Leverage Networks and Market Contagion

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Abstract

Using detailed data of margin investors' leverage ratios and trading activities, we provide novel evidence for the effect of margin-induced trading on the cross-section of stock returns during the recent market turmoil in China. We first document deleverage-induced sales. Aggregating this behavior across margin investors, we find a significant return spillover: a stock's return can be strongly forecasted by a portfolio of stocks with which it shares common margin-investor ownership. This pattern is subsequently reversed, and is present only in market downturns. Exploiting three government bailouts of the stock market, we provide additional evidence for the shock transmission role of, and the systematic importance of central stocks in, the leverage network.

Keywords: margin trading, leverage, contagion, network centrality

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 a healthy 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-securities 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. Specifically, a levered investor may be forced to liquidate her positions if her portfolio value falls (or is expected to fall) below some pre-determined level; this margin-induced selling then feeds back into asset prices, leading to a downward spiral. Indeed, both financial economists and the popular press have long associated margin trading with some of the worst market crashes in history (e.g., Schwert, 1989).

A growing theoretical literature carefully models this two-way interaction between security returns and leverage constraints.[1] The core idea is that an initial reduction in security price lowers the collateral value, making the leverage constraint more binding. This then leads to additional selling by levered investors and depresses the price further, which triggers even more selling by levered investors and an even lower price. Moreover, to the extent that investors indiscriminately downsize all their holdings—including those that have not gone down in value and thus have little to do with the initial tightening of the leverage constraint—in face of negative shocks, such deleverage-induced trading could generate a contagion across assets that are linked solely through common ownership by levered investors. In other words, idiosyncratic shocks to one security can be amplified and transmitted to other securities through a margin-investor-holdings network. A similar mechanism, albeit to a much less extent, may also be at work with an initial, positive shock to security value, so

[1] See, for example, Gromb and Vayanos (2002); Fostel and Geanakoplos (2003); Brunnermeier and Pedersen (2009).

long as (some) margin investors take advantage of the loosening of leverage constraints to scale up their holdings.

Despite its obvious importance to researchers, regulators, and investors, testing the asset pricing implications of margin-induced trading has been empirically challenging. We take on this challenge in the paper by exploiting novel *account-level* data from China that track hundreds of thousands of investors' margin borrowing and trading activities (with aggregate margin debt exceeding RMB 100Billion in our sample). The Chinese stock market, together with its economy, has witnessed tremendous growth in the past three decades; in 2015, its total market value, second largest largest in the world, was roughly one third that of the US market.[2]

Our datasets cover an interesting period–from May to July 2015–during which the Chinese stock market experienced a roller-coaster ride: the Shanghai Composite Index climbed more than 15% from the beginning of May (and over 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.[3] Indeed, as evident in Figure 1, the aggregate amount of broker-financed margin debt (exceeding RMB 2 trillion at its peak) and the Shanghai Composite Index moved in near lockstep during this period, with a correlation of over 90%. This is potentially consistent with the narrative that the ability to buy stocks on margin fueled the initial stock market boom and the subsequent deleverage 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 (shadow) margin lending, contain detailed, complete

[2]Despite this unparalleled development, the Chinese stock market remains dominated by individual investors. According to the official statistics released by the Shanghai Stock Exchange, retail trading accounted for over 85% of the total trading volume in 2015.See `http://www.sse.com.cn/aboutus/publication/yearly/documents/c/tjnj_2015.pdf`.

[3]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.

records of individual accounts' leverage ratios, as well as their holdings and trading activity, all at a daily frequency. Among all the margin accounts in our sample, the average leverage ratio of shadow-financed margin accounts is substantially higher than that of the broker-financed ones (6.95 vs. 1.60). Overwhelmingly, levered investors are more speculative than their non-levered peers: e.g., they tend to hold stocks with higher turnover and higher idiosyncratic volatilities.

More important for our purpose, the granularity of our account-level data and the large fluctuation in market returns during our sample period allow us to examine a) trading behavior of margin investors in response to realized portfolio returns (further as a function of the investor's leverage ratio), and b) the impact of such trading on asset prices in both good and bad market conditions. In particular, we are interested in 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, relate to systematic price movements.

In our first set of analyses, we examine trading by individual margin accounts as a function of their lagged portfolio returns. We conjecture that margin investors downsize their holdings after experiencing negative portfolio returns, possibly due to the tightening of margin constraints. It is worth noting that the margin constraint can take its toll even before the account reaches its maintenance margin (beyond which the investor will either have to top up her margin account or be forced to liquidate); as argued theoretically (e.g., Garleanu and Pedersen, 2011), margin investors may downsize their holdings *preemptively* in anticipation of future margin calls.[4]

This prediction is strongly borne out in the data: net trading by individual margin accounts (defined as the RMB value of buy orders minus sell orders, divided by the lagged account value) is significantly and positively related to lagged account returns; in other words, negative account returns indeed predict portfolio downsizing. Importantly, this positive

[4]Consistent with this notion of preemptive downsizing, margin calls and forced liquidation are rarely observed in our data. In Section 4.1, we write down a simple, stylized model of preemptive margin trading to motivate our empirical analyses.

association strengthens with an account's lagged leverage ratio, and is significant only in the subsample in which realized portfolio returns are negative. Moreover, exploiting cross-sectional variations in maintenance margin in our shadow-financed sample (as the terms are negotiated bilaterally), we show that margin-induced selling is particularly strong when the account is close to receiving a margin call (after controlling for the leverage ratio), a prediction that is unique to the deleverage channel.[5]

We next analyze implications of margin-induced trading for the cross-section of asset returns. To the extent that margin investors, collectively, can affect prices, we hypothesize that a stock's future return can be forecasted by the returns of other stocks with which it shares common margin-investor ownership. To test this prediction, we construct a "margin-account linked portfolio" (MLP) for each stock at the end of each day. More specifically, we create a matrix T_0, in which each off-diagonal term $(i,\ j)$ corresponds to the *leverage-weighted* sum of common ownership in the stock pair $(i,\ j)$ by all margin accounts in our sample, scaled by some measure of liquidity (such as market capitalization). A margin account with a leverage ratio of two (debt over equity) thus has twice the weight in each element of T_0 as a margin account with a leverage ratio of one; by the same token, a margin account with a leverage ratio close to zero has virtually no impact on our common-ownership measure.[6] The diagonal elements are deliberately set to zero to isolate the effect of cross-sectional "contagion" from the stock-level return continuation/reversal. The margin-account linked portfolio return ($MLPR$) is then the product of matrix T_0 from the previous day and the vector of daily stock returns.[7]

Our prediction is again borne out in the data. $MLPR$ significantly and positively fore-

[5]In our broker-financed sample, all margin accounts face the same maintenance margin set forth by the China Securities Regulatory Commission (CSRC), so the account leverage ratio is perfectly correlated with its distance to a margin call.

[6]Our definition of stock linkages differentiates our study from prior research on common ownership by mutual funds (e.g., Greenwood and Thesmar, 2011), where leverage does not play any role.

[7]In our main analyses, we report results based on the combined sample of broker-financed and shadow-financed margin accounts to maximize the test power. In Online Appendix Tables, we show that our results hold with either type of margin accounts.

casts the stock's next-day return, which is then gradually reversed in the subsequent two weeks. This return pattern is present only in the market crash period, and remains economically and statistically large after controlling for the stock's own leverage and other known predictors of future returns. Moreover, the return pattern is absent if we use instead non-margin account holdings to construct a similarly-defined linked portfolio.[8] Taken together, these empirical results—a) the gradual return reversal, b) asymmetry between market booms and busts, and c) differences between margin and non-margin accounts—help alleviate the concern that our documented return-spillover pattern is a reflection of stocks with common investor ownership experiencing common fundamental shocks. (In subsequent tests, we use government bailouts as plausibly exogenous shocks to a subset of stocks, and study how these shocks are then transmitted to other stocks in margin-investor's portfolios, to provide potentially causal evidence for the shock-transmission role of the leverage network.)

Our next set of analyses ties the here-documented margin-induced contagion to the well-known asymmetry in return comovement—the ubiquitous finding that in nearly all asset markets, securities comove much more strongly in bust periods than in boom periods.[9] In a simple regression to explain cross-sectional variation in pairwise return comovement (defined as the product of daily excess returns of two stocks), our result reveals 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 common margin-investor ownership is associated with a 0.17 (10^{-4}, t-statistic = 3.18) increase in return comovement in market downturns and a much smaller 0.05 (10^{-4}, t-statistic = 5.83) increase in market booms. For reference, the difference in average pairwise comovement between up and down markets in our sample is about $1 * 10^{-4}$. Again, this

[8] This result runs contrary to prior findings that common ownership by mutual funds (mostly unlevered) also leads to cross-stock return predictability (e.g., Anton and Polk, 2016). One likely explanation is that the return pattern based on mutual fund holdings is due to the strong flow-performance relation, which is absent in the setting of non-levered household portfolios.

[9] An equivalent way of stating this fact is that market volatilities are higher in down markets than in up markets. See, for example, Bates (1997), Bakshi et al. (1997), and Dumas et al. (1998).

asymmetry disappears if we focus instead on common ownership by non-margin accounts.

Finally, we draw on recent development in network theory to shed more light on how direct, as well as indirect, links between stocks resulting from common margin-investor holdings may relate to aggregate market movements. In particular, we argue that stocks that are central in this leverage network—i.e., the ones that are subject to adverse shocks originated from any part of the network—should experience more selling pressure and therefore lower returns than peripheral stocks during the market downturn. Using eigenvector centrality as our main measure of a stock's importance in the network, we find that after controlling for a comprehensive list of stock characteristics, a one-standard-deviation increase in a stock's network centrality is associated with a 10bps (t-statistic = 2.19) lower daily return during the bust period. Importantly, much of this negative return can be attributed to central stocks' higher downside betas relative to peripheral stocks.

The fact that central stocks are systematically important has useful implications for the Chinese government, which shortly after the market meltdown, pledged/devoted hundreds of billions of RMB in an effort to stabilize the market. We have obtained the entire list of stocks on the Shanghai Stock Exchange that were purchased by the Chinese government in three separate bailout waves, and have three interesting findings. First, the initial bailout effort did not focus on central stocks in our leverage network; the government then targeted more central firms in the second, and especially the third wave. Second, the average centrality of stocks purchased by the government in each day is positively associated with the the same- and next-day market returns, suggestive that shocks to central stocks have a larger impact on the entire market. Third, in these bailout waves, not only did the stocks purchased by the government rise in value, but so did the ones that a) were *not* directly purchased by the government but b) were *linked to* the ones purchased through common margin-investor ownership, relative to other stocks in the market. This last result provides possibly causal evidence for the role of the leverage network in propagating idiosyncratic shocks across stocks.

2 Related Literature and Contributions

Our paper is closely tied to the recent theoretical literature on how asset liquidity and returns interact with leverage constraints. Gromb and Vayanos (2002, 2017), Geanakoplos (2003), Fostel and Geanakoplos (2008), Brunnermeier and Pedersen (2009) and Garleanu and Pedersen (2011) develop competitive equilibrium models in which smart investors (arbitrageurs or market makers) may provide sub-optimal amounts of liquidity because they face time-varying margin (collateral) constraints. This further impacts asset returns and return correlations. Our paper, using account-level data, is the first to provide supportive evidence for the model predictions that levered investors indeed scale down their holdings in response to the tightening of leverage constraints, which depresses prices and causes contagion across a wide range of securities. Closely related to our paper is some recent work by Kahraman and Tookes. By comparing marginable vs. otherwise similar non-marginable stocks in the Indian market, Kahraman and Tookes (2018a, 2018b) analyze the impact of margin trading on stock liquidity as well as commonality in liquidity. While it is not the focus of their analyses, Kahraman and Tookes (2018b) also examine the relation between common margin-investor ownership and stock return comovement and find that the link is stronger in periods of market distress. Our detailed account-level data, however, allow us to precisely measure each account's daily leverage ratio (which is not available in the Indian setting) and examine its impact on account trading, and ultimately stock returns.[10]

Our paper also complements the recent literature on excess volatility and comovement induced by common institutional ownership (e.g., Greenwood and Thesmar, 2011; Lou, 2012; Anton and Polk, 2014). These studies focus on common holdings by non-margin investors such as mutual funds, and the transmission mechanism examined there is a result of the well-

[10]The instrument used by Kahraman and Tookes (2018a, 2018b)—that stocks are periodically added to/deleted from the marginable list (a featured also shared by the Chinese market)—is invalid in our setting. This is because a) virtually all margin investors in our sample hold both marginable and non-marginalble stocks (a margin investor can use his own money to buy non-marginable stocks and borrowed money to buy marginable stocks), and b) this rule does not apply to shadow-financed margin accounts.

known flow-performance relation. Our paper contributes to the literature by highlighting the role of leverage, in particular deleveraging-induced selling, in driving asset returns.[11] A unique feature of our leverage channel is that its return effect is asymmetric (Hardouvelis and Theodossiou, 2002); using the recent boom-bust episode in the Chinese stock market as our testing ground, we show that the leverage-induced return pattern is present only in market downturns. Relatedly, our findings are also consistent with recent studies that document a higher correlation in hedge fund returns following adverse shocks (see, Boyson, Stahel, and Stulz, 2010, and Dudley and Nimalendran, 2011, Jiang, 2015, among others). Our account-level leverage and holdings data allow us to provide direct evidence for the mechanism underlying the asymmetric rise in return correlations.

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

Finally, given the increasing importance of the Chinese market in the world economy (second only to the US), understanding the boom and bust episode in 2015 is an informative exercise in and of itself. Taking advantage of our novel account-level data, we provide the first comprehensive evidence of how margin-induced trading may affect asset prices in the

[11] In contrast to prior studies on mutual funds, non-margin accounts in our sample trade in the opposite direction of past returns.

cross-section during this extraordinary episode. In a contemporaneous paper working with the same datasets, Bian, He, Shue, and Zhou (2018) study leverage-induced fire sales in the stock market and the resulting price impact. While we also present evidence of leverage-induced trading (preemptive and forced) by margin investors, our focus is squarely on the cross-sectional transmission of negative shocks across stocks that are connected through common margin-investor ownership. Moreover, looking at the initial boom of the same episode in China, Hansman, Hong, Jiang, Liu, and Meng (2018) provide evidence that margin debt indeed helped fuel the initial rally in the Chinese stock market, a result that nicely complements ours. They do not, however, study account-level behavior nor the contagion effect as we do. Finally, Peng and Liao (2018) study the interplay between extrapolative beliefs and the disposition effect using account-level trading records during the same 2014-15 Chinese stock market bubble; they do not, however, analyze the behavior of margin investors during this episode.

3 Data

3.1 Institutional Background

The last two decades have witnessed tremendous growth in the Chinese stock market. As of May 2015, the total market capitalization of China's two stock exchanges, Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE), exceeded 10 trillion USD, second only to the US. Despite this unparalleled growth, margin trading was not officially authorized until 2010, although it occurred informally on a small scale. The China Securities Regulatory Commission (CSRC) launched a pilot program of margin financing via brokerage firms in March 2010 and margin financing was officially authorized for a subset of securities in October 2011. To obtain margin financing from a registered broker, an investor needs to have a trading account with the same brokerage firm for at least 18 months, with a total account value (cash and stock holdings combined) over RMB500,000 (or about USD80,000).[12] The initial margin (= 1-debt value/total holding value) is set at 50% and the maintenance margin is 23%. A list of around 900 stocks eligible for margin trading is determined by the CSRS, and is periodically reassessed and updated.[13]

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

In part to circumvent the strict regulations on broker-financed margin borrowing imposed by the CSRC, peer-to-peer (shadow) financed margin trading became popular after 2014. These informal financing arrangements come in many different shapes and forms, but most of them allowed 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 small investors provide an initial injection of cash to a mother account, for instance 20% of the total trust's value. The remaining 80% is then funded by margin debt, usually from retail investors, in the form of wealth management/savings products. As such, the umbrella trust structure can achieve a much higher leverage ratio on the many child accounts linking to the mother account, than what is allowed by the official rule. In addition, this umbrella trust structure allows small investors to bypass the RMB500,000 minimum threshold required to obtain margin financing from registered brokers.

[12]The account-age requirement was lowered to six months in 2013.

[13]We do not exploit the variation in the marginal-stock list, because a) nearly all margin investors in our sample hold both marginable and non-marginable stocks, and b) as detailed later, shadow-financed margin investors are not bound by this rule.

The vast majority of this shadow-financed borrowing takes place on a handful of online trading platforms with peer-to-peer financing capabilities.[14] Some of these trading platforms may allow further splits of a single umbrella trust, increasing the effective leverage further still and allowing different maintenance margins across different investors (child accounts). Finally, shadow-financed margin borrowing allows investors to take levered positions on any stocks, including those not on the marginable-securities list.

Since shadow-financed margin trading falls in the unregulated grey area, there is no official statistics regarding its size and effective leverage ratio. Estimates of its total size from various sources range from RMB 0.8 trillion to RMB 3.7 trillion. It is widely believed that the amount of margin debt in this shadow system is at least as large as that through the formal broker channel. For example, Huatai securities Inc., one of China's leading brokerage firms, estimates that the total margin debt peaked in 2015 at 7.2% of the total market capitalization of all listed firms, with half of that coming from the unregulated shadow financial system. This ratio goes up to 19.6% if one considers only the free-floating shares, as a significant fraction of the market is owned by the Chinese Government and other state-owned enterprises.[15]

With both types of margin trading in China, the lender takes control of the account if the margin value falls below the maintenance level. The lender would generally liquidate all assets in the account aggressively with little consideration for execution quality. In anticipation of a large liquidation discount in the event of a margin call, margin investors tend to manage their margin borrowing pro-actively and preemptively by delevering long before hitting their maintenance margins. We sketch a stylized model of such preemptive margin trading behavior in Section 4.1.

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

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

3.2 Data Samples and Summary Statistics

Our study utilizes two proprietary account-level databases. The first contains the complete records of equity holdings, cash balances, and trade executions of all accounts from a leading brokerage firm in China for the period May to July, 2015. It has over five million active accounts, over 95% of which are retail accounts.[16] A little less than 180,000 accounts are qualified for margin trading. For each margin account, we observe its end-of-day debit ratio, defined as the account's total value (cash plus equity) divided by its outstanding debt. The CSRC mandates a minimum debit ratio of 1.3, equivalent to a maintenance margin of 23% (=(1.3-1)/1.3). On a typical day, our brokerage data account for nearly 5% of the combined trading volume in the Shanghai and Shenzhen stock exchanges. The total amount of margin debt in our brokerage data accounts for 5-6% of the aggregate brokerage-financed margin debt in China. Moreover, the correlation in trading volume between our brokerage data and the whole market is over 90%. These statistics indicate that our brokerage accounts constitute a sizable and representative sample of the whole market.

Our second dataset, obtained from a leading online trading platform, contains daily trading and holding records of more than 250,000 accounts for the same time period with margin trading capability. After carefully applying all the data filters (e.g., with non-missing information on daily cash and stock holdings, and outstanding margin debt), we end up with a sample of 153,000 margin accounts. More details of the data cleaning/filtering procedures are described in Appendix A. As described above, these margin accounts are linked to a set of mother accounts on the same trading platform. Margin calls are rarely observed in either sample: they are virtually none-existent in the broker-financed sample; in the shadow-financed sample, forced liquidation resulting from margin calls accounts for less than 4% of all sell transactions. (Galbraith, 2009 makes similar observations in the US.)

In addition to these two proprietary account-level databases, we also obtain stock-level

[16] Consistent with the dominance of retail trading in China, removing institutional accounts from our sample has virtually no impact on our results.

data, including daily trading volume, stock returns, market capitalizations, along with many other stock characteristics from WIND, a leading financial data provider in China.

Table 1 presents summary statistics of our sample. As can be seen from Panel A (which shows the aggregate statistics of the two data sources), the total amount of margin debt in the brokerage sample is around RMB 100 billion, and that in the shadow-financed sample is around RMB 44 billion. Margin debt accounts for about a third of total account value in the brokerage sample, and accounts for over two thirds in the shadow-financed sample, indicating higher leverage in the shadow market.

For comparison (also serving as a benchmark), we assemble 330,000 (180K+150K) matched non-margin accounts from the brokerage sample, using a propensity-score-matching approach. Specifically, we estimate a logit model of the probability that an account is a margin account based on the following characteristics: the number of stocks held, RMB value of stocks held, total account value, number of stocks traded, RMB value of stocks traded, and number of orders submitted. We then identify, for each margin account, a matched non-margin account using the nearest neighbor matching technique without replacement. The amount of margin debt is, by definition, zero for these accounts.

Similar to Adrian and Shin (2010) and Ang et al. (2011), We define the leverage ratio of each margin account as:

$$ACC\_LEVER = \frac{\textit{Total Portfolio Value}}{\textit{Total Portfolio Value-Total Debt Value}}. \quad (1)$$

For our brokerage-financed sample, we directly observe the leverage ratio at the end of each day. For the sample of shadow-financed margin accounts, we observe the end-of-day value of equity and cash holdings, as well as the amount of margin debt, which allow us to compute the leverage ratio for each account. Unlike the broker-financed sample (which is strictly regulated), shadow-financed margin accounts have leverage ratios that vary substantially both in the cross-section and in the time-series, reflecting the fact that both the initial margin and maintenance margin are negotiated bilaterally—between the investor (or borrower) and the lender—without regulatory supervision.

Figure 2 plots the value-weighted average leverage ratios of both brokerage-financed and shadow-financed margin accounts, where the weight is proportional to each account's equity value (i.e., portfolio value minus debt value).

A few observations are worth noting. First, although the average leverage ratio of shadow-financed margin accounts is substantially higher than that of brokerage-financed accounts, the two move in near lock-step. One way to think about this result is that while investors with different risk preferences sort themselves into different trading venues, they are nonetheless affected by similar market-wide shocks (be it sentiment or risk bearing capacity). Second, the average leverage ratios of both the shadow-financed and broker-financed samples decrease steadily from May to June of 2015. A big part of this decline can be attributed to the contemporaneous market rally in the first half of the year. Indeed, as shown in Figure 1, the total amount of outstanding margin debt increases substantially in the first six months of 2015, just not as dramatic as the market run-up. Third, Figure 2 also shows a sudden and dramatic increase in leverage ratios of both brokerage-financed and shadow-financed margin accounts in the last two weeks of June and the first week of July; this is again largely due to the contemporaneous market movements. Finally, despite the big negative market returns in the second half of July, the leverage ratio in both samples plummeted, possibly driven by both voluntary and forced de-leveraging.

Panels B and C of Table 1 then examine various account and stock characteristics associated with these different investment accounts. Three observations are worth pointing out: a) broker-financed margin accounts are larger and more active relative to both broker-non-margin accounts and shadow-financed margin accounts; b) shadow-financed margin accounts have, on average, much higher leverage ratios than broker-financed margin accounts (6.95 vs. 1.60); c) broker accounts, both margin and non-margin, tend to hold stocks with similar characteristics, while shadow-financed margin accounts tend to hold stocks with higher past returns and lower book-to-market ratios (growth and winner stocks). These results suggest that broker-financed margin investors (who are larger and more active) and shadow-financed margin investors (who take on substantially higher leverage) can both play an important role in propagating shocks across stocks.

3.3 Investor and Stock Characteristics

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

$$ACC\_LEVER_{j,t+1} = \alpha + \beta \times AccountCharacteristics_{j,t} + \varepsilon_{j,t+1}, \tag{2}$$

where $ACC\_LEVER_{j,t+1}$ is the leverage ratio of account j at the end of day t+1. The set of investor characteristics includes $\#STOCKS$ (the number of stocks held by the account), $ACCOUNT\ VALUE$ (cash value plus stock holdings), and $ACCOUNT\ AGE$ (since account opening). As can be seen from Panel A of Table 2, there is an interesting difference between broker-financed margin accounts and shadow-financed accounts. For the brokerage-financed sample, investors with higher leverage ratios have, on average, a larger account value and a larger number of stock holdings (in other words, larger accounts with more diversified holdings). The opposite, interestingly, is true for the shadow-financed sample, which is likely due to the different risk preferences of the two types of investors.

Next, we describe the types of stocks that are more commonly held by levered investors. Specifically, for each stock in each day, we define leverage as the weighted-average leverage ratio of all margin accounts that hold the stock, where the weights are proportional to each account's own capital. We then conduct the following panel regression:

$$LEVERAGE_{i,t+1} = \alpha + \beta \times StockCharacteristics_{i,t} + \varepsilon_{i,t+1}, \tag{3}$$

where $LEVERAGE_{i,t+1}$ is the average leverage ratio for stock i at the end of day t+1. The set of stock characteristics includes $DRET$ (stock returns in the previous day), $BMRATIO$ (book to market ratio at the end of the previous month), $MOMENTUM$ (cumulative stock returns during the previous 120 trading days), $TURNOVER$ (the turnover ratio during the prior 120 trading days), $IDVOL$ (the idiosyncratic volatility after controlling for the Chinese Fama-French three factors and the Carhart momentum factor, during the previous 120 trading days), and $MCAP$ (lagged market capitalization based on tradable shares at the end of the previous month). As shown in Column 7 of Panel B, which includes all stock characteristics in the same specification, levered investors are more likely to hold larger stocks and more speculative stocks—those with higher idiosyncratic volatilities and share turnover. Consequently, shocks to speculative stocks, even if idiosyncratic in nature, may be propagated to other stocks in the market through common margin-investor ownership.

4 Empirical Analyses of the Leverage Network

4.1 A Stylized Model

Given that margin calls and forced liquidations are generally rare (Galbraith, 2009), we sketch a simple stylized model of preemptive trading to motivate our empirical measures of deleverage-induced selling. For tractability, we make two simplifying assumptions following Greenwood, Landier, and Thesmar (2015). First, a margin investor starts each period at her optimal leverage ratio, which may be time-varying. An immediate implication of this assumption is that at the end of each period, the margin trader has an incentive to adjust her positions to undo the impact of portfolio returns on her leverage ratio.

More specifically, let A and D denote the dollar values of the margin trader's assets and margin debt, respectively, then her beginning-of-the-period leverage ratio is: $L_{0,j} = \frac{A_{0,j}}{A_{0,j}-D_{0,j}}$. Let $r_{1,j}$ denote her portfolio return in the period. Further assume zero interest on the margin debt. At the end of the period (before any portfolio adjustment), her leverage ratio becomes $L_{1,j} = \frac{A_{0,j}(1+r_{1,j})}{A_{0,j}(1+r_{1,j})-D_{0,j}}$. To restore the account leverage ratio back to its optimal level, $L_{0,j}$, she needs to buy $X_{1,j}$ worth of risky stocks through margin borrowing (a negative X indicates de-leveraging), such that:

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

where $L_{0,j}-1$ can be interpreted as an alternative definition of the leverage ratio: debt value/(portfolio value-debt value). It is clear that after experiencing a negative portfolio return, the margin trader needs to liquidate a larger fraction of her portfolio if her initial leverage ratio is higher.

Our second simplifying assumption is that the margin trader scales up or down all her positions *proportionally* based on the initial portfolio weights. In other words, the dollar amount of leverage-induced trading in stock i by margin trader j is:

$$X_{1,i,j} = A_{0,j}\omega_{0,i,j}(L_{0,j}-1)r_{1,j}. \tag{5}$$

Aggregating this across a total of M margin traders, we derive the total amount of margin-induced trading in stock i:

$$X_{1,i} = \Sigma_{j=1}^{M}[A_{0,j}\omega_{0,i,j}(L_{0,j}-1)r_{1,j}]. \tag{6}$$

Next, scaling the dollar amount of trading in each stock by some measure of liquidity provision ($Liq_{0,i}$, which can be proxied by market capitalization or daily trading volume), we define margin-induced price pressure as:

$$\frac{1}{Liq_{0,i}}\Sigma_{j=1}^{M}[A_{0,j}\omega_{0,i,j}(L_{0,j}-1)r_{1,j}]. \tag{7}$$

For expositional convenience, we recast everything using matrix algebra. Let R denote an $N \times 1$ vector of stock returns, Ω an $M \times N$ matrix of portfolio weights such that each row sums up to 1, $diag(A_0)$ an $M \times M$ diagonal matrix whose diagonal terms are $A_{0,j}$, $diag(L_0)$ an $M \times M$ diagonal matrix whose diagonal terms are $L_{0,j}$; $diag(LIQ_0)$ an $N \times N$ diagonal matrix whose diagonal terms are $Liq_{0,i}$. The vector of margin-induced price pressure on all stocks can then be expressed as:

$$T \times R, \text{ where } T = diag(LIQ_0)^{-1} \times \Omega' \times diag(A_0) \times [diag(L_0) - I] \times \Omega. \tag{8}$$

One way of interpreting the transmission matrix, T, is that it governs the propagation of idiosyncratic shocks through common ownership by margin investors; in particular, the higher the leverage ratio of the margin investor, the larger her weight in transmitting idiosyncratic shocks. We further set the diagonal terms of T to zero (and denote the resulting matrix T_0), to isolate the contagion effect across stocks from individual stocks' own return continuation/reversal. We then define margin-account linked portfolio returns ($MLPR$) as $T_0 \times R$. Intuitively, $MLPR_i$ captures the price impact stemming from all stocks that are connected to stock i via common ownership by margin traders.

4.2 Leverage-Induced Trading

In our first set of analyses, we examine the key premise in our stylized model that margin investors scale up/down their existing holdings in the direction of past portfolio returns. In particular, we conduct a panel regression of daily trading by each margin account on its lagged portfolio returns, leverage ratio, as well as the interaction between the two:

$$TRADE_{j,t+1} = \alpha + \beta_1 ACC\_RET_{j,t} + \beta_2 ACC\_LEVER_{j,t} + \beta_3 ARET_{j,t} \times ACC\_LEVER_{j,t} + \varepsilon_{i,t+1}, \tag{9}$$

where $TRADE_j$ is the value of all buys orders minus that of all sell orders by investor j, divided by the lagged account value; ACC_RET_j is the lagged portfolio return of investor j. To capture the potential asymmetry between leverage-induced buying vs. leverage-induced selling, we separate portfolio returns into positive and negative realizations: $PositiveACC\_RET$ and $NegativeACC\_RET$. We also include in our regression account- and date-fixed effects to absorb any account-level as well as market-wide variations.

The results are reported in Table 3. Column 1 shows the result from the sample of broker-financed margin accounts. The coefficient estimates on $PositiveARET$ and $NegativeARET$ are both negative, suggesting that absent leverage (i.e., $ACC\_LEVER = 0$), households in China are contrarian traders.[17] The coefficients on the interaction terms between lagged portfolio returns and lagged leverage ratios are significantly positive. This is consistent with our predictions that a) margin investors adjust their portfolios in the direction of past account returns, arguably to restore their optimal leverage, and b) margin investors trade more aggressively when their initial leverage is higher. Moreover, the coefficient on this interaction term following negative portfolio returns is nearly two times as large as that following positive returns (0.165 vs. 0.083). The difference of 0.082 is highly statistically significant. Again, this is consistent with our prediction that margin investors have a stronger tendency to reduce leverage when faced with a more binding leverage constraint than a tendency to increase risky holdings in response to a less binding leverage constraint.

Columns 2 repeats the same exercise with shadow-financed margin accounts. The results are similar to those reported in Column 1. In particular, the coefficients on the interaction

[17] This is consistent with the findings of Shumway and Wu (2006), Bian, Chan, Shi, and Zhu (2018), and Peng and Liao (2018).

terms (of past returns and leverage ratios) are not statistically different between the broker-financed sample and the shadow-financed sample: 0.083 vs. -0.014 for positive portfolio returns and 0.165 vs. 0.188 for negative portfolio returns. Given this similarity in margin investors' response to past portfolio returns, we combine the two samples in our subsequent analyses at the stock level, to maximize the power of detecting any impact of margin-induced trading on asset prices.

In Column 3, we explore variations in maximally-allowed leverage ratios (or maintenance margins) across shadow-financed margin accounts, which are bilaterally negotiated. In other words, we hone in on cases in which the two shadow-financed margin accounts have the exact same leverage ratio but face different degrees of margin constraints, due to differences in their maintenance margins. There is no similar variation in maintenance margins across broker-financed accounts, as this ratio is determined by the CSRC and applies to all broker-financed margin accounts. More specifically, we add, to the right hand side of the regression equation, an account's distance to the maximally-allowed leverage ratio and its interactions with past account returns. The coefficient on the interaction term between negative portfolio returns and the distance to a margin call is significantly negative, indicating that shadow-financed margin investors indeed downsize their holdings more aggressively when they are closer to receiving margin calls. Moreover, the interaction term between negative portfolio returns and the leverage ratio itself is no longer significant, which suggests that it is the leverage constraint (i.e., distance to a margin call), rather than margin borrowing itself, that triggers de-leverage following negative portfolio returns.

After establishing that margin investors indeed downsize their holdings in response to negative portfolio returns, we next explore the characteristics of stocks that are more likely to be sold by levered investors in response to the tightening of margin constraints in Appendix Table A1. To this end, we conduct a three-dimensional panel regression, where the dependent variable is the net trading in a stock by each margin account on any given day—defined as the value bought minus sold in the stock divided by the lagged account value. On the right hand side of the equation, we include triple interaction terms of lagged account returns (negative only) × the leverage ratio × various stock characteristics, as well as all all the double-interaction terms and the underlying variables themselves.

While both broker-financed and shadow-financed margin accounts tend to sell growth stocks in response to negative portfolio returns, their selling behavior differs along other dimensions: shadow-financed accounts (Column 2), relative to their broker-financed peers (Column 1), are more likely to scale down positions with lower idiosyncratic volatilities and smaller portfolio weights. In other words, when faced with the pressure to deleverage, shadow-financed margin accounts choose to concentrate their bets on stocks with higher idiosyncratic volatilities. Column 3 reports regression results combining the broker-financed and shadow-financed samples. The small R^2 values across all specifications suggest that the decision to scale down does not vary systematically with observable stock characteristics.

4.3 Margin-Account Linked Portfolio Returns

We now take the main prediction of our stylized model to the data—whether common margin-investor ownership (weighted by account leverage ratios) can indeed lead to a return spillover effect. Our main independent variable is the margin-account linked portfolio return ($MLPR$) introduced in Section 4.1; the variable measures the buying/selling pressure stemming from stocks that are linked to the one in question through the margin-investor-holdings network. Our predictions are that a) $MLPR$ should positively forecast stock returns in the near future, as margin investors adjust their portfolios; b) since the return is driven by non-fundamental price impact, it should revert in the longer run; c) the effect should be stronger when the market is doing poorly than when the market is doing well.

To test these predictions, we conduct Fama-MacBeth forecasting regressions of future stock returns:

$$RET_{i,t+1} = \alpha + \beta \times MLPR_{i,t} + \sum_{k=1}^{K} \gamma_k \times CONTROL_{i,k,t} + \varepsilon_{i,t+1}, \tag{10}$$

where $RET_{i,t+1}$ is the return of stock i on day t+1. Along with a set of stock characteristics that are known to forecast future returns, we also include on the right hand side of the equation the non-margin-account linked portfolio return ($NMLPR$), defined in a similar manner as $MLPR$. More precisely, $NMLPR$ is computed using 330K matched non-margin accounts described in Section 3.2—so the account leverage ratio (account value divided by own capital) is a constant of one for all these accounts.

The results are shown in Table 4. Column 1 reports coefficient estimates from the whole sample. There is a significant and positive correlation between $MLPR$ and the next-day stock return. A one-standard-deviation increase in $MLPR$ predicts a higher next-day return to stock i of 19 bps ($= 0.21 \times 0.009$, t-statistic = 2.24). This result holds after controlling for the stock's lagged leverage ratio, past returns, and an array of other stock characteristics.

Columns 3 and 5 repeat the same exercise but now for up markets and down markets separately. We define up and down markets using June 12, 2015 (the peak of the market) as the cutoff.[18] It is clear from these two columns that the return predictive power of $MLPR$ is present only in market downturns. Specifically, the coefficient estimates on $MLPR$ for the up market and down market are 0.002 (t-statistic = 0.41) and 0.014 (t-statistic = 2.97), respectively.[19] This asymmetry in margin-induced price impact between up and down markets is consistent with the notion that when faced with a tightened margin constraint, investors have to scale down their holdings *immediately*, leading to a significant price effect;

[18] We also use an alternative definition of market booms/busts based on the number of stocks that a) hit the -10% price limit in the day or b) are suspended from trading from the opening, and obtain very similar results.

[19] In Appendix Table A2, we repeat the exercise separately for broker-financed and shadow-financed margin accounts. Our results indicate that both types of margin investors contribute to the here-documented return pattern.

the reverse, however, is not true for a loosened margin constraint.

In Columns 2, 4, and 6, we conduct similar regressions as those reported in Columns 1, 3, and 5, except that now we also include $NMLPR$ on the right hand side. In stark contrast to what we see for $MLPR$, in all specifications, the coefficient on $NMLPR$ stays economically small and statistically insignificant; in some specifications, it even has the wrong sign. So long as margin investors and non-margin investors (with similar account characteristics given our matching procedure) do not differ systematically in their portfolio choice, these results suggest that the return forecastability of $MLPR$ is likely due to margin investors' tendency to trade in response to changing margin requirements/conditions.

To provide further support for the mechanism of deleverage-induced price impact, we conduct another placebo test using account-level data from 2007, when the Chinese stock market experienced a similarly-spectacular boom-bust cycle.[20]. Given that margin trading was completely banned in this period, we construct $NMLPR$ using the largest 300,000 investors from a leading brokerage firm in China. We then conduct similar return forecasting regressions as in Table 4, both jointly and separately for the boom and bust periods in 2007. Similar to what we see in Columns 2, 4, and 6, $NMPLR$ remains statistically and economically insignificant (untabulated for brevity). This result helps highlight the importance of deleverage-induced sales in transmitting adverse shocks in market crashes.

Finally, since the short-term return effect associated with $MLPR$ is the result of uninformed price pressure, we expect the return pattern to revert in subsequent days. To test this, we repeat the same regression as in equation (10), but now focus on stock returns over the longer horizon (the next 10 trading days, for example). The results are shown in Table 5; we consider only the bust period as the return predictability of $MLPR$ is entirely from the bust period. For ease of comparison, we also include the result for day $t+1$ in Column (1). Consistent with the price-impact interpretation, there is a full reversal to the initial

[20]The Shanghai Stock Exchange Composite Index nearly tripled from November 2006 to May 2007; this was then followed by a dramatic crash of about -60% (see, e.g., Andrade, Bian, and Burch, 2013)

price effect in the subsequent two weeks; by the end of the 10th trading day, the cumulative return associated with $MLPR$ is indistinguishable from zero.

4.4 Asymmetry in Return Comovement

The results from the previous section suggest that leverage-induced trading can help propagate shocks (especially adverse shocks) across stocks that are commonly held by margin investors. Another way of demonstrating this contagion effect is to analyze pairwise stock comovement. In particular, as margin investors indiscriminately downsize all their holdings in response to tightening leverage constraints, we expect to see stronger comovement among stock pairs with larger common margin-investor ownership, especially during market downturns. This prediction allows us to speak directly to the well-known, ubiquitous finding that return comovement is generally higher when the market is performing poorly than when the market is performing well.

To test this prediction, at the end of each day, we measure common margin-investor ownership (CMO) of a pair of stocks as the total holding value in these two stocks by all levered investors that hold both stocks, weighted by each investor's leverage ratio. More specifically, CMO is defined as:

$$CMO_{i,j,t} = \frac{\sum_{m=1}^{M}(HV_{i,t}^{m} + HV_{j,t}^{m}) \times L_{t}^{m}}{MV_{i,t} + MV_{j,t}}, \tag{11}$$

where $HV_{i,t}^{m}$ is the value of holdings in stock i by levered investor m and $MV_{i,t}$ is the market capitalization of firm i.[21] It is worth noting that $CMO_{i,j}$ for a stock pair i and j is closely related to the i,jth and j,ith elements of the transmission matrix T discussed above. The key difference is that $CMO_{i,j}$ is divided by the combined market capitalizations of the two stocks (so is symmetric), whereas $T_{i,j}$ is scaled by the market capitalization of stock i and

[21] CMO bears a close resemblance to the common ownership measure in Greenwood and Thesmar (2011) and Anton and Polk (2014); the key difference is that the weight of each investor in our definition is proportional to her leverage ratio.

$T_{j,i}$ by the market capitalization of stock j. In a placebo test, we construct a similar measure of common non-margin-investor ownership ($CNMO$) for each pair of stocks drawing on the sample of 330K matched non-margin accounts; again, the account leverage ratio (account value divided by own capital) is a constant of one for all non-margin accounts.

Following Anton and Polk (2014), we then estimate a Fama-MacBeth cross-sectional regression of realized return comovement of each stock pair on its lagged CMO (log transformed to mitigate the impact of outliers):

$$COV_{i,j,t+1} = \alpha + \beta \times CMO_{i,j,t} + \sum_{k=1}^{K} \gamma_k \times CONTROL_{i,j,k,t} + \varepsilon_{i,t+1}, \tag{12}$$

where $COV_{i,j}$, the pairwise return comovement between i and j, is the product of daily market-adjusted returns of the two stocks.[22] We also include on the right-hand side of the equation a host of variables that are known to be associated with stock return comovement: the number of analysts covering both firms ($COMANALY$); absolute differences in percentile rankings based on firm size ($SIZEDIFF$), book-to-market ratio ($BMDIFF$), and cumulative past returns ($MOMDIFF$), as well as a dummy variable that equals one if the two firms are from the same industry (and zero otherwise) ($SAMEIND$). We calculate Newey and West (1987) standard errors (four lags) of the Fama and MacBeth (1973) estimates to take into account autocorrelations in the cross-sectional slopes.

The results are shown in Table 6. Column 1 reports results based on the full sample. After controlling for similarities in observable firm characteristics, the coefficient estimate on CMO of 0.097 (t-statistic = 4.12) is both economically large and statistically significant. In Columns 3 and 5, we repeat our analyses for up and down markets separately (again, using June 12, 2015 as the cutoff). The coefficient on CMO in the down market is more

[22] We also measure correlations using intraday returns based on 30-minute intervals and find qualitatively similar results. The economic magnitude, based on this alternative correlation measure, is slightly smaller (but still statistically significant). The reduced economic magnitude is likely due to the frequent trading halts during this period, which tends to bias the correlation estimate toward zero.

than three times as large as that in the up market (0.145 vs. 0.043), and the difference is highly statistically significant with a t-statistic of 2.56.[23] In terms of economic magnitudes, a one-standard-deviation increase in common margin-investor ownership is associated with a 0.17 (*10^{-4}) increase in return comovement in market downturns and a 0.05 (*10^{-4}) increase in market booms. For reference, the difference in average pairwise comovement between the boom and crash periods in our sample is less than 1 (*10^{-4}).

In Columns 2, 4, and 6, we conduct a similar set of analyses, except that now we also include common non-margin-investor ownership ($CNMO$) on the right hand side of the equation. Consistent with the results in Tables 4 and 5: a) the coefficient estimate on $CNMO$ is economically small, and b) there is no visible variation in the coefficient between the up market and down market (0.062 vs. 0.055). These results suggest that our documented effect of CMO on the next-day pairwise stock return comovement is unlikely driven by differences in stock variances between up and down markets, and is instead the result of investors' preemptive (or forced) trading in response to tightening margin constraints.[24]

4.5 Leverage Network Centrality

In our next set of analyses, we draw on recent development in network theory to shed more light on the impact of the leverage network on stock returns. In particular, we are interested in how direct, as well as indirect, links among stocks resulting from common margin-investor ownership may relate to aggregate market movements. Motivated by recent work of Acemoglu et al. (2012), Ahern (2013) and Di Maggio, Kermani, and Song (2017), we conjecture that central stocks in the leverage network, which are likely affected by shocks originated in any part of the network, should experience larger aggregate selling pressure and

[23] In Appendix Table A3, we show that both broker-financed and shadow-financed margin accounts contribute to the asymmetry in pairwise return comovement between up and down markets.

[24] In another placebo test, we again use account-level trading data from 2007. $CNMO$ in this alternative sample has no effect on stock return comovement, which does not exhibit any variation between up and down markets.

thus lower stock returns in the crash period. Moreover, we should also see a disproportionate increase in central stocks' market betas during the crash period compared to peripheral stocks.

Following prior literature (e.g., Borgatti, 2005; Ahern, 2013), we use eigenvector centrality (which measures the average connectedness of all nodes that are linked to the node in question) as our main measure of the importance of each stock in our leverage network.[25] Intuitively, by tracing out all possible paths in the network, eigenvector centrality measures the likelihood that idiosyncratic shocks may be propagated to any given stock in the network. (Our results also hold using diffusion centrality.) Consistent with the results from Section 3.3, Table 7 shows that more central stocks in our leverage network tend to be larger, held by more levered accounts, and have higher idiosyncratic volatilities.

To analyze the effect of network centrality on expected stock returns, we conduct the following Fama-MacBeth regression:

$$RET_{i,t+1} = \alpha + \beta \times CENTRALITY_{i,t} + \sum_{k=1}^{K} \gamma_k \times CONTROL_{i,k,t} + \varepsilon_{i,t+1}, \tag{13}$$

where $RET_{i,t+1}$ is the stock return in t+1 and $CENTRALITY_{i,t}$ is its eigenvector centrality in t. We also include in the regression an interaction term between $CENTRALITY$ and the t+1 market return to capture differences in market betas between central stocks and peripheral stocks. (In order to estimate the differences in market beta across stocks as a function of $CENTRALITY$, we conduct panel regressions with date fixed effects and without the contemporaneous market return itself.) Again, we conduct the same analysis separately for the boom and bust periods, using June 12th as the cutoff.

The results are shown in Table 8. Columns 1-3 correspond to the up market. As shown in Columns 1 and 2, the coefficient on centrality is economically small and statistically insignificant. Column 3 further includes the interaction term between lagged eigenvector

[25] See Jackson (2017) for a detailed discussion of various measures of network centrality.

centrality and the same-day market return; the coefficient estimate is indistinguishable from zero, suggesting that up-side betas are not different between central stocks and peripheral stocks.

Columns 4-6 depict a very different picture for the crash period. In this sample, central stocks on average earn significantly lower returns; as shown in Column 4, a one-standard-deviation increase in eigenvector centrality lowers the next-day return by nearly 13 bps (t-statistic = 4.34). This result remains economically and statistically significant with the inclusion of additional controls in Column 5. In Column 6, we again include the interaction term between lagged centrality and the same-day market return on the right-hand-side of the equation. There is now a significant, disproportionate rise in market beta for central stocks, relative to peripheral stocks, in the bust period: a one-standard-deviation increase in eigenvector centrality is associated with a 0.23 (t-statistic = 3.63) increase in downside beta. Moreover, this increase in downside beta accounts for more than half of the negative return we observe in Column 5.[26]

4.6 Government Bailout

Our finding that central stocks in the leverage network are systematically important has useful implications for the Chinese government, which shortly after the initial market meltdown, pledged/devoted hundreds of billions of RMB in an effort to stabilize the market.[27] We obtain from the Shanghai Stock Exchange (SSE) the entire list of stocks purchased by the Chinese government in three separate bailout waves: July 6-9, July 15-17, and July 28-31. By the end of July, the stock market had stopped free-falling and started to slowly recover.

[26] In Appendix Table A4, we repeat the same set of analyses separately for broker-financed and shadow-financed margin accounts, and find similar patterns with both subsamples.

[27] On July 4, 2015, the chairman of the CSRC convened an emergency meeting with the CEOs of twelve securities firms in China, and devised a detailed plan to stablize the stock market. The following Monday, July 6th, government-controlled trading accounts started to purchase in large quantities a list of designated stocks. See `http://finance.ifeng.com/a/20150705/13818786_0.shtml` for more details.

Table 9 compares the characteristics of stocks included in the bailout program vs. those not included. The set of characteristics includes the stock's eigenvector centrality in our leverage network, its market capitalization, and its membership in the HS300 index (one of the most popular stock indices in China). As evident from Table 9, throughout the three bailout waves, the government primarily targeted large-cap firms that were part of a major stock index (HS300). Interestingly, as we move from the first bailout wave to the third, we see a steady increase in the median centrality score of the stocks purchased by the government (from 0.023 to 0.103). In Figure 3, we plot the average centrality of the stocks purchased by the Chinese government in day t vs. the cumulative stock market return in days t and $t+1$. There exists a generally positive relation between the two.[28] One interpretation of this positive correlation is that buying pressure on central stocks have a larger impact on the entire network, thus leading to higher market returns.

Finally, we use the government bailouts in July 2015 as plausibly exogenous shocks to a subset of stocks to provide cleaner evidence for the transmission mechanism of idiosyncratic price movements through the leverage network. To this end, we conduct a panel regression of future stock returns on two key right-hand-side variables: a) a government-purchase dummy, which equals one if the stock was purchased by the Chinese government and zero otherwise; b) for stocks that were not purchased by the Chinese government, their connectedness to the ones bought by the government through common margin investor ownership. As can be seen from Table 10, not only did the stocks purchased by the government rise in value, but so did the ones that a) were not purchased by the government but b) were linked to the ones bought by the government in the leverage network. Specifically, stocks in the top quintile ranked by their connectedness to the set of government-purchased stocks have 1.6% higher returns (t-statistic = 5.51) in the three days after the government bailout, relative to stocks in the other four quintiles. Moreover, compared to direct government purchases, the indirect price effect through common margin-investor ownership comes in with a one-day

[28] Given the small sample size, this correlation is statistically insignificant.

delay. To the extent that government purchases were unrelated to common shocks to firms, this evidence points to a causal interpretation of the shock transmission role of our leverage network.

5 Conclusion

Investors can amplify portfolio returns by borrowing against the securities they hold. This practice, however, makes investors vulnerable to temporary fluctuations in security value and funding conditions. A series of recent studies theoretically analyze the interplay between margin constraints and asset prices. Testing the predictions of these models, however, has been empirically challenging, due to the lack of granular data on margin borrowing. In this paper, we tackle this challenge by taking advantage of novel *account-level* data from China that track hundreds of thousands of margin investors' borrowing and trading activity at a daily frequency.

Our main analysis covers a three-month period—May to July of 2015—during which the Chinese stock market experienced a roller-coaster ride. Our results indicate that idiosyncratic shocks to an individual stock can indeed be propagated to other stocks with which it shares common margin-investor ownership. This spillover effect is gradually reversed in subsequent weeks and is present only during the bust period, consistent with the notion that margin investors indiscriminately scale down their holdings in response to the tightening of leverage constraints. We further show that such deleverage-induced selling can largely account for the well-known asymmetry in stock return comovement between up markets and down markets. Finally, drawing on recent development in network theory, we show that stocks that are more central in the leverage network experience larger selling pressure and lower returns during the market crash; moreover, this negative return can be accounted for by the larger downside beta of central stocks compared to peripheral stocks.

Our results have useful implications for academics, policy makers, and practitioners who are interested in the effect of margin trading on asset return dynamics. While margin lending and borrowing is an integral part of a well-functioning financial system, it can also lead to contagions across securities, especially in market downturns. A related, perhaps more important, question is whether idiosyncratic shocks, propagated through this leverage network, can aggregate up to systematic price movements; and if so, how much of the aggregate market volatility can be attributed to idiosyncratic shocks to individual securities. Our finding that central stocks in the leverage network have larger downside betas than peripheral stocks is a first step toward understanding this issue.

Appendix A: Details of Shadow-Financed Margin Accounts

We adopt the following data cleaning and filtering procedures on our account-level data from the online trading platform.

1. We eliminate all accounts with invalid initial margin and maintenance margin information. Both ratios are bilaterally negotiated between the borrower and lender and are recorded by the online trading platform, so can vary substantially across accounts and over time. We require that the initial account leverage ratio (portfolio value divided by own capital) be less than 100. There are a few accounts with extremely high initial leverage ratios. They are usually introduced as a starting bonus to attract investors with little own capital. We also require the maintenance margin to be less than the initial margin, but above one.

2. We further require that the first cash-flow record of the margin account be a cash inflow from the mother account, before any reported trading activity. These cash inflows usually occur right after accounts open, and include the loans from the lenders together with the own capital contributed by the borrowers. In other words, we exclude margin accounts that do not have any cash inflows from the mother accounts, as well as accounts whose first cash flows are from the child accounts to the mother accounts. We then compare the size of the initial cash flows and the initial debt information provided by the trading platform, and further eliminate accounts whose initial cash flows deviate substantially from the initial debt reported by the online trading platform.

After applying all these filter, we end up with a sample of about 150K margin accounts. This dataset includes all the variables in the brokerage sample, except for the end-of-day leverage ratio. Instead, the trading platform provides detailed information on the initial debt, as well as all subsequent cash flows between the mother accounts and child accounts. For two thirds of the child accounts, the platform provides detailed descriptions of each cash flow—whether it is a new loan, an interest payment, or a loan repayment. With this information, we can calculate each account's daily outstanding debt and leverage ratio. For the remaining accounts (for which we do not observe such payment descriptions), we assume that cash flows to (from) the mother account exceeding 20% of the current margin debt in the child account reflects a payment of existing debt (additional borrowing). Using other cutoffs (e.g., 15% or 5%) has virtually no impact on our results.

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Table 1. Summary Statistics

This table reports summary statistics of our sample, which spans the period May 1st to July 31st, 2015. Our sample includes trading accounts (both margin and matched non-margin accounts) from a major brokerage in China, as well as trading accounts on an online trading platform (i.e., shadow-financed margin accounts). In Panel A, we report the total number of accounts (*#ACCOUNTS*), total amount of margin debt (*$DEBT*) and account value (*$HOLDINGS*) of two samples. The statistics are first aggregated across accounts and then averaged across days. Panel B reports account characteristics, including the end-of-day holdings in both shares (*#HOLDINGS*) and RMB value (*$HOLDINGS*), daily trading volume in both shares (*#TRADINGS*) and RMB value (*$TRADINGS*), the number of orders submitted (*# SUBMISSIONS*) and end-of-day account leverage ratio (*ACC_LEVER*). Panel C describes portfolio-average stock characteristics (weighted by portfolio weights), including the market capitalization (*MCAP*), book-to-market ratio (*BMRATIO*), cumulative return over the previous 120 trading days (*MOMENTUM*), share turnover defined as average daily trading volume divided by the number of tradable shares in the previous 120 trading days (*TURNOVER*), and idiosyncratic return volatility defined as the standard deviation of residual daily returns after controlling for the Fama-French three factors and the Carhart momentum factor (constructed using Chinese data) in the previous 120 trading days (*IDVOL*). Statistics in Panels B and C are first averaged across investor accounts in each day and then averaged across days.

	Broker-Financed Margin Accounts		Matched Broker Non-Margin Accounts		Shadow-Financed Margin Accounts	
Panel A: Aggregate Statistics						
	Mean	Median	Mean	Median	Mean	Median
#ACCOUNTS	177,571	177,571	330,000	330,000	153,381	153,381
¥DEBT (10^9)	99.414	105.992	0.00	0.00	44.205	43.845
¥HOLDINGS (10^9)	354.955	363.294	335.030	322.786	64.158	62.016
Panel B: Account Characteristics						
#HOLDINGS (10^3)	319.631	65.000	117.384	4.100	71.882	9.656
¥HOLDINGS (10^4)	626.472	122.987	196.362	5.496	149.367	22.130
#TRADINGS (10^3)	131.446	14.100	34.391	2.400	33.496	6.900
¥TRADINGS (10^4)	216.248	26.196	60.366	4.038	61.222	13.117
#SUBMISSIONS	16.884	6.000	9.441	5.000	7.717	5.000
ACC_LEVER	1.602	1.541	1.000	1.000	6.950	4.293
Panel C: Portfolio-Weighted-Average Stock Characteristics						
MCAP (10^9)	81.609	40.853	89.692	44.808	62.486	29.748
BMRATIO	1.304	0.749	1.330	0.851	0.958	0.596
MOMENTUM	1.031	0.908	1.082	0.970	1.406	1.232
TURNOVER	0.041	0.040	0.042	0.041	0.044	0.042
IDVOL	0.027	0.027	0.028	0.028	0.029	0.028

Table 2. Determinants of Leverage Ratios

This table reports panel regressions to examine the determinants of leverage ratios across accounts (Panel A) and across stocks (Panel B). The dependent variable in Panel A is the daily account leverage ratio (*ACC_LEVER*) on the next day. The set of independent variables includes the number of distinct stocks in the account (*#STOCKS*), total account wealth which includes both cash holdings and stock holdings (*ACCOUNT_ VALUE*), and the number of days since the account was opened (*ACCOUNT_AGE*). The dependent variable in Panel B is the weighted average leverage ratio in the next day of all margin accounts that hold stock *i* (*LEVERAGE*), where the weights are proportional to each investor's own capital. The list of independent variables includes stock *i*'s return in the previous day (*DRET*), cumulative return in the previous 120 trading days (*MOMENTUM*), share turnover defined as average daily trading volume divided by the number of tradable shares in the previous 120 trading days (*TURNOVER*), idiosyncratic return volatility defined as the standard deviation of residual daily returns after controlling for the Fama-French three factors and the Carhart momentum factor (constructed using Chinese data) in the previous 120 trading days *(IDVOL*), and market capitalization at the end of previous month (*MCAP*). The sample period is May 1st to July 31st, 2015. All regressions include account (or stock) fixed effects and date fixed effects. T-statistics, reported below the coefficients, are based on standard errors clustered by account (or stock) and date. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Dependent Variable = Account Leverage Next Day				
	Brokerage Margin Accounts		Shadow Margin Accounts	
	(1)	(2)	(3)	（4）
# STOCKS	0.032***	0.023***	-0.068***	-0.067***
	(27.05)	(26.99)	(-7.61)	（-7.60）
ACCOUNT VALUE	0.154***	0.154***	-0.425**	-0.426**
	(48.45)	(48.36)	(-2.54)	（-2.55）
ACCOUNT AGE		-0.0001		0.018***
		(-0.66)		（3.24）
Account FE	YES	YES	YES	YES
Date FE	YES	YES	YES	YES
Adj. R^2	0.70	0.70	0.53	0.53
No. Obs.	4,046,044	4,039,390	2,482,787	2,481,507

Panel B: Dependent Variable = Stock Leverage Next Day							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DRET	-4.867***						-3.558***
	(-7.74)						(-6.12)
BMRATIO		-0.178					0.019
		(-1.24)					(0.74)
MOMENTUM			0.048				-0.169***
			(1.00)				(-3.51)
TURNOVER				0.187***			0.104*
				(3.23)			(1.95)
IDVOL					0.507***		0.446***
					(7.84)		(5.75)
MCAP						1.189***	0.704***
						(6.27)	(3.59)
Stock FE	YES	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.25	0.29	0.28	0.29	0.29	0.29	0.26
No. Obs.	143,497	173,011	175,355	174,275	175,355	174,095	141,895

Table 3. Margin Investors' Trading Activity

This table reports panel regressions to examine the determinants of margin investors' trading activity. The dependent variable is the daily net trading of each margin account, defined as the total value of buys minus that of sells on day *t* scaled by the account holding value at the beginning of day *t*. The set of independent variables includes past account returns, account leverage, and the interaction term between the two. Account returns on day *t-1* (*ACC_RET*) are further separated into positive and negative realizations. *ACC_LEVER* is the account leverage ratio measured on day *t-5* to avoid a mechanical relation with past account returns. Likewise, *DISTANCE* is the distance between the account leverage ratio and its maximum allowed leverage ratio on day *t-5* (for shadow-financed accounts only). Other controls include account value and account age; their coefficients are not reported for brevity. Column (1) corresponds to the sample of broker-financed margin accounts, Columns (2) and (3) correspond to the sample of shadow-financed margin accounts. The sample period is May 1st to July 31st, 2015. Account and date fixed effects are included in all regressions. T-statistics, reported below the coefficients, are based on standard errors clustered by account and date. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable = Net Trading by Margin Investors Next Day			
	Brokerage-Financed	Shadow-Financed	
	(1)	(2)	(3)
Positive ACC_RET	-0.608***	-0.703***	-0.721***
	(-8.03)	(-9.64)	(-12.89)
Positive ACC_RET x ACC_LEVER	0.083**	-0.014	0.005**
	(2.19)	(-1.11)	(2.23)
Positive ACC_RET x DISTANCE			0.023*
			(1.75)
Negative ACC_RET	-0.022	0.240*	1.282***
	(-0.29)	(1.89)	(6.26)
Negative ACC_RET x ACC_LEVER	0.165***	0.188***	-0.004
	(3.16)	(6.44)	(-1.15)
Negative ACC_RET x DISTANCE			-0.164***
			(-5.93)
ACC_LEVER	-0.010	0.006***	-0.00003
	(-3.59)	(9.05)	(-0.02)
DISTANCE			-0.0002
			(-0.25)
Account FE	YES	YES	YES
Date FE	YES	YES	YES
Adj. R^2	0.13	0.24	0.24
No. Obs.	2,316,589	1,073,608	1,073,608

Table 4: Forecasting Stock Returns

This table reports Fama-MacBeth forecasting regressions of future returns. The dependent variable is stock *i*'s return on day *t*+1. The main independent variable is *MLPR*, the margin-account linked portfolio return in day *t*, calculated as the weighted average return of all stocks that are connected to stock *i* through common ownership by margin investors (detailed definition in Section 4.1). The variable *NMLPR* is defined similarly but using common ownership of non-margin investors. Other controls include stock *i*'s leverage ratio on day *t*, defined as the weighted average leverage ratio of all margin accounts that hold stock *i* (*LEVERAGE*), return on day *t* (*DRET*), book-to-market ratio on day *t* (*BMRATIO*), cumulative stock return in the previous 120 trading days (*MOMENTUM*), share turnover defined as average daily trading volume divided by the number of tradable shares in the previous 120 trading days (*TURNOVER*), idiosyncratic return volatility defined as the standard deviation of residual returns after controlling for the Fama-French three factors and the Carhart momentum factor (constructed using Chinese data) in the previous 120 trading days *(IDVOL*), and market capitalization at the end of previous month (*MCAP*). Columns (1) and (2) include the whole sample of May 1st to July 31st, 2015. We then split the sample based on the general market trend: Columns (3) and (4) include the subsample of May 1st to June 12th, 2015 (Up Market), and Columns (5) and (6) include the subsample of June 15th to July 31st, 2015 (Down Market). T-statistics, with Newey-West adjustments of four lags, are reported below the coefficients. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable = Stock Returns on Day *t*+1					
	Whole Sample		Up Market		Down Market	
	(1)	(2)	(3)	(4)	(5)	(6)
MLPR	0.009**	0.009**	0.002	0.003	0.014***	0.014***
	(2.24)	(2.34)	(0.41)	(0.49)	(2.97)	(2.95)
NMLPR		-0.001		-0.002*		0.0002
		(-0.71)		(-1.85)		(0.13)
LEVERAGE	-0.0005	-0.0005	-0.001	-0.001	0.00002	0.00002
	(-1.27)	(-1.28)	(-1.35)	(-1.36)	(-0.12)	(-0.11)
DRET	0.274***	0.274***	0.188***	0.187***	0.350***	0.350***
	(7.70)	(7.69)	(10.00)	(10.04)	(6.65)	(6.66)
BMRATIO	0.00003	0.00003	-0.00003	-0.00003	0.0001*	0.0001**
	(1.04)	(1.06)	(-1.21)	(-1.19)	(1.94)	(1.95)
MOMENTUM	-0.001	-0.001	0.001	0.001	-0.002**	-0.002**
	(-0.85)	(-0.84)	(1.14)	(1.14)	(-2.14)	(-2.11)
TURNOVER	0.054**	0.054**	0.038	0.039	0.068*	0.067*
	(2.47)	(2.50)	(1.53)	(1.61)	(1.90)	(1.88)
IDVOL	-0.324***	-0.322***	-0.535***	-0.536***	-0.138	-0.134
	(-3.10)	(-3.08)	(-3.94)	(-3.95)	(-1.10)	(-1.07)
MCAP	-0.002	-0.002	-0.004***	-0.004***	0.001	0.001
	(-1.56)	(-1.63)	(-4.91)	(-4.90)	(0.65)	(0.59)
Adj. R^2	0.18	0.18	0.15	0.15	0.21	0.21
No. Obs.	173,836	173,836	80,515	80,515	93,321	93,321

Table 5: Forecasting Cumulative Stock Returns in the Down Market

This table reports Fama-MacBeth forecasting regressions of future returns in the down market (June 15th to July 31st, 2015). The dependent variables are stock *i*'s return in day *t*+1 (Column 1), in *t*+1 to *t*+2 (Column 2), *t*+1 to *t*+5 (Column 3), *t*+1 to *t*+7 (Column 4), and *t*+1 to *t*+10 (Column 5). The main independent variable is *MLPR*, the margin-account linked portfolio return in day *t*, calculated as the weighted average return of all stocks that are connected to stock *i* through common ownership by margin investors (detailed definition in Section 4.1). The variable *NMLPR* is defined similarly but using common ownership of non-margin investors. Other controls include stock *i*'s leverage ratio on day *t*, defined as the weighted average leverage ratio of all margin accounts that hold stock *i* (*LEVERAGE*), return on day *t* (*DRET*), book-to-market ratio on day *t* (*BMRATIO*), cumulative stock return in the previous 120 trading days (*MOMENTUM*), share turnover defined as average daily trading volume divided by the number of tradable shares in the previous 120 trading days (*TURNOVER*), idiosyncratic return volatility defined as the standard deviation of residual returns after controlling for the Fama-French three factors and the Carhart momentum factor (constructed using Chinese data) in the previous 120 trading days *(IDVOL*), and market capitalization at the end of previous month (*MCAP*). T-statistics, with Newey-West adjustments of four lags, are reported below the coefficients. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable = Future Stock Returns (Down Market Only)					
	R_{t+1}	$R_{t+1,\ t+2}$	$R_{t+1,\ t+5}$	$R_{t+1,\ t+7}$	$R_{t+1,\ t+10}$
MLPR	0.014***	0.023**	0.016	0.013	-0.001
	(2.95)	(3.68)	(1.19)	(0.69)	(-0.04)
NMLPR	0.0003	-0.003	-0.004	-0.004	-0.008
	(0.13)	(-0.89	(-0.70)	(-0.65)	(-1.13)
LEVERAGE	-0.00002	0.00003	0.0005	0.001*	0.001**
	(-0.14)	(0.11	(1.05)	(1.81)	(2.28)
DRET	0.350***	0471***	0.600***	0.575***	0.459***
	(6.66)	(6.47)	(5.60)	(4.10)	(3.22)
BMRATIO	0.0001*	0.0001	0.0002	0.0002	0.0002
	(1.95)	(1.26)	(1.10)	(0.87)	(0.55)
MOMENTUM	-0.002**	-0.004**	-0.008**	-0.011***	-0.014***
	(-2.11)	(-2.27)	(-2.60)	(-3.02)	(-3.60)
TURNOVER	0.067*	0.130*	0.338**	0.405**	0.465**
	(1.88)	(1.80)	(2.29)	(2.23)	(2.27)
DVOL	-0.134	-0.253	-0.500	-0.460	-0.285
	(-1.07)	(-0.90)	(-0.82)	(-0.60)	(-0.33)
MCAP	0.001	0.001	0.002	0.001	0.0004
	(0.59)	(0.18)	(0.16)	(0.15)	(0.04)
Adj. R^2	0.21	0.18	0.16	0.15	0.15
No. Obs.	93,321	93,321	93,321	93,321	93,321

Table 6: Pairwise Stock Return Comovement

This table reports Fama-MacBeth forecasting regressions of future return comovement. The dependent variable is the pairwise stock return comovement, defined as the product of daily market-adjusted returns of a pair of stocks (*i* and *j*) on day *t*+1. The main independent variable, Common-Margin-Investor-Ownership (*CMO*), is a measure of common ownership of stocks *i* and *j* by all margin investors on day *t*. Specifically, it is defined as the sum of each margin investor's leverage ratio multiplied by his holdings in the two stocks, divided by the total market capitalizations of the two stocks. The variable *CNMO* (Common-Non-Margin-Investor-Ownership) is constructed similarly except that we use the 330,000 non-margin brokerage accounts instead. 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 in the previous 120 trading days (*MOMDIFF*). *SAMEIND* is a dummy that equals one if the two firms are in the same industry, and zero otherwise. *SIZE1* and *SIZE2* are the size percentile rankings of the two firms. Columns (1) and (2) correspond to the whole sample. Columns (3) and (4) include the subsample of May 1st to June 12th, 2015 (Up Market), and Columns (5) and (6) include the other subsample of June 15th to July 31st,2015 (Down Market). T-statistics, with Newey-West adjustments of four lags, are reported below the coefficients. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable = Pairwise Stock Return Comovement Next Day						
	Whole Sample		Up Market		Down Market	
	(1)	(2)	(3)	(4)	(5)	(6)
CMO	0.097***	0.093***	0.043***	0.039***	0.145***	0.141***
	(4.12)	(3.47)	(6.28)	(5.83)	(3.34)	(3.18)
CNMO		0.059		0.062***		0.055
		(1.38)		(6.84)		(0.70)
BMDIFF	0.001***	0.001***	0.001***	0.001***	0.001**	0.001**
	(3.23)	(3.68)	(3.37)	(3.44)	(2.37)	(2.54)
COMANALY	0.0003***	0.0003***	0.0004***	0.0004***	0.0002*	0.0002*
	(3.80)	(3.83)	(7.24)	(7.18)	(1.67)	(1.65)
MOMDIFF	-0.0002	-0.0002	0.0004**	0.0004**	-0.001	-0.001
	(-0.27)	(-0.29)	(2.27)	(2.35)	(-0.59)	(-0.61)
SAMEIND	0.014***	0.015***	0.013***	0.013***	0.016***	0.017***
	(4.81)	(4.63)	(5.30)	(5.36)	(3.02)	(2.97)
SIZE1	0.024***	0.023***	0.010**	0.010**	0.036**	0.035**
	(3.08)	(3.03)	(2.47)	(2.45)	(2.87)	(2.80)
*SIZE1*SIZE2*	-0.004***	-0.004***	-0.002***	-0.002***	-0.006**	-0.006**
	(-3.05)	(-3.01)	(-3.05)	(-3.04)	(-2.83)	(-2.78)
SIZE2	0.024***	0.023***	0.010**	0.009**	0.036**	0.035**
	(3.08)	(3.03)	(2.47)	(2.45)	(2.87)	(2.80)
SIZEDIFF	0.015***	0.015***	0.006***	0.006***	0.022**	0.035**
	(3.10)	(3.06)	(4.01)	(4.02)	(2.83)	(2.80)
Adj. R^2	0.02	0.02	0.01	0.01	0.03	0.03
No. Obs. (*1000)	31,887	31,887	14,049	14,049	17,838	17,838

Table 7: Determinants of Leverage Network Centrality

This table reports panel regressions to examine the determinants of individual stocks' centrality in the leverage network. The dependent variable is the percentile ranking of network centrality of stock *i* on day t+1. Stock centrality is defined as the eigenvector centrality in the leverage network, where the link between any pair of stocks reflects the common ownership of the two stocks by all margin investors (detailed definition in Section 4.5). Other controls include stock *i*'s leverage ratio on day t, defined as the weighted average leverage ratio of all margin accounts that hold stock *i* (*LEVERAGE*), return on day t (*DRET*), book-to-market ratio (*BMRATIO*), cumulative stock return in the previous 120 trading days (*MOMENTUM*), average daily turnover ratio in the previous 120 trading days (*TURNOVER*), idiosyncratic return volatility after controlling for the Fama-French three factors and the Carhart momentum factor (constructed using Chinese data) in the previous 120 trading days (*IDVOL*), and market capitalization at the end of day t (*MCAP*). The sample period is May 1st to July 31st, 2015. Stock and date fixed effect are included in all regressions. T-statistics, reported below the coefficients, are based on standard errors clustered by stock and date. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable = Stock Centrality in the Leverage Network Next Day								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LEVERAGE	0.033***							0.033***
	(10.87)							(10.68)
DRET		-0.914***						-0.507***
		(-9.58)						(-6.02)
BMRATIO			-0.072					-0.025
			(-1.48)					(-1.30)
MOMENTUM				0.034***				-0.010
				(3.06)				(-0.87)
TURNOVER					0.042***			2.100
					(3.48)			(1.60)
IDVOL						0.110***		6.903***
						(12.77)		(6.98)
MCAP							0.333***	0.111**
							(7.95)	(2.28)
Stock FE	YES	YES	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.62	0.60	0.60	0.60	0.60	0.61	0.61	0.61
No. Obs.	173,836	173,836	173,836	173,836	173,836	173,836	173,836	173,836

Table 8: Network Centrality and Future Stock Returns

This table reports forecasting regressions of future returns. The dependent variable is stock *i*'s return on day *t*+1. The main independent variable is *CENTRALITY*, the centrality measure of stock *i* on day *t*, defined as the eigenvector centrality of each stock in the leverage network. The link in this network between any pair of stocks reflects the common ownership of the two stocks by all margin investors (detailed definition in Section 4.5). We also include an interaction term between the market return on day *t*+1 and the centrality measure to pick up the effect of exposures to market risk. Other controls include stock *i*'s leverage ratio on day *t*, defined as the weighted average leverage ratio of all margin accounts that hold stock *i* (*LEVERAGE*), return on day *t* (*DRET*), book-to-market ratio on day *t* (*BMRATIO*), cumulative stock return in the previous 120 trading days (*MOMENTUM*), share turnover defined as average daily trading volume divided by the number of tradable shares in the previous 120 trading days (*TURNOVER*), idiosyncratic return volatility defined as the standard deviation of residual returns after controlling for the Fama-French three factors and the Carhart momentum factor (constructed using Chinese data) in the previous 120 trading days (*IDVOL*), and market capitalization at the end of previous month (*MCAP*). Columns (1) and (3) include the subsample of May 1st to June 12th, 2015 (Up Market), and Columns (4) to (6) include the subsample of June 15th to July 31st, 2015 (Down Market). Columns (1), (2), (4) and (5) conduct Fama-MacBeth regressions; T-statistics, with Newey-West adjustments of four lags, are reported below the coefficients. Columns (3) and (6) conduct pooled OLS regressions with date fixed effects; T-statistics, reported below the coefficients, are based on standard errors clustered by date. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable = Stock Returns on Day t+1						
	Up Market			Down Market		
	(1)	(2)	(3)	(4)	(5)	(6)
CENTRALITY	0.0003	0.00002	-0.0001	-0.0013***	-0.0006**	-0.0003
	(1.18)	(0.11)	(-0.53)	(-4.34)	(-2.19)	(-1.36)
*MRET **			-0.002			0.246***
CENTRALITY			(-0.01)			(3.63)
LEVERAGE		-0.001	-0.003***		0.0001	-0.0003***
		(-1.50)	(-4.26)		(-0.53)	(-5.28)
DRET		0.189***	0.185***		0.362***	0.234***
		(9.98)	(7.37)		(6.76)	(6.53)
BMRATIO		-0.00003	-0.00002		0.0001**	0.00004
		(-1.10)	(-0.58)		(2.16)	(0.67)
MOMENTUM		0.001	0.0002		-0.001**	-0.002**
		(1.15)	(0.33)		(-2.10)	(-2.10)
TURNOVER		0.037	0.044*		0.062*	0.082**
		(1.47)	(1.82)		(1.84)	(2.78)
IDVOL		-0.534***	-0.473***		-0.119	-0.216
		(-3.91)	(-4.36)		(-1.01)	(-1.56)
MCAP		-0.004***	-0.005***		0.001	-0.0004
		(-4.90)	(-5.17)		(0.53)	(-0.33)
Date FE	FM	FM	YES	FM	FM	YES
Adj. R^2	0.01	0.14	0.33	0.01	0.20	0.68
No. Obs.	80,515	80,515	80,515	93,321	93,321	93,321

Table 9: Government Bailouts in July 2015

This table compares the characteristics of stocks that the Chinese government purchased in July 2015, vs. those not purchased in three government bailout waves. Wave 1 is from July 6th to 9th; wave 2 from July 15th to 17th; and wave 3 from July 28th to 31st. We compare the mean and median of three stock characteristics between the two samples: a) whether the stock is included in the HS300 index (one of the most popular stock indices in China); b) the stock's market capitalization; and c) the stock's leverage-network eigenvector centrality. In the last two columns, we conduct T-test of the difference in means and the Wilcoxin Z-test of the difference in medians between the two samples.

	Purchased by the Government	Not purchased by the Government	T-statistic of the difference	Z-statistic of the difference
Wave 1				
% in *HS300*	34	0		
Mean of *Log MCAP*	24.030	22.511	41.70***	
Median of *Log MCAP*	23.914	22.517		35.41***
Mean of *CENT*	0.163	0.278	-2.49**	
Median of *CENT*	0.023	0.035		-5.23***
Wave 2				
% *in HS300*	45	0.2		
Mean of *Log MCAP*	24.291	22.772	31.77***	
Median of *Log MCAP*	24.052	22.712		25.91***
Mean of *CENT*	0.322	0.344	-0.47	
Median of *CENT*	0.098	0.115		-1.81*
Wave 3				
% in *HS300*	23	4.3		
Mean of *Log MCAP*	23.577	22.566	24.29***	
Median of *Log MCAP*	23.439	22.528		24.10***
Mean of *CENT*	0.322	0.285	1.16	
Median of *CENT*	0.103	0.088		2.66***

Table 10: Government Bailouts and Stock Returns

This table reports forecasting regressions of stock returns during three government bailout waves. Wave 1 is from July 6th to 9th; wave 2 from July 15th to 17th; and wave 3 from July 28th to 31st. The dependent variables are stock *i*'s return on day *t*+1 (Column 1), day *t*+2 (Column 2), day *t*+3 (Column 3), and cumulative return from *t*+1 to *t*+3 (Column 4). The main independent variables are *BDUM* (the bailout dummy) and *BLPRDUM* (bailout linked-portfolio return dummy) *BDUM* is a dummy that equals 1 if the stock is purchased by the government on day *t*. *BLPR* is defined in a similar way to *MLPR* in table 5 except that we use *BDUM* as an instrument for realized stock returns (which is equal to one for all the stocks purchased by the government and zero otherwise). *BLPRDUM* is then defined as a dummy variable that equals 1 if *BLPR* is in the top quintile, and 0 otherwise. Other controls include stock *i*'s leverage ratio on day *t*, defined as the weighted average leverage ratio of all margin accounts that hold stock *i* (*LEVERAGE*), return on day *t* (*DRET*), book-to-market ratio on day *t* (*BMRATIO*), cumulative stock return in the previous 120 trading days (*MOMENTUM*), share turnover defined as average daily trading volume divided by the number of tradable shares in the previous 120 trading days (*TURNOVER*), idiosyncratic return volatility defined as the standard deviation of residual returns after controlling for the Fama-French three factors and the Carhart momentum factor (constructed using Chinese data) in the previous 120 trading days (*IDVOL*), and market capitalization at the end of previous month (*MCAP*). We conduct pooled OLS regressions with date fixed effects. T-statistics, reported below the coefficients, are based on block-bootstrapped standard errors to account for the small number of periods. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable = Future Stock Returns			
	R_{t+1}	R_{t+2}	R_{t+3}	$R_{t+1,\ t+3}$
	(1)	(2)	(3)	(4)
BDUM	0.022***	-0.002	-0.014***	0.006*
	(11.51)	(-1.19)	(-8.23)	(1.89)
BLPRDUM	0.001	0.010***	0.004**	0.016***
	(1.07)	(7.04)	(2.31)	(5.51)
LEVERAGE	-0.0002**	-0.00004	0.0003**	0.0001
	(-2.42)	(-0.36)	(2.25)	(0.28)
TURNOVER	0.023	-0.061***	-0.012	-0.052
	(1.38)	(-2.88)	(-0.49)	(-0.93)
IDVOL	-0.019	0.499***	0.581***	1.134***
	(-0.38)	(7.58)	(9.79)	(7.76)
MCAP	-0.0004	-0.004***	-0.005***	-0.011***
	(-0.97)	(-7.15)	(-8.55)	(-7.69)
BMRATIO	-0.0001	-0.001	-0.00003	-0.001
	(-0.45)	(-0.30)	(-0.07)	(-0.30)
Date FE	YES	YES	YES	YES
Adj. R^2	0.59	0.26	0.13	0.41
No. Obs.	7,944	7,940	7,935	7,935

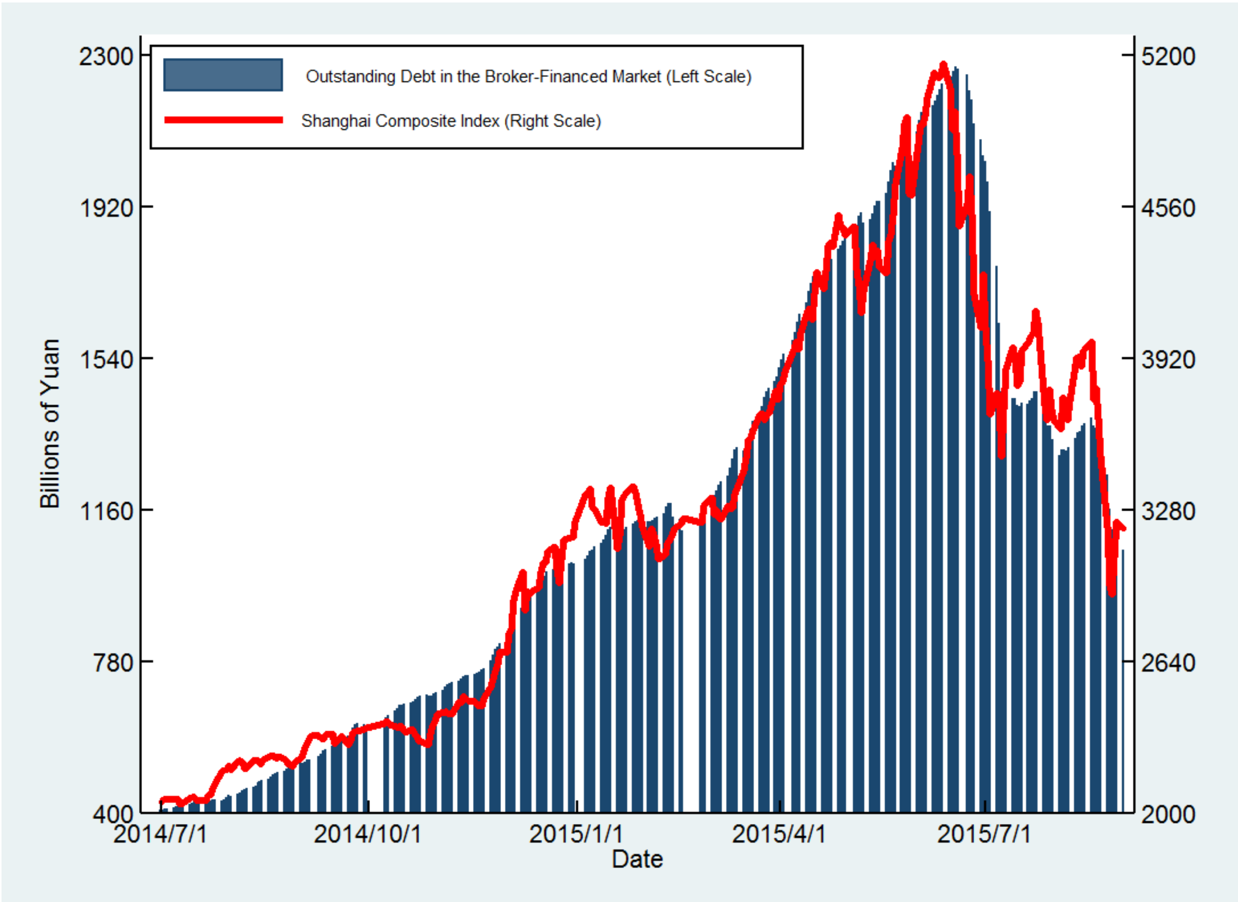

Figure 1. This figure shows the Shanghai Stock Exchange (SSE) Composite Index (red line, right scale), as well as the aggregate amount of broker-financed margin debt (blue bars, in billions, left scale), for the period October 2014 to August 2015.

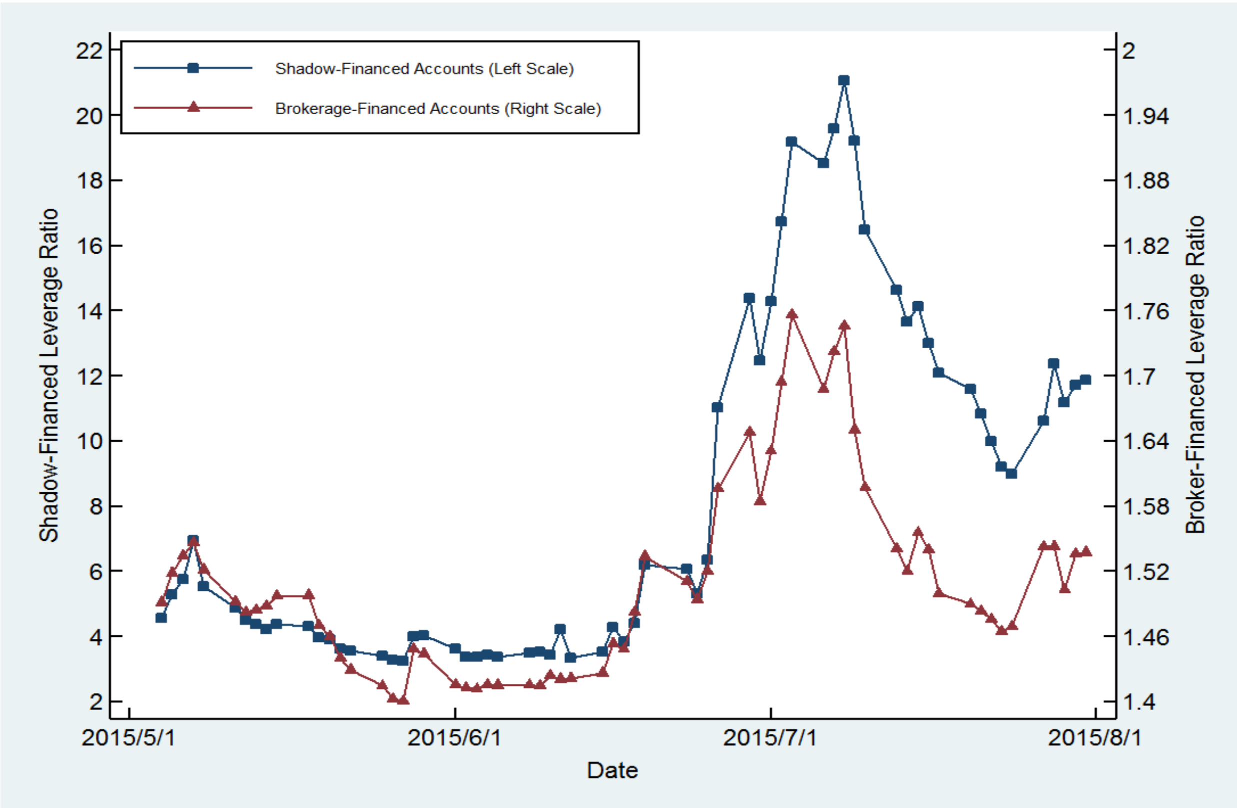

Figure 2. This figure shows the average daily leverage ratio of broker-financed margin accounts (red line, right scale) and that of shadow-financed margin accounts (blue line, left scale) for the period May to July 2015. The account leverage ratio is defined as the end-of-day portfolio value divided by the amount of own capital contributed by the investor herself. Reported in the figure is the weighted-average leverage ratio in each day, where the weights are proportional to each account's end-of-day own capital.

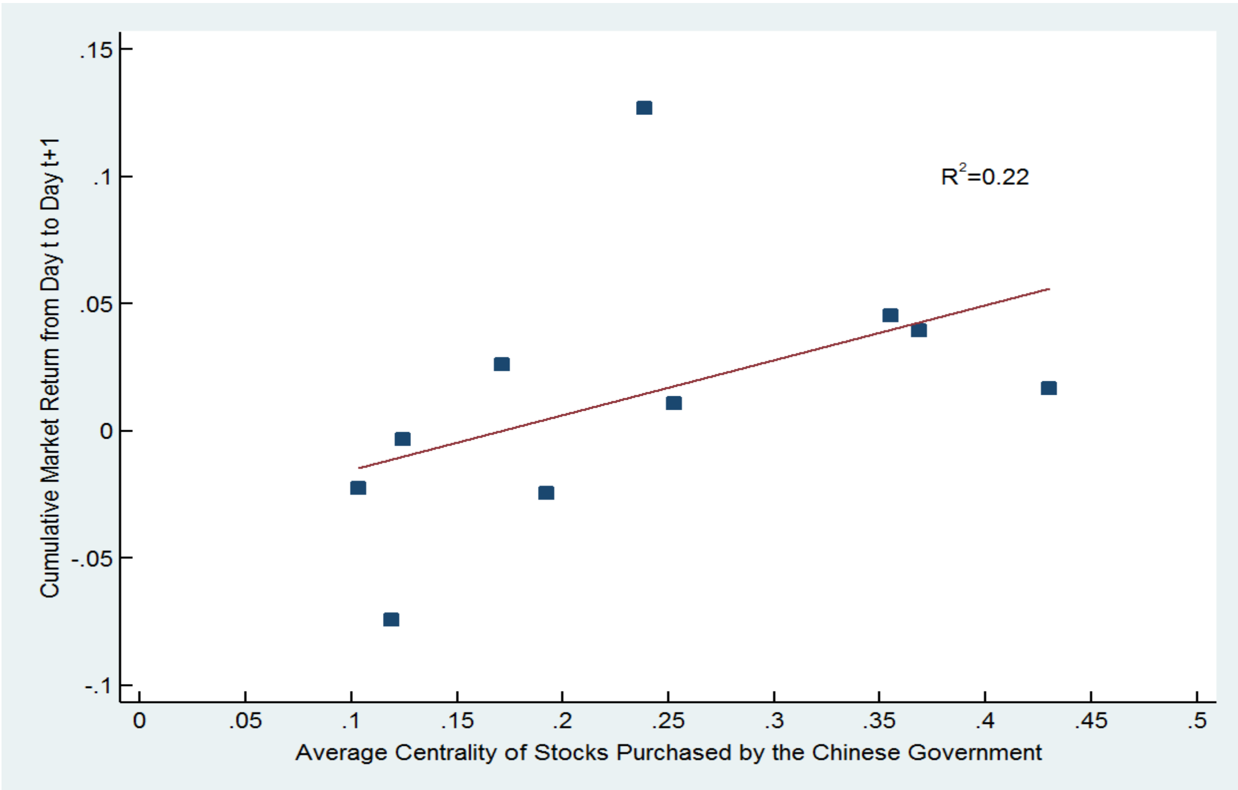

Figure 3. This figure shows the two-day cumulative market return on the day of and the day subsequent to a government bailout as a function of the average centrality measure of stocks purchased by the Chinese government on that day. We then fit a line through the 10 data points by regressing the cumulative market return on the average centrality measure. The adj-R^2 is 0.22.

Online Appendix to

"Leverage Networks and Market Contagion"

Table A1. Characteristics of Stocks Sold by Margin Investors

This table reports panel regressions to examine trading activity of margin investors following *negative* portfolio returns. The dependent variable is the net trading in stock *i* by account *j* on day *t*, defined as the numbers of shares bought minus that sold scaled by the lagged number of shares held. While the regressions include all stand-alone terms and their double interaction terms, for brevity, we only report coefficients on the triple interaction terms of the account return in day *t-1* (*ACC_RET*) * account leverage ratio in day *t-5* (*ACCT_LEVER*) * *various* stock characteristics. The list of stock characteristics includes stock returns in the previous day (*DRET*), cumulative stock return in the previous 120 trading days (*MOMENTUM*), market capitalization (*MCAP*), book-to-market ratio (*BMRATIO*), share turnover, defined as the average daily trading volume divided by the number of tradable shares in the previous 120 days (*TURNOVER*), idiosyncratic return volatility, defined as the standard deviation of residual returns after controlling for the Fama-French three factors and the Carhart momentum factor (all constructed using Chinese data) in the previous 120 trading days *(IDVOL*), and the portfolio weight of the stock (*WEIGHT*). Column (1) corresponds to the broker-financed margin account sample, Column (2) corresponds to the shadow-financed margin account sample, and Column (3) includes both. The sample period is May 1st to July 31st, 2015. The regressions only include accounts experiencing negative returns in day *t*-1. Stock and date fixed effects are included in all specifications. T-statistics, reported below the coefficients, are based on standard errors clustered by stock and date. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable = Net Trading by Margin Investors Next Day			
	Brokerage-Financed	Shadow-Financed	All Margin Traders
	(1)	(2)	(3)
Triple-interaction terms:			
ACC_RET x ACC_LEVER	-0.079**	0.014	-0.004
x MOMENTUM	(-2.75)	(0.89)	(-0.16)
ACC_RET x ACC_LEVER	-0.027**	0.011	0.010
x MCAP	(-2.63)	(1.48)	(1.07)
ACC_RET x ACC_LEVER	-0.073***	-0.005	-0.029**
x BMRATIO	(-2.98)	(-0.38)	(-2.05）
ACC_RET x ACC_LEVER	-0.205	-0.005	0.336
x TURNOVER	(-0.42)	(-0.02)	（1.22）
ACC_RET x ACC_LEVER	2.326	-5.873**	-5.920
x IDVOL	(0.95)	(-2.61)	（-1.59）
ACC_RET x ACC_LEVER	-0.100	-0.267***	-0.256***
x WEIGHT	(-1.30)	(-7.05)	（-6.63）
Original Variables	Yes	Yes	Yes
Double Interaction Terms	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes
Adj. R^2	0.02	0.06	0.06
No. Obs.	5,347,777	2,889,393	8,252,881

Table A2: Forecasting Stock Returns (Broker- vs. Shadow-Financed Accounts)

This table reports Fama-MacBeth forecasting regressions of future returns. The dependent variable is stock *i*'s return on day *t*+1. The main independent variable is *MLPR*, the margin-account linked portfolio return in day *t*, calculated as the weighted average return of all stocks that are connected to stock *i* through common ownership by margin investors (detailed definition in Section 4.1). The variable *NMLPR* is defined similarly but using common ownership of non-margin investors. Other controls include stock *i*'s leverage ratio on day *t*, defined as the weighted average leverage ratio of all margin accounts that hold stock *i* (*LEVERAGE*), return on day *t* (*DRET*), book-to-market ratio on day *t* (*BMRATIO*), cumulative stock return in the previous 120 trading days (*MOMENTUM*), share turnover defined as average daily trading volume divided by the number of tradable shares in the previous 120 days (*TURNOVER*), idiosyncratic return volatility defined as the standard deviation of residual returns after controlling for the Fama-French three factors and the Carhart momentum factor (constructed using Chinese data) in the previous 120 trading days *(IDVOL*), and market capitalization at the end of previous month (*MCAP*). Columns (1) to (3) correspond to the sample of broker-financed margin accounts, and Columns (4) to (6) correspond to the sample of shadow-financed margin accounts. Columns (1) and (4) include the entire sample period, columns (2) and (5) include the subsample of May 1st to June 12th, 2015 (Up Market), and Columns (3) and (6) include the subsample of June 15th to July 31st, 2015 (Down Market). T-statistics, with Newey-West adjustments of four lags, are reported below the coefficients. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable = Stock Returns on Day *t*+1					
	Broker-Financed Accounts			Shadow-Financed Accounts		
	Full	Up	Down	Full	Up	Down
	(1)	(2)	(3)	(4)	(5)	(6)
MLPR	0.0111*	0.0036	0.0174*	0.0155***	0.0120*	0.0187***
	(1.79)	(0.49)	(1.86)	(3.69)	(1.91)	(3.34)
LEVERAGE	-0.0021	-0.0053***	0.0007	-0.0001	-0.0001	-0.0001
	(-1.60)	(-2.91)	(0.62)	(-0.64)	(-0.48)	(-0.49)
DRET	0.2827***	0.1949***	0.3576***	0.2614***	0.1611***	0.3498***
	(7.78)	(9.23)	(6.84)	(6.21)	(8.62)	(5.52)
BMRATIO	0.00004	-0.00003	0.0001**	0.00004	-0.00002	0.0001**
	(1.29)	(-1.04)	(2.12)	(1.42)	(-1.06)	(2.32)
MOMENTUM	-0.0005	0.001	-0.001**	-0.0013**	-0.0004	-.0021**
	(-0.80)	(1.15)	(-2.14)	(-2.45)	(-0.54)	(-3.02)
TURNOVER	0.054**	0.043*	0.063*	-0.0021	-0.0330	0.0252
	(2.46)	(1.66)	(1.79)	(-0.09)	(-1.04)	(0.88)
IDVOL	-0.341***	-0.588***	-0.129	0.0070	-0.0881	0.0909
	(-3.16)	(-4.53)	(-1.02)	(0.11)	(-0.79)	(1.23)
MCAP	-0.001	-0.004***	-0.007	-0.0013	-0.0038***	0.0010
	(-1.43)	(-4.60)	(0.56)	(-1.31)	(-4.17)	(0.77)
Adj. R^2	0.18	0.15	0.20	0.15	0.12	0.19
No. Obs.	169,775	77,318	92,457	169,863	78,519	91,344

Table A3: Pairwise Return Comovement (Broker- vs. Shadow-Financed Accounts)

This table reports Fama-MacBeth forecasting regressions of future return comovement. The dependent variable is the pairwise stock return comovement, defined as the product of daily market-adjusted returns of a pair of stocks (*i* and *j*) on day *t*+1. The main independent variable, Common-Margin-Investor-Ownership (*CMO*), is a measure of common ownership of stocks *i* and *j* by margin investors on day *t*. Specifically, it is defined as the sum of each margin investor's leverage ratio multiplied by his holdings in the two stocks, divided by the total market capitalizations of the two stocks. The variable *CNMO* (Common-Non-Margin-Investor-Ownership) is constructed similarly except that we use the 330,000 non-margin brokerage accounts instead. 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 in the previous 120 trading days (*MOMDIFF*). *SAMEIND* is a dummy that equals one if the two firms are in the same industry, and zero otherwise. *SIZE1* and *SIZE2* are the size percentile rankings of the two firms. Columns (1) to (3) correspond to the sample of broker-financed margin accounts, and Columns (4) to (6) correspond to the sample of shadow-financed margin accounts. Columns (1) and (4) include the entire sample period, columns (2) and (5) include the subsample of May 1st to June 12th, 2015 (Up Market), and Columns (3) and (6) include the subsample of June 15th to July 31st, 2015 (Down Market). T-statistics, with Newey-West adjustments of four lags, are reported below the coefficients. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable =Pairwise Stock Return Comovement Next Day						
	Broker-Financed Accounts			Shadow-Financed Accounts		
	Full	Up	Down	Full	Up	Down
	(1)	(2)	(3)	(4)	(5)	(6)
CMO	0.092***	0.043***	0.134***	0.557***	0.209***	0.864***
	(3.60)	(7.18)	(3.21)	(3.56)	(3.87)	(3.50)
BMDIFF	0.001***	0.001***	0.001**	0.001***	0.001***	0.001**
	(3.47)	(3.24)	(2.38)	(4.00)	(4.97)	(2.40)
COMANALY	0.0003***	0.0004***	0.0002*	0.0004***	0.0004***	0.0004***
	(3.87)	(6.99)	(1.73)	(5.25)	(10.66)	(2.68)
MOMDIFF	-0.0002	0.0004**	-0.001	0.001	0.001***	0.0004
	(-0.27)	(2.29)	(-0.60)	(1.07)	(4.52)	(0.38)
SAMEIND	0.014***	0.013***	0.016***	0.025***	0.016***	0.033***
	(4.76)	(5.22)	(3.01)	(4.71)	(5.55)	(3.84)
SIZE1	0.024***	0.010**	0.004***	0.035***	0.011**	0.057***
	(3.08)	(2.47)	(2.87)	(2.88)	(2.48)	(2.82)
*SIZE1*SIZE2*	-0.004***	-0.002***	-0.006***	-0.006***	-0.002***	-0.010***
	(-3.05)	(-3.09)	(-2.83)	(-2.85)	(-2.99)	(-2.78)
SIZE2	0.024***	0.010**	0.036***	0.035***	0.011**	0.057***
	(3.08)	(2.47)	(2.87)	(2.88)	(2.48)	(2.82)
SIZEDIFF	0.015***	0.006***	0.022***	0.020***	0.007***	0.033***
	(3.10)	(4.16)	(2.83)	(2.92)	(4.05)	(2.82)
Adj. R^2	0.02	0.01	0.03	0.02	0.01	0.03
No. Obs. (*1000)	31,395	14,766	16,609	4,847	2,889	1,958

Table A4: Network Centrality and Future Stock Returns (Broker- vs. Shadow-Financed Accounts)

This table reports forecasting regressions of future returns. The dependent variable is stock *i*'s return on day *t*+1. The main independent variable is *CENTRALITY*, the centrality measure of stock *i* on day *t*, defined as the eigenvector centrality of each stock in the leverage network. The link in this network between any pair of stocks reflects the common ownership of the two stocks by all margin investors (detailed definition in Section 4.5). We also include an interaction term between the market return on day *t*+1 and the centrality measure to pick up the effect of exposures to market risk. Other controls include stock *i*'s leverage ratio on day *t*, defined as the weighted average leverage ratio of all margin accounts that hold stock *i* (*LEVERAGE*), return on day *t* (*DRET*), book-to-market ratio on day *t* (*BMRATIO*), cumulative stock return in the previous 120 trading days (*MOMENTUM*), share turnover defined as average daily trading volume divided by the number of tradable shares in the previous 120 trading days (*TURNOVER*), idiosyncratic return volatility defined as the standard deviation of residual returns after controlling for the Fama-French three factors and the Carhart momentum factor (constructed using Chinese data) in the previous 120 trading days *(IDVOL*), and market capitalization at the end of previous month (*MCAP*). Panel A corresponds to the sample of broker-financed margin accounts, and Panel B corresponds to the sample of shadow-financed margin accounts. Columns (1) and (3) include the subsample of May 1st to June 12th, 2015 (Up Market), and Columns (4) to (6) include the subsample of June 15th to July 31st, 2015 (Down Market). Columns (1), (2), (4) and (5) conduct Fama-MacBeth regressions; T-statistics, with Newey-West adjustments of four lags, are reported below the coefficients. Columns (3) and (6) conduct pooled OLS regressions with date fixed effects; T-statistics, reported below the coefficients, are based on standard errors clustered by date. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Broker-Financed Margin Accounts						
	Up Market			Down Market		
	(1)	(2)	(3)	(4)	(5)	(6)
CENTRALITY	0.0003	0.0002	0.0001	-0.0003	-0.00013	0.0001
	(1.48)	(1.09)	(0.63)	(-0.97)	(-0.63)	(0.45)
*MRET **			0.0001			0.1907***
CENTRALITY			(0.04)			(4.27)
LEVERAGE		-0.0052***	-0.0099***		-0.0005	-0.0082***
		(-2.78)	(-5.56)		(-0.33)	(-9.03)
DRET		0.1949***	0.1914***		0.3621***	0.2322***
		(9.20)	(7.44)		(6.76)	(6.42)
BMRATIO		-0.00003	-0.00002		0.0001**	0.00003
		(-1.05)	(-0.53)		(2.19)	(0.63)
MOMENTUM		0.0008	0.0002		-0.0015**	-0.0019**
		(1.16)	(0.35)		(-2.18)	(-2.44)
TURNOVER		0.0430	0.0508**		0.0602*	0.0890***
		(1.65)	(2.01)		(1.78)	(3.02)
IDVOL		-0.5884***	-0.5523***		-0.1216	-0.2541*
		(-4.53)	(-4.78)		(-0.99)	(-1.79)
MCAP		-0.0037***	-0.0036***		0.0006	0.0003
		(-4.58)	(-4.04)		(0.52)	(0.26)
Date Fixed Effects	FM	FM	YES	FM	FM	YES
Adj. R^2	0.01	0.15	0.31	0.01	0.20	0.68
No. Obs.	77,318	77,318	77,318	92,457	92,457	92,457

Panel B: Shadow-Financed Margin Accounts						
	Up Market			Down Market		
	(1)	(2)	(3)	(4)	(5)	(6)
CENTRALITY	0.0001	0.00003	-0.0001	-0.0010***	-0.0007***	-0.0004
	(0.89)	(0.18)	(-0.28)	(-3.93)	(-3.33)	(-1.08)
*MRET * CENTRALITY*			-0.1134			0.1489**
			(-0.53)			(2.24)
LEVERAGE		-0.0001	-0.0010***		-0.0001	-0.0001***
		(-0.59)	(-4.43)		(-0.78)	(-3.86)
DRET		0.1622***	0.1604***		0.3573***	0.2068***
		(8.60)	(6.50)		(5.66)	(5.99)
BMRATIO		-0.00002	-0.00002		0.0001**	0.00005
		(-1.04)	(-0.51)		(2.43)	(0.84)
MOMENTUM		-0.0004	-0.0010		-0.0021***	-0.0027***
		(-0.53)	(-1.61)		(-3.08)	(-3.44)
TURNOVER		-0.0338	-0.0237		0.0215	0.0183
		(-1.07)	(-0.84)		(0.76)	(0.67)
IDVOL		0.0877	-0.0418		0.1013	0.1247
		(0.78)	(-0.39)		(1.42)	(1.10)
MCAP		-0.0038***	-0.0040***		0.0010	0.0002
		(-4.19)	(-4.43)		(0.81)	(0.17)
Date Fixed Effects	FM	FM	YES	FM	FM	YES
Adj. R^2	0.01	0.114	0.33	0.01	0.18	0.69
No. Obs.	78,519	78,519	78,519	91,344	91,344	91,344