Leverage Network and Market Contagion*

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[PRELIMINARY]

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Abstract

Using daily account-level data that track hundreds of thousands of margin-investors' leverage ratios, trading activity, and portfolio holdings, we examine the effect of margin-induced trading on stock prices during the recent market turmoil in China. We start by providing evidence that individual margin investors have a strong tendency to scale down their holdings after experiencing negative portfolio returns. Aggregating this result 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 aggregate order imbalance and future returns; this transmission effect is particularly strong in market downturns. Our results thus suggest that idiosyncratic, adverse shocks to individual stocks can be amplified and transmitted to other securities through a de-leveraging channel. Following a similar logic, we find that the well-known, ubiquitous asymmetry in pairwise return comovement between market booms and busts can be largely attributed to deleveraging-induced trading in the bust period. Finally, using a network-based approach, we show that stocks with more as well as stronger connections to other stocks through common margin investor ownership experience larger selling pressure and crash risk in market downturns.

Keywords: margin trading, leverage, contagion, crash risk

JEL Classification: G11, G23

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 functioning of 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 by scaling 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, as well as to regulators and investors, testing the asset pricing implications of margin trading, however, 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.

Our datasets cover an extraordinary period – from January to July 2015 – during which the Chinese stock market experienced a rollercoaster ride: the Shanghai Stock 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.[1] Indeed, as evident in Figure 1, the aggregate amount of margin borrowing through brokers 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 initial stock market boom and the subsequent de-leverage exacerbated the bust.

Our data, obtained from a major broker in China, as well as an online trading platform designed to facilitate peer-to-peer margin lending, contain detailed records of individual accounts' leverage ratios and their holdings and trading activity at a daily frequency.

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[1] 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.

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 peer-financed margin accounts is substantially higher than that of the broker-financed ones (7.0 vs. 1.6). 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) an existing holding if other stocks in the portfolio have done poorly (well), plausibly due to the tightening (loosening) of margin constraints. Our results are consistent with this prediction: order imbalance (defined as the RMB amount of buy orders minus that of sell orders, divided by lagged holding value) in a stock is significantly and positively related to lagged returns of other stocks in the same portfolio. This effect strongly increases in the leverage ratio of the margin account, and is present only when the average return of the other stocks in the portfolio is negative, consistent with deleveraging-induced trading being a possible driver of the result. Further, in a placebo test where we replace margin investors with non-margin accounts, we observe no clear relation between order imbalance and lagged portfolio returns.

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" (MALP)—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. An alternative way of thinking about MALP is that we construct an adjacency matrix A, where each cell (i, j) represents the common ownership in the stock pair (i, j) by all margin accounts (scaled by the total market capitalization of the two stocks). The return of MALP is then the product of matrix A and a vector of 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. Margin-account linked portfolio returns significantly and positively forecast the stock's future 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. This return predictive pattern is much stronger 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). This asymmetry between market booms and busts helps alleviate the concern that our return forecasting result is entirely due to omitted fundamental factors. The return pattern is again absent if we instead use non-margin accounts to calculate order imbalance or define the linked portfolio.

Our next test aims to tie the here-documented margin-induced contagion mechanism to the puzzling, ubiquitous finding that in nearly all markets, asset return comovement is higher in market downturns than in market booms. 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 3.1% (t-statistic = 6.61) increase in the pairwise correlation in order imbalances by all margin accounts, and a 4.2% (t-statistic = 6.08) increase in excess pairwise return correlations. Once again, these comovement patterns are much stronger in market downturns. For comparison, the average pairwise return correlation in the crash period in our sample is around 6% higher than that in the boom period.

Our final set of tests takes a network-based approach to shed more light on the direct and indirect links between stocks. In particular, we focus squarely on the leverage network (adjacency matrix A) 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 higher crash risk, than peripheral stocks. 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 0.9% increase (t-statistic = 4.51) in daily selling pressure by margin investors, and a 4.4% (t-statistic = 2.15) increase in crash risk (measured by left skewness) subsequently. We label these central stocks "systemically important'' as they likely play a central role in transmitting shocks, especially adverse shocks, through the leverage network. These results have potentially important implications for the Chinese government (and regulatory agencies), which shortly after the market meltdown, devoted hundreds of billions of RMB to trying to sustain the market.

Other studies also show that investors buy or sell at the same time, due to common ownership structure, might induce stock prices to fluctuate unrelated to fundamentals (e.g., Greenwood and Thesmar, 2011). These studies typically consider the common holding among non-margin investors such as mutual fund holders. Our paper differs from theirs in that we show a leverage (de-leverage) channel through which the common ownership might enlarge and spread the idiosyncratic shock from one stock to the other, after controlling for the common holding from non-margin holders. The leverage channel in our study is asymmetric, with the contagion effect dominant during the market downturns, with potential to cause systematic market price movement. We illustrate this argument with an example from China's recent market turmoil. In a companion paper, Bian et al (2017) also look at China's recent market crash. They focus more on the different roles played by the brokerage-financed or the shadow-financed (or peer-financed) margin systems in the market turmoil, whereas our study emphasize the effect of common holdings from all margin (both brokerage-financed and shadow-financed) holders. The findings from these two paper are complementary to each other.

The rest of the paper is organized as follows. Section 2 gives background information about the Chinese stock market and regulations on margin trading. Section 3 discusses our data and screening procedures. Section 4 presents our main empirical results, while Section 5 conducts robustness checks. Finally, Section 6 concludes.

2. Institutional Backgrounds of the Chinese Margin Trading System

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 US dollars, second only to the US market. Despite the size of the stock market, margin trading was not popular in China. In fact, margin financing was not legally allowed in the Chinese stock market until 2010, although it occurred informally on a small scale. The China Securities Regulatory Commission (CSRC) launched a pilot program for margin financing through brokerage firms in March 2010 and margin financing was officially authorized for a large set of securities in October 2011. To obtain margin financing from a registered brokerage firm, investors need to have a trading account with that brokerage for at least 18 months, with a total account value (cash and stock holdings combined) exceeding RMB500,000 (or about USD80,000).[2] The initial margin (= 1 - debt value/total holding value) is set at 50% and the maintenance margin is typically 23%. A list

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

of around 900 stocks is chosen by the CSRS as eligible for margin buying; the list is periodically reassessed and modified.

The aggregate broker-financed margin debt has grown exponentially since its introduction. Starting from mid-2014, it has closely tracked the performance of the Chinese stock market and peaked around RMB 2.26 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 models.

In part to circumvent the tight regulation on brokerage-financed leverage, peer-to-peer 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 percent of the total trust's value. The remaining 80 percent is then funded by borrowing from others, usually retail investors, in the form of wealth management products offering juicy yields – typically higher than the risk-free rate. As such, the umbrella trust structure can achieve a much higher leverage ratio than what is allowed by regulation; 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 required to obtain margin financing from brokerage firms.

The vast majority of the peer-to-peer margin lending (including that through umbrella trusts) takes place on a handful of peer-financed trading platforms with peer-financing capabilities.[3] Some of these peer-financed trading platforms allow further splits of a single

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

umbrella trust, increasing the effective leverage further still. Finally, peer-to-peer financed margin trading allows investors to take levered positions on any stocks, including those not on the marginable security list.

Since peer-to-peer based 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 debt in this shadow financial system is as big as the amount of leverage financed through the formal broker channel. For example, Huatai securities Inc., one of China's leading brokerage firms, estimates that the total margin debt in the market is around 7.2% of the market capitalization of the Chinese stock market, with half coming from the unregulated shadow financial system, and 19.6% of the market capitalization of the total free float (as a significant fraction of the shares of Chinese public firms are held by the Chinese Government).[4]

3. Data and Preliminary Analysis

Our paper takes advantages of two unique proprietary account-level datasets. The first dataset contains the complete equity holdings, cash balance, order submission, and trade execution records 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 accounts are eligible for margin trading. A unique feature of the data is that, for each margin account, we have its end-of-day debit ratio, defined as the account's total value (cash plus equity holding) divided by its outstanding debt. The CSRC mandates a minimum debit ratio of 1.3, translating to a maintenance margin of about 23% (= (1.3-1)/1.3).

To check the coverage and representativeness of our brokerage-account data, we aggregate the daily trading volume and corresponding RMB amount across all accounts in our

[4] Excessive leverage through the shadow financial system is often blamed for causing the dramatic stock market gyration in 2015. Indeed, in mid-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.

data. Our dataset, on a typical day, accounts for roughly 5% - 10% of the total trading reported by both the Shanghai and Shenzhen stock exchanges. Similarly, we find that the total amount of debt taken by all margin investors in our dataset accounts for around 10% of the aggregate brokerage-financed margin debt in the market. Moreover, the cross-sectional correlation in trading volume between our dataset and the entire market is over 90%. All of these suggest that our broker dataset is a representative sample of the market.

Our second dataset contains all the trading and holdings records of more than 250,000 agent accounts from a major peer-financed trading platform for the period from July 2014 to July 2015. These agent accounts are all connected to a few principal accounts maintained by the same trading platform. Unlike the brokerage data, the peer-financed platform maintains much looser regulatory rules on accounts holding and trading activities. Non-margin investors are eligible to trade in this platform as well. We thus apply a few filters to select the eligible margin accounts in our study.

First, we eliminate the agent accounts with invalid initial margin and maintenance margin information. The platform provides each agent account with the initial lending ratio of the borrower, defined as the maximum amount of loans the investor could borrow given the her margin deposit and the ratio of remaining asset / initial loans that will trigger the margin call. We require the initial maximum lend ratio to be less than 100. There are some accounts with extremely high initial lending ratios. They are usually used as bonus to investors with much lower lending ratios and typically carry with very little assets. On the other hand, we require the maintenance margin to be less than 1, i.e, investors will receive the margin calls before outstanding debt exceeds the current asset wealth. Agent accounts with margin information not with these ranges might be maintained by non-margin accounts.

Second, we require the first record in the margin accounts to be a cash flow from the principal account, before the account starts any trading activities. These cash flows happen usually right after the account was open, and include the loans from the lenders together with the deposited margins from the borrowers. We then compare the initial the size of initial cash flows and the initial debt information provided by the trading platform. We eliminate observations from accounts that either never have any cash flows from / the principal accounts, or the first cash flows are from the agent accounts to the principal accounts. We then further eliminate observations from accounts for which the size of initial cashflow deviate significantly from the initial debt reported by the online trading system.

This dataset includes all variables as in the brokerage-account data, except for the end-of-day debit ratio. Instead, the trading platform provides us with detailed information on the initial debt, as well as the subsequent cash flows between the principle-account and agent-accounts, with the agent-accounts directly linked to stock trading activities. (The lenders will control the principal account, while the borrowers have access to the agent accounts.) We can thus manually back out the end-of-day wealth and debt value for each agent-account. The database also provides details about the minimum wealth-debt ratio to trigger a margin call, which varies across accounts. To infer the daily outstanding debt, we turn to the cashflow between the agent and principal accounts and the remarks provided by the peer-financed trading platform. The platform provides with us detailed remarks for each cash flows for about two thirds of the accounts (whether the cash flow is an issued loan or loan repayment), with which we can safely infer daily outstanding debt level. For the remaining accounts, note that our peer-financed account data provide detailed information on daily cash inflows and outflows between the principal account and each agent account. These daily cash flows, combined with the initial margin debt when the account was first opened, allow us to keep track of the margin debt level in the account over time. We assume that cash flows to (from)the principal account exceeding 20% of the margin debt in the agent account reflects a payment of existing debt (additional borrowing).[5] We can thus back out daily outstanding debt for each margin account in the web-trading platform.

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

One thing noteworthy is that since margin investors in this electronic platform usually link their agent-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 accounts overlap. We carefully eliminate those accounts from the peer-financed peer-to-peer data.

Finally, our sample of peer-financed trading platform includes 155, 731 margin accounts. These accounts are with daily information of cash and stock holdings and outstanding debts, as well as information about each transaction generated from these accounts. We find, unlike the brokerage accounts, the margin accounts in the peer-financed trading platform tend to short lived, with average lifetime of 25 days, and these accounts almost never refinance.

In addition to the two proprietary account-level datasets, we also acquire intraday level-II data, as well as daily closing prices, trading volume, stock returns and other stock characteristics from WIND database. The level-II data includes details on each order submitted, withdrawn, and executed, and the price at which the order is executed in the Chinese stock market (similar to the Trade and Quote database in the US).

3.1. Sample Summary Statistics

Table I presents summary statistics of our sample. During the three-month period from May to July 2015, our brokerage-financed account data sample contains more than 5 million accounts, out of which around 180,000 are margin accounts. Our peer-financed account data contain over 160,000 margin accounts. We first compute the outstanding debt and wealth in terms of cash and equity holdings for each account at the daily frequency, and then sum these measures for the subsamples of the brokerage-financed margin accounts, brokerage non-margin accounts, and peer-financed margin accounts. The results indicate that for broker-financed margin accounts, around one third of the portfolio value is financed by margin borrowing, whereas that ratio for peer-financed margin accounts shoots up to over 50%.

3.2. Comparison of Margin and Non-Margin Accounts

In Panel B of Table I, we compare investors' holding and trading behavior across the three subsamples. Since the focus of our paper is margin trading, we do not include all 4.5 million non-margin accounts from our brokerage sample in our analysis. Instead, we randomly sample one million non-margin accounts to make our analysis more manageable. Among the three account types, margin accounts at the brokerage firm are the most active. On a typical day, each account trades 15,000 shares, submits 6 orders, and holds 63,000 shares, with a leverage ratio of about 1.5. Peer-financed margin accounts are on average smaller than the brokerage-financed ones, both in terms of holdings and trading, but are typically associated with much higher leverage ratios (4.1 vs. 1.5). Both types of margin accounts have higher portfolio value and exhibit more active trading behavior relative to non-margin investors.

We next examine the types of stocks that are held by margin vs. non-margin investors. As can be seen from Panel C of Table I, both types of investment accounts at the brokerage firm – broker-financed margin accounts and non-margin accounts – hold very similar stocks, along a number of dimensions. Interestingly, peer-financed margin accounts tend to hold smaller stocks with larger growth options and higher past returns, compared to investment accounts at the brokerage firm.

3.3. Leverage Ratio

Except for the variables analyzed above, an important variable that is critical to our story is account-level daily leverage ratio. Following prior literature (e.g., Ang et al., 2011), we define the leverage ratio for each trading account. as:

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

In other words, to back out the daily leverage ratio for each brokerage-financed margin account, we divide the debit ratio by itself minus one. For each peer-financed margin account, we compute its daily leverage ratio using the inferred daily account wealth and debt value. We measure the total wealth of each account by summing up its equity holdings and cash balance. The resulting leverage ratio varies substantially across 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. As such, peer-financed margin accounts typically have a much higher leverage ratio than brokerage-financed accounts. For instance, it is not uncommon to see leverage ratio in the peer-financed system exceeding ten. In contrast, the maintenance margin of 0.23 in the brokerage-financed margin account implies a maximum leverage ratio of 4.33 (= 1/0.23).

Panel B of Table I presents the summary statistics of account leverage ratios for brokerage margin and peer-financed margin accounts. We can see that the peer-financed margin accounts are on average with much higher leverage ratios compared to the brokerage margin accounts (4.1 vs. 1.5).

Time Series of Leverage Ratios

Figure 2 plots the weighted average leverage ratios of both brokerage-financed margin accounts and peer-financed margin accounts. We use each account's portfolio value as the weight in computing the average leverage ratio. These time-series plots can give us some initial images of the activities of margin investors in this two markets.

First, we show that, although the average leverage ratio of the peer-financed margin accounts is substantially higher than that of brokerage-financed accounts, the two ratios are strongly correlated in our sample period.

Second, in the time-series, the weighted average leverage ratio of peer-financed margin accounts decreases from January to mid-June of 2015. This trend coincides with the run-up of Shanghai composite index during the same period (see Figure 1), suggesting that the decreasing leverage ratio during the first half of 2015 was probably due to the increase in equity value rather than active de-leveraging by the investors. Indeed, as evidenced in Figure 1, outstanding margin debt was increasing during the first half of 2015. Figure 2 also shows a sudden and dramatic increase in leverage ratios of both brokerage-financed and peer-financed margin accounts in the second half of June 2015, followed by a total collapse in the first week of July. The sudden increase in leverage ratio in mid- to late- June was likely caused by the plummet of market value in these two weeks; whereas the subsequent drop in leverage ratio was likely due to de-leveraging activities, either voluntarily by the investors themselves or forced by the lending intermediaries.

Account-Leverage Cross-Sectional Predictive Model

Which investors are more likely to use high leverage in trading and what stocks are likely to be favored by these highly levered investors? Our account-level leverage data uniquely allow us to examine these important questions.

We first conduct an account-level analysis. We pool together all margin accounts (both broker-financed and peer-to-peer financed) and run Fama-MacBeth regressions of account leverage on several account characteristics. The regression equation is as follows:

$$LEVER_{i,t+1} = c_i + \gamma * CONTROL_{i,t} + \varepsilon_{i,t+1} \tag{1}$$

where $LEVER_{i,t+1}$ is the leverage ratio for account *i* at day *t+1*, γ is the coefficients for the account-level characteristics. These characteristics include *DIVERS* (the number of different stocks held by the account), *WEALTH* (the account's total wealth which includes cash holdings and stock holdings measured in yuan), *DUMMY* (the dummy variable which equals to 1 if the account is a peer-financed margin account), and the interaction between *DIVERS* and *WEALTH* and *DUMMY*. Other characteristic variables in the *CONTROL* vector for stock *i* at day *t* include *DRET* (average stock returns in each account's portfolio holdings in the previous day), *MOMENTUM* (average cumulative stock return in the portfolio during the prior 120 trading days), *TURNOVER* (average turnover ratios during the prior 120 trading days), *IDVOL* (average idiosyncratic return volatility after controlling for the Fama-French three factor model (constructed using Chinese data) in the previous 120 trading days), and *MCAP* (market capitalization of all tradable shares at the end of prior month), all weighted by each account's holding of the portfolio.

Panel A of Table II contains the results from the account-level analysis in (1). Column 1 reports negative and significant coefficient on *DIVERS* (the number of different stocks held by the account) and positive and significant coefficient on *WEALTH* (value of the account holdings), suggests that across the full sample, accounts with higher leverage tend to be large and hold less stocks. When we interact the peer-financed account dummy with account characteristics in Column 2, we find high-leverage brokerage-financed margin accounts to hold more stocks but high-leverage peer-financed margin accounts to hold less stocks.

Column 3 of Panel A includes additional stock characteristics measured at the account level by value-weighing them across different stocks in the same account. The negative and significant relation between the current account leverage and past account performance (measured by *DRET* and *MOMENTUM*) can be mechanical since a decline in equity value automatically translates to a higher account leverage.

Stock-Leverage Cross-Sectional Predictive Model

Next, we conduct a stock-level analysis. For each stock in each day, we compute a *LEVERAGE* variable as the weighted average leverage ratio of all margin accounts that hold that stock. We then run Fama-MacBeth regressions of *LEVERAGE* on various stock characteristics in the following form.

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

where $LEVERAGE_{i,t+1}$ is the leverage ratio for stock *i* at day *t+1*, β is the coefficients for the stock characteristics. These characteristics include *DRET* (stock returns in the previous day), *MOMENTUM* (average cumulative stock return in the portfolio during the prior 120 trading days), *TURNOVER* (average turnover ratios during the prior 120 trading days), *IDVOL* (average idiosyncratic return volatility after controlling for the Fama-French three factor model (constructed using Chinese data) in the previous 120 trading days), and *MCAP* (market capitalization of all tradable shares at the end of prior month).

The results in Panel B again suggest that highly levered margin traders are more likely to hold small stocks with high idiosyncratic volatility. Consequently, large negative idiosyncratic shocks on these stocks can easily propagate to other stocks as they force the margin investors to de-lever by selling other stocks in their portfolios. *LEVERAGE* is also negatively related to stock returns in the previous day. This relation, albeit significant, could again be mechanical. Finally, *LEVERAGE* is positively associated with recent turnover and momentum in the stock; however, the latter relation becomes less significant after controlling for other stock characteristics in Column 6.

4. Empirical Analyses of Common Holding through Margin Accounts

In this subsection, we examine the effect of margin trading on stock returns and their co-movement through a network structure. The 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.

4.1. Predictive Models with Margin-Account Linked Portfolio Returns

In our first set of analyses, we examine trading in each stock by *individual* margin accounts as a function of lagged portfolio returns. In particular, for each stock *i* in a portfolio, we decompose the corresponding portfolio return into two parts: one component with only stock *i*, and the other that includes the rest. More formally, the portfolio return can be expressed as $\omega_i r_i + \omega_i^{\perp} r_i^{\perp}$, where $r_i^{\perp}$ is the return of the portfolio excluding stock *i* and $\omega_i^{\perp}$ is the portfolio weight excluding *i*. We then regress subsequent trading in stock *i* by individual margin investors (defined as the RMB amount of buy orders minus that of sell orders, divided by lagged holding value) on both $\omega_i r_i$ and $\omega_i^{\perp} r_i^{\perp}$. We also control for stock-date fixed effects in all our specifications to purge out fluctuations in stock specific trading activity. Our prediction is that margin investors are more likely to downsize (expand) an existing holding if other stocks in the portfolio have done poorly (well), plausibly due to the tightening (loosening) of margin constraints.

Our results, as shown in Table III, are consistent with this prediction. Panel A presents results based on unconditional trading activity. Margin investors from both the broker and online trading platform scale up (down) their holdings in response to positive (negative) past portfolio returns. In the first three columns of Panel B, we further introduce an interaction term between past portfolio returns and account leverage. As can be seen from column 1, the coefficient on the interaction term between *Connected Return* and *Leverage* of 0.161 (*t*-statistic = 4.94) is economically large and statistically significant, indicating that more levered accounts indeed are more responsive to past performance.

In Columns 4-6 of Panel B, we separate lagged portfolio returns into positive vs. negative ones. As can be seen from Column 4, the coefficient on *Positive Connected Return* * *Leverage* is -0.458 (*t*-statistic = -4.66), while that on *Negative Connected Return* * *Leverage* is 0.343 (*t*-statistic = 5.95). This suggests that more levered investors scale down their holdings to a larger extent in response to negative return shocks relative to less levered investors; the relation does not hold for positive return shocks. Finally, in a placebo test where we replace margin investors with non-margin accounts, we observe no clear relation between order imbalance and lagged portfolio returns.

4.2. Predictive Models with Margin-Account Linked Portfolio Returns

To the extent that investors scale up or down their holdings in response to the tightening or loosening of leverage constraints with a delay, we could observe predictability in stock returns and investor behaviors. To illustrate, imagine that stock A is initially hit by a negative shock, which then lowers the portfolio value of all investors holding stock A. Among these investors, margin investors, facing funding constrains, start to sell other positions in their portfolios indiscriminately in the next day or week to de-lever, then stock's A return is a leading indicator of other stocks with which it shares common ownership by levered investors. In other words, future trading and returns of a stock can be predicted by the current return of its linked stocks.

To test this conjecture, for each stock, we first compute its margin-account linked portfolio return (*MLPR*) as the weighted average returns of all stocks with which it shares common holdings by margin investors. 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 the two stocks held by all leveraged investors, divided by the total market capitalization of the two stocks. We label this variable "Margin Holdings" (*MARHOLD*):

$$MARHOLD_{i,j,t} = \frac{\sum_{m=1}^{M}\left(S_{i,t}^{m}P_{i,t} + S_{j,t}^{m}P_{j,t}\right) * L_{t}^{M}}{TS_{i,t}P_{i,t} + TS_{j,t}P_{j,t}} \tag{4}$$

Where $S_{i,t}^{m}$ is the number of shares of stock *i* held by levered investor *m*, $TS_{i,t}$ is the number of tradable shares outstanding, and $P_{i,t}$ the close price of stock *i* on day *t*. We log transform *MARHOLD* (i.e., take the natural log of *MARHOLD* plus one) to deal with outliers. To compute MLPR for each stock i at day t, we then calculate the average of all the stocks linked to stock i through common ownership from margin investors, weighted by the *MARHOLD* stock i and each of its linked stock.

A. Forecasting Stock Returns

To test our conjecture, we regress future stock returns on the margin-account linked portfolio return, along with other controls that are known to forecast stock returns:

$$RET_{i,t+1} = a + b * MLPR_{i,t} + \sum_{k=1}^{K} b_k * CONTROL_{i,k} + \varepsilon_{i,t+1} \tag{3}$$

We look at stock returns in the same next one to three days. The regression is based on the sample with both brokerage and peer-financed margin accounts, over a period from May to July, 2015.

In Columns 1 and 2 of Table IV, 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 in Column 1 and additional stock characteristics in Column 2. For example, after controlling for common return predictors, a 1% increase in *MLPR* today predicts a higher return to stock *i* tomorrow by 0.227% (*t*-statistic = 2.42).

Columns 3 and 4 examine returns in the next three days. The predictive power of *MLPR* persists. For example, Column 4 shows that a 1% increase in *MLPR* today predicts a higher return to stock *i* in the next three days by 0.587% (*t*-statistic = 2.22).

Columns 5 and 6 suggest that the return predictive power of *MLPR* is much stronger when a large number of stocks hit the -10% price limit and are suspended from trading. For example, in days where the fraction of stocks having trading halts due to trading suspension or hitting the -10% price limit is below the sample median, a 1% increase in *MLPR* today predicts a higher return of 0.267% over the next three days (Column 6). For comparison, in days where the fraction is above the sample median, a 1% increase in *MLPR* today predicts a higher return of 0.906% over the next three days (Column 5), more than three time as large as the coefficient in Column 6.

B. Forecasting Stock Order Imbalance

The previous subsection shows that stock return can be a leading indicator of the returns of stocks connected to this stock through common ownership by margin investors. This is consistent with our conjecture that margin holders sell indiscriminately to de-lever, leading to a contagion among commonly held stocks. To further confirm this hypothesis, we compute the order imbalance for stock *i* at day *t+1* as the difference of the buyer-initiated yuan trading volume minus the seller-initiated yuan trading volume, normalized by the total trading volume at day *t*. We use two different datasets to compute these order imbalance. We first compute the order imbalance measures using the peer-financed account data, then we compute the order imbalance using WIND Level-II data. Our intuition is that the contagious effect is mainly driven by the de-lever trades from high leveraged margin investors. From Table I, we know that high leveraged margin investors cluster at the peer-financed trading platform, we thus expect to see the connected portfolio returns today can positively predict order imbalance from high leveraged investors (buy minus sell) the next day. And because trades from high levered margin investors, especially during the down markets, drive the stock returns, we expect the their trades to dominate market trades as well. We thus expect the connected portfolio returns to predict

Because China runs a pure limit order market, it is inappropriate to apply the Lee and Ready (1993) algorithm. We thus take a unique advantage from the WIND level-II data, which directly obtain the buyer-/seller- initiated indicators from the stock exchange by determining which trades move the prices. As the web based account data comprises the high leverage margin traders in the Chinese market, we expect the trades from these traders to drive the market movements.

We first regress future order imbalance (*OI*) in the next one to three days on a stock on its margin-account linked portfolio return, along with other controls that are included in Table II Panel B:

$$OI_{i,t+1} = a + b * MLPR_{i,t} + \sum_{k=1}^{K} b_k * CONTROL_{i,k} + \varepsilon_{i,t+1} \quad (2)$$

where $MLPR_{i,t}$ is the margin-account linked portfolio return for stock *i* on day *t*. We first compute order imbalance by each investor as the total number of buy orders minus the number of sell order in the stock in question scaled by the sum of the two. We then aggregate across all accounts to derive the stock level order imbalance.

In Columns 1 to 2 of Appendix Table I shows that the margin-account linked portfolio return positively and significantly predicts next-day order imbalance. Even after controlling for other stock characteristics, a 1% drop today in the average return on linked stocks with common holdings by margin investors predicts a 1.2% (*t*-statistic = 1.94) more selling pressure tomorrow. In column 3 and 4, we extend our sample period to January 2015, and find this relationship remains. Columns 5 to 6 confirm that such a selling pressure persists well beyond the next day.

4.3. Predictive Model with Common Holding by Margin Investors

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 the two stocks held by all leveraged investors, divided by the total market capitalization of the two stocks. We label this variable "Margin Holdings" (*MARHOLD*):

$$MARHOLD_{i,j,t} = \frac{\sum_{m=1}^{M}\left(S_{i,t}^{m}P_{i,t} + S_{j,t}^{m}P_{j,t}\right) * L_{t}^{M}}{TS_{i,t}P_{i,t} + TS_{j,t}P_{j,t}} \tag{4}$$

Where $S_{i,t}^{m}$ is the number of shares of stock *i* held by levered investor *m*, $TS_{i,t}$ is the number of tradable shares outstanding, and $P_{i,t}$ the close price of stock *i* on day *t*. We log transform *MARHOLD* (i.e., take the natural log of *MARHOLD* plus one) to deal with outliers.

We first confirm that stocks commonly held by margin traders are likely to be traded together as well. We measure correlated trading using the pair wise order imbalance correlation computed using half-hour order imbalances on day *t*+1.We estimate Fama-MacBeth regressions of realized correlations of each stock pair on lagged *MARHOLD* :

$$\rho_{i,j,t+1} = a + b * MARHOLD_{i,j,t} + \sum_{k=1}^{K} b_k * CONTROL_{i,j,k} + \varepsilon_{i,j,t+1} \tag{5}$$

Following Anton and Polk (2014), we also control for a host of variables that are known to be associated with stock return correlations: 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. Moreover, as a placebo test, we randomly select 200,000 brokerage non-margin accounts, and conduct identical analyses on these, except that the leverage ratio is a constant one across all these accounts.

Table V presents results of forecasting pair wise stock order imbalance correlations for the pooled sample between May and July, 2015. As shown in Column 1, the coefficient on *MARHOLD* is 0.041 with a t-statistic of 6.61, even after controlling for similarities in firm characteristics. The placebo test in Column 2 results in a negative coefficient on *NMARHOLD* . This is suggestive that the effect we document is due to the contagion caused by levered trading above and beyond the common holding effect as in Lou (2012) and Anton and Polk (2014).

In Columns 3 and 4, we repeat our analysis in Columns 1 in two subsample periods: the Boom period from May 1st to June 12th; and the Bust period from June 13th to July 31st. We find the coefficient on *MARHOLD* is more than twice as large in Column 3 (the Bust period) as that in Column 4 (the Boom period). The evidence further supports the contagion channel through margin trading. As margin constraints are more likely to be binding in the Bust period, stocks linked through margin holdings are more likely to be sold together and hence their returns co-move more.

In addition, we split the sample into two halves based on the fraction of stocks in the market hitting the -10% threshold in each day: columns 5 corresponds to the sub-period where the fraction is above the sample median, and column 6 corresponds to the sub-period where the fraction is below the sample median. We find the coefficient on *MARHOLD* is again more than twice as large in Column 5 as that in Column 6. The evidence again supports the contagion channel as margin constraints are more likely to be binding on days when many stocks hit the lower price limits.

Overall, common holdings by margin traders strongly predict correlated trading in the next day, more so when aggregate margin constraints are binding. In contrast, common holdings by non-margin traders predict less correlated trading.

Table VI conducts similar analysis as in Table V except that we now focus on return correlations between a pair of stocks. The dependent variable is the pair wise return correlation, again computed from half-hour returns in day t+1. Results in Table VI corroborate those in Table V and reinforce the contagion channel induced by margin trading. As shown in Column 1,the coefficient on *MARHOLD* is 0.056 with a t-statistic of 6.08, even after controlling for similarities in firm characteristics. The placebo test in Column 2 results in an insignificant coefficient on *NMARHOLD* .

In Columns 3 and 4, we confirm that the coefficient on *MARHOLD* is twice as large in Column 3 (the Bust period) as that in Column 4 (the Boom period). We also find the coefficient on *MARHOLD* is twice as large in Column 5 as that in Column 6. Indeed, as margin constraints are more likely to be binding, stocks linked through margin holdings are more likely to be sold together and hence their returns co-move more.

4.4. A Network-Based Approach

In this section, we construct a leverage network across stocks in the Chinese market based on the common ownership from levered investors. In so doing, we can more directly examine the transmission mechanism of leverage-induced price impact in the entire cross-section of stocks.

A. Network Representation of Leveraged Common holdings

Our leverage network is defined by a symmetric adjacency matrix, denoted A, where each entry $\alpha_{i,j}$ represents the level of "connectedness," as measured by equation (2), between stocks *i* and *j*. If there is no common ownership in the two stocks by levered investors, the connectedness measure is set to zero. Given the computational complexity, we focus on the constituents of the Zhongzheng 800 index, to form an 800X800 matrix.

It is important to note that through this network structure, shocks to one stock can be transmitted to stocks that are not directly linked to it. To illustrate, imagine stock A that is connected to stock B via common ownership, which is also linked to stock C. Negative shocks to stock A can trigger selling pressure on stock B, which is further transmitted to stock C, even though stocks A and C may not share any common margin investors. To capture this indirect relation, we use A^n --- that is, matrix A raised to the power of *n* --- to measure how shocks may be transmitted from one stock to another going through *n* intermediary steps.

B. Network Centrality

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. Hence, if we define the eigenvector centrality of node *j* as c_j, then c_j is proportional to the sum of the c_j's for all other nodes $j \neq 1$;

$$c_j = \frac{1}{\lambda} \sum_{j \in M(j)} c_j = \frac{1}{\lambda} \sum_{j=1}^{J} A_{i,j,c_j}$$

where $M(i)$ is the set of nodes that are connected to node *i* and λ is a constant. In matrix notation, we have $Ac = \lambda c$. Thus, *c* is the principal eigenvector of the adjacency matrix.

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.

In sum, eigenvector centrality 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.

We start by analyzing the stock characteristics that are associated with the centrality measure. As shown in Table VII, stocks with high idiosyncratic volatilities, higher turnover, and lower past returns tend to be more central in the leverage network structure. Shocks to these stocks are more likely to propagate throughout the network and affect the entire market. In other words, they are likely to be systemically important.

C. Network Centrality, Order Submission, Stock Returns, and Stock Skewness.

Given that central stocks are likely to be hit by idiosyncratic shocks to any stocks in the network, and that negative shocks are more likely to be propagated through the network than positive shocks, we expect that stocks with a higher centrality score to be more likely sold by margin accounts, have lower unconditional returns and higher crash risk (negative return skewness) compared to stocks with a lower centrality score.

To test this prediction, we conduct Fama-MacBeth regressions of individual stock order imbalance on the stocks' eigenvector centrality measured in the previous day:

$$OI_{i,t+1} = a + b * CENTRAL_{i,t} + \sum_{k=1}^{K} b_k * CONTROL_{i,k} + \varepsilon_{i,t+1} \tag{6}$$

where $CENTRAL_{i,t}$ is the standardized centrality measure for stock *i* measured in day *t*. We include the same set of control variables as in Table II Panel B. We examine order imbalance in the next one to three days.

Table VIII confirms that eigenvector centrality forecasts future trading of the stock. For example, Column 6 shows that a one-standard-deviation increase in a stock's centrality is associated with a 0.9% increase (*t*-statistic = 4.51) in the daily selling pressure by margin investors in the next three days, even after controlling for other stock characteristics.

We then examine if the centrality measure predicts lower future returns by running the following Fama-MacBeth regression:

$$RET_{i,t+1} = a + b * CENTRAL_{i,t} + \sum_{k=1}^{K} b_k * CONTROL_{i,k} + \varepsilon_{i,t+1} \quad (7)$$

where we examine returns in the next one to three days.

Table IX shows the regression results. As can be seen from Columns 1-3, eigenvector centrality negatively forecasts next-day stock returns, although the forecasting power is only marginally significant. This is because a negative idiosyncratic shock to stock A may take more than a day to reach a central stock that is not directly connected. Indeed, when we examine next three-day returns in Columns 4-6, the centrality measure significantly predicts future returns, even after controlling for the stock's own past returns and its own leverage ratio. Since the centrality measure is standardized, its coefficient suggests that a one-standard-deviation increase in centrality leads to a return that is 30 (*t*-statistic = -3.84) basis points lower over the next three days.

Finally, we analyze the relation between crash risk and eigenvector centrality by regressing future return skewness on our centrality measure:

$$SKEW_{i,t+1} = a + b * CENTRAL_{i,t} + \sum_{k=1}^{K} b_k * CONTROL_{i,k} + \varepsilon_{i,t+1} \quad (8)$$

where $SKEW_{i,t+1}$ is the average daily skewness of stock *i* in the next day or the next three days. Daily return skewness, in turn, is calculated based on stock returns over 10-minute intervals.

The centrality measure and other control variables are identical to those in equation (5). We look at return skewness in the next one to three days.

As shown in Column 6 Table X, eigenvector centrality significantly and negatively forecasts stock return skewness in the next 3 days; a one-standard-deviation in network centrality is associated with a -0.044 (*t*-statistic = -2.15) change in return skewness in the next three days, after controlling for various firm characteristics (such as past returns and past leverage ratio).

D. Network Asymmetry and Stock Market Return.

So far, we have shown that common ownership by margin traders can cause idiosyncratic shocks to propagate through the leverage network. A related question is can idiosyncratic shocks aggregate to systematic price movements? We follow Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) to analyze the conditions under which idiosyncratic shocks to individual securities in the leverage network may lead to aggregate price movements. The key insight of Acemoglu et al. (2012) is that when there exists significant asymmetry in the network structure, idiosyncratic shocks are not washed away in aggregate.

To quantify the network asymmetry, we follow Gabaix (2011) and Gabaix and Ibragimov (2011) to estimate the power-law shape parameter of the distribution of first-order degrees of all stocks in the leverage network. Specifically, we run the following regression:

$$\log(\text{Rank} - 0.5) = a - b*\log(\text{Degree})$$

where Rank is the cross-sectional ranking of all nodes based on the corresponding first-order degrees. The leverage network asymmetry measure, *SHAPEPARAM*, can be computed as some transformation of the coefficient b. We then regress future market returns on *SHAPEPARAM*, *LEVERAGE*, their interaction, and additional controls.

$$RET_{t+1} = a + b * SHAPEPARAM_t + c * LEVERAGE_t + d * INTERACTION_t + \varepsilon_{t+1} \quad (9)$$

where RET_{t+1} is the cumulative market return in the following week (skipping one day).

The first three columns of Table XI report similar results in the Full sample regardless how *SHAPEPARAM* is computed exactly. While high leverage in general predicts higher future returns, its interaction with *SHAPEPARAM* is associated with a significantly negative coefficient. The negative coefficient implies that when the leverage network is highly concentrated, higher aggregate leverage predicts lower future stock market returns. In other words, when the market leverage is high and concentrated on a few stocks, the network is "fragile." De-leveraging on a few systemically important stocks can quickly lead to market-wide selling frenzy.

Column (5) offers another way to look at this result. In the subperiod in which the market leverage is above its sample median, a one-standard-deviation increase in *SHAPEPARAM* forecasts a 2.73% (*t*-statistic = 2.32) lower cumulative market return in the following week. Our results thus suggest that margin-induced trading, coupled with the asymmetric nature of the leverage network, may have contributed to and exacerbated the precipitous drop in market value in July 2015.

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 (as well as order imbalance) 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. 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 lower returns and higher crash risk going forward. Finally, consistent with the key insight of Acemoglu, Carvalho, Ozdaglar and Tahbaz-Salehi (2012), we provide evidence that the cross-sectional asymmetry in the leverage network (i.e., the degree to which some stocks are central and others are peripheral) negatively forecasts future market returns.

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Table I: 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 trading and non-margin trading) at a major brokerage in China, as well as the summary statistics of all trading accounts on a peer-to-peer lending platform (i.e., peer-financed margin accounts). We report in this panel the total number of the brokerage and peer-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. For comparison, we also report the total market capitalization of all A shares ($MARKET), as well as the tradable component ($TRADABLE) during the same period. Panel B reports information at the account level. In particular, we report in this panel each accounts' 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 60 trading days (MOMENTUM), share turnover defined as daily trading volume divided by the number of outstanding tradable shares (TURNOVER), and idiosyncratic return volatility defined as the standard deviation of the residual of return after controlling for the Fama-French three factor model (constructed using Chinese data)in the previous 120 trading days (IDVOL). # denotes the number of shares or accounts, while $ denotes the RMB (Yuan) amount.

	Broker-Financed Margin Accounts		Broker Non-Margin Accounts		Peer-Financed Margin Accounts	
Panel A: Full Sample Summary						
	Mean	Median	Mean	Median	Mean	Median
# of Accounts	177,571	177,571	5,726,109	5,726,109	164,937	164,937
$DEBT (10^9)	99.4	106.0	0	0	39.4	39.0
$HOLDINGS (10^9)	355.0	363.3	290.87	287.91	62.4	58.3
Panel B: Accounts Characteristics						
#HOLDINGS (10^3)	362.18	62.80	12.20	3.30	61.09	7.60
$HOLDINGS (10^4)	701.42	121.25	149.86	4.70	119.22	14.29
#TRADING (10^3)	126.39	14.90	11.09	1.80	26.12	4.80
$TRADING (10^4)	208.14	27.30	18.46	2.81	45.20	8.60
#SUBMISSIONS	15.18	6.00	6.08	3.00	6.70	4.00
LEVERAGE	1.60	1.53	1	1	7.01	4.14
Panel C: Stock Characteristics						
$MKTCAP (10^9)	112.48	44.22	119.82	40.45	78.69	26.22
$TRADABLE (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 II: Determinants of Leverage Ratios

This table examines determinants of individual account's leverage ratio, as well as of the individual stocks' 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 (*DIVERSE*), each investor's total wealth which include cash holdings and stock holdings measured in Yuan (*WEALTH*), the dummy variable which equals to 1 if the account is a peer-financed margin account (*DUMMY*), and the interaction between *DIVERSE* and *WEALTH* and *DUMMY*. Other control variables include average daily stock returns in each account's portfolio holdings(*DRET*), average cumulative stock return in the portfolio during the 120 prior trading days (*MOMENTUM*), average daily turnover ratios during the prior 120 trading days (*TURNOVER*), average idiosyncratic return volatility after controlling for the Fama-French three factor model (constructed using Chinese data) in the previous 120 trading days (*IDVOL*), the Amihud ratio during the previous month (*AMIHUD*), and the average market capitalization of the stocks held in each account's portfolio(*MCAP*), all weighted by each account's holding of the portfolio. 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*), its 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*), and market capitalization at day *t* (*MCAP*).We conduct Fama-Macbeth regressions in all columns. T-statistics, reported below the coefficients, are based on standard errors with Newey-West adjustment of 8 lags. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Dependent Variable = Account-level Leverage Ratio			
	(1)	(2)	(3)
DIVERSE	-0.012***	0.003***	0.004***
	(-5.65)	(10.17)	(7.93)
WEALTH	0.034***	0.028***	0.085***
	(10.24)	(20.32)	(9.82)
DUMMY	5.999***	4.829***	5.081***
	(12.02)	(18.40)	(18.48)
*DIVERSE*DUMMY*		-0.450***	-0.380***
		(-4.79)	(-4.74)
*WEALTH*DUMMY*		0.176***	0.145**
		(2.89)	(2.54)
DRET			-7.771***
			(-13.21)
MOMENTUM			-0.035
			(-1.20)
TURNOVER			-3.817***
			(-5.21)
MCAP			-0.0001
			(-0.48)
IDVOL			-22.428***
			(-5.36)
Adj. R^2	0.18	0.18	0.19
No. Obs.	14,187,423	14,187,423	14,187,423

Panel B: Dependent Variable = Stock-level Leverage Ratio						
	(1)	(2)	(3)	(4)	(5)	(6)
DRET	-2.530***					-2.281***
	(-4.55)					(-4.30)
MOMENTUM		0.098***				0.008
		(4.46)				(0.42)
TURNOVER			5.853***			1.518***
			(7.94)			(6.74)
IDVOL				10.195***		9.808***
				(5.82)		(8.20)
MCAP					-0.001***	-0.0005***
					(-9.04)	(-10.53)
Adj. R^2	0.006	0.006	0.012	0.002	0.001	0.012
No. Obs.	176,922	176,922	176,922	176,922	176,922	176,922

Table III: Account Level Trading

This table reports results of forecasting regressions of margin investors' trading activity on lagged portfolio returns. The dependent variable in both panels is the order imbalance in stock *i* by account *j* in day *t* +1 (defined as the RMB amount of buy orders minus that of sell orders, divided by lagged holding value). The main independent variables of interest are *Self Return* and *Connected return* in day *t*, defined as follows. For each stock *i* in a portfolio, we decompose the corresponding portfolio return into two parts: one component with only stock *i*, and the other that includes the rest. More formally, the portfolio return can be expressed as $\omega_i r_i + \omega_i^{\perp} r_i^{\perp}$, where $r_i^{\perp}$ is the return of the portfolio excluding stock *i* and $\omega_i^{\perp}$ is the portfolio weight excluding *i*. We label $\omega_i r_i$ *Self Return*, and $\omega_i^{\perp} r_i^{\perp}$ *Connected Return*. We also include further lags (up to five days) of both *Self Return* and *Connected Return* in all regressions. Panel A reports results based on unconditional trading activity. In the first three columns of Panel B, we introduce interaction terms of lagged *Self Return* and *Connected Return* with account leverage. In the next three columns of Panel B, we further divide *Self Return* and *Connected Return* into positive and negative observations. We conduct pooled OLS with stock*date fixed effects in all columns. T-statistics, reported below the coefficients, are based on standard errors clustered by date. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Dependent Variable = $Trading_{i,j,t+1}$			
	All	Brokerage	Peer-financed
	[1]	[2]	[3]
Self Return	0.307**	0.016	0.671***
	(2.39)	(0.16)	(4.36)
Connected Return	0.061	0.042	0.200**
	(1.38)	(1.08)	(2.26)
Lag2_Self Return	0.037	-0.003	0.180**
	(0.57)	(-0.05)	(2.42)
Lag3_Self Return	0.046	0.032	0.086
	(0.77)	(0.46)	(1.31)
Lag4_Self Return	0.078	0.029	0.070
	(1.48)	(0.47)	(1.29)
Lag5_Self Return	-0.007	0.006	-0.072
	(-0.14)	(0.11)	(-1.40)
Lag2_Connected Return	-0.021	-0.010	-0.029
	(-0.50)	(-0.39)	(-0.48)
Lag3_Connected Return	-0.024	-0.003	-0.104
	(-0.54)	(-0.12)	(-1.46)
Lag4_Connected Return	-0.020	-0.010	-0.048
	(-0.46)	(-0.36)	(-0.73)
Lag5_Connected Return	-0.059	-0.027	-0.068
	(-1.57)	(-1.11)	(-1.09)
Leverage	-0.018***	-0.003**	-0.008***
	(-11.48)	(-2.08)	(-7.36)
Adj-R^2	0.052	0.029	0.104
No. Obs.	13,475,223	9,612,720	3,862,503

Panel B: Dependent Variable = $Trading_{i,j,t+1}$						
	All Returns			Positive vs. Negative Returns		
	All	Broker	Shadow	All	Broker	Shadow
	[1]	[2]	[3]	[4]	[5]	[6]
Self Return	-0.304***	-0.158**	0.162			
	(-2.73)	(-2.26)	(1.34)			
Self Return	0.243***	0.120***	0.112***			
**Leverage*	(7.59)	(2.94)	(4.41)			
Connected Return	-0.296***	-0.068*	-0.240**			
	(-4.04)	(-1.78)	(-2.43)			
Connected Return	0.161***	0.075**	0.097***			
**Leverage*	(4.94)	(2.27)	(4.03)			
Positive Self Return				0.079	-0.103**	0.185
				(1.39)	(-2.09)	(1.27)
Negative Self Return				-0.008	0.046	-0.019
				(-0.34)	(0.96)	(-0.86)
Positive Self Return				0.353***	0.246**	0.954***
**Leverage*				(3.56)	(2.03)	(4.95)
Negative Self Return				0.391***	0.371***	0.198***
**Leverage*				(7.80)	(4.33)	(4.61)
Positive Connected Return				0.041	0.006	-0.697***
				(0.69)	(0.09)	(-3.96)
Negative Connected Return				-0.052**	0.065	0.054*
				(-2.08)	(1.50)	(1.83)
Positive Connected Return				-0.458***	0.093**	0.281
**Leverage*				(-4.66)	(2.02)	(1.54)
Negative Connected Return				0.343***	0.030	0.149***
**Leverage*				(5.95)	(0.64)	(3.17)
Adj-R^2	0.053	0.029	0.105	0.055	0.030	0.106
No. Obs.	13,475,223	9,612,720	3,862,503	13,475,223	9,612,720	3,862,503

Table IV: Forecasting Stock Returns

This table reports results of return forecasting regressions. The dependent variable in columns 1 and 2 is stock *i*'s return in day *t*+1, and that in columns 3-6 is stock *i*'s cumulative stock return in days *t*+1 to *t*+3. The main independent variable of interest is *MALP*, 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 peer-financed margin accounts, where the weights are proportional to *MARHOLD* as defined in Table III. 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 day *t* (*MCAP*). In columns 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 corresponds to the sub-period where the fraction is above the sample median, and column 6 corresponds to the sub-period where the fraction is below the sample median. We conduct Fama-Macbeth regressions in all columns. T-statistics, reported below the coefficients, are based on standard errors with Newey-West adjustment of 8 lags. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable = Future Stock Returns					
	Returns in *t*+1		Returns in *t*+1 to *t*+3			
	(1)	(2)	(3)	(4)	(5)	(6)
MALP	0.243**	0.227**	0.735**	0.587**	0.907***	0.267
	(2.50)	(2.42)	(2.02)	(2.22)	(2.98)	(0.55)
LEVERAGE	-0.00004	0.0001	-0.0004	0.0002	-0.0001	0.0005
	(-0.16)	(0.63)	(-0.58)	(0.31)	(-0.07)	(0.77)
DRET	0.206***	0.194***	0.224***	0.181***	0.225*	0.137***
	(5.29)	(5.21)	(3.22)	(2.76)	(1.90)	(2.84)
MOMENTUM		-0.002**		-0.008***	-0.012**	-0.004*
		(-2.45)		(-2.59)	(-2.20)	(-1.81)
TURNOVER		-0.030		-0.079	-0.178	0.020
		(-1.39)		(-1.23)	(-1.75)	(0.346)
IDVOL		-0.084		-0.026	0.286	-0.337
		(-0.73)		(-0.06)	(0.40)	(-1.12)
MCAP		0.0002		-0.001	0.0003	-0.002**
		(0.06)		(-0.86)	(0.17)	(-2.16)
Adj. R^2	0.09	0.14	0.06	0.13	0.18	0.08
No. Obs.	51,200	51,200	51,200	51,200	26,400	24,800

Table V: Pairwise Order-Imbalance Correlation

This table reports forecasting regressions of pairwise correlations in order imbalance. The dependent variable in each column is the daily order-imbalance correlation between a pair of stocks (*i* and *j*), computed from half-hour windows 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. *NMARHOLD* is defined in a similar way, but using the non-margin trading accounts. 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 (*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 peer-financed margin accounts. In column 2, we focus solely on the non-margin accounts in the brokerage data (thus a constant leverage ratio of 1). In columns 3 and 4, we split the sample in column 1 into two halves: column 3 corresponds to the period June 13th to July 31st, and column 4 corresponds to the period May 1st to June 12th. In columns 5 and 6, we again 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 5 corresponds to the sub-period where the fraction is above the sample median, and column 6 corresponds to the sub-period where the fraction is below the sample median. We conduct Fama-Macbeth regressions in all columns. T-statistics, reported below the coefficients, are based on standard errors with Newey-West adjustment of 8 lags. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable = Pairwise Order-Imbalance Correlations						
	Full Sample		Booms vs. Busts		Frac of Trading Halts	
	(1)	(2)	(3)	(4)	(5)	(6)
MARHOLD	0.041***		0.047***	0.022***	0.049***	0.020***
	(6.61)		(8.31)	(3.94)	(8.66)	(4.29)
NMARHOLD		-0.013*				
		(-1.97)				
COMANALY	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(5.57)	(6.68)	(4.38)	(5.36)	(3.90)	(6.42)
SIZEDIFF	0.001	0.011	0.002	-0.005**	0.002	-0.004**
	(0.26)	(0.31)	(0.88)	(-2.30)	(0.71)	(-2.03)
BMDIFF	0.007***	0.007***	0.006***	0.006***	0.006***	0.006***
	(11.35)	(11.44)	(7.23)	(9.00)	(7.82)	(7.71)
MOMDIFF	0.001**	0.001**	0.001	0.001***	0.001	0.001***
	(2.02)	(2.29)	(0.82)	(5.05)	(0.74)	(4.73)
SAMEIND	0.025***	0.026***	0.015***	0.024***	0.015***	0.024***
	(9.45)	(9.86)	(4.80)	(7.58)	(4.52)	(7.32)
SIZE1	-0.009***	-0.009***	-0.005	-0.014***	-0.006	-0.013***
	(-3.04)	(-3.06)	(-1.59)	(-5.56)	(-1.68)	(-5.16)
SIZE2	-0.009***	-0.009***	-0.005	-0.014***	-0.006	-0.013***
	(-3.04)	(-3.06)	(-1.59)	(-5.58)	(-1.68)	(-5.17)
*SIZE1*SIZE2*	0.001*	0.001*	0.001	0.002***	0.001	0.002***
	(1.84)	(1.89)	(0.68)	(4.48)	(0.75)	(4.13)
Adj. R^2	0.014	0.016	0.018	0.010	0.049	0.010
No. Obs. (*1000)	33,450	33,450	17,403	16,047	16,824	16,626

Table VI: Pairwise Return Comovement

This table reports forecasting regressions of pairwise stock return comovement. The dependent variable in each column is the daily return comovement between a pair of stocks (*i* and *j*), computed from half-hour returns 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. *NMARHOLD* is defined in a similar way, but using the non-margin trading accounts. 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 (*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 peer-financed margin accounts. In column 2, we focus solely on the non-margin accounts in the brokerage data (thus a constant leverage ratio of 1). In columns 3 and 4, we split the sample in column 1 into two halves: column 3 corresponds to the period June 13th to July 31st, and column 4 corresponds to the period May 1st to June 12th. In columns 5 and 6, we again 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 5 corresponds to the sub-period where the fraction is above the sample median, and column 6 corresponds to the sub-period where the fraction is below the sample median. We conduct Fama-Macbeth regressions in all columns. T-statistics, reported below the coefficients, are based on standard errors with Newey-West adjustment of 8 lags. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable = Pairwise Return Correlations						
	Full Sample		Booms vs. Busts		Frac of Trading Halts	
	(1)	(2)	(3)	(4)	(5)	(6)
MARHOLD	0.056***		0.061***	0.032***	0.063***	0.030***
	(6.08)		(4.91)	(7.21)	(5.06)	(8.34)
NMARHOLD		-0.003				
		(-0.44)				
COMANALY	0.0002***	0.001***	0.001***	0.002***	0.001***	0.002***
	(5.73)	(6.53)	(3.10)	(6.83)	(2.77)	(6.87)
SIZEDIFF	0.011**	0.011**	0.020***	-0.005**	0.020***	-0.004**
	(2.00)	(1.99)	(2.93)	(-2.47)	(2.84)	(-2.15)
BMDIFF	0.010***	0.009***	0.007**	0.009***	0.008***	0.009***
	(7.11)	(6.77)	(5.02)	(5.18)	(5.29)	(4.85)
MOMDIFF	0.002***	0.006***	0.002**	0.003***	0.002**	0.003***
	(3.81)	(3.23)	(2.50)	(5.38)	(2.46)	(5.14)
SAMEIND	0.040***	0.037***	0.026***	0.038***	0.027***	0.036***
	(7.65)	(6.95)	(3.68)	(8.30)	(3.75)	(7.25)
SIZE1	-0.004	-0.003	0.003	-0.015***	0.003	-0.015***
	(-1.33)	(-0.98)	(0.96)	(-8.53)	(0.94)	(-7.89)
SIZE2	-0.004	-0.003	0.003	0.002***	0.003	-0.015***
	(-1.32)	(-0.96)	(0.99)	(5.44)	(0.97)	(-7.89)
*SIZE1*SIZE2*	0.001***	-0.001	-0.003***	-0.015***	-0.003**	0.002***
	(-0.69)	(-0.73)	(-2.67)	(-8.53)	(-2.59)	(4.79)
Adj. R^2	0.034	0.037	0.050	0.016	0.051	0.016
No. Obs. (*1000)	33,450	33,450	17,403	16,047	16,824	16,626

Table VII: Determinants of Leverage Network Centrality

This table examines determinants of individual stocks' importance in the leverage network. The dependent variable in each column is, *CENTRAL*, the centrality measure of stock *i* in day *t*+1; 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 (*MARHOLD*). 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*), and the amihud measure during the previous month (*AMIHUD*). We conduct Fama-Macbeth regressions in all columns. T-statistics, reported below the coefficients, are based on standard errors with Newey-West adjustment of 8 lags. ***, **, 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)
LEVERAGE	-0.056***						-0.059***
	(-6.24)						(-6.08)
DRET		-0.14					-0.483
		(-0.43)					(-1.06)
MOMENTUM			-0.012				-0.093***
			(-0.42)				(-3.15)
TURNOVER				5.721***			4.637***
				(12.20)			(7.74)
IDVOL					12.19***		15.440***
					(4.55)		(5.73)
AMIHUD						-0.18***	-0.18***
						(-3.52)	(-3.35)
MCAP							-0.001
							(-0.20)
Adj. R^2	0.009	0.005	0.008	0.011	0.009	0.021	0.060
No. Obs.	51,200	51,200	51,200	51,200	51,200	51,200	51,200

Table VIII: Centrality and Future Order Imbalance

This table reports results of return forecasting regressions. The dependent variable in columns 1-3 is stock *i*'s order imbalance in day *t*+1, and that in columns 4-6 is stock *i*'s cumulative order imbalance in days *t*+1 to *t*+3. The main independent variable of interest is *CENTRAL*, 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 (*MARHOLD*). 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 month (*MOMENTUM*), its daily turnover ratios in the previous month (*TURNOVER*), idiosyncratic return volatility after controlling for the Fama-French three factor model (constructed using Chinese data) in the previous 120 trading days (*IDVOL*), and market capitalization at the end of previous month (*MCAP*). We conduct Fama-Macbeth regressions in all columns. T-statistics, reported below the coefficients, are based on standard errors with Newey-West adjustment of 8 lags. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable = Future Order Imbalance						
	Order imbalance in *t*+1			Order imbalance in *t*+1 to *t*+3		
	(1)	(2)	(3)	(4)	(5)	(6)
CENTRAL	-0.008**	-0.009**	-0.009**	-0.009***	-0.009***	-0.009***
	(-3.08)	(-3.64)	(-3.48)	(-3.92)	(-4.67)	(-4.51)
LEVERAGE		-0.006	0.005		-0.006	-0.005
		(-1.70)	(-1.42)		(-1.68)	(-1.44)
DRET		-0.328***	-0.334***		-0.151***	-0.144***
		(-3.41)	(-3.32)		(-2.37)	(-2.00)
MOMENTUM			0.001			0.002
			(0.22)			(0.70)
TURNOVER			-0.267			-0.246
			(-2.07)			(-2.08)
IDVOL			0.013			-0.362
			(0.03)			(-0.83)
MCAP			-0.0003			-0.0003
			(-2.41)			(-2.48)
Adj. R^2	0.005	0.078	0.112	0.005	0.050	0.088
No. Obs.	51,200	51,200	51,200	51,200	51,200	51,200

Table IX: Centrality and Future Stock Returns

This table reports results of return forecasting regressions. The dependent variable in columns 1-3 is stock *i*'s return in day *t*+1, and that in columns 4-6 is stock *i*'s cumulative stock return in days *t*+1 to *t*+3. The main independent variable of interest is *CENTRAL*, 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 (*MARHOLD*). 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 Fama-Macbeth regressions in all columns. T-statistics, reported below the coefficients, are based on standard errors with Newey-West adjustment of 8 lags. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable = Future Stock Returns						
	Returns in *t*+1			Returns in *t*+1 to *t*+3		
	(1)	(2)	(3)	(4)	(5)	(6)
CENTRAL	-0.001	-0.001**	-0.001**	-0.002***	-0.003***	-0.003***
	(-1.77)	(-2.00)	(-2.05)	(-3.41)	(-4.40)	(-3.84)
LEVERAGE		-0.0001	0.0001		-0.001	-0.0002
		(-0.33)	(0.24)		(-0.86)	(-0.27)
DRET		0.219***	0.205***		0.254***	0.204***
		(5.17)	(5.37)		(3.37)	(2.83)
MOMENTUM			-0.002**			-0.008**
			(-2.24)			(-2.51)
TURNOVER			-0.027			-0.074
			(-1.28)			(-1.14)
IDVOL			-0.091			-0.025
			(-0.78)			(-0.06)
MCAP			-0.0003			-0.002
			(-0.72)			(-1.22)
Adj. R^2	0.005	0.085	0.130	0.006	0.052	0.111
No. Obs.	51,200	51,200	51,200	51,200	51,200	51,200

Table X: Centrality and Future Return Skewness

This table reports results of return forecasting regressions. The dependent variable in columns 1-3 is stock *i*'s return skewness, computed from half-hour windows, in day *t*+1, and that in columns 4-6 is stock *i*'s average return skewness in days *t*+1 to *t*+3. The main independent variable of interest is *CENTRAL*, 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 (*MARHOLD*). 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 month (*MOMENTUM*), its daily turnover ratios in the previous month (*TURNOVER*), idiosyncratic return volatility after controlling for the Fama-French three factor model (constructed using Chinese data) in the previous 120 trading days (*IDVOL*), and market capitalization at the end of previous month (*MCAP*). We conduct Fama-Macbeth regressions in all columns. T-statistics, reported below the coefficients, are based on standard errors with Newey-West adjustment of 8 lags. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable = Future Return Skewness						
	Skewness in *t*+1			Skewness in *t*+1 to *t*+3		
	(1)	(2)	(3)	(4)	(5)	(6)
CENTRAL	-0.066*	-0.030**	-0.081**	-0.058*	-0.061**	-0.074**
	(-1.78)	(-1.96)	(-2.04)	(-1.84)	(-2.08)	(-2.15)
LEVERAGE		0.017	0.019		0.005	0.006
		(1.18)	(1.23)		(0.48)	(0.53)
DRET		5.532***	4.599***		2.553***	1.621*
		(5.35)	(5.09)		(3.31)	(1.67)
MOMENTUM			0.019			0.005
			(1.23)			(0.32)
TURNOVER			3.470			2.873
			(1.48)			(1.39)
IDVOL			-4.489			-2.606
			(-0.64)			(-0.41)
MCAP			-0.025*			-0.027**
			(-1.77)			(-1.99)
Adj. R^2	0.009	0.056	0.096	0.007	0.049	0.096
No. Obs.	51,200	51,200	51,200	51,200	51,200	51,200

Table XI: Network Asymmetry and Future Market Returns

This table reports results of forecasting regressions for market returns. The dependent variable in all columns is the cumulative market return in the following week (skipping one day). The main independent variable is the shape parameter of the power-law distribution of first-order degrees of all nodes in the leverage network. Specifically, following Gabaix and Ibragimov (2011), we estimate the power-law distribution shape parameter from the following equation: log(Rank – 0.5) = a – b*log(Degree), where Rank is the cross-sectional ranking of all nodes based on the corresponding first-order degrees. The main independent variable is the shape parameter (or some transformation of it). In column 1, *SHAPEPARAM* is the estimate for b from the above equation. In column 2, *SHAPEPARAM* is defined as (b-1)/b. In columns 3-5, it is defined as 800^((b-1)/b), given that there are 800 stocks in our market index. We also include in the regression a quintile dummy based on the average market leverage ratio (*LEVERAGE*) – it takes the values of 0 through 4 corresponding to the five quintiles sorted by daily market leverage. *INTERACTION* is the interaction term between *SHAPEPARAM* and *LEVERAGE*. Other control variables include the market return in the same day as the leverage network is constructed (*MKTRF0*), market return in the prior week (*LMKTRF*), market volatility in the prior week (*LMKTVOL*), and fraction of stocks that hit the -10% threshold in a day which would result in an automatic trading halt (*FRACHALT*). In column 4, we include only the days in which the leverage ratio is below the sample median, and in column 5, we include only the days in which the leverage ratio is above the sample median. T-statistics, reported below the coefficients, are based on standard errors with Newey-West adjustment of 8 lags. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable = Future Market Returns					
	(1)	(2)	(3)	(4)	(5)
		Full Sample		<= Median	> Median
SHAPEPARAM	0.226	0.299	0.018	0.000	-0.023**
	(0.169)	(0.192)	(0.016)	(0.011)	(0.010)
LEVERAGE	0.145**	0.008	0.027**		
	(0.060)	(0.008)	(0.013)		
INTERACTION	-0.135**	-0.153***	-0.014***		
	(0.053)	(0.060)	(0.005)		
MKTRF0	-0.203	-0.194	-0.202	-0.558	0.138
	(0.350)	(0.358)	(0.328)	(0.559)	(0.352)
LMKTRF	0.367***	0.332***	0.423***	0.087	0.474***
	(0.135)	(0.135)	(0.132)	(0.225)	(0.179)
LMKTVOL	1.793***	1.763***	1.793***	1.872*	1.967**
	(0.551)	(0.551)	(0.554)	(1.113)	(0.811)
FRACHALT	-0.013	-0.015	-0.007	0.031	0.062
	(0.075)	(0.079)	(0.066)	(0.391)	(0.063)
Adj. R^2	0.122	0.109	0.153	0.000	0.257
No. Obs.	64	64	64	32	32

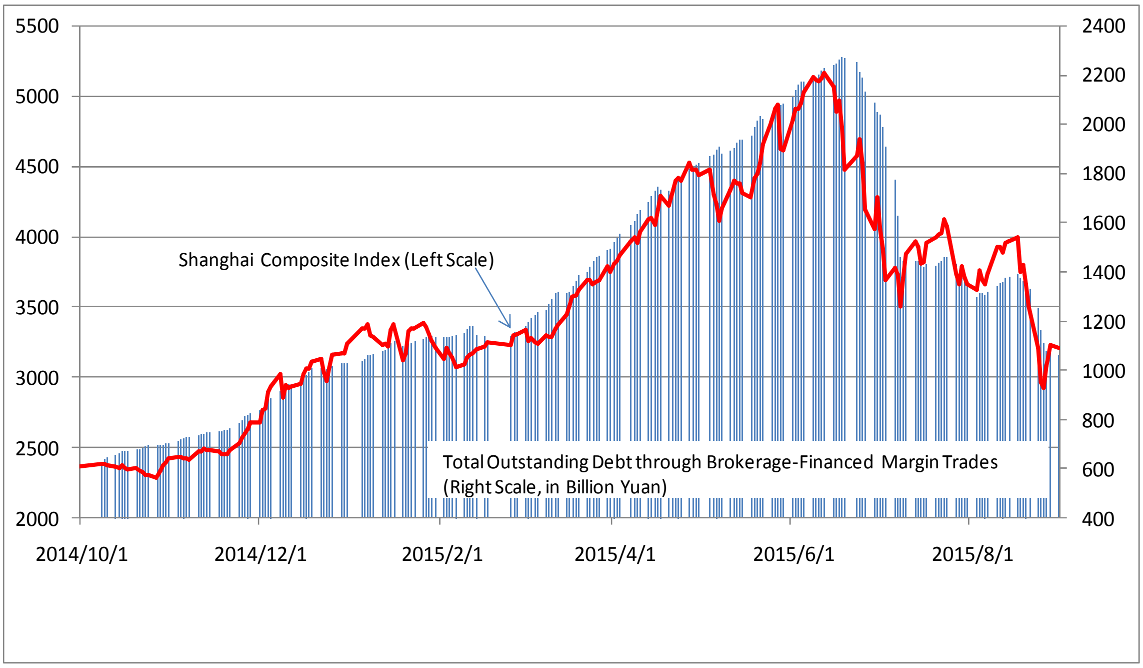

Figure 1. This figure shows the Shanghai Stock Exchange (SSE) Composite Index (the red line), as well as the aggregate brokerage-financed margin debt (blue bars, in billions), at the end of each day for the period October 2014 to August 2015.

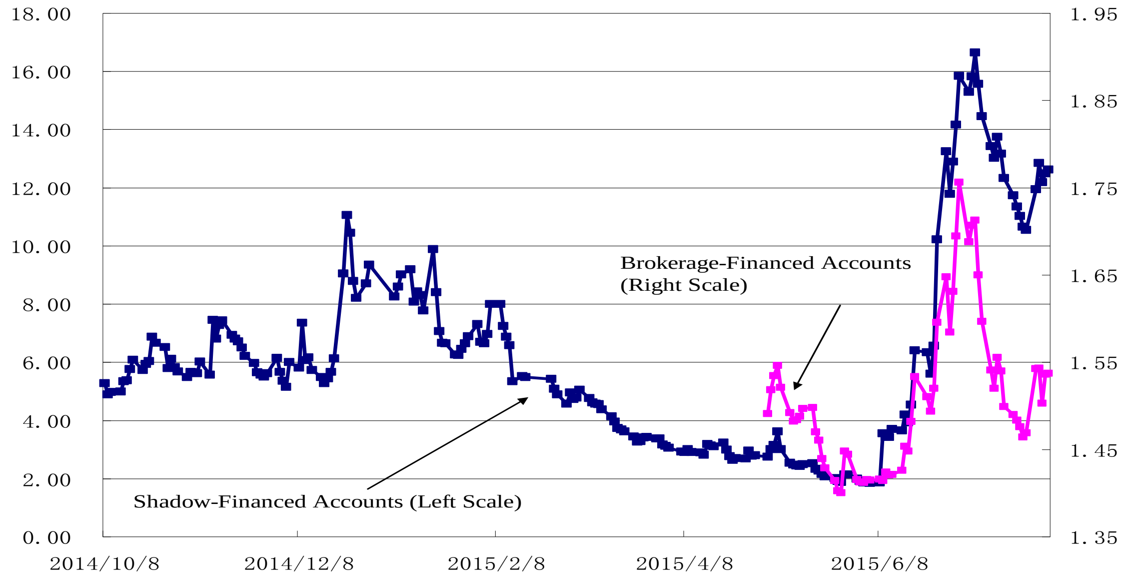

Figure 2. This figure shows the average leverage ratio of brokerage-financed margin accounts (red line) and that of shadow-financed (or peer-financed) margin account at the end of each day for the period May to July 2015 and October 2014 to August 2015, respectively. Account-level leverage ratio is defined 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).