Leverage Network and Market Contagion*

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Abstract

Using unique account-level data that track hundreds of thousands of margin investors' leverage ratios, trading activity, and portfolio holdings at a daily frequency, we examine the effect of margin trading on stock prices during the recent market turmoil in China. We show that idiosyncratic shocks to individual stocks can be amplified and transmitted to other securities with which they share common ownership by levered investors. This transmission effect is particularly strong in market downturns, consistent with forced deleveraging being a possible driver. Further, using a network-based approach, we show that stocks that have more as well as stronger connections to other stocks through common margin ownership have larger selling pressure and crash risk.

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 the Capital Asset Pricing Model, for instance, 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 from China that track hundreds of thousands of margin investors' borrowing (with aggregate debt amount exceeding 100 billion Yuan), 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 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%) for 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.

[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.

Our data, obtained from a major broker in China, as well as an online stock 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. 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 (9.2 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 high past returns.

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.

To carry out our empirical exercise, for each stock at the end of 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. 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.

In our first set of analyses, we examine trading in individual stocks by margin investors as a function of lagged MALP returns. Our prediction is that margin investors are more likely to downsize (expand) an existing holding if other stocks in their portfolios have done poorly (well), plausibly due to the tightening (loosening) of their margin constraints. Our result reveals that the aggregate order imbalance (i.e., total buyer-initiated Yuan volume minus seller-initiated Yuan volume) by all margin accounts in a stock is significantly and positively related to lagged returns of the stock's linked portfolio through margin accounts. Moreover, the response by margin investors is much more pronounced 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), than in other times. Further, in a placebo test where we replace margin investors with non-margin accounts (both in terms of defining order imbalances and linked portfolios), we observe no clear relation between order imbalance and lagged linked portfolio returns.

Building on the trading behavior of margin investors, we next examine the asset pricing implications of margin-induced trading. Specifically, 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 again 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. Again, this return predictive pattern is much stronger in market downturns, and is absent if we instead use non-margin accounts to define the linked portfolio. This asymmetry between market booms and busts helps alleviate the concern that our return forecasting result is due to omitted fundamental factors.

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. (An alternative way of stating this fact is that market volatilities are higher in downturns than in 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 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 resort to the leverage network, in which the strength of each link between a pair of stocks is determined by margin investors' common ownership (i.e., the adjacency matrix A). 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 = 2.53) increase in crash risk (measured by left skewness) subsequently. We label these central stocks "systemically important'' as they 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 Yuan to trying to sustain the market.

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 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

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

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 web-based trading platforms with peer-financing capabilities.[3] Some of these web-based trading platforms allow further splits of a single 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

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

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. For each margin account, our data vendor calculates its end-of-day debit rate, defined as the account's total value (cash plus equity holding) divided by its outstanding debt. The CSRC mandates a minimum debit rate 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 data. Our dataset, on a typical day, accounts for 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

[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.

5-10% 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 95%, suggesting that our broker dataset is a representative sample of the market.

Our second dataset contains all the trading and holdings records of nearly 200,000 accounts from a major web-based trading platform for the period July 2014 to July 2015 (the coverage is rather thin in 2014). 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.

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.

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. Leverage Ratio

We start by defining the leverage ratio for each trading account. Following prior literature (e.g., Ang et al., 2011; Jiang, 2014), we define the leverage ratio 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 web-based margin account, we compute its daily leverage ratio using the inferred daily account wealth and debt value. Note that our web-based account data provide detailed information on daily cash inflows and outflows to 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 10% of the margin debt in the agent account reflects a payment of existing debt (additional borrowing).[5]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, web-based 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 web-based 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).

Figure 2 plots the weighted average leverage ratios of both brokerage-financed margin accounts and web-based margin accounts. We use each account's portfolio value as the weight in computing the average leverage ratio. First, we show that, although the average leverage ratio of the web-based margin accounts is substantially higher than that of brokerage-financed accounts, the two ratios are strongly correlated in our sample period.

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

Second, in the time-series, the weighted average leverage ratio of web-based 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 web-based 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.

3.2. 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 web-based account data contain a little over 130,000 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 web-based 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 web-based margin accounts shoots up to over 50%. Moreover, the total outstanding debt in this period of May to July 2015 is nearly RMB 200 billion, which is roughly 5-10% of the total margin debt in the Chinese market.

3.3. 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. Web-based 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, web-based margin accounts tend to hold smaller stocks with larger growth options and higher past returns, compared to investment accounts at the brokerage firm.

4. Empirical Analyses

4.1. Determinants of Margin Trading

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. Panel A of Table II contains the results from the account-level analysis. Column 1 reports negative and significant coefficients on *DIVERS* (the number of different stocks held by the account) and *WEALTH* (value of the account holdings), suggests that across the full sample, accounts with higher leverage tend to be larger yet hold fewer stocks. This result is primarily driven by the differences between broker-financed and peer-to-peer financed margin accounts. As evident from Table I, peer-financed accounts tend to be smaller, hold fewer stocks but also associated with higher leverage ratios, which is again confirmed in the regression setting by a positive and significant coefficient on the peer-financed account dummy.

When we interact the peer-financed account dummy with account characteristics in Column 2, we find leverage to increase in account size for broker-financed accounts but decrease in account size for peer-financed accounts. This difference is likely due to the fact that a handful of small peer-financed accounts were offered extremely high leverage initially as part of the promotional efforts by the online trading platform.

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. At the same time, we find a positive and significant coefficient on *IDVOL*, suggesting that highly levered accounts favor stocks with higher idiosyncratic volatilities.

We then 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 as shown in Table II Panel B.

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 in the stock; however, the relation becomes insignificant after controlling for other stock characteristics in Column 6.

4.2. 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. 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 "connected" 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.

A. Forecasting Order Submission and Stock 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 stock return predictability. 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. If these investors start to sell other positions in their portfolios in the next day or week, 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 connected stocks.

To test this hypothesis, for each stock, we compute its margin-account linked portfolio ($MALP$) return as the weighted average returns of all stocks with which it shares common holdings by margin investors. We first regress future order imbalance (OI) in the next one to three days on a stock on its margin-account link portfolio return, along with other controls that are included in Table II Panel B:

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

where $MALP_{i,t}$ is the margin-account link 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 3 of Table III shows that the margin-account link 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 = 2.52) more selling pressure tomorrow. Columns 4 to 6 confirm that such a selling pressure persists well beyond the next day.

We then regress future stock returns on the margin-account link portfolio return, along with other controls that are known to forecast stock returns:

$$RET_{i,t+1} = a + b * MALP_{i,t} + \sum_{k=1}^{K} b_k * CONTROL_{i,k} + \varepsilon_{i,t+1}. \quad (3)$$

We look at stock returns in the same next one to three days.

In Columns 1 and 2 of Table IV, we find that $MALP$ returns significantly and positively predict 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 $MALP$ returns today predicts a higher return to stock i tomorrow by 0.204% (t-statistic = 2.42).

In Columns 3 and 4 of Table V, we examine the stock return over the next three days and find the return predictive power of $MALP$ returns to persist. For example, Column 4 shows that a 1% increase in $MALP$ returns today predicts a higher return to stock *i* of 0.612% (*t*-statistic = 2.22) over the next three days, again, after controlling for other known return predictors.

Finally, results in Columns 5 and 6 suggest that the return predictive power of $MALP$ returns is much stronger when a large number of stocks hit the -10% price limit and the aggregate margin constraints are binding. For example, in days where the fraction of stocks having trading halts due to hitting the -10% price limit is below the sample median, a 1% increase in $MALP$ returns today predicts a higher return of 0.228% over the next three days (Column 6). For comparison, in days where the fraction is above the sample median, a 1% increase in $MALP$ returns today predicts a higher return of 0.887% over the next three days (Column 5), more than three time as large as the coefficient in Column 6.

B. Forecasting Correlated Trading and Stock Comovement with Common Holding by Margin Investors

We measure common ownership by margin investors in a way motivated by 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" ($MARHOLD$):

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

Where $S_{i,t}^{m}$ is the number of shares of stock i held by levered investor *m,* $TS_{i,t}$ the number of tradable shares outstanding, and $P_{i,t}$ the close price of stock i on day *t*. 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 pairwise 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 $MARHOLD$:

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

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 400,000 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 pairwise 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 an insignificant 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 pairwise 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 (where the fraction of stocks hitting the lower limit is above the sample median) as that in Column 6 (where the fraction is below the sample median). Indeed, as margin constraints are more likely to be binding, stocks connected through margin holdings are more likely to be sold together and hence their returns co-move more.

4.3. A Network-Based Approach

In this section, we construct a leverage network across stocks in the Chinese market based on their common ownership by 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 i as c_i, then c_i is proportional to the sum of the c_j's for all other nodes $j \neq i$; $c_i = \frac{1}{\lambda}\sum_{j \in M(i)} c_j = \frac{1}{\lambda}\sum_{j=1}^{J} A_{ij c_j}$, 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 higher 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 originated at any part of 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:

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

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:

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

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 basis points (*t*-statistic = -4.02) 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 30-min return 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 increase 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(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 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.

$$RET_{t+1} = a + b * SHAPEPARAM_t + c * LEVERAGE_t + d * INTERACTION_t \\ + \sum_{k=1}^{K} e_k * CONTROL_k + \varepsilon_{t+1} \tag{9}$$

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 "connected" 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 connected 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 1. Summary Statistics

This table reports summary statistics of our sample, which spans the period of May 1st to July 31st, 2015. Panel A reports statistics of all accounts (both margin 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: Forecasting Order Imbalance

This table reports results of return forecasting regressions. The dependent variable in columns 1 to 2 is stock s order imbalance in day t +1, and in columns 3 to 6 is for days t+1 to t+3, respectively. The order imbalance variables are calculated as the difference of Yuan volume of buys minus the Yuan volume of sells divided by the sum of Yuan volume of buys and sells from each margin account who trades the stock. We then use each account s leverage ratio as the weight to obtain the order imbalance at each stock level. 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 shadow-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 month (*MOMENTUM*), its average 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)
MALP	2.577***	2.002***	1.670**	3.213***	2.267**	2.004***
	(4.25)	(3.04)	(2.52)	(3.84)	(2.69)	(2.66)
LEVERAGE		-0.030***	-0.029***		-0.041***	-0.039***
		(-4.29)	(-4.32)		(-5.97)	(-5.89)
DRET		2.783***	2.660***		1.421***	1.342***
		(13.59)	(13.74)		(11.56)	(10.50)
MOMENTUM			-0.014***			-0.012***
			(-3.98)			(-3.12)
TURNOVER			-0.210			-0.307
			(-0.71)			(-0.88)
IDVOL			0.326			0.316
			(0.39)			(0.33)
MCAP			-0.004			-0.001*
			(-1.18)			(-1.94)
Adj. R^2	0.088	0.133	0.197	0.070	0.054	0.115
No. Obs.	51,200	51,200	51,200	51,200	26,400	24,800

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** (-3.08)	-0.009** (-3.64)	-0.009** (-3.48)	-0.009*** (-3.92)	-0.009*** (-4.67)	-0.009*** (-4.51)
LEVERAGE		-0.006 (-1.70)	0.005 (-1.42)		-0.006 (-1.68)	-0.005 (-1.44)
DRET		-0.328*** (-3.41)	-0.334*** (-3.32)		-0.151*** (-2.37)	-0.144*** (-2.00)
MOMENTUM			0.001 (0.22)			0.002 (0.70)
TURNOVER			-0.267 (-2.07)			-0.246 (-2.08)
IDVOL			0.013 (0.03)			-0.362 (-0.83)
MCAP			-0.0003 (-2.41)			-0.0003 (-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

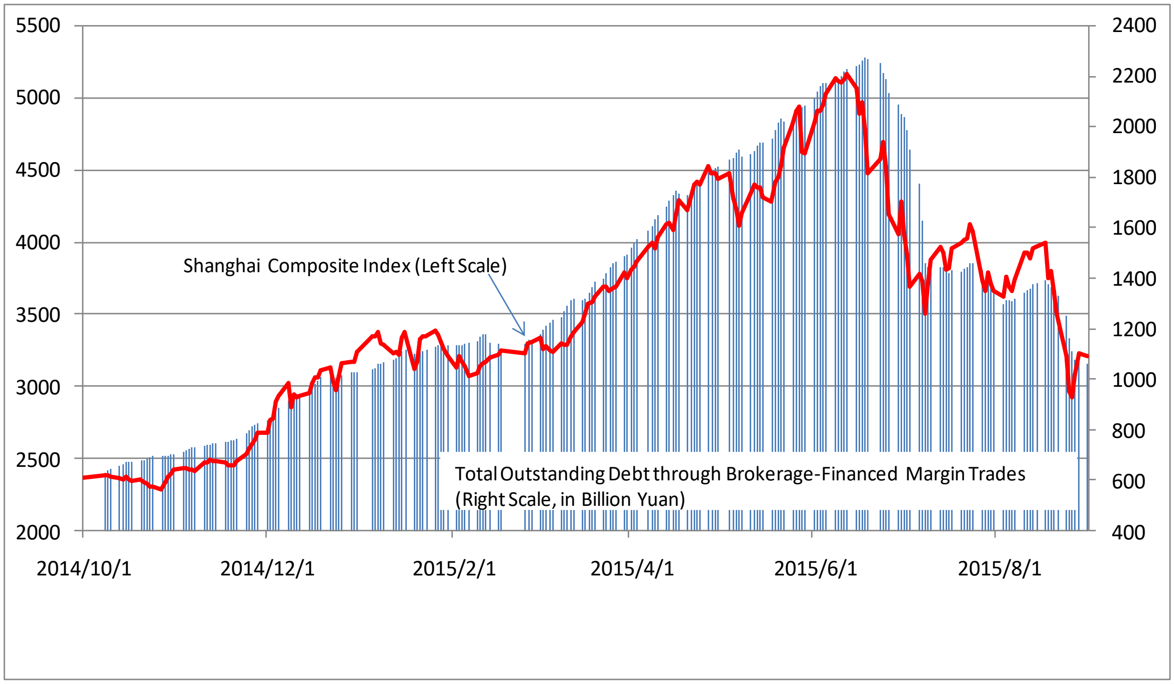

Figure 1. This figure shows the Shanghai Stock Exchange (SSE) Composite Index (the red line), as well as the aggregate brokerage-financed margin debt (blue bars, in billions), at the end of each day for the period October 2014 to August 2015.

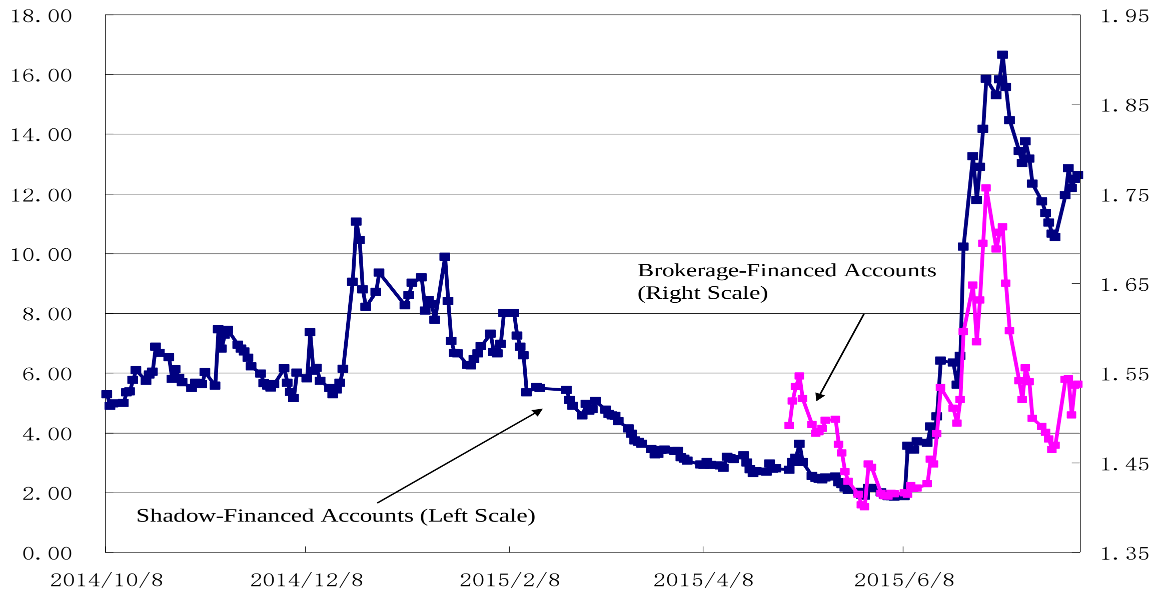

Figure 2. This figure shows the average leverage ratio of brokerage-financed margin accounts (red line) and that of shadow-financed (or peer-financed) margin account at the end of each day for the period May to July 2015 and October 2014 to August 2015, respectively. Account-level leverage ratio is defined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