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# Not all market participants are alike when facing crisis: Evidence from the 2015 Chinese stock market turbulence

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ABSTRACT

We propose a novel framework to analyze the potentially heterogeneous roles played by different market participants in the fire-sale process during a market crash and illustrate the methodology with the 2015–16 Chinese stock market turbulence. Unlike conventional analysis focusing on one particular channel of fire sales, we establish a market-level measure of fire sales based on the decomposition of diffusion processes to quantitatively compare the contribution of various channels in driving stock prices to plummet. Empirical results identify mutual funds as the main fire-sale propagator, as well as the heterogeneities in response to the price crash among different market participants.

## 1. Introduction

The Chinese stock market experienced significant turbulence in the summer of 2015. During the 17 trading days from June 15 to July 9 of that year, the China Securities Index (CSI) 300, the major market barometer covering the performance of the top 300 stocks traded in Shanghai and Shenzhen stock exchanges, declined from 5362 to 3898. On July 9, 2015, the Chinese government stepped in by launching a set of intervention measures in the hope of rescuing the market. For instance, The China Banking Regulatory Commission authorized banks to adjust the maturity of loans backed by equity collateral. Nevertheless, these policies did not prevent the situation of the stock market from further deteriorating. Until August 26, 2015, all of the three major stock indices of the country, including the Shanghai Stock Exchange (SSE) Composite Index, Shenzhen Stock Exchange (SZSE) Component Index, and CSI 300 Index, shrunk their values by >45% (particularly, SSE from 5176 to 2850, SZSE from 18,211 to 9713, and CSI from 5362 to 2952). Almost all individual stocks experienced price drops to different extents during the period. The sharp decline in the stock market was accompanied by a remarkable surge in the price correlation among the stocks: it rose to 0.4 on July 9 and 0.5 on August 26, respectively, in stark contrast to the average level of 0.3 before the outbreak of the turbulence. Fig. 1 below displays the CSI 300 Index and the average correlation coefficient of the component stocks from December 10, 2014, to November 15, 2015.

Without changes in the fundamentals or external economic environment, fire sales are likely to be the main driving force behind the price slump of the stock market. There has been a growing body of literature on the mechanism of fire sales (e.g., Adrian and Shin, 2010; Shleifer and Vishny, 2011; Bargigli et al., 2014; Wang et al., 2020). Essentially, forced sales are conventionally conducted to remain sufficient liquidity by shocked financial institutes (Coval and Stafford, 2007; Brown et al., 2010; Wagner, 2011; Khandani and

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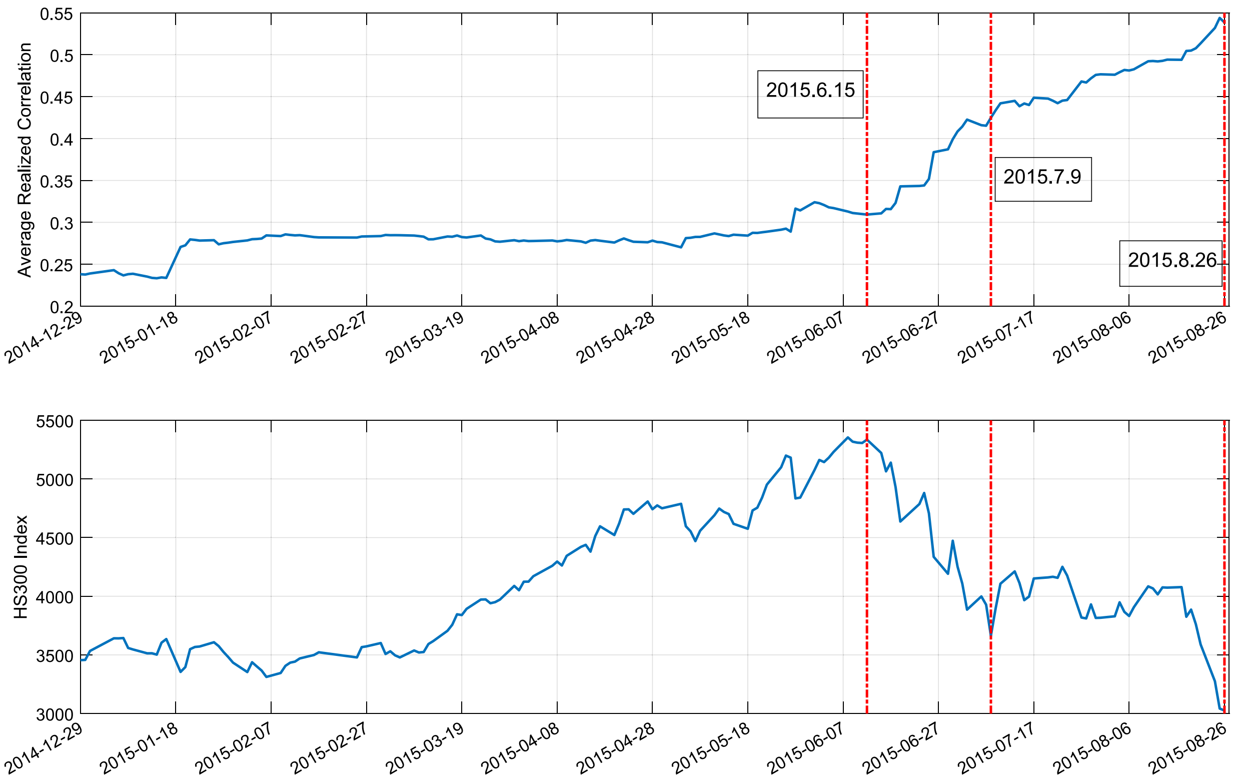


**Fig. 1.** The CSI 300 Index and the Average Realized Correlation.
*Notes*. This Figure shows the CSI 300 Index (bottom) and the average realized correlation of the component stocks (top) from December 10th, 2014, to November 15th, 2015. The average realized correlation is the average correlation between all pairs of the component stocks listed in the CSI 300 Index and is calculated based on a rolling window of 150 trading days.

Lo, 2011). When the demand for assets is not perfectly elastic, or assets are subject to mark-to-market pricing, fire sales will be formed and lead to risk contagion (Brunnermeier and Pedersen, 2005; Cifuentes et al., 2005). In particular, during an economic turmoil or financial crisis, fire sales can exacerbate the crisis and cause systemic risks (Diamond and Rajan, 2011; Shleifer and Vishny, 2011; Bluhm and Krahnen, 2014).

Fire sales have significant externalities (Chernenko and Sunderam, 2020). The price pressure of one market participant brings more market participants into the same plight, forming a spiral decline in market price that leads to the steady worsening of market conditions. Previous studies find that fire sales may be triggered by different channels. Various market participants, such as mutual funds, insurance companies, pension funds, and non-financial firms, have the potential to become the channels of fire sales. When experiencing massive capital outflows, mutual funds are forced to reduce their current positions, which will bring price pressure to the stocks (Coval and Stafford, 2007; Dyakov and Verbeek, 2013; Chernenko and Sunderam, 2020). Similarly, the forced sales of assets by fixed-income funds can also have a negative impact on bond prices (Falato et al., 2021). Corporate bond funds, in contrast, have different strategies for liquidity management (Choi et al., 2020). Due to regulatory restrictions, insurance companies are also identified for their forced sales of assets that trigger shocks to asset prices (Ellul et al., 2011; Nanda et al., 2019; Girardi et al., 2021). When facing shocks, pension funds may choose to reduce their shareholdings, resulting in price pressure (Larrain et al., 2017; Bastias and Ruiz, 2022). Non-financial firms' sales of equity stakes in publicly listed third parties may also be a source of fire sales and can lead to more severe impacts than those by funds (Dinc et al., 2017). Fire sales can also be identified during non-financial firms' mergers and acquisitions when the target industry is in distress (Oh, 2018). Under leverage restrictions, margin credit accounts are forced to fire sales, causing a market slump (Bian et al., 2018). Short sales may lead to enhanced endogeneity and correlation between assets and hence fire sales (Brunnermeier and Oehmke, 2014; Cont and Wagalath, 2013). The haircuts and liquidation of collaterals form a feedback loop, i.e., a liquidity spiral (Lillo and Pirino, 2015; Choi and Cook, 2012; Gorton and Metrick, 2012). Besides, fire sales can also be caused by financing constraints (Pulvino, 1998) and capital constraints (Greenwood et al., 2015; Cont and Schaanning, 2017).

Previous studies (e.g., Bian et al., 2018) suggest that leverage trading, in particular the shadow-financed margin investors, triggered the reversal of the stock market in 2015. However, the consequent market crash and accompanying fire sales cannot simply be attributed to leverage trading: there are many potential propagation channels of fire sales, especially under extreme market conditions, and focusing on one particular type of market participant or influencing factor provides no information about the relative importance to the propagation of fire sales and hence cannot identify the main channel causing the price slump. Besides, the market crash was unlikely caused by market inefficiency since recent studies (e.g., Carpenter et al., 2021) indicate that the Chinese stock market was as efficient as the U.S. stock market. Different market participants hold stocks for different reasons, and they are subject to different market constraints and risks. Therefore, different market participants can have different reactions toward fire sales. With institutional investors including mutual funds, insurance companies, pension funds, and non-financial firms having become the dominating shareholders of the Chinese stock market, one question of theoretical and practical importance is yet to be addressed: Under worsened market conditions, how do different types of market participants encounter the strike of fire sales (and which market participant dominates the fire-sale process)? The answer to this question contributes to the understanding of the mechanism behind the stock market slump and hence the prevention of systemic financial risks.

The main contribution of this paper is twofold. First, most empirical studies in the relevant literature have focused on a single type of market participant or risk factor that may cause fire sales. However, it is more valuable and crucial for the purpose of regulation to identify the contributions of various channels in a market slump in the presence of their joint influence on the stock market, which can be used for better mitigating systemic risks. To our best knowledge, we are the first to propose a framework for quantitatively analyzing the heterogeneity in the influence on fire sales from different channels under worsened market conditions, with a particular focus on the heterogeneity in economic behaviors among different market participants. Inspired by Cont and Wagalath (2013, 2016), we quantify the fire-sale magnitude of the whole market by estimating the scale of fire sales on the level of individual stocks. The appealing feature of this approach is that minimal assumptions are needed on the mechanism of fire sales for it to work. Specifically, market-level estimates on the magnitude of fire sales are calculated based on the decomposition of the realized covariance matrix into the covariance caused by fundamentals and the excess covariance caused by liquidity changes in the crisis. The resulting estimator maintains largely the influence of all the contributing factors to fire sales from the raw data. To quantify the conditional mean effect of different channels on fire sales, we conduct a regression analysis, with the estimated magnitude of fire sales taken as the dependent variable, and the channels for fire sales taken as the independent variables, including different types of market participants, such as mutual funds, financial institutions (mainly insurance companies and pension funds) and non-financial firms, and different potential factors, such as margin trading, short sales and collateral liquidation. A conceptionally similar measure is the stock price fragility based on the change in covariance between stock returns proposed by Greenwood and Thesmar (2011). However, the measure requires comprehensive portfolio information of all market participants, which is merely obtainable. Other methods, such as those proposed by Coval and Stafford (2007), Larrain et al. (2017) and Oh (2018), are naturally designated for a single market participant, which provides very limited information about the relative importance of different market participants during the fire-sale propagation. Furthermore, one fundamental issue that has drawn limited attention is the quantification of fire sales under severely worsened market conditions: market crashes are accompanied by fire sales, while fire sales do not necessarily lead to market crashes. Thus, it is important to realize the limitation of conventional fire-sale measures and take the extreme market conditions into account when quantifying fire sales.

Second, based on the newly proposed framework, we have found empirical evidence regarding the propagation of fire sales during a market crash: Not all market participants are alike when facing a financial crisis. In the 2015 stock market crash, we find that almost all stocks experienced fire sales to various extents during the stock market crash, and that, driven by different economic rationales, various types of market participants demonstrate a high degree of heterogeneity in their roles played during the propagation of fire sales, thus contributing differently to the stock market crash: mutual funds become the main participants that exacerbate the stock fire sale during the stock market slump, and stocks with higher shareholding by mutual funds are subject to more intensive fire sales during a crisis. Insurance companies and pension funds merely received impacts and did not participate in the stock fire sales, and stocks with higher shareholding by insurance companies and pensions show no significant difference in terms of fire sales. In contrast, stocks with higher shareholding by non-financial firms suffer fewer fire sales. With the drops in prices being opportunities for enhancing shareholdings, non-financial firms are likely to hold and buy stocks, which can effectively alleviate the extent of fire sales. Further analysis of fund flows confirms that abnormal volatilities of the stock market drove capital flowing into less risky markets, with funds serving as flow channels. The stocks held by mutual funds are generally of good growth potential, and the reduction in the shareholding of these stocks can be the consequence of forced sales under massive redemption pressure. These empirical findings have important policy implications. When the stock market undergoes a price slump due to fire sales, liquidity supplements through financial institutions to the market, like the strategy taken by the Chinese government in 2015, can effectively prevent further price drops in the stock market and mitigate financial systemic risks. More importantly, better recovering efficiency can be achieved when the liquidity supplement is more pertinent based on the type of market participants, in particular, mutual funds.

The rest of the paper is organized as follows. Section 2 introduces the estimation method for fire sales and presents estimation results. Section 3 scrutinizes the influence of investors (mutual funds, financial institutes, and non-financial firms), margin trading, short sales, and collateral liquidation on fire sales. Section 4 analyzes the capital flows of different types of funds. Section 5 examines the performance of stocks held by mutual funds after stock fire sales. Section 6 concludes the paper.

## 2. Estimation of fire sales

As noted in the Introduction, our investigation of the 2015 Chinese stock market crash consists of two stages. In the first stage, we need to estimate the scale of the fire sale of individual stocks from the entire market; in the second stage, we regress the trading volumes under fire sale estimated from the first stage against several explanatory variables to examine the causes of the fire sale. We will introduce the estimation of the fire-sale magnitude in this section and perform the regression analysis in Section 3.

### 2.1. Correlation-based measure of fire sales

It is widely documented in the literature that the fire sale in a stock crash can yield endogenous feedback effects between price decline and forced sales (e.g., Choi and Cook, 2012) and, as a result, strengthen the correlations among asset prices, even between originally uncorrelated ones (Kyle and Xiong, 2001; Raffestin, 2014). For example, as can be seen in Fig. 1, the correlations between stock prices were significantly enhanced during the price slump of the stock market in the third quarter of 2015. Under worsened market conditions, the rise in the correlations cannot be solely attributed to changes in fundamentals (Boyer et al., 2006), and the realized covariance matrix can be decomposed into the covariance caused by fundamentals and the excess covariance caused by liquidity changes in the crisis (Cont and Wagalath, 2013).

Compared with other prevailing measures of fire sales, such as the selling volume and negative money flow, the correlation-based measure of fire sales developed by Cont and Wagalath (2013, 2016) can more accurately capture the market-level response with the intensification of fire sales. More specifically, conventional measures of fire sales including selling volume and negative money flow are subject to the influence of downward pressure of stock prices, leading to potential estimation bias of fire sales. In contrast, the correlation-based measure does not suffer from this deficiency. Noteworthily, as evident from robustness checks, using traditional measures of fire sales (i.e., selling volume and negative money flow) leads to consistent empirical results. Unlike previous studies that focus on the enhancement in correlation among one particular type of market participants (e.g., mutual funds in Cont and Wagalath, 2013, 2016), we quantify the magnitude of fire sales of each stock and hence establish a market-level measurement of fire sales, which allows us to identify the roles played by different market participants based on the proposed two-stage framework. This is of great importance for financial regulation since identifying the main propagator of fire sales is crucial for effective market intervention and policymakers can make role-specific strategies for different market participants under the budget constraint.

Assuming there exists no fire sale in the market during $[0, T]$, and fire sales exist during $[T, T+\tau]$. Then, following Cont and Wagalath (2016), the fire-sale magnitude during $[T, T+\tau]$ can be derived as $P_T M(P_T - P_{T+\tau})$, with $P_T$ being the stock price at time $T$ and $M$ being the *adjusted rate of liquidation*. Under regular conditions, the matrix of the adjusted rate of liquidation among all stocks is a function of the realized covariance matrix satisfying the equation

$$f(\boldsymbol{M}) = g\left(\boldsymbol{\Sigma}_{[T,\ T+\tau]} - \boldsymbol{\Sigma}_{[0,\ T]},\ \boldsymbol{L}\right)$$

where $\boldsymbol{L}$ is the diagonal matrix of the market depth and $\boldsymbol{\Sigma}_{[a,b]}$ denotes the realized covariance matrix during $[a, b]$. The details of $f$ and $g$ are referred to Cont and Wagalath (2016).

Conventionally, the realized covariance matrix of $n$ stocks during $[a, b]$ based on the time gridding of $N$ steps can be calculated by

$$\widehat{\boldsymbol{\Sigma}}^N_{[a,b]} = \frac{1}{b-a}\left(S^N_b - S^N_a\right)$$

where $S^N_a$ is the matrix with the element

$$\sum_{1 \le l \le [aN]} \left(lnP^j_{l/N} - lnP^j_{(l-1)/N}\right)\left(lnP^k_{l/N} - lnP^k_{(l-1)/N}\right)$$

for $1 \le j, k \le n$. The realized covariance matrix in (1) can then be estimated for a sufficiently large $N$ based on the fact that $\widehat{\boldsymbol{\Sigma}}^N_{[a,b]} \xrightarrow{N\to\infty} \boldsymbol{\Sigma}_{[a,b]}$. The estimations of the market depth and the integrated average of the stock price are straightforward from the literature.

One thing that deserves mentioning is that, when $n$ is very large, estimating the matrix of the adjusted rate of liquidation among all stocks, i.e., $\boldsymbol{M}$, can be challenging due to the curse of dimensionality. As a rule of thumb from empirical studies, the estimation results are relatively stable when $n$ lies in 10 to 30, and become significantly biased for $n > 40$. To this end, we adopt a *randomized block-wise sampling scheme* for matrix calculation. More specifically, we calculate local estimates of $\boldsymbol{M}$ based on random subsamples of size $m$, and the average of the local estimates for each stock is taken as the final estimate. Note that the local estimates quantify the increase in correlation intensity among stocks within the subsample, then the ergodicity of the randomized sampling implies that the final estimate of $\boldsymbol{M}$ properly measures the intensified correlation matrix of all stocks. In this study, we randomly select 20 stocks from the 236 stocks to calculate the local estimate and repeat for 100 thousand rounds in total, which means that each stock is selected >8000 times on average.

For robustness, in a later section, we also consider alternative measures of fire-sale magnitude such as the negative volume flow and selling volume, which lead to consistent empirical results regarding the contribution of different market participants.

### 2.2. Fire sales in the 2015 market slump

In the first half of the year 2015, the stock market remained an increasing trend and reached a peak on June 15th, 2015, with the CSI 300 Index being 5362. It is reasonable to assume no significant influence on fire sales. Therefore, the first trading day (i.e., January 5th) in 2015 is set to be time 0, and June 15th is set to be time $T$. All of a sudden, the stock market began to drop fiercely. The CSI 300 Index dropped to 3898 on July 9th, 2015, and further dropped to 2952 on August 26th, 2015. It is intuitive to conjecture the existence of fire sales in the stock market during the period. As can be observed from Fig. 1, the correlation among stocks presented different trends before and after July 9th, 2015. Therefore, we examine two time periods: the first is the 17 trading days from June 15th to July

9th, 2015 with $\tau_1 = 17$, and the second is the 51 trading days from June 15th to August 26th, 2015 with $\tau_2 = 51$. There are 108 trading days in the whole sampling period.

## 3. Propagators of fire sales under market crash

### 3.1. Variable and data

#### 3.1.1. Dependent variable

To examine the roles played by various market participants in the process of stock fire sales, we make use of the magnitude of fire sales estimated in Section 2 to construct the dependent variable. As the estimated magnitude quantifies the fire sales on a single-stock basis, we can scrutinize the impact of individual channels.

Notably, there are differences in market value and outstanding volume among stocks. To mitigate the influence of these issues, we create the *Fire Sale Ratio* (*FSR*) by scaling the magnitude of fire sales by the total market value and taking logarithm transformation. Besides, the estimated magnitude may be negative, indicating nonidentification of fire sales. For such cases, we set the fire-sale magnitude to zero.

#### 3.1.2. Independent variables

To examine the potential influence of different market participants on the magnitude of fire sales, we define the independent variables as the shareholding ratio of each type of market participant. If an independent variable has a significantly positive coefficient, then it means that larger shareholding by the corresponding market participant leads to more intensive fire sales. Clearly, this can help us identify the heterogeneity in responses to stock fire sales by various market participants.

We categorize the market participants into three groups: mutual funds, financial institutions, and non-financial firms. For each stock, we calculate the shareholding amounts by each of the three types of market participants divided by the total outstanding amounts of the stock and take these ratios as the measure of behavior by different market participants. Here financial institutions refer to all financial institutional investors except mutual funds (mainly insurance companies and pension funds). We combine insurance companies and pension funds into one category for two reasons: First, they all face regulatory restrictions and make investments in similar manners; second, the further classification may lead to many sparse vectors in calculations.

The three types of market participants, i.e., mutual funds, financial institutions (mainly insurance companies and pension funds) and non-financial firms have different constraints and investment strategies in the stock market. Mutual funds aim at continuous profitability and face massive redemption pressure and liquidity constraint. Insurance companies and pensions mainly seek long-term investment and are subject to regulatory restrictions. The shareholding purposes of non-financial firms are not only investing but also participating and controlling.

#### 3.1.3. Other variables

Other than the influence of various market participants, margin trading, short sales and collateral liquidation can also cause fire sales and create pressure on asset prices.

We measure the margin-trading activities by the surplus amount of stocks purchased by way of financing. With regard to the Chinese stock market, margin credit accounts consist of brokerage-financed margin accounts (margin credits provided by securities companies) and shadow-financed margin accounts (loans provided by umbrella trusts). Shadow-financed margin accounts are subject to fewer regulatory constraints. As the statistics of shadow-financed margin accounts are not publicly obtainable, only data on brokerage-financed margin accounts will be used for analysis.

We take short sale surplus, defined as the surplus amount of stocks sold by way of securities loans, as the measure of short sales of the stock market. Both margin trading and short sales were introduced into China's stock market in 2010. Since then, there has been a dramatic unbalanced development between margin trading and short sales. In general, the ratio of margin credit surplus to short sale surplus is about 50, which reached a peak of as high as 400 between 2015 and 2016.

We take the proportion of shares outstanding served as collaterals as the measure of collateral liquidation. Collateral liquidation is commonly used for financing by investors, especially main shareholders. When the values of collaterals become insufficient, creditors have the right to require selling the stocks served as collaterals. If stocks served as collateral are sold, shareholders will suffer from severe problems in cashflows, leading to negative impacts on production and operation.

Besides, we control for the known cross-sectional effects as suggested by the literature, including the size effect (Fama and French, 1993; Ang et al., 2006), momentum effect (Jegadeesh and Titman, 1993; Ang et al., 2006) and turnover effect (Chou et al., 2013).

The definition and measurement of all variables are summarized in the Appendix.

#### 3.1.4. Data

We take the daily data of closing prices and trading volumes of stocks listed in the CSI 300 Index as the research sample. For accurate and reliable estimation, stocks under suspension (i.e., no trading activities) for >20 days are excluded from the sample, resulting in data consisting of 236 stocks. All data are collected from the Wind database. The mutual fund shareholding ratio, finance institution shareholding ratio, and firm shareholding ratio are calculated based on the data of the 2nd quarter of 2015. Margin trading and short sales are calculated as the average of the margin credit surplus and the short sale surplus between June 15th and July 9th and between June 15th and August 26th, 2015, respectively. The proportion of shares outstanding served as collaterals is calculated based on the daily data of June 15th, 2015. The size effect is measured by the natural logarithm of the total market value of stocks on June

**Table 1**
Descriptive Statistics of the Estimation Results for the Fire Sales of the Component Stocks.

| | The First Slump Period | The Whole Slump Period |
|---|---|---|
| Observations | 236 | 236 |
| Min. | −13,631 | −4792 |
| 1st Qu. | 4372 | 4118 |
| Median | 6458 | 5313 |
| 3rd Qu. | 8869 | 6573 |
| Max. | 27,421 | 32,577 |
| Mean | 5290 | 6212 |
| Std. Dev. | 7995 | 6386 |
| Kurtosis | 0.939 | 3.218 |
| Skewness | −0.490 | 1.377 |

*Notes*. This table shows the descriptive statistics of the estimation results for the fire sales of the 236 stocks listed in the CSI 300 Index for the first slump period (June 15th to July 9th, 2015) and the whole slump period (June 15th to August 26th, 2015), respectively. The detailed calculation procedure is described in Section 2.

**Table 2**
Descriptive Statistics.

| | Mean | Median | Std. Dev. | Kurtosis | Skewness | Minimum | Maximum |
|---|---|---|---|---|---|---|---|
| *FSR_F* | 4.02 | 4.81 | 2.19 | 2.48 | −0.89 | 0.00 | 7.90 |
| *FSR_W* | 4.18 | 4.86 | 1.97 | 3.16 | −1.02 | 0.00 | 8.09 |
| *MUTUAL FUND* | 4.61 | 3.81 | 3.94 | 12.95 | 2.36 | 0.10 | 31.08 |
| *INSTITUTION* | 8.13 | 5.76 | 9.60 | 34.45 | 4.61 | 0.14 | 93.33 |
| *FIRM* | 44.29 | 48.09 | 25.27 | 2.12 | −0.14 | 0.00 | 97.63 |
| *MARGIN_TRADE_F* | 4.15 | 2.79 | 4.65 | 35.52 | 4.75 | 0.00 | 44.97 |
| *MARGIN_TRADE_W* | 3.22 | 2.19 | 3.60 | 35.11 | 4.75 | 0.00 | 34.36 |
| *SHORT_SALE_F* | 9.36 | 6.07 | 12.16 | 19.11 | 3.64 | 0.00 | 86.27 |
| *SHORT_SALE_W* | 6.71 | 4.06 | 8.63 | 15.15 | 3.22 | 0.00 | 58.07 |
| *COLLATERAL* | 4.40 | 0.13 | 9.76 | 13.71 | 2.91 | 0.00 | 75.77 |
| *SIZE* | 25.19 | 24.97 | 0.85 | 5.17 | 1.37 | 23.91 | 28.47 |
| *MOMENTUM* | 55.00 | 49.37 | 32.18 | 8.35 | 1.60 | −4.24 | 243.08 |
| *TURNOVER_F* | 121.41 | 117.36 | 45.28 | 5.71 | 1.17 | 20.71 | 301.00 |
| *TURNOVER_W* | 302.70 | 296.50 | 115.35 | 4.83 | 0.82 | 57.80 | 860.30 |

*Notes*. This table presents the descriptive statistics for the main variables. *FSR_F* and *FSR_W* denote the *Fire Sale Ratio* (defined as the forced sale amount divided by the market value) for the first and the whole slump periods, respectively. *MUTUAL FUND*, *INSTITUTION* and *FIRM* represent the mutual fund shareholding ratio, financial institution shareholding ratio and firm shareholding ratio during the second quarter of 2015, respectively. *MARGIN_TRADE_F* and *MARGIN_TRADE_W* represent the average capital financing surplus (in billions), and *SHORT_SALE_F* and *SHORT_SALE_W* represent the average of the short sales (in millions) for the two slump periods, respectively. *COLLATERAL* represents the proportion of shares outstanding served as collaterals on June 15th, 2015. *SIZE* represents the natural logarithm of the total market value of stocks on June 15th, 2015, and measures company scales. *MOMENTUM* represents the return rate for the three months prior to June 15th, 2015. *TURNOVER_F* and *TURNOVER_W* represent the average daily turnover for the two slump periods, respectively.

**Table 3**
Baseline Regression Results for the First Slump Period.

| | Dependent Variable: *FSR_F* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *MUTUAL FUND* | 0.1228 *** | | | 0.0819 ** |
| | (0.0338) | | | (0.0327) |
| *INSTITUTION* | | 0.0333 | | 0.0060 |
| | | (0.0201) | | (0.0108) |
| *FIRM* | | | −0.0190 *** | −0.0130 ** |
| | | | (0.0055) | (0.0063) |
| *SIZE* | −0.6779 *** | −0.7958 *** | −0.6943 *** | −0.6645 *** |
| | (0.1529) | (0.1495) | (0.1462) | (0.1488) |
| *MOMENTUM* | 0.0072 | 0.0096 ** | 0.0081** | 0.0070 |
| | (0.0041) | (0.0041) | (0.0039) | (0.0040) |
| *TURNOVER* | −0.0060 | −0.0071 | −0.0067* | −0.0049 |
| | (0.0040) | (0.0041) | (0.0039) | (0.0042) |
| Adjusted $R^2$ | 0.17 | 0.15 | 0.18 | 0.19 |
| Observations | 236 | 236 | 236 | 236 |

*Notes*. This table shows the baseline regression results based on the estimated amount of fire sales for the 236 stocks between June 15th and July 9th, 2015. The results of the four models discussed are presented in each of the columns. *** and ** indicate significance at the 1% and 5% levels, respectively. The numbers in brackets are heteroscedasticity-consistent standard errors.

**Table 4**
Baseline Regression Results of Stock Fire Sales for the Whole Slump Period.

| | Dependent Variable: *FSR_W* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *MUTUAL FUND* | 0.1145 *** | | | 0.0848 *** |
| | (0.0290) | | | (0.0278) |
| *INSTITUTION* | | 0.0291 | | 0.0050 |
| | | (0.0187) | | (0.0090) |
| *FIRM* | | | −0.0154 *** | −0.0092 |
| | | | (0.0052) | (0.0060) |
| *SIZE* | −0.6774 *** | −0.7933 *** | −0.7094 *** | −0.6612 *** |
| | (0.1314) | (0.1292) | (0.1241) | (0.1289) |
| *MOMENTUM* | 0.0061 | 0.0082 | 0.0072 | 0.0058 |
| | (0.0041) | (0.0042) | (0.0041) | (0.0042) |
| *TURNOVER* | −0.0014 | −0.0016 | −0.0017 | −0.0010 |
| | (0.0014) | (0.0015) | (0.0015) | (0.0015) |
| Adjusted $R^2$ | 0.17 | 0.14 | 0.16 | 0.18 |
| Observations | 236 | 236 | 236 | 236 |

*Notes*. This table shows the baseline regression results based on the estimated amount of stock fire sales for the 236 stocks between June 15th and August 26th, 2015. The results of the four models discussed are presented in each of the columns. *** and ** indicate significance at the 1% and 5% levels, respectively. The numbers in brackets are heteroscedasticity-consistent standard errors.

15th, 2015. The momentum effect is measured by the return rate of the three-month period prior to June 15th, 2015. The turnover effect is measured by the average daily turnover between June 15th and July 9th and between June 15th and August 26th. The descriptive statistics are shown in Table 1.

### 3.2. Empirical results

#### 3.2.1. Estimated fire-sale magnitudes

The descriptive statistics of the estimated fire-sale magnitudes of the 236 component stocks are shown in Table 2.

As can be seen from Table 2, from June 15th to July 9th, 194 out of 236 stocks have significant positive estimated fire sales, taking up 82% of the whole sample. From June 15th to August 26th, 207 stocks have significant positive estimated fire sales, taking up 88% of the total sample. It is evident that most stocks were subject to fire sales during the slump period.

#### 3.2.2. Baseline results

For baseline regression analysis, we only control for cross-sectional effects in fundamentals and examine potential differences in economic behaviors by different market participants. More specifically, we fit cross-sectional regression models to the dataset consisting of the FSR, shareholding of various market participants and control variables. As mentioned earlier, the China Banking Regulation Commission released an amendment on collateral liquidation on July 9th, and the CSI 300 Index shows a quite different trend before and after the date. For this reason, we consider both the *FSR* for the whole period (referred to as *FSR_W* hereinafter) and the *FSR* for the first period (referred to as *FSR_F* hereinafter). The baseline regression results are shown in Tables 3 and 4, where Columns (1)–(3) present the individual effect of each type of market participant and Column (4) presents the marginal effects given the presence of all types of market participants.

As can be seen in Columns (1)–(3) of both Tables 3 and 4, the coefficients of *MUTUAL FUND* are 0.1228 and 0.1145 for the first and whole slump periods, both of which are significant at the 1% level. These indicate that stocks with higher shareholding by mutual funds are subject to more intensive fire sales during a crisis. The coefficient of *INSTITUTION* is 0.0333 for the first slump period, which is significant at the 10% level, and 0.0291 for the whole slump period, which is insignificant at the 10% level. These indicate that the shareholding by financial institutions has a very mild contribution to the fire-sale propagation of storks. The coefficients of *FIRM* are −0.0190 and −0.0154 for the first and whole slump periods, both of which are significant at the 1% level. These indicate that stocks with higher shareholding by non-financial firms suffer fewer fire sales.

Column (4) of both Tables 3 and 4 shows similar results regarding the marginal contributions of different market participants. For example, the coefficients of *MUTUAL FUND* are 0.0819 and 0.0848 for the first and whole slump periods, both of which are significant at the 1% level, suggesting that the shareholding by mutual funds has a significant positive effect on the fire sales of stocks in the market crash. It is worth noting that the empirical results remain consistent when more control variables, such as the price-earnings ratio, profitability and investment level, are added into the regression models.[1]

Our explanations for the heterogeneous economic behaviors of different types of market participants are as follows. When financial assets are mainly held by a few investors, asset prices can become very fragile when experiencing shocks (Greenwood and Thesmar, 2011). Stocks are no exception. Thus, mutual funds become the main participants that exacerbate the stock fire sale during the stock market slump in 2015. With stable cashflows, insurance companies and pension funds often take stocks as long-term investments.

[1] The authors thank the anonymous reviewers for the insightful discussion about the selection of control variables.

**Table 5**
Regression Results Controlling for Other Influencing Channels for the First Slump Period.

| | Dependent Variable: *FSR_F* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *MUTUAL FUND* | 0.1233 *** | | | 0.0800 ** |
| | (0.0351) | | | (0.0335) |
| *INSTITUTION* | | 0.0324 | | 0.0006 |
| | | (0.0221) | | (0.0122) |
| *FIRM* | | | −0.0217 *** | −0.0165 ** |
| | | | (0.0057) | (0.0066) |
| *MARGIN_TRADE* | −0.0269 | −0.0113 | −0.0577 * | −0.0536 |
| | (0.0279) | (0.0277) | (0.0344) | (0.0330) |
| *SHORT_SALE* | −0.0106 | −0.0121 | −0.0081 | −0.0095 |
| | (0.0085) | (0.0092) | (0.0082) | (0.0082) |
| *COLLATERAL* | −0.0125 | −0.0147 | −0.0170 | −0.0136 |
| | (0.0165) | (0.0168) | (0.0195) | (0.0187) |
| *SIZE* | −0.5287 *** | −0.6858 *** | −0.4657 ** | −0.4268 ** |
| | (0.1920) | (0.1961) | (0.1886) | (0.1900) |
| *MOMENTUM* | 0.0072 | 0.0097 ** | 0.0078 ** | 0.0067 |
| | (0.0041) | (0.0042) | (0.0041) | (0.0040) |
| *TURNOVER* | −0.0073 | −0.0085 ** | −0.0080 | −0.0064 |
| | (0.0041) | (0.0042) | (0.0041) | (0.0043) |
| Adjusted $R^2$ | 0.17 | 0.15 | 0.18 | 0.19 |
| Observations | 236 | 236 | 236 | 236 |

*Notes*. This table shows the results of the four regression models controlling for other influencing channels for the first slump period. The results of the four models discussed are presented in each of the columns. *** and ** indicate significance at the 1% and 5% levels, respectively. The numbers in brackets are heteroscedasticity-consistent standard errors.

**Table 6**
Regression Results Controlling for Other Influencing Channels for the Whole Slump Period.

| | Dependent Variable: *FSR_W* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *MUTUAL FUND* | 0.1172 *** | | | 0.0866 *** |
| | (0.0308) | | | (0.0292) |
| *INSTITUTION* | | 0.0286 | | 0.0012 |
| | | (0.0202) | | (0.0105) |
| *FIRM* | | | −0.0173 *** | −0.0116 |
| | | | (0.0056) | (0.0064) |
| *MARGIN_TRADE* | −0.0186 | −0.0004 | −0.0476 | −0.0444 |
| | (0.0247) | (0.0241) | (0.0300) | (0.0292) |
| *SHORT_SALE* | −0.0196 ** | −0.0194 ** | −0.0150 | −0.0171 |
| | (0.0092) | (0.0098) | (0.0092) | (0.0089) |
| *COLLATERAL* | −0.0052 | −0.0071 | −0.0093 | −0.0060 |
| | (0.0132) | (0.0134) | (0.0155) | (0.0150) |
| *SIZE* | −0.5382 *** | −0.7044 *** | −0.5251 ** | −0.4642 *** |
| | (0.1736) | (0.1780) | (0.1683) | (0.1749) |
| *MOMENTUM* | 0.0067 | 0.0089 ** | 0.0074 | 0.0061 |
| | (0.0043) | (0.0044) | (0.0043) | (0.0043) |
| *TURNOVER* | −0.0018 | −0.0021 | −0.0020 | −0.0014 |
| | (0.0015) | (0.0016) | (0.0016) | (0.0016) |
| Adjusted $R^2$ | 0.17 | 0.14 | 0.16 | 0.17 |
| Observations | 236 | 236 | 236 | 236 |

*Notes.* This table shows the regression results controlling for other influencing channels for the whole slump period. The results of the four models discussed are presented in each of the columns. *** and ** indicate significance at the 1% and 5% levels, respectively. The numbers in brackets are heteroscedasticity-consistent standard errors.

Therefore, they merely received impacts and did not participate in the stock fire sales. Although non-financial firms' trading of equity stakes may be the cause for fire sales (Dinc et al., 2017; Oh, 2018), the empirical results draw a quite different picture: more shareholding by non-financial firms can prevent stocks from fire sales. The shareholdings of non-financial firms generally aim for control rights or long-term investments, and the drops in prices may turn out to be opportunities for enhancing shareholdings. Therefore, non-financial firms are likely to buy stocks, which can effectively alleviate the extent of fire sales.

Li et al. (2019) find that, under normal market conditions, not all trading behaviors of different types of investors can cause comovement and mutual funds' trading activities lead to stock comovement. We further contribute to the literature by establishing that, under worsened market conditions, different types of market participants can have very different roles in the fire sales of stocks.

**Table 7**
Robustness Analysis Based on *Selling Volume*.

| | Dependent Variable: *Selling Volume* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *MUTUAL FUND* | 0.0576 *** | | | 0.0328 ** |
| | (0.0162) | | | (0.0138) |
| *INSTITUTION* | | 0.0097 | | −0.0117 *** |
| | | (0.0105) | | (0.0043) |
| *FIRM* | | | −0.0143 *** | −0.0142 *** |
| | | | (0.0015) | (0.0014) |
| *MARGIN_TRADE* | 0.0638 *** | 0.0727 *** | 0.0346 *** | 0.0292 *** |
| | (0.0154) | (0.0154) | (0.0094) | (0.0083) |
| *SHORT_SALE* | 0.0059 | 0.0062 | 0.0093 *** | 0.0093 *** |
| | (0.0036) | (0.0040) | (0.0023) | (0.0023) |
| *COLLATERAL* | −0.0017 | −0.0030 | −0.0035 | −0.0033 |
| | (0.0019) | (0.0023) | (0.0025) | (0.0023) |
| *SIZE* | −0.4382 *** | −0.5191 *** | −0.3738 *** | −0.3280 *** |
| | (0.0882) | (0.0934) | (0.0670) | (0.0612) |
| *MOMENTUM* | 0.0024 *** | 0.0036 *** | 0.0021 ** | 0.0016 ** |
| | (0.0009) | (0.0011) | (0.0009) | (0.0007) |
| *TURNOVER* | 0.0022 *** | 0.0020 *** | 0.0024 *** | 0.0024 *** |
| | (0.0003) | (0.0004) | (0.0002) | (0.0002) |
| Adjusted $R^2$ | 0.59 | 0.50 | 0.75 | 0.79 |
| Observations | 236 | 236 | 236 | 236 |

*Notes.* This table shows the regression results based on the selling volume of aggressive orders over 0.2 million RMB. *** and ** indicate significance at the 1% and 5% levels, respectively. The numbers in brackets are heteroscedasticity-consistent standard errors.

#### 3.2.3. *Control for other influencing channels*

To further scrutinize the difference among different market participants, we incorporate margin trading, short sales and collateral liquidation into the regression analysis for two reasons. First, these factors are also the potential causes of fire sales. Therefore, we examine their influence on the magnitude of fire sales. Second, we check the robustness of the effect of different market participants after controlling for the three influencing factors. The results are shown in Tables 5 and 6.

As shown in Tables 5 and 6, the influences of three types of market participants on fire sales are highly consistent with those from the baseline analysis. More specifically, from Columns (1)–(3), the coefficients of *MUTUAL FUND* are 0.1233 and 0.1172 for the first and whole slump periods, both of which are significant at the 1% level, confirming that stocks with higher shareholding by mutual funds suffer from more intensive fire sales. The coefficients of *INSTITUTION* are 0.0324 and 0.0286 for the first and whole slump periods, neither of which is significant at the 10% level, confirming that the shareholding by financial institutions has almost no contribution to the propagation of fire sales. The coefficients of *FIRM* are −0.0217 and −0.0173 for the first and whole slump periods, both of which are significant at the 1% level, confirming that stocks with higher shareholding by non-financial firms suffer fewer fire sales. Also, from Column (4), the coefficients of *MUTUAL FUND* are significantly positive; the coefficients of *INSTITUTION* are insignificant; and the coefficients of *FIRM* are significantly negative. The fact that the coefficient and statistical significance of the market participant are merely affected by the addition of other influencing channels confirms that the influences of market participants on fire sales are substantial and cannot be attributed to other influencing channels. Like the baseline analysis, the empirical results remain consistent when more control variables are added into the regression models. In brief, after controlling for other influencing channels, the differences in responses to stock fire sales among market participants are still distinct.

### 3.3. *Alternative measures of fire sales*

To further confirm the different roles played by different market participants on the stock market during the slump period, we consider two alternative measures of market performance as proxies for fire sales, namely *Selling Volume* and *Negative Money Flow*.

*Selling Volume* is defined as the selling volume of aggressive orders,[2] which reflects stock transactions with forced sales[3] as aggressive orders are more likely to be adopted by traders under forced sale pressures. During the market slump, investors intend to take aggressive orders for the forced sale of stocks due to liquidity constraints.

Selling volumes with huge amounts are likely to be caused by fire sales. Therefore, we only take *Selling Volume* over 0.2 million RMB into account for regression analysis. For simplicity, we only consider the whole sampling period. The results are shown in Table 7.

From Table 7, we can find that the influences of the three types of market participants are highly consistent with previous results. More specifically, from Columns (1)–(3), the coefficient of *MUTUAL FUND* is 0.0576, which is significant at the 1% level; the coefficient of *INSTITUTION* is 0.0097, which is insignificant at the 10% level; and the coefficient of *FIRM* is −0.0143, which is significant at the 1% level. From Column (4), the coefficient of *MUTUAL FUND* is significantly positive, and the coefficients of both *INSTITUTION*

[2] The aggressive order refers to a trader entering a bid above the offer price or entering an offer below the bid price.
[3] *Selling Volume* is the number of contracts that change hands at the bid price, based on whether a transaction occurs at the bid price or ask price.

**Table 8**
Robustness Analysis Based on *Negative Money Flow*.

| | Dependent Variable: *Negative Money Flow* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *MUTUAL FUND* | 0.0584 *** | | | 0.0325 *** |
| | (0.0144) | | | (0.0122) |
| *INSTITUTION* | | 0.0095 | | −0.0128 ** |
| | | (0.0117) | | (0.0059) |
| *FIRM* | | | −0.0149 *** | −0.0150 *** |
| | | | (0.0015) | (0.0134) |
| *MARGIN_TRADE* | 0.0735 *** | 0.0825 *** | 0.0428 *** | 0.0369 *** |
| | (0.0206) | (0.0206) | (0.0132) | (0.0121) |
| *SHORT_SALE* | 0.0045 | 0.0049 | 0.0080 *** | 0.0081 *** |
| | (0.0037) | (0.0043) | (0.0023) | (0.0023) |
| *COLLATERAL* | −0.0022 | −0.0036 | −0.0041 | −0.0040 |
| | (0.0020) | (0.0024) | (0.0026) | (0.0025) |
| *SIZE* | −0.3748 *** | −0.4566 *** | −0.3054 *** | −0.2578 *** |
| | (0.0914) | (0.0989) | (0.0731) | (0.0640) |
| *MOMENTUM* | 0.0026 *** | 0.0038 *** | 0.0022 ** | 0.0017 ** |
| | (0.0010) | (0.0013) | (0.0009) | (0.0007) |
| *TURNOVER* | 0.0022 *** | 0.0019 ** | 0.0024 *** | 0.0023 *** |
| | (0.0003) | (0.0005) | (0.0002) | (0.0002) |
| Adjusted $R^2$ | 0.57 | 0.47 | 0.75 | 0.79 |
| Observations | 236 | 236 | 236 | 236 |

*Notes.* This table shows the regression results based on the accumulated negative money flows above 0.2 million RMB. *** and ** indicate significance at the 1% and 5% levels, respectively. The numbers in brackets are heteroscedasticity-consistent standard errors.

and *FIRM* are significantly negative.

*Negative Money Flow* is defined as the accumulated negative money flow of each stock during the sampling period. Negative money flow is routinely used for calculating the money flow index.[4] Basically, when the price advances from one period to the next, the trading volume is added to the positive or negative money flow, depending on whether the raw money flow is positive or negative.

Again, we only consider *Negative Money Flow* above 0.2 million RMB and the whole sampling period for regression analysis. The results are shown in Table 8.

From Table 8, we can see that the results are very similar to those based on *Selling Volume*, and are highly consistent with previous results. More specifically, from Columns (1)–(3), the coefficient of *MUTUAL FUND* is 0.0584, which is significant at the 1% level; the coefficient of *INSTITUTION* is 0.0095, which is insignificant at the 10% level; and the coefficient of *FIRM* is −0.0149, which is significant at the 1% level. From Column (4), the coefficient of *MUTUAL FUND* is significantly positive, and the coefficients of both *INSTITUTION* and *FIRM* are significantly negative.

It is worth noting that, when *Selling Volume* and *Negative Money Flow* are taken as the proxies for fire sales, the influences of both margin trading and short sale become significantly positive. The main reason lies in the difference in the construction of fire sale measures.

The fire sale measure based on the framework of Cont and Wagalath (2013) builds on the realized correlation between stocks, which dedicatedly characterizes the contagiousness and negative externalities of fire sales (Cifuentes et al., 2005; Chernenko and Sunderam, 2020). In other words, this fire sale measure captures the changes in the financial interconnectedness within the whole market system and reflects the evolution of systemic risks with the accumulation of spillovers. In contrast, both *Selling Volume* and *Negative Money Flow* quantify fire sales and active trading, reflecting the downward pressure of stock prices. That is, both measures capture more than the magnitude caused by the contagiousness and negative externalities of fire sales. Furthermore, as both *Selling Volume* and *Negative Money Flow* are not a direct measure of correlation, they may not necessarily be linked to correlation-caused contagion. For example, the sale of one single stock can cause direct changes in *Selling Volume* and *Negative Money Flow*, but may not lead to significant changes in market-level correlation. This explains why the influences of margin trading on both measures are significantly positive, which is consistent with Bian et al. (2018), and the influences of short sales on both measures are also significantly positive, which is consistent with Brunnermeier and Oehmke (2014). In contrast, when the fire sale ratio is taken as the dependent variable, the influence of margin trading is not significant. This is consistent with Lv and Wu (2019), who conclude that margin buying and margin debt are unrelated to future crash risk and reject the mechanism of fire sales.

More importantly, the effects of different market participants (i.e., mutual funds, financial institutions and non-financial firms) are highly consistent, regardless of the chosen proxy for fire sales. Again, it deserves mentioning that the empirical results remain consistent when the regression models contain more control variables. That is, the identification of the roles played by different market participants during the propagation of fire sales is very robust.

[4] The Money Flow Index is a technical oscillator for identifying overbought or oversold conditions in assets based on prices and volumes. It can also be used for inspecting trend changes in prices. The oscillator ranges from 0 to 100.

**Table 9**
Fund Flows (2nd Quarter of 2014 to 1st Quarter of 2016).

| | 2014Q2 | 2014Q3 | 2014Q4 | 2015Q1 | 2015Q2 | 2015Q3 | 2015Q4 | 2016Q1 |
|---|---|---|---|---|---|---|---|---|
| Panel A: Equity Funds | | | | | | | | |
| *N* | 294 | 328 | 349 | 398 | 412 | 685 | 763 | 811 |
| *N+* | 51 | 80 | 170 | 136 | 142 | 124 | 258 | 481 |
| *N–* | 243 | 248 | 179 | 262 | 270 | 561 | 505 | 330 |
| *FLOW* | 1.91 | −75.46 | 161.58 | 10.16 | 224.59 | −788.03 | −47.46 | −16.79 |
| *TNA* | 382.02 | 421.93 | 754.79 | 987.27 | 1253.42 | 908.13 | 1081.57 | 973.23 |
| Panel B: Bond Funds | | | | | | | | |
| *N* | 543 | 588 | 619 | 662 | 676 | 708 | 732 | 793 |
| *N+* | 191 | 217 | 246 | 320 | 283 | 405 | 399 | 405 |
| *N–* | 352 | 371 | 373 | 342 | 393 | 303 | 333 | 388 |
| *FLOW* | −38.62 | −9.78 | 16.30 | 35.63 | −24.22 | 100.76 | 109.92 | 104.59 |
| *TNA* | 228.28 | 246.46 | 294.48 | 361.59 | 355.26 | 482.95 | 611.89 | 763.34 |
| Panel C: Hybrid Funds | | | | | | | | |
| *N* | 595 | 660 | 681 | 720 | 744 | 1051 | 1131 | 1345 |
| *N+* | 117 | 117 | 155 | 210 | 219 | 155 | 329 | 562 |
| *N–* | 478 | 543 | 526 | 510 | 525 | 896 | 802 | 783 |
| *FLOW* | −33.01 | −80.82 | −127.14 | −19.48 | −37.29 | −1102.23 | 20.88 | −218.65 |
| *TNA* | 1049.88 | 1155.79 | 1164.48 | 1515.82 | 1731.71 | 1408.48 | 1964.83 | 1724.27 |
| Panel D: Money Market Funds | | | | | | | | |
| *N* | 228 | 281 | 309 | 368 | 380 | 410 | 428 | 466 |
| *N+* | 109 | 143 | 184 | 154 | 195 | 267 | 214 | 220 |
| *N–* | 118 | 137 | 124 | 212 | 183 | 135 | 203 | 235 |
| *FLOW* | 47.19 | 166.57 | 205.74 | 49.56 | 187.12 | 1291.06 | 691.31 | −293.42 |
| *TNA* | 1644.73 | 1917.03 | 2135.64 | 2293.69 | 2489.68 | 3831.32 | 4542.13 | 4343.32 |

*Notes.* This table displays the summary of capital flows of the four types of funds (stock, bond, hybrid, and money market funds) from the 2nd quarter of 2014 to the 1st quarter of 2016 including the total number of funds (*N*), the number of funds with net inflows (*N+*) and the number of funds with net outflows (*N–*). The fund flow of each category is the total fund flow of all funds in the corresponding category, i.e., $FLOW_t = \sum_j FLOW_{j,t}$. Following Coval and Stafford (2007), the fund flow for each fund is calculated as $FLOW_{j,t} = TNA_{j,t} - TNA_{j,t-1} \times (1 + R_{j,t})$. The total net asset of each category is the sum of the total net assets of all funds in the corresponding category, i.e., $TNA_{t-1} = \sum_j TNA_{j,t-1}$.

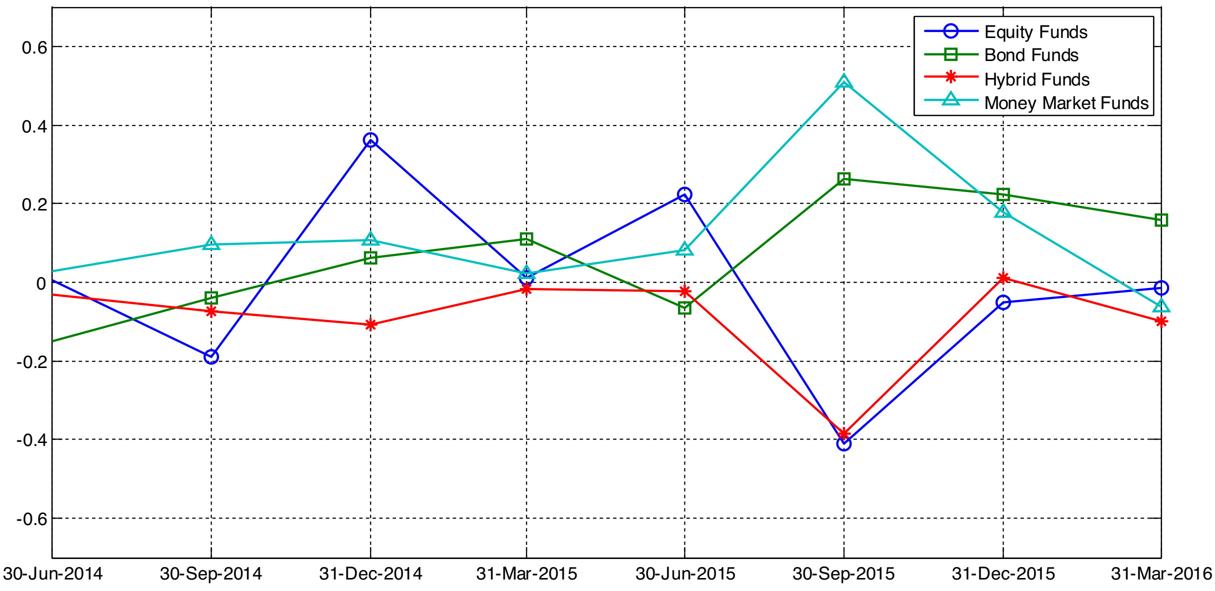


**Fig. 2.** Net Flow Rates of Funds (2nd Quarter of 2014 to 1st Quarter of 2016).
*Notes.* The fund flow in quarter *t* is defined as the fund flow in quarter *t* divided by the total net assets at quarter *t*–1, i.e., $FUND\_FLOW_t = \frac{FLOW_t}{TNA_{t-1}}$. The total net assets of each category are the total of the total net assets of all funds in the corresponding category, i.e., $TNA_{t-1} = \sum_j TNA_{j,t-1}$.

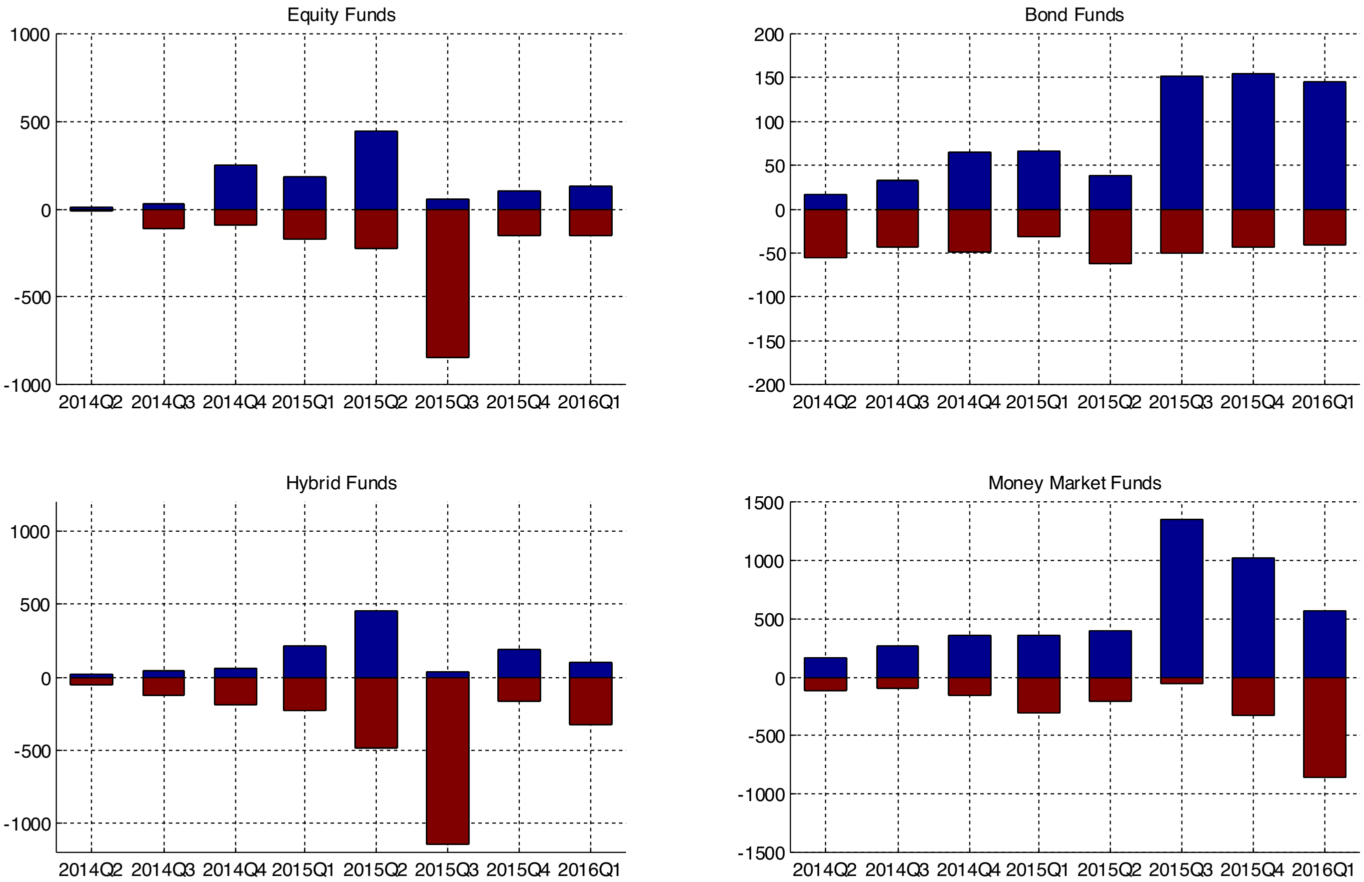


**Fig. 3.** Net Inflows and Net Outflows of Funds (2nd Quarter of 2014 to 1st Quarter of 2016).
*Notes*. This figure shows the capital outflows and inflows of the four types of funds (stock funds, bond funds, hybrid funds, and money market funds) from the 2nd quarter of 2014 to the 1st quarter of 2016. The positive and negative parts of the y-axis represent inflows and outflows, respectively. The capital inflow in quarter $t$ is the total fund flows of funds with net inflows during the period. The capital outflow in quarter $t$ is the total fund flows of funds with net outflows during the period.

**Table 10**
Performance of Stocks Held by Funds.

| | Min. | 1st Qu. | Median | Mean | 3rd Qu. | Max. | W | $\chi^2$ | D |
|---|---|---|---|---|---|---|---|---|---|
| Panel A: Ln(Company Size) | | | | | | | | | |
| High | 24.07 | 24.53 | 24.93 | 25.08 | 25.52 | 28.18 | 7833 | 2.759 | 0.1186 |
| Low | 23.91 | 24.66 | 25.04 | 25.29 | 25.71 | 28.47 | (0.0969) | (0.0967) | (0.3773) |
| Panel B: Growth rate of net value (%) | | | | | | | | | |
| High | −18.03 | 7.80 | 17.27 | 27.83 | 28.02 | 320.93 | 4802 | 16.966 | 0.2712 |
| Low | −21.98 | 1.31 | 9.13 | 14.79 | 21.16 | 132.13 | (0.0000) | (0.0001) | (0.0003) |
| Panel C: Growth rate of net profit (%) | | | | | | | | | |
| High | −1024.76 | −5.27 | 16.27 | 8.94 | 40.23 | 568.87 | 4647 | 19.488 | 0.3136 |
| Low | −9505.05 | −41.36 | −0.837 | −142.65 | 17.84 | 285.40 | (0.0000) | (0.0000) | (0.0000) |
| Panel D: Growth rate of profit per share (%) | | | | | | | | | |
| High | −3443.75 | −6.77 | 11.73 | −17.34 | 37.02 | 556.06 | 4292 | 25.924 | 0.3305 |
| Low | −7141.03 | −47.65 | −7.04 | −126.49 | 11.62 | 1210.53 | (0.0000) | (0.0000) | (0.0000) |
| Panel E: Growth rate of ROE (%) | | | | | | | | | |
| High | −55.55 | −0.26 | −0.08 | −0.74 | 0.15 | 6.99 | 4991 | 14.127 | 0.2119 |
| Low | −74.91 | −0.54 | −0.18 | −1.50 | −0.03 | 12.30 | (0.0002) | (0.0002) | (0.0100) |

*Notes.* The stocks are categorized into two groups according to their fund shareholding ratio. This table displays the descriptive statistics of the two groups, each consisting of 118 stocks, and the statistical testing results between the two groups. Descriptive statistics include the minimum, first quartile, median, mean, third quartile, and maximum. The fund shareholding ratio is based on the data from the 2nd quarter of 2015. Company Size is the natural logarithm of the total market value of stocks on June 15th, 2015. The four growth rates are calculated based on the growth rates between 2014 and 2015. The three columns labeled W, $\chi^2$, and D are the statistics of the Wilcoxon rank-sum test, the Kruskal-Wallis rank-sum test, and the Two-sample Kolmogorov-Smirnov test, respectively, with the *p*-values shown in brackets.

## 4. Fund flows

In previous sections, we find that mutual funds acted as the intensifier of fire sales during the stock market slump. Was the redemption pressure faced by stock funds in distressed market conditions the main cause for the forced sales of stocks? To address this question, we categorize funds into stock funds, bond funds, hybrid funds, and money market funds, and examine the capital flows of all open funds in China from the 2nd quarter of 2014 to the 1st quarter of 2016. We adopt conventional measures of capital flows following the literature (e.g., Coval and Stafford, 2007; Dyakov and Verbeek, 2013; Larrain et al., 2017). More specially, the fund flow for each category is defined as

$$FUND\_FLOW_t = \frac{FLOW_t}{TNA_{t-1}} = \frac{\sum_j FLOW_{j,t}}{\sum_j TNA_{j,t-1}} = \frac{\sum_j \left(TNA_{j,t} - TNA_{j,t-1} \times \left(1 + R_{j,t}\right)\right)}{\sum_j TNA_{j,t-1}},$$

where $TNA_{j,t}$ is the total net assets for fund $j$ in quarter $t$.

Besides, we also examine measures including the number of funds with net inflows ($N+$), the net inflow amount ($FLOW+$), the number of funds with net outflows ($N-$), and the net outflow amount ($FLOW-$) during the period for each category. The results are summarized in Table 9.

From Table 9, we can observe that stock funds and hybrid funds experienced massive redemption during the 2nd quarter of 2015. The number of funds with net outflows was much more than the number of funds with net inflows: the ratios of the two numbers were 561/124 for stock funds and 896/155 for hybrid funds. There were abnormally huge net outflows with −788.03 billion RMB and −1102.23 billion RMB for stock funds and hybrid funds, respectively. The total net assets declined in value dramatically. In contrast, the total net assets of bond funds and money market funds increased significantly. The number of funds with net outflows was less than the number of funds with net inflows: the ratios of the two numbers were 303/405 for bond funds and 135/267 for money market funds. There were net inflows of 100.76 billion RMB and 1291.06 billion RMB for bond funds and money market funds, respectively.

Figs. 2 and 3 show the fund flow, the net inflow, and the net outflow of the four types of funds from the 2nd quarter of 2014 to the 1st quarter of 2016.

From Fig. 2, we find that the net flow reached −40% for both stock funds and hybrid funds, while the net flow reached 50% for money market funds and 26% for bond funds during the 2nd quarter of 2015. Funds holding stocks experienced 40% capital outflows, i.e., outflows from the stock market. It is clearly observable from Fig. 3 that capital outflows were by far more than capital inflows for both stock funds and hybrid funds during the 2nd quarter of 2015, and capital flowed into the less risky market (i.e., money market and bond market).

Mutual funds are faced with redemption pressure when the market performs poorly. The expectation of redemption by other investors can further exacerbate the pressure (Chen et al., 2010). In the second half of the year 2015, the poor performance of the Chinese stock market causes the redemption of stock funds. Under the redemption pressure and experiencing huge capital outflows, mutual funds have to make adjustments to their portfolios and profitless trading, forming fire sales (Coval and Stafford, 2007). Meanwhile, when mutual funds cannot alleviate the liquidity pressure by internal financing, the spillover of fire-sale assets occurs (Chernenko and Sunderam, 2020). This paper not only confirms the above theories and findings but also has a substantial contribution to the literature. Previous studies, such as Coval and Stafford (2007), Ellul et al. (2011), Greenwood and Thesmar (2011), Hau and Lai (2017), and Choi et al. (2020), mainly examine specific channels or mechanisms and their relationship with fire sales. In contrast, the framework proposed in this paper can be used to scrutinize the role played by different market participants during the market crash, providing an innovative perspective for analysis.

## 5. Performance of stocks held by mutual funds

To further confirm the forced sales of stocks due to the redemption pressure rather than the selling of stocks with bad growth potentials, we examine the post-event performances of stocks held by mutual funds. Specifically, we rank the 236 component stocks listed in the CSI 300 Index according to the mutual fund shareholding ratio in the 2nd quarter of 2015 and divide them into the group with high mutual fund shareholding ratios and the group with low mutual fund shareholding ratios (referred to as the *high group* and the *low group* hereinafter). Then, we compare the post-event performances of stocks held by mutual funds between the two groups based on a series of measures including the log-transformed company size, growth rate of net value, growth rate of ROE, growth rate of net profit, and growth rate of profitability per share. The descriptive statistics are shown in Table 10.

It is worth noting that the variables shown in Table 10 are not normally distributed as indicated by the normality tests. Thus, parametric statistical inferences based on the assumption of normality can be misleading. To address this issue, we adopt three nonparametric tests, including the Wilcoxon rank-sum test, Kruskal-Wallis rank-sum test, and two-sample Kolmogorov-Smirnov test to examine the potential difference between the two groups. The test results are shown in the last three columns of Table 10.

As indicated by the descriptive statistics and nonparametric tests, stocks with higher mutual fund shareholding ratios generally have better performance than stocks with lower mutual fund shareholding ratios. This confirms that the stocks held by mutual funds are generally of good growth potential, and the reduction in the shareholding of these stocks can be the consequence of forced sales under pressure. This is because, as professional institutional investors, mutual funds tend to hold stocks of good potential for better profitability; however, when redemption pressures arise from worsened market conditions, the overlapping in assets by funds becomes the channel of risk contagions and can lead to financial systemic risk. The seemingly optimal decision rules for individual funds under normal market conditions become the propagator of fire sales during a crisis.

To check the robustness of the results, we recategorize the 236 stocks into the high, medium, and low groups according to the mutual fund shareholding ratio and redo the comparison. The descriptive statistics and the nonparametric test results still support the previous finding that stocks held by mutual funds are of better potential. For conciseness, the results are not presented in the paper.

Our findings are consistent with Carpenter et al. (2021), who suggest that the Chinese stock market is as efficient as the U.S. stock market and that stock prices contain more and more information about future profitability. The stock market crash in 2015 is caused by the chaining effect of forced sales by market participants. The empirical analysis identifies mutual funds as the main propagator of the fire-sales process and the main contributor to the market crash.

## 6. Conclusions

Not all market participants are alike when facing a financial crisis. Unlike the existing literature on fire sales that mainly focuses on one particular type of market participants or influencing channels, we propose a two-stage framework to examine the roles played by different types of market participants in the propagation of fire sales under worsened market conditions. Distinct from most previous studies, a market-based measure of fire sales is constructed to quantify the heterogeneity in influence on the magnitude of fire sales by market participants.

Empirical results indicate that, regardless of whether heterogeneities in trading activities are taken into account, different market participants have very different influences on the propagation of fire sales: mutual funds have a significantly positive effect, non-financial firms have a significantly negative effect, and financial institutions (mainly insurance companies and pension funds) have a non-significant positive effect. The results remain the same when the measure of fire sales is replaced by conventional proxies including selling the volume and negative money flow. It is also found that margin trading, short sales and collateral liquidation merely have marginal influences on fire sales, although the influence becomes more significant with alternative fire sale measures incorporating downward price pressure.

Examining the capital flows of funds during the market slump identifies the redemption pressure as the main motivation for forced sales by stock funds, which is further confirmed by the post-event analysis of the performance of stocks held by mutual funds. Both stock and hybrid funds experienced massive capital outflows to less risky markets, which further exacerbated the magnitude of fire sales.

Liquidity management strategies have a direct influence on fire sales. The Chinese government prevented the real economy from financial risk contagions and reduced the financial systemic risk by supplying the stock market with liquidity through financial institutions in 2015. More importantly, during the process of government intervention, liquidity supplements can be more pertinent based on the role played by different market participants, which can largely increase the recovering efficiency and effectively reduce recovering costs.

## Declaration of Competing Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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## Appendix A. Variable definition and measurement

| Variable | Definition | Measurement |
|---|---|---|
| *FSR* | Fire sale ratio | Forced sale amount scaled by the market value |
| *MUTUAL FUND* | Mutual funds | Mutual fund shareholding ratio |
| *INSTITUTION* | Financial institutions (mainly insurance companies and pension funds) | Financial institution shareholding ratio |
| *FIRM* | Non-financial firms | Non-financial firm shareholding ratio |
| *MARGIN_TRADE* | Margin trading | Average capital financing surplus |
| *SHORT_SALE* | Short sales | Average of the short sales |
| *COLLATERAL* | Collateral liquidation | Proportion of shares outstanding served as collaterals |
| *SIZE* | Size | Natural logarithm of the total market value |
| *MOMENTUM* | Momentum | Three-month return rate |
| *TURNOVER* | Turnover | Average daily turnover |
| *Selling Volume* | Selling volume of aggressive orders | Aggressive orders over 0.2 million RMB |
| *Negative Money Flow* | Accumulated negative money flow | Negative money flow above 0.2 million RMB |

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