Can Stock Trading Suspension Calm Down Investors During Market Crises?

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Abstract

This paper studies the trading behavior of investors facing a large number of firm-initiated stock trading suspension events during the Chinese stock market crisis in July of 2015. Using account-level trading data from the Shanghai Stock Exchange, we find that investors with a higher fraction of holding value in suspension *sell less* (or purchase more) of non-suspended stocks. Consequently, non-suspended stocks whose shareholders having high average account-level suspension fraction experience a relative price appreciation, which subsequently reverses. These evidences indicate that trading suspension can calm down investors and therefore helps to stabilize the volatile market in crisis time.

JEL classification: G01; G14

Keywords: Stock trading suspension; Market crisis; Event study

1 Introduction

After the October 1987 market crash, market-wide circuit breakers were introduced in the U.S. to prevent similar crashes in the future. Since then, circuit breakers were triggered once in 1997 and four times in year 2020. One rationale behind circuit breakers is to allow market-clearing participants to get some breathing room and calm them in moments of panic (Subrahmanyam (2012)). However, circuit breakers may cause investors to advance trades in time and exacerbate price movements prior to the triggering of the breaker (Subrahmanyam (1994)). For example, the Chinese stock market regulators briefly introduced and then quickly removed the market-wide circuit breakers in January 2016, because the frequent triggering and the resulting heightened stock market volatility (Chen, Petukhov, and Wang (2019)).

Besides the market-wide circuit breakers, trading suspension may be imposed onto individual stocks. For example, during the Chinese stock market crisis in July of 2015, about half of the listed firms chose to suspend trading on their stocks. There are two competing views on these suspension events at the time. On the one hand, opponents of trading suspension argue that suspension reduces the tradability of investors' stock portfolio, and this may exacerbate the panic selling among constrained investors on other non-suspended stocks. Consequently, the large number and the seemingly-arbitrary nature of the firm-initiated trading suspension were broadly criticized by the international investment community.[1] On the other hand, supporters of trading suspension argue that the stale prices after trading suspension may relax the investors' leverage constraints from margin trading, hence reduces the selling pressure on other non-suspended stocks. In this case, trading suspension may calm down investors and therefore helps to stabilize the volatile market during crises.

In this paper, we assess empirically whether trading suspension of some stocks helps to alleviate or exacerbate investors' panic selling on other stocks during the Chinese stock market crisis of July 2015. To shed light on which of the above two competing arguments dominates investors' reaction to trading suspension, we utilize account-level trading data from the Shanghai Stock Exchange to study the impact of a large number of firm-initiated suspension events on trading activities of both individual and institutional investors, covering the crisis period from July 2 to July 23, 2015.

[1]For example, it was cited as one of the main reasons that MSCI rejected the inclusion of Chinese A-shares in its emerging market index in early 2016. Only after the tightening of the trading suspension rules by regulators in May 2016, MSCI announced the inclusion of Chinese A-shares in June 2017.

As the first step of our analysis, we use sorting to study the impact of suspension on investors' trading behavior. Specifically, for each investor account, we construct two variables: (i) suspension fraction, which is the fraction of account value that is in trading suspension; and (ii) net selling intensity, which is defined as the net selling (i.e., sell-minus-buy) scaled by the tradable value in the account. We sort accounts within each investor type (individual or institution) according to their suspension fraction at the beginning of each trading day, compute the average net selling intensity within the day for the sorted groups, and then average over dates. We find that accounts with higher suspension fraction *sell less* on-net than those with lower suspension fraction. This indicates that suspension generates a positive spillover effect on non-suspended stocks. In other words, trading suspension has a *calming down* effect on investors, and it holds for both individual and institutional investors.

To further control for both the account heterogeneity and time fixed effects, we employ formal panel regressions to infer the impact of suspension on investors' trading behavior. We find that adding account and time fixed effects greatly enhances the negative relationship between net selling intensity and suspension fraction–indicating the importance of controlling for account-level heterogeneity and time varying overall market conditions. Moreover, the negative relationship still holds after we control for time-varying account-level past returns and past trading. Finally, to better understand the impact of suspension on different components of trading, we decompose the net selling into three components and find that accounts with higher suspension fraction (i) sell less and (ii) buy more of their existing holdings, as well as (iii) buy more of non-holding stocks. This indicates that the calming down effect of suspension holds for all three components of investors' trading activities.

Our account-level analysis reveals that trading suspension has a positive calming down effect on investors, countering the negative view on suspension. In addition, this finding is robust after we control for account-level heterogeneity and time varying market conditions, and it holds for both individual and institutional investors. To shed more light on the potential channels through which suspension affects investors' trading, we next explore how the calming down effects may vary across investors with different account characteristics.

The first account heterogeneity we explore is the difference in potential leverage constraints across accounts. In particular, margin accounts are traded on margin and therefore have higher leverage constraints. To study the effect of leverage constraints, we create a dummy for margin accounts and interact it with the suspension fraction. We find that the interaction term is negative–meaning that the calming down effect of suspension is stronger for margin accounts. This is consistent with the interpretation that trading suspension helps to relax the leverage constraints of margin accounts, leading to stronger positive calming down effects on them.

The second account heterogeneity we explore is the difference in available cash across accounts. Since we do not observe directly the available cash at the account-level, we instead use the account-level past trading as a proxy. The reasoning is that high past net-selling will give investors more liquidity in the form of cash. To test this idea, we create a dummy variable for accounts that have above-median net-selling intensity in the past 10 trading days, and interact the dummy with the suspension fraction. We find that the calming down effect of suspension is much stronger for individual investors that have high selling intensity in the past 10 trading days. However, we find the calming down effect is only slightly stronger (insignificant) for institutions with high past-10 selling intensity. One argument is that individuals are more likely to hold the cash from past net-selling, while institutions are more likely to use the cash from past selling to meet fund outflows. Therefore, our finding is consistent with the interpretation that trading suspension has a stronger calming down effects for investors who have more available cash to purchase stocks.

The third account heterogeneity we explore is the difference in the past returns across accounts. Past returns can play an important role in investors' trading decisions. For example, investors may exhibit extrapolation or disposition effect, or both in their trading behavior.[2] Therefore, we would like to study how past returns are related to the calming down effect of suspension. For this purpose, we create a dummy variable for accounts with above-median returns in the past-10 days and interact it with the account-level suspension fraction. We find that the calming down effect of suspension is much stronger for individuals with high past returns. However, the calming down effect of suspension is similar across institutional investors with different past returns. One possible interpretation is that higher suspension fraction may lead to individuals with high past returns to be more extrapolative in their trading behavior, and such effect is very small for institutions.

The final account heterogeneity we explore is the difference in the down-side risks of suspended stocks across accounts. The idea is that suspension may change investors' perception

[2]Extrapolation effect refers to using past price changes to positively form expectations about future price changes (Fuster, Laibson, and Mendel (2010) and Barberis (2018)), and disposition effect refers to the tendency to sell stocks trading at gains and hold on to stocks with losses (Odean (1998) and Barber and Odean (2013)). Liao and Peng (2019) show that both effects exist among Chinese individual investors.

about the down-side risk of suspended stocks. For example, investors may view them to have lower down-side risks, because their prices become stale upon suspension. Alternatively, investor may understand that price will fluctuate again upon resumption and therefore view the suspension itself as indication of higher down-side risk for these stocks in the future. To test this idea, we create a dummy variable for accounts with above median down-side risks of suspended holdings–which we proxy by the account-level average skewness of suspended stocks before their suspension. We find that the calming down effect of suspension is weaker for accounts with higher downside risks (i.e., lower skewness). We interpret this result as indicating that investors do not naively view the stale price of suspended stocks as reducing the down-side risks–instead they seem to view the suspension as temporary, and once the trading is resumed in the near future, the risks for these stocks will be reflected again in the time-varying stock prices.

In the next step of our analysis, we further demonstrate the robustness of our main findings. First, the calming down effect also holds if we scale the net selling amount by the total account value, instead of the tradable value adopted in our main analysis. Second, the calming effect also holds in the early period (before July 8th) during which the market experienced a sharp decline in prices–indicating that our results on the calming down effect of suspension are not driven by the intense government intervention in the later period (after July 8th). Third, the calming down effect is similar under good or bad market-wide conditions as measured by market return, indicating that the calming down effect is not driven by favorable market-wide conditions. Fourth, the newly and previously suspended stocks have similar calming down effect on investors–indicating that it takes time for investors to react to suspension in their trading activities. Fifth, the subsample of accounts that have experienced a large range of suspension fraction in our sample period also shows a strong calming down effect of suspension on trading. Finally, we run similar panel regressions at the account-stock level by controlling for the stock-time fixed effect besides the account fixed effect. The result shows that the calming down effect still holds–that is, for a given stock, accounts with higher suspension fraction sell less on-net on that stock than accounts with lower suspension fraction. This result indicates that our account-level result is less likely driven by the difference in characteristics of stock holdings across accounts.

In the final step of our analysis, we study how the calming down effect of suspension on investors' trading may impact the prices of tradable stocks. For each non-suspended stock, we construct a suspension spillover exposure by computing the average suspension fraction across its shareholders, using their holding value as the weight. For example, if a stock is held by investors with a higher average suspension fraction, then the buying demand on this stock will be higher due to the positive spillover effect from suspension. In this case, we would expect that the prices of stocks with higher suspension spillover exposure be higher. In addition, if the trading demand is temporary, we should expect the prices to reverse in the future. We find supporting evidences. In particular, stocks with higher suspension spillover exposure indeed have higher short-term returns, reaching at peak after around 10 trading days, and then reversing back after 40 trading days. That is, suspension spillover effect on trading also generates a short-term positive impact on the prices of those non-suspended stocks.

Our paper is most closely related to the literature on the effect and consequence of trading restrictions. One of the most prominent restrictions is the market wide circuit breakers. Subrahmanyam (1994) shows that a circuit breaker may cause agents to advance trades in time and exacerbate price movements prior to the triggering of the breaker. Goldstein and Kavajecz (2004) confirm such a "magnet effect" on Octomber 27, 1997, the first time the circuit breaker has been triggered in the US since its introduction after the 1987 crash. Motivated by the brief introduction and then quick termination of circuit breakers in the Chinese stock market in January of 2016, Chen, Petukhov, and Wang (2019) develop an equilibrium model to examine the impact of circuit breakers and find that circuit breakers can lower stock prices and increase stock volatility. Another trading restriction in the Chinese stock market is the 10% daily price limit. Chen, Gao, He, Jiang, and Xiong (2019) find that the daily price limit rules induce large individual investors to purse a destructive trading strategy of pushing prices to the upper limit and then profiting from selling on the next day. We differ from these studies by focusing on the spillover effect of firm-initiated trading suspensions during a market crisis.

Our paper is also closely related to the recent studies on the trading suspension during stock market crises.[3] Huang, Shi, Song, and Zhao (2020) study the same suspension events as ours, but they focus their research on the determinants and impact of firm-initiated trading suspension on suspended stocks. We complement their analysis by studying the spillover effect of suspended stocks on other non-suspended stocks. Liu, Xu, and Zhong (2017) also examine the role played by trading suspension during the 2015 Chinese stock market crash. Using

[3]Other studies on trading suspension focus on the information dissemination purpose under normal market-wide conditions across different exchanges, see e.g., Kryzanowski (1979), Lee, Ready, and Seguin (1994), Kabir (1994), Wu (1998), and Tan and Yeo (2003).

quarterly holding data on mutual funds' stock portfolios, they infer that a stock is more likely to be sold if its major holders are exposed to a larger proportion of non-traded stocks in their portfolio. In contrast, we use daily trading data on all institutional investors, and find that trading suspension has a calming down effect during the narrow window of crisis time.

Finally, our paper is broadly related to a growing literature on the Chinese stock market.[4] For example, Carpenter, Lu, and Whitelaw (2020) study the price informativeness of Chinese stock market and its capital allocation efficiency in corporate investment. Liao and Peng (2019) test the interaction of investors' extrapolative beliefs and the disposition effect based on account-level data on the 2014-2015 Chinese stock market bubble. Bian, Da, He, Lou, Shue, and Zhou (2020) show that margin constraints can lead to contagion and fire sales during the Chinese stock market crash of 2015. Their analysis provides direct evidence that margin constraints can generate a negative spillover effect on trading and stock prices. Hansman, Hong, Jiang, Liu, and Meng (2019) study the impact of the 2010-2015 staggered deregulation of stock margin lending by brokerages and banks in China. They show that some sophisticated investors are able to anticipate the timing of credit availability and trade accordingly. Our analysis complements these studies by providing evidence on the positive spillover effect of firm-initiated trading suspension on non-suspended stocks in the 2015 Chinese stock market crash.

We make two contributions to the literature. First, we provide direct evidences that trading suspension can calm down investors and therefore helps to stabilize the volatile market during the Chinese stock market crash in July 2015. This counters the common perception that suspension amplifies investors' anxiety and therefore has a negative spillover effect on other stocks. Second, we provide further evidence that suspension can generate a short-term positive pricing impact on non-suspended stocks–further corroborating the conclusion that stock-level trading suspension helps to stabilize the market during panic periods.

The rest of the paper is organized as follows. Section 2 reviews the institutional background related to the trading suspension in the Chinese stock market. Section 3 describes the data. Section 4 studies the account-level trading activities of investors, and Section 5 analyzes the spillover effect of trading suspension on stock prices. Finally, Section 6 concludes.

[4]There are also recent studies on the Chinese bond market. For example, Chen, Chen, He, Liu, and Xie (2019) provide causal evidence for the value of asset pledgeability based on a policy shock that renders a class of Chinese corporate bonds ineligible for repurchase agreement on one of the two segmented markets. Ding, Xiong, and Zhang (2019) study the overpricing of Chinese corporate bond issuances driving by underwriter competition.

2 Institutional Background

According to the statistics published by the China Securities Regulatory Commission (CSRC), there are 2827 publicly listed companies in the Chinese stock market by the end of 2015, with a total market capitalization of 53.1 Trillion RMB (or 8.2 Trillion USD). There are two stock exchanges in Shanghai and Shenzhen. Huang, Shi, Song, and Zhao (2020) provide a short discussion on the difference between these two stock exchanges. Carpenter and Whitelaw (2017) review the development of China's stock market and provide a survey of the relevant literature.

In the Chinese stock market, the exchanges allow companies to suspend their stocks' trading if there are "major corporate events" that can materially affect firm valuation, including the on-going negotiations of mergers and acquisitions. Note that both exchanges err on the side of conservatism and almost always approve requests for trading suspension. So the decision power shifts from regulators to corporations in deciding whether or not to suspend trading on their stocks.

According to Huang, Shi, Song, and Zhao (2020), at the peak of the July 2015 crisis, a total of 1442 firms chose to suspend trading, representing 52 percent of the number of Chinese exchange-listed stocks and 36 percent of total market capitalization. The median duration of trading suspension during this period is four trading days. Such a large number of clustered suspension events indicates that corporations are exploiting the loophole in the trading suspension rule, rather than having material corporate events. This makes the crisis period an ideal setting to study the spillover effect of suspension on other non-suspended stocks, without worrying about the contaminating effect of corporate events underlying the suspension decision in normal time.

During the crisis, firms applied to the exchanges for suspension under rather arbitrary reasons, such as "we are planning a major event" in one day and "after careful examination this does not qualify as a major event" several days after. The seemly arbitrary suspension initiated by firms has drawn criticisms, especially from international investors. After the large scale suspension events, both Shanghai and Shenzhen exchanges announced in May 2016 new rules regarding trading suspension and resumption–putting time limits on the suspension duration. More recently, on November 21, 2018, both exchanges announced new guidance to further restrict the cases that are eligible for trading suspension, and reduce suspension duration to within 10 trading days, with a maximum of 25 trading days.

3 Data

The main data source for our study comes from the Shanghai Stock Exchange, which provides detailed account-level holding and trading data on stocks that are listed in its exchange. The account-level trading data creates a rich cross-section of accounts, which makes it possible for studying the impact of suspension on trading behavior across investors. Another data source for our analysis is the China Stock Market and Accounting Research (CSMAR) database, which contains stock-level trading and accounting information for each publicly listed company. Our analysis covers the crisis period in the Chinese stock market from July 2 to July 23, 2015, during which a large number of listed firms chose to suspend trading on their own stocks.

In order to have a meaningful portfolio of stocks for our analysis of trading activities, we require accounts to hold at least 3 stocks and the total holding value to be above 100,000 RMB as of July 1, 2015. We then keep track of the trading activities of these selected accounts over our sample period. Table 1 reports the summary statistics for both the full sample and our selected sample separately for individual and institutional investors. In total, there are over 43 million individual accounts with holding value of 8.3 trillion RMB, and over 17 thousand institutional accounts with holding value of 3.6 trillion RMB. The average number of stocks for each individual account is only 2, indicating that Chinese individual investors on average hold a very concentrated portfolio. In contrast, institutions hold on average 26 stocks in their portfolios. Despite only 13% of individual accounts are selected for our analysis, they represents 57% of the total individual holdings, and about 52% of total individual buying and selling activities. Our selected institutional accounts represent 76% of total institutional investors, 90% of total institutional holdings, and about 96% of institutional trading activities. The average number of stocks increases to 6 for individuals and 33 for institutions in our selected sample.

We are particularly interested in studying the effect of trading suspension on investors' trading behavior. For this purpose, we measure the account-level suspension fraction as follows,[5]

$$S_{t-1}^{j} = \frac{\text{value of suspended stocks (in account } j \text{ at the open of day-}t)}{\text{value of all stocks (in account } j \text{ at the open of day-}t)}. \tag{1}$$

[5]For ease of notation, we use subscript '$t-1$' to represent information that is available before the normal trading on day-t.

Since the suspended stocks are no longer tradable, investors can only trade on the non-suspended stocks. Therefore, we focus our study on the spillover effect of suspension on other non-suspended stocks. In particular, for each non-fully suspended account, we define the net-selling intensity as,

$$\Delta_t^j = \frac{\text{net selling amount (by account } j \text{ on day-}t)}{\text{value of tradable stocks (in account } j \text{ at the open of day-}t)}. \tag{2}$$

This measure captures the intensity of net selling relative to the tradable value in the account. Note that some accounts may not trade on a particular day, in this case we assign a zero net trading instead of a missing value. In our robustness analysis, we also normalize the net selling amount by the account's total holding value–including the suspended stocks, for which we use the pre-suspension price in computing the holding value.

Table 1 reports that the equal-weighted average suspension fraction is 11% for individual investors and 22% for institutional investors.[6] The net-selling intensity is -2.1% for individual investors and -17.1% for institutions. The negative number indicates that, averaging over our selected time period, both types of investors are on-net buying tradable stocks. Of course, there are large variations in both the suspension fraction and net-selling intensity over time, which we explore in details in our formal analysis.

In the empirical analysis, our main task is to estimate the relationship between the account-level net selling intensity and the account-level suspension fraction. In addition, we also decompose the net selling of each account into three components: (i) selling on stocks with existing holdings, (ii) buying on stocks with existing holdings, and (iii) buying on stocks without existing holdings. We then study the relationship between each of these three trading components and the account-level suspension fraction.

Note that investors may trade differently because they differ in other dimensions. To control for such heterogeneity, we take two steps. In the first step, we rely on panel regressions in which we include account fixed effect to control for time-invariant account heterogeneity. In the second step, we further control for the time-varying account characteristics, such as past returns and past trading activities. In particular, we control for the cumulative daily

[6] The value-weighted average suspension fraction is 13% for individual investors and 9% for institutional investors. Note that the fraction of suspended stocks is lower in the Shanghai Stock Exchange comparing to that of Shenzhen Stock Exchange, mainly because the former listed relative large firms while the later listed more of small and medium enterprises. For example, Huang, Shi, Song, and Zhao (2020) report that there are 334 (735) out of total 942 (1377) stocks listed on Shanghai (Shenzhen) Stock Exchange suspended trading in our selected time period.

returns for each account for the past 10 trading days ($R^j_{t-10,t-1}$). Similarly, we also control for the cumulative net selling amount in the past 10 trading days and scale it by the current holding value ($C^j_{t-10,t-1}$). To reduce the influence of outliers, we winsorize the key variables (net-selling intensity, past-10 day return, and past-10 day net selling) at both top and bottom 0.5%.

4 Account-level Trading Activities

In this section, we study the impact of suspension on investors' trading activities of tradable stocks. In the main analysis of Section 4.1, we study the relationship between investors' net selling intensity and their accounts' suspension fraction. We explore further account heterogeneity in Section 4.2 and perform robustness analysis in Section 4.3. Finally, we study the characteristics of traded stocks and assess how they are related to suspension fraction in Section 4.4.

4.1 Main analysis

A Sorting

To study the relationship between investors' net selling intensity and account-level suspension fraction, we first sort accounts according to the account-level suspension fraction, separately for individual and institutional investors. We then average over accounts within the same sorting group and report the time series average value for each group. In particular, we form one group for accounts with zero suspension fraction (group 1), and 5 equally spaced groups (groups 2 to 6) for suspension fraction between zero and one for the rest of accounts.

Table 2 reports the sorting result. For individuals, there are more than 3.4 million accounts have zero suspension. There are more than 0.8 million accounts that have suspension fraction between 0 and 0.2 (group 2). The number of accounts gradually decreases from 0.46 million for group 3 to 0.13 million for group 6. Note that the average account holding value is very similar, except that the highest suspension group 6 has slightly larger size. For the trading measures, the equal-weighted average net selling intensity is overall decreasing in suspension fraction–note that the relationship is monotonic for positive suspension fraction (groups 2 to 6), but the zero-suspension accounts (group 1) have lower net-selling than the low-suspension group (group 2). For example, the individual investors in group 2 sold 0.6% on-net relative to their accounts' tradable value, while investors in group 6 bought 22.9% on-net. The value-weighted averages have the similar patterns: the net-selling intensity decreases from selling 2.6% for group 2 to buying 6.7% for group 6.

For institutions, the number of accounts are more spread out across groups. For example group 1 contains 3475 accounts, less than that of group 2 (3588 accounts), and even the highest suspension group 6 has more than 700 accounts. The average account size, however, is quite different: it is 573 million RMB for group 2, but it drops dramatically to only 44 million for group 6. That is, accounts with higher suspension fraction are much smaller institutions. For the trading measures, the pattern is similar to that of individuals. In particular, the equal-weighted net selling intensity decreases from buying 0.7% for group 2 to buying 141.2% for group 6. The value-weighted net selling intensity is also trending down along with suspension fraction, with group 2 selling 0.7% and group 6 buying 24.8%.

The above sorting results show that accounts with higher suspension fraction on net sell less than those with lower suspension fraction. This indicates that suspension has a calming down effect on investors, such that they sell less, not more, when a larger fraction of their account holdings is suspended trading. This calming down effect of suspension holds for both individual and institutional investors, with the effect on institutions much stronger.

B Panel regression

Note that the above sorting result is only suggestive, as it does not take into account potential account-level heterogeneity as well as the differential impact across trading dates on each group. For example, the group with zero suspension fraction has more observations in the early period when the overall suspension fraction is low. In addition, the average account value for institutions is negatively correlated with suspension fraction. To address these potential issues, we employ panel regressions which allow us to control for both the account and time fixed effects.

Specifically, we run the following panel regressions separately for individual and institutional investors:

$$\Delta_t^j = \beta S_{t-1}^j + \lambda R_{t-10,t-1}^j + \eta C_{t-10,t-1}^j + \mu_t + \alpha_j + \epsilon_t^j, \quad (3)$$

where Δ_t^j is the net-selling intensity of account j on day-t, S_{t-1}^j is the account j's suspension fraction at the open of day-t, $R_{t-10,t-1}^j$ is the account j's past-10 day cumulative return, and $C_{t-10,t-1}^j$ is account j's past-10 day net selling (or net cash outflow from trading) scaled by the account value at the open of day-t. In order to control for other time-invariant account characteristics and time-varying market wide conditions, we include both the time and account fixed effects (μ_t and α_j). Note that coefficient β captures the effect of suspension on investors' trading activities. For example, a negative estimate on β implies that accounts with higher suspension fraction sell less on net. In this case, suspension generates a positive spillover effect on non-suspended stocks, and therefore we infer that suspension has a calming down effect on investors.

Panel-A of Table 3 reports the results for individual investors. In the simplest specification (1a), we regress the net-selling intensity on the account's suspension fraction without any other controlling variables and fixed effects. The negative coefficient on the suspension fraction indicates that accounts with higher suspension fraction sell less on-net than those with lower suspension fraction. This result holds after we control for either one of the two or both fixed effects (specifications, 1b-1d). Note that adding the two fixed effects, and in particular the account fixed effect, enhances the magnitude of the coefficient on suspension fraction by a factor of 3 (-0.10 in model (1a) vs. -0.33 in model (1d)). In other words, controlling for the fixed effects, the negative relationship between net-selling intensity and suspension fraction that we reported in Table 2 based on simple sorting becomes much stronger. Moreover, the effect of suspension on trading is the same after we also control for the account's past 10-day return (model-2) and past 10-day cumulative trading (model-3). Note that individuals seem to sell less if they experienced higher past account return or they sold more in the recent past, with the past trading retaining high statistical significance in model-(3). The negative coefficient on the past selling can be interpreted as mean-reverting in trading: if an account sold more in the past, it is more likely for the investor to buy more now to rebalance its stock exposure. Moreover, the account-level past selling shows a strong explanatory power–it increases the adjusted R-square from 1.22% in model-(2) to 9.29% in model-(3). The overall message is that trading suspension has a calming down effect on individual investors, and such a positive effect is robust after we control for account-level heterogeneity and time varying market conditions.

Panel-B of Table 3 reports the results for institutional investors. Similar to the effect on individual investors, suspension also has a calming down effect on institutional investors. There are both similarities and differences. First, the calming down effect for institutions is also stronger after we control for account heterogeneity and time fixed effect. For example, the coefficient on suspension fraction increases from -1.03 in model (1a) without fixed effect to -2.24 in model-(1d) with both fixed effects. Second, the positive calming down effect on institutional investors is much stronger than that on individual investors. For example, the coefficient on the suspension fraction is -2.07 for institutions and -0.32 for individuals (both in model (3)). Third, the effect of past return on net selling is much stronger for institutions than individuals. For example, the coefficient on past return is insignificant -0.02 for individuals but significant -0.95 for institutions (both in model (3)). That is, institutions are more likely to use the past return as a guidance for their current trading–implicitly assuming the continuity in account-level returns. Finally, even though the effect of past trading is significant for both types of investors, the coefficient is larger for individual investors (-0.04 for individuals vs. -0.03 for institutions both in model (3)). Despite all these subtle differences, the main message is the same: trading suspension also has a robust and strong calming down effect on institutions.

To better understand the source of the positive calming down effect of trading suspension, we decompose the net selling by each account into three components: (i) selling on stocks with existing holdings; (ii) buying on stocks with existing holdings; and (iii) buying stocks without current holdings, all scaled by the tradable value in the account. That is, we decompose the net-selling intensity into one selling intensity and two buying intensities. We then run the same panel regressions on each of these three components, and investigate whether the calming down effect exists in all these three types of trades.

Table 4 reports the result. Panel-A shows that for individuals, higher account-level suspension fraction leads to (i) less selling of existing holdings, (ii) more buying of existing holdings, and (iii) more buying of non-holding stocks. That is, the calming down effect of suspension exists for all three components of individual investors' trading. In addition, the effect from buying is much stronger than that of selling. In particular, the coefficient on suspension fraction is only -0.02 for selling existing holdings, and 0.05 for buying existing holdings, and increases dramatically to 0.17 for buying non-holding stocks. Panel-B shows that similar results also hold for institutional investors, with the suspension has a much stronger effect on purchase of non-holding stocks. In particular, the coefficient on suspension fraction is 1.69 for buying non-holding stocks, but only 0.04 for buying existing holdings and -0.04 for selling existing holdings. That is, institutions tend to buy stocks that they currently do not own–possibly due to their strong diversification motives.

In summary, we find that accounts with higher suspension fraction sell less on-net relative to their tradable holdings than those with lower suspension fraction. We also show that such a positive spillover effect of suspension exists on trading activities involving not only current holding stocks in the account but also non-holding stocks outside the account. Overall, the evidence suggests that suspension has a calming down effect on investors, and this holds true for both individual and institutional investors.

4.2 Exploring further account heterogeneity

As we documented above, trading suspension can have a calming effect on investors, countering the common perception that suspension may amplify investors' anxiety and generates a negative spillover effect on other non-suspended stocks. To better understand the potential channels through which suspension affects investors' trading behavior, in this section we explore how the positive calming down effect vary along different dimensions of account heterogeneity.

A Leverage constraint

The first account heterogeneity we explore is the difference in potential leverage constraints across accounts. In particular, margin accounts are traded on margin and therefore should have higher, either current or expected future, leverage constraints than normal accounts. Intuitively, suspension prevents further large price drops within a certain time period, which borrows time for the investors to find liquidity and therefore helps to relax investors' leverage constraints. Combining these two arguments together, we conjecture that the calming down effect of suspension is stronger among margin accounts.

To test this idea, we create a dummy for margin accounts and interact it with the account-level suspension fraction. Specifically, we employ the following panel regressions,

$$\Delta_t^j = \beta_{margin} I_{margin}^j \times S_{t-1}^j + \beta S_{t-1}^j + \lambda R_{t-10,t-1}^j + \eta C_{t-10,t-1}^j + \mu_t + \alpha_j + \epsilon_t^j, \tag{4}$$

where I_{margin}^j is the dummy for margin account j, and β_{margin} captures the extra calming down effect from suspension on margin accounts relative normal accounts. Based on the above argument, we expect the value of β_{margin} to be negative.

We report the result for both individuals (model-(1a)) and institutions (model-(1b)) in Table 5. It shows that the calming down effect of suspension is indeed stronger among accounts that are traded on margin relative to normal accounts. This is true for both individual and institutional investors. For example, the coefficient on suspension fraction is -0.29 for normal individual accounts and -0.39 for individual margin accounts, with the difference to be statistically significant at the 5% level. Similarly, the coefficient on suspension fraction is -2.03 for normal institutional accounts and -2.72 for institutional margin accounts, with the difference to be statistically significant at the 10% level. These results are consistent with the interpretation that trading suspension helps to relax the leverage constraints of margin accounts, leading to stronger positive calming down effects on them.

B Available cash

The second account heterogeneity we explore is the difference in available cash across accounts. Intuitively, the calming down effect should be stronger for investors who have more cash available to purchase stocks. Unfortunately, we do not observe directly the available cash at the account-level, therefore we use the account-level past trading as a proxy. The reasoning is that high past net-selling activities will give investors more liquidity in the form of cash for stock purchase.

To test this idea, we create a dummy variable for accounts that have above-median net-selling intensity in the past 10 trading days. We then interact it with the account-level suspension fraction and run the following panel regressions:

$$\Delta_t^j = \gamma I_{high,t-1}^j + \beta_{high} I_{high,t-1}^j \times S_{t-1}^j + \beta S_{t-1}^j + \lambda R_{t-10,t-1}^j + \eta C_{t-10,t-1}^j + \mu_t + \alpha_j + \epsilon_t^j, \quad (5)$$

where $I_{high,t-1}^j$ is the dummy for account j if it belongs to high group of above-median net-selling intensity. We add the dummy in the regression because the dummy itself can change over time such that it cannot be captured by the time-invariant account fixed effect. In comparison, the static margin dummy is absorbed by the account fixed effect in regression (4). We are particularly interested in the coefficient on the interaction term, β_{high}, which captures the extra calming down effect on accounts with high past selling activities relative to those of low past selling. We conjecture a negative estimate of β_{high}.

We report the result for both individuals (model-(2a)) and institutions (model-(2b)) in Table 5. Model-(2a) shows that the calming down effect of suspension is indeed stronger for individual investors with higher past net selling. Specifically, the coefficient on suspension is -0.22 for low past-trading accounts, and -0.41 for high past-trading accounts, with the difference to be statistically significant at 5% level. Model-(2b) shows that even though institutions also show a slightly stronger calming down effect for accounts with higher past net selling, the difference between high and low past selling accounts is statistically not significant.

One potential explanation is that individuals are more likely to hold the cash from the past net-selling, while institutions are more likely to use the cash from the past selling to meet the demand of fund outflows.

Therefore, our finding is overall consistent with the interpretation that the trading suspension has a stronger calming down effects for investors, especially individual investors, who have more available cash to purchase stocks.

C Expectation on future return

The third account heterogeneity we explore is the difference in the investors' expectations about future returns, which affect the trading behavior directly. Unfortunately, we cannot observe investors' expectations. Instead, we rely on past account-level returns as an indirect proxy of investors' expectations. For example, Liao and Peng (2019) show that both the extrapolation and disposition effects are prevalent among Chinese individual investors. Therefore, we would like to study how past returns may affect the calming down effect of suspension.

To test this idea, we assign a high past return dummy for accounts that have past 10-day returns higher than the median value and interact it with the account-level suspension fraction similar to Equation (5). We report the result for both individuals (model-(3a)) and institutions (model-(3b)) in Table 5. It shows that the calming down effect of suspension is much stronger for individuals with high past returns. However, the calming down effect of suspension is similar across institutional investors with different past returns. In particular, individuals with high past-10 return tends to sell more on-net (the coefficient on the dummy is significant positive), and suspension has a stronger calming down effect on them (the coefficient on the interaction term is significant negative). In contrast, institutions with high past-10 return tends to sell less on-net (the coefficient on the dummy is insignificant negative), and suspension has a similar calming down effect on them (the coefficient on the interaction term is insignificant negative). One possible explanation is that higher suspension fraction may induce individuals to be more extrapolative in their trading behavior, and such effect is very small for institutions.

In short, we find some evidence that suspension has a stronger calming down effect on individual investors who experience high past account-level returns. However, such pattern does not exist for institutional investors–possibly reflecting the differential methods employed by individual and institutional investors in forming their expectation about future returns based on past returns.

D Downside-risk of suspended holdings

The final account heterogeneity we explore is the difference in the down-side risks of suspended stocks across accounts. Suspension may change investors' perception about the down-side risk of suspended stocks. On one hand, the stale price upon suspension may be viewed as having low down-side risks. On the other hand, the suspended stocks are self-selected to suspend trading mainly because of their high down-side risks. That is, depending on different views, investors may perceive their holdings of the suspended stocks to be more or less risky after suspension.

To test this idea, we employ return skewness as a measure of down-side risks. In particular, a lower (negative) skewness implies possible larger losses, and therefore represents higher down-side risks. We compute the stock-level skewness by using the past 60 trading days, and then we average over all suspended stocks within an account by using the pre-suspension holding value as weights. If suspension indeed reduces the perceived down-side risks of suspended stocks, then the calming down effect will be stronger for accounts that have higher downside risks for their suspended holdings.

We perform a similar analysis as in Equation (5) by creating a high downside risk dummy for accounts with average skewness of suspended stocks below the median value. We conjecture that the interaction term between suspension fraction and the high downside risk dummy has a negative coefficient. We report the result for both individuals (model-(4a)) and institutions (model-(4b)) in Table 5. Model-(4a) shows that the calming down effect is weaker for individual accounts that have higher down-side risks–with the coefficient for the interaction term to be positive and significant at 5% level. This also holds true for institutional investors as reported in Model-(4b). These findings counter our conjecture. In other words, we do not find any evidence that investors view suspended stocks to have lower downside risks.[7]

We interpret the above result as indication that investors do not naively view the stale price of suspended stocks as having low down-side risks, instead they seem view the suspended stocks as more risky. As a result, the suspension has a weaker calming down effect on investors who have high down-side risks for their suspended holdings.

[7] We also test this idea by using standard deviation as a measure of risk and find that the calming down effect is weaker for accounts with higher average stock volatility.

4.3 Robustness analysis

In this section, we provide further robustness analysis on the calming down effect of trading suspension on investors' trading activities.

A Scaling trading by total account value

In the analysis so far, we scale the net selling amount by the tradable holding value within each account. This is a natural choice since our goal is to study how trading suspension affects investors' trading activities on non-suspended tradable stocks. An alternative choice is to scale the net selling amount by the total account value–including both the suspended and tradable stocks. We perform similar panel regressions as in our main analysis by replacing the rescaling factor for net selling amount in Equation (2) from tradable holding value to total account value.

We report the result in model-(1) of Table 6. First, the positive calming down effect of suspension on investors' trading activities still holds after we scale the net selling by total account value. Moreover, the positive effect is highly significant after we control for past return and past trading. Second, comparing with the result reported in Table 3, the magnitude of the calming down effect, i.e., the coefficient on the account-level suspension fraction, is smaller since we normalize the net selling amount by a larger value. For individual investors, the coefficient for suspension fraction is -0.32 when we scale the net selling by tradable account value (model-(3) in Table 3), it decreases to -0.13 if we scale the net selling by total account value (model-(1) in Table 6). Similarly, for institutions, the coefficient is -2.07 when we scale the net trading by tradable account value, and it reduces to -0.46 when we scale the net trading by total account value. Note that despite the reduction in the magnitude for the coefficient on suspension fraction, the statistical significance in terms of t-stat (all larger than 6 in absolute value) is very high and comparable between the two alternative choices of scaling factor for trading activities.

Therefore, we conclude that the calming down effect of trading suspension on investors' trading activities is robust and highly significant for both individual and institutional investors, either we scale the net selling amount by tradable holdings in the account or by total account holding value.

B Time period: early vs. late

In our main analysis, we utilize observations covering the full time period from July 2 to 23, 2015. One may argue that the positive calming down effect of trading suspension is driven mainly by the later period during which the government intervened in the market. This is a valid concern. To show that our result is not driven by the later period, we created a 'Late Period' dummy for time period on and after July 8, during which the government intervened aggressively on the market. Note that the overall market is in a panic mode in the early period (before July 8) as the number of suspended stocks increases dramatically in that period. We would like to show that the calming down effect estimated from the full sample period also holds in the early period.

We report the result in model-(2) of Table 6. First, the positive calming down effect of trading suspension is also highly significant for the early period for both individual and institutional investors. Second, comparing with the early period, the positive calming down effect of trading suspension in the late period is slightly stronger for individual investors but less strong (insignificant) for institutional investors. These results indicate that the positive calming down effect of trading suspension in the full sample period is not driven by the government intervention in the late period.

C Market conditions: good vs. bad

In our main analysis, we estimate the average calming down effect of trading suspension on investors' trading activities across dates. One may argue that the positive calming down effect comes mainly from dates on which the overall market conditions are favorable. To show the robustness of the calming down effect across dates with different market conditions, we create a dummy ('High MKT Return') for days that have above the median market return in our sample period. We then interact the dummy with the account-level suspension fraction to estimate the difference in the calming down across good and bad market conditions.

We report the result in model-(3) of Table 6. First, the calming effect of trading suspension is highly significant under bad market conditions for both individual and institutional investors. Second, the calming down effect of trading suspension under better market conditions is slightly stronger for individuals but slightly weaker for institutions. In other words, the calming down effect of trading suspension is similar across days with either high or low market returns. This result corroborates the above findings that the calming down effect is not driven by government intervention in the late period.

It is worth noting that our analysis does not imply the irrelevance of government intervention or the overall market condition on investors trading activities. In our panel regression analysis, we included the time fixed effect, which effectively takes out any aggregate market effect on each trading day. Our message above is based on the within-day cross-sectional relationship between net selling intensity and the account-level suspension fraction. That is, we conclude only that the cross-sectional calming down effect of trading suspension is not affected by the overall market conditions in any significant way.

D Suspension timing: new vs. old

In our analysis so far, we construct the suspension fraction by using all suspended stocks within an account irrespective of their timing of suspension. In this section, we explore the potential differential impact of suspension on trading related to the timing of suspension. In particular, we decompose the suspension fraction into two components: (i) newly suspended stocks–those that start suspension at the open of the current day, and (ii) previously suspended stocks–those that suspended trading before the current day, both scaled by the account's tradable value at the open of the current day. The account-level suspension fraction is the sum of the two fractions.

We report the result in model-(4) of Table 6. First, both the newly suspended stocks ('New') and the previously suspended stocks ('Old') have a calming down effect on individual and institutional investors. Second, while both types of suspension have the same calming down effect on institutions, the calming down effect of previously suspended stocks is stronger than those of newly suspended stocks on individual investors. For example, for individual investors, the coefficient on suspension fraction is -0.21 for newly suspended stocks, and -0.37 for previously suspended stocks. In contrast, for institutions, the coefficient for both types of suspension is close to -2.06.

These results imply that trading suspension can impact investors' trading activities not only on the current day, but also for the near future. In other words, trading suspension can have a long lasting calming down effect on investors' trading activities.

E Effect of daily price limits

In the analysis so far, we measure the net trading activities of each account on all tradable stocks. One may argue that accounts with higher suspension fraction are more likely to hold more risky stocks, which may more often hit the daily price limit–making them effectively also not freely tradable.[8] In other words, the lower selling intensity by accounts with higher suspension fraction may be driven by the low tradability of those non-suspended stocks in their account. This is a valid concern. To remove such an effect, we create a dummy for each tradable stock to indicate if it experienced either limit-up or limit-down in the price within the trading day. Then, for each account, we use only stocks that do not experience the price-limits within the day to compute the net selling intensity. That is, we study how account-level suspension fraction affects the trading activities of investors on those stocks that do not hit the daily price limits.

We report the result in model-(5) of Table 6. First, for individual investors, the effect of suspension on the trading of stocks without hitting the daily price-limit is similar to that of all tradable stocks. Second, the calming down effect of suspension on institutions is even stronger after we remove the stocks that hit daily price limits. For example, the coefficient on suspension fraction is -2.07 on all tradable stocks (model-(3) in Table 3), and -2.53 on tradable stocks that did not hit the price limits (model-(5) in Table 6).

Therefore, based on the above evidence, we conclude that the calming down effect of trading suspension is robust after we control for the potential impact of daily price limits on tradable stocks. In other words, the calming down effect holds for investors' trading activities on stocks that are freely tradable.

F Account-level suspension experiences

In our main analysis, we study the relationship between net selling intensity and the most recent account-level suspension fraction. One may argue that some accounts are more likely to experience a higher level of suspension fraction because they hold predominantly smaller and riskier stocks. In other words, the account-level suspension fraction may be correlated with the accounts' holding characteristics. Note that the account fixed effect absorbs at least partially the time invariant components of such account heterogeneity in holding characteristics. To further address this concern, we select accounts that have experienced a large range of suspension fraction in our sample period–such that the account-level suspension fraction is highly dynamic and therefore has lower correlation with slow moving holding characteristics.

[8] For majority of Chinese stocks, there is a daily price limit of 10% in both directions relative to previous day's close price. For a small number of stocks that get special treatment because of two consecutive years of operating losses, the daily price limit is 5% in both directions.

In particular, we require each account to experience at least 4 out of the 6 groups of suspension fraction defined in Table 2. We then study the effect of suspension fraction on trading activities among these selected accounts.

We report the result in model-(6) of Table 6. It shows that the calming down effect of trading suspension still holds for the selected individual and institutional investors. Comparing with our main analysis, the calming down effect of trading suspension is stronger among accounts that experienced a large range of value for suspension fraction. For example, the coefficient on suspension fraction is -0.75 (-2.89) for individuals (institutions) in the selected accounts with similar experience, comparing to the value of -0.32 (-2.07) in the main result reported in Table 3. Therefore, we conclude that the calming down effect of trading suspension we document in our main analysis is less likely driven by the account-level correlation between holding characteristics and suspension fraction.

G Account-stock-level trading

So far, our analysis is based on the account-level net trading activities. One potential criticism is that different accounts may hold different stocks, and the characteristics of these stocks also vary over time, such that a constant account fixed effect would not capture such time-varying heterogeneity. This is a valid concern. To address such potential heterogeneity, we repeat the above regression analysis at the account-stock-level, which allows us to control for the stock-level heterogeneity through stock-date fixed effect.

The account-stock-level net selling intensity for a non-suspended stock is defined as:

$$\Delta_{i,t}^{j} = \frac{\text{net selling (of stock } i \text{ by account } j \text{ on day-}t)}{\text{holding (of stock } i \text{ in account } j \text{ at the open of day-}t)}, \tag{6}$$

where the trading is in dollar amount and the denominator is the holding value.

We then ask how trading on a given stock can be different across accounts with different suspension fraction by running the following panel (account-stock-date) regression:

$$\Delta_{i,t}^{j} \;\; = \;\; \beta S_{t-1}^{j} + \lambda R_{t-10,t-1}^{j} + \eta C_{t-10,t-1}^{j} + \nu_{i,t} + \alpha_j + \epsilon_{i,t}^{j}, \tag{7}$$

where $\nu_{i,t}$ is the stock-date fixed effect, which captures any time varying effect at the stock level. Due to the extremely large number of account-stock observations for individual investors, we reduce the sample size by selecting individual accounts with ID number ends with either '1' or '6'.[9] For institutions, we keep all the account-stock observations without any further

[9] The last digit of an account ID does not contain any specific account characteristics, and therefore our

sampling.

Table 7 reports the results for the account-stock level analysis. First, the calming down effect of trading suspension still holds at the account-stock level for both individual and institutional investors. Second, the magnitude of the calming effect is weaker than those of the account-level since it only captures the trading of current shareholders, but ignored the potential purchases by non-holding investors–which is included in the account-level measure of trading. For example, the coefficient for suspension fraction is -0.05 (-0.57) for individuals (institutions) under the account-stock level regression, comparing to the corresponding values of -0.32 (-2.07) under the account-level regression. These results indicate that the calming down effect at the account-level is less likely driven by the heterogeneity in the characteristics of stock holdings across accounts with different suspension fraction.

4.4 Characteristics of traded stocks

In the analysis so far, we focused exclusively on the amount of trading across accounts with different suspension fraction. In this section, we study the characteristics of investors' traded stocks. That is, what kind of stocks do investors buy and sell across accounts with different suspension fraction? To answer this question, we assign a number from 1 to 10 for each stock, according to its position in the cross-sectional sorting of a particular characteristics, including size, B/M, past returns, profitability (ROE), and asset growth rate.[10] We then sort accounts by their suspension fraction, and compute the average ranking of characteristics of stocks that are bought and sold separately.[11] Finally, we construct the ranking difference in stock characteristics between buying and selling orders on each day, and then compute the time series averages.

Table 8 reports the result. Panel-A shows that individuals tend to buy stocks with smaller size, lower B/M, lower past return, low profitability, and lower growth rate comparing to stocks that they sell. This pattern holds for all six suspension fraction groups. However, the difference in the ranking of stock characteristics between buying and selling orders is relatively

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choice is equivalent to a random 20% sampling of all account-stock observations.

[10]The size and book-to-market are measured on June 30, 2015, past return is the cumulative returns of the past 10 trading days, ROE is based on the second quarter of 2015, and the asset-growth rate is based on the growth from first to second quarter of 2015.

[11]We only use accounts that have trading activity to compute the ranking of traded stocks' characteristics. If an account does not have buying or selling order, then the corresponding characteristics ranking is labelled as missing.

small, with the maximum difference of only 0.35 out of a scale of 10, in the case of past 10-day return for the suspension fraction group 2.

Panel-B shows that the result is slightly different for institutions. In particular, institutions with low suspension fraction behave very similar to the individual investors in terms of the difference in buying and selling stock characteristics. However, institutions with high suspension fraction trade in the opposite direction: they buy stocks with larger size, higher book-to-market, higher past return, higher profitability, and higher asset growth rate, relative to stocks that they sell. Therefore, institutions that have lower suspension fraction seem tilt towards stocks with higher risks, while institutions with higher suspension fraction tilt towards higher quality stocks.

In summary, while individuals with higher suspension fraction on net sell less of tradable stocks than those with lower suspension fraction, they all prefer smaller, higher valuation, worse recent return, lower profitability, and lower growth stocks. In contrast, institutions with higher suspension fraction on net sell less of tradable stocks, and prefer larger, lower valuation, recent winners, higher profitability, and higher growth stocks, relative to institutions with lower suspension fraction. In other words, institutions with higher suspension fraction not only sell less on net, they also tilt their portfolio towards higher quality.

5 Shareholders' Trading Suspension Exposure and S-tock Prices

In the previous section we find that trading suspension generates a positive calming down effects on investors' trading activities. In this section, we further study how the effect of trading suspension on trading activities may in turn create pricing impact on other tradable stocks.

According to the results reported above, investors with higher account-level suspension fraction sell less or buy more of other tradable stocks in their account. In other words, the selling pressure on a particular stock depends on the suspension fraction of its shareholders. Therefore, we construct a trading-suspension-exposure for each non-suspended stock, according to the holding-weighted average suspension fraction across investors. Specifically, for each stock i, we define,

$$\Psi_{i,t-1} = \sum_{j \in \{j' | h^{j'}_{i,t-1} > 0\}} \frac{h^j_{i,t-1}}{H_{i,t-1}} S^j_{t-1}, \tag{8}$$

where $h^j_{i,t-1}$ ($H_{i,t-1}$) is the holding fraction of stock i by account j (all of our selected accounts) at the open of day-t, and S^j_{t-1} is the account's suspension fraction by the open of day-t. This simple definition summarizes the average account suspension fraction across all shareholders in our selected sample, with the weight being the holding fraction of that particular stock in each account.

We are particularly interested in the relationship between the stock-level shareholders' trading suspension exposure and the subsequent stock returns. In particular, we run the following panel regressions of stock-level cumulative returns from day $t-1$ to $t-1+h$ ($R_{i,t-1+h}$) on the suspension spillover exposure ($\Psi_{i,t-1}$):

$$R_{i,t+h} = \beta_h \Psi_{i,t-1} + \gamma_h \ln(size_{i,t-10}) + \lambda_h R_{i,t-10,t-1} + \alpha_t + \epsilon_{i,t+h}, \quad h = 1, 3, 5, 10, 20, 30, 40, 50, \tag{9}$$

where h represents the number of trading days after day $t-1$. Note that we control for both the stock's size and its past 10-day return,[12] and include a time fixed effect α_t to absorb aggregate market fluctuations. Since higher value of $\Psi_{i,t-1}$ implies that the stock's shareholders on average have higher suspension fraction, the net selling pressure on this stock is lower due to the calming down effect of trading suspension. Therefore, we expect the return of stocks with higher trading suspension exposure to be higher in the near term. In the long term, we expect the price to come back to normal. That is, we conjecture that $\beta_h > 0$ for small h, and $\beta_h = 0$ for large h.

Table 9 reports the results. It shows that the cumulative returns of stocks with higher shareholders' suspension spillover exposure indeed are higher in the short-run and reverse back in the long run, confirming that the positive trading effect of suspension can also generate a positive pricing impact in the short-run on other tradable stocks. For example, the coefficient on Ψ is highest for the 10-day cumulative return, it stays significant until 30-days, and then decreases and becomes insignificant after 40 days. For one standard deviation difference in the trading suspension exposure ($\sigma(\Psi) = 6\%$), it can generate a sizeable difference of $0.77 * 6\% = 4.6\%$ for the 10-day cumulative returns.

We conclude that trading suspension helps to calm down investors' trading activities, and at the same time, it also generates a positive short-term pricing impact on those non-suspended stocks, which reverses in the longer-term.

[12] We also tried to control for longer period of past returns, breaking them into subperiods similar to that of the cumulative returns defined in Equation (9). We find the results are qualitatively similar.

6 Conclusion

In this paper, we study the effect of firm-initiated trading suspension on investors' trading activities during the Chinese stock market crisis in July of 2015. Based on account-level trading data from the Shanghai Stock Exchange, we find that accounts with higher fraction of holding value in suspension sell less (or purchase more) of other tradable stocks. This finding is robust after we control for account-level heterogeneity, and holds for both individual and institutional investors.

We also find evidence in support of the explanation that trading suspension reduces investors leverage constraints or relaxes their cash-hoarding motive, contributing to the positive calming down effect. Moreover, we find some evidence that trading suspension may increase investors' expectation about future returns–helping to explain the calming down effect, but we do not find investors perceive a lower risks for the suspended stocks–that is, the calming down effect is less likely generated through risk-reduction perceptions.

Finally, we also find that trading suspension generates a short-term positive pricing impact on non-suspended stocks. The positive effects on both trading activities and prices of non-suspended stocks indicate that trading suspension can calm down investors and therefore helps to stabilize the volatile stock market during crisis time.

In a companion paper using the same trading suspension events as ours, Huang, Shi, Song, and Zhao (2020) find that firms suspend trading on their stocks mainly to reduce investors' panic selling, corroborating our account-level finding that trading suspension indeed has a calming down effect on investors. Moreover, they also find that market participants do not seem to punish in terms of firm-valuation such a dramatic restriction on stocks' trading. In light of these findings, a combination of firm- and regulator-initiated interventions may be more effective in fighting extreme price movement during crises, and we leave this interesting topic for future research.

Table 1: **Summary statistics for individual and institutional accounts**

This table reports the summary statistics for individual and institutional accounts that are registered to trade stocks listed on the Shanghai Stock Exchange. The top panel reports the summary statistics for the full sample, and the lower panel reports the corresponding statistics for our selected sample, which requires accounts to hold at least 3 stocks and the account holding value to be above 100 thousand RMB–both restrictions are imposed on July 1, 2015. The average numbers are equal-weighted value across accounts for the period from July 2, to July 23, 2015.

Sample	Variable	Individuals	Institutions
Full Sample	Average number of stocks per account	2	26
	Total number of accounts	43,404,880	17,804
	Average daily holding amount (Billion RMB)	8298	3625
	Average daily buying amount (Billion RMB)	688	92
	Average daily selling amount (Billion RMB)	650	118
Our Selected Sample	Average number of stocks per account	6	33
	Fraction of total accounts	13%	76%
	Fraction of holding amount	57%	90%
	Fraction of buying amount	54%	97%
	Fraction of selling amount	48%	95%
	Average suspension fraction	0.110	0.224
	Average net-selling scaled by account tradable value	-0.021	-0.171

Table 2: **Suspension fraction sorted accounts**

This table reports the summary statistics for suspension fraction sorted accounts. To include in our analysis, we require accounts to hold at least 3 stocks and the account holding value to be above 100 thousand RMB as of July 1, 2015. We form 6 groups: one for zero-suspension accounts, and 5 groups with equal space between 0 and 1 for the suspension fraction. We first compute the average for each group on each trading day, and then average over time period from July 2, to July 23, 2015.

Investor Type	Suspension Group	Suspension Range	Account Number	Average Account Value (Million RMB)	(Net Selling)/(Tradable Value) Equal-weight	(Net Selling)/(Tradable Value) Value-weight
Individuals	1	0	3476724	0.61	-0.0208	0.0187
	2	(0,.2]	829593	0.95	0.0059	0.0258
	3	(.2,.4]	463319	0.67	0.0000	0.0232
	4	(.4,.6]	280636	0.69	-0.0200	0.0150
	5	(.6,.8]	181219	0.79	-0.0631	-0.0040
	6	(.8,1)	131914	1.30	-0.2286	-0.0669
Institutions	1	0	3475	140	-0.0921	0.0105
	2	(0,.2]	3588	573	-0.0073	0.0070
	3	(.2,.4]	1928	135	-0.0445	0.0185
	4	(.4,.6]	1099	89	-0.1486	0.0117
	5	(.6,.8]	748	68	-0.5067	-0.0145
	6	(.8,1)	710	44	-1.4116	-0.2479

Table 3: **Panel regressions: main results**

This table reports the main results from panel regressions of net selling scaled by tradable value on account-level suspension fraction. Our analysis covers the time period from July 2, to July 23, 2015. To include in our analysis, we require accounts to hold at least 3 stocks and the account holding value to be above 100 thousand RMB as of July 1, 2015. The t-statistics in parentheses are based on standard errors double clustered by account and date.

(A): Individual investors

	(1a)	(1b)	(1c)	(1d)	(2)	(3)
Suspension Fraction	-0.1045	-0.1172	-0.2543	-0.3347	-0.3373	-0.3152
	(-5.99)	(-10.29)	(-4.08)	(-6.82)	(-6.85)	(-7.27)
Past-10-Day Return					-0.0583	-0.0201
					(-1.76)	(-0.73)
Past-10-Day Net Selling						-0.0437
						(-13.82)
Intercept	-0.0099					
	(-1.89)					
Time Fixed Effect	No	Yes	No	Yes	Yes	Yes
Account Fixed Effect	No	No	Yes	Yes	Yes	Yes
Adj R-square	0.0028	0.0062	0.0072	0.0120	0.0122	0.0929
Number of Observation	85814465	85814465	85814465	85814465	85814465	85814465

(B): Institutional investors

	(1a)	(1b)	(1c)	(1d)	(2)	(3)
Suspension Fraction	-1.0256	-1.0863	-1.8524	-2.2415	-2.3044	-2.0652
	(-5.20)	(-4.92)	(-7.29)	(-7.53)	(-7.52)	(-6.91)
Past-10-Day Return					-0.9261	-0.9481
					(-2.42)	(-2.45)
Past-10-Day Net Selling						-0.0289
						(-8.10)
Intercept	0.0592					
	(2.42)					
Time Fixed Effect	No	Yes	No	Yes	Yes	Yes
Account Fixed Effect	No	No	Yes	Yes	Yes	Yes
Adj R-square	0.0176	0.0229	0.0639	0.0736	0.0749	0.0963
Number of Observation	184754	184754	184754	184754	184754	184754

Table 4: **Panel regressions: trading decomposition**

This table reports the result from panel regressions for each component of net selling scaled by tradable value on account-level suspension fraction. Our analysis covers the time period from July 2, to July 23, 2015. To include in our analysis, we require accounts to hold at least 3 stocks and the account holding value to be above 100 thousand RMB as of July 1, 2015. The net-selling contains three components: (i) selling on existing holdings, (ii) buying on existing holdings, and (iii) buying on non-holding stocks (buying new), all scaled by tradable value in the account. The t-statistics in parentheses are based on standard errors double clustered by account and date.

(A): Individual investors

	(1) Selling Existing	(2) Buying Existing	(3) Buying New
Suspension Fraction	-0.0222	0.0478	0.1685
	(-3.47)	(5.43)	(7.05)
Past-10-Day Return	0.0890	0.0658	0.0301
	(4.34)	(4.86)	(1.44)
Past-10-Day Net Selling	-0.0067	0.0049	0.0200
	(-9.42)	(11.35)	(13.50)
Time Fixed Effect	Yes	Yes	Yes
Account Fixed Effect	Yes	Yes	Yes
Adj R-square	0.3313	0.1739	0.1613
Number of Observation	85814465	85814465	85814465

(B): Institutional investors

	(1) Selling Existing	(2) Buying Existing	(3) Buying New
Suspension Fraction	-0.0379	0.0408	1.6887
	(-1.55)	(2.15)	(6.92)
Past-10-Day Return	0.0328	0.0366	0.7646
	(0.75)	(1.56)	(2.68)
Past-10-Day Net Selling	-0.0015	0.0003	0.0213
	(-10.45)	(1.66)	(8.26)
Time Fixed Effect	Yes	Yes	Yes
Account Fixed Effect	Yes	Yes	Yes
Adj R-square	0.3218	0.1796	0.1053
Number of Observation	184754	184754	184754

Table 5: **Panel regressions: account heterogeneity**

This table reports the result from panel regressions of net selling scaled by tradable value on account-level suspension fraction, focusing on the suspension effect along several dimensions of account heterogeneity. We assign a dummy value of 1 to accounts that are traded on margin, and 0 otherwise; and assign a high-past-selling dummy value of 1 to accounts that have past 10-day net selling intensity above median value, and 0 otherwise; and assign a high-past-return dummy value of 1 to accounts that have past 10-day return above median value, and 0 otherwise; and assign a high-downside-risk dummy value of 1 to accounts that have average skewness below median value for the suspended stocks, and 0 otherwise. Our analysis covers the time period from July 2, to July 23, 2015. To include in our analysis, we require accounts to hold at least 3 stocks and the account holding value to be above 100 thousand RMB as of July 1, 2015. We include both time and account fixed effects in all models. The t-statistics in parentheses are based on standard errors double clustered by account and date.

	(A): Individual investors				**(B): Institutional investors**			
	(1a)	(2a)	(3a)	(4a)	(1b)	(2b)	(3b)	(4b)
Suspension Fraction	-0.2864	-0.2191	-0.1538	-0.9378	-2.0308	-1.9711	-1.9912	-3.0070
	(-7.14)	(-7.05)	(-2.94)	(-8.19)	(-6.82)	(-8.43)	(-3.94)	(-8.03)
Suspension Fraction × Margin Account Dummy	-0.1046				-0.6882			
	(-2.64)				(-1.91)			
Suspension Fraction × High Past-10-Day Net Selling Dummy		-0.1918				-0.0901		
		(-7.67)				(-0.45)		
High Past-10-Day Net Selling Dummy		-0.0542				-0.1430		
		(-4.33)				(-2.78)		
Suspension Fraction × High Past-10-Day Return Dummy			-0.1305				-0.0461	
			(-6.11)				(-0.17)	
High Past-10-Day Return Dummy			0.0206				-0.0916	
			(3.20)				(-1.12)	
Suspension Fraction × High Downside-Risk Dummy				0.2002				0.7908
				(6.89)				(4.67)
High Downside-Risk Dummy				-0.0379				0.0705
				(-4.76)				(0.62)
Past-10-Day Return	-0.0195	0.0018	-0.0445	-0.0481	-0.9470	-0.9375	-0.7755	-1.7809
	(-0.71)	(0.07)	(-1.40)	(-1.05)	(-2.44)	(-2.47)	(-2.24)	(-2.23)
Past-10-Day Net Selling	-0.0436	-0.0417	-0.0437	-0.0436	-0.0288	-0.0279	-0.0289	-0.0306
	(-13.83)	(-14.44)	(-13.83)	(-9.27)	(-8.08)	(-8.26)	(-8.04)	(-2.75)
Adj R-square	0.0931	0.0988	0.0936	0.0939	0.0964	0.0848	0.0964	0.1055
Number of Observation	85814465	85814465	85814465	30186889	184754	184538	184754	129162

Table 6: **Panel regressions: robustness analysis**

This table reports the result from panel regressions of net selling on account-level suspension fraction. We scale the net selling by total (tradable) account value in model-(1) (all other models). In model-(2), we assign a late-period dummy value of 1 to dates on and after July 8, and 0 for dates before July 8. In model-(3), we assign a high-market-return dummy value of 1 to dates on which the market return is above the median value, and 0 otherwise. In model-(4), we decompose the suspension fraction into two components: (i) suspension starting on day-t (new suspension), and (ii) suspension before day-t (old suspension), both scaled by the tradable account value. In model-(5), we remove stocks that hit the daily price limits when computing the net selling intensity. Finally, in model-(6), we require each account experiences at least 4 out of the 6 groups of suspension fraction (see the classification of suspension fraction groups in Table 2). Our analysis covers the time period from July 2, to July 23, 2015. To include in our analysis, we require accounts to hold at least 3 stocks and the account holding value to be above 100 thousand RMB as of July 1, 2015. We include both time and account fixed effects in all models. The t-statistics in parentheses are based on standard errors double clustered by account and date.

(A): Individual investors

	Scaled by total value (1)	Two subperiods (2)	Market condition (3)	New suspension (4)	Remove price-limit (5)	Similar experience (6)
Suspension Fraction	-0.1266	-0.2377	-0.2864		-0.3152	-0.7544
	(-9.76)	(-5.47)	(-4.93)		(-5.78)	(-11.95)
Suspension Fraction × Late Period Dummy		-0.1117				
		(-2.98)				
Suspension Fraction × High MKT Return Dummy			-0.0480			
			(-1.19)			
Suspension Fraction (New)				-0.2127		
				(-6.14)		
Suspension Fraction (Old)				-0.3748		
				(-9.97)		
Past-10-Day Return	-0.0053	-0.0298	-0.0214	-0.0294	-0.0065	-0.0317
	(-0.28)	(-1.12)	(-0.82)	(-0.85)	(-0.32)	(-0.31)
Past-10-Day Net Selling	-0.0323	-0.0438	-0.0437	-0.0436	-0.0555	-0.0527
	(-13.91)	(-13.87)	(-13.87)	(-13.81)	(-13.28)	(-14.99)
Adj R-square	0.0810	0.0935	0.0931	0.0942	0.0750	0.0921
Number of Observation	85814465	85814465	85814465	85814465	72933126	6593837

(B): Institutional investors

	(1)	(2)	(3)	(4)	(5)	(6)
Suspension Fraction	-0.4585	-2.8016	-2.1501		-2.5276	-2.8905
	(-6.27)	(-3.26)	(-4.10)		(-6.19)	(-5.59)
Suspension Fraction × Late Period Dummy		1.0179				
		(1.21)				
Suspension Fraction × High MKT Return Dummy			0.1517			
			(0.33)			
Suspension Fraction (New)				-2.0598		
				(-4.82)		
Suspension Fraction (Old)				-2.0665		
				(-7.09)		
Past-10-Day Return	-0.2488	-0.9017	-0.9458	-0.9486	-0.6813	-2.8199
	(-2.22)	(-2.52)	(-2.45)	(-2.47)	(-1.63)	(-2.07)
Past-10-Day Net Selling	-0.0092	-0.0283	-0.0288	-0.0288	-0.0634	-0.0289
	(-8.69)	(-8.63)	(-8.21)	(-8.04)	(-6.47)	(-2.42)
Adj R-square	0.0918	0.0994	0.0964	0.0963	0.0845	0.1098
Number of Observation	184754	184754	184754	184754	159119	48531

Table 7: **Panel regressions: account-stock level result**

This table reports the result from panel regressions of net selling intensity at the account-stock level on account-level suspension fraction. Our analysis covers the time period from July 2, to July 23, 2015. To include in our analysis, we require accounts to hold at least 3 stocks and the account holding value to be above 100 thousand RMB as of July 1, 2015. For individual investors, we further select only accounts whose ID ending with either '1' or '6'. The t-statistics in parentheses are based on standard errors double clustered by account and date.

(A): Individual investors

	(1)	(2)	(3)
Suspension Fraction	-0.0531	-0.0537	-0.0537
	(-48.67)	(-48.92)	(-48.92)
Past-10-Day Return		-0.0151	-0.0151
		(-10.06)	(-10.06)
Past-10-Day Net Selling			0.0000
			(-3.62)
Stock-Time Fixed Effect	Yes	Yes	Yes
Account Fixed Effect	Yes	Yes	Yes
Adj R-square	0.0599	0.0600	0.0600
Number of Observation	86472279	86472279	86472279

(B): Institutional investors

	(1)	(2)	(3)
Suspension Fraction	-0.7494	-0.7722	-0.5712
	(-9.47)	(-9.26)	(-7.05)
Past-10-Day Return		-0.2285	-0.2434
		(-2.32)	(-2.41)
Past-10-Day Net Selling			-0.0262
			(-4.71)
Stock-Time Fixed Effect	Yes	Yes	Yes
Account Fixed Effect	Yes	Yes	Yes
Adj R-square	0.0401	0.0401	0.0407
Number of Observation	3968915	3968915	3968915

Table 8: **Characteristics of traded stocks**

This table reports the difference in characteristics between buying and selling across suspension fraction sorted groups. To include in our analysis, we require accounts to hold at least 3 stocks and the account holding value to be above 100 thousand RMB as of July 1, 2015. We form 6 groups: one for zero-suspension accounts, and 5 groups with equal space between 0 and 1 for the suspension fraction. We first compute the average for each group on each trading day, and then average over time period from July 2, to July 23, 2015. The size and book-to-market are measured on June 30, 2015, past 10 day return is the cumulative returns of the past-10 trading days, ROE is based on the second quarter of 2015, and the asset-growth rate is based on the growth from the first to the second quarter of 2015.

(A): Individual investors

Suspension Group	Size	B/M	Past-10-Day Return	ROE	Asset Growth
1	-0.1276	-0.2067	-0.3173	-0.1463	-0.0796
	(-134.36)	(-198.46)	(-281.68)	(-130.01)	(-76.68)
2	-0.1240	-0.1789	-0.3487	-0.1341	-0.0681
	(-65.33)	(-85.42)	(-154.76)	(-59.96)	(-33.04)
3	-0.1207	-0.1701	-0.1883	-0.1311	-0.0761
	(-39.66)	(-51.16)	(-53.22)	(-36.99)	(-23.17)
4	-0.1154	-0.1715	-0.1182	-0.1175	-0.0674
	(-26.92)	(-36.69)	(-24.08)	(-23.63)	(-14.66)
5	-0.1229	-0.1953	-0.1276	-0.1271	-0.0670
	(-20.95)	(-30.58)	(-19.26)	(-18.82)	(-10.67)
6	-0.1619	-0.2919	-0.1560	-0.1668	-0.0889
	(-18.31)	(-30.51)	(-15.84)	(-16.46)	(-9.47)

(B): Institutional investors

Suspension Group	Size	B/M	Past-10-Day Return	ROE	Asset Growth
1	-0.0637	-0.0240	-0.1301	-0.1235	-0.1983
	(-2.00)	(-0.66)	(-3.64)	(-3.55)	(-5.73)
2	-0.1155	-0.1768	0.1628	-0.1026	-0.1914
	(-5.83)	(-7.95)	(7.47)	(-5.08)	(-9.81)
3	-0.2284	-0.1820	0.1190	-0.1255	-0.1307
	(-8.25)	(-6.00)	(4.00)	(-4.44)	(-4.87)
4	-0.0493	0.1119	0.0069	-0.0448	-0.1574
	(-1.25)	(2.52)	(0.16)	(-1.08)	(-3.93)
5	0.1548	0.0665	0.0450	0.1178	0.0133
	(2.64)	(1.10)	(0.75)	(2.00)	(0.23)
6	0.3280	0.2455	0.3205	0.2838	0.0534
	(3.84)	(2.69)	(3.56)	(3.20)	(0.62)

Table 9: **Price impact of suspension exposure**

This table reports the pricing impact of trading suspension exposure on non-suspended stocks. The cumulative future returns (CumRet) of different length are regressed on the current measure of suspension exposure. Our analysis covers the time period from July 2, to July 23, 2015. To include in our analysis, we require accounts to hold at least 3 stocks and the account holding value to be above 100 thousand RMB as of July 1, 2015. We construct the stock-level trading suspension exposure (Ψ) from holding of both individual and institutional investors. The size is measured 10-days before the day of measuring the suspension exposure. The t-statistics in parentheses are based on standard errors double clustered by stock and date.

	CumRet (1-Day)	CumRet (3-Day)	CumRet (5-Day)	CumRet (10-Day)	CumRet (20-Day)	CumRet (30-Day)	CumRet (40-Day)	CumRet (50-Day)
Suspension Exposure	0.0524	0.3126	0.4099	0.7708	0.4635	0.6985	0.1997	0.1783
	(1.85)	(3.26)	(5.55)	(4.94)	(2.63)	(3.81)	(1.21)	(0.94)
ln(size)	-0.0001	0.0006	-0.0045	-0.0104	-0.0472	-0.0333	-0.0217	-0.0323
	(-0.03)	(0.12)	(-0.76)	(-1.60)	(-5.57)	(-3.28)	(-3.09)	(-4.14)
Past-10-Day Return	-0.0053	-0.0451	-0.0845	-0.1557	0.0278	-0.1955	-0.0360	-0.0152
	(-0.35)	(-1.48)	(-2.06)	(-2.10)	(0.25)	(-1.91)	(-0.50)	(-0.20)
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-square	0.7330	0.7722	0.6070	0.5691	0.2977	0.5930	0.2164	0.1862
Number of Observation	9759	9759	9759	9759	9759	9759	9759	9759

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