De-Leverage and Illiquidity Contagion*

Conghui Hu

University of International Business and Economics
huconghui@uibe.edu.cn

Yu-Jane Liu

Guanghua School of Management, Peking University
yjliu@gsm.pku.edu.cn

Ning Zhu

PBC School of Finance
Tsinghua University

zhun@pbcsf.tsinghua.edu.cn

First Draft: November 2015
Current Draft: November, 2016

* The authors thank Brad Barber, Harrison Hong, Wei Xiong, Jianfeng Yu, Gang Zeng, Weiqiang Zhang, and participants at seminars at the Shanghai Stock Exchange. All common disclosures apply.

De-Leverage and Illiquidity Contagion

ABSTRACT

This paper investigates how variations in stock-level leverage lead to dynamic intraday trading behavior and illiquidity transmission across different stocks by utilizing a unique, precise, stock-level margin trading dataset. We document that leveraged investors' need to meet margin call requirements and liquidity demands due to prior market drop results in subsequent selloffs in otherwise stable stocks, particularly in afternoon sessions. This effect exists both within and across different industries and is stronger for stocks with less information asymmetry, better liquidity, higher past stock performance, less return co-movement, and even during trading suspension. Taken together, such findings suggest that our results are driven by illiquidity contagion instead of information spillover. Our study contributes to the research on asset fire sales, margin trading, and funding liquidity during the intraday deleveraging process in financial market turmoil.

Keywords: Leverage; Illiquidity spillover; Market crash; Intraday, China

I. Introduction

An emerging branch of literature shows that funding liquidity—the availability of investment and arbitrage capital—is responsible for system-wide market liquidity, volatility, and market turmoil in both the stock and bond markets (Hameed et al. 2010; Nagel 2012; Acharya et al. 2013). While most recent literature explores how institutional investors' common portfolio holdings (Coval and Stafford 2007; Greenwood and Thesmar 2011; Manconi et al. 2012; Greenwood et al. 2015) influences funding availability and asset price formation, the paper explores another important yet less explored manifestation of funding constraint, namely the formation of commonality in market-wide illiquidity from deleveraging at intraday interval. Particularly, we document how variations in stock-level leverage result in illiquidity contagion when leveraged traders encounter margin call pressure and/or increasing liquidity requirements at the market level.

According to the extant theoretical literature (e.g. Gromb and Vayanos 2002; Brunnermeier 2009; Hanson and Sunderam 2014), leveraged investors face stronger funding constraints and liquidity needs to meet margin call requirements during market drops. Considering such liquidity crunch risks, some investors may therefore choose to voluntarily reduce their risk exposure facing increasing market volatility in order to avoid forced liquidation and trading losses. As Kyle and Xiong (2001) argue, inaccurate prices resulting from constrained arbitrageurs may lead to deleveraging and contagious sell-off, which may create its own version of market-level funding illiquidity and crisis.

Our current study seeks to empirically understand how deleveraging in certain stocks originating from margin call requirements and involuntary liquidation influences trading in other stocks at relatively high frequency. Leveraged investors face intra-day liquidity needs (funding constraints) due to both voluntary risk management and involuntary liquidation (i.e. margin calls) by their lending brokers. If liquidity-constrained investors have to liquidate their positions in other stocks in order to meet margin requirements in stocks with big losses, the liquidity shortage in leveraged stocks will lead investors to sell other more liquid stocks that have not fallen as much. Such selling, in turn, will drive down the prices of otherwise stable or liquid stocks, further aggravating liquidity of other stocks and at the market level.

Data limitations hinder similar direct evidence between leverage and asset prices/illiquidity in the equities market. Most extant studies on this topic, such as Garleanu and Pedersen (2011), Hong et al. (2012) and Richardson et al. (2015), rely on an indirect measure (e.g. short interest or derivatives trading data) as a proxy for liquidity constraints. A unique dataset of precise stock-level margin trading information from China enables us to directly investigate how variations in stock-level leverage lead to trading and liquidity transmission across different stocks at intraday intervals.

Moreover, China's stock market's crash in 2015 and daily stock price movement limit of up to 10% (in either direction) in China provides a unique semi-natural experiment setup to investigate how variations in stock-level leverage result in differences in the liquidity demand for and selling pressure on distinct stocks during market turmoil. Investors holding highly leveraged long positions in stocks reaching daily downward price movement limit during the crash would face considerable need to meet their margin call and liquidity requirements and may transfer such liquidity demand to other stocks through their trading.

To the best of our knowledge, our findings are among the first to document that illiquidity spillover from deleveraging can explain how financial contagion spreads through margin trading in equities markets and the formation of commonality in market-wide liquidity at an intraday level. Our primary findings show that, among the sample of listed companies eligible for margin trading in the Chinese stock market, sudden stock price drops in some companies lead to a negative order imbalance of stocks within the same industry and across different industries. More central to the current study, we show that the spillover effect is larger for stocks with higher leverage. That is, deleveraging needs stemming from margin requirements during market drops lead to incremental sales of other stocks at intraday intervals.

Moreover, the illiquidity spillover becomes stronger if the price of a stock declines or is highly likely to reach the negative price movement limit. Such findings indicate that liquidity-constrained stocks have a bigger spillover impact on other stocks when demand for liquidation is stronger. Economically, on average, a 10 percentage point price drop for stocks with a typical leverage ratio of 8% leads to a 5.19 (3.97) percentage point decrease (approximately a 0.25 standard deviation) in order imbalance for stocks within the same industry (across industries) over the subsequent five-minute interval. When the leverage ratio increases from the 25^{th} percentile value (2%) to the 75^{th} percentile value (12%), the intensity of resulting selling pressure, on average, rises by over 50%, to a price drop of over 7 percentage points.

This paper further explores the dynamic evolution of illiquidity contagion within different intraday periods. Our result indicates that the spillover effect is much stronger in afternoon sessions than in morning sessions. To take a further step, we study the selling pressure for leverage and non-leveraged stocks separately, and find that leveraged stocks are more susceptible to the contagion effect resulting from deleveraging than non-leveraged stocks, particularly in the afternoon session. For example, the selling pressure on non-leveraged stocks transmitted from deleveraging is insignificant during the first trading hour and gradually intensifies as intra-day trading develops when the need for meeting liquidity demand increases and selling pressure for leveraged stocks grows.

Finally, we find that stocks with various characteristics are impacted by the illiquidity contagion differently. Our evidence suggests that stocks with less information asymmetry, better liquidity, and higher past performance are more likely impacted by price drops in leveraged stocks, lending further support to the conclusion that margin requirements and related liquidity demand are responsible for our findings. By analyzing how selling pressures spread across stocks during a liquidity crunch, our paper finds that investors display a disproportional pattern in selling stocks, thus shedding lights on the research of asset fire sale.

We acknowledge that it is plausible that leveraged investors may bring new information (Seguin 1990; Mayhew et al. 1995) that affects investors' expectations and thereby alters their trading behaviors. In addition, the relationship between leverage and illiquidity spillover may convey some new market-level and firm-level information (Cespa and Foucault 2014). Therefore, we conduct a series of additional tests and confirm that illiquidity contagion, instead of information spillover, drives our findings.

First, the intraday variations of illiquidity contagion is more consistent with deleveraging than information spillover given the afternoon period (in particular the period from 1:30 p.m. to 2:30 p.m.) is more likely to face margin calls and liquidity demand, and less likely to be affected by the release of new information (Admati and Pfleiderer 1988; Foster and Viswanathan 1993; Ederington and Lee 1993).

Moreover, we utilize trading suspension as an additional identification strategy to examine the illiquidity spillover related to margin requirements. Trading suspension offers a unique advantage in assessing leveraged behavior and any consequences it might have for illiquidity spillover because incorporation of new information into stock prices on a particular leveraged stock is blocked. We show that even during trading suspension when information cannot be transmitted through regular trading, highly leveraged stocks, which may face greater deleveraging pressure after trading resumes, have a greater impact on other stocks' trading when the market declines.

In addition, to rule out the possibility of return co-movement driving our results, we construct a direct measure for return co-movement and show that the documented illiquidity spillover effect is indeed more pronounced among firms with lower return co-movement, contrary to the alternative co-movement explanations.

Our findings make three primary contributions to the extant literature. First, we provide direct evidence of how leverage influences trading and liquidity dry-up in equities markets at the intraday interval. Particularly, we expose leverage as another important channel through which funding constraints affect individual security trading and contribute to systematic financial contagion. A growing branch of literature addresses commonality in institutional ownership. For example, Greenwood and Thesmar (2011) provide evidence that an asset can be fragile because its owners face correlated liquidity shocks and Greenwood et al. (2015) show that forced asset sales may make certain banks vulnerable than others In addition, Manconi et al. (2012) show that liquidity-constrained mutual funds with exposure to securitized bonds played a role in propagating the crisis from securitized to unsecuritized corporate bonds.

The current study provides empirical evidence that de-leveraging resulting from margin call requirement in equities market can serve as another important channel through which funding constraints influence investors' trading behavior and consequently asset price and volatility. Our paper highlights that security-level leverage and margin requirement may induce its own funding constraints across different types of investors and systematic sell-offs and market slump. Unlike previous studies that focus on particular types of financial institutions, our findings reveal that such transmission of deleveraging and illiquidity is pervasive at the market level and varies considerably depending on company ex-ante liquidity before the crash.

Second, we contribute to the literature that explores the role of leverage by taking advantage of precise stock-level margin data to establish a direct link between (de-)leverage and market liquidity in the equities market. Extant studies in this field have to rely on indirect proxies for leverage and focus on longer daily or weekly horizons. For example, Garleanu and Pedersen (2011) present a model to show how margin constraints affect asset prices and exploit the spread between credit default swaps and bond to empirically support the predictions. Hong et al. (2012) document that prices of highly shorted stocks are more sensitive to fundamental shocks compared with stocks with little short interest.

Our analysis of liquidity variations at intraday, instead of daily intervals, bridges the gap in the literature by documenting consistent intraday variations in liquidity spillover and shows how margin requirements of individual stocks may inadvertently cause market-wide panic and volatility dynamically at higher frequencies. Such evidence not only helps extend our understanding of phenomena such as flash crashes and market crashes (Kirilenko et al. 2016; Kyle and Obizhaeva 2016), but also facilitates the disentanglement between the respective impact of leverage and information (Seguin 1990; Mayhew et al. 1995; Boehmer et al. 2008; Engelberg et al. 2012).[1]

Further, as some studies (Hirose et al. 2009; Chang et al. 2014) indicate, margin traders in Asian financial stock markets tend to be mostly retail investors. Unlike existing studies focusing primarily on institutional investors (e.g. Hong et al. 2012; Manconi et al. 2012; Nyborg and Östberg 2014), our findings provide additional insights into how different investor clientele may affect market leverage and liquidity. Such findings are especially useful to emerging markets, where retail investors play a greater role in determining asset prices than their counterparts in developed economies.

Third, a growing strand of literature highlights the importance of the impact of liquidity commonality on investor trading and asset prices (e.g. Chordia et al. 2000; Næs et al. 2011; Karolyi et al. 2012). Our findings provide a specific mechanism through which liquidity transmits and liquidity commonality at the aggregate market level develops. We show that sudden market drops in China, triggered by the unwinding of leveraged long positions in highly leveraged stocks, induced selling of other stocks within the same industry and across industries. Such a shift in investors' trading behavior, induced by margin requirements and deleveraging, in turn caused worsening liquidity and price drops in other stocks that were not originally leveraged or falling, and hence created a vicious cycle of market-wide drops and liquidity dry-up. We thereby show that liquidity shocks have an asymmetric impact on market stability and systematic liquidity spillover, depending on the market's direction.

In particular, unlike existing literature, our paper utilizes high frequency intraday data (five minute intervals) and precise margin information as a proxy for liquidity and complements existing evidence on liquidity commonality and liquidity spillover at lower frequencies (i.e. Hameed et al. 2010; Karolyi et al. 2012). Because considerations of inventory and asymmetry information may vary at high- and low-frequencies, our paper bridges the gap in the literature by providing evidence of

[1] There is scant literature directly addressing the link between leverage and information. Some papers cited here focus on short sellers.

how correlation of liquidity spreads across different stocks at higher frequencies. Our findings are valuable to future theoretical study on causes and consequences of market crashes and market-wide liquidity crunches caused by liquidity dry-up and the resulting spillover.

The rest of the paper proceeds as follows. Section II outlines the institutional background and data utilized in the study. Section III introduces the empirical framework to identify illiquidity contagion triggered by deleveraging and presents basic results. Section IV investigates the intraday and cross-sectional variations to provide additional evidence consistent with illiquidity contagion. Section V and Section VI host further analyses to alleviate the concern of alternative explanations and robustness checks for our findings, respectively. Section VII concludes.

II. Institutional Background and Data

A. Margin Trading and the Recent Crash of China's Stock Market

Between June 2014 and June 2015, China's Shanghai Composite Index rose by about 150%; it reached a high of 5,166 on June 12, 2015. Within a month of June 15, 2015, the Shanghai Composite Index fell by about 35%.[2] It slumped by more than 43% to a low of 2,927, on August 31, less than three months after market peak in June.[3] Many practitioners and the media suggest that margin trading is largely responsible for China's latest stock market booms and busts.[4]

The margin trading system was first introduced to the Chinese stock market on March 31, 2010. At the beginning, only 90 stocks that were listed on the Shanghai Stock Exchange (SSE) 50 index and the Shenzhen Composite Index were allowed to be traded on margin (including both long and short sales). Over time, the number of stocks eligible for margin trading has increased many folds. As of September 13, 2014,

[2] A series of extraordinary interventions by the Chinese government, including establishing a stabilizing fund to directly purchase stocks and sending short-sellers to prison helped stabilize the market temporarily and pushed it back up to 4,000.

[3] The total combined trading volume of the Shanghai Stock Exchange and the Shenzhen Stock Exchange was cut in half to less than 1 trillion Yuan from its peak of more than 2 trillion Yuan several months prior.

[4] See the following websites for related media reports: http://www.economist.com/news/business-and-finance/21662092-china-sneezing-rest-world-rightly-nervous-causes-and-consequences-chinas ; http://www.reuters.com/article/us-china-stocks-idUSKCN0PI04Q20150708.

the number of stocks allowed to be traded on margin in the Chinese A-shares market is about 820.

Margin trading can greatly increase investors' profits during market run ups and magnify losses during market slumps. We plot a time-series of leverage patterns (measured by the equal-weighted average leverage) and cumulative returns of all stocks from June 1, 2015, to August 31, 2015, in Figure 1. *Leverage* is defined as the dollar balance of margin debt of a stock divided by the market value of floating shares of the same stock at the end of May 2015.[5] The Shanghai Stock Exchange and the Shenzhen Stock Exchange not only announce the aggregate volume of margin trading regularly, but also provide daily updates on the share volume and dollar balance of margin trading for each stock. Such data enables us to calculate the scale of leveraged trading for each stock at a daily frequency. Figure 1 shows that the volume of margin trading shifts considerably depending on market performance. The total dollar balance of margin debt in the Chinese stock market rose from 400 billion Yuan at the end of June, 2014 (about 4% of float market capitalization), to 2.26 trillion Yuan (about 8% of total float market capitalization) at the end of June 2015, before falling back to 0.95 trillion Yuan (less than 4% of float market capitalization) at the end of August 2015.

Insert Figure 1 Here

The liquidity dry-up resulting from initial losses in the over-leveraged Chinese market may be responsible for sustained market corrections even into early 2016. Investors are forced to liquidate part of their positions to repay margin requirements, and their need to raise capital by selling stocks may have played a prominent role in China’s recent stock market crash. Hence, initial market declines exacerbated stock market liquidity and induced further market decline. To examine the relationship between leverage and stock return performance, we plot the cumulative daily return of stock portfolios sorted on *Leverage* in Figure 2. We rank firms into three groups by

[5] This measure provides a good way to gauge the significance of margin trading by comparing it with all shares that are available for public trading.

their respective *Leverage* in the last trading day and compute the equal-weighted average cumulative returns in each group. Figure 2 shows that stocks with higher leverage experience more extreme returns, consistent with the argument on the amplification effect of leverage in stock market booms and crashes.

Insert Figure 2 Here

The Shanghai and Shenzhen Stock Exchange both implement daily price limits and trading suspension. During the 2016 market crash period, about half of stocks listed on the Shanghai and the Shenzhen reached their downward price movement limit for at least one trading day. More than half of all listed Chinese companies chose to suspend the trading of their shares voluntarily while the remaining suspension was due to the stock price reaching their respective price movement limit. While limits on sharp stock movements and/or trading halts prevented hundreds of stocks from logging sharper declines, they also considerably reduced market liquidity and made it harder for investors to exit positions. Oftentimes during this period, investors had to sell stocks that were previously less affected by negative shocks (e.g. blue chip stocks) to meet their liquidity demand from margin trading. This is also true for mutual funds and hedge funds, which were forced to liquidate relatively liquid positions to meet redemption demand from their clients. Unfortunately, such flight to liquidity triggered an even greater sell off in otherwise sound and liquid stocks and aggravated the spread of market collapse.

B. Trading Systems and Margin Trading Rules

The Shanghai Stock Exchange and Shenzhen Stock Exchange are the only two stock exchanges in mainland China. The trading process for stocks on both exchanges is similar. Both exchanges run order-driven, automated markets, without designated market makers. The market constitutes opening call auctions and continuous double auctions during the intraday trading period. During the opening call auction, investors can only submit limit orders to determine the execution price in strict price and time priority. During the regular intraday period, traders can submit limit orders and market orders, which are executed in a consolidated electronic order book. An incoming buy (sell) order is automatically matched against the best sell (buy) order in the order book. If an order cannot be matched, the unfilled order will be added to the limit order book. The public limit order book discloses the best five unfilled buy (sell) quotes and volumes and is updated by the exchanges every three seconds.

The two exchanges get to determine the list of underlying securities for margin trading based on information such as the number of shareholders, market capitalization, turnover, volatility, and other conditions. Generally, firms that are qualified for margin trading tend to be larger, have better liquidity, lower volatility, and lower propensity to be affected by abnormal trading.

After the initial introduction of margin trading, the China Securities Regulatory Commission (CSRC), China's counterpart to the SEC, implemented an investor eligibility requirement and allowed only select investors to open margin accounts to protect retail investors from the elevated risk accompanied by leverage trading. For example, brokerage clients who apply for margin trading are required to have at least six months' of trading experience and maintain an average daily balance of no less than 500,000 Yuan. However, during the 2014-2015 China stock market run-up, many brokers did not strictly implement such requirements and allowed retail investors with account balance of as low as 10,000 Yuan to trade on margin.

Initial margin requirements were uniformly set by the two exchanges at 50% during our sample period.[6] When the maintenance guarantee ratio of clients is lower than 130%, brokerage firms make automatic margin calls demanding additional capital from their clients. If additional capital is not pledged on the day after the margin call (T+1 trading day), the security firms will automatically liquidate clients' leveraged positions.

[6] Initial margin requirement was later raised to 100% on Nov 23, 2015 to strengthen the risk management of margin trading. It is worth pointing out that to hedge against market risks, some major brokers, such as Haitong Securities and Xingye Securities, decided to exercise greater discretion and raised their initial margin ratio requirement as early as May 2015, immediately before the peak of recent stock bubble.

C. High Frequency Data

To examine the spillover effect of liquidity needs arising from margin trading, our sample only includes firms that are qualified for margin trading at the stock exchanges. The sample period ranges from June 15, 2015 to August 31, 2015 including the sharp drop in the Chinese stock market during the 2015 turmoil. For each stock, we construct five-minute time series of stock prices using the last transaction price of each five-minute trading interval. The complete tick-by-tick transaction data was obtained from the Dafuweng Database, which provides high-quality, high frequency data on the Chinese financial markets.[7] All other firm-level data are obtained from the CSMAR database, which is a widely subscribed database about firm-level data in China.

We use order imbalance to measure the relative selling pressure of each stock.[8] We define order imbalance as $\frac{\text{buy orders}-\text{sell orders}}{0.5\times(\text{buy orders}+\text{sell orders})}$, where, buy (sell) orders include executed purchase (sell) orders and best five unfilled purchase (sell) orders.[9] All orders are measured by dollar value.[10] In most regressions, we average the order imbalance for each five-minute interval for each stock to construct the time series of order imbalance (*OI*). Table 1 presents the distribution of main variables in our paper. The mean value of *OI* is -4.51%, suggesting that investors tend to sell 4.51% more than what they purchase for each five-minute interval during the sample period. The maximum (minimum) value of *OI* equals 200% (-200%), implying that the stock price hits the upward (downward) 10% limit.

We utilize stock-level margin trading information to directly investigate how illiquidity transmitted across different stocks at intraday intervals during the sudden

---

[7] http://www.licai668.cn

[8] Please note that order imbalance is negatively indicative of selling pressure.

[9] An alternative way to measure the selling pressure is to calculate the imbalance between buyer-initiated trades and seller-initiated trades. However, this measure is problematic when stock prices reach their 10% downward limit, as seller-initiated trades cannot get executed and accordingly almost all trades would be buyer-initiated. Under this situation, this measure would be simply meaningless and indeed misleadingly indicates that there is strong buying pressure in the market. Given that we are particularly interested in the illiquidity spillover when the market sustains considerable drops, we did not exploit this measure to avoid such a mechanical problem.

[10] We also calculate the order imbalance using orders measured in the number of shares and the results are similar.

market turmoil in the Chinese stock market in 2015. *Leverage* is defined as the dollar balance of margin debt scaled by the market value of floating shares at the end of May 2015. The average leverage of all stocks is 5.28%, with a maximum (minimum) value 26.11% (0.12%). As Figure 1 indicates, the average leverage of Chinese stocks reached its highest level around June, 2015, before dropping significantly during the market crash later that year.

Insert Table 1 Here

Figure 3 plots the intraday pattern of order imbalances of stock portfolios sorted on *Leverage* from June 1, 2015, to August 31, 2015. We rank firms into three groups by their respective *Leverage* in the last trading day and compute the equal-weighted order imbalance in each group. There are two interesting and distinguishing patterns in Figure 3. First, selling pressure is much stronger in the afternoon, when private information released through trading is less likely and margin call pressure is greater in a broker's practice. Second, firms with higher leverage experience greater selling pressure, especially in the afternoon, suggesting leverage may be associated with stock sales and market drops.

Insert Figure 3 Here

III. Main Findings

This paper argues that leveraged investors have to sell otherwise normal stocks in order to raise capital to meet their margin call or for risk management purposes. Therefore, it is plausible that the price drops in stocks with high leverage may trigger the sell-off of other stocks that were otherwise trading normally. In particular, once the upward/downward price movement limit is reached, no further buying/selling at higher/lower prices is allowed until the next trading day. Investors, especially leveraged investors, with positions in stocks that are very likely to approach the downward price movement limit, would have great difficulty in selling these stocks and have to turn to selling other stocks if they need to raise capital to meet their margin requirement. This paper further conjectures that, during market slumps, stocks with greater leverage are more likely to suffer funding constraints as these investors decide, or are forced, to unwind their positions in order to meet liquidity demands by stocks that cannot be readily liquidated. Therefore, the change in leverage would have a greater impact on the trading and liquidity of other stocks during market drops than during market increases.

We describe the amplification effect associated with leverage and adverse price movement as "illiquidity contagion". Operationally, we take advantage of the interaction of leverage and order imbalance to capture the interplay between investors' liquidity demands and the price impact exerted by trading conducted by investors with varying levels of liquidity demand. In our baseline regression, we regress subsequent five-minute order imbalance at industry-level or across industries on five-minute lagged individual stock returns, individual stock leverage, and their interaction.

Specifically, we formulate our regression as follows:

$$Ind\_OI_{i,t}(CrossInd\_OI_{i,t}) = \\ b_0 + b_1 R_{i,t-1} + b_2 Leverage_{i,d-1} + b_3 R_{i,t-1} * Leverage_{i,d-1} + Controls \tag{1}$$

$$Ind\_OI_{i,t}(CrossInd\_OI_{i,t}) = b_0 + b_1 R_{i,t-1} + b_2 Leverage_{i,d-1} + b_3 R_{i,t-1} * Leverage_{i,d-1} \\ + b_4 (Large) Down_{i,t-1} * R_{i,t-1} * Leverage_{i,d-1} + Controls \tag{2}$$

The dependent variable Ind_OI_{it} is defined as the average order imbalance for all firms in the same industry except firm *i,* whereas the dependent variable $CrossInd\_OI_{it}$ is defined as the average order imbalances for all firms other than those that are in the same industry as firm *i*, within the most recent five-minute interval before time *t*.[11] We use the Shenwan Level I industry code, a popular industry classification in China, to classify industry sectors.

The main explanatory variables include stock return of firm *i* until the lagged one period, stock-level leverage in the last trading day, and the interaction between the

[11] We also exploit intraday intervals at other frequency (e.g. ten minutes). The results are basically similar and available on request.

above two. In our setting, t indicates the trading time at intraday frequency and $t-1$ ($t-2$, $t-3$) is defined on the lags of five-minute intervals, whereas d represents the trading day at daily frequency. Individual stock return ($R_{i,t-1}$) is intended to capture intraday dynamic information shock to firm i and is defined as $\frac{P_{t-1}-P_{d-1}}{P_{d-1}}$, where P_{t-1} is the last transaction price of firm i until $t-1$ and P_{d-1} is the close price of firm i in the last trading day. We use previous day's closing price, instead of the current day's opening price, to calculate the intraday return until time t because we want to capture the cumulative return shock at intraday frequency from the previous day, so that the calculating period is more consistent for different intra-day horizons. For example, the cumulative returns would be mechanically smaller near market opening than near market close, largely because of the longer period of time over the course of a trading day. We have also used alternative approach which calculates intraday returns using current day opening price and the results remain qualitatively the same.[12] This situation is more relevant to our context because most brokers use price change based on previous day's closing price as a benchmark for making their decisions related to margin call. The coefficient of $R_{i,t-1}$measures the average influence of intraday lagged individual stock returns on the trading of other firms. If the coefficient is positively significant, it implies the price information of one stock can influence the trading of other stocks.

We define $Leverage_{i,d-1}$ as the dollar balance of margin debt for firm i on day $d-1$ scaled by the market value of floating shares at the end of May 2015.[13] Because liquidity is known to have an amplifying effect on stock trading regardless of market rise or drop, we expect leverage to have a significant impact on the trading of other stocks.

More to the central theme of the current study, we include a two-way interaction ($R_{i,t-1}*Leverage_{i,d-1}$) between past returns and leverage in order to capture the

[12] The literature on the magnet effect documents a significant tendency for stock prices to accelerate towards upper (lower) bounds as stock prices approach the bound (Cho et al., 2003). We have also exploited the opening price and the last transaction price in the lagged five-minute interval to calculate intraday return. The results are consistent with our main findings and will be available on request.

[13] We also tried alternative specifications in which we define leverage as the dollar balance of margin debt divided by the market capitalization of each stock in the last trading day. Our results remain qualitatively the same.

compounding effect between leverage and market movement on stock trading.[14] Further, the current study is more interested in empirically examining the impact the three-way interaction between return, leverage, and market drops ($(Large)Down_{i,t-1}*R_{i,t-1}*Leverage_{i,d-1}$), on industry- (market-) wide trading. That is, we are particularly interested in understanding how sudden market drops may modify leverage's impact on other stocks' trading. $Down_{i,t-1}$ ($LargeDown_{i,t-1}$) is a dummy variable that takes the value of one if $R_{i,t-1}$ is less than zero (-7%), and the value of zero otherwise.[15] We expect the coefficient of the three-way interaction term between past stock returns, leverage, and a big market downturn to be significantly positive, suggesting that leverage has a particularly strong impact during a market slump.

In addition, we include lagged dependent variables to control for the persistence of order imbalances (Chordia et al., 2002). We divide a whole trading day into 48 five-minute intervals and include interval dummy variables to control for the intraday time-series of order imbalances. We evaluate the significance of regression coefficients using standard errors clustered by firm.

Table 2 shows that, consistent with the existing literature on stock return co-movement, the coefficient of $R_{i,t-1}$ is significantly positive, suggesting that the negative (positive) shocks to individual stocks could spread to other stocks and significantly reduce (increase) their order imbalance. As expected, the coefficient on leverage is negative, providing a hint that highly leveraged stocks indeed have greater negative impact on trading by other stocks. More importantly, the coefficient of the interaction between lagged stock return and leverage ($R_{i,t-1}*Leverage_{i,d-1}$) is significantly positive, indicating that firms with higher leverage have greater impact on industry- (market-)wide trading. Such findings are consistent with our expectation and confirm that not only stock returns, but also variations in leverage and therefore liquidity demand, is responsible for the significant influence on the order imbalance of trading on other stocks.

[14] Given that the highest frequency at which margin data available is daily, we have no other choice but to combine the order imbalance at higher frequency and daily margin data. We acknowledge that there can indeed be intra-day variations in margin and have exploited such changes and addressed this issue in Section IV.A.
[15] The results are basically similar when we adopted other cutoffs such as -5%, -8% and -9%.

In particular, we show that such an effect is particularly strong when stock price drops at all, drops by at least 7%, and drops to its respective downward price movement limit. As expected, we find that the coefficient of three-item interactions (*(Large)Down*$_{i,t-1}$*$R_{i,t-1}$**Leverage*$_{i,d-1}$) are significantly positive even when controlling for the interaction of intraday stock returns with leverage, suggesting that the contagion effect arising from leverage is intensified in the event of negative shocks, especially substantial negative shocks. Specifically, in specifications 1-4 of Table 2, we show that a negative return raises the regression coefficient for the interaction term between stock returns and leverage (*Down*$_{i,t-1}$*$R_{i,t-1}$**Leverage*$_{i,d-1}$.) by 1.012, whereas the coefficient of *LargeDown*$_{i,t-1}$*$R_{i,t-1}$**Leverage*$_{i,d-1}$ is 2.603, more than twice as large, for the trading on stocks within the same industries.[16] This evidence confirms that leveraged investors are more likely to sell other stocks to raise capital, probably to meet margin requirement during market crash.

Economically, a 10 percentage point price drop for stocks with a typical leverage ratio of 8% leads to a 5.19 percentage point decrease (approximately a 0.25 standard deviation), in order imbalance for stocks within the same industry over the next five-minute interval.[17] When the leverage ratio increases from the 25th percentile value (2%) to the 75th percentile value (12%), the intensity of resulting selling pressure, on average, rises by 58.19%, for a price drop of over 7 percentage points. Leverage causes significant impact on other stocks' trading during sharp price drops. Such three-way interaction has far greater economic impact than the two-way interaction between past returns and leverage, again confirming the importance of illiquidity contagion in the face of market crashes.

Our results in specifications 5-8 of Table 2 suggest that investors facing capital

[16] The coefficient of three-item interaction with *HitFloor*$_{i,t-1}$ that indicates a firm hits the downward price movement limit is a bit lower than that with *LargeDown*$_{i,t-1}$. One plausible explanation is that investors, especially leveraged investors have started unwinding their losing positions before their holdings reached deep losses.

[17] For a large price drop (over 7%) of a leveraged stock, the economic influence on the subsequent order imbalance is estimated by $R_{i,t-1}*(Leverage_{i,d-1}*(b_3+b_4)+b_1)$ according to equation (2). In this case, when substituting the coefficients in column 3 of Table 2, it equals -5.19% [-10%*(8%*(2.603-0.364)+0.34)]. In addition, the standard deviation of industry(market)-level order imbalance during normal periods is 22.34% (14.93%) . For a given trading day, if the equal-weighted average return of all stocks on this day is within +/-4% range, we classify it into normal periods.

constraints need to sell stocks not only within industries, but also across industries, in order to raise much-needed capital when the market decreases. Economically, a 10 percentage point price drop for stocks with a typical leverage ratio of 8% leads to a 3.97 percentage point decrease (more than 0.25 standard deviations) in order imbalance for stocks across industries over the next five-minute interval. When the leverage ratio increases from the 25th percentile value (2%) to the 75th percentile value (12%), the intensity of resulting selling pressure, on average, rises by 50.28%, for a price drop of over 7 percentage points.

Insert Table 2 Here

Our findings confirm our hypothesis that liquidity needs related to deleveraging can exert significant influence on the order imbalance of other stocks. [18] A growing literature suggests that liquidity constrained investors are likely to sell other assets that have not been affected with the initial shock amplified in a broader financial market. Manconi et al. (2012) find that mutual funds retained securitized bonds and sold corporate bonds during the financial crisis. Nyborg and Östberg (2014) show that as the lending cost in the interbank market rises, banks are forced to sell assets in the stock market for liquidity demands. More generally, our study adds to literature that explores how funding constraints lead to the market-wide crisis by documenting that negative shocks to individual stock could spread to other stocks and reduce their order imbalance through the liquidity channel of deleveraging and have a greater impact on the trading of other stocks during market declines.

IV. Additional Investigations

We attribute the spillover effect associated with leverage trading to investors'

[18] In unreported results, we add more firm-level controls including firm size, book-to-market ratio, proportional spreads, the Amihud illiquidity ratio, and industry dummy variables and their interactions with stock returns into regression equations. The regression results remain quantitatively the same, indicating that the effect of deleveraging is not influenced by these firm or industry characteristics. Such results are available from the authors upon request.

liquidity needs by providing additional evidence on illiquidity spillover effects. In this section, we first investigate the dynamic evolution of illiquidity contagion at different intraday trading sessions. We further explore issues on fire sales by investigating what kinds of stocks are more susceptible when investors suffer liquidity constraints.

A. Intraday Variations of Illiquidity Contagion

High frequency data allows us to further investigate the dynamic illiquidity spillover patterns during the intraday period. Trading in the morning session is generally considered as more likely to incorporate new information than that in the afternoon session (e.g. Foster and Viswanathan 1993). If the contagion effect associated with leverage is more related to liquidity pressure instead of cross-stock information learning, we expect the effect to be more pronounced in the afternoon sessions than in the morning sessions. In this sense, the intraday variations of the spillover effect also help us distinguish information learning explanations from liquidity needs.

It is also interesting to know whether illiquidity contagion clusters at certain periods. Market microstructure studies highlight that trading patterns vary with different intraday periods (e.g. Admati and Pfleiderer 1988). According to media reports and our communication with regulators and practitioners,[19] many brokerage firms choose to make margin calls and initiate forced liquidations in the afternoon. Such anecdotal evidence provides some additional rationale for the argument that our documented contagion effect in the afternoon is primarily induced by deleveraging spillover, instead of information spillover.

In Table 3, we divide a whole trading day into a morning session and an afternoon session. The regression equations are specified identically to those in Table 2, in which average order imbalances for firms within (outside) the same industry in morning/afternoon trading session are regressed on lagged intraday stock returns, leverage, and the two-way and three-way interaction terms using five-minute data. To conserve space, we only report the coefficients of intraday stock returns and their interactions with leverage. The differences of three-way interactions' coefficients

[19] See the website (http://wallstreetcn.com/node/219752) for related media coverage.

between trading sessions are estimated using the seemingly unrelated regression (SUR) model and the x^2 statistics are reported.

The results show that the coefficients of $Down_{i,t-1}*R_{i,t-1}*Leverage_{i,d-1}$ during the morning session are all significantly negative, indicating that in the morning session, the lagged negative shock to firms with higher leverage indeed has a weaker spillover effect than the positive shock. In contrast, these coefficients during the afternoon session all turn out significantly positive with a larger magnitude, reflecting that the negative influence induced by deleveraging on the subsequent order imbalances of other stocks are more pronounced in the afternoon session. Though the coefficients of $LargeDown_{i,t-1}*R_{i,t-1}*Leverage_{i,d-1}$, are positive in all sessions, the magnitude in the afternoon sessions is much larger than that in the morning session. Specifically, for a stock with a typical leverage ratio of 8%, a 10 percentage point price drop during the afternoon session results in a 6.27 (4.70) percentage point increase in selling pressure of stocks within the same industry (across industries), compared to the same price drop during the morning session, which only leads to a 3.23 (3.91) percentage point increase. These intraday patterns of contagion effect contradict the prediction of information-driven trading hypothesis, lending more support that our hypothesized illiquidity contagion associated with leverage is driven by lack of liquidity.

Insert Table 3 Here

One might argue that the trading at the very beginning and end of the afternoon session may also be more likely dominated by informed trading.[20] To further disentangle the impact of information trading in the afternoon session, we investigate whether the contagion effect induced by leverage is still significant in the session from 1:30 p.m. to 2:30 p.m. (excluding the first and last thirty minutes in the afternoon trading session) than the morning session.

The results suggest that the coefficients of three-way interactions

[20]Admati and Pfleiderer (1988) show that informed trading is likely to occur at the beginning and end of the day as high volume provides a sufficient disguise for their information. Further studies (e.g. Ederington and Lee, 1993) show that new information will be mainly released within fifteen minutes after market open.

($(Large)Down_{i,t-1}*R_{i,t-1}*Leverage_{i,d-1}$) in the session from 1:30 p.m. to 2:30 p.m. are all positive and higher than that in the morning session, providing additional support for the proposition that the more intensive contagion effect in the afternoon session is indeed less likely to be driven by informed trading.

An interesting issue is whether illiquidity contagion induced by leverage varies depending on a firm's leverage condition at intraday interval. Everything else being equal, we expect investors to be more inclined to sell leveraged stocks when the prices fall to, or close to respective downward price movement limit, near market close. If the prices of leveraged stocks were to fall even further, leveraged investors will have greater difficulty in selling their leveraged position due to protracted selling and trading suspension, and would therefore be better off selling their non-leveraged positions to raise much needed liquidity. Consequently, we expect that even completely non-leveraged stocks are be impacted in the deleveraging process, after leveraged stocks withstand the first wave of deleveraging.

Operationally, we sort impacted stocks into leverage and non-leverage groups depending on a stock's pre-crisis leverage and compute the equal-weighted order imbalances in each group. The average order imbalances for stocks with different leverage trading are, respectively, regressed on lagged stock returns, leverage, and their interactions using five-minute data. The explanatory variables and control variables in the regressions are identical to those in Table 2. Inspired by the intraday variations of illiquidity contagion shown in Table 3, we conduct the regressions within different intraday periods. To conserve space, we only report the three-way interactions' coefficients for large price decline and the differences between groups. The significance of the differences is evaluated using the seemingly unrelated regression (SUR) model and the x^2 statistics are reported.

Table 4 shows that, the coefficient for leveraged stocks is significantly higher than that for non-leveraged stocks within each respective period, indicating that leveraged stocks are more susceptible to the contagion effect resulting from deleveraging than non-leveraged stocks in general. Consistent with intraday pattern documented in Table 3, the selling pressure among leveraged stocks is much higher in the afternoon than that in the morning. Interestingly, the selling pressure transmitted from deleveraging is insignificant in the first trading hour for non-leveraged stocks, possibly as investors collect information on price movement and liquidity pressure. However, as time goes by during intraday trading hours, the selling pressure for even non-leveraged stocks becomes intensified and significant, possibly reflecting that investors turn to non-leveraged stocks for the demand of liquidity when there is greater need for liquidity and greater difficulty in liquidating leveraged stocks.

Insert Table 4 here.

B. Cross-sectional Variations of Illiquidity Contagion

In this section, we distinguish what types of stocks leveraged investors may choose to sell when they face capital constraints and what types of stocks have a greater marginal impact on the trading of other stocks during market slumps. Specifically, we further explore how illiquidity due to deleveraging spreads to other stocks using cross-sectional variations in firm characteristics with respect to different information asymmetry, asset liquidity, and stock performance.

B1. Information Asymmetry

We explore whether the illiquidity contagion induced by leverage is more likely to be associated with stock characteristics known to relate to information asymmetry. If information drives investors' selling decisions, we expect that investors choose to first sell firms with more information asymmetry because these stocks should be more sensitive to new negative information reflected in the leveraged trading. On the other hand, if the contagion effect associated with leverage is primarily due to the lack of liquidity, it is plausible that the liquidity dry-up would be more pronounced for firms with less information asymmetry. Stocks with less information asymmetry usually involve lower price impacts (Kyle 1985) and thus can facilitate fire sale for liquidity constrained investors. Moreover, even though all stock prices tend to deviate from their fundamental values during crisis, it should be those stocks with less information asymmetry that suffer less temporary underpricing. Therefore, investors should choose to first sell stocks with less information asymmetry, which are less impacted by sudden market drops.

Size is a commonly used proxy for information asymmetry (e.g. Chae 2005). We argue that stocks with larger market capitalization are associated with lower levels of information asymmetry. *Size* is defined as the market value of a firm's floating shares outstanding at the end of May 2015. We sort all firms into five groups by *Size* and compute the equal-weighted order imbalances in each group. The average order imbalances for firms with different levels of information asymmetry ($Size\_OI_{jt}$) are, respectively, regressed on lagged stock returns, leverage, and their interactions using five-minute data. The explanatory variables and control variables in the regressions are identical to those in Table 2. To save space, we only report the coefficients of intraday stock returns, leverage, and their interactions using the order imbalances in the smallest (lowest), middle and largest (highest) group as dependent variables in Tables 5, 6, and 7.

Table 5 shows that when leveraged investors suffer capital constraints in the face of negative shocks, the selling pressure for larger firms is much greater than smaller firms. Take the coefficient of $LargeDown_{i,t-1}*R_{i,t-1}*Leverage_{i,d-1}$ for example: the coefficient for firms in the largest market capitalization group is 2.970, and merely 1.021 for firms in the smallest group. This pattern contradicts the prediction of cross-stock information spillover and confirms that in a crash, investors tend to obtain liquidity from stocks with less information asymmetry, lending more support to the illiquidity contagion hypothesis.

Insert Table 5 Here

B2. Stock Liquidity

The selling pressure arising from liquidity needs of leveraged investors should be felt differentially across stocks, depending on their degree of asset liquidity. By definition, a trade in a highly liquid asset involves lower price impact, or transaction costs, on average, than an equivalent trade in a less liquid asset (Kyle, 1985).

Particularly, during market crash episodes, illiquid assets are predicted to become more illiquid. Thus, confronted with capital constraints, leveraged investors are more likely to liquidate positions from more liquid stocks than less liquid ones.

In Table 6, we exploit *Amihud*, which is defined as the absolute value of a firm's daily return divided by its dollar trading volume, as the proxy for asset liquidity.[21] We first sort all firms into five groups by their respective average *Amihud* in the last five trading days and compute the equal-weighted order imbalances in each group. The average order imbalances for firms with different levels of asset liquidity ($Amihud\_OI_{jt}$) are, respectively, regressed on lagged stock returns, leverage, and their interactions using five-minute data. The explanatory variables in the regressions are identical to those in Table 2.

The results show that stocks with lower *Amihud* illiquidity ratios are more susceptible to the contagion effect of deleveraging than those with higher *Amihud* illiquidity ratios. The difference in the coefficient of $Down_{i,t-1}*R_{i,t-1}*Leverage_{i,d-1}$ ($LargeDown_{i,t-1}*R_{i,t-1}*Leverage_{i,d-1}$) between firms in the highest and lowest group is as high as 3.07 (3.845). Our evidence confirms that firms with better liquidity suffer greater selling pressure when leveraged investors unwind positions to obtain liquidity in a crisis, again supporting our illiquidity contagion hypothesis.

Insert Table 6 Here

B3.Stock Performance

The selling pressure in the illiquidity contagion could behave differentially, depending on firms' past performance. Leveraged investors are mostly individual investors (Hirose et al. 2009; Chang et al. 2014), and they are more likely to sell better performing stocks than underperforming stocks (Dhar and Zhu 2006; Barber et al. 2007). Also, stocks with relatively better performance in the crisis indicate that their prices are less distorted by the market crash, whereas firms with worse

[21] We exploit the Amihud illiquidity ratio as a proxy for asset liquidity. Zhang et al. (2013) provide evidence that the illiquidity ratio proposed by Amihud (2002) is the best indirect liquidity measure in Chinese stock market.

performance are likely to suffer under-pricing and tend to reverse in the future. Therefore, we predict that the liquidity dry-up resulting from illiquidity contagion should be more evident among firms with better past performance.

In Table 7, we first sort all firms into five groups by the cumulative returns of each stock in the last five trading days (*Cret_lag5*) and compute the equal-weighted order imbalances in each group. The average order imbalances for firms with different past cumulative returns ($Cret\_OI_{jt}$) are, respectively, regressed on lagged stock returns, leverage, and their interactions using five-minute data. The explanatory variables in the regressions are similar to those in Table 2.

The results show that the selling pressures transmitted from deleveraging are much stronger for stocks with better past performance than those with worse past performance. Among firms with best stock performance, the coefficients of three-way interactions are all positively significant with a magnitude of around 2.5, whereas the corresponding coefficients among firms with worse performance are much smaller and some even turn negative, confirming our predictions.

Consistent with the findings in Nyborg and Östberg (2014), where the authors find that tighter interbank markets are associated with relatively more volume in more liquid stocks and infer that banks "pull back" liquidity through selling more liquid stocks, we provide direct evidence on fire sales in equities market when leveraged investors face margin requirement and funding constraints. Furthermore, we reveal that leveraged investors are indeed more likely to sell stocks with less information asymmetry, better liquidity, and higher past performance and such concentrated selling pressure among select stocks may spread and propagate across markets during market crashes.

Insert Table 7 Here

V. Further Tests on Alternative Explanations

The amplified contagion effect of highly leveraged stocks could be due to either information spillover or illiquidity contagion. In this section, we exploit some additional empirical setups to further distinguish our findings from alternative explanations.

A. Trading suspension

Individual firms' trading suspension provides an alternative identification strategy to distinguish between information spillover and illiquidity contagion because it blocks new information incorporation into stock prices. The identification here relies on both cross-sectional and time-series variation of trading suspension, as whether to suspend trading is a firm-level decision which is normally not related to the decision of other companies. We acknowledge that trading suspension itself may convey some information about both the market and firm. To address this concern, we add the lagged market return into the regressions to control for the potential influence of market crash on firms' decision to suspend their trading. In addition, we remove the first trading day after the start of trading suspension from the sample and re-run the regressions in order to isolate a potential remaining information effect from the pre-suspension period.

If the strengthened contagion associated with leverage results primarily from information spillover, we expect that TS firms (firms that are subject to trading suspension) should have less spillover effect than non-TS firms because it is impossible for TS firms to dynamically reflect new information through trading (French and Roll, 1986). However, if the contagion effect is driven by excess liquidity demand, we then expect that trading suspension in the crash period could further deteriorate the liquidity shortage as investors who hold TS firms need to sell other stocks to obtain liquidity when the market declines, and this process accelerates the spread of initial liquidity shocks to other stocks. Therefore, the negative influence of TS firms on other stocks' order imbalance should be more apparent than that of non-TS firms. Our regression model is specified as follows:

$$Ind\_OI_{i,d}(CrossInd\_OI_{i,d})=b_0+b_1\,Suspension_{i,d}+b_2\,Leverage_{i,d-1}+b_3\,MktDown_d \\ +b_4\,MktDown_d*Suspension_{i,d}*Leverage_{i,d-1}+b_5\,MktRet_{d-1}+controls \qquad (3)$$

We conduct this regression by aggregating the high-frequency data into daily data. The dependent variables are $Ind\_OI_{i,d}$ and $CrossInd\_OI_{i,d}$, respectively, where $Ind\_OI_{i,d}$ is the average order imbalance of firms within the same industry as firm i except firm i itself on day d; $CrossInd\_OI_{i,d}$ is the average order imbalance of firms outside the same industry as firm i on day d. We include $Suspension_{i,d}$, $Leverage_{i,d-1}$, $MktDown_d$ and their interactions as explanatory variables. $Suspension_{i,d}$ is a dummy variable and takes the value of one if firm i is subject to trading suspension due to voluntary filing, instead of reaching price movement limit, on day d and zero otherwise. $MktDown_d$ is a dummy variable, which equals one if the return on the equal-weighted market index is negative on day d and zero otherwise. [22]

Our focus is the coefficient of the three-way interaction (b_4), which measures the influence on the order imbalance of other stocks within/outside the same industry, by firms that are subject to trading suspension and a high level of leveraged trading right before market declines. Two-way interactions and the lagged dependent variables are included as control variables.

We report the results in Table 8. It is interesting that the coefficient of $Suspension_{i,d}$ is insignificant, implying that individual firms' trading suspension in general has no impact on the order imbalance of other stocks within (outside) the same industry. The coefficient of $Leverage_{i,d-1}$ is negative with t-statistics about -1.5, hinting that firms with higher leverage tend to exacerbate other stocks' order imbalance in the crash period to some extent. It is no surprise that the coefficient of $MktDown_d$ is negative since the order imbalance synchronously changes with market return.

To the center of our interests, the coefficient of $MktDown_d*Suspension_{i,d}$ is negatively significant, suggesting that when the market goes down, individual firms' trading suspension tend to exert negative influence on the demand for other stocks. More importantly and consistent with our expectations, the coefficient of $MktDown_d*Suspension_{i,d}*Leverage_{i,d-1}$ is negatively significant, indicating that TS firms with high leverage have a negative influence on the order imbalance of other

[22] We got consistent results when using the value-weighted market index as an alternative proxy variable for the market's direction.

stocks when the market declines.

These results confirm that investors of TS firms, especially those with a great deal of margin purchases, are likely to obtain liquidity through selling other stocks right before a market decline and suggest that during the period of market crash, trading suspension further deteriorates liquidity shortages, consistent with the prediction of illiquidity contagion. It is worth noting that the impact of trading suspension varies considerably with market conditions. The coefficient of $Suspension_{i,d}*Leverage_{i,d-1}$ is indeed positively significant, suggesting that the negative influence of TS firms with high leverage on other stocks is much weaker when the market goes up.

In column (3) and column (4), we remove the first trading day after the start of trading suspension from the sample. We indeed obtain similar results to our main findings, implying that our results are not sensitive to potential information on the first day after trading suspension was initiated.

Insert Table 8 Here

B. Return Co-movement

One may argue that the documented relationship between leverage and other stocks' trading may simply be due to return co-movement and sentiment spillover, instead of illiquidity spillover. To address this potential issue, we directly construct a measure for return co-movement and investigate the contagion associated with leverage among stocks with different levels of return co-movement. If the contagion is driven by return co-movement, we expect that the contagion effect should be more pronounced among stocks with higher return co-movement. However, if the contagion is similar among different groups of stocks or even more pronounced among firms with lower return co-movement, the illiquidity contagion explanation seems more valid.

We exploit the most popular definition of return co-movement by estimating the adjusted R^2 of the equation (4) using the daily returns within the three months before the market crash, from March 13, 2015, to June 12, 2015 (Chan et al., 2007).

$$R_{id} = b_0 + b_1 Mktret_d + b_2 Indret_d \tag{4}$$

Next, we rank stocks into two groups by the estimated adjusted R^2, calculate the industry-level (cross-industry) order imbalance within the same return co-movement group and repeat basic regressions in each group. The results are displayed in Table 9. The coefficient of $Down_{i,t-1}*R_{i,t-1}*Leverage_{i,d-1}$ is positively significant in the low R^2 group and turns insignificant in the high R^2 group. Moreover, the coefficient of $LargeDown_{i,t-1}*R_{i,t-1}*Leverage_{i,d-1}$ is larger in the low R^2 group than that in the high R^2 group. As a whole, these results indicate that the contagion effect induced by leverage is more pronounced among firms with lower return co-movement than those with high return co-movement, which contradicts the prediction that return co-movement drives the phenomenon. The intuition is probably that, when suffering from price declines and inevitably forced to unwind their positions, investors are more likely to sell stocks with low return co-movement as these stocks are less affected by the market crash. This finding is consistent with our previous evidence that liquidity constrained investors are more likely to choose stocks that are less affected by stock fire sale. In sum, our findings do not support the possibility of return co-movement as the potential explanation for our findings, and confirms the hypothesis of illiquidity contagion.

Insert Table 9 Here

VI. Robustness Checks

A. Non-Leveraged Stocks

In this section, we directly investigate if deleveraging is responsible for the contagion effect, whether the contagion effect of leveraged stocks tend to be more noticeable than that of non-leveraged stocks. Given that there are certain qualifications for leverage trading, we do not directly pool the leveraged and non-leveraged stocks together to compare the contagion effect. Instead, we exploit the non-repeated matching approach to select a matched non-leveraged stock for each leveraged stock to address the potential selection bias in our study sample. Specifically, we first sort firms into five groups by its floating market value at the end of May 2015. We then select the non-leveraged stock that is in the same industry and size group and has the closest idiosyncratic volatility to the target leveraged stock as the matched stock.[23]

The average order imbalances within the same industry or across industries are regressed on individual stock returns, the dummy variable for price decline, and their interactions, among both leveraged stocks and matched non-leveraged stocks. The coefficient of $(Large)Down_{i,t-1}*R_{i,t-1}$ captures the influence of negative shocks to individual firms on other stocks within (outside) the same industry. The results in Table 10 show that the coefficients of $(Large)Down_{i,t-1}*R_{i,t-1}$ among leveraged stocks are much larger than those among matched non-leveraged stocks and the coefficient difference is significant when evaluated using SUR methods. These results suggest that the contagion associated with leveraged stocks is more pronounced than that for non-leveraged stocks, confirming that leveraged trading plays an important role in the spread of the negative shock.[24]

Insert Table 10 Here

B. Industry-adjusted stock returns

To control for the industry-level information contained in intraday stock returns, we substitute $AR_{i,t-1}$ for $R_{i,t-1}$ and re-run the baseline regressions in Table 2. $AR_{i,t-1}= R_{i,t-1}- R_{ind,t-1}$, where $R_{ind,t-1}$ is the equal-weighted average $R_{i,t-1}$ of all firms in an industry except firm *i*. All other variables have the same definitions as in Table 2. In

[23] Volatility is an important dimension that the exchanges use to determine whether a stock is qualified for margin trading. We also experimented with matching criteria not including idiosyncratic volatility and our results remain the same. Idiosyncratic volatility is estimated by the market model using daily data over three months before the market crash. Once a firm is selected into the matched sample, we drop it from the sample of candidates for future matching. This approach ensures that we have a one-to-one matched sample at the expense of slight matching accuracy.

[24] We only successfully find matched non-leveraged stocks for 415 firms out of 816 firms using the non-repeated matching. We also exploit the alternative matching method that allows different firms to have the same matched firm and obtain similar results, with slightly lower statistical significance.

unreported results, we find that the coefficient of $AR_{i,t-1}$ turns negative, indicating that the return shock specific to a firm has a reverse effect on other firms' order imbalance. The coefficient of $AR_{i,t-1}*Leverage_{i,d-1}$ remains significantly positive and more importantly, the coefficients sum of both $AR_{i,t-1}$ and $AR_{i,t-1}*Leverage_{i,d-1}$ remain significantly positive too, suggesting that the return shock to firms with higher leverage have a positive spillover effect on the order imbalances of other stocks. Put differently, leveraged trading tends to counteract the reverse effect of idiosyncratic stock returns on other firms' order imbalances. Particularly, the coefficient of $LargeDown_{i,t-1}*AR_{i,t-1}*Leverage_{i,d-1}$ is still significantly positive. This evidence indicates that for extremely negative shocks, deleveraging indeed further magnifies the contagion effect. Overall, the documented contagion induced by deleveraging still exists after adjusting contemporaneous industry intraday returns.

C. Investment styles

We also exploit an alternative model to explore whether the contagion could spread within and across different investment styles. Instead of classifying stocks into different industry sectors, we classify stocks into alternative styles in this alternative specification. For simplicity of exposition, our style-based results use firm size and book-to-market ratio as respective style definitions. Each firm is assigned to one of the 25 size-and-B/M portfolios at the end of May 2015. Similar to our main findings, the three-way interaction term is highly positively significant, confirming that illiquidity contagion within and across styles is pronounced for stocks experiencing large price declines. Additionally, we note that the across-style influence of illiquidity contagion is slightly smaller than the within-style one, again confirming leveraged investors' preference for selling off similar stocks when they sell stocks to raise capital during market collapse.

VII. Conclusions

Recent financial market turmoil has attracted considerable attention regarding how shortages in funding liquidity may spill over across different securities and regions and eventually cause financial crisis. This study utilizes a unique dataset on margin trading during the 2015 stock market turmoil in China and empirically investigates how investors' need to deleverage and unwind their margin trading in selected stocks dynamically spreads to subsequent market-wide selling and scrambling for liquidity.

We show that deleveraging needs stemming from margin requirements during market drops lead to incremental sales of other stocks during the intraday intervals, specifically in the afternoon sessions. This afternoon selling pressure is, in particular, larger for leveraged stocks. This effect exists both within and across different industries and is stronger for stocks with less information asymmetry, better liquidity, higher past stock performance, less return co-movement, and even during trading suspension. Our findings highlight the potential liquidity shock and systematic risks caused by margin requirements enforced by individual brokers and offer important lessons to regulators on stock market and financial system stability and suggest how to prevent or mitigate future market slumps.

References

1. Acharya, V. V., Amihud, Y., & Bharath, S. T. (2013). Liquidity risk of corporate bond returns: conditional approach. *Journal of Financial Economics*, 110(2), 358-386.
2. Admati, A. R., & Pfleiderer, P. (1988). A theory of intraday patterns: Volume and price variability. *Review of Financial Studies*, 1(1), 3-40.
3. Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, 5(1), 31-56.
4. Barber, B. M., Lee, Y. T., Liu, Y. J., & Odean, T. (2007). Is the aggregate investor reluctant to realise losses? Evidence from Taiwan. *European Financial Management*, 13(3), 423-447.
5. Boehmer, E., Jones, C. M., & Zhang, X. (2008). Which shorts are informed?*Journal of Finance*, 63(2), 491-527.
6. Brunnermeier, M. K. (2009). Deciphering the liquidity and credit crunch 2007–2008. *Journal of Economic Perspectives*, 23(1), 77-100.
7. Brunnermeier, M. K., & Pedersen, L. H. (2009). Market liquidity and funding liquidity. *Review of Financial Studies*, 22(6), 2201-2238.
8. Cespa, G., & Foucault, T. (2014). Illiquidity contagion and liquidity crashes. *Review of Financial Studies*, 27(6), 1615-1660.
9. Chae, J. (2005). Trading volume, information asymmetry, and timing information. *Journal of Finance,* 60(1), 413-442.

10. Chan, L. K., Lakonishok, J., & Swaminathan, B. (2007). Industry classifications and return comovement. *Financial Analysts Journal*, 63(6), 56-70.
11. Chang, E. C., Luo, Y., & Ren, J. (2014). Short-selling, margin-trading, and price efficiency: Evidence. *Journal of Banking & Finance*, 48, 411-424.
12. Chordia, T., Roll, R., & Subrahmanyam, A. (2000). Commonality in liquidity. *Journal of Financial Economics*, 56(1), 3-28.
13. Chordia, T., Roll, R., & Subrahmanyam, A. (2002). Order imbalance, liquidity, and market returns. *Journal of Financial Economics*, 65(1), 111-130.
14. Coval, J., & Stafford, E. (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics*, 86(2), 479-512.
15. Dhar, R., & Zhu, N. (2006). Up close and personal: Investor sophistication and the disposition effect. *Management Science*, 52(5), 726-740.
16. Ederington, L. H., & Lee, J. H. (1993). How markets process information: News releases and volatility. *Journal of Finance*, 48(4), 1161-1191.
17. Engelberg, J. E., Reed, A. V., & Ringgenberg, M. C. (2012). How are shorts informed?: Short sellers, news, and information processing. *Journal of Financial Economics*, 105(2), 260-278.
18. French, K. R., & Roll, R. (1986). Stock return variances: The arrival of information and the reaction of traders. *Journal of Financial Economics*, 17(1), 5-26.
19. Foster, F. D., & Viswanathan, S. (1993). Variations in trading volume, return volatility, and trading costs; Evidence on recent price formation models. *Journal of Finance*, 48(1), 187-211.
20. Garleanu, N., & Pedersen, L. H. (2011). Margin-based asset pricing and deviations from the law of one price. *Review of Financial Studies*, 24(6), 1980-2022.
21. Greenwood, R., & Thesmar, D. (2011). Stock price fragility. *Journal of Financial Economics*, 102(3), 471-490.
22. Greenwood, R. Landier, A, & Thesmar, D. (2015), Vulnerable Banks, Journal of Financial Economics, 115-3, 471-85.
23. Gromb, D., & Vayanos, D. (2002). Equilibrium and welfare in markets with financially constrained arbitrageurs. *Journal of Financial Economics*, 66(2), 361-407.
24. Hameed, A., Kang, W., & Viswanathan, S. (2010). Stock market declines and liquidity. *Journal of Finance*, 65(1), 257-293.
25. Hanson, S. G., & Sunderam, A. (2014). The growth and limits of arbitrage: Evidence from short interest. *Review of Financial Studies*, 27(4), 1238-1286.
26. Hirose, T., Kato, H. K., & Bremer, M. (2009). Can margin traders predict future stock returns in Japan? *Pacific-Basin Finance Journal*, 17(1), 41-57.
27. Hong, H., Kubik, J. D., & Fishman, T. (2012). Do arbitrageurs amplify economic shocks? *Journal of Financial Economics*, 103(3), 454-470.
28. Karolyi, G. A., Lee, K. H., & Van Dijk, M. A. (2012). Understanding commonality in liquidity around the world. *Journal of Financial Economics*, 105(1), 82-112

29. Kirilenko, A. A., Kyle, A. S., Samadi, M., &Tuzun, T. (2016). The flash crash: The impact of high frequency trading on an electronic market. *Journal of Finance*, Forthcoming.
30. Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica*, 53(6), 1315-1335.
31. Kyle, A. S., & Xiong, W. (2001). Contagion as a wealth effect. *Journal of Finance*, 56(4), 1401-1440.
32. Kyle, A. S., & Obizhaeva, A. A. (2016). Large bets and stock market crashes. *Working Paper*, available at SSRN 2023776.
33. Manconi, A., Massa, M., & Yasuda, A. (2012). The role of institutional investors in propagating the crisis of 2007–2008. *Journal of Financial Economics*, 104(3), 491-518.
34. Mayhew, S., Sarin, A., & Shastri, K. (1995). The allocation of informed trading across related markets: an analysis of the impact of changes in equity—option margin requirements. *Journal of Finance*, 50(5), 1635-1653.
35. Næs, R., Skjeltorp, J. A., & Ødegaard, B. A. (2011). Stock market liquidity and the business cycle. *Journal of Finance*, 66(1), 139-176.
36. Nagel, S. (2012). Evaporating liquidity. *Review of Financial Studies*, 25(7), 2005-2039.
37. Nyborg, K. G., & Östberg, P. (2014). Money and liquidity in financial markets. *Journal of Financial Economics*, 112(1), 30-52.
38. Richardson, S. A., Saffi, P. A., & Sigurdsson, K. (2015). Deleveraging risk. Available at SSRN 2180785.
39. Seguin, P. J. (1990). Stock volatility and margin trading. *Journal of Monetary Economics*, 26(1), 101-121.
40. Zhang, Z., Lee, Y. T., Zhang, Y. & Liu, X. (2013). A test on indirect liquidity measures in china stock market: an empirical analysis of the direct and indirect measures of bid-ask spread. *China Economic Quarterly*,13(1), 233-262. (*In Chinese*)

Figure 1 Leverage and Market Performance

Figure 1 plots the equal-weighted average leverage and average cumulative returns of all stocks from June 1, 2015 to August 31, 2015. For each stock, *Leverage* is defined as the dollar balance of margin debt issued by the exchange scaled by the market value of floating shares at the end of May 2015.

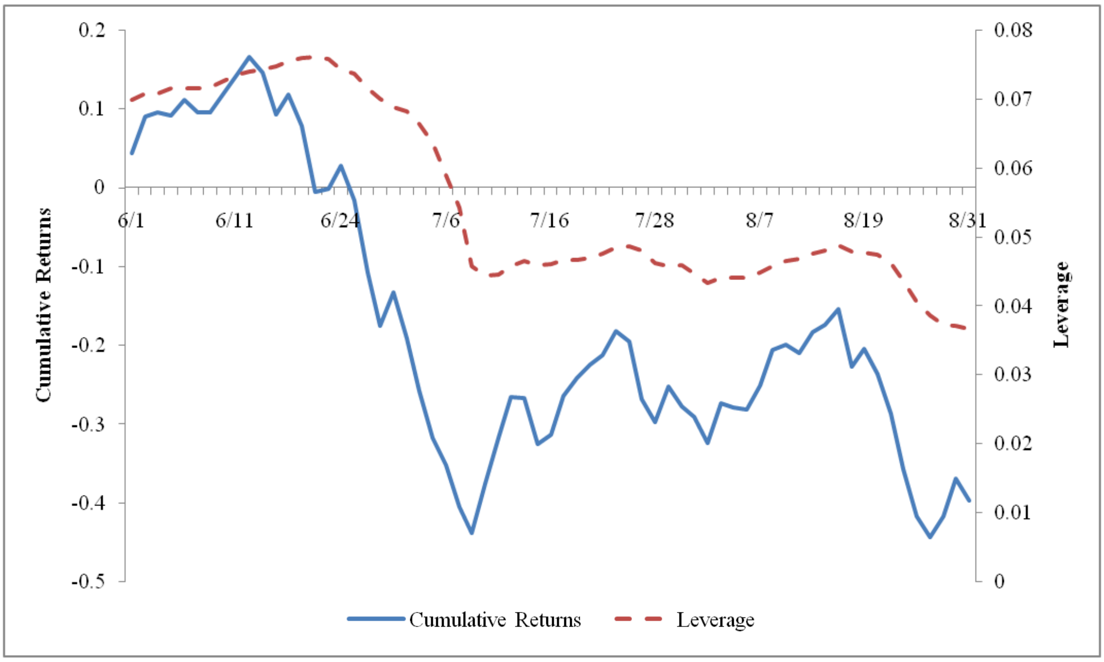

Figure 2 Leverage and Stock Returns

Figure 2 plots the cumulative daily return of stock portfolios sorted on *Leverage*. *Leverage* is defined as the dollar balance of margin debt issued by the exchange scaled by the market value of floating shares at the end of May 2015.We rank firms into three groups by the *Leverage* on the last trading day and compute the equal-weighted average cumulative returns in each group.

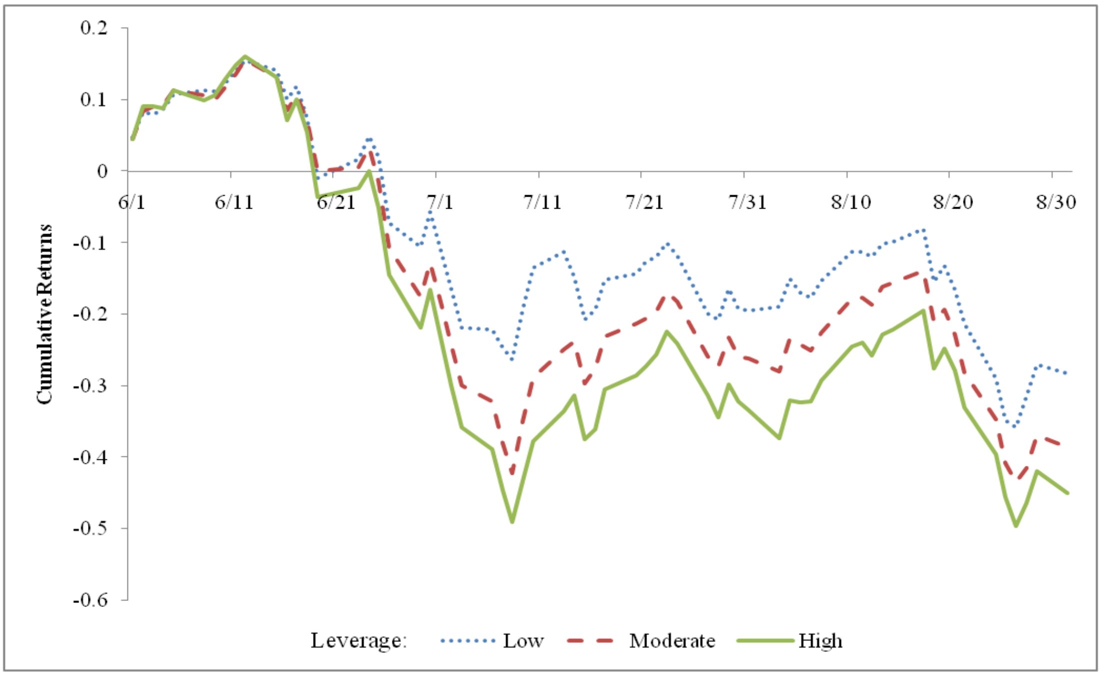

Figure 3 Intraday Pattern of Order Imbalance

The figure plots the intraday order imbalances of stock portfolios sorted on *Leverage* from June 1, 2015 to August 31, 2015. The order imbalance equals $\frac{\text{buy orders}-\text{sell orders}}{0.5\times(\text{buy orders}+\text{sell orders})}$ and orders are measured by dollar value. The order book in the exchange is updated every three seconds and we average the order imbalances for each stock every five minutes. *Leverage* is defined as the dollar balance of margin debt issued by the exchange scaled by the market value of floating shares at the end of May 2015. We rank firms into three groups by the *Leverage* on the last trading day and compute the equal-weighted order imbalance in each group.

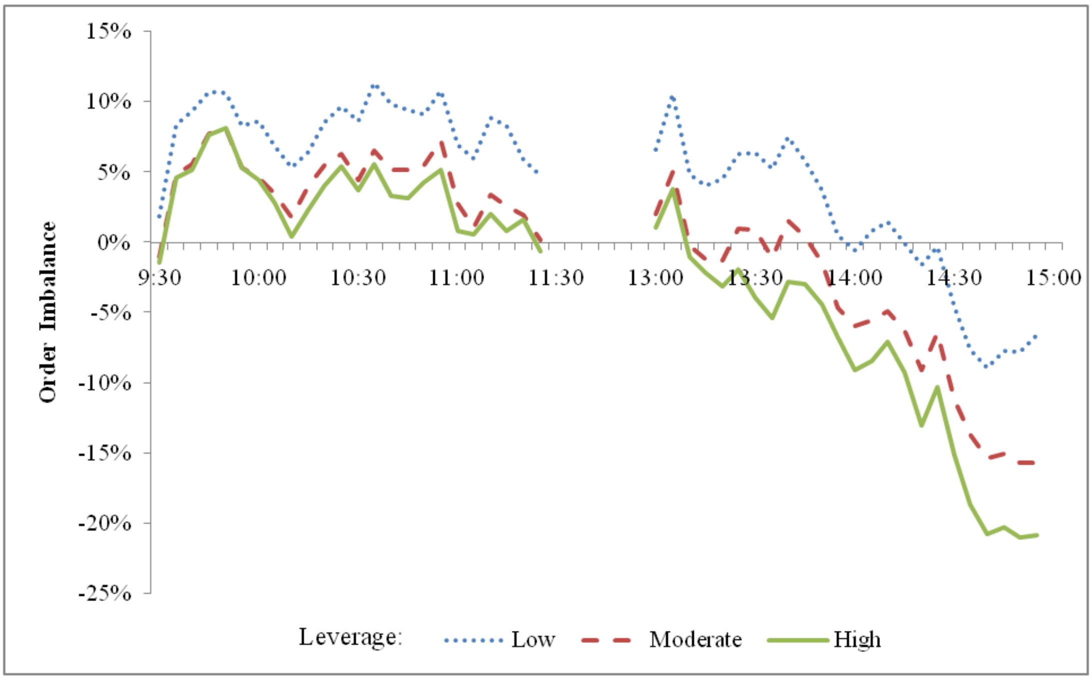

Table 1 Summary Statistics

This table reports descriptive statistics of main variables. *OI* is the average order imbalance of a firm within five minutes. The order imbalance equals $\frac{\text{buy orders}-\text{sell orders}}{0.5\times(\text{buy orders}+\text{sell orders})}$ and orders are measured by dollar values. The order book is updated every three seconds and we average the order imbalances for each stock every five minutes. The intraday stock return ($R_{i,t-1}$) equals $\frac{P_{t-1}-P_{d-1}}{P_{d-1}}$, where P_{t-1} is the close price of firm *i*in the last 5 minutes and P_{d-1} is the close price of firm *i* in the last trading day. *Leverage* is defined as the dollar balance of margin debt issued by the exchange scaled by the market value of floating shares at the end of May 2015. *Size* is the market value of a firm's floating shares outstanding at the end of May 2015. *Amihud* equals the absolute value of a firm's daily return divided by its dollar trading volume. *Cret(-5,-1)*is the cumulative daily returns of firm *i* in the last five trading days. *OI* and $R_{i,t-1}$ are firm - five minutes variables and others are firm-date variables. R^2 is the measure for return co-movement which is estimated by equation (4) using the daily returns from March 13, 2015, to June 12, 2015.

VARIABLES	N	Mean	Std	Min	P25	P50	P75	Max
Leverage	49,529	7.61%	4.28%	0.12%	4.44%	6.89%	10.08%	26.11%
OI	6,307,103	-4.51%	87.46%	-200.00%	-48.71%	-2.83%	42.48%	200.00%
$\boldsymbol{R_{i,t-1}}$	6,307,103	-0.75%	5.45%	-10.03%	-4.02%	-0.47%	2.53%	10.42%
Size(billion Yuan)	133,908	18.86	70.52	0.44	4.21	7.38	14.50	2223.19
Amihud(*10^{-9})	133,908	1.06	16.11	0.00	0.04	0.13	0.31	6669.22
Cret(-5,-1)	133,908	-3.97%	17.75%	-50.19%	-15.46%	-2.86%	7.98%	35.40%
$\boldsymbol{R^2}$	2,562	32.99%	18.31%	1.32%	20.36%	32.92%	44.82%	94.49%

Table 2 Leverage and Illiquidity Contagion Within and Across Industries

The average order imbalances for firms within and outside the same industry are regressed on lagged stock returns, leverage, and their interactions using five-minute data. Ind_OI_{it} is the average order imbalances for all firms in the same industry as firm *i* except firm *i* itself within the most recent five minutes at time *t*. $CrossInd\_OI_{it}$ is the average order imbalances for all firms other than those that are in the same industry with firm *i* within the most recent five minutes at time *t*. Here we use the Shenwan Level I industry classification as criteria. The intraday stock return ($R_{i,t-1}$) equals $\frac{P_{t-1}-P_{d-1}}{P_{d-1}}$, where P_{t-1} is the close price of firm *i* in the last five minutes and P_{d-1} is the close price of firm *i* in the last trading day. *Leverage* is defined as the dollar balance of margin debt issued by the exchange scaled by the market value of floating shares at the end of May 2015. An interaction dummy variable $Down_{i,t-1}$ ($LargeDown_{i,t-1}$) that takes the value of one if and only if $R_{i,t-1}$ is less than zero (-7%) is added into the regressions. $Hitfloor_{i,t-1}$ is a dummy variable, which equals one if $R_{i,t-1}$ declines to -10% and otherwise zero. The lagged dependent variables are included to control for the persistence of order imbalances. *t-1* (*t-2*,*t-3*) is defined on the basis of five-minute frequency. The whole trading day is divided into 48 five-minute intervals and the interval dummy variables are included to control for the intraday pattern of order imbalances. The value in parentheses is *t*-statistics calculated using standard errors clustered by firm. Here, *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	***Y=Ind_OI$_{it}$***				***Y=CrossInd_OI$_{it}$***			
$\boldsymbol{R_{i,t-1}}$	0.300***	0.307***	0.340***	0.332***	0.246***	0.249***	0.273***	0.266***
	(15.06)	(13.76)	(13.43)	(22.59)	(15.83)	(14.70)	(14.09)	(23.46)
Leverage$_{i,d-1}$	-0.041***	-0.018***	-0.009*	-0.025***	-0.018***	-0.009**	0.004	-0.008***
	(-8.70)	(-3.01)	(-1.79)	(-4.88)	(-6.97)	(-2.27)	(1.39)	(-2.64)
$R_{i,t-1}$*Leverage$_{i,d-1}$	1.204***	0.532***	-0.364**	0.253*	0.845***	0.575***	-0.190	0.292***
	(7.19)	(2.74)	(-2.35)	(1.72)	(9.39)	(4.04)	(-1.64)	(2.65)
Down$_{i,t-1}$*$R_{i,t-1}$*Leverage$_{i,d-1}$		1.012***				0.412***		
		(4.89)				(2.82)		
LargeDown$_{i,t-1}$*$R_{i,t-1}$*Leverage$_{i,d-1}$			2.603***				1.736***	
			(9.43)				(6.24)	
HitFloor$_{i,t-1}$*$R_{i,t-1}$*Leverage$_{i,d-1}$				2.285***				1.330***
				(8.72)				(5.39)
Y_{it-1}- Y_{it-3}	Y	Y	Y	Y	Y	Y	Y	Y
Intraday Dummy	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,978,606	1,978,606	1,978,606	1,978,606	1,990,377	1,990,377	1,990,377	1,990,377
Adj R-squared	0.882	0.884	0.884	0.884	0.907	0.910	0.910	0.910

Table 3 Intraday Variations of Illiquidity Contagion

The whole trading day is divided into three trading sessions including a morning session, an afternoon session, and the period from 1:30 p.m. to 2:30 p.m. In each trading session, the average order imbalances for firms within (outside) the same industry are regressed on lagged stock returns, leverage and their interactions using five-minute data. The definitions of all variables are identical to those in Table 2. The lagged dependent variables and intraday dummy are also included. To save space, we only report the coefficients of intraday stock returns, leverage, and their interactions. The value in parentheses is *t*-statistics calculated using standard errors clustered by firm. The differences of three-item interactions' coefficients between trading sessions are estimated using the seemingly unrelated regression (SUR) model and the x^2 statistics are reported. Here, *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) Mor	(2) Aft	(3) 1:30 p.m.-2:30 p.m.	(4) Mor	(5) Aft	(6) 1:30 p.m.-2:30 p.m.
	$Y=Ind\_OI_{it}$			$Y=CrossInd\_OI_{it}$		
$R_{i,t-1}$	0.138***	0.455***	0.376***	0.184***	0.349***	0.269***
	(7.15)	(11.70)	(17.97)	(12.34)	(13.38)	(10.55)
$Leverage_{i,d-1}$	-0.118***	0.026***	0.001	-0.084***	0.024***	0.005
	(-11.09)	(3.97)	(0.16)	(-13.29)	(4.95)	(1.27)
$R_{i,t-1}*Leverage_{i,d-1}$	3.462***	-0.931***	-0.410**	2.813***	-0.616***	-0.104
	(11.55)	(-4.73)	(-2.28)	(13.09)	(-4.38)	(-0.85)
$Down_{i,t-1}*R_{i,t-1}*Leverage_{i,d-1}$	-0.963***	2.156***	1.208***	-1.229***	1.520***	0.710***
	(-3.63)	(9.33)	(6.05)	(-6.34)	(9.14)	(5.22)
Observations	990,188	988,418	535,073	993,945	996,432	539,734
Adj R-squared	0.785	0.932	0.932	0.817	0.954	0.956
$Dif(Down_{i,t-1}*R_{i,t-1}*Leverage_{i,d-1})$		(2)-(1)	(3)-(1)		(5)-(4)	(6)-(4)
		$x^2=123.4$***	$x^2=97.1$***		$x^2=109.3$***	$x^2=68.5$***
$R_{i,t-1}$	0.165***	0.491***	0.406***	0.207***	0.373***	0.287***
	(8.13)	(10.53)	(17.37)	(12.89)	(11.76)	(19.37)
$Leverage_{i,d-1}$	-0.086***	0.019***	0.005	-0.046***	0.019***	0.009***
	(-9.03)	(3.99)	(1.03)	(-9.57)	(5.41)	(3.20)
$R_{i,t-1}*Leverage_{i,d-1}$	1.977***	-1.419***	-1.037***	1.427***	-0.896***	-0.499***
	(8.33)	(-8.85)	(-7.07)	(8.31)	(-7.78)	(-5.05)
$LargeDown_{i,t-1}*R_{i,t-1}*Leverage_{i,d-1}$	1.397***	3.134***	2.354***	0.954***	2.104***	1.436***
	(7.74)	(9.30)	(6.58)	(6.73)	(8.21)	(5.22)
Observations	990,188	988,418	535,073	993,945	996,432	539,734
Adj R-squared	0.788	0.936	0.936	0.819	0.957	0.958

Dif(LargeDown$_{i,t-1}$*R$_{i,t-1}$*Leverage$_{i,d-1}$)		(2)-(1)	(3)-(1)		(5)-(4)	(6)-(4)
		x^2=63.6***	x^2=35.4***		x^2=39.1***	x^2=10.8***

Table 4 Illiquidity Contagion within Leveraged and Non-leveraged stocks

We sort stocks into leveraged and non-leveraged groups in light of a stock's pre-crisis leverage and compute the equal-weighted order imbalances in each group. The average order imbalances for stocks with different leverage trading are, respectively, regressed on lagged stock returns, leverage, and their interactions within different intraday periods. The explanatory variables and control variables in the regressions are identical to those in Table 2. To conserve space, we only report the coefficients of three-way interactions for large price decline. The value in parentheses is *t*-statistics calculated using standard errors clustered by firm. The significance of differences between groups is evaluated using the seemingly unrelated regression (SUR) model and the x^2 statistics are reported. Here, *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

	9:30-10:30	**10:30-11:30**	**13:00-14:00**	**14:00-15:00**
	$\boldsymbol{LargeDown_{i,t-1}*R_{i,t-1}*Leverage_{i,d-1}}$			
Leveraged stocks	0.854***	2.027***	2.920***	2.563***
	(5.78)	(9.69)	(12.31)	(11.98)
Non-leveraged stocks	0.343	1.608***	1.861***	1.816***
	(1.36)	(5.51)	(8.73)	(7.63)
Leveraged - Non-leveraged	0.511***	0.419***	1.059***	0.747***
	(x^2=30.2)	(x^2=23.9)	(x^2=50.6)	(x^2=35.1)

Table 5 Information Asymmetry and Illiquidity Contagion

Size, the proxy for information asymmetry, is the market value of a firm's floating shares outstanding at the end of May 2015. We first sort all firms into five groups by *Size* and compute the equal-weighted order imbalances in each group. The average order imbalances for firms with different levels of information asymmetry ($Size\_OI_{jt}$) are, respectively, regressed on lagged stock returns, leverage and their interactions using five-minute data. The explanatory variables and control variables in the regressions are identical to those in Table 2. To save space, we only report the coefficients of intraday stock returns, leverage, and their interactions using the order imbalances in the smallest, moderate, and largest group as dependent variables. The value in parentheses is *t*-statistics calculated using standard errors clustered by firm. The differences of three-item interactions' coefficients between groups are estimated using the seemingly unrelated regression (SUR) model and the x^2 statistics are reported. Here, *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

	$Y=Size\_OI_{jt}$		
VARIABLES	***j*=Smallest**	***j*=Moderate**	***j*=Largest**
$R_{i,t-1}$	0.216***	0.292***	0.332***
	(11.92)	(13.75)	(16.33)
$Leverage_{i,d-1}$	-0.010***	0.002	0.023***
	(-3.46)	(0.63)	(6.25)
$R_{i,t-1}*Leverage_{i,d-1}$	0.127	-0.066	-0.914***
	(1.25)	(-0.52)	(-6.75)
$LargeDown_{i,t-1}*R_{i,t-1}*Leverage_{i,d-1}$	1.021***	1.726***	2.970***
	(7.95)	(5.17)	(12.87)
Observations	1,990,377	1,990,377	1,990,377
Adj R-squared	0.832	0.918	0.935
$Dif(LargeDown_{i,t-1}*R_{i,t-1}*Leverage_{i,d-1})$	(3)-(1) :1.949*** (x^2=99.7)		
$R_{i,t-1}$	0.197***	0.266***	0.304***
	(22.29)	(24.31)	(26.56)
$Leverage_{i,d-1}$	-0.032***	-0.015***	0.029***
	(-9.54)	(-3.61)	(5.92)
$R_{i,t-1}*Leverage_{i,d-1}$	1.004***	0.809***	-0.393**
	(8.04)	(5.21)	(-2.34)
$Down_{i,t-1}*R_{i,t-1}*Leverage_{i,d-1}$	-0.411***	0.230	1.939***
	(-3.49)	(1.47)	(10.59)
Observations	1,990,377	1,990,377	1,990,377
Adj R-squared	0.835	0.916	0.923
$Dif(Down_{i,t-1}*R_{i,t-1}*Leverage_{i,d-1})$	(3)-(1) :2.35*** (x^2=100.2)		

Table 6 Asset Liquidity and Illiquidity Contagion

Amihud, which equals the absolute value of a firm's daily return divided by its dollar trading volume, is the proxy for asset liquidity. We first sort all firms into five groups by average *Amihud* in the last five trading days and compute the equal-weighted order imbalances in each group. The average order imbalances for firms with different levels of asset liquidity ($Amihud\_OI_{jt}$) are, respectively, regressed on lagged stock returns, leverage and their interactions using five-minute data. The explanatory variables and control variables in the regressions are similar to those in Table 2. To save space, we only report the coefficients of intraday stock returns, leverage, and their interactions using the order imbalances in the lowest, moderate, and highest group as dependent variables. The value in parentheses is *t*-statistics calculated using standard errors clustered by firm. The differences of three-item interactions' coefficients between groups are estimated using the seemingly unrelated regression (SUR) model and the x^2 statistics are reported. Here, *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

	$Y=Amihud\_OI_{jt}$		
VARIABLES	***j*=Lowest**	***j*=Moderate**	***j*=Highest**
	Panel A		
$R_{i,t-1}$	0.362***	0.298***	0.180***
	(16.72)	(13.30)	(13.01)
$Leverage_{i,d-1}$	0.031***	0.009**	-0.018***
	(8.27)	(2.35)	(-7.44)
$R_{i,t-1}*Leverage_{i,d-1}$	-1.293***	-0.367***	0.370***
	(-9.04)	(-2.74)	(4.42)
$LargeDown_{i,t-1}*R_{i,t-1}*Leverage_{i,d-1}$	3.367***	2.251***	0.297***
	(10.99)	(7.97)	(4.56)
Observations	1,990,377	1,990,377	1,990,377
Adj R-squared	0.946	0.903	0.819
$Dif(LargeDown_{i,t-1}*R_{i,t-1}*Leverage_{i,d-1})$	*Lowest-Highest:* 3.07*** (x^2=122.5)		
	Panel B		
$R_{i,t-1}$	0.331***	0.267***	0.169***
	(27.03)	(23.63)	(23.46)
$Leverage_{i,d-1}$	0.048***	-0.003	-0.049***
	(9.45)	(-0.64)	(-16.27)
$R_{i,t-1}*Leverage_{i,d-1}$	-1.009***	0.448***	1.319***
	(-5.71)	(2.73)	(12.72)
$Down_{i,t-1}*R_{i,t-1}*Leverage_{i,d-1}$	2.669***	0.803***	-1.176***
	(8.46)	(4.74)	(-7.54)
Observations	1,990,377	1,990,377	1,990,377
Adj R-squared	0.935	0.901	0.815
$Dif(Down_{i,t-1}*R_{i,t-1}*Leverage_{i,d-1})$	*Lowest-Highest:* 3.845*** (x^2=156.3)		

Table 7 Liquidation Pressures and Illiquidity Contagion

We exploit the cumulative returns in the last five trading days (*Cret(-5,-1)*) to proxy for the liquidation pressures of each stock. We first sort all firms into five groups by *Cret(-5,-1)* and compute the equal-weighted order imbalances in each group. The average order imbalances for firms with different levels of liquidation pressures ($Cret\_OI_{jt}$) are, respectively, regressed on lagged stock returns, leverage, and their interactions using five-minute data. The explanatory variables and control variables in the regressions are similar to those in Table 2. To save space, we only report the coefficients of intraday stock returns, leverage and their interactions using the order imbalances in the lowest, moderate and highest group as dependent variables. The value in parentheses is *t*-statistics calculated using standard errors clustered by firm. The differences of three-item interactions' coefficients between groups are estimated using the seemingly unrelated regression (SUR) model and the x^2 statistics are reported. Here, *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

	$Y=Cret\_OI_{jt}$		
VARIABLES	***j*=Lowest**	***j*=Moderate**	***j*=Highest**
	Panel A		
$R_{i,t-1}$	0.218***	0.292***	0.343***
	(13.64)	(13.28)	(16.61)
$Leverage_{i,d-1}$	-0.021***	0.014***	0.024***
	(-7.19)	(4.01)	(7.43)
$R_{i,t-1}*Leverage_{i,d-1}$	0.462***	-0.326**	-1.056***
	(4.75)	(-2.42)	(-8.39)
$LargeDown_{i,t-1}*R_{i,t-1}*Leverage_{i,d-1}$	0.336***	2.198***	2.754***
	(4.20)	(8.46)	(11.04)
Observations	1,990,377	1,990,377	1,990,377
Adj R-squared	0.879	0.891	0.951
$Dif(LargeDown_{i,t-1}*R_{i,t-1}*Leverage_{i,d-1})$	*Highest-Lowest:*2.418*** (x^2=121.5)		
	Panel B		
$R_{i,t-1}$	0.207***	0.262***	0.315***
	(14.20)	(13.44)	(17.35)
$Leverage_{i,d-1}$	-0.051***	-0.003	0.043***
	(-13.88)	(-0.82)	(9.08)
$R_{i,t-1}*Leverage_{i,d-1}$	1.391***	0.656***	-0.970***
	(11.49)	(3.93)	(-6.21)
$Down_{i,t-1}*R_{i,t-1}*Leverage_{i,d-1}$	-1.110***	0.513***	2.401***
	(-9.75)	(3.11)	(10.92)
Observations	1,990,377	1,990,377	1,990,377
Adj R-squared	0.867	0.883	0.939
$Dif(Down_{i,t-1}*R_{i,t-1}*Leverage_{i,d-1})$	*Highest-Lowest:*3.511*** (x^2=159.2)		

Table 8 Trading Suspension and Illiquidity Contagion

The dependent variables are $Ind\_OI_{i,d}$ and $CrossInd\_OI_{i,d}$, respectively. $Ind\_OI_{i,d}$ is the average order imbalance of firms within the same industry as firm *i* except firm *i* itself on day *d*. $CrossInd\_OI_{i,d}$ is the average order imbalance of firms outside the same industry as firm *i* on day *d*. We include $Suspension_{i,d}$, $Leverage_{i,d-1}$, $MktDown_d$ and their interactions as explanatory variables. $Suspension_{i,d}$ equals one if firm *i* is subject to trading suspension on day *d* and zero otherwise. $Leverage_{i,d-1}$is defined as the firm's dollar balance of margin debt on day *d-1*scaled by the market value of floating shares at the end of May 2015. $MktDown_d$ is a dummy variable, which equals one if the return on the equal-weighted market index is negative on day *d* and zero otherwise. $MktRet_{d-1}$ is the return on the equal-weighted market index on day *d-1*. The lagged dependent variables are also included. The value in parentheses is *t*-statistics calculated using standard errors clustered by firm. Here, *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

	(1)	**(2)**	**(3)**	**(4)**
VARIABLES	Ind_OI_{id}	$CrossInd\_OI_{id}$	Ind_OI_{id}	$CrossInd\_OI_{id}$
$Suspension_{i,d}$	0.048	0.043	0.041	0.035
	(0.70)	(0.89)	(0.72)	(0.94)
$Leverage_{i,d-1}$	-0.512	-0.531	-0.508	-0.528
	(-1.43)	(-1.46)	(-1.42)	(-1.45)
$MktDown_d$	-0.175*	-0.214**	-0.174*	-0.213**
	(-1.98)	(-2.29)	(-1.98)	(-2.29)
$Suspension_{i,d}$* $Leverage_{i,d-1}$*$MktDown_d$	-1.342*	-1.429*	-1.262*	-1.357*
	(-1.78)	(-1.88)	(-1.77)	(-1.90)
$Suspension_{i,d}$* $MktDown_d$	-0.095***	-0.059**	-0.083***	-0.046**
	(-2.76)	(-2.25)	(-2.94)	(-2.27)
$Suspension_{i,d}$* $Leverage_{i,d-1}$	1.435**	1.335**	1.465**	1.373**
	(2.20)	(2.10)	(2.19)	(2.12)
$MktDown_d$* $Leverage_{i,d-1}$	-0.240	0.150	-0.246	0.146
	(-0.46)	(0.28)	(-0.47)	(0.27)
$MktRet_{d-1}$	2.051***	2.180**	2.043***	2.173**
	(2.81)	(2.60)	(2.80)	(2.59)
Y_{id-1}- Y_{id-3}	Y	Y	Y	Y
Observations	50,898	50,898	50,420	50,420
Adj R-squared	0.584	0.630	0.581	0.628

Table 9 Return Co-Movement and Illiquidity Contagion

We first rank stocks into two groups by the estimated adjusted R^2 and calculate the Ind_OI_{it} ($CrossInd\_OI_{it}$) within the same return co-movement group. Then the average order imbalances for firms with different levels of return co-movement (R^2) are, respectively, regressed on lagged individual stock returns, leverage and their interactions using five-minute data. The adjusted R^2 is estimated by equation (4) using the daily returns from March 13, 2015, to June 12, 2015. The explanatory variables and control variables in the regressions are similar to those in Table 2. The value in parentheses is *t*-statistics calculated using standard errors clustered by firm. Here, *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Y=Ind\_OI_{it}$				$Y=CrossInd\_OI_{it}$			
VARIABLES	**Low R^2**		**High R^2**		**Low R^2**		**High R^2**	
$R_{i,t-1}$	0.297***	0.335***	0.316***	0.348***	0.252***	0.285***	0.267***	0.290***
	(7.59)	(7.81)	(10.08)	(9.34)	(8.51)	(8.56)	(10.43)	(9.58)
$Leverage_{i,d-1}$	-0.006	0.003	-0.033**	-0.014	0.002	0.014**	-0.019**	-0.003
	(-0.59)	(0.28)	(-2.15)	(-1.23)	(0.42)	(2.41)	(-2.55)	(-0.65)
$R_{i,t-1}*Leverage_{i,d-1}$	0.397	-0.439	0.987***	-0.115	0.446*	-0.311	0.703***	-0.145
	(1.17)	(-1.56)	(4.23)	(-0.62)	(1.69)	(-1.43)	(3.85)	(-0.98)
$Down_{i,t-1}*R_{i,t-1}*Leverage_{i,d-1}$	1.344**		0.441		0.870***		0.151	
	(2.61)		(1.15)		(2.92)		(0.76)	
$LargeDown_{i,t-1}*R_{i,t-1}*Leverage_{i,d-1}$		2.844***		2.363***		2.199***		1.596***
		(7.21)		(6.64)		(8.54)		(5.73)
Y_{it-1}- Y_{it-3}	Y	Y	Y	Y	Y	Y	Y	Y
Intraday Dummy	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,304,061	1,304,061	1,304,061	1,304,061	1,304,061	1,304,061	1,304,061	1,304,061
Adj R-squared	0.884	0.884	0.887	0.887	0.907	0.907	0.912	0.912

Table 10 The Contagion Effect: Leveraged Stocks vs. Matched Non-leveraged Stocks

The average order imbalances within (outside) the same industry are regressed on individual stock returns, the dummy variable for price decline, and their interactions among both the leveraged stocks and the matched non-leveraged stocks. We exploit the non-repeated matching approach to select a matched non-leveraged stock for each leveraged stock (See Section V.A for the detailed matching procedure). The definitions of variables are the same as given in Table 2. The value in parentheses is *t*-statistics calculated using standard errors clustered by firm. The differences of three-item interactions' coefficients between groups are estimated using seemingly unrelated regression (SUR) models and the x^2 statistics are reported. Here, *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	Leveraged Stocks			
VARIABLES	***Y=Ind_OI$_{it}$***		***Y=CrossInd_OI$_{it}$***	
$R_{i,t-1}$	0.330***	0.290***	0.287***	0.258***
	(11.92)	(12.32)	(10.93)	(11.34)
$Down_{i,t-1}*R_{i,t-1}$	0.138***		0.117***	
	(3.49)		(3.32)	
$LargeDown_{i,t-1}*R_{i,t-1}$		0.316***		0.258***
		(7.96)		(7.49)
Y_{it-1}- Y_{it-3}	Y	Y	Y	Y
Intraday Dummy	Y	Y	Y	Y
Firm Num	395	395	395	395
Observations	849,306	849,306	849,306	849,306
Adj R-squared	0.894	0.894	0.908	0.909
	Matched Non-Leveraged Stocks			
$R_{i,t-1}$	0.311***	0.254***	0.271***	0.225***
	(4.89)	(4.95)	(3.90)	(4.08)
$Down_{i,t-1}*R_{i,t-1}$	0.077***		0.056**	
	(2.97)		(2.72)	
$LargeDown_{i,t-1}*R_{i,t-1}$		0.248***		0.192***
		(8.05)		(7.31)
Y_{it-1}- Y_{it-3}	Y	Y	Y	Y
Intraday Dummy	Y	Y	Y	Y
Firm Num	395	395	395	395
Observations	838,173	838,173	838,173	838,173
Adj R-squared	0.891	0.891	0.906	0.906
	Coefficient Difference Tests (Leveraged - Matched Non Leveraged)			
$Down_{i,t-1}*R_{i,t-1}$	0.062**		0.064**	
	(x^2=5.55)		(x^2=5.27)	
$LargeDown_{i,t-1}*R_{i,t-1}$		0.068***		0.066**
		(x^2=6.45)		(x^2=5.23)