Leverage Network and Market Contagion

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Abstract

Using daily account-level data that track hundreds of thousands of margin investors' leverage ratios, trading activities, and portfolio holdings, we examine the effect of margin-induced trading on stock prices during the recent market turmoil in China. We start by showing that individual margin investors have a strong tendency to scale down their holdings after experiencing negative portfolio shocks. Aggregating this behavior across all margin accounts, we find that returns of stocks that share common margin-investor ownership with the stock in question help forecast the latter's future return, which is subsequently reversed. This transmission mechanism is present only in market downturns, suggesting that idiosyncratic, adverse shocks to individual stocks can be amplified and transmitted to other securities through a de-leveraging channel. As a natural extension, we also show that the previously-documented asymmetry in return comovement between market booms and busts can be largely attributed to deleveraging-induced selling in the bust period. Finally, we show that stocks that are more central in the margin-holding network have significantly larger downside betas than peripheral stocks.

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1 Introduction

Investors can use margin trading—that is, the ability to lever up their positions by borrowing against the securities they hold—to amplify returns. A well-functioning lending-borrowing market is crucial to the financial system. In most of our standard asset pricing models (e.g., the Capital Asset Pricing Model), investors with different risk preferences lend to and borrow from one another to clear both the risk-free and risky security markets. Just like any other type of short-term financing, however, the benefit of margin trading comes at a substantial cost: it makes investors vulnerable to temporary fluctuations in security value and funding conditions. For example, a levered investor may be forced to liquidate her positions if her portfolio value falls temporarily below some pre-determined level.

A growing theoretical literature carefully models this two-way interaction between security returns and leverage constraints (e.g., Gromb and Vayanos, 2002; Fostel and Geanakoplos, 2003; Brunnermeier and Pedersen, 2009). The core idea is that an initial reduction in security prices lowers the collateral value, thus making the leverage constraint more binding. This then leads to additional selling by (some) levered investors and depresses the price further, which triggers even more selling by levered investors and an even lower price. Such a downward spiral can dramatically amplify the initial adverse shock to security value; the degree to which the price falls depends crucially on the characteristics of the margin traders that are holding the security. A similar mechanism, albeit to a much less extent, may also be at work with an initial, positive shock to security value. This can happen as long as (some) margin investors take advantage of the loosening of leverage constraints to scale up their holdings.

This class of models also makes predictions in the cross section of assets. When faced with the pressure to de-lever (or, to a less extent, the opportunity to increase leverage), investors may indiscriminately downsize (expand) all their holdings, including those that have not gone down (up) in value and thus have little to do with the tightening (loosening) of leverage constraints. This indiscriminate selling (buying) pressure could generate a contagion across assets that are linked solely through common holdings by levered investors. In other words, idiosyncratic shocks to one security can be amplified and transmitted to other securities through a latent leverage network structure. In some situations (e.g., in the spirit of Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi, 2012), idiosyncratic shocks to individual securities, propagated through the leverage network, can aggregate to and result in systematic price movements.

Despite its obvious importance to researchers, regulators, as well as investors, testing the asset pricing implications of margin trading has been empirically challenging. This is primarily due to the limited availability of detailed leverage data. In this paper, we fill this gap in the literature by taking advantage of unique *account-level* data in China that track hundreds of thousands of margin investors' borrowing (with aggregate debt amount exceeding RMB 100Billion), along with their trading and holding activity.[1]

Our datasets cover an extraordinary period – from May to July 2015 – during which the Chinese stock market experienced a rollercoaster ride: the Shanghai Composite Index climbed more than 60% from the beginning of the year to its peak at 5166.35 on June 12th, before crashing nearly 30% by the end of July. Major financial media around the world have linked this incredible boom and bust in the Chinese stock market to the growing popularity, and subsequent government crackdown, of margin trading in China.[2] Indeed, as evident in Figure 1, the aggregate amount of broker-financed margin debt and the Shanghai Composite Index moved in near lockstep (with a correlation of over 90%) during this period. This is potentially consistent with the narrative that the ability to buy stocks on margin fueled the

[1] The Chinese stock market has experienced tremendous growth in the past two decades, and is now the second largest in the world. Despite this unparalleled development, the Chinese market remains an individual-dominated market – according to the official statistics published by the Shanghai Stock Exchange, retail investors in 2015 accounted for over 85% of the total trading volume (`http://www.sse.com.cn/aboutus/publication/yearly/documents/c/tjnj_2015.pdf`).

[2] For example, "Chinese firms discover margin lending's downside," Wall Street Journal, June 30, 2015; "China's stock market crash: A red flag," Economist, July 7, 2015; "China cracks down on margin lending before markets reopen," Financial Times, July 12, 2015.

initial stock market boom and the subsequent de-leverage exacerbated the bust.

– Insert Figure 1 about here –

Our data, obtained from a major broker in China, as well as an online trading platform designed to facilitate peer-to-peer (shadow) margin lending, contain detailed records of individual accounts' leverage ratios and their holdings and trading activities at a daily frequency. Compared to non-margin accounts, the typical margin account is substantially larger and more active; for example, the average portfolio size and daily trading volume of margin accounts are more than ten times larger than those of non-margin accounts. Out of all margin accounts, the average leverage ratio of shadow-financed margin accounts is substantially higher than that of the broker-financed ones (4.55 vs. 1.53). Overwhelmingly, we find that levered investors are more speculative than their non-levered peers: e.g., they tend to hold stocks with high idiosyncratic volatilities and turnover.

More important for our purpose, the granularity of our data allows us to directly examine the impact of margin trading on asset prices: specifically, how idiosyncratic shocks to individual firms, transmitted through the nexus of margin-account holdings, can lead to a contagion in the equity market and, ultimately, aggregate to systematic price movements.

In our first set of analyses, we examine trading in each stock by individual margin accounts as a function of lagged portfolio returns. Our prediction is that margin investors are more likely to downsize (expand) their holdings after their portfolios have done poorly (well), plausibly due to the tightening (loosening) of margin constraints. Our results are consistent with this prediction: net purchases by each margin account (defined as the RMB amount of buy orders minus that of sell orders, divided by lagged account value) is significantly and positively related to lagged account returns. This effect strongly increases in the leverage ratio of the margin account, and is present only in market downturns, consistent with deleveraging-induced selling being a possible driver. Further, in a placebo test where we replace margin investors with non-margin accounts, we observe a *negative* relation between account trading and lagged portfolio returns (possibly due to individual investors' tendency to follow a contrarian strategy).[3]

Building on this trading behavior of margin investors, we next examine the asset pricing implications of margin-induced trading. To this end, for each stock in each day, we construct a "margin-account linked portfolio" (MLP)—namely, a portfolio of stocks that share common margin-investor ownership with the stock in question (aggregated across all margin investors). The weight of each stock in this linked portfolio is determined by the size of common ownership with the stock in question. More specifically, we construct an adjacency matrix T_0, where each cell (i, j) represents the common ownership in the stock pair (i, j) by all margin accounts scaled by market capitalization of the first stock (detailed derivation of the matrix is in Section 4.1). The margin-account linked portfolio return ($MLPR$) is then the product of matrix T_0 and the vector of daily stock returns.

To the extent that margin investors' collective trading can affect prices (at least temporarily), we expect the returns of a security be forecasted by the returns of other securities with which it shares a common margin-investor base. This prediction is strongly borne out in the data. Returns of the margin-account linked portfolio significantly and positively forecast the stock's next-day return; this result easily survives the inclusion of controls for the stock's own leverage and other known predictors of stock returns in the cross-section. Consistent with a price pressure story, this predicted return is quickly reversed in the following days; indeed, the positive return we observe on day one is nearly completely reversed by the end of day five. This hump-shaped return pattern is again present only in market downturns, as measured by both daily market returns and the fraction of stocks that hit the -10% threshold in each day (which would result in an automatic trading halt). Moreover, the return pattern is absent if we instead use non-margin accounts to define the linked portfolio. All these results (the strong return reversal, asymmetry between market booms and busts, and

[3]This is consistent with prior results that Chinese investors are quick to realize capital gains but reluctant to realize capital losses (see, for example, Shumway and Wu, 2006 and Bian et al., 2017). Without margin constraints, the wealth effect as in Kyle and Xiong (2001), in itself, is unlikely to generate contagion in the Chinese market.

asymmetry between margin and non-margin accounts) help alleviate the concern that our return forecasting result is driven by omitted fundamental factors.

A ubiquitous finding in nearly all asset markets is that securities comove much more strongly in market downturns than in market booms. Our next analysis ties the here-documented margin-induced contagion mechanism to the asymmetry in return comovement. Our results indicate that, after controlling for similarities in industry operations, firm size, book-to-market ratio, analyst coverage, institutional ownership, and other firm characteristics, a one-standard-deviation increase in our measure of common margin-investor ownership is associated with a 0.11% (t-statistic = 4.89) increase in the excess pairwise return comovement measure. Once again, these comovement patterns are much stronger in market downturns than in market upturns: a one-standard-deviation move in common margin-investor ownership is associated with a 0.16% (t-statistic = 3.80) increase in excess return comovement measure in market downturns and a 0.07% (t-statistic = 4.40) increase in market booms. For comparison, the average pairwise return comovement measure in the bust period in our sample is 0.15% higher than that in the boom period.

The ultimate question is, of course, whether deleveraging-induced trading was, at least partially, contributing to the spectacular market crash in 2015. In our final set of tests, we draw from the recent literature on network theory to shed more light on the direct and indirect links between stocks, and how these links are associated with aggregate market movements. In particular, we focus squarely on the leverage network (adjacency matrix T_0) constructed above, in which the strength of each link between a pair of stocks is determined by margin investors' common ownership. We argue that stocks that are more central to this leverage network—i.e., the ones that are more vulnerable to adverse shocks that originate in any part of the network—should experience more selling pressure and lower returns than peripheral stocks in market downturns. Using eigenvector centrality as our main measure of a stock's importance in the network, we find that after controlling for various stock characteristics, a one-standard-deviation increase in a stock's centrality is associated with a

10 bps (t-statistic = 2.38) lower return in the following day during the bust period. This negative return pattern is primarily due to the fact that central stocks have significantly larger downside market betas than peripheral stocks. These results have potentially useful implications for the Chinese government and financial regulatory agencies—which shortly after the market meltdown, devoted hundreds of billions of RMB to stabilizing the market—as to which set of stocks the rescue effort should concentrate on.

To further illustrate the role of leverage-induced trading in driving asset returns, we examine yet another boom-bust episode in the Chinese stock market in 2007, when margin trading was not allowed. Interestingly, both the boom and bust episodes lasted longer in 2007, potentially consistent with the view that margin-induced trading exacerbates price movements. More importantly, a formal analysis of the 2007 episode reveals a contagion pattern across accounts and stocks only during the boom period but not in the bust period. This is the exact opposite to what we observe in the more recent 2015 sample, in which margin-induced trading arguably plays an important role.

Our results are closely tied to the recent theoretical literature on how asset liquidity and returns interact with leverage constraints. Gromb and Vayanos (2002, 2017), Geanakoplos (2003), Fostel and Geanakoplos (2008) and Brunnermeier and Pedersen (2009) develop competitive equilibria in which smart investors (arbitrageurs or market makers), under certain conditions, provide sub-optimal amounts of liquidity because they face time-varying margin (collateral) constraints. This further impacts asset returns and return correlations. Our paper is the first to provide supportive evidence for these models that levered investors indeed scale down their holdings in response to the tightening of leverage constraints, which depresses prices and causes contagion across a wide range of securities.

Our paper is also related to the recent literature on excess volatility and comovement induced by common institutional ownership (e.g., Greenwood and Thesmar, 2011, Anton and Polk, 2014). These studies focus on common holdings by non-margin investors such as mutual funds, and the transmission mechanism examined there is a direct result of the flow-performance relation. Our paper contributes to the literature by highlighting the role of leverage, in particular deleveraging-induced selling in driving asset returns as well as contagion across assets. (In sharp contrast to prior studies on mutual funds, the non-margin accounts in our sample trade in the opposite direction of past returns.) A unique feature of this leverage channel is that its return effect is asymmetric; using the recent boom-bust episode in the Chinese stock market as our testing ground, we show that the leverage-induced return pattern is indeed present only in market downturns and is absent in market booms. Relatedly, our findings are also consistent with recent studies that document a higher correlation in hedge fund returns following adverse shocks (see, Boyson, Stahel, and Stulz, 2010, and Dudley and Nimalendran, 2011, among others). Our account-level holding and trading data allow us to shed more light on the mechanism underlying the asymmetric rise in return correlations.

Our paper also contributes to the booming literature on network theory. Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) and Gabaix (2011) argue theoretically that in a network with certain features, idiosyncratic shocks to individual nodes in the network do not average out; instead, they aggregate to systematic risks. Recent empirical work provides some support for these predictions. For example, Barrot and Sauvagnat (2016) and Carvalho, Nirei, Saito and Tahbaz-Salehi (2017), exploiting the production shocks caused by the Great East Japan Earthquake of 2011, show that production networks help propagate shocks in a manner that is consistent with theory. Closest to our results on the differences between central vs. peripheral stocks in the margin-holdings network is the work by Ahern (2013), who finds that more central industries in the input-output network have, on average, higher market betas than peripheral industries.

Finally, given the increasing importance of the Chinese market to the world economy, understanding the incredible boom and burst episode in 2015 is an informative exercise in and of itself. Taking advantage of our unique account-level data, we offer the first set of comprehensive cross-sectional evidence of margin constraints leading to the contagion of negative shocks. Our network analysis also provides potential recipes to financial regulators in their future market stabilization efforts. In a contemporaneous paper based on the same datasets, Bian, He, Shue, and Zhou (2017) study the differences in leverage-induced fire sale behavior between broker-financed and shadow-financed margin accounts and the implications for asset prices. While we also make this distinction, it is not the focus of our paper. Instead, we center our analyses on the cross-sectional transmission and amplification of negative shocks among stocks connected through common margin holdings.

The rest of the paper is organized as follows. Section 2 describes the institutional details of the Chinese stock market and regulations on margin trading. Section 3 discusses our datasets and screening procedures. Section 4 presents our empirical results. Section 5 concludes.

2 Institutional Background

The last two decades have witnessed tremendous growth in the Chinese stock market. As of May 2015, the total market capitalization of China's two stock exchanges, Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE), exceeded 10 trillion USD, second only to the US market. Despite the size of the market, margin trading was not authorized until 2010, although it occurred informally on a small scale. The China Securities Regulatory Commission (CSRC) launched a pilot program for margin financing via brokerage firms in March 2010 and margin financing was officially authorized for a subset of securities in October 2011. To obtain margin financing from a registered broker, investors need to have a trading account with that brokerage firm for at least 18 months, with a total account value (cash and stock holdings combined) over RMB500,000 (or about USD80,000).[4] The initial margin (= 1 - debt value/total holding value) is set at 50% and the maintenance margin is 23%. A list of around 900 stocks eligible for margin trading is determined by the CSRS, and is

[4]This account-opening requirement was lowered to six months in 2013.

periodically reassessed and updated.

The aggregate broker-financed margin debt has grown exponentially since its introduction. Starting in mid-2014, it has closely tracked the performance of the Chinese stock market and peaked around RMB2.26 trillion in June 2015 (see Figure 1). It is about 3% to 4% of the total market capitalization of China's stock market. This ratio is similar to that found in the New York Stock Exchange (NYSE) and other developed markets. The crucial difference is that margin traders in China are mostly unsophisticated retail investors, whereas in the US and other developed markets, margin investors are usually institutional investors with sophisticated risk management tools.

In part to circumvent the tight regulations on broker-financed leverage, peer-to-peer (shadow) financed margin trading has also become popular since 2014. These informal financing arrangements come in many different shapes and forms, but most of them allow investors to take on even higher leverage when speculating in the stock market. For example, Umbrella Trust is a popular arrangement where a few large investors or a group of smaller investors provide an initial injection of cash, for instance 20% of the total trust's value. The remaining 80% is then funded by margin debt, usually from retail investors, in the form of wealth management (savings) products. As such, the umbrella trust structure can achieve a much higher leverage ratio than what is allowed by the official rule; in the example above, the trust has an effective leverage ratio of 5. In addition, this umbrella trust structure allows small investors to bypass the RMB500,000 minimum threshold that is required to obtain margin financing from brokers.

The vast majority of this shadow-financed borrowing takes place on a handful of online trading platforms with peer-to-peer financing capabilities.[5] Some of these trading platforms allow further splits of a single umbrella trust, increasing the effective leverage further still. Finally, shadow financed margin trading allows investors to take levered positions on any stocks, including those not on the marginable security list.

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

Since shadow-financed margin trading falls in an unregulated grey area, there is no official statistic regarding its size and effective leverage ratio. Estimates of its total size from various sources range from RMB 0.8 trillion to RMB 3.7 trillion. It is widely believed that the amount of margin debt in this shadow financing system is at least as large as the that via the formal broker channel. For example, Huatai securities Inc., one of China's leading brokerage firms, estimates that the total margin debt peaked at 7.2% of the total market capitalization of all listed firms, with half of that coming from the unregulated shadow financial system. This ratio goes up to 19.6% if one considers only the free-floating shares, as a significant fraction of the market is owned by the Chinese Government.[6]

3 Data and Summary Statistics

Our study exploits two proprietary account-level datasets. The first dataset contains the complete records of equity holdings, cash balance, order submissions, and trade executions of all existing accounts from a leading brokerage firm in China for the period May to July of 2015. It has over five million active accounts, over 95% of which are retail accounts. Around 180,000 are eligible for margin trading. For each margin account, we have its end-of-day debit ratio, defined as the account's total value (cash plus equity) divided by its outstanding debt. The CSRC mandates a minimum debit ratio of 1.3, equivalent to a maintenance margin of 23% (=(1.3-1)/1.3).

To ensure the quality of our data, we conduct the following analyses. To start, we aggregate the daily trading volume and corresponding RMB amount across all accounts in our data. On a typical day, our data account for nearly 10% of the combined trading volume in the Shanghai and Shenzhen stock exchanges. The total amount of debt in our data also

[6]Excessive leverage through the shadow financial system is often blamed for causing the dramatic stock market gyration in 2015. Indeed, in June 2015, CSRC ruled that all online trading platforms must stop providing leverage to their investors. By the end of August, such levered trading accounts have all but disappeared from these electronic trading platforms.

accounts for roughly 10% of the aggregate brokerage-financed margin debt in the market. Moreover, the cross-sectional correlation in trading volume between our account-level data and the whole market is over 90%. These summary statistics suggest that our dataset is a sizable, representative sample of the market.

Our second dataset, obtained from a major online trading platform, contains all the trading and holdings records of more than 250,000 accounts for the period July 2014 to July 2015. As described above, these margin accounts are owned by a number of mother accounts on the same trading platform. Since the trading platform (as well as all accounts on the platform) is not regulated by the CSRC, the data quality is lower compared to the brokerage data. Consequently, we apply a number of data filters to identify eligible margin accounts in our study. These filters are described in detail in the appendix. After applying these filters, our final dataset contains 155,000 margin accounts, with complete information on their cash and stock holdings, as well as outstanding margin debt, on a daily basis.

In addition to the proprietary account-level data, we also obtain security data such as daily closing prices, trading volume, stock returns and other stock characteristics from WIND.

3.1 Sample Summary Statistics

Table 1 shows the summary statistics of our sample. In Panel A, we compute the total debt and holding value (cash plus equity) aggregated across all accounts for each day; we then report various statistics (across days) for the subsamples of brokerage-financed margin accounts and shadow-financed margin accounts. The results indicate that for the broker-financed sample, around 30% of the aggregate holdings is financed by margin borrowing; that same ratio for shadow-financed margin accounts is over 60%. For comparison, we also include non-margin accounts from the brokerage data. To make the calculation more manageable, we select the largest 400,000 non-margin accounts in terms of holding value (as margin accounts tend to be larger than non-margin accounts).[7]

– Insert Table 1 about here –

We next compare investors' holdings and trading behavior across the three subsamples. As can be seen from Panel B, broker-financed margin accounts are the most active. The median broker-financed margin account in our sample, on a typical day, submits 6 orders, turns over 15,000 shares (worth over 270,000 RMB), and holds 63,000 shares (worth over 1.2 million RMB). Since there is no minimum account value requirement on the online trading platform, shadow-financed margin accounts are smaller than the brokerage-financed ones, both in terms of holdings and daily trading, but have much higher leverage ratios (4.5 vs. 1.5).

We also examine the types of stocks that are likely held by margin vs. non-margin investors. As shown in Panel C, broker-financed margin and non-margin accounts tend to hold stocks with similar characteristics, along the dimensions of firm size, book-to-market ratio, past returns, turnover, and idiosyncratic volatilities. Shadow-financed margin accounts, relative to the brokerage sample, tend to hold stocks that are more growthy and have higher past returns.

3.2 Margin Accounts' Leverage Ratios

Following prior literature (e.g., Ang et al., 2011), we define the leverage ratio of each margin account as follows:

$$\textit{Leverage Ratio} = \frac{\textit{Total Portfolio Value}}{\textit{Total Portfolio Value-Total Debt Value}} \tag{1}$$

For our brokerage sample, we directly observe this leverage ratio at the end of each day. For the sample of shadow-financed margin accounts, we observe the value of equity and

[7]We pick 400,000 non-margin accounts to make their sample size comparable to that of our initial margin account sample (brokerage-financed and shadow-finance combined). We confirm that the results are similar if we instead pick the 300,000 or 200,000 largest non-margin accounts.

cash holdings, as well as the amount of margin debt, on a daily basis. The imputed daily leverage ratio varies substantially across shadow-financed margin accounts, reflecting the fact that both the initial margin and maintenance margin are negotiated directly between the investor (i.e., the borrower) and the lender without any regulatory supervision. Figure 2 plots value-weighted average leverage ratios of both brokerage-financed and shadow-financed margin accounts, where the weight is equal to each account's capital value (i.e., portfolio value minus debt value).

– Insert Figure 2 about here –

There are a few interesting observations. First, although the average leverage ratio of shadow-financed margin accounts is substantially higher than that of brokerage-financed accounts, the two move in near lock-step. One way to think about this is that while investors with different risk preferences sort themselves into different trading venues, they are nonetheless affected by similar market-wide shocks. Second, the average leverage ratio of shadow-financed margin accounts decreases steadily from January to June of 2015 (and similarly for our brokerage sample between May and June). A big part of this declining pattern is due to the contemporaneous market rally in the first half of the year. Indeed, as shown in Figure 1, outstanding margin debt increases substantially in the first six months of 2015, just not as much as the market run-up. Third, Figure 2 also shows a sudden and dramatic increase in leverage ratios of both brokerage-financed and shadow-financed margin accounts in the last two weeks of June and the first week of July; this is again largely due to contemporaneous market movements. Forth, despite the fact that the market keeps crashing in the second half of July, the leverage ratio in both samples plummeted, possibly driven by voluntary and involuntary de-leveraging activities.

3.3 Investor and Stock Characteristics

We start our analyses by examining the set of investor characteristics that are associated with the account leverage ratio. To this end, we conduct the following panel regression of account leverage on investor characteristics, separately for brokerage-financed and shadow-financed margin accounts:

$$LEVERAGE_{j,t+1} = c_j + \gamma * CHARACTERISTICS_{j,t} + \varepsilon_{j,t+1}. \tag{2}$$

where $LEVERAGE_{j,t+1}$ is the leverage ratio of account j at the end of day t+1. The set of investor characteristics includes $\#STOCKS$ (the number of stocks held by the account), $ACCOUNT_VALUE$ (cash plus stock holdings), and $ACCOUNT_AGE$ (days since the account opening). As can be seen from Panel A of Table 2, there is an interesting difference between brokerage-financed and shadow-financed margin accounts. For the brokerage sample, investors with higher leverage ratios tend to have larger account value and a larger number of stock holdings. The opposite, however, is true for the shadow-financed sample.

– Insert Table 2 about here –

Next, we examine the types of stocks that are more commonly held by levered investors. Specifically, for each stock in each day, we compute a stock-level $LEVERAGE$ measure as the weighted average leverage ratio of all margin accounts that hold the stock. We then conduct the following panel regression of $LEVERAGE$ on various stock characteristics:

$$LEVERAGE_{i,t+1} = c_i + \beta * CHARACTERISTICS_{i,t} + \varepsilon_{i,t+1} \tag{3}$$

where $LEVERAGE_{i,t+1}$is the leverage ratio for stock i at day t+1. The set of stock characteristics includes $DRET$ (the stock return in the previous day), $MOMENTUM$ (average cumulative stock return in the previous 120 trading days), $TURNOVER$ (average turnover ratio in the prior 120 trading days), $IDVOL$ (average idiosyncratic volatility, after controlling for the Chinese Fama-French three factor model, in the previous 120 trading days), and $MCAP$ (lagged market capitalization based on tradable shares). As shown in Column 6 of Panel B, levered investors are more likely to hold larger stocks with higher idiosyncratic volatilities and higher share turnover.

4 Empirical Analyses of the Leverage Network

In this section, we examine the effect of margin trading on stock returns and their co-movement through a network of levered investors. The main idea is that a negative idiosyncratic shock to stock A may lead some investors to de-lever. If these investors sell indiscriminately across all their holdings, this selling pressure could cause a contagion among stocks that are "linked" to stock A through common ownership by levered investors. A similar story, albeit to a less extent, can be told for a positive initial shock – for example, as one's portfolio value increases, he/she may take on more leverage to expand his/her current holdings. Our sample data with comprehensive leverage ratios can greatly help identify this contagion phenomenon.

We first sketch a stylized model of margin trading. The model formalizes the shock propagation through trading by margin traders. It also motivates the empirical measures and guides our subsequent empirical analyses.

4.1 A Stylized Model

For analytical tractability, we make two simplifying assumptions following Greenwood, Landier, and Thesmar (2015). We first assume that every margin trader j starts each period with an optimal target leverage ($L_{0,j}$), and at the end of the period, she will trade her portfolio in order to return to her target leverage.

Let A and D denote dollar values of asset and margin debt, respectively, then $L_{0,j} = \frac{A_{0,j}}{A_{0,j}-D_{0,j}}$. Let $r_{1,j}$ denote her portfolio return during the period. Assume no interest on the margin debt, at the end of the period, her leverage becomes $L_{1,j} = \frac{A_{0,j}(1+r_{1,j})}{A_{0,j}(1+r_{1,j})-D_{0,j}}$. To restore the account leverage back to its optimal level $L_{0,j}$, she needs to trade $X_{1,j}$, which can be solved by setting:

$$\frac{A_{0,j}(1+r_{1,j})+X_{1,j}}{A_{0,j}(1+r_{1,j})-D_{0,j}} = L_{0,j} \Rightarrow X_{1,j} = A_{0,j}(L_{0,j}-1)r_{1,j} \tag{4}$$

It is clear that the trader has to sell more stocks if her initial leverage is higher and when her portfolio return is more negative.

Our second simplifying assumption is that when the trader trades, she scales her portfolio up or down proportionally according to initial portfolio weights. In other words, the dollar amount of leverage-induced trading on stock i at the end of the period by trader j is:

$$X_{1,i,j} = \omega_{0,i,j}A_{0,j}(L_{0,j}-1)(r_{1,i} * \omega_{0,i,j} + r^{\perp}_{1,i,j} * \omega^{\perp}_{0,i,j}). \tag{5}$$

The dollar trading amount is therefore determined by: lagged holding size, initial leverage ratio, stock i's own return (amplification channel), and returns of other stocks in the same portfolio (contagion channel). The account-level trading evidence in Section 4.2 confirms that equation (5) is a reasonable description of actual trading behavior of margin investors in our sample.

Now aggregate across M margin traders who hold stock i and assume price pressure is proportional to the market cap of the stock ($M_{0,i}$), the leverage-induced price pressure ($LIPP$) on stock i at the end of the period is:

$$LIPP_{1,i} = \frac{1}{M_{0,i}}\Sigma_{j=1}^{M}[A_{0,j} * \omega_{0,i,j}(L_{0,j}-1)(r_{1,i} * \omega_{0,i,j} + r^{\perp}_{1,i,j} * \omega^{\perp}_{0,i,j})]. \tag{6}$$

For expositional convenience, we now recast everything using matrix representation. Let R denote a $N \times 1$ vector of stock returns; Ω a $M \times N$ matrix of portfolio weights so that each row sums up to 1; $diag(A_0)$ a $M \times M$ diagonal matrix whose diagonal terms are $A_{0,j}$;

$diag(L_0)$ a $M \times M$ diagonal matrix whose diagonal terms are $L_{0,j}$; $diag(M_0)$ a $N \times N$ diagonal matrix whose diagonal terms are $M_{0,i}$. $LIPP$ can be expressed as:

$$\begin{aligned} LIPP &= TR \\ &= diag(M_0)^{-1}\Omega' diag(A_0)[diag(L_0) - I]\Omega R. \end{aligned} \tag{7}$$

If we set the diagonal terms of the matrix T to zero and denote the resulting matrix T_0, then margin-account linked portfolio return ($MLPR$) can be computed simply as $MLPR = T_0 R$. Intuitively, $MLPR_i$ isolates the price pressure coming from stocks that are (directly) connected to stock i through common ownership by margin traders. In other words, $MLPR$ directly measures the contagion effect. Section 4.3 confirms that connection via common ownership by margin trades predicts future stock returns and return correlations.

The contagion-induced price pressure can be propagated further in the leverage network. For example, $T_0^2 R$ captures the contagion effect in the second round of propagation; $T_0^3 R$ captures that in the third round; etc. In the limit, $T_0^n R$ (in absolute term after normalization) converges to the eigenvalue centrality of this leverage network as n goes to infinity.

A number of measures have been proposed in prior literature to quantify the importance of each node in a given network. These include degree, closeness, betweenness, and eigenvector centrality. Borgatti (2005) reviews these measures and compare their advantages and disadvantage based on their assumptions about how traffic flows in the network. Following Ahern (2015), we use the eigenvector centrality as our main measure of leverage network centrality.

Eigenvector centrality is defined as the principal eigenvector of the network's adjacency matrix (Bonacich, 1972). A node is more central if it is connected to other nodes that are themselves more central. The intuition behind eigenvector centrality is closely related to the stationary distribution. The Perron-Frobenius theorem stipulates that every Markov matrix has an eigenvector corresponding to the largest eigenvalue of the matrix, which represents the stable stationary state. Equivalently, this vector can be found by multiplying the transition matrix by itself infinite times. As long as the matrix has no absorbing states, then a non-trivial stationary distribution will arise in the limit. If we consider the normalized adjacency matrix as a Markov matrix, eigenvector centrality then represents the stationary distribution that would arise as shocks transition from one stock to another for an infinite number of times.

Section 4.5 examines the properties and return predictability of our leverage network centrality measure and discusses policy implications for a government who intend to bail out the stock market during a crash period.

4.2 Leverage-Induced Trading: Account-Level Evidence

In our first set of analyses, we examine trading of individual margin accounts as a function of lagged portfolio returns. In particular, we conduct a panel regression where the dependent variable is the daily net trading of each margin account, defined as the total amount of buys minus total amount of sells divided by the lagged account value:

$$TRADE_{j,t+1} = a + b * RET_{j,t} + c * LEVERAGE_{j,t} + d * RET_{j,t} * LEVERAGE_{j,t} + \varepsilon_{i,t+1}. \quad (8)$$

In our baseline regression, we include daily portfolio returns in the previous five days on the right hand side. We also include account and date fixed effects in the regression to subsume any account-invariant as well as market-wide components. As can be seen from Panel A of Table 3, without conditioning on the leverage ratio, there is a weak relation between past portfolio returns and subsequent trading.

For comparison, Columns 7 and 8 repeat the analysis for the largest non-margin accounts. For non-margin traders, we observe a *negative* and significant relation between account trading and lagged portfolio returns, possibly due to individual investors' tendency to follow a contrarian strategy. Indeed, prior literature has documented strong evidence that Chinese investors are quick to realize capital gains but reluctant to realize capital losses (see, for example, Shumway and Wu, 2006 and Bian et al., 2017). Without margin constraints, negative past returns do not automatically generate selling pressure even among the largest Chinese investors.

– Insert Table 3 about here –

In Panel B, we further include the lagged account leverage ratio, as well as the interaction between lagged portfolio returns and account leverage, in the regression. Column 1 corresponds to the sample of broker-financed margin accounts, Column 3 corresponds to the sample of shadow-financed margin accounts, while Column 5 combines the two samples. The coefficient estimates on the interaction term in Columns 1, 3, 5 of 0.037 (t-statistic = 2.42), 0.091 (t-statistic = 5.22), and 0.129 (t-statistic = 5.68) are economically large and statistically significant. These results indicate that margin accounts with higher leverage ratios indeed scale up (down) their portfolio holdings in response to positive (negative) return shocks to a larger extent compared to accounts with lower leverage. In Columns 2 (broker-financed), 4 (shadow-financed), and 6 (combined), we further divide lagged portfolio returns into positive vs. negative realizations. Consistent with the intuition that levered investors should be more responsive to negative return shocks than to positive ones, we find that the positive association between past portfolio returns and future trading activity is present only with negative shocks, and is absent when lagged portfolio returns are positive.

– Insert Table 4 about here –

In Table 4, we examine the characteristics of stocks that are more likely to be bought or sold by levered investors in response to changing margin constraints. To this end, we conduct a three-dimensional panel regression, where the dependent variable is the net trading in a stock by a margin account on a given day—defined as the number of shares bought minus that of shares sold divided by lagged holdings. On the right hand side of the equation, we include a triple interaction term of lagged account return $\times$ leverage ratio $\times$ stock characteristic, as well as all the double-interaction terms and the underlying variables themselves. Hau and Lai (2017) study the liquidation choice of equity mutual funds following the 2007/2008 financial crisis and find that distressed funds prefer to liquidate better performing stocks in their portfolios. In contrast, the average individual margin investor' liquidation choice does not seem to depend heavily on recent performance in China. Interestingly, broker-financed margin accounts, in response to negative (positive) past returns, are more likely to sell (buy) stocks with smaller size and larger idiosyncratic volatility, managing portfolio risk consistent with the movement in margin constraints. Shadow-financed margin accounts, when faced with the same shocks, are more likely to sell (buy) stocks with larger size and turnover, in a way to minimize trading costs. The difference in response to lagged portfolio returns between the two types of margin accounts is likely due to their differences in risk attitudes.

4.3 Margin-Account Linked Portfolio: Stock-level Evidence

After confirming that margin constraints affect trading activities at the account level, we then examine the direct contagion effect. Our main variable of interest is the margin-account linked portfolio return ($MLPR$) as defined in section 4.1. $MLPR$ measures the price pressure coming from stocks that are linked to stock i through common ownership by margin traders. In the cross-section, stocks with more negative $MLPR$ today are predicted to have lower returns in the near future. To the extent that the lower future return reflects negative price pressure, it should be reverted afterwards.

To test this prediction, we run Fama-MacBeth cross-sectional regressions of the next-day stock return on $MLPR$, along with other controls that are known to forecast stock return:

$$RET_{i,t+1} = a + b * MLPR_{i,t} + \sum_{k=1}^{K} b_k * CONTROL_{i,k,t} + \varepsilon_{i,t+1}. \tag{9}$$

The results are reported in Table 5. To differentiate the role of the margin investors from that of the non-margin investors, we include the non-margin-account linked portfolio return ($NMLPR$) as a control. The only two differences between $NMLPR$ and $MLPR$ are: (1)

$NMLPR$ is computed using non-margin accounts; and (2) we set leverage (L_0) to 2 to eliminate any cross-sectional variation that comes from the leverage channel.

– Insert Table 5 about here –

In Column 1, we find that $MLPR$ significantly and positively predicts the next-day return. This holds even after controlling for the stock's own leverage and its own lagged returns and additional stock characteristics. For example, after controlling for common return predictors, a one standard deviation decrease in MLPR today predicts a lower return to stock i tomorrow by 19 bps ($= 0.21 \times 0.009$, t-statistic $= 2.45$). Controlling for $NMLPR$ in Column 2 does not change the result much. In contrast to the significant coefficient on $MLRP$, the coefficient on $NMLPR$, while positive, is insignificant. The result shows that contagion induced by the margin investors has a much stronger impact on stock prices.

Columns (3) to (6) examine the predictive power of $MLPR$ during the boom and bust days separately. Days when a large (small) number of stocks hit the -10% price limit are labelled as "Bust" ("Boom"). Classifying boom and bust days using the fraction of stocks hitting the down price limit is potentially superior than that using the market return, as market return may not properly reflect true valuation when a significant fraction of the market hits the price limit and stops trading. In addition, the fraction of stocks hitting the price limit captures the margin constraints better. When trading stops for a significant fraction of the market, levered investors have even less options to de-lever their portfolios. We confirm that results are similar if we use the market return to classify boom and bust days.

The results in Columns (3) to (6) clearly demonstrate that the return predictive power of $MLPR$ concentrates on the bust days. The asymmetry between boom and bust days is again not surprising as investors tend to be more patient in levering up their portfolios. In sharp contrast, when tightening margin constraint forces them to de-lever, they have to sell stocks in a hurry, thus resulting in more price pressure.

To the extent that the return predictability associated with $MLPR$ reflects price pressure, we would expect it to revert itself subsequently. To examine this conjecture, we repeat the regressions in equation (9) for future returns on days t+2, t+3, t+4 and t+5 as well. The results are reported in Table 6. For easy comparison, we reproduce the result for next-day (t+1) return in Column (1).

– Insert Table 6 about here –

The results in Table 6 suggest that the return predictability of $MLPR$ is mostly concentrated on day 1. It is still positive but insignificant on day 2. Afterwards, we start to see a reversal in the predictability. The coefficient on $MLPR$ is negative across days 3 to 5 and is significant for day 3. In terms of magnitude, we find the positive predictability from the first two days is completely reverted by day 5.

4.4 Return Comovement

The results so far support the notion that margin-constraint-induced trading can propagate shocks from one stock to other stocks that are connected through common ownership by margin investors. The effect is stronger in the down market. Another way to demonstrate such a contagion effect is to examine pairs of stocks. The prediction is that two stocks sharing more common ownership by margin investors should also co-move more in the near future, especially in the down market. The prediction thus links margin-induced contagion mechanism to the asymmetric comovement pattern. To test this prediction, we follow the empirical framework in Anton and Polk (2014) closely.

We measure common ownership by margin investors in a way similar to Anton and Polk (2014). At the end of each day, we measure common ownership of a pair of stocks as the total value of stock holdings across all leveraged investors who hold both stocks, scaled by the investors' account leverages, divided by the total market capitalization of the two stocks.

We label this variable "Common Margin Holding" ($MARHOLD$):

$$MARHOLD_{i,j,t} = \frac{\sum_{m=1}^{M}(S_{i,t}^{m}P_{i,t} + S_{j,t}^{m}P_{j,t}) * L_t^m}{TS_{i,t}P_{i,t} + TS_{j,t}P_{j,t}}, \tag{10}$$

where $S_(i,t)^m$ is the number of shares of stock i held by levered investor m, $TS_(i,t)$ the number of tradable shares outstanding, and $P_(i,t)$ the close price of stock i on day t. $MARHOLD$ is very similar to the individual element in the adjacency matrix T_0 except that we use the sum of market capitalizations of the two stocks as the scaling factor.[8] We log transform $MARHOLD$ (i.e., take the natural log of $MARHOLD$ plus one) to deal with outliers. Since the number of stock pairs increases exponentially with the number of stocks in our sample, to reduce computation burden, for this particular test, we focus on pairwise $MARHOLD$ for component stocks in the Zhongzhen 800 index.

We then estimate Fama-MacBeth regressions of realized return comovements of each stock pair on lagged $MARHOLD$:

$$COV_{i,j,t+1} = a + b * MARHOLD_{i,j,t} + \sum_{k=1}^{K} b_k * CONTROL_{i,j,k,t} + \varepsilon_{i,t+1}. \tag{11}$$

The pairwise return comovement (COV) is computed as the product of excess returns (over the market) on the two stocks on day $t+1$. Following Anton and Polk (2014), we also control for a host of variables that are known to be associated with stock return comovements: the number of analysts that are covering both firms ($COMANALY$); the absolute difference in percentile rankings based on firm size ($SIZEDIFF$), book-to-market ratio ($BMDIFF$), and cumulative past returns ($MOMDIFF$), a dummy that equals one if the two firms are in the same industry, and zero otherwise ($SAMEIND$). We also include in the regression, $SIZE1$ and $SIZE2$, the size percentile rankings of the two firms, as well as the interaction between the two. The results are reported in Table 7.

[8] In contrast, element (i,j) in A_0 uses the market capitalization of stock i as the scaling factor, while element (j,i) uses the market capitalization of stock j.

– Insert Table 7 about here –

As shown in Column (1), the coefficient on $MARHOLD$ is 0.081 with a t-statistic of 4.89, even after controlling for similarities in firm characteristics. In Columns (2) and (3), we repeat our analysis in Columns (1) for boom and bust days separately. We find the coefficient on $MARHOLD$ is again more than twice as large on bust days (0.112) as that on boom days (0.05). Given a cross-sectional standard deviation of 0.014 for $MARHOLD$, these coefficients imply that a one-standard-deviation move in common margin-investor ownership is associated with a 0.16% (t-statistic = 3.80) increase in excess return comovement measure in market downturns and a 0.07% (t-statistic = 4.40) increase in market booms. For comparison, the average pairwise return comovement measure in the bust period in our sample is only around 0.05% higher than that in the boom period. Indeed, as margin constraints are tightening, stocks linked through margin holdings are more likely to be sold together and hence their returns co-move more.

4.5 Leverage Network Centrality

After examining the contagion effect at the account-level, the stock-level, and across pairs of stocks, we now take a network view, hoping to shed light on the ultimate question of whether margin-induced trading was, at least partially, responsible for the spectacular market crash in 2015. As discussed in Section 4.1, we construct the leverage network of stocks that are connected through common holdings by margin investors.

We focus on the eigenvector centrality which provides a measure of how important a node is in the network. It directly measures the strength of connectedness of a stock, considering the importance of the stocks to which it is connected. Equivalently, by tracing out all paths of a random shock in a network, eigenvector centrality measures the likelihood that a stock will receive a random shock that transmits across the network. As such, stocks that are central to the network likely bear the bulk of aggregate risk following a negative shock, and are predicted to earn lower returns in the near future. In the other direction, central stocks are predicted to earn higher future returns following positive shocks but the effect should be much weaker.

In Table 8, we regress day-t+1 return on day-t centrality measure ($CENT$), its interaction with day-t+1 market return ($MRET * PCENT$), and other day-t controls:

$$RET_{i,t+1} = a+b*CENT_{i,t}+c*MRET_{i,t+1}PCENT_{i,t}+\sum_{k=1}^{K} d_k*CONTROL_{i,k,t}+\varepsilon_{i,t+1}. \quad (12)$$

We run the regressions for boom and bust days separately.

– Insert Table 8 about here –

Column (1) shows that central stocks do earn higher future returns following positive shocks. The coefficient on $CENT$, however, is not significant and it drops to zero when other controls are included in the regression as in Column (2). The insignificant coefficient on $MRET * PCENT$ in Column (3) shows that central stocks' betas are not different from those of other stocks on boom days.

Columns (4) to (6) paint a very different picture for the bust days. Following negative shocks, central stocks do earn significantly lower returns on the next day. A one standard deviation increase in $CENT$ lower the next-day return by 10 bps (t-statistic = 2.38). The effect remains significant when other controls are included in Column (5). Column (6) shows that the beta for central stocks becomes much higher compared to other stocks on bust days. Since we use percentile ranking of the centrality measure ($PCENT$) in the interaction term, its coefficient of 0.003 means that the most central stocks (in the top percentile) have a beta 0.3 higher than that of the least central stocks (in the bottom percentile). This higher beta actually explains why central stocks earn lower returns on bust days. Hence the coefficient on $CENT$ is no longer significant once the interaction term $MRET * PCENT$ is included in Column (6).

What are the characteristics of the central stocks in the leverage network? We examine this question in Table 9 by regressing the percentile rank of the centrality measure ($PCENT$) on various stock characteristics:

$$PCENT_{i,t+1} = c_i + \beta * CONTROL_{i,t} + \varepsilon_{i,t+1} \tag{13}$$

– Insert Table 9 about here –

Column (1) of Table 9 shows that the centrality measure is highly persist for individual stocks. Columns (2) to (7) show that the centrality measure is highly correlated with many stock characteristics. Comparing these univariate regression results to the multivariate ones reported in Column (8), several consistent correlations stand out. For example, not surprisingly, large stocks which are widely held by many margin investors tend to be central stocks. Importantly, central stocks are associated with higher idiosyncratic volatilities and more negative returns today. Moreover, they are more likely held by highly levered investors. All these correlations point towards a coherent story. A negative idiosyncratic shock on the central stock can trigger heavy and coordinated selling by the most constrained margin investors. Given its central location in the leverage network, its idiosyncratic shock can quickly spread to the entire network and becomes a source of systemic risk. While not conclusive, our evidence so far does suggest that margin-induced trading has the potential to exacerbate the stock market crash through stocks that are central to the leverage network.

More importantly, our results have direct policy implications for the Chinese government and, more generally, financial regulatory agencies that intend to stabilize the market during a crisis. Shortly after the initial market meltdown in June, on July 4th, 2015, president of the China Securities Regulatory Commission (CSRC) convened a meeting with CEO's from 12 securities firms, and decided to devote hundreds of billions of Yuan (RMB) to bail out the stock market.[9] This market-rescue plan, similar in spirit to the QE program in US, aimed at stabilizing the stock market. On the following Monday, July 6th, several

[9]See `http://finance.ifeng.com/a/20150705/13818786_0.shtml` for details.

government-controlled trading accounts started to purchase selected stocks on a large scale.

We obtain from the Shanghai Stock Exchange (SSE) the list of stocks that the Chinese government has purchased on July 6th as part of its bailout effort. There were 376 SSE stocks in that list, whereas the remaining 541 traded SSE stocks did not received buy orders from the government.[10] Table 10 compares these "bailout" stocks to the remaining active stocks on the SSE.

– Insert Table 10 about here –

It is clear from Table 10 that in an attempt to sustain market, the Chinese government has chosen to bail out the larger stocks that are in the benchmark stock market index (HS300). Unfortunately, these stocks are not always the most centrally located in the leverage network. In fact, the stocks that were ignored by the government actually has slightly higher centrality measure on average (although the difference is not significant).

The initial bailout effort turned out be less effective than expected.[11] Had the government chosen to purchase the most central stocks on that day, they probably could have done a more effective job in supporting the market. In other words, our methodology can inform future bailout attempts as to which set of stocks the rescue effort should concentrate on.

4.6 Placebo test using the 2007 crash

In this subsection, we conduct a placebo test using market crash in the 2007 China. Chinese stock market experienced another boom and crash in the mid of 2007. During the 6-month period from Nov, 29, 2006 to May 29, 2007, the Shanghai stock index has a cumulative return equal to 178%, which is the highest 6-month return in the 2000-2010 period. To alleviate a potential asset price bubble, the Chinese government suddenly tripled the stock transaction tax on May 30th, 2007. As a consequence, on that day, out of the 1301 stocks being traded,

[10]On July 6th, 2015, more than 1400 stocks were either suspended from trading, or stopped trading because they hit the -10% lower price limits.

[11]See `http://finance.sina.com.cn/stock/zldx/20150707/051622607495.shtml` for details.

887 hit their low price limits. The decline in the stock market index continued all the way to the end of 2007 (see Andrade, Bian, and Burch, 2013).

Importantly, there was no margin trading in 2007, allowing us to conduct placebo tests. Comparing the durations of both the boom and bust periods in 2007 to those in 2015, the boom and bust seem much shorter in 2015, consistent with the narrative that margin trading helps to fuel the initial boom and exacerbate the subsequent bust.

More formally, we conduct similar return predictability tests as in Table 5, but using $NMLPR$ during the period from April to July in 2007 when there was no margin trading. Specifically, $NMLPR$ is construct in a similar fashion as $MLPR$ but using the holdings of the largest 300,000 investors at another leading brokerage firm in China. To corroborate our results in Table 5, we split the whole sample into two subsamples, with April to May 29th, 2007 representing the boom period, and May 30th, to July 31st representing the bust period.

– Insert Table 11 about here –

The results are presented in Table 11. In Column 1, we find that $NMLPR$ significantly and positively predicts the next-day return. And the coefficient (0.011) is similar to the coefficient in Table 5 (0.009). This holds even after controlling for the stock's own leverage and its own lagged returns and additional stock characteristics. Column (2) to (3) examine the predictive power of $NMLPR$ during the boom and bust periods. In sharp contrast to the results using $MLPR$ in Table 5, Column 2 and 3 demonstrate that the return predictive power of $NMLPR$ concentrates in the boom period in 2017. This pattern is more consistent with the results using $NMLPR$ in Table 5. In both bust periods, without the leverage constraints, Chinese investors tend to hold stock that have encounter losses, consistent with the disposition effect. Results in Tables 5 and 11 therefore highlight the unique role played by the leverage constraint in exacerbating the stock market collapse.

5 Conclusion

Investors can lever up their positions by borrowing against the securities they hold. This practice subjects margin investors to the impact of borrowing constraints and funding conditions. A number of recent studies theoretically examine the interplay between funding conditions and asset prices. Testing these predictions, however, has been empirically challenging, as we do not directly observe investors' leverage ratios and stock holdings. In this paper, we tackle this challenge by taking advantage of unique account-level data from China that track hundreds of thousands of margin investors' borrowing and trading activities at a daily frequency.

Our main analysis covers a three-month period of May to July 2015, during which the Chinese stock market experienced a rollercoaster ride: the Shanghai Stock Exchange (SSE) Composite Index climbed 15% from the beginning of May to its peak at 5166.35 on June 12th, before crashing 30% by the end of July. Major financial media around the world have linked this boom and bust in the Chinese market to the popularity of, and subsequent government crackdown on, margin trading in China.

We show that idiosyncratic shocks in the market can cause contagion across assets when these assets are linked through common holdings by margin investors. In particular, the returns of one security strongly and positively forecast the returns of other securities with which it shares a common margin investor base. Relatedly, stocks with common ownership by margin investors also exhibit excess return comovement, plausibly due to margin investors' indiscriminately scaling up or down their holdings in response to the loosening or tightening of their leverage constraints. This transmission mechanism is present only in market downturns, suggesting that idiosyncratic, adverse shocks to individual stocks can be amplified and transmitted to other securities through a de-leveraging channel. Further, using a network-based approach, we show that stocks that are linked to more other stocks through common holdings by margin investors (i.e., that are more central to the leverage network) tend to experience more selling pressure, have higher downside betas and lower future stock returns, in a down market.

Appendix: The construction of shadow-financed margin account data

First, we eliminate the agent accounts with invalid initial margin and maintenance margin ratios. Both ratios are at the discretion of the online trading platform and can vary across accounts. We require the initial maximum account leverage to be less than 100. There are some accounts with extremely high initial leverage ratios. They are usually introduced as part of a promotional effort to encourage investors with less assets to start trading. We also require the maintenance margin to be less than the initial margin.

Second, we require the first record in the margin account to be a cash flow from the mother account, before the account starts any trading activities. These cash flows usually occur right after the accounts were opened, and include the loans from the lenders together with the equity received from the borrowers. We then compare the size of initial cash flows and the initial debt information provided by the trading platform. We eliminate accounts that either never have any cash flows from the mother account, or whose first cash flows are from the agent accounts to the mother accounts. We also eliminate accounts whose initial cash flows deviate significantly from the initial debts reported by the online trading platform.

This dataset includes all variables as in the brokerage-account data, except for the end-of-day leverage ratio. Instead, the trading platform provides us with detailed information on the initial debt, as well as the subsequent cash flows between the mother-account and agent-accounts, with the agent-accounts directly linked to stock trading activities. For two thirds of the accounts, the platform provides detailed remarks for each cash flows (whether it reflects an issued loan or a loan repayment). With this information, we can accurately infer the end-of-day outstanding debt and the leverage ratio. For the remaining accounts, we assume that cash flows to (from) the mother account exceeding 20% of the current margin debt in the agent account reflects a payment of existing debt (additional borrowing). For these accounts, their end-of-day leverages are therefore measured with some errors.[12]

[12]We have tried other cutoffs, e.g., 15% 5%; the results are virtually unchanged.

Since margin investors on this online trading platform usually link their accounts to non-margin brokerage accounts, it is possible that there are overlaps between our broker non-margin accounts and our trading-platform agent-accounts. With the help of the data provider, we find there are about 200 overlapping accounts. We carefully eliminate them from the shadow financed account data to avoid double counting.

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Table 1: Summary Statistics

This table reports summary statistics of our sample, which spans the period of May 1st to July 31st, 2015. Panel A reports statistics of all accounts (both margin and non-margin) at a major brokerage in China, as well as the summary statistics of all trading accounts on a shadow-financed lending platform (i.e., shadow-financed margin accounts). We report in this panel the total number of the brokerage and shadow-financed margin accounts （# of Accounts), as well as the aggregate amount of debt financing (*$DEBT*) and holdings value (*$HOLDINGS*) across all accounts at the end of each day. Panel B reports information at the account level. In particular, we report in this panel each account' end-of-day holdings both in shares (*#HOLDINGS*) and in Yuan value (*$HOLDINGS*), as well as daily trading volume in terms of both the number of shares (*#TRADING*) and Yuan value(*$TRADING*), the number of orders submitted (*# SUBMISSIONS*), some of which are cancelled or not-filled, as well as the end-of-day leverage ratio (*LEVERAGE*). Panel C describes some key characteristic of the stocks held by these investors, which include: the market capitalization (*MCAP*), book-to-market ratio (*B/M*), cumulative return over the previous 120 trading days(*MOMENTUM*), share turnover defined as average daily trading volume divided by the number of outstanding tradable shares during the previous 120 days (*TURNOVER*), and idiosyncratic return volatility defined as the standard deviation of the residual of return after controlling for the Fama-French three factor and the Carhart momentum factor model (constructed using Chinese data)in the previous 120 trading days *(IDVOL*). For all these stock characteristics variables, we calculate weighted average measures, using each investor s holding as the weight. In all the measures, # denotes the number of shares or accounts, while $ denotes the RMB (Yuan) amount.

	Broker-Financed Margin Accounts		Large Broker Non-Margin Accounts		Shadow-Financed Margin Accounts	
Panel A: Full Sample Summary						
	Mean	Median	Mean	Median	Mean	Median
# of Accounts	177,571	177,571	400,000	400,000	155,731	155,731
$DEBT ($10^9$)	99.41	105.99	0	0	39.4	39.0
$HOLDINGS ($10^9$)	354.96	363.29	260.29	239.04	62.4	58.3
Panel B: Accounts Characteristics						
#HOLDINGS (10^3)	362.18	62.80	527.01	21.10	69.82	9.10
$HOLDINGS ($10^4$)	701.42	121.25	588.17	31.48	94.94	7.74
#TRADING (10^3)	126.39	14.90	27.12	5.50	26.12	4.80
$TRADING ($10^4$)	208.14	27.30	45.48	9.91	45.20	8.60
#SUBMISSIONS	15.18	6.00	8.57	4.00	6.70	4.00
LEVERAGE	1.60	1.53	1	1	10.35	4.55
Panel C: Stock Characteristics						
$MCAP ($10^9$)	47.25	46.32	47.25	46.32	47.25	46.32
B/M	0.76	0.41	0.77	0.47	0.58	0.34
MOMENTUM	0.34	0.32	0.38	0.34	0.55	0.50
TURNOVER	0.04	0.04	0.05	0.05	0.06	0.05
IDVOL	0.03	0.03	0.03	0.03	0.03	0.03

Table 2: Determinants of Leverage Ratios

This table examines determinants of individual account s leverage ratio, as well as of the individual stock's leverage ratio. Panel A examines account-level leverage ratio. The dependent variable in each column is leverage ratio for each account, *LEVERAGE*. The independent variables in each column include the number of different stocks in each investor's portfolio (*#STOCKS*), each investor's total wealth which include cash holdings and stock holdings measured in Yuan (*ACCOUNT_ VALUE*),and the days since the account was opened(*ACCOUNT_ AGE*). We run regressions separately for the sample of brokerage margin accounts and the sample of shadow margin accounts. Panel B examines stock-level leverage ratios. The dependent variable in each column is, *LEVERAGE*, the weighted average leverage ratio of all margin accounts that hold stock i in day $t+1$. Other controls include stock i's return in day t (*DRET*), its cumulative stock return in the previous 120 trading days (*MOMENTUM*), share turnover defined as average daily trading volume divided by the number of outstanding tradable shares during the previous 120 days (*TURNOVER*), and idiosyncratic return volatility defined as the standard deviation of the residual of return after controlling for the Fama-French three factor and the Carhart momentum factor model (constructed using Chinese data)in the previous 120 trading days *(IDVOL*), and market capitalization at the end of previous month (*MCAP*).Both Panel A and Panel B run panel regressions, withaccount fixed effects and date fixed effects included. Standard errors are double clustered by account and date. T-statistics are reported below the coefficients. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Dependent Variable = Account-level Leverage Ratio				
	Brokerage Margin Accounts		Shadow Margin Accounts	
	(1)	(2)	(3)	(4)
#STOCKS	0.019***	0.019***	-0.070***	-0.070***
	(16.19)	(16.08)	(-7.32)	(-7.32)
ACCOUNT VALUE	0.141***	0.141***	-0.407***	-0.407***
	(40.89)	(40.73)	(-2.62)	(-2.62)
ACCOUNT AGE		0.002		-0.029
		(0.29)		(-0.19)
Adj. R^2	0.65	0.63	0.53	0.42
No. Obs.(*1000)	4046	4046	2482	2482

Panel B: Dependent Variable = Stock-level Leverage Ratio						
	(1)	(2)	(3)	(4)	(5)	(6)
DRET	-3.521***					-1.983***
	(-5.48)					(-3.59)
MOMENTUM		0.084*				-0.082**
		(1.85)				(-1.97)
TURNOVER			18.00***			10.235*
			(3.17)			(1.92)
IDVOL				52.120***		44.916***
				(8.55)		(6.16)
MCAP					1.136***	0.610***
					(6.33)	(3.31)
Adj. R^2	0.26	0.29	0.29	0.29	0.29	0.27
No. Obs.	176899	176899	176899	176899	176899	176899

Table 3:Margin Investors' Trading Activity

This table reports regressions of margin investors' trading activity on lagged portfolio returns. The dependent variable inboth panels is the daily net trading of each margin account, defined as the total amount of buys minus total amount of sells divided by the lagged account value. The main independent variables are the daily portfolio returns in the previous five days. Panel Areports the baseline regression results. Panel B further includes the lagged account leverage ratio, as well as the interaction between lagged portfolio returns and account leverage, in the regression. We also divide lagged portfolio returns into positive vs. negative realizations. Columns 1 and 2 correspond to the sample of broker-financed margin accounts, Columns 3 and 4 correspond to the sample of shadow-financed margin accounts, while Columns 5 and 6 combine the two samples. Stock and date fixed effects are included in all columns. T-statistics, reported below the coefficients, are based on standard errors clustered by stock and date. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Account Trading in Response to Lagged Portfolio Returns

	Brokerage-Financed Margin Accounts		Shadow-Financed Margin Accounts		All Margin Accounts		Non-Margin Accounts	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Account_Return (t-1)	-0.146	-0.142	0.081	0.088	-0.044	-0.048	-0.108***	-0.121***
	(-1.52)	(-1.34)	(0.90)	(0.89)	(-0.44)	(-0.43)	(-3.00)	(-3.03)
Account_Return (t-2)		-0.063		-0.037		-0.051		0.032
		(-0.90)		(-0.58)		(-0.69)		(1.14)
Account_Return (t-3)		-0.074*		-0.078*		-0.070		-0.014
		(-1.68)		(-1.90)		(-1.43)		(-0.47)
Account_Return (t-4)		-0.023		-0.016		-0.017		0.035
		(-0.72)		(-0.50)		(-1.31)		(1.21)
Account_Return (t-5)		0.018		0.030		0.025		0.056*
		(0.55)		(0.47)		(0.66)		(1.93)
Adj-R^2	0.28	0.29	0.17	0.16	0.22	0.22	0.05	0.05
No. Obs. (*1000)	3201	3201	2604	2191	5805	5106	17,897	16,412

Panel B:Interacting Portfolio Returns with Leverage Ratio						
	Brokerage-Financed Margin Accounts		Shadow-Financed Margin Accounts		All Margin Accounts	
	(1)	(2)	(3)	(4)	(5)	(6)
Account_ Return (t-1)	-0.206**		-0.363***		-0.422***	
	(-2.12)		(-5.85)		(3.13)	
*Account_ Return(t-1) *Leverage*	0.037**		0.091***		0.129***	
	(2.64)		(7.00)		(5.86)	
Positive Account_ Return (t-1)		0.229		-0.211**		0..304
		(1.47)		(-2.37)		(1.60)
*Positive Account_ Return (t-1) * Leverage*		-0.036		0.033		-0.054**
		(-0.86)		(1.38)		(-2.51)
Negative Account_ Return(t-1)		-0.671***		-0.454***		-1.094***
		(-4.30)		(-3.60)		(-6.75)
*Negative Account_ Return (t-1) * Leverage*		0.104***		0.144***		0.289***
		(3.47)		(6.26)		(8.25)
Leverage	0.004***	0.006***	0.002**	0.004***	-0.001	0.004***
	(4.12)	(3.28)	(2.11)	(4.16)	(1.08)	(3.97)
Adj-R^2	0.28	0.29	0.17	0.17	0.22	0.23
No. Obs.(*1000)	3201	3201	2603	2191	5804	5106

Table 4:Characteristics of Stocks Traded by Margin Investors

This table reports three-dimensional panel regressions,where the dependent variable is the net trading in a stock by a margin account on a given day--defined as the number of shares bought minus that of shares sold divided by lagged holdings. The independent variables include a triple interaction term of lagged account return * leverage ratio*stock characteristics, as well as all the double interaction terms and the underlying variables themselves. The list of stock characteristics includesthe stock returns in the previous day (*DRET*), its cumulative stock return in the previous 120 trading days (*MOMENTUM*), market capitalization (MCAP), book-to-market ratio (BM), share turnover, defined as the average daily trading volume divided by the number of tradable shares,in the previous 120 days (*TURNOVER*), idiosyncratic return volatility, defined as the standard deviation of the residual return after controlling for the Fama-French three factors and the Carhart momentum factor (all constructed using Chinese data)in the previous 120 trading days *(IDVOL*), and the portfolio weight of the stock in question (*WGHT*). Column (1) uses the brokerage margin account sample. Column (2) uses the shadow margin account sample. Column (3) combine brokerage and shadow margin accounts. Stock*date fixed effects are included in all columns. T-statistics, reported below the coefficients, are based on standard errors clustered by stock and date. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable = Net Buy in a Stock by a Margin Account			
	(1)	(2)	(3)
	Broker-Financed Accounts	Shadow Accounts	All Margin Accounts
Account Return	-1.063**	1.344**	-1.156**
	(-2.27)	(2.01)	(-2.32)
Leverage	-0.021	-0.046***	-0.051***
	(-1.03)	(-7.67)	(-7.28)
Weight	0.007	-0.092***	-0.019***
	(1.02)	(-15.33)	(-4.75)
*Account Return * LEVERAGE*	0.745**	-0.384***	0.127
	(2.27)	(-2.84)	(0.847)
*Account Return * MOMENTUM*	0.109**	-0.103	-0.117*
	(2.53)	(-1.45)	(-1.95)
*Account Return * MCAP*	0.044**	--0.107***	0.019
	(2.10)	(3.69)	(0.79)
*Account Return * BM*	0.014	0.023	0.053
	(0.40)	(0.50)	(1.47)
*Account Return * TURNVOER*	-0.511	-2.776**	-1.756**
	(-0.62)	(-2.13)	(-2.56)
*Account Return * IDVOL*	-15.275**	15.785	0.803
	(-2.26)	(1.42)	(0.90)
*Account Return * WGHT*	0.345***	0.452***	0.512
	(3.56)	(3.86)	(5.75)
*LEVERAGE * MOMENTUM*	-0.020***	-0.004	-0.000
	(-10.00)	(-4.00)	(0.0001_
*LEVERAGE * MCAP*	-0.000	0.001***	-0.001***
	(-0.01)	(2.88)	(-3.10)
*LEVERAGE * BM*	0.002	0.002**	0.000
	(1.00)	(2.00)	(1.00)

*LEVERAGE * TURNOVER*	-0.039 (1.08)	0.009 (0.75)	0.022** (2.20)
*LEVERAGE * IDVOL*	1.452*** (6.94)	0.376*** (4.42)	-0.111 (-1.17)
*LEVERAGE * WGHT*	-0.026*** (-8.67)	-0.006*** (-5.88)	-0.019*** (-9.02)
*Account Return * LEVERAGE *MOMENTUM*	-0.136*** (-4.68)	0.008 (0.57)	-0.005 (0.28)
*Account Return * LEVERAGE *MCAP*	-0.032** (2.13)	0.025*** (4.17)	0.004 (0.5)
*Account Return * LEVERAGE *BM*	0.007 (0.32)	-0.006 (-0.60)	-0.017 (-1.42)
*Account Return * LEVERAGE *TURNOVER*	-0.223 (-0.43)	0.699*** (2.68)	0.688*** (3.09)
*Account Return * LEVERAGE *IDVOL*	7.724** (2.21)	-2.812 (-1.21)	0.173 (0.06)
*Account Return * LEVERAGE * WGHT*	-0.056 (-1.33)	-0.044 (-1.57)	-0.082*** (-2.83)
Adj. R^2	0.02	0.04	0.04
No. Obs.（*1000)	9473	5615	15090

Table 5: Forecasting Stock Returns

This table reports results of return forecasting regressions. The dependent variable in all columns are stock *i*'s return in day *t*+1. The main independent variable of interest is *MLPR*, the margin-account linked portfolio return in day *t*; it is calculated as the weighted average return in day *t* of all stocks that are connected to stock *i* through common ownership of both brokerage-financed and shadow-financed margin accounts, where the weights are proportional to the leverage of each account that hold the stock. The variable *NMLPR* is similarly defined as *MLPR*, but using non-margin brokerage accounts instead. Other controls include stock *i*'s leverage ratio in day *t*, defined as the weighted average leverage ratio of all margin accounts that hold stock *i* (*LEVERAGE*), stock *i*'s return in day *t* (*DRET*), its cumulative stock return in the previous 120 trading days (*MOMENTUM*), share turnover defined as average daily trading volume divided by the number of outstanding tradable shares during the previous 120 days (*TURNOVER*), and idiosyncratic return volatility defined as the standard deviation of the residual of return after controlling for the Fama-French three factor and the Carhart momentum factor model (constructed using Chinese data)in the previous 120 trading days *(IDVOL*), and market capitalization at the end of previous month (*MCAP*). In columns 3, 4, 5 and 6, we split the sample into two halves based on the fraction of stocks in the market hitting the -10% threshold or under trading halts in each day: columns 5 and 6corresponds to the sub-period where the fraction is above the sample median (BUST period), and column 3 and 4 corresponds to the sub-period where the fraction is below the sample median (BOOM period). We conduct Fama-Macbeth regressions in all columns. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable = Stock Returns on day *t*+1						
	Whole Sample		Boom		Bust	
	(1)	(2)	(3)	(4)	(5)	(6)
MLPR	0.009**	0.009**	0.001	0.001	0.018***	0.018***
	(2.45)	(2.45)	(0.19)	(0.13)	(3.09)	(3.08)
NMLPR		0.0003		0.001		-0.0001
		(1.22)		(1.45)		(-0.01)
LEVERAGE	-0.001**	-0.001**	-0.001*	-0.001*	-0.0004*	-0.0004*
	(-2.32)	(-2.33)	(-1.74)	(-1.88)	(-1.80)	(-1.83)
DRET	0.277***	0.280***	0.198***	0.197***	0.356***	0.356***
	(8.83)	(8.81)	(8.53)	(8.83)	(6.45)	(6.44)
MOMENTUM	-0.001	-0.001	0.001*	0.001*	-0.002***	-0.002***
	(-1.02)	(-1.01)	(1.76)	(1.76)	(-2.69)	(-2.69)
TURNOVER	0.056***	0.056***	0.041**	0.041**	0.072**	0.072**
	(3.08)	(3.09)	(2.07)	(2.09)	(2.36)	(2.36)
IDVOL	-0.332***	-0.321***	-0.622***	-0.620***	-0.023	-0.023
	(-3.82)	(-3.82)	(-5.37)	(-5.39)	(-0.23)	(-0.23)
MCAP	-0.002*	-0.002*	-0.004***	-0.004***	0.001	0.001
	(-1.94)	(-1.94)	(-4.76)	(-4.77)	(0.68)	(0.68)
Adj. R^2	0.18	0.18	0.14	0.15	0.22	0.22
No. Obs.	173829	173829	86038	86038	87791	87791

Table 6: Forecasting StockReturnsin the Following Week

This table reports results of return forecasting regressions. The dependent variablesare stock i's returns in day t+1 (column 1), day t+2 (column 2), day t+3 (column 3), day t+4 (column 4), and day t+5 (column 5). The main independent variable of interest is *MLPR*, the margin-account linked portfolio return in day t; it is calculated as the weighted average return in day t of all stocks that are connected to stock i through common ownership of both brokerage-financed and shadow-financed margin accounts, where the weights are proportional to the leverage of each account that hold the stock. Other controls include stock i's leverage ratio in day t, defined as the weighted average leverage ratio of all margin accounts that hold stock i (*LEVERAGE*), stock i's return in day t (*DRET*), its cumulative stock return in the previous 120 trading days (*MOMENTUM*), share turnover defined as average daily trading volume divided by the number of outstanding tradable shares during the previous 120 days (*TURNOVER*), and idiosyncratic return volatility defined as the standard deviation of the residual of return after controlling for the Fama-French three factor and the Carhart momentum factor model (constructed using Chinese data)in the previous 120 trading days *(IDVOL)*, and market capitalization at the end of previous month (*MCAP*). In columns 3, 4, 5 and 6, we split the sample into two halves based on the fraction of stocks in the market hitting the -10% threshold or under trading halts in each day: columns 5 and 6corresponds to the sub-period where the fraction is above the sample median (BUST period), and column 3 and 4 corresponds to the sub-period where the fraction is below the sample median (BOOM period). We conduct Fama-Macbeth regressions in all columns. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable = Daily Stock Returns in *t+1* to *t+5*					
	(1)	(2)	(3)	(4)	(5)
MLPR	0.009**	0.002	-0.010**	-0.002	-0.004
	(2.45)	(0.32)	(-2.55)	(-0.55)	(-0.99)
LEVERAGE	-0.001**	-0.001**	-0.001	-0.001*	-0.001**
	(-2.32)	(-2.00)	(-1.23)	(-1.71)	(-2.18)
DRET	0.277***	0.077***	0.056**	0.043*	0.011
	(8.83)	(3.19)	(2.49)	(1.88)	(0.55)
MOMENTUM	-0.001	-0.001	0.002*	-0.001*	-0.001*
	(-1.02)	(-1.59)	(1.90)	(-1.87)	(-1.67)
TURNOVER	0.056***	0.060*	0.063***	0.064***	0.060***
	(3.08)	(2.90)	(2.91)	(3.05)	(2.87)
IDVOL	-0.332***	-0.350***	-0.273***	-0.282***	-0.275***
	(-3.82)	(-3.96)	(-3.40)	(-3.41)	(-3.48)
MCAP	-0.002*	-0.002**	-0.003*	-0.001*	0.001
	(-1.94)	(-2.30)	(-1.87)	(-1.69)	(1.45)
Adj. R^2	0.18	0.13	0.12	0.12	0.11
No. Obs.	173829	173829	173829	173829	173829

Table 7: Pairwise Return Comovement

This table reports forecasting regressions of pairwise stock return comovement. The dependent variable in each column is the product of daily excess return between a pair of stocks (*i* and *j*) in day t+1. The main independent variable of interest, *MARHOLD*, is a measure of common ownership of stocks *i* and *j* by margin accounts in day t. Specifically, it is defined as the sum of each investor's leverage ratio multiplied by his holdings in the two stocks, divided by the total market capitalizations of the two stocks. Other control variables include the number of analysts that are covering both firms (*COMANALY*); the absolute difference in percentile rankings based on firm size (*SIZEDIFF*), book-to-market ratio (*BMDIFF*), and cumulative past returns for the previous 120 trading days (*MOMDIFF*). *SAMEIND* is a dummy that equals one if the two firms are in the same industry, and zero otherwise. We also include in the regression, *SIZE1* and *SIZE2*, the size percentile rankings of the two firms, as well as the interaction between the two. In column 1, we combine the brokerage-financed and shadow-financed margin accounts and conduct analysis for the entire three month period (Whole Sample). In columns 2 and 3, we split the sample into two halves, now based on the fraction of stocks in the market either hitting the -10% threshold or under the trading halts in each day: columns 3 corresponds to the sub-period where the fraction is above the sample median (BUST), and column 2 corresponds to the sub-period where the fraction is below the sample median (BOOM). We conduct Fama-Macbeth regressions in all columns. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable = Excess Return Comovement in t+1			
	(1)	(2)	(3)
	Whole Sample	BOOM	BUST
MARHOLD	0.081***	0.050***	0.112***
	(4.89)	(4.40)	(3.80)
BMDIFF	0.0001***	0.001***	0.001*
	(3.23)	(3.95)	(1.81)
COMANALY	0.0003***	0.0004***	0.0002
	(3.83)	(5.20)	(1.60)
MOMDIFF	-0.0002***	0.0004**	-0.007
	(-0.31)	(2.17)	(-0.62)
SAMEIND	0.014***	0.012***	0.017***
	(4.96)	(4.62)	(3.25)
SIZE1	0.024***	0.009**	0.038***
	(3.40)	(2.29)	(3.02)
*SIZE1*SIZE2*	-0.004***	-0.002***	-0.007***
	(-3.39)	(-2.71)	(3.01)
SIZE2	0.023***	0.009**	0.038***
	(3.39)	(2.29)	(3.02)
SIZEDIFF	0.015***	0.006***	0.024***
	(3.47)	(3.47)	(3.04)
Adj. R^2	0.02	0.01	0.03
No. Obs. (*1000)	31850	16191	15659

Table 8: Centrality and Future Stock Returns

This table reports results of return forecasting regressions. The dependent variable is stock *i*'s return in day *t*+1. The main independent variable of interest is *CENT*, the centrality measure of stock *i* in day *t*; it is defined as the eigenvector centrality of the leverage network, where each link between a stock pair reflects the common ownership of the stock pair by all margin accounts. For the ease of interpretation, we standardize the centrality measure by subtracting the cross-sectional mean and dividing by the cross-sectional standard deviation in each day. We also include an interaction term that is product of market return at day t+1 and Percentile ranking centrality measure, which is the percentile distribution of centrality measure.Other controls include stock *i*'s leverage ratio in day *t*, defined as the weighted average leverage ratio of all margin accounts that hold stock *i* (*LEVERAGE*), stock *i*'s return in day *t* (*DRET*), its cumulative stock return in the previous 120 trading days (*MOMENTUM*), share turnover defined as average daily trading volume divided by the number of outstanding tradable shares during the previous 120 days (*TURNOVER*), and idiosyncratic return volatility defined as the standard deviation of the residual of return after controlling for the Fama-French three factor and the Cohart momentum factor model (constructed using Chinese data)in the previous 120 trading days *(IDVOL)*, and market capitalization at the end of previous month (*MCAP*). We split the sample into two halves based on the fraction of stocks in the market hitting the -10% threshold or under trading halts in each day: columns 4to 6 corresponds to the sub-period where the fraction is above the sample median (BUST period), and column 1 to 3 corresponds to the sub-period where the fraction is below the sample median (BOOM period).We conduct Fama-Macbeth regressions in columns (1), (2), (4), and (5). We conduct pooled OLS regression in column (3) and (6), with date fixed effect included. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable = Future Stock Returns						
		Boom			Bust	
	(1)	(2)	(3)	(4)	(5)	(6)
CENT	0.0002	-0.00001	-0.0001	-0.001**	-0.001**	-0.0002
	(1.21)	(-0.04)	(-0.45)	(-2.38)	(-2.20)	(-0.64)
*MRET * PCENT*			-0.020			0.300***
			(-0.16)			(3.99)
DRET		0.199***			0.369***	
		(8.50)			(6.51)	
LEVERAGE		-0.001			-0.001	
		(-1.85)			(-2.08)	
IDVOL		-0.619***			-0.005	
		(-5.35)			(-0.06)	
MCAP		-0.004***			0.001	
		(-4.81)			(0.57)	
MOMENTUM		0.001**			-0.002***	
		(1.78)			(-2.66)	
TURNOVER		0.039**			0.068**	
		(1.98)			(2.27)	
Date FE	No	No	Yes	No	No	Yes
Adj. R^2	0.001	0.15	0.22	0.001	0.21	0.63
No. Obs.	86038	86038	86038	87791	87791	87791

Table 9: Determinants of Leverage Network Centrality

This table examines determinants of individual stocks' importance in the leverage network. The dependent variable in each column is, *PCENT*, the percentile ranking centrality measure of stock i in day t+1. Stock centrality is defined as the eigenvector centrality of the leverage network, where each link between a stock pair reflects the common ownership of the stock pair by all margin accounts. We then calculate the percentile distribution of the centrality. For the ease of interpretation, we standardize the centrality measure by subtracting the cross-sectional mean and dividing by the cross-sectional standard deviation in each day. Other controls include stock i's leverage ratio in day t, defined as the weighted average leverage ratio of all margin accounts that hold stock i (*LEVERAGE*), stock i's return in day t (*DRET*), its cumulative stock return in the previous 120 trading days (*MOMENTUM*), its average daily turnover ratios in the previous 120 trading days (*TURNOVER*), idiosyncratic return volatility after controlling for the Fama-French three factor model (constructed using Chinese data) in the previous 120 trading days (*IDVOL*), market capitalization at end of day t (*MCAP*).We conduct pooled OLS regressions in all columns, adding stock fixed effect and date fixed effect. T-statistics, reported below the coefficients, are based on standard errors clustered by stock and date. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable = Stock Centrality in the Leverage Network							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LPCENT	0.007***							
	(42.73)							
LEVERAGE		0.01***						0.010***
		(10.40)						(10.26)
DRET			-0.24***					-0.14***
			(-9.35)					(-5.79)
MOMENTUM				0.008***				-0.004
				(2.55)				(-1.43)
TURNOVER					0.84**			0.230
					(2.46)			(0.62)
IDVOL						2.82***		1.788***
						(11.82)		(6.35)
MCAP							0.010***	0.004**
							(7.43)	(2.69)
Adj. R^2	0.82	0.62	0.60	0.60	0.60	0.61	0.61	0.61
No. Obs.	173829	173829	173829	173829	173829	173829	173829	173829

Table 10: Chinese Government Rescue Effort in 2015

This table compares the characteristics of the set of stocks that the Chinese government purchased on July 6th, 2015, versus those of the stocks that the government did not purchase on that day. We include in this analysis stocks traded on the Shanghai Stock Exchange. Out of the 917 stocks that were traded on July 6^{th}, 2015, a set of 376 stocks were bought by the government. We look at three stock characteristics: a) whether the stock is included in the HS300 index, b) the stock's market capitalization (in log terms), and c) the stock's leverage-network eigenvector centrality. In the last column, we conduct a T-test of the difference in mean between the two subsamples.

	Purchased by the Government	Not purchased by the Government	T-statistic of the difference
% in HS300	43%	2%	15.62
Mean of *Log MCAP*	24.05	22.46	25.26
Mean of *CENT*	0.17	0.25	-0.97

Table 11: Forecasting Stock Returns in 2007

This table reports results of return forecasting regressions around the market crash in 2007. The dependent variable in all columns are stock *i*'s return in day t+1. The main independent variable of interest is *NMLPR*, which is similarly defined as *MLPR*, but using 300, 000 brokerage accounts in 2007 instead. Other controls include stock *i*'s return in day t (*DRET*), its cumulative stock return in the previous 120 trading days (*MOMENTUM*), share turnover defined as average daily trading volume divided by the number of outstanding tradable shares during the previous 120 days (*TURNOVER*), and idiosyncratic return volatility defined as the standard deviation of the residual of return after controlling for the Fama-French three factor and the Carhart momentum factor model (constructed using Chinese data)in the previous 120 trading days *(IDVOL*), and market capitalization at the end of previous month (*MCAP*). Column 1 includes the whole sample period from April to July, 2007. In columns 2 and 3, we split the sample into two halves: columns 3 corresponds to the sub-period from May 30th to July 31st (BUST period), and column 2 corresponds to the sub-period from April 1st to May 29th (BOOM period). We conduct Fama-Macbeth regressions in all columns. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable = Stock Returns on day t+1			
	Whole Sample	Boom	Bust
NMLPR	0.010***	0.011***	0.007
	(4.58)	(4.65)	(1.44)
DRET	0.116***	0.110***	0.131***
	(6.99)	(6.25)	(3.33)
MOMENTUM	0.0001	0.001***	-0.003***
	(0.15)	(3.70)	(-3.15)
TURNOVER	-0.071***	-0.052**	-0.122**
	(-2.75)	(-1.87)	(-2.09)
IDVOL	-0.009	-0.013**	0.004
	(-1.65)	(-2.01)	(0.53)
MCAP	-0.0001	-0.001	0.001
	(-0.13)	(-1.51)	(1.13)
Adj. R^2	0.07	0.05	0.11
No. Obs.	123412	55505	67907

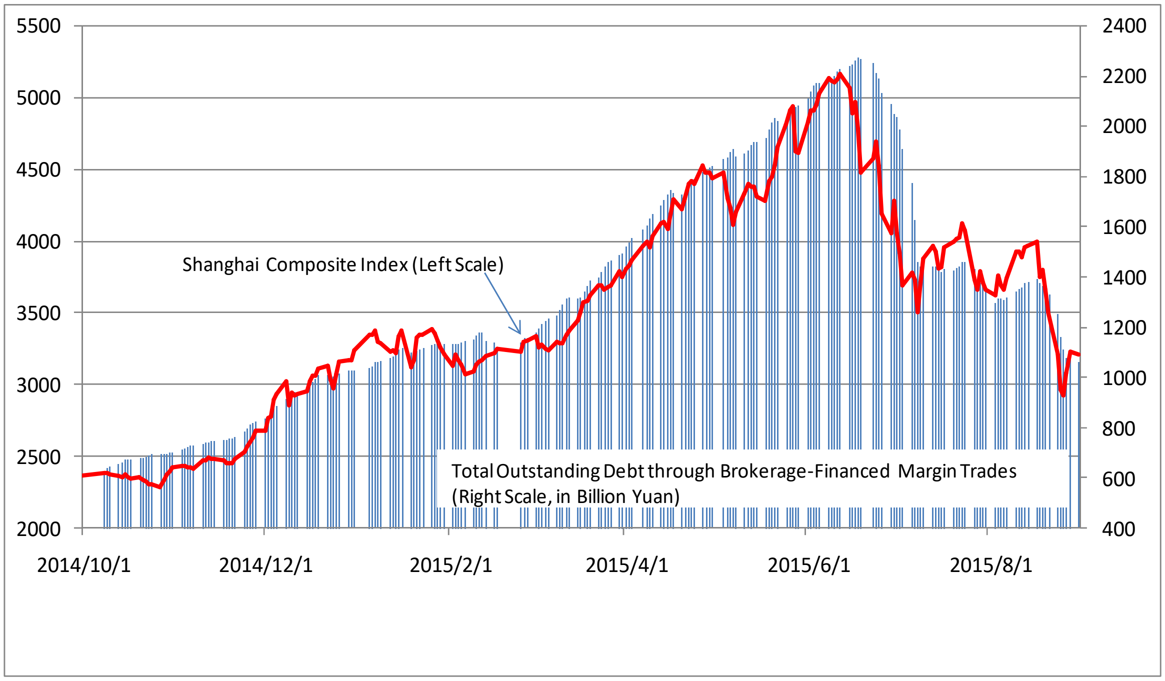

Figure 1. This figure shows the Shanghai Stock Exchange (SSE) Composite Index (the red line), as well as the aggregate brokerage-financed margin debt (blue bars, in billions), at the end of each day for the period October 2014 to August 2015.

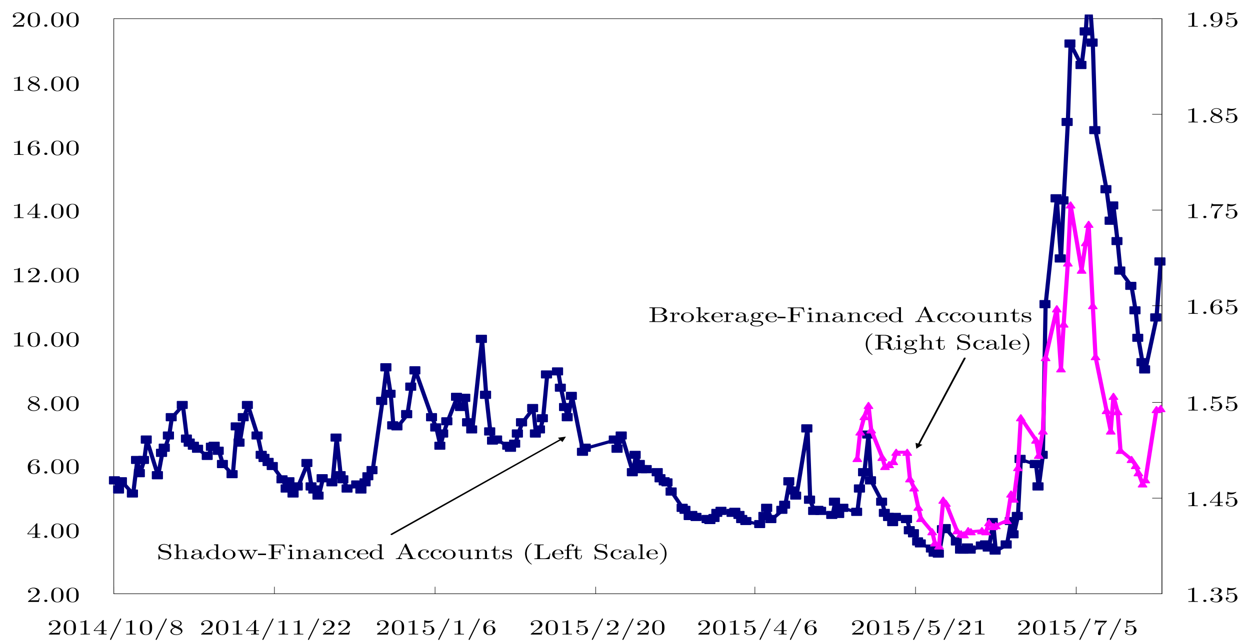

Figure 2. This figure shows the average leverage ratio of brokerage-financed margin accounts (red line) and that of shadow-financed margin account at the end of each day for the period May to July 2015 and October 2014 to August 2015, respectively. Account-level leverage ratio is defined as the end-of-the-day portfolio value divided by the amount of capital contributed by the investor himself. The average leverage ratio across accounts is weighted by each account's end-of-the-day capital value (in other words, it is equal to the aggregate portfolio value divided by aggregate capital value contributed by investors themselves).