio*, the ratio of remaining assets to debt, that will trigger a margin call.

A.1 Data Filter

We adopt the following procedure to clean our data.

1. We eliminate accounts with invalid initial margin and maintenance margin information. We require the initial lending ratio to be less than 100. There are some accounts with extremely high initial lending ratios. They are usually used as a bonus to investors with much lower lending ratios and typically carry very little assets. On the other hand, we require *the minimum coverage ratio* to be above 1, i.e, investors will receive the margin calls before outstanding debt exceeds the current asset wealth. Agent accounts with margin information outside these ranges might be maintained by non-margin accounts.

2. We require the first record in the margin accounts to be a cash flow from the mother account, before the account starts any trading activities. These cash flows usually occur right after the account opens, and includes the loans from the lenders together with the deposited margins from the borrowers. We eliminate observations from accounts that either never have any cash flows from mother accounts, or the first cash flows are from the child accounts to the mother accounts.

3. We compare the size of initial cash flows and the initial debt information provided by the trading platform, and further eliminate observations from accounts for which the size of the initial cash flow deviates significantly from the initial debt reported by the online trading system.

A.2 Construction of daily debt level

The shadow accounts data includes all variables in the brokerage account data, except for the end-of-day leverage numbers. Instead, the trading platform provides detailed information on the initial debt, subsequent cash flows between the mother account (controlled by the lender) and child accounts (controlled by the borrowers), and all trades by the child accounts. We can thus manually calculate the end-of-day asset and debt value for each child account.

To construct daily outstanding debt for each margin child account in our dataset, we rely on the cash flow information between the mother and child accounts, as well as transaction remarks, both provided by the trading platform. For about two-thirds of the accounts, the platform provides detailed remarks for each cash flow (whether it is an issued loan or loan repayment), which helps us calculate the exact daily outstanding debt levels. For the remaining accounts without transaction remarks, we assume that cash flows to (from) the mother account exceeding 20% of the margin debt in the child account reflects a payment of existing debt (additional borrowing). This 20% cutoff rule is suggested by practitioners in the trading platform.

B Internet Appendix: Figures and Tables

Table B.1
Investor Selling Intensity Conditional on Day t Market Returns

This table presents the regression counterpart to Figure 5. Panels A and B present the same regression as in Table 2, with the sample restricted to days in which the market return was positive or negative, respectively. Distance-to-Margin-Call is defined as of the start of each trading day. The sample includes brokerage- and shadow-financed margin accounts, as well as brokerage non-margin accounts which comprise the omitted category. Standard errors are allowed to be clustered at the account-date level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Positive Market Return Day

Net selling	Full	Broker	Shadow
	(1)	(2)	(3)
Distance to Margin Call Z > 20	-0.000324	-0.000604	0.0239***
	(0.000375)	(0.000379)	(0.00375)
Distance to Margin Call Z in (15,20]	-0.00168***	-0.00219***	0.0223***
	(0.000578)	(0.000603)	(0.00389)
Distance to Margin Call Z in (10,15]	-0.00327***	-0.00402***	0.0183***
	(0.00071)	(0.000794)	(0.00384)
Distance to Margin Call Z in (7.5,10]	-0.00657***	-0.00502***	0.0132***
	(0.000997)	(0.0016)	(0.00388)
Distance to Margin Call Z in (5,7.5]	-0.0106***	-0.00109	0.00803**
	(0.00107)	(0.00211)	(0.00388)
Distance to Margin Call Z in (4,5]	-0.00830***	0.00798**	0.0100**
	(0.00144)	(0.00407)	(0.00399)
Distance to Margin Call Z in (3,4]	-0.00417***	0.0133***	0.0142***
	(0.00152)	(0.00406)	(0.00402)
Distance to Margin Call Z in (2,3]	0.0153***	0.0220***	0.0342***
	(0.00172)	(0.0057)	(0.00409)
Distance to Margin Call Z in (1,2]	0.0416***	0.0376***	0.0610***
	(0.00198)	(0.00722)	(0.00421)
Distance to Margin Call Z in (0,1]	0.0789***	0.0493***	0.0996***
	(0.00242)	(0.00755)	(0.00446)
Distance to Margin Call Z <= 0	0.110***	0.199***	0.126***
	(0.00214)	(0.0139)	(0.00426)
Account FE	Yes	Yes	Yes
Stock-Date FE	Yes	Yes	Yes
R-squared	0.154	0.149	0.155
Observations, margin accounts	10,522,531	7,517,467	3,005,064
Observations, total	155,281,448	152,284,817	147,763,127

Table B.1
Investor Selling Intensity Conditional on Day t Market Returns (Continued)

Panel B: Negative Market Return Day

Net selling	Full	Broker	Shadow
	(1)	(2)	(3)
Distance to Margin Call Z > 20	0.00240***	0.00229***	-0.00860**
	(0.000376)	(0.000378)	(0.00434)
Distance to Margin Call Z in (15,20]	0.0107***	0.0125***	-0.0171***
	(0.00061)	(0.000635)	(0.00449)
Distance to Margin Call Z in (10,15]	0.0132***	0.0146***	-0.0118***
	(0.000752)	(0.000821)	(0.00445)
Distance to Margin Call Z in (7.5,10]	0.0174***	0.0224***	-0.00863*
	(0.0011)	(0.00169)	(0.00448)
Distance to Margin Call Z in (5,7.5]	0.0212***	0.0374***	-0.00536
	(0.0012)	(0.0025)	(0.00447)
Distance to Margin Call Z in (4,5]	0.0370***	0.0562***	0.0110**
	(0.0016)	(0.00417)	(0.00459)
Distance to Margin Call Z in (3,4]	0.0688***	0.0704***	0.0441***
	(0.00175)	(0.00457)	(0.00464)
Distance to Margin Call Z in (2,3]	0.114***	0.0978***	0.0906***
	(0.00194)	(0.00625)	(0.00471)
Distance to Margin Call Z in (1,2]	0.178***	0.124***	0.156***
	(0.00226)	(0.00989)	(0.00483)
Distance to Margin Call Z in (0,1]	0.248***	0.154***	0.228***
	(0.00264)	(0.00928)	(0.00505)
Distance to Margin Call Z <= 0	0.253***	0.235***	0.230***
	(0.00223)	(0.0128)	(0.00481)
Account FE	Yes	Yes	Yes
Stock-Date FE	Yes	Yes	Yes
R-squared	0.148	0.141	0.149
Observations, margin accounts	9,638,713	6,947,772	2,690,941
Observations, total	144,673,651	141,988,849	137,725,171

Table B.2
Regulatory Tightening

This table presents the regression counterpart to Figure 6. Regulatory tightening announcements occurred after hours on Friday May 22, 2015 and Friday June 12, 2015. This table shows the coefficients λ_k from the regression defined in Table 2, estimated separately for the brokerage- and shadow-financed margin account samples on the five trading days immediately before and after the regulatory tightening events. The sample includes brokerage- and shadow-financed margin accounts, as well as brokerage non-margin accounts which comprise the omitted category. Missing coefficients in Columns 1 and 3 result from insufficient observations in the corresponding Distance-to-Margin-Call bin. Standard errors are allowed to be clustered at the account-date level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Net selling	May 22 event		June 12 event	
	Broker	Shadow	Broker	Shadow
	(1)	(2)	(3)	(4)
Distance to Margin Call Z > 20	0.00600***	0.0389***	-0.00157*	0.0394***
	(0.000824)	(0.0118)	(0.000807)	(0.0102)
Distance to Margin Call Z in (15,20]	0.00183	0.0376***	0.00184	0.0339***
	(0.00167)	(0.0121)	(0.00184)	(0.0105)
Distance to Margin Call Z in (10,15]	-0.00123	0.0211*	-0.00238	0.0220**
	(0.00262)	(0.0122)	(0.00300)	(0.0106)
Distance to Margin Call Z in (7.5,10]	-0.00874	-0.00303	-0.00322	0.00324
	(0.00742)	(0.0123)	(0.0115)	(0.0107)
Distance to Margin Call Z in (5,7.5]	-0.0171	-0.0316**	0.0148	-0.0100
	(0.0125)	(0.0123)	(0.0199)	(0.0107)
Distance to Margin Call Z in (4,5]	-0.0522	-0.0474***	-0.0176	-0.0175
	(0.0384)	(0.0125)	(0.0436)	(0.0110)
Distance to Margin Call Z in (3,4]	-0.0715	-0.0649***	-0.0150	-0.0210*
	(0.0494)	(0.0126)	(0.0518)	(0.0112)
Distance to Margin Call Z in (2,3]	-0.0241	-0.0764***	-0.0318	-0.0259**
	(0.0736)	(0.0127)	(0.0517)	(0.0115)
Distance to Margin Call Z in (1,2]	-0.186***	-0.0685***	-0.219	-0.0207*
	(0.0438)	(0.0131)	(0.274)	(0.0120)
Distance to Margin Call Z in (0,1]	-0.270**	-0.0669***	-0.0298	0.0133
	(0.112)	(0.0138)	(0.0459)	(0.0133)
Distance to Margin Call Z <= 0	0.490***	-0.0417***	0.195**	0.00561
	(0.0755)	(0.0143)	(0.0987)	(0.0124)
Distance to Margin Call Z > 20 * after	-0.00147**	0.0170***	0.0123***	0.0311***
	(0.000715)	(0.00353)	(0.000747)	(0.00245)
Distance to Margin Call Z in (15,20] * after	0.00106	0.00658*	0.0172***	0.0200***
	(0.00192)	(0.00387)	(0.00184)	(0.00251)
Distance to Margin Call Z in (10,15] * after	-0.00377	0.00441*	0.0172***	0.0198***
	(0.00318)	(0.00243)	(0.00289)	(0.00180)
Distance to Margin Call Z in (7.5,10] * after	0.000113	-0.000581	0.0167	0.0236***
	(0.0104)	(0.00261)	(0.0126)	(0.00220)
Distance to Margin Call Z in (5,7.5] * after	0.0222	0.00657**	0.0195	0.0283***
	(0.0210)	(0.00259)	(0.0187)	(0.00220)
Distance to Margin Call Z in (4,5] * after	0.0119	0.000657	0.0340	0.0398***
	(0.0525)	(0.00433)	(0.0510)	(0.00378)
Distance to Margin Call Z in (3,4] * after	0.0315	0.0206***	0.0684	0.0628***
	(0.0601)	(0.00489)	(0.0790)	(0.00439)
Distance to Margin Call Z in (2,3] * after	-0.164	0.0612***	0.0322	0.105***
	(0.152)	(0.00623)	(0.0698)	(0.00549)
Distance to Margin Call Z in (1,2] * after	-0.396	0.0962***	0.239	0.160***
	(0.307)	(0.00840)	(0.276)	(0.00699)
Distance to Margin Call Z in (0,1] * after	-0.00574**	0.171***		0.186***
	(0.00236)	(0.0111)		(0.00986)
Distance to Margin Call Z <= 0 * after		0.115***		0.158***
		(0.00987)		(0.00773)
Stock-Date FE	Yes	Yes	Yes	Yes
R-squared	0.183	0.189	0.173	0.18
Observations, margin accounts	2,128,407	1,008,044	2,240,158	1,255,170
Observations, total	42,017,612	40,892,886	44,574,230	43,585,977

Table B.3

Distance-to-Margin-Call and Investor Selling Intensity, Controlling for Past Account Returns

This table presents the same regression as in Table 2, with the addition of a control variable for the account's return over the past ten days. Standard errors are allowed to be clustered at the account-date level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Net selling	Full	Broker	Shadow
	(1)	(2)	(3)
Distance to Margin Call Z > 20	0.000736***	0.000510*	0.00753***
	(0.000279)	(0.000282)	(0.0029)
Distance to Margin Call Z in (15,20]	0.00419***	0.00475***	0.00295
	(0.000443)	(0.000465)	(0.003)
Distance to Margin Call Z in (10,15]	0.00427***	0.00478***	0.0025
	(0.00054)	(0.000598)	(0.00297)
Distance to Margin Call Z in (7.5,10]	0.00439***	0.00842***	0.00124
	(0.000763)	(0.00121)	(0.00299)
Distance to Margin Call Z in (5,7.5]	0.00387***	0.0169***	9.45E-05
	(0.000829)	(0.00175)	(0.00299)
Distance to Margin Call Z in (4,5]	0.0124***	0.0314***	0.00868***
	(0.0011)	(0.00299)	(0.00307)
Distance to Margin Call Z in (3,4]	0.0312***	0.0417***	0.0281***
	(0.00118)	(0.00316)	(0.0031)
Distance to Margin Call Z in (2,3]	0.0647***	0.0606***	0.0624***
	(0.00134)	(0.00436)	(0.00316)
Distance to Margin Call Z in (1,2]	0.112***	0.0807***	0.110***
	(0.00155)	(0.00606)	(0.00325)
Distance to Margin Call Z in (0,1]	0.170***	0.101***	0.170***
	(0.00187)	(0.00629)	(0.00343)
Distance to Margin Call Z <= 0	0.187***	0.217***	0.184***
	(0.0016)	(0.0106)	(0.00326)
Account return [t-10, t-1]	0.00439***	0.00493***	0.00566***
	(0.000239)	(0.00024)	(0.000229)
Account FE	Yes	Yes	Yes
Stock-Date FE	Yes	Yes	Yes
R-squared	0.136	0.131	0.137
Observations, margin accounts	20,161,244	14,465,239	5,696,005
Observations, total	299,988,054	294,297,933	285,522,202

Table B.4
Fire Sales and Reversals, λ-weighted

This table presents the same regression as in Table 7 Panel A, with the following modifications. Instead of constructing fire sale exposure as the fraction of shares held in fire sale accounts, fire sale exposure equals the fraction of shares held in all margin accounts, with each account weighted by its corresponding λ_k. Standard errors are allowed to be clustered at the date level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

CAR:	[t]	[t, t+3]	[t, t+5]	[t, t+10]	[t, t+20]	[t, t+40]
	(1)	(2)	(3)	(4)	(5)	(6)
Fire sale exposure	-12.64***	-31.02***	-45.86***	-58.27***	-22.23**	1.422
	(3.309)	(6.597)	(9.125)	(12.34)	(9.183)	(6.097)
Return volatility [t-60, t-1]	-0.245	-0.421	-0.438	-0.202	0.534	0.232
	(0.164)	(0.352)	(0.456)	(0.575)	(0.646)	(0.409)
Log market value [t-3]	-0.0661***	-0.203***	-0.322***	-0.564***	-0.820***	-0.741***
	(0.00766)	(0.0147)	(0.0198)	(0.028)	(0.0305)	(0.0202)
Avg turnover [t-60, t-1]	-0.0924	-0.302**	-0.496***	-0.957***	-2.168***	-1.151***
	(0.0679)	(0.128)	(0.161)	(0.171)	(0.176)	(0.173)
Cumulative return [t-10, t-1]	-0.0550**	-0.0909*	-0.0746	0.0431	-0.0977	0.167***
	(0.0236)	(0.0523)	(0.0704)	(0.0837)	(0.0777)	(0.0491)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Past 10-day daily return	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.255	0.335	0.391	0.512	0.627	0.705
Observations	109,675	109,675	109,675	109,675	109,675	109,675

Table B.5
Fire Sales and Reversals, FSE calculated using $Z < 0$ accounts

This table presents the same regressions as in Table 7 Panel A, with the following modifications. Fire sale exposure equals the fraction of shares held in all margin accounts with $Z < 0$, i.e., accounts in which control has transferred from the borrower to the lender. Standard errors are allowed to be clustered at the date level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

CAR:	[t]	[t, t+3]	[t, t+5]	[t, t+10]	[t, t+20]	[t, t+40]
	(1)	(2)	(3)	(4)	(5)	(6)
Fire sale exposure	-2.600***	-6.361***	-8.419***	-9.471***	-1.322	-0.0597
	(0.661)	(1.531)	(2.058)	(2.692)	(1.783)	(1.529)
Return volatility [t-60, t-1]	-0.246	-0.423	-0.443	-0.211	0.526	0.233
	(0.164)	(0.352)	(0.457)	(0.576)	(0.646)	(0.409)
Log market value [t-3]	-0.0662***	-0.203***	-0.322***	-0.565***	-0.820***	-0.741***
	(0.00767)	(0.0147)	(0.0198)	(0.0281)	(0.0304)	(0.0202)
Avg turnover [t-60, t-1]	-0.0928	-0.303**	-0.497***	-0.960***	-2.170***	-1.150***
	(0.0679)	(0.129)	(0.161)	(0.171)	(0.176)	(0.173)
Cumulative return [t-10, t-1]	-0.0551**	-0.0911*	-0.0753	0.0415	-0.0995	0.167***
	(0.0236)	(0.0524)	(0.0706)	(0.0837)	(0.0776)	(0.0491)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Past 10-day daily return	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.255	0.335	0.391	0.512	0.627	0.705
Observations	109,675	109,675	109,675	109,675	109,675	109,675

Table B.6

Fire Sales and Reversals, Standardized Coefficients

This table presents the same regressions as in Table 7, but measures fire sale exposure as a standardized variable. The coefficient for fire sale exposure represents the expected change in abnormal returns for a one standard deviation change in each independent variable. Standard deviations are measured within the relevant regression sample. Standard errors are allowed to be clustered at the date level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: FSE Calculated Using All Margin Accounts

CAR:	[t]	[t, t+3]	[t, t+5]	[t, t+10]	[t, t+20]	[t, t+40]
	(1)	(2)	(3)	(4)	(5)	(6)
Fire sale exposure	-0.00103***	-0.00255***	-0.00398***	-0.00506***	-0.00162*	0.000438
	(0.00028)	(0.000554)	(0.000772)	(0.00107)	(0.000844)	(0.000558)
Return volatility [t-60, t-1]	-0.00315	-0.00541	-0.00562	-0.00261	0.0068	0.00295
	(0.0021)	(0.0045)	(0.00584)	(0.00736)	(0.00827)	(0.00524)
Log market value [t-3]	-0.0653***	-0.200***	-0.318***	-0.557***	-0.809***	-0.732***
	(0.00756)	(0.0145)	(0.0195)	(0.0277)	(0.0301)	(0.0199)
Avg turnover [t-60, t-1]	-0.00237	-0.00774**	-0.0127***	-0.0245***	-0.0554***	-0.0294***
	(0.00174)	(0.00328)	(0.00411)	(0.00436)	(0.0045)	(0.00443)
Cumulative return [t-10, t-1]	-0.0131**	-0.0217*	-0.0178	0.0102	-0.0233	0.0396***
	(0.00561)	(0.0124)	(0.0167)	(0.0199)	(0.0185)	(0.0117)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Past 10-day daily return	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.255	0.335	0.391	0.512	0.627	0.705
Observations	109,675	109,675	109,675	109,675	109,675	109,675

Table B.6
Fire Sales and Reversals, Standardized Coefficients (Continued)

Panel B: FSE Calculated Using Brokerage Margin Accounts

CAR:	[t]	[t, t+3]	[t, t+5]	[t, t+10]	[t, t+20]	[t, t+40]
	(1)	(2)	(3)	(4)	(5)	(6)
Fire sale exposure	-0.000187**	-0.000441***	-0.000784***	-0.00106***	-0.00118***	0.000326
	(0.0000861)	(0.000141)	(0.000228)	(0.000211)	(0.000339)	(0.000463)
Return volatility [t-60, t-1]	-0.00319	-0.00553	-0.0058	-0.00284	0.00678	0.00295
	(0.0021)	(0.00451)	(0.00586)	(0.00739)	(0.00828)	(0.00524)
Log market value [t-3]	-0.0655***	-0.201***	-0.319***	-0.558***	-0.810***	-0.732***
	(0.00759)	(0.0146)	(0.0197)	(0.0278)	(0.03)	(0.02)
Avg turnover [t-60, t-1]	-0.00241	-0.00782**	-0.0128***	-0.0247***	-0.0555***	-0.0294***
	(0.00174)	(0.0033)	(0.00413)	(0.00437)	(0.00449)	(0.00444)
Cumulative return [t-10, t-1]	-0.0133**	-0.0222*	-0.0186	0.00912	-0.0234	0.0396***
	(0.00562)	(0.0125)	(0.0168)	(0.02)	(0.0185)	(0.0117)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Past 10-day daily return	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.255	0.334	0.39	0.512	0.627	0.705
Observations	109,675	109,675	109,675	109,675	109,675	109,675

Panel C: FSE Calculated Using Shadow Margin Accounts

CAR:	[t]	[t, t+3]	[t, t+5]	[t, t+10]	[t, t+20]	[t, t+40]
	(1)	(2)	(3)	(4)	(5)	(6)
Fire sale exposure	-0.00108***	-0.00269***	-0.00414***	-0.00523***	-0.00112	0.0003
	(0.000308)	(0.000652)	(0.000875)	(0.00121)	(0.000988)	(0.000448)
Return volatility [t-60, t-1]	-0.00317	-0.00547	-0.00572	-0.00275	0.00674	0.00296
	(0.0021)	(0.0045)	(0.00585)	(0.00736)	(0.00828)	(0.00524)
Log market value [t-3]	-0.0652***	-0.200***	-0.318***	-0.557***	-0.809***	-0.732***
	(0.00756)	(0.0145)	(0.0195)	(0.0276)	(0.0302)	(0.0199)
Avg turnover [t-60, t-1]	-0.00237	-0.00773**	-0.0127***	-0.0245***	-0.0555***	-0.0294***
	(0.00173)	(0.00328)	(0.00411)	(0.00436)	(0.0045)	(0.00443)
Cumulative return [t-10, t-1]	-0.0132**	-0.0220*	-0.0183	0.00947	-0.0236	0.0397***
	(0.00562)	(0.0125)	(0.0168)	(0.0199)	(0.0185)	(0.0117)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Past 10-day daily return	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.255	0.335	0.391	0.513	0.627	0.705
Observations	109,675	109,675	109,675	109,675	109,675	109,675

Table B.7

Fire Sales and Reversals, Excluding Imputed Prices

This table presents the same regressions as in Table 7, but exclude stocks that ever experienced a full day of suspended trading during the event period $[t, t+40]$. In our baseline analysis, we impute stock prices and returns for trading days in which a particularly stock did not trade. The imputation procedure uses information on the most recent traded prices before and after the trading suspension. Standard errors are allowed to be clustered at the date level. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

CAR:	[t]	[t, t+3]	[t, t+5]	[t, t+10]	[t, t+20]	[t, t+40]
	(1)	(2)	(3)	(4)	(5)	(6)
Fire sale exposure	-1.858***	-4.762***	-7.988***	-9.802***	-4.283**	-1.442
	(0.678)	(1.465)	(2.24)	(2.583)	(1.842)	(1.127)
Return volatility [t-60, t-1]	-0.215	-0.456	-0.449	-0.13	0.595	1.049**
	(0.186)	(0.38)	(0.474)	(0.617)	(0.665)	(0.437)
Log market value [t-3]	-0.0625***	-0.189***	-0.304***	-0.544***	-0.814***	-0.715***
	(0.00898)	(0.0164)	(0.0241)	(0.0382)	(0.0389)	(0.0203)
Avg turnover [t-60, t-1]	-0.108	-0.302**	-0.548***	-1.061***	-2.223***	-1.689***
	(0.0674)	(0.118)	(0.138)	(0.156)	(0.181)	(0.155)
Cumulative return [t-10, t-1]	-0.0640**	-0.0763	0.000787	0.178*	-0.045	0.122**
	(0.0271)	(0.0668)	(0.0837)	(0.0912)	(0.0821)	(0.0594)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Past 10-day daily return	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.252	0.348	0.404	0.514	0.637	0.734
Observations	68,063	68,063	68,063	68,063	68,063	68,063