Leverage-Induced Fire Sales and Stock Market Crashes*

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March 22, 2018

Abstract

This paper provides direct evidence of leverage-induced fire sales contributing to a major stock market crash. Our analysis uses proprietary account-level trading data for brokerage- and shadow-financed margin accounts during the Chinese stock market crash in the summer of 2015. We find that 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 investors facing financial constraints experience high selling pressure and abnormal price declines that subsequently reverse over the next 40 trading days. Unregulated shadow-financed margin accounts, facilitated by FinTech lending platforms, contributed more to the market crash even though these shadow accounts had higher leverage limits and held a smaller fraction of market assets 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, 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 leading 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

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

the global economy. 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 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 falls in a regulatory grey 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; 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

[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.

[3]The maximum leverage or Pingcang Line corresponds to the reciprocal of the maintenance margin in the US.

[4]This confirmed in our sample. The equal-weighted average leverage (measured as assets/equity) is 6.62 for shadow accounts, while only 1.43 for brokerage accounts.

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]

We begin our empirical analysis by identifying the role of leverage constraints in affecting individual investor trading behavior. For each account-date, we observe the account's leverage (defined as the ratio of asset value to equity value) and "proximity to the Pingcang Line," i.e., how close the account's current leverage is to its Pingcang Line. Theories such as Brunnermeier and Pedersen (2009) and Garleanu and Pedersen (2011) predict that investors will sell assets as the account's leverage approaches its Pingcang Line. Costly forced sales occur if leverage exceeds the account's Pingcang Line and the account is taken over by the lender. 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 held in the account increase with the account's proximity to its Pingcang Line. The effect is non-linear, and increases sharply when leverage is very close to the Pingcang Line. Using variation in Pingcang Lines across shadow accounts, we further test how the level of leverage interacts with proximity to the Pingcang Line to affect individual selling behavior. Conditional on the current level of proximity, leverage magnifies the sensitivity of each account's change in proximity to any future changes in the value of assets held. This amplification channel may lead investors with precautionary motives to delever if leverage is high, particularly if the account is already close to hitting the Pingcang Line. Indeed, we find in the data that investors are much more likely to sell assets if proximity and

[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 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 start to sell before hitting the constraint. Lastly, 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)).

leverage are jointly high.

We also find evidence of strong interactions between leverage-induced selling, market movements, and government regulations. The relation between proximity 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 halt trading for individual stocks when their within-day price change exceeds 10% may have 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 move on to show that stocks that are disproportionately held by margin accounts near their Pingcang Lines experience high selling pressure. We classify accounts whose leverages are close to their Pingcang Lines 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 portfolio 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. We find a similar U-shaped return response using regression analysis, which allows us to better control for other factors that could influence returns, such as past returns, volatility, and stock and date fixed effects.

Finally, our unique data sample 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? 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 CSRC. Thus, even though brokerage accounts have lower leverage on average, these account may also be closer to hitting leverage constraints. We find that the data strongly 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 relatively 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 offers much stronger explanatory power for price movements than a similar fire sale exposure measure constructed from the brokerage accounts data sample, even though the data samples are approximately equal in size.

Related Literature Our paper is related to the large literature on fire sales and their impact on various asset markets including the stock market, housing market, derivatives market, and even markets for real assets (e.g., aircrafts). 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) directly 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. (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 original paper by Shleifer and Vishny (1992) and the subsequent theory literature focuses 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 examining 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), among others;[7] help academics and policymakers understand these linkages in the aftermath of the recent global financial crisis. There is also a large empirical literature that connects

[7]Another important strand of literature explore the 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).

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 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, but not in bear 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.[8]

There are several concurrent academic articles investigating the Chinese stock market crash in the summer of 2015; most of them use stock-level rather than account-level brokerage and shadow margin trading data, e.g., Huang et al. (2016) and Chen et al. (2017). Our analysis and conclusions are complementary to a companion paper by Bian et al. (2017), which uses the same dataset on margin traders in the Chinese stock market in 2015. Bian et al. (2017) focuses on examining 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. (2017) also show that this within-account contagion can be further transmitted across account networks, again amplified

[8]As explained in Section 2.4, in China there also exists a list of stocks that are eligible for obtaining margin credit, but investors can purchase and hold non-eligible stocks in their margin accounts. As a result, both eligible and non-eligible stocks are subject to leverage-induced fire sales during the stock market crash.

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. (2017), 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 Institution Background

Our empirical analysis exploits account-level margin trading data in 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 in 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 at 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.[9]

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

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

[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 byBian et al. (2017), 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.

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; they can also borrow from the China Securities Finance Corporation (CSFC) at a rate slightly higher than the interbank rate.[11] Brokers then lent 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 Figure 1).[12] With a risk-free rate of around 4% at that time, 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 on 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 that 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

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

[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.

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-assets ratio of a margin account increases beyond 1/1.3, and if borrowers fail not inject equity to reduce the account's debt-to-asset ratio the next day, the account is subject to being taken over by brokerage firms who then liquidate all account holdings indiscriminately.

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" in Chinese. 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]

2.3 Shadow-Financed Margin Accounts

During the first half of 2015, 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 (also called peer-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 grey 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

[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. 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.

interest rates around 11-14%, which are 3-5 percentage points above 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 system, with each mother account offering trading access to many (in most cases, hundreds of) child accounts. The mother account, which is connected to a distinct trading account registered in a brokerage firm, belonged to the lender who was usually a professional financing company. On the other hand, each child account was managed by individual retail margin traders. Through this umbrella-style structure, a lender could lend funds to multiple margin traders, while maintaining different leverage limits for each trader (child account).

On the the surface, mother accounts appear to be normal unlevered brokerage accounts, albeit with unusually large asset holdings and trading volume. In reality, these large brokerage accounts were mother accounts, which used a software program to transmit the orders submitted by associated child accounts in real time to stock exchanges. Similar to brokerage-financed margin accounts, child accounts in the shadow-financed margin system had maximum allowable leverage limits—i.e., the Pingcang Line—beyond which the child account would be taken over by the mother account (the lender), triggering fire sales. Often, this switch of ownership was automated through the software system, by simply triggering the expiration of the borrowers' passwords and immediate activation of that of the lender. Unlike the brokerage-financed margin system, there were no regulations concerning the maximum allowable leverage for each child account. Instead, the lender and the borrower 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 account. In our sample, unregulated shadow accounts have a much higher Pingcang Line on average than their regulated brokerage peers (see Table 1).

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

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

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 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 grey color on the right hand side of Figure 1, the shadow-financed margin system operated in the "shadow." Regulators do not know the detailed breakdown of their funding sources shown in Figure 1 and therefore the 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, right 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

[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 at 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

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 negotiated account-specific Pingcang Line, without any regulation on 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 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 6th, 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.

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

model with extrapolative beliefs and the disposition effect; and Bian et al. (2017) 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.

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

significant cross-account heterogeneity. We then define each account's proximity to the Pingcang Line, which measures the tightness of the financial 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 about 10% of the market share in the brokerage business. 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 market accounts represents about 5% of the outstanding regulated 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 mentions one reasonable estimate that the debt funding going to shadow accounts peaked to around 1-1.4 trillion Yuan, implying that our sample covers about 5% of the shadow-financed margin system.

As emphasized, the unique advantage of these two datasets is that we observe the assets and debt of each margin account, and hence its leverage.[22] In addition to the two proprietary account-level datasets, we obtain daily closing prices, trading volume, stock returns and other stock characteristics

[22]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.

from the WIND database, which is widely regarded as the leading vendor for Chinese market data.

3.2 Leverage

Following Ang et al. (2011) and **Adrian et al. (2014)**, among others, we define leverage as

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

for account j at the start of day t. $Total\, assets_{jt}$ 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.

The Pingcang Line is the maximum leverage the investor can hold before control of the account is transferred to the lender (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 her leverage after receiving a margin call, her account will be taken over by the lender. Although the lender is then expected to liquidate stock holdings for deleveraging purposes, the lender may be unable to sell due to trading suspensions and/or daily price limits (the 10-percent-rule) in the Chinese stock market. In the latter case, stock prices may continue to drop by -10% every day before orders can be executed, and hence the leverage of the child account can increase well above the Pingcang Line. 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.

Figure 2 plots the equity-weighted-average leverage for the brokerage- and shadow-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 the 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, leverage of shadow accounts fluctuates in a much more dramatic way than that of brokerage accounts; this pattern is consistent with the widely-held belief that shadow accounts have been a driving force of the market fluctuations in 2015. 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 SSE index increased from the beginning of May to the middle of June, average shadow leverage declined. When the stock index began to plummet in the middle of June, shadow leverage grew and hit its peak around July 10th, when SSE index reached its lowest point. Overall, Figure 2 shows that leverage displays significant counter-cyclical trends and across-account heterogeneity.[23]

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. Figure 3 shows that, relative to the equity-weighted average, asset-weighted levels of leverage were much higher throughout our sample period and sharply increased 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 Proximity to Pingcang Line

Theoretically speaking, leverage-induced fire sales are a consequence of financing constraints in models with leverage-financed agents, and their economic forces depend on the extent to which

[23]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 explain 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 Figure 2.

the constraint binds (or may bind in the future). We emphasize that a leverage constraint is not leverage itself. Because the account's leverage constraint binds when leverage hits the account's Pingcang Line, we construct the "proximity to the Pingcang Line" for each account-day observation as follows:

$$P_{jt} = \frac{Lev_{jt} - 1}{\overline{Lev_j} - 1}. \tag{2}$$

Here, P_{jt} is the proximity of account j's leverage to its Pingcang Line at the start of day t, Lev_{jt} is the leverage for account j at the start of day t, and $\overline{Lev_j}$ is the Pingcang Line of account j. A higher proximity implies the investor is closer to losing control of the account, and therefore proxies for a tighter leverage constraint. As explained in Section 3, although $\overline{Lev_j}$ is the maximum allowable leverage for a margin account, Lev_{jt} may exceed $\overline{Lev_j}$ if investors and lenders cannot sell their holdings due to trading suspensions or daily price limits.

Figure 2 shows the distribution of account-level proximity for each day, pooling together the brokerage and shadow samples. A key advantage of our analysis is that we can exploit the within-day heterogeneity in proximity among leveraged margin accounts. We observe a qualitatively similar pattern for the evolution of leverage constraints: the lower percentile lines (20th and 50th) remain relatively flat throughout the sample period, whereas the 80th and 90th percentile lines rise quickly when the market index plummeted. Starting at the end of June 2015, the 90th percentile of account-level proximity to the Pingcang Line exceeds 1, implying that, at that time, more than 10% of accounts were taken over by lenders.

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 Figure 2, we find average leverage in shadow accounts is more than four times larger than that in brokerage accounts. Shadow accounts also have Pingcang Lines that are, on average, more than three times larger than 4.3, the Pingcang Line that applies to all brokerage accounts. Despite the fact that shadow accounts tend to have higher maximum allowable levels of leverage, shadow accounts are also more likely to face financing constraints. On average, shadow accounts are more than four times closer to their Pingcang Lines than brokerage-financed margin accounts. Finally, shadow accounts display substantially greater dispersion in leverage, with a standard deviation of 12.7 compared to a standard deviation of 0.5 for brokerage accounts.

In some analysis, 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, these accounts are not included when we refer to "brokerage accounts" which always refer to brokerage-financed margin accounts.

4 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 appear to be driven by the small pool of shadow-financed margin accounts that faced severe leverage constraints.

4.1 Selling Intensity

We first show that account-level funding constraints, as measured by proximity to the Pingcang Line (defined in Equation (2)), cause investors to sell assets. We sort P_{jt} into 10 equally spaced bins, indexed by k and construct a dummy variable of $I^j_{kt} = 1$ if $P_{jt} \in [(k-1)/10, k/10\rangle$ where $k = 1, 2, ..., 10$. We also create two additional bins: bin 0 for unlevered accounts ($P_{jt} = 0$ is classified in bin 0 rather than bin 1); and bin 11 for accounts with $P_{jt} \geq 1$, which occurs if Lev_{jt} exceeds $\overline{Lev_j}$.

We then examine how proximity to the Pingcang Line at the start of each day t affects investor selling during day t. We estimate the following regression

$$\delta_{it}^{j} = \sum_{k=1}^{11} \lambda_k I_{kt}^{j} + \nu_{it} + \alpha_j + \varepsilon_{it}^{j} \tag{3}$$

where δ_{it}^{j}, which is the account j's net selling of stock i, is defined as

$$\delta_{it}^{j} = \frac{\text{net shares sold of stock } i \text{ by account } j \text{ on day } t}{\text{shares of stock } i \text{ held by account } j \text{ at the start of day } t}.$$

Because we are interested in selling behavior, the sample is restricted to stocks held by account j at the start of day t.[24] The sample is also restricted to stock-days during which the stock did not experience a trading suspension for any reason. We regress net selling δ_{it}^{j} on dummy variables for each bin representing proximity to the Pingcang Line. 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, which measure the difference in selling intensity within each bin relative to the omitted category of unlevered accounts. If closeness to the Pingcang Line causes net selling, we expect that the selling intensity λ_k will increase with k.

It is worth emphasizing that in Equation (3), we also control for 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 by accounts with different proximity to the Pingcang Line. The account fixed effects captures the account-specific unobservable effect–e.g., some accounts may be more likely to sell than others on average during our sample period.

Figure 5 shows the selling intensity λ_k for each bin representing proximity to the Pingcang Line. The regression analogue for the figure is presented in Column 1 of Table 2. We find that λ_k increases with k, consistent with our conjecture that closeness to financing constraints induces investors to

[24]Net buying of stock i by account j on date t results in negative values for δ_{it}^{j}, and the observation can go 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.

sell their holdings. Relative to unlevered accounts, accounts in bin 10 (where leverage is within 10% of the Pingcang Line) increase net selling by 0.18, equivalent to 60% of a standard deviation in the level of net selling activity across accounts.

In Figure 5, λ_k is close to zero for accounts that are far away from their Pingcang Lines, and increases sharply when the proximity to the Pingcang Line approaches 0.6. For this reason, from now on, we refer to accounts with a proximity to the Pingcang Line greater than 0.6 as "fire sale accounts." These accounts are significantly more likely to face funding constraints and to contribute to fire sales of assets. In later tests, we also show that our results are not sensitive to the exact 0.6 cutoff.

4.1.1 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 call to exhibit high selling intensity, even when the aggregate market does well. However, conditional on a given proximity to the Pingcang Line 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 proximity and selling intensity will be stronger if the market return on day t is negative.

Figure 7 and Table 4 show how proximity to the Pingcang Line at the start of day t affects selling intensity, conditional on whether the market return is positive or negative on day t. We find significant interactions between leverage-induced selling and market movements. Consistent with these predictions, we find that higher proximity leads to higher selling intensity even when market returns are positive. We also find that the relation between proximity 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 proximity.

4.1.2 Leverage Amplification

Next, we examine how tightened leverage constraints (as proxied by proximity to the Pingcang Line) interacts with each account's level of leverage. An increase in leverage has the direct effect of moving each account closer to its Pingcang Line, thereby increasing its proximity. Controlling for the account's current level of proximity, leverage should still matter, because leverage amplifies the sensitivity of each account's change in proximity to any future stock price fluctuations for assets held by the account. This amplification channel may lead investors with the same proximity to the Pingcang Line to delever more when leverage is higher, particularly if the account is already close to the Pingcang Line.

We test this mechanism by analyzing how selling intensity is affected by proximity, leverage, and the interaction between leverage and an indicator for whether the account is close to its Pingcang Line (a fire sale account). We focus this analysis on shadow-financed margin accounts, because Pingcang Lines vary across accounts in the shadow sample, allowing us to separately identify the effects of proximity, leverage, and potential interactions. Note, we cannot do this analysis for the brokerage sample, because all accounts have the same Pingcang Line, so there is a one-to-one mapping between leverage and proximity.

In Table 3, we regress net selling on proximity bins as defined before, five bins in leverage, interactions between the leverage bins and an indicator for fire sale accounts, as well as stock-date fixed effects and account fixed effects. We find that proximity continues to predict higher selling intensity, after controlling for leverage. Moreover, the interaction between the largest leverage bins and the indicator for fire sale accounts is significantly positive. This implies that, controlling for proximity, investors are more likely to sell assets if proximity and leverage are jointly high.

We also find that the relation between net selling and leverage is non-linear. While very high leverage predicts increased net selling, the relation between leverage and net selling is reversed conditional on leverage being among the lower bins. 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 (proximity) constant. However, as leverage constraints begin to bind, investors become more likely to sell assets if the level of leverage is also high.

4.1.3 Total Account Risk

Overall, we expect that selling intensity of each trading account should be an increasing function of proximity, leverage, and volatility of the underlying assets held, as all these three contribute to the risk of losing control of the account. In our next test, we show how net selling relates to a summary measure of total account risk that combines these three pieces of information at the account level. For each account at the start of each day, we calculate Z equal to the number of standard deviations of downward changes to the value of stock portflio held by the account, so that this shock necessary moves the account from its current proximity level to a proximity of one (at which point the creditor seizes control of the account). As Z approaches zero, the borrower's risk of losing control of the account increases. Thus, we expect net selling to increase as Z approaches zero.

Specifically, consider an account with leverage $Lev_{jt} = A_{jt}/E_{jt}$ at date t, and let σ_{jt}^A be the volatility of the stock portfolio currently held in the account.[25] Then we define Z such that

$$\frac{A_{jt} - A_{jt}\sigma_{jt}^A Z}{E_{jt} - A_{jt}\sigma_{jt}^A Z} = \frac{1 - \sigma_{jt}^A Z}{\frac{1}{Lev_{jt}} - \sigma_{jt}^A Z} = \overline{Lev}_j.$$

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. For for each account-date

[25]We calculate σ_A as the weighted average of the annualized return volatilities of the stocks held in the account, with stock return volatility being calculated based on the 2014 sample.

observation with some positive leverage but still below Pingcang Line, we can calculate Z_{jt} to be an explicit function of current leverage Lev_{jt}, Proximity P_{jt}, and asset volatility σ^A_{jt}:[26]

$$Z_{jt} = \frac{1 - P_{jt}}{\sigma^A_{jt} \cdot Lev_{jt}}.$$

Figure 6 shows the regression coefficients when we reestimate Equation (3), but substitute the bins for proximity P with equally spaced bins in terms of the account risk Z. As before, the regression is estimated at the account-stock-day level and we control for account and stock-day fixed effects. Overall, the estimation results are similar to previous results. We find that selling intensity increases as Z approaches zero. The relation is also non-linear. Selling intensity is low for most values of Z and then increases starting when Z moves into the range of 3 to 2. Intuitively, investors begin to intensify their selling when a two to three standard deviation return movement would lead to loss of control of their accounts.

4.1.4 Potential Alternative Mechanisms

We conclude this section by addressing potential alternative or complementary mechanisms for the relation between proximity to the Pingcang Line (a proxy for leverage constraints) and account selling intensity in Figure 5. As discussed previously, because we control for stock-date and account fixed effects in our baseline specification, the relation cannot be explained by any mechanisms that only vary at the stock-date or account level.

We begin by noting that leverage, even in the absence of financing constraints, may lead investors to sell assets. For example, Merton (1971) presents a model in which a risk-averse agent chooses to delever after experiencing a negative shock which increases her leverage, even when the agent faces no financial or leverage constraints. If so, the relation between selling intensity and proximity documented in Figure 5 would represent the additional selling intensity due to a combined effect of higher leverage and leverage constraints (because our measure of proximity is correlated with

[26]For accounts that has already exceeded its Pingcang Line, $P_{jt} > 1$ and hence Z is negative; while for accounts currently with no debt (so leverage is 1), Z is defined as an arbitrary large number. These treatment matters little as we are estimating the relation between the account risk Z and its selling intensity in a flexible nonlinear way.

leverage). Since we are mainly interested in the aggregate implications of leverage and leverage constraints in later sections, we leave the detailed quantitative distinction between the leverage effect and the leverage constraint effect for future research.

However, we can made some headway in isolating a leverage constraint effect. First, as previously discussed in Section 4.1.2, we can take advantage of the fact that shadow accounts have variation in proximity for the same level of leverage. We find that higher proximity (i.e., a tighter leverage constraint) leads to higher selling intensity after controlling for account-level leverage.

We also present a second test whose qualitative patterns can help isolate and identify the existence of a leverage constraint effect, at least in the region in which proximity exceeds one. Recall that, in our sample, lenders take control once an account's proximity to the Pingcang Line exceeds one. As discussed previously, proximity can rise beyond one if the lender is unable to immediately sell stocks due to trading suspensions and/or daily price limits (the 10-percent-rule). In this region, lenders can also exercise discretion in terms of whether and what to sell. In the expanded version of the regression described by Equation (3), we create additional dummy variables I_{kt}^{j} for these taken-over accounts with proximity above one. A standard Merton-style portfolio rebalancing model would predict that selling intensity should keep rising after proximity exceeds one, because leverage continues to increase with proximity in this region. In contrast, the leverage constraints theory predicts that the selling intensity can remain flat or even decrease for accounts with proximity beyond one, because the lender who controls the account will sell only to maximize her recovery value.[27] Consistent with a leverage constraints model, we show in Appendix Figure B.1 that selling intensity does not monotonically increase with proximity when proximity exceeds one. In later results in Section 4.4.2, we will present further evidence in support of leverage constraints, by examining the differential reactions of the selling intensities of brokerage and shadow accounts in response to shadow-targeted regulatory shocks.

We also explore another, more behavioral, explanation. Margin accounts that have recently

[27] The lender would like to sell as long as the account value exceeds the face value of debt. When the account value drops below the face value of debt (a notional negative equity), the lender will internalize the trading losses and hence becomes cautious, which should lower the selling intensity.

experienced poor account-level returns will tend to be accounts with high proximity. 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 (3). In supplementary results, shown in Appendix Table B.1, we find a similar and slightly stronger relation between proximity 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.

4.2 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 are close to their Pingcang Lines, i.e., fire sale accounts with proximity $P_{jt} > 0.6$, to be more exposed to fire sale risk. To test this hypothesis, we define stock i's fire sale exposure (FSE) on day t as:

$$FSE_{it} = \frac{\text{total shares of stock } i \text{ held in fire sale accounts at the start of day } t}{\text{outstanding shares of stock } i \text{ on day } t}. \tag{4}$$

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.

We estimate the following regression to examine the effect of FSE on stock-level selling pressure:

$$\delta_{it} = \beta \cdot FSE_{it} + controls_{it} + s_i + \tau_t + \varepsilon_{it}. \tag{5}$$

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 (5), $controls_{it}$ 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 corresponding Equation (5). 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 14.4%. This R-squared is large relative to the R-squared of 18.7% 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 8, 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[28] (shown later in Figure 12), which motivates our next set of tests which examine the asset pricing implications of selling pressure from fire sale accounts.

[28]Our sample of margin accounts represents approximately 5% of the margin market, so total net selling pressure from fire sale accounts are likely to be approximately twenty times larger (see Section 4.4 for details). Note that the large sharp drops in net selling correspond to days with halted market-wide trading.

4.3 Fire Sale Exposure and Stock Prices

In this section, we show how fire sale exposure affects stock prices. Selling pressure from margin accounts close to their Pingcang Lines can cause stock-level fire sales if there is insufficient liquidity in the market to absorb the selling pressure. These fire sales should cause stock prices to decline in the short run; while in the long run, prices should revert to fundamental value if liquidity returns to the market. Thus, we expect stocks with high FSE to under-perform stocks with low FSE over the short-run and to revert to similar levels in the long-run.

We present two empirical strategies to test this conjecture. For both empirical strategies, we impute stock returns for days in which the stock experienced a full day of suspended trading using prices before and after the trading suspension, assuming equally compounded daily returns during the suspension period. For days in which stocks experienced trading suspensions midway during the day (e.g., after hitting a daily price limit of 10%), we use the actual return on that day.[29]

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 9, 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

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

which FSE is measured. The difference in performance reverts toward zero with 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:

$$CAR_{i,t+h} = \gamma_h \cdot FSE_{it} + controls_{it} + s_i + \tau_t + \varepsilon_{it}, \tag{6}$$

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 6 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.

4.4 Brokerage- vs. Shadow-Financed Margin Accounts

As explained in Section 2, two types of leveraged margin accounts active 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 4.4.3, many estimates suggest that total market assets held within the regulated brokerage-financed system greatly exceeded that in the unregulated shadow-financed system. Second, because brokerage accounts have a lower (and uniformly imposed) Pingcang Line, brokerage accounts may have been closer to their Pingcang Lines (and to facing 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 maintain lower leverage as a fraction of the Pingcang Lines. Equivalent, shadow margin accounts have higher leverage limits and greater proximity, 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 more detail in this subsection. We believe our findings can shed light on the consequences of regulation or lack thereof.

4.4.1 Selling Intensities for Brokerage and Shadow Accounts

In Section 4.1, 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 proximity to the Pingcang Line above the cutoff of 0.6 (i.e., $P_{jt} \geqslant 0.6$ as in Equation 2). 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 10 and the corresponding regression coefficients are presented in Table 2 Column 2 and 3. We find that the estimated selling intensities increase with the proximity to the Pingcang Line for both samples, consistent with the leverage-induced fire sales mechanism.

There are several features in Figure 10 worth discussing. First, conditional on a bin for proximity to the Pingcang Line, selling intensities are much larger for shadow accounts. In fact, for P_{jt} in the range between 0.5 and 1, the selling intensity in shadow accounts is about twice as large as that of brokerage accounts. This pattern is consistent with the leverage amplification effect that we studied in Section 4.1.2. Conditional on a proximity to the Pingcang Line bin, shadow accounts have higher leverage than brokerage accounts. As shown earlier in Table 3 in Section 4.1.2, when we compare the net selling of the same stock on the same day, held by two accounts with the same proximity to the Pingcang Line, the higher leverage of the shadow accounts will amplify any negative fundamental shock (of the stock price), leading to more precautionary selling behavior by shadow account holders.

Second, once either account type crosses over the Pingcang Line and is taken over by the lender (the last bin with $P_{jt} > 1$), the selling intensity of brokerage accounts rises dramatically, and is even slightly higher than that of shadow accounts. At this point, the lender starts to aggressively sell all assets, and differences in borrowers' precautionary motives across brokerage and shadow account types no longer matter.[30]

4.4.2 Regulatory Shocks

We also investigate how the selling intensities of brokerage and shadow accounts differ in their responses to the regulatory shocks that occurred before the onset of the market crash. As mentioned toward the end of Section 2.3, 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

[30]It is interesting to observe that shadow accounts, after being taken over by lenders, exhibit less aggressive selling behaviors than similarly defaulted brokerage accounts. Although our data does not allow us to investigate this issue fully, one plausible explanation is that some lenders 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 risk management systems.

announcements, which were released after-hours on Fridays. The results are plotted in Figure 7, and detailed regression results are presented in Table 7. We find that the two regulatory announcements led to small and inconsistent changes in the selling intensities for brokerage accounts (note that very few brokerage occupied the far right bins representing proximity close to one, so the estimated selling intensities for those far right bins are insignificantly different from zero). In contrast, news of regulatory tightening significantly increased the selling intensities of shadow accounts within each bin for proximity to the Pingcang Line. The June 12 announcement, in particular, led to more than a tripling of selling intensities for shadow accounts with proximity greater than 0.6. 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 to further identify a causal link between financing constraints and selling pressure from shadow accounts with high proximity. The sharp increase in selling intensity by shadow accounts immediately following these regulatory announcements (and the concurrent muted reaction by brokerage margin investors) is consistent with high proximity shadow accounts selling because they feared increased constraints due to regulatory oversight. As with the previous account-level evidence presented in Figure 5, 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 high proximity shadow accounts held an unobservably different set of assets or engaged in different selling behaviors on average during the event study sample period.

4.4.3 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 reflected by Figure 12, 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.[31]

[31] 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

However, Panel A in Figure 12 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, farther from their Pingcang Lines, and exhibit lower selling intensities conditional on proximity to their Pingcang Lines. In Panel B, we instead plot total assets held in fire sale accounts, i.e., accounts with $P_{jt} \geq 0.6$. These fire sale accounts are much more likely to receive margin calls and to exhibit greater selling intensity, as shown earlier in Figure 5.

Once we focus on the asset holdings of fire sale accounts in Panel B, we see a very 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 exceeds 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 that of shadow fire sale accounts.

Next, we show that shadow accounts matter more for selling pressure at the stock-day level. First, we repeat the exercise in Panel A of Table 5, but with a measure of Fire Sale Exposure FSE in (4) that is constructed using data for each account type separately. The results are reported in Panels B and C of Table 5. We find that FSE has a 67% larger impact on selling pressure when FSE is measured using shadow account data rather than brokerage account data. This difference in magnitudes is consistent with our previous finding in Figure 10 that, conditional on a given proximity to the Pingcang Line, shadow accounts exhibit much larger selling intensities.

Finally, we show that shadow accounts matter more for fire sales and reversals, i.e., the U-shaped pattern in cumulative abnormal returns for the long-short portfolio constructed base on the FSE-sorting shown in Panel A of Table 6. The results are reported in Panels B and C of Table 6. 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 approximately

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 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%.

five times larger 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.5. We find that a one standard deviation change in FSE as measured in the shadow sample leads to a seven-times larger dip in returns than a one standard deviation change in FSE as measured in the brokerage sample. The FSE coefficient within the shadow sample also has a much larger t-statistic, consistent with the shadow sample offering more explanatory power. Overall, the differences in magnitudes and explanatory power 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.

4.4.4 Discussion: Shadow Accounts Played a More Important Role

Overall, the results in this section support for view that, relative to brokerage accounts, shadow-financed margin accounts contributed more to China's stock market crash in 2015. Panel B of Figure 12 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 Yuan 8.7 trillion during the week of June 1, 2015.[32] 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 triggered a leverage spiral, turning more and more shadow accounts into fire sale accounts, 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, and their fire sales contributed to the continuous market collapse in early July 2015. The leverage-induced fire sale spiral finally stemmed around July 6th, when it is widely believed that

[32]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.

the Chinese government started to heavily intervene using large-scale market purchases.

5 Other Tests and Robustness

In this section, we first explore the implications of leverage-induced fire sale in the presence of price limits, which is an interesting institutional feature of Chinese stock market. We then show that our findings remain qualitatively similar using alternative weighting schemes, cutoffs, sample splits, and imputation procedures.

5.1 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 which would halt all trading for the stock for the rest of the day. 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 we have shown in Table 2, margin investors are significantly more likely to sell assets when their account-level leverage nears their Pingcang Line limit. 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 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 proximity bins defined earlier, the price limit fraction, and the interaction between the price limit fraction and the proximity bins. We restrict the regression sample to stocks that do not face trading restrictions on day t. The results for the full sample of brokerage and shadow margin accounts are reported in Table 8 Column 1. As expected, we find that accounts with higher proximity are significantly more likely to sell. Moreover, the interaction between proximity and price limit is significant and positive for all proximity bins, and increasing in magnitude with proximity. 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 higher proximity). In Columns 2 and 3, we find that the coefficients on the interaction between price limits and each proximity bin tend to be much larger in the shadow accounts sample than the brokerage accounts sample. This is again consistent with deleveraging pressures being bigger for shadow accounts on average, because shadow accounts tend to be more leveraged for a given level of proximity.

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 on 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 8 control for each account's day t counterfactual returns assuming no stocks are bought or sold on day t, interacted with the set of proximity 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.

5.2 Robustness

Appendix Table B.2 shows that the results presented earlier in Table 5 are robust to the choice of the $P_{jt} \geq 0.6$ 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 proximity to the Pingcang Line at the start of each day. Instead of measuring selling pressure as the fraction of shares outstanding sold by fire sale accounts, we estimate selling pressure as the fraction of shares outstanding sold by any leveraged margin account, again with each account's net selling weighted by the corresponding selling intensities λ_k . We continue to find that fire sale exposure leads to increased selling pressure at the stock-day level, controlling for stock and date fixed effects as well as recent performance and characteristics of each stock. Appendix Table B.3 shows that this alternative λ_k-weighted measure of fire sale exposure predicts the same U-shaped return pattern.

Appendix Table B.5 presents standardized coefficients, as discussed earlier in Section 4.4. Finally, Appendix Table B.4 shows that our results are unlikely to be driven by errors or biases in 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 trading suspension. In this robustness test, we exclude stock-day observations from the regressions sample if the stock ever experience a fully 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% in value. 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 other 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 1~1.5 billion dollars in the beginning of 1920's to 17 billion dollars at 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 in the US by the Securities and Exchange Act of 1934). In response to the regulatory void, individual traders took on excessive leverage both in US in 1929 and in China in 2015, leading to fire sale externalities (e.g., Lorenzoni (2008), and 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

This figure depicts the structure and funding sources in the brokerage- and shadow-financed margin systems in the Chinese stock market.

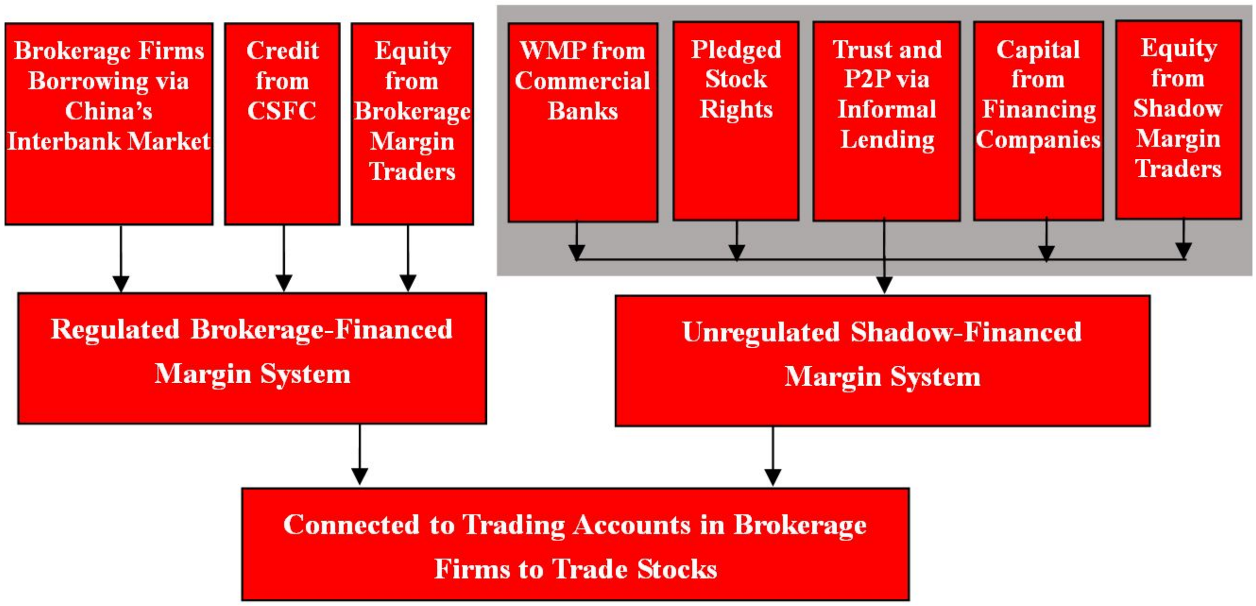


Figure 2
Leverage in Brokerage and Shadow Margin Accounts

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.

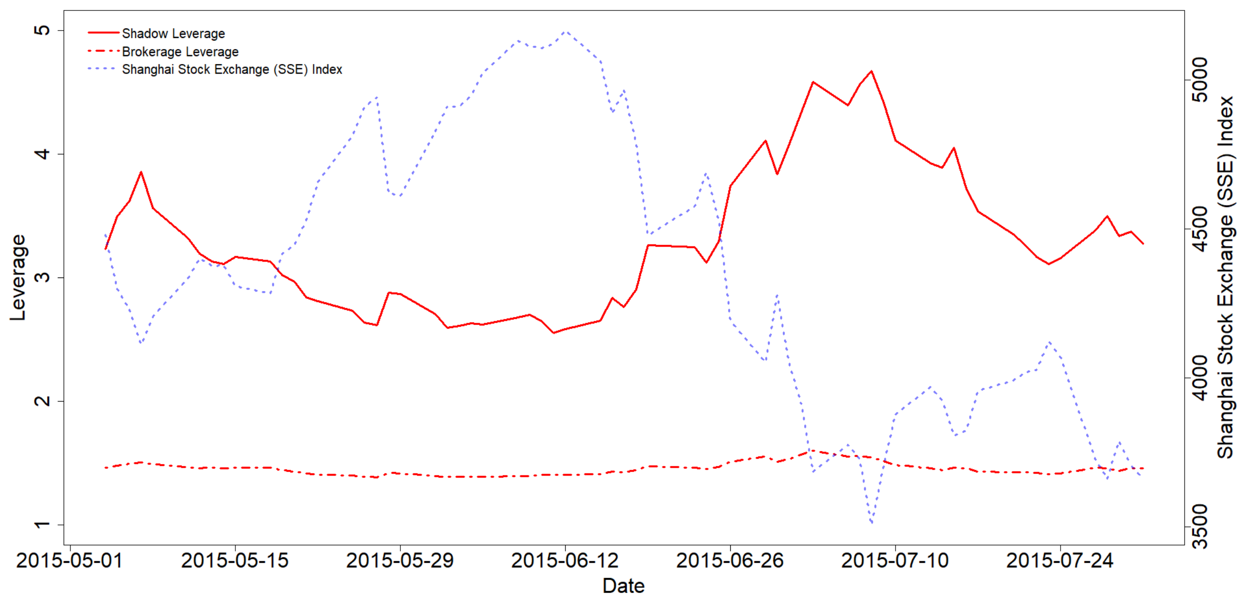


Figure 3
Asset-Weighted and Equity-Weighted Leverage

This figure depicts the Shanghai Stock Exchange (SSE) composite index (the dashed blue line), the asset-weighted average leverage for all 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.

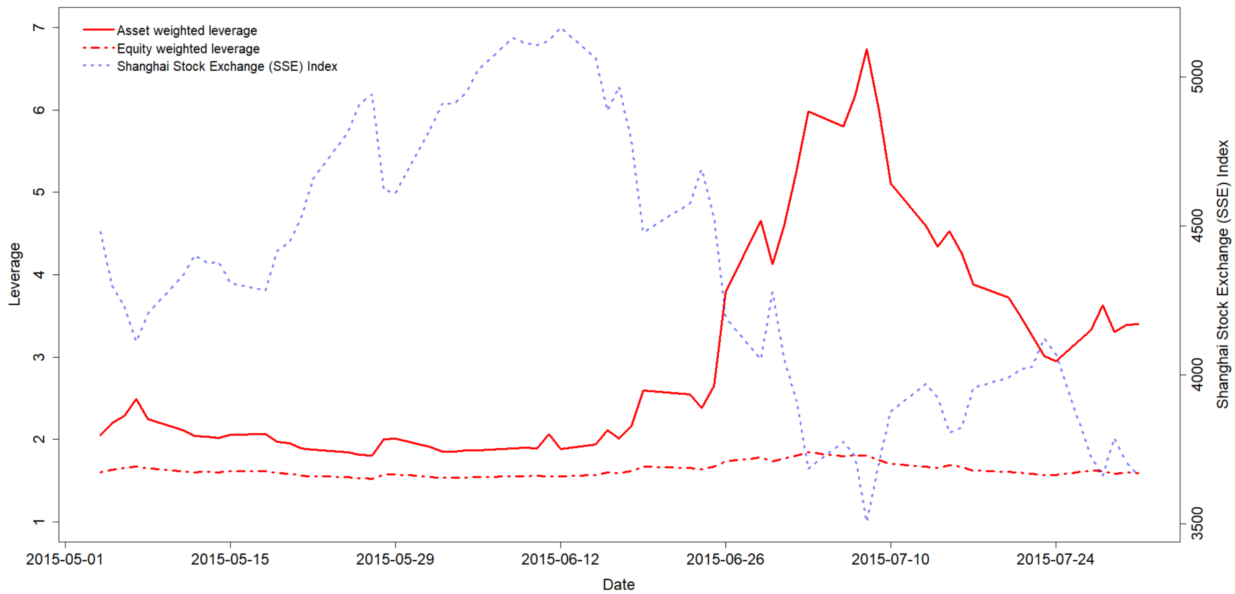


Figure 4
Proximity Dispersion

This figure depicts the Shanghai Stock Exchange (SSE) composite index (the dashed blue line) and the margin account proximity at the 20th (dashed-dotted red line), 50th (dashed red line), and 80th (dot-dashed red line) and 90th (solid red line) percentiles of the full sample including both brokerage- and shadow-financed margin accounts, at the end of each day from May to July, 2015.

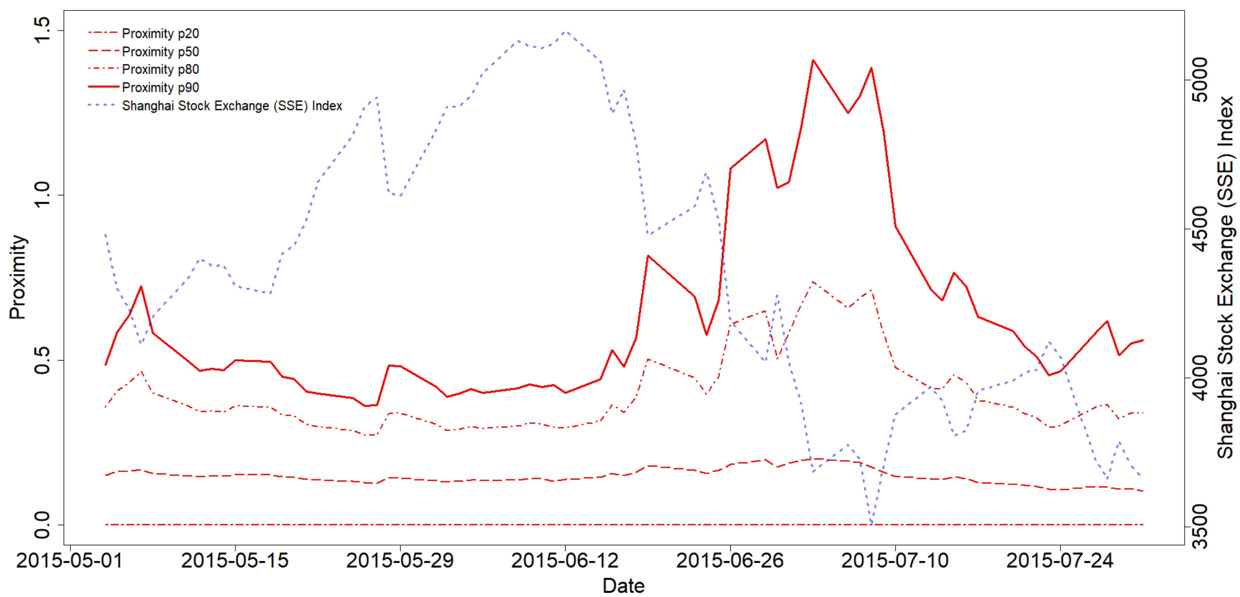


Figure 5
Proximity to the Pingcang Line and Investor Selling Intensity

This figure plots the coefficients λ_k of the regression equation

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

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 equally spaced bins for each account's proximity to its 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.

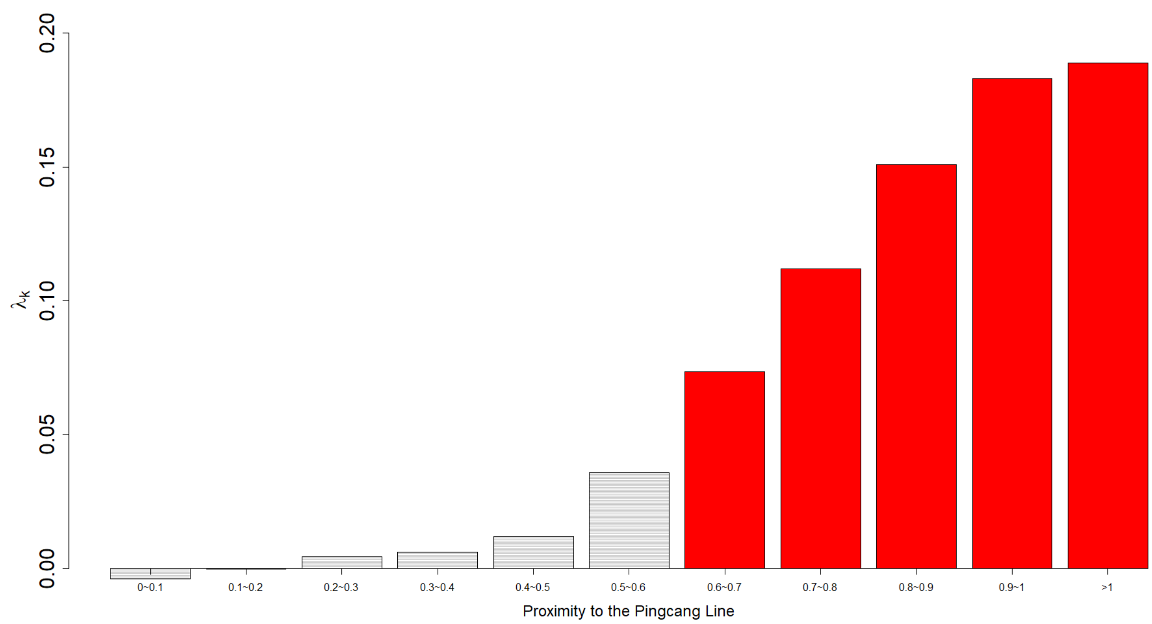


Figure 6
Total Account Risk and Investor Selling Intensity

This figure shows how net selling relates to a summary measure of total account risk that combines information on the proximity, leverage, and volatility of assets held in each account. For each account at the start of each day, let $lev_0 = A_0/E_0$. Let σ_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 past month). We define Z such that $\frac{A_0 - A_0\sigma_A Z}{E_0 - A_0\sigma_A Z} = \overline{lev}$. 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 is negative, the account has already exceeded its Pingcang Line, and borrower has lost control. We reestimate Equation (3), but substitute the bins of proximity with equally spaced bins in terms of Z. All sample restrictions, measures, and other control variables are as described in Figure 5.

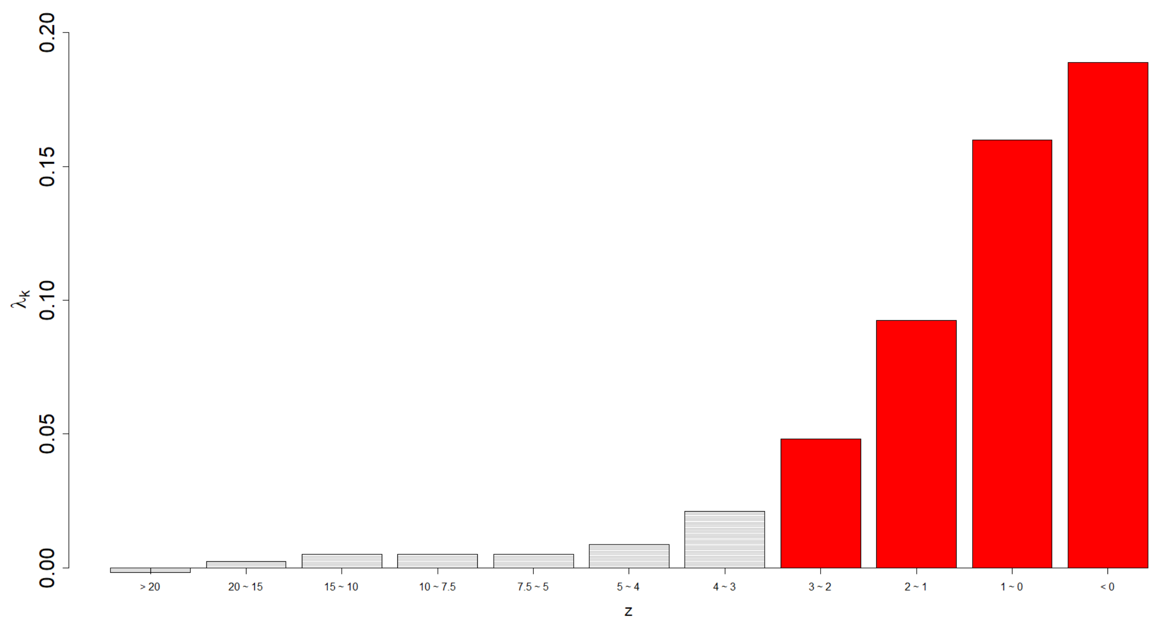


Figure 7

Proximity to the Pingcang Line and Investor Selling Intensity: Market Returns

This figure plots the the coefficients λ_k from the regression defined in Figure 5, estimated separately for the samples in which the market return on day t is positive and negative. The time period is from May to July, 2015.

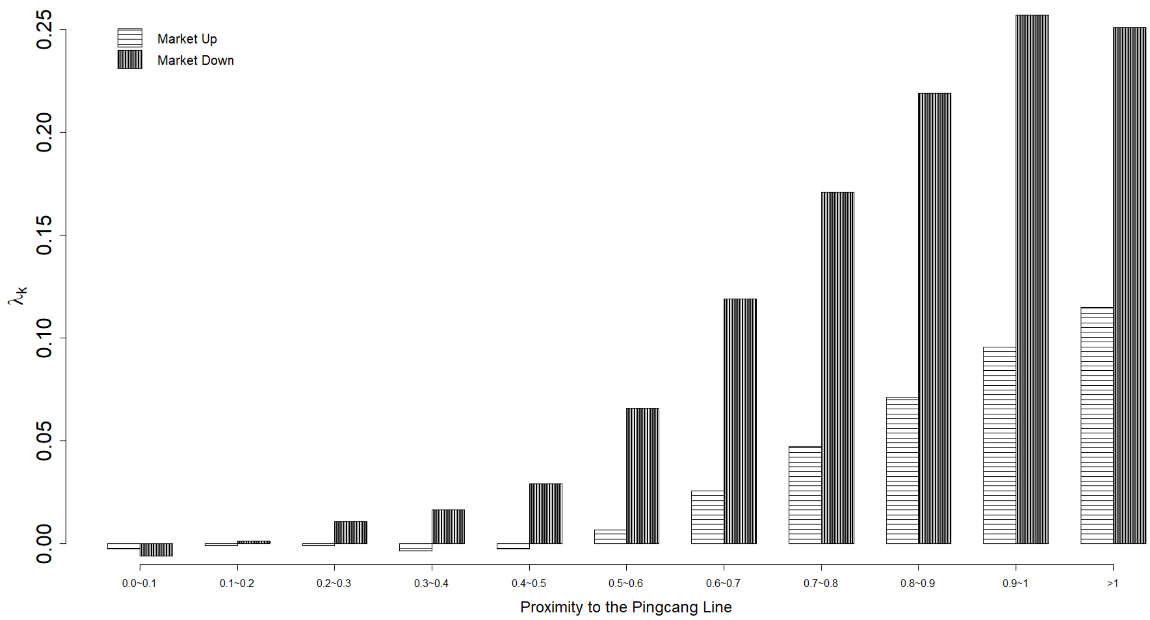


Figure 8
Net Selling by Fire Sale Accounts

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 on that day, and then equal-weight across stocks. Note that the large dips in net selling correspond to market-wide trading halts.

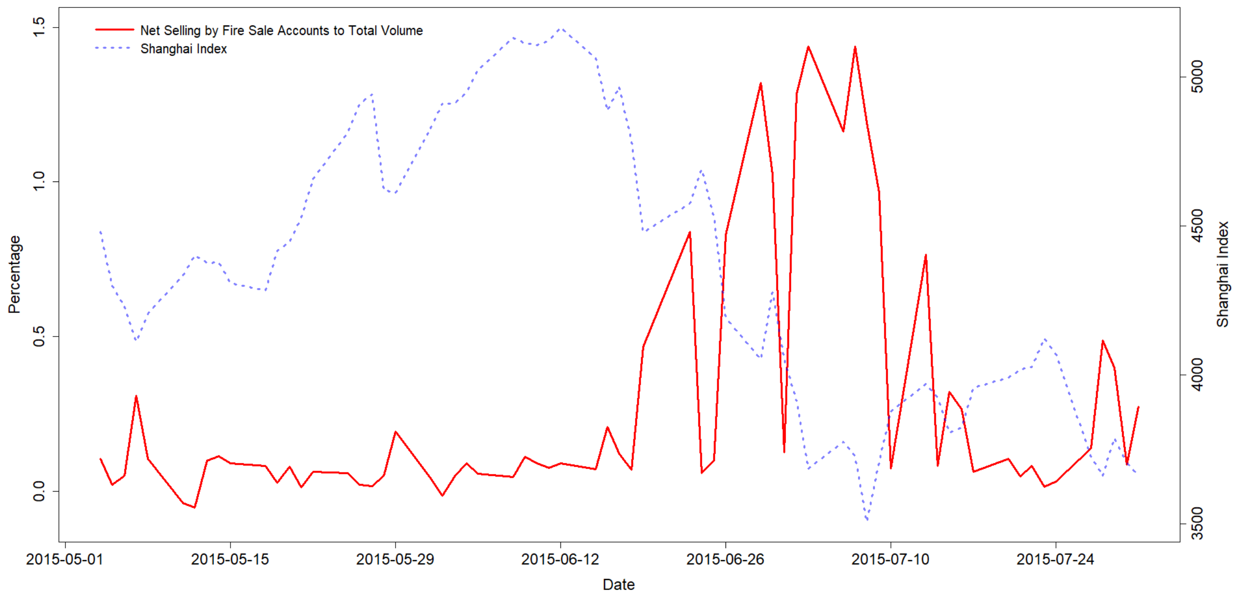


Figure 9
Returns Following Fire Sales: Long-Short Portfolio

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 no experience suspended trading on day t.

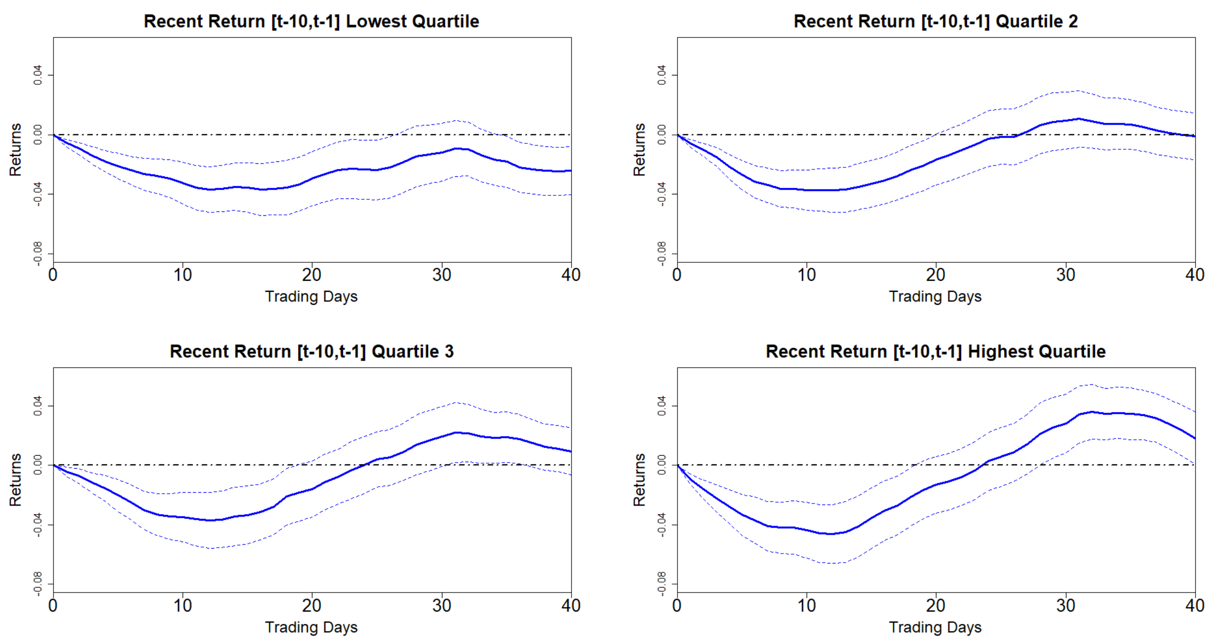


Figure 10
Proximity to the Pingcang Line and Investor Selling Intensity: Brokerage and Shadow Accounts

This figure plots the the coefficients λ_k from the regression defined in Figure 5, estimated separately for the brokerage- and shadow-financed margin account samples. The time period is from May to July, 2015.

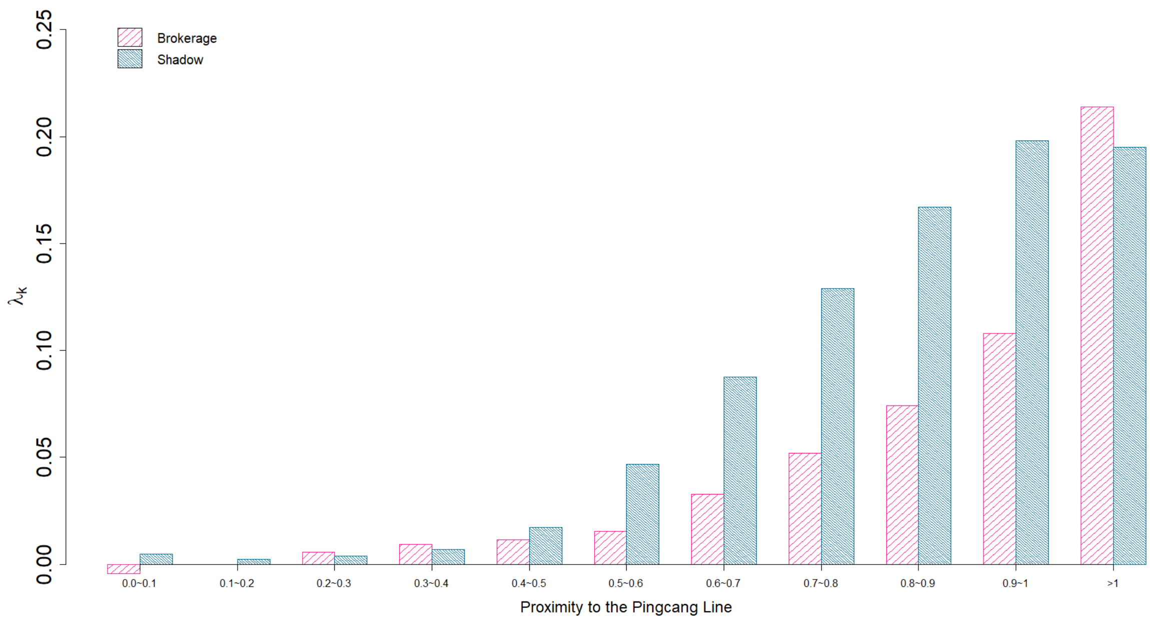


Figure 11
Regulatory Tightening

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 5, estimated separately for the brokerage- and shadow-financed margin account samples for the five trading days immediately before and after the regulatory tightening events.

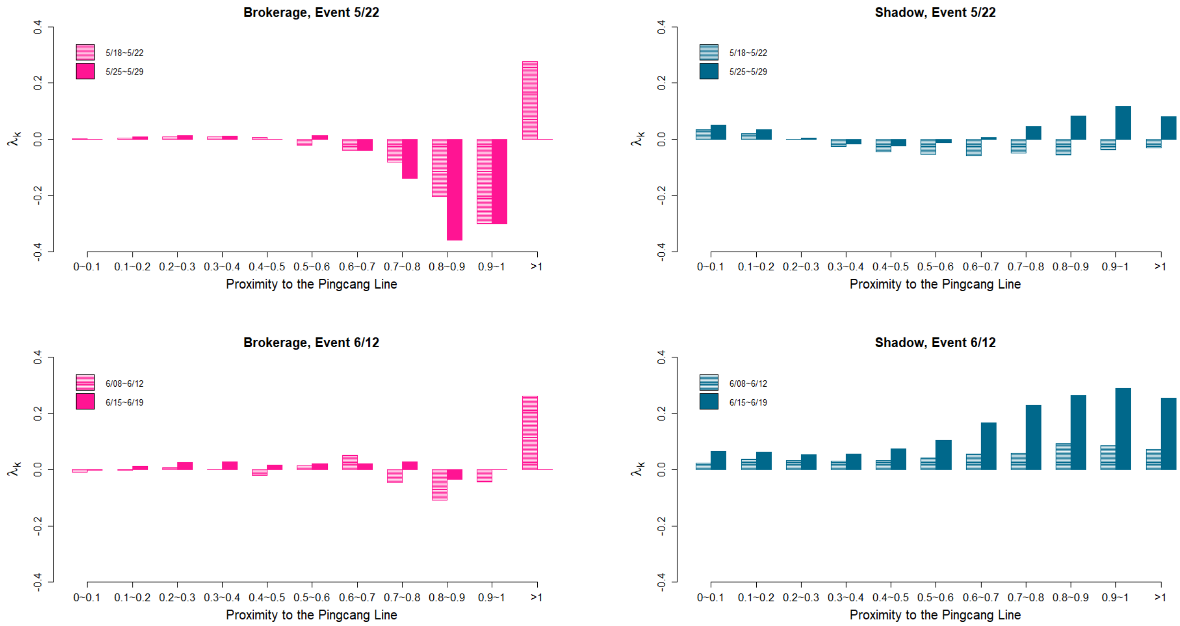
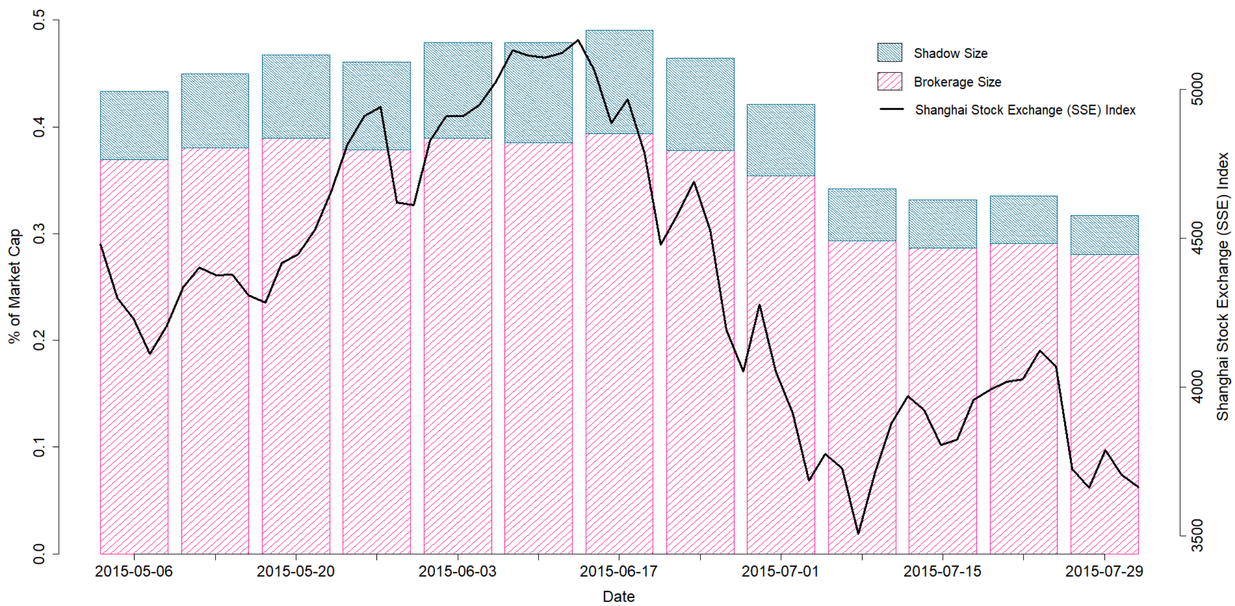


Figure 12
Market Capitalization of Brokerage and Shadow Accounts

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 leverage in excess of 60% of the Pingcang Line ($P_{jt} > 0.6$). The solid black line depicts the Shanghai Stock Exchange (SSE) composite index.

Panel A: All Accounts



Panel B: Fire Sale Accounts

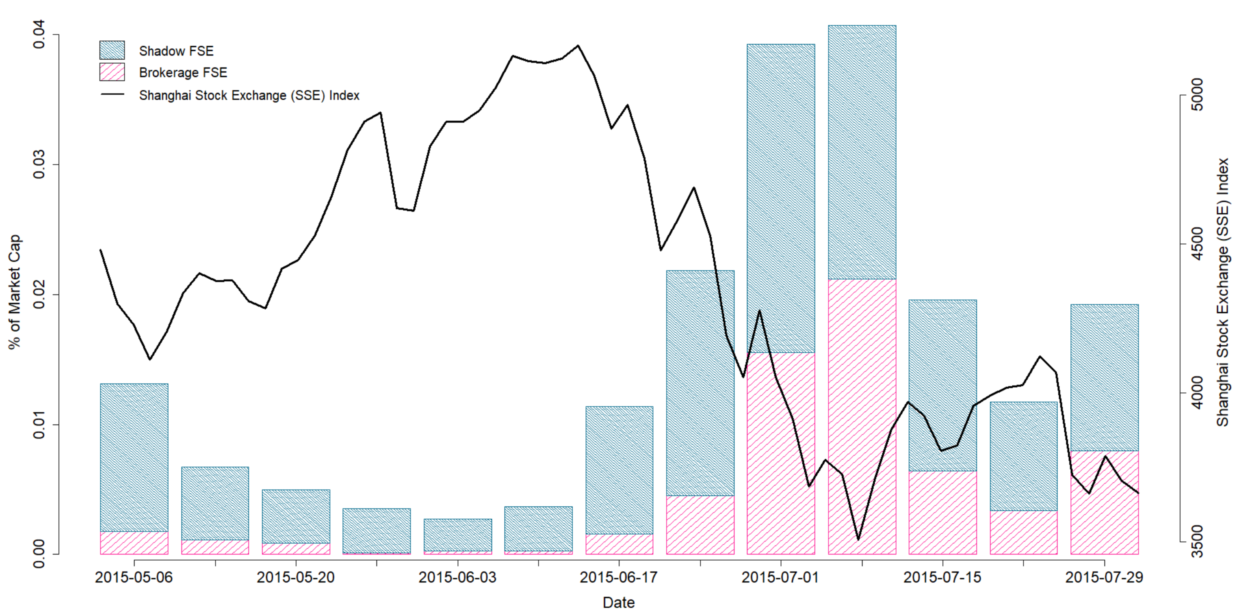


Table 1
Summary Statistics

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. Proximity is the ratio of leverage minus 1 to the Pingcang Line minus 1. An account is classified as a fire sale account on day t if the proximity to the Pingcang Line exceeds 0.6. 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	1.1246	1.9728	1	1	1	1	100	114670045
Leverage, shadow accounts	6.6138	12.7284	1	3.0413	4.3042	6.00182	100	2308872
Leverage, brokerage accounts	1.4283	0.4709	1	1	1.35088	1.69444	100	3108015
Leverage, non-margin accounts	1	0	1	1	1	1	1	109253158
Pingcang Line, full sample	1.3008	1.7324	1	1	1	1	100	114670045
Pingcang Line, shadow accounts	11.4948	5.361	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
Proximity, full sample	0.321	0.9597	0	0.0547	0.1894	0.3367	79.99114	5416887
Proximity, shadow accounts	0.5785	1.4205	0	0.202023	0.33558	0.5127	79.99114	2308872
Proximity, brokerage accounts	0.1298	0.1427	0	0	0.10633	0.21044	30	3108015
Proximity, non-margin accounts	0	0	0	0	0	0	0	109253158
Account assets, full sample	3044616	26786339	0.02	174390	603171	1789408	1.3E+10	5416887
Account assets, shadow accounts	1516900	6191487	0.02	60275	215716	753166	5.1E+08	2308872
Account assets, brokerage accounts	4179520	34914588	3.85	429942	996645	2494872	1.3E+10	3108015

Panel B: Account-Stock-Day Level

	Mean	S.D.	Min	p25	p50	p75	Max	Obs
Net selling, full sample	0.074	0.3153	-1.2	0	0	0	1	351404205
Net selling, shadow accounts	0.2238	0.4547	-1.2	0	0	0.5	1	6228429
Net selling, brokerage accounts	0.0859	0.3344	-1.2	0	0	0	1	16658787
Net selling, non-margin accounts	0.0706	0.3103	-1.2	0	0	0	1	328516989

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	0.000202	-0.00503	0.00000	0.00000	0.00001	0.02594	116809
Selling pressure, shadow accounts	0.000012	0.000170	-0.00503	0.00000	0.00000	0.00001	0.02594	116809
Selling pressure, brokerage accounts	0.000005	0.000106	-0.00234	0.00000	0.00000	0.00000	0.01955	116809
Fire sale exposure, all margin accoun	0.000204	0.000771	0.00000	0.00001	0.00004	0.00015	0.05391	116809
Fire sale exposure, shadow accounts	0.000153	0.000569	0.00000	0.00000	0.00003	0.00012	0.05391	116809
Fire sale exposure, brokerage accoun	0.000051	0.000491	0.00000	0.00000	0.00000	0.00000	0.05327	116809
CAR [t]	-0.0003	0.0417	-0.1824	-0.0270	-0.0036	0.0245	0.2164	109735
CAR [t,t+3]	-0.0007	0.0816	-0.3971	-0.0489	-0.0034	0.0460	0.5344	109735
CAR [t,t+5]	-0.0006	0.1095	-0.5303	-0.0626	-0.0005	0.0641	0.5425	109735
CAR [t,t+10]	0.0034	0.1576	-0.7929	-0.0827	0.0107	0.0985	0.7455	109735
CAR [t,t+20]	0.0080	0.2048	-1.0486	-0.1160	0.0186	0.1374	1.1256	109735
CAR [t,t+40]	-0.0021	0.2071	-1.2508	-0.1300	-0.0033	0.1200	1.1301	109735
Cumulative return [t-10,t-1]	1.0311	0.2377	0.3487	0.8962	1.0371	1.1706	2.6017	116809
Return volatility [t-60, t-1]	0.0442	0.0128	0.0000	0.0343	0.0424	0.0532	0.1016	116809
Log market value [t-3]	9.47	0.98	7.36	8.78	9.29	9.97	14.78	116809
Avg turnover [t-60,t-1]	0.0494	0.0257	0.0002	0.0314	0.0449	0.0624	0.2446	116809

Table 2
Proximity to the Pingcang Line and Investor Selling Intensity

This table shows the coefficients λ_k of the regression equation

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

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 equally spaced bins for each account's proximity to its 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)
Proximity in (0/10, 1/10)	-0.00398***	-0.00429***	0.00473*
	(0.000398)	(0.000409)	(0.00283)
Proximity in [1/10, 2/10)	-0.000279	-0.000108	0.00243
	(0.000330)	(0.000342)	(0.00288)
Proximity in [2/10, 3/10)	0.00426***	0.00565***	0.00379
	(0.000370)	(0.000395)	(0.00289)
Proximity in [3/10, 4/10)	0.00597***	0.00917***	0.00676**
	(0.000486)	(0.000573)	(0.00291)
Proximity in [4/10, 5/10)	0.0119***	0.0113***	0.0171***
	(0.000695)	(0.00111)	(0.00294)
Proximity in [5/10, 6/10)	0.0356***	0.0153***	0.0469***
	(0.000907)	(0.00151)	(0.00301)
Proximity in [6/10, 7/10)	0.0735***	0.0327***	0.0876***
	(0.00120)	(0.00269)	(0.00312)
Proximity in [7/10, 8/10)	0.112***	0.0518***	0.129***
	(0.00157)	(0.00335)	(0.00330)
Proximity in [8/10, 9/10)	0.151***	0.0743***	0.167***
	(0.00208)	(0.00473)	(0.00357)
Proximity in [9/10, 10/10)	0.183***	0.108***	0.198***
	(0.00269)	(0.0104)	(0.00395)
Proximity >= 1	0.189***	0.214***	0.195***
	(0.00150)	(0.0104)	(0.00318)
Account FE	Yes	Yes	Yes
Stock-Date FE	Yes	Yes	Yes
R-squared	0.140	0.135	0.141
Observations, margin accounts	23,255,820	16,937,423	6,318,397
Observations, total	351,389,930	345,167,235	334,730,594

Table 3
Proximity and Leverage Interactions

This table examines how leverage levels and proximity to the Pingcang Line impact net selling. The sample is restricted to shadow-financed margin accounts, as well as brokerage non-margin accounts which comprise the omitted category. Other sample restrictions are the same as in Table 2. Column 1 replicates Column 3 of Table 2. 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 is considered a fire sale account. The leverage bins are spaced so that the number of observations in proximity 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)
Proximity in (0/10, 1/10)	0.00473*	0.00960***
	(0.00283)	(0.00284)
Proximity in [1/10, 2/10)	0.00243	0.0193***
	(0.00288)	(0.00313)
Proximity in [2/10, 3/10)	0.00379	0.0276***
	(0.00289)	(0.00321)
Proximity in [3/10, 4/10)	0.00676**	0.0349***
	(0.00291)	(0.00327)
Proximity in [4/10, 5/10)	0.0171***	0.0444***
	(0.00294)	(0.00339)
Proximity in [5/10, 6/10)	0.0469***	0.0670***
	(0.00301)	(0.00347)
Proximity in [6/10, 7/10)	0.0876***	0.0958***
	(0.00312)	(0.00603)
Proximity in [7/10, 8/10)	0.129***	0.120***
	(0.00330)	(0.00601)
Proximity in [8/10, 9/10)	0.167***	0.143***
	(0.00357)	(0.00610)
Proximity in [9/10, 10/10)	0.198***	0.161***
	(0.00395)	(0.00639)
Proximity >= 1	0.195***	0.132***
	(0.00318)	(0.00650)
Lev Bin 1		-0.0181***
		(0.00160)
Lev Bin 2		-0.0107***
		(0.000791)
Lev Bin 3		-0.0278***
		(0.00171)
Lev Bin 4		-0.00105
		(0.00103)
Lev Bin 5		0.0290***
		(0.00508)
Lev Bin 1 * 1{Proximity >= 0.6}		-0.00437
		(0.00695)
Lev Bin 2 * 1{Proximity >= 0.6}		-0.0172***
		(0.00365)
Lev Bin 3 * 1{Proximity >= 0.6}		-0.0102***
		(0.00285)
Lev Bin 4 * 1{Proximity >= 0.6}		0.0167***
		(0.00497)
Lev Bin 5 * 1{Proximity >= 0.6}		0.0286***
		(0.00747)
Account FE	Yes	Yes
Stock-Date FE	Yes	Yes
R-squared	0.141	0.141
Observations, margin accounts	6,318,397	6,318,397
Observations, total	334,730,594	334,730,594

Table 4
Investor Selling Intensity Conditional on Day t Market Returns

Panels A and B present the same regression as in Table 2, with the sample restricted days in which the market return was positive or negative, respectively. 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)
Proximity in (0/10, 1/10)	-0.00249***	-0.00311***	0.0213***
	(0.000518)	(0.000532)	(0.00367)
Proximity in [1/10, 2/10)	-0.000950**	-0.00119***	0.0169***
	(0.000427)	(0.000444)	(0.00375)
Proximity in [2/10, 3/10)	-0.00102**	-0.000371	0.0137***
	(0.000492)	(0.000530)	(0.00378)
Proximity in [3/10, 4/10)	-0.00334***	-0.00120*	0.0110***
	(0.000627)	(0.000714)	(0.00381)
Proximity in [4/10, 5/10)	-0.00258***	-0.000249	0.0129***
	(0.000890)	(0.00134)	(0.00385)
Proximity in [5/10, 6/10)	0.00656***	-0.00156	0.0257***
	(0.00113)	(0.00166)	(0.00393)
Proximity in [6/10, 7/10)	0.0256***	0.00866***	0.0463***
	(0.00153)	(0.00299)	(0.00407)
Proximity in [7/10, 8/10)	0.0473***	0.0203***	0.0697***
	(0.00196)	(0.00309)	(0.00432)
Proximity in [8/10, 9/10)	0.0711***	0.0324***	0.0931***
	(0.00257)	(0.00642)	(0.00460)
Proximity in [9/10, 10/10)	0.0957***	0.0465***	0.119***
	(0.00361)	(0.00757)	(0.00536)
Proximity >= 1	0.115***	0.197***	0.130***
	(0.00198)	(0.0135)	(0.00417)
Account FE	Yes	Yes	Yes
Stock-Date FE	Yes	Yes	Yes
R-squared	0.155	0.150	0.141
Observations, margin accounts	12,106,979	8,779,209	3,327,770
Observations, total	181,307,821	178,031,345	172,674,014

Table 4
Investor Selling Intensity Conditional on Day t Market Returns (Continued)

Panel B: Negative Market Return Day

Net selling	Full	Broker	Shadow
	(1)	(2)	(3)
Proximity in (0/10, 1/10)	-0.00587***	-0.00583***	-0.0122***
	(0.000547)	(0.000560)	(0.00422)
Proximity in [1/10, 2/10)	0.00116***	0.00200***	-0.0134***
	(0.000448)	(0.000461)	(0.00429)
Proximity in [2/10, 3/10)	0.0108***	0.0127***	-0.00530
	(0.000491)	(0.000514)	(0.00432)
Proximity in [3/10, 4/10)	0.0165***	0.0194***	0.00426
	(0.000684)	(0.000800)	(0.00434)
Proximity in [4/10, 5/10)	0.0290***	0.0243***	0.0241***
	(0.000996)	(0.00154)	(0.00438)
Proximity in [5/10, 6/10)	0.0658***	0.0342***	0.0685***
	(0.00134)	(0.00233)	(0.00449)
Proximity in [6/10, 7/10)	0.119***	0.0600***	0.125***
	(0.00173)	(0.00358)	(0.00463)
Proximity in [7/10, 8/10)	0.171***	0.0887***	0.180***
	(0.00223)	(0.00521)	(0.00486)
Proximity in [8/10, 9/10)	0.219***	0.112***	0.227***
	(0.00309)	(0.00758)	(0.00525)
Proximity in [9/10, 10/10)	0.257***	0.164***	0.264***
	(0.00360)	(0.0134)	(0.00562)
Proximity >= 1	0.251***	0.231***	0.248***
	(0.00209)	(0.0129)	(0.00469)
Account FE	Yes	Yes	Yes
Stock-Date FE	Yes	Yes	Yes
R-squared	0.152	0.145	0.152
Observations, margin accounts	11,140,320	8,158,147	2,982,173
Observations, total	170,052,033	167,114,226	162,025,568

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 account. 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 in Panel A, the brokerage account sample in Panel B and the shadow account sample in Panel C. 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. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: FSE Calculated Using All Margin Accounts

	Selling pressure			
	(1)	(2)	(3)	(4)
Fire sale exposure	0.0996***	0.102***	0.102***	0.102***
	(0.0221)	(0.0259)	(0.0259)	(0.0259)
Return volatility [t-60, t-			-0.000385**	-0.000215
			(0.000192)	(0.000203)
Log market value [t-3]			2.48e-05***	1.44e-05*
			(7.12e-06)	(8.15e-06)
Avg turnover [t-60, t-1]			9.59e-06	4.92e-05
			(0.000170)	(0.000174)
Cumulative return [t-10,			-2.44e-05***	7.14e-05**
			(5.80e-06)	(2.83e-05)
Stock FE	No	Yes	Yes	Yes
Date FE	No	Yes	Yes	Yes
Past 10-day daily returns	No	No	No	Yes
R-squared	0.144	0.186	0.186	0.188
Observations	116,809	116,809	116,809	116,809

Table 5
Stock-Level Fire Sale Exposure and Selling Pressure (Continued)

Panel B: FSE Calculated Using Brokerage Margin Accounts

	Selling pressure			
	(1)	(2)	(3)	(4)
Fire sale exposure	0.0756***	0.0747***	0.0747***	0.0746***
	(0.0153)	(0.0156)	(0.0157)	(0.0157)
Return volatility [t-60, t-			-0.000184*	-0.000143
			(9.99e-05)	(0.000110)
Log market value [t-3]			-3.07e-06	-2.43e-06
			(3.03e-06)	(3.52e-06)
Avg turnover [t-60, t-1]			9.32e-05	9.71e-05
			(7.30e-05)	(7.34e-05)
Cumulative return [t-10,			-1.51e-06	2.03e-05
			(1.70e-06)	(1.77e-05)
Stock FE	No	Yes	Yes	Yes
Date FE	No	Yes	Yes	Yes
Past 10-day daily returns	No	No	No	Yes
R-squared	0.122	0.151	0.151	0.151
Observations	116,809	116,809	116,809	116,809

Panel C: FSE Calculated Using Shadow Margin Accounts

	Selling pressure			
	(1)	(2)	(3)	(4)
Fire sale exposure	0.113***	0.125***	0.124***	0.124***
	(0.0341)	(0.0417)	(0.0418)	(0.0418)
Return volatility [t-60, t-			-0.000115	3.13e-05
			(0.000168)	(0.000173)
Log market value [t-3]			2.05e-05**	1.03e-05
			(8.73e-06)	(7.14e-06)
Avg turnover [t-60, t-1]			-0.000119	-8.14e-05
			(0.000142)	(0.000146)
Cumulative return [t-10,			-2.01e-05***	6.46e-05**
			(7.50e-06)	(2.48e-05)
Stock FE	No	Yes	Yes	Yes
Date FE	No	Yes	Yes	Yes
Past 10-day daily returns	No	No	No	Yes
R-squared	0.144	0.189	0.189	0.191
Observations	116,809	116,809	116,809	116,809

Table 6
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. 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	-1.342***	-3.552***	-4.896***	-5.657***	-2.465***	0.464
	(0.310)	(0.540)	(0.784)	(1.177)	(0.872)	(0.573)
Return volatility [t-60, t-1]	-0.242	-0.412	-0.426	-0.192	0.525	0.215
	(0.164)	(0.351)	(0.456)	(0.574)	(0.642)	(0.408)
Log market value [t-3]	-0.0662***	-0.203***	-0.323***	-0.565***	-0.820***	-0.741***
	(0.00767)	(0.0147)	(0.0198)	(0.0281)	(0.0304)	(0.0202)
Avg turnover [t-60, t-1]	-0.0930	-0.303**	-0.497***	-0.960***	-2.162***	-1.147***
	(0.0680)	(0.129)	(0.161)	(0.170)	(0.175)	(0.173)
Cumulative return [t-10, t-1]	-0.0550**	-0.0904*	-0.0742	0.0424	-0.0982	0.167***
	(0.0236)	(0.0524)	(0.0705)	(0.0836)	(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	0.513	0.627	0.705
Observations	109,735	109,735	109,735	109,735	109,735	109,735

Table 6
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	-0.519**	-1.778***	-1.911***	-0.902	-1.804***	0.603
	(0.216)	(0.476)	(0.687)	(0.787)	(0.446)	(0.679)
Return volatility [t-60, t-1]	-0.247	-0.423	-0.445	-0.219	0.519	0.215
	(0.164)	(0.352)	(0.458)	(0.576)	(0.644)	(0.409)
Log market value [t-3]	-0.0664***	-0.204***	-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]	-0.0943	-0.306**	-0.502***	-0.966***	-2.164***	-1.147***
	(0.0681)	(0.129)	(0.162)	(0.171)	(0.175)	(0.173)
Cumulative return [t-10, t-1]	-0.0559**	-0.0928*	-0.0778	0.0373	-0.0994	0.167***
	(0.0236)	(0.0526)	(0.0707)	(0.0839)	(0.0779)	(0.0492)
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	109,735	109,735	109,735	109,735	109,735	109,735

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	-2.310***	-5.646***	-8.411***	-11.24***	-3.254*	0.305
	(0.612)	(1.299)	(1.763)	(2.311)	(1.867)	(0.853)
Return volatility [t-60, t-1]	-0.246	-0.424	-0.442	-0.208	0.516	0.217
	(0.164)	(0.352)	(0.456)	(0.573)	(0.643)	(0.409)
Log market value [t-3]	-0.0660***	-0.202***	-0.322***	-0.564***	-0.820***	-0.741***
	(0.00765)	(0.0146)	(0.0197)	(0.0279)	(0.0306)	(0.0202)
Avg turnover [t-60, t-1]	-0.0923	-0.301**	-0.495***	-0.956***	-2.162***	-1.147***
	(0.0679)	(0.128)	(0.161)	(0.170)	(0.176)	(0.173)
Cumulative return [t-10, t-1]	-0.0556**	-0.0923*	-0.0766	0.0401	-0.0997	0.167***
	(0.0236)	(0.0524)	(0.0705)	(0.0836)	(0.0777)	(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	109,735	109,735	109,735	109,735	109,735	109,735

Table 7
Regulatory Tightening

Regulatory tightening events 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. 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	May 22 event		June 12 event	
	Broker	Shadow	Broker	Shadow
	(1)	(2)	(3)	(4)
Proximity in (0/10 1/10)	0.00109	0.0343***	-0.00785***	0.0248***
	(0.000917)	(0.00951)	(0.000872)	(0.00821)
Proximity in [1/10 2/10)	0.00438***	0.0194**	-0.000581	0.0381***
	(0.000805)	(0.00978)	(0.000816)	(0.00856)
Proximity in [2/10 3/10)	0.00856***	-0.00150	0.00818***	0.0330***
	(0.000989)	(0.00993)	(0.00109)	(0.00868)
Proximity in [3/10 4/10)	0.00846***	-0.0261***	0.000411	0.0310***
	(0.00188)	(0.0100)	(0.00227)	(0.00878)
Proximity in [4/10 5/10)	0.00622	-0.0455***	-0.0191***	0.0327***
	(0.00442)	(0.0101)	(0.00703)	(0.00892)
Proximity in [5/10 6/10)	-0.0223**	-0.0528***	0.0143	0.0428***
	(0.00885)	(0.0103)	(0.0191)	(0.00924)
Proximity in [6/10 7/10)	-0.0394	-0.0579***	0.0513	0.0561***
	(0.0293)	(0.0106)	(0.0460)	(0.00974)
Proximity in [7/10 8/10)	-0.0812**	-0.0485***	-0.0460	0.0594***
	(0.0407)	(0.0112)	(0.0404)	(0.0106)
Proximity in [8/10 9/10)	-0.204***	-0.0550***	-0.109**	0.0940***
	(0.0578)	(0.0118)	(0.0483)	(0.0118)
Proximity in [9/10 10/10)	-0.301***	-0.0384***	-0.0438	0.0851***
	(0.0971)	(0.0129)	(0.0745)	(0.0129)
Proximity >= 1	0.276	-0.0310***	0.262***	0.0718***
	(0.199)	(0.0120)	(0.0964)	(0.0105)
Proximity in (0/10 1/10) * after	-0.00111	0.0165***	0.00646***	0.0401***
	(0.00101)	(0.00368)	(0.00102)	(0.00253)
Proximity in [1/10 2/10) * after	0.00427***	0.0139***	0.0138***	0.0243***
	(0.000934)	(0.00225)	(0.000872)	(0.00165)
Proximity in [2/10 3/10) * after	0.00531***	0.00586***	0.0184***	0.0204***
	(0.00123)	(0.00194)	(0.00111)	(0.00158)
Proximity in [3/10 4/10) * after	0.00239	0.00934***	0.0268***	0.0258***
	(0.00258)	(0.00210)	(0.00232)	(0.00178)
Proximity in [4/10 5/10) * after	-0.00581	0.0210***	0.0354***	0.0408***
	(0.00772)	(0.00282)	(0.00750)	(0.00235)
Proximity in [5/10 6/10) * after	0.0359**	0.0412***	0.00783	0.0624***
	(0.0166)	(0.00404)	(0.0210)	(0.00345)
Proximity in [6/10 7/10) * after	-0.00138	0.0643***	-0.0298	0.110***
	(0.0533)	(0.00571)	(0.0503)	(0.00484)
Proximity in [7/10 8/10) * after	-0.0573	0.0931***	0.0735	0.171***
	(0.0683)	(0.00780)	(0.0502)	(0.00683)
Proximity in [8/10 9/10) * after	-0.156	0.137***	0.0745	0.171***
	(0.173)	(0.0106)	(0.0644)	(0.00887)
Proximity in [9/10 10/10) * after	8.40e-05	0.156***		0.204***
	(0.00678)	(0.0136)		(0.0113)
Proximity >= 1 * after		0.111***		0.184***
		(0.00768)		(0.00640)
Stock FE	Yes	Yes	Yes	Yes
R-squared	0.181	0.186	0.169	0.175
Observations, margin accounts	2,750,920	1,239,652	2,973,261	1,535,084
Observations, total	53,107,983	51,622,705	58,483,326	57,068,524

Table 8
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 halt 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 proximity bins. All other variables are as defined in Table 2. The sample is restricted to stocks that do not face trading restrictions 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)
Proximity in (0/10, 1/10)	0.00228***	0.00139***	0.00895***
	(0.000509)	(0.000520)	(0.00245)
Proximity in [1/10, 2/10)	0.00838***	0.00879***	0.0105***
	(0.000525)	(0.000537)	(0.00253)
Proximity in [2/10, 3/10)	0.00971***	0.0139***	0.00705***
	(0.000572)	(0.000592)	(0.00255)
Proximity in [3/10, 4/10)	0.00572***	0.0148***	0.00485*
	(0.000670)	(0.000736)	(0.00258)
Proximity in [4/10, 5/10)	0.00642***	0.0130***	0.00832***
	(0.000811)	(0.00104)	(0.00261)
Proximity in [5/10, 6/10)	0.0227***	0.0168***	0.0264***
	(0.000989)	(0.00154)	(0.00267)
Proximity in [6/10, 7/10)	0.0514***	0.0344***	0.0547***
	(0.00124)	(0.00226)	(0.00276)
Proximity in [7/10, 8/10)	0.0846***	0.0533***	0.0879***
	(0.00154)	(0.00332)	(0.00293)
Proximity in [8/10, 9/10)	0.117***	0.0815***	0.118***
	(0.00197)	(0.00594)	(0.00316)
Proximity in [9/10, 10/10)	0.144***	0.131***	0.144***
	(0.00239)	(0.00822)	(0.00344)
Proximity >= 1	0.145***	0.282***	0.142***
	(0.00184)	(0.0102)	(0.00300)
Price limit fraction	0.0128***	0.0230***	0.00608***
	(0.000876)	(0.000873)	(0.000976)
Price limit fraction * proximity in (0/10 1/10)	0.0127***	0.00639***	0.0727***
	(0.00189)	(0.00198)	(0.00565)
Price limit fraction * proximity in [1/10 2/10)	0.0109***	0.00655***	0.0393***
	(0.00167)	(0.00176)	(0.00411)
Price limit fraction * proximity in [2/10 3/10)	0.0235***	0.0109***	0.0570***
	(0.00180)	(0.00196)	(0.00378)
Price limit fraction * proximity in [3/10 4/10)	0.0403***	0.0102***	0.0738***
	(0.00240)	(0.00275)	(0.00403)
Price limit fraction * proximity in [4/10 5/10)	0.0661***	0.0139***	0.107***
	(0.00323)	(0.00405)	(0.00463)
Price limit fraction * proximity in [5/10 6/10)	0.0873***	0.0199***	0.133***
	(0.00439)	(0.00609)	(0.00561)
Price limit fraction * proximity in [6/10 7/10)	0.109***	0.0302***	0.153***
	(0.00558)	(0.00920)	(0.00668)
Price limit fraction * proximity in [7/10 8/10)	0.0891***	0.0296***	0.135***
	(0.00656)	(0.0108)	(0.00797)
Price limit fraction * proximity in [8/10 9/10)	0.0820***	-0.0109	0.130***
	(0.00801)	(0.0139)	(0.00953)
Price limit fraction * proximity in [9/10 10/10)	0.0821***	-0.0366	0.119***
	(0.00999)	(0.0256)	(0.0110)
Price limit fraction * proximity >= 1	0.0773***	-0.145***	0.0842***
	(0.00570)	(0.0247)	(0.00583)
Counterfactual portfolio returns x proximity bins	Yes	Yes	Yes
Account FE	Yes	Yes	Yes
Stock-date FE	Yes	Yes	Yes
R-squared	0.178	0.151	0.194
Observations, margin accounts	16,824,575	11,272,738	5,551,837
Observations, total	28,151,322	22,689,418	17,070,028

A 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 few mother accounts maintained by the same trading platform. For each 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 / initial 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 not within 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 also 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 the practitioners in the trading platform.

B Appendix: Figures and Tables

Figure B.1
Proximity to the Pingcang Line and Investor Selling Intensity: Proximity ≥ 1

This figure plots the the coefficients λ_k from the regression defined in Figure 5, estimated for three additional bins in which proximity exceeds one, a region in which the lender holds control of the account. The time period is from May to July, 2015.

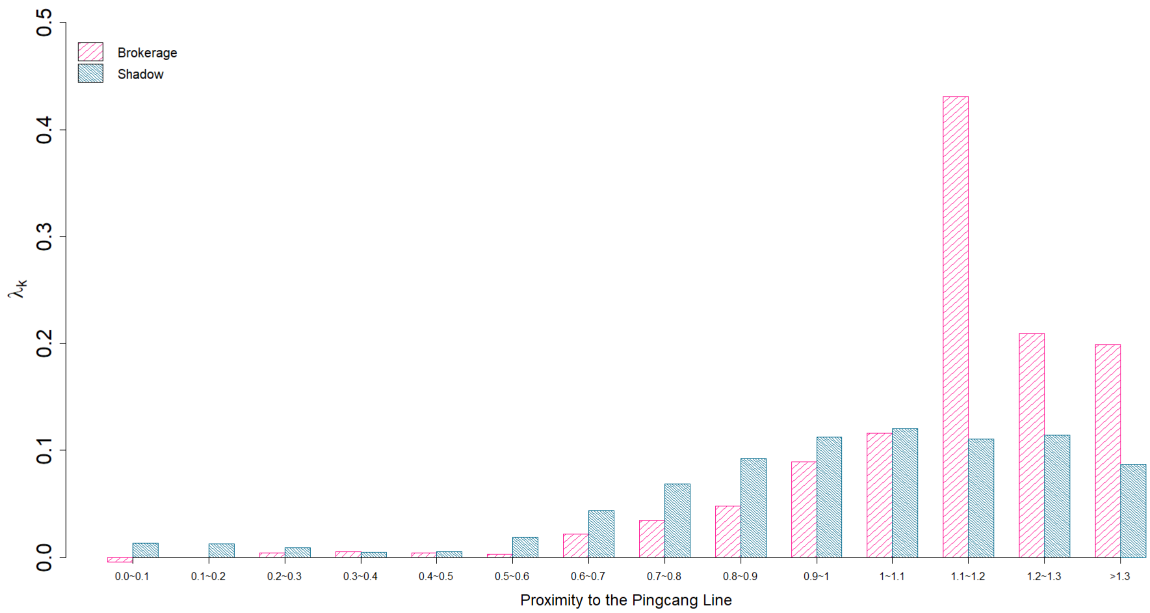


Table B.1

Proximity to the Pingcang Line and Investor Selling Intensity, Controlling for Past Account Returns

This table presents the same regression as in Table 4, with the addition of a control variable for 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)
Proximity in (0/10, 1/10)	-0.00409***	-0.00438***	0.00407
	(0.000398)	(0.000408)	(0.00283)
Proximity in [1/10, 2/10)	-0.000465	-0.000280	0.00204
	(0.000330)	(0.000342)	(0.00288)
Proximity in [2/10, 3/10)	0.00411***	0.00545***	0.00386
	(0.000370)	(0.000395)	(0.00290)
Proximity in [3/10, 4/10)	0.00604***	0.00915***	0.00716**
	(0.000485)	(0.000572)	(0.00292)
Proximity in [4/10, 5/10)	0.0122***	0.0116***	0.0178***
	(0.000696)	(0.00111)	(0.00295)
Proximity in [5/10, 6/10)	0.0361***	0.0159***	0.0477***
	(0.000909)	(0.00152)	(0.00302)
Proximity in [6/10, 7/10)	0.0742***	0.0335***	0.0886***
	(0.00120)	(0.00268)	(0.00312)
Proximity in [7/10, 8/10)	0.113***	0.0530***	0.130***
	(0.00157)	(0.00333)	(0.00330)
Proximity in [8/10, 9/10)	0.152***	0.0756***	0.169***
	(0.00208)	(0.00474)	(0.00357)
Proximity in [9/10, 10/10)	0.184***	0.109***	0.200***
	(0.00269)	(0.0103)	(0.00395)
Proximity >= 1	0.190***	0.216***	0.197***
	(0.00150)	(0.0105)	(0.00318)
Account return [t-10,t-1]	0.0116***	0.0120***	0.0141***
	(0.000251)	(0.000253)	(0.000250)
Account FE	Yes	Yes	Yes
Stock-Date FE	Yes	Yes	Yes
R-squared	0.140	0.135	0.141
Observations, margin accounts	23,255,820	16,937,423	6,318,397
Observations, total	351,389,930	345,167,235	334,730,594

Table B.2
Stock-Level Fire Sale Exposure and Selling Pressure, λ-weighted

This table presents the same regression as in Table 5, 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 as estimated for the relevant sample in Table 2. δ_{it} measures stock-level selling pressure from all margin accounts, with each account weighted by its corresponding λ_k as estimated for the relevant sample in Table 2. 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

	Selling pressure			
	(1)	(2)	(3)	(4)
Fire sale exposure	0.873***	0.955***	0.960***	0.975***
	(0.148)	(0.192)	(0.192)	(0.192)
Return volatility [t-60, t-			0.00388***	0.00429***
			(0.00140)	(0.00143)
Log market value [t-3]			0.000114***	0.000248***
			(3.50e-05)	(4.27e-05)
Avg turnover [t-60, t-1]			0.00188**	0.00172**
			(0.000780)	(0.000778)
Cumulative return [t-10,			0.000194***	0.000437***
			(4.44e-05)	(0.000154)
Stock FE	No	Yes	Yes	Yes
Date FE	No	Yes	Yes	Yes
Past 10-day daily returns	No	No	No	Yes
R-squared	0.010	0.029	0.030	0.031
Observations	116,809	116,809	116,809	116,809

Table B.2

Stock-Level Fire Sale Exposure and Selling Pressure, λ-weighted (Continued)

Panel B: FSE Calculated Using Brokerage Margin Accounts

	Selling pressure			
	(1)	(2)	(3)	(4)
Fire sale exposure	1.351***	1.466***	1.479***	1.504***
	(0.218)	(0.291)	(0.294)	(0.298)
Return volatility [t-60, t-			0.00370***	0.00396***
			(0.00135)	(0.00131)
Log market value [t-3]			-1.41e-05	0.000160***
			(3.25e-05)	(3.82e-05)
Avg turnover [t-60, t-1]			0.00162**	0.00140*
			(0.000715)	(0.000714)
Cumulative return [t-10,			0.000230***	0.000427***
			(4.07e-05)	(0.000142)
Stock FE	No	Yes	Yes	Yes
Date FE	No	Yes	Yes	Yes
Past 10-day daily returns	No	No	No	Yes
R-squared	0.006	0.018	0.020	0.022
Observations	116,809	116,809	116,809	116,809

Panel C: FSE Calculated Using Shadow Margin Accounts

	Selling pressure			
	(1)	(2)	(3)	(4)
Fire sale exposure	0.709***	0.951***	0.940***	0.932***
	(0.176)	(0.219)	(0.220)	(0.221)
Return volatility [t-60, t-			0.000177	0.000301
			(0.000488)	(0.000487)
Log market value [t-3]			0.000126***	8.65e-05***
			(1.78e-05)	(1.73e-05)
Avg turnover [t-60, t-1]			0.000273	0.000321
			(0.000299)	(0.000301)
Cumulative return [t-10,			-3.59e-05**	1.71e-06
			(1.47e-05)	(5.68e-05)
Stock FE	No	Yes	Yes	Yes
Date FE	No	Yes	Yes	Yes
Past 10-day daily returns	No	No	No	Yes
R-squared	0.028	0.073	0.075	0.076
Observations	116,809	116,809	116,809	116,809

Table B.3
Fire Sales and Reversals, λ-weighted

This table presents the same regression as in Table 6, 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 as estimated for the relevant sample in Table 2. 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	-9.685***	-26.80***	-37.83***	-42.87***	-16.64**	2.311
	(2.516)	(4.758)	(6.679)	(9.714)	(6.277)	(4.034)
Return volatility [t-60, t-1]	-0.241	-0.407	-0.419	-0.184	0.526	0.215
	(0.164)	(0.351)	(0.456)	(0.573)	(0.641)	(0.408)
Log market value [t-3]	-0.0663***	-0.203***	-0.323***	-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	-0.302**	-0.496***	-0.959***	-2.162***	-1.147***
	(0.0679)	(0.128)	(0.161)	(0.170)	(0.175)	(0.173)
Cumulative return [t-10, t-1]	-0.0548**	-0.0897*	-0.0731	0.0436	-0.0980	0.167***
	(0.0236)	(0.0523)	(0.0704)	(0.0835)	(0.0775)	(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	0.513	0.627	0.705
Observations	109,735	109,735	109,735	109,735	109,735	109,735

Table B.3
Fire Sales and Reversals, λ-weighted (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	-6.152***	-22.23***	-29.76***	-20.91***	-21.28***	3.039
	(2.133)	(4.803)	(5.520)	(4.343)	(5.525)	(10.38)
Return volatility [t-60, t-1]	-0.246	-0.420	-0.438	-0.212	0.522	0.216
	(0.165)	(0.352)	(0.458)	(0.575)	(0.643)	(0.409)
Log market value [t-3]	-0.0664***	-0.204***	-0.323***	-0.566***	-0.821***	-0.741***
	(0.00769)	(0.0148)	(0.0199)	(0.0282)	(0.0303)	(0.0202)
Avg turnover [t-60, t-1]	-0.0943	-0.306**	-0.502***	-0.966***	-2.164***	-1.147***
	(0.0681)	(0.129)	(0.162)	(0.171)	(0.175)	(0.174)
Cumulative return [t-10, t-1]	-0.0558**	-0.0922*	-0.0768	0.0384	-0.0989	0.167***
	(0.0237)	(0.0526)	(0.0708)	(0.0839)	(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	0.513	0.627	0.705
Observations	109,735	109,735	109,735	109,735	109,735	109,735

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	-13.25***	-32.86***	-48.90***	-65.76***	-21.62**	-2.244
	(3.593)	(7.587)	(9.970)	(13.83)	(10.21)	(4.351)
Return volatility [t-60, t-1]	-0.247	-0.424	-0.443	-0.210	0.516	0.218
	(0.164)	(0.352)	(0.457)	(0.574)	(0.643)	(0.409)
Log market value [t-3]	-0.0659***	-0.202***	-0.321***	-0.563***	-0.820***	-0.741***
	(0.00765)	(0.0146)	(0.0197)	(0.0279)	(0.0306)	(0.0202)
Avg turnover [t-60, t-1]	-0.0925	-0.302**	-0.495***	-0.956***	-2.162***	-1.146***
	(0.0679)	(0.128)	(0.161)	(0.170)	(0.176)	(0.173)
Cumulative return [t-10, t-1]	-0.0557**	-0.0925*	-0.0769	0.0397	-0.0997	0.167***
	(0.0236)	(0.0525)	(0.0706)	(0.0836)	(0.0777)	(0.0495)
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	109,735	109,735	109,735	109,735	109,735	109,735

Table B.4
Fire Sales and Reversals, Excluding Imputed Prices

This table presents the same regressions as in Table 6, 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.

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	-1.428***	-3.613***	-5.467***	-6.539***	-2.748**	-1.434**
	(0.487)	(0.953)	(1.460)	(1.759)	(1.209)	(0.698)
Return volatility [t-60, t-1]	-0.210	-0.443	-0.432	-0.114	0.572	1.026**
	(0.186)	(0.379)	(0.473)	(0.613)	(0.659)	(0.436)
Log market value [t-3]	-0.0626***	-0.190***	-0.304***	-0.544***	-0.815***	-0.715***
	(0.00899)	(0.0165)	(0.0242)	(0.0383)	(0.0388)	(0.0203)
Avg turnover [t-60, t-1]	-0.108	-0.303**	-0.549***	-1.061***	-2.211***	-1.682***
	(0.0676)	(0.118)	(0.138)	(0.156)	(0.180)	(0.155)
Cumulative return [t-10, t-1]	-0.0638**	-0.0758	0.00102	0.177*	-0.0461	0.123**
	(0.0272)	(0.0668)	(0.0837)	(0.0911)	(0.0821)	(0.0595)
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	0.349	0.404	0.514	0.637	0.734
Observations	68,123	68,123	68,123	68,123	68,123	68,123

Table B.4
Fire Sales and Reversals, Excluding Imputed Prices (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	-0.524	-1.054	-0.251	0.504	-0.833	-3.531***
	(0.506)	(0.975)	(1.460)	(1.507)	(0.977)	(0.853)
Return volatility [t-60, t-1]	-0.216	-0.460	-0.462	-0.152	0.560	1.029**
	(0.187)	(0.381)	(0.476)	(0.616)	(0.662)	(0.437)
Log market value [t-3]	-0.0628***	-0.190***	-0.305***	-0.545***	-0.815***	-0.715***
	(0.00902)	(0.0166)	(0.0244)	(0.0385)	(0.0387)	(0.0203)
Avg turnover [t-60, t-1]	-0.109	-0.306**	-0.553***	-1.066***	-2.213***	-1.683***
	(0.0677)	(0.119)	(0.139)	(0.156)	(0.180)	(0.155)
Cumulative return [t-10, t-1]	-0.0648**	-0.0785	-0.00389	0.171*	-0.0482	0.123**
	(0.0272)	(0.0672)	(0.0842)	(0.0914)	(0.0826)	(0.0597)
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	0.349	0.404	0.514	0.637	0.734
Observations	68,123	68,123	68,123	68,123	68,123	68,123

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	-1.939***	-5.061***	-8.418***	-10.52***	-3.831*	-0.249
	(0.685)	(1.585)	(2.417)	(2.858)	(1.990)	(0.983)
Return volatility [t-60, t-1]	-0.214	-0.452	-0.444	-0.127	0.566	1.018**
	(0.186)	(0.380)	(0.474)	(0.614)	(0.660)	(0.437)
Log market value [t-3]	-0.0624***	-0.189***	-0.303***	-0.543***	-0.814***	-0.715***
	(0.00898)	(0.0164)	(0.0241)	(0.0381)	(0.0389)	(0.0203)
Avg turnover [t-60, t-1]	-0.108	-0.302**	-0.547***	-1.059***	-2.210***	-1.683***
	(0.0675)	(0.118)	(0.138)	(0.156)	(0.181)	(0.155)
Cumulative return [t-10, t-1]	-0.0645**	-0.0775	-0.00136	0.175*	-0.0475	0.121**
	(0.0273)	(0.0671)	(0.0840)	(0.0911)	(0.0822)	(0.0597)
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	0.349	0.404	0.514	0.637	0.734
Observations	68,123	68,123	68,123	68,123	68,123	68,123

Table B.5

Fire Sales and Reversals, Standardized Coefficients

This table presents the same regressions as in Table 6, 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 regression sample used in each column of the table. 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	-0.000978***	-0.00259***	-0.00357***	-0.00413***	-0.00180***	0.000338
	(0.000226)	(0.000394)	(0.000572)	(0.000858)	(0.000636)	(0.000418)
Return volatility [t-60, t-1]	-0.00310	-0.00526	-0.00545	-0.00246	0.00671	0.00275
	(0.00210)	(0.00449)	(0.00584)	(0.00734)	(0.00821)	(0.00522)
Log market value [t-3]	-0.0654***	-0.201***	-0.319***	-0.558***	-0.810***	-0.732***
	(0.00757)	(0.0145)	(0.0196)	(0.0277)	(0.0300)	(0.0200)
Avg turnover [t-60, t-1]	-0.00238	-0.00774**	-0.0127***	-0.0245***	-0.0553***	-0.0293***
	(0.00174)	(0.00329)	(0.00412)	(0.00436)	(0.00448)	(0.00443)
Cumulative return [t-10, t-1]	-0.0131**	-0.0215*	-0.0176	0.0101	-0.0233	0.0396***
	(0.00562)	(0.0124)	(0.0168)	(0.0199)	(0.0184)	(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	109,735	109,735	109,735	109,735	109,735	109,735

Table B.5
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	-0.000258**	-0.000883***	-0.000949***	-0.000448	-0.000896***	0.000300
	(0.000107)	(0.000236)	(0.000341)	(0.000391)	(0.000222)	(0.000337)
Return volatility [t-60, t-1]	-0.00316	-0.00541	-0.00569	-0.00280	0.00664	0.00275
	(0.00210)	(0.00451)	(0.00585)	(0.00737)	(0.00824)	(0.00523)
Log market value [t-3]	-0.0656***	-0.201***	-0.319***	-0.559***	-0.810***	-0.732***
	(0.00760)	(0.0146)	(0.0197)	(0.0278)	(0.0299)	(0.0200)
Avg turnover [t-60, t-1]	-0.00241	-0.00783**	-0.0128***	-0.0247***	-0.0553***	-0.0293***
	(0.00174)	(0.00330)	(0.00413)	(0.00437)	(0.00448)	(0.00444)
Cumulative return [t-10, t-1]	-0.0133**	-0.0220*	-0.0185	0.00887	-0.0236	0.0396***
	(0.00561)	(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	109,735	109,735	109,735	109,735	109,735	109,735

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	-0.00117***	-0.00286***	-0.00427***	-0.00570***	-0.00165*	0.000155
	(0.000311)	(0.000659)	(0.000894)	(0.00117)	(0.000947)	(0.000433)
Return volatility [t-60, t-1]	-0.00315	-0.00542	-0.00565	-0.00266	0.00659	0.00277
	(0.00210)	(0.00450)	(0.00584)	(0.00733)	(0.00823)	(0.00523)
Log market value [t-3]	-0.0652***	-0.200***	-0.318***	-0.557***	-0.810***	-0.732***
	(0.00756)	(0.0145)	(0.0195)	(0.0276)	(0.0302)	(0.0200)
Avg turnover [t-60, t-1]	-0.00236	-0.00771**	-0.0127***	-0.0244***	-0.0553***	-0.0293***
	(0.00174)	(0.00328)	(0.00411)	(0.00435)	(0.00450)	(0.00443)
Cumulative return [t-10, t-1]	-0.0132**	-0.0219*	-0.0182	0.00953	-0.0237	0.0397***
	(0.00561)	(0.0125)	(0.0168)	(0.0198)	(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	109,735	109,735	109,735	109,735	109,735	109,735