Bubble-Creating Stock Market Attacks and Exploitation of Retail Investors' Behavioral Biases: Widespread Evidence in the Chinese Stock Market

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Abstract

In existing literature, arbitrageurs attack stock prices to *burst* bubbles. In this paper, we study a novel form of bubble-*creating* attacks in the stock market, in which speculators implicitly coordinate to pump up the stock price *without* any significant fundamental news and exploit behavioral-biased investors. We propose a simple model of bubble-creating attacks and provide empirical evidence in the Chinese stock market that is consistent with the model predictions. First of all, stocks with low mutual fund ownership and stocks with high average purchase costs of existing shareholders are more likely to be attacked. Second, stocks with these characteristics experience subsequent price reversals. Third, individual accounts that are like to be held by speculators purchase shares to pump up prices on event days and dump them at the inflated price. These accounts also realize abnormally high return during the event days.

Attacks on currencies have been studied extensively since Obstfeld (1996). Abreu and Brunnermeier (2002) and Abreu and Brunnermeier (2003) use synchronized attacks to model the mispricing correction process in the stock market. In both these works, arbitrageurs attack stock prices to burst bubbles. In this paper, we study a novel form of attacks in the stock market that create bubbles. We propose a simple model of coordinated attacks, in which a large group of speculators, triggered by a news event that has minimal informational content on the stock's fundamental value, drive up the stock's price and volume dramatically to create a bubble. The subsequent inflated price is supported in equilibrium by new rounds of buyers who are subject to the extrapolation bias and by existing stockholders who are reluctant to sell due to the disposition effect. We empirically confirm the model's predictions using data from the Chinese stock market.

Bubble-creating stock attacks happen frequently in the Chinese stock market. One illustrative example is the cases of the so-called "Nobel Prize Concept" stocks. On October 8, 2012, the Nobel Prize in Physiology or Medicine was awarded to two scientists for their contributions in stem cell research. After this announcement, the price soared for VcanBio, a biotechnology firm that specializes in detection and storage of stem cell sources in China. During the two subsequent days, the return of VcanBio reached 16% on a trading volume that was on average 16 times the previous day trading volume. Announcements of other Nobel Prizes in 2012 also led to extreme increase in price and trading volume of related stocks in China.[1] [2] The corresponding technologies of these Nobel Prizes are proven valid long before the announcements and their merit is hardly news to the market. It is a consensus that none of the involved firms could gain any new benefit fundamentally from the technology or the announcement of the Nobel Prizes.[3]

Stock bubbles are not rare, even in mature stock markets. Instantaneous bubble-creating attacks, however, rarely happen in free and mature stock markets because the quick and dramatic rise in price and volume immediately invites large selling orders that dampen or erase the effect of attacks: existing shareholders (including speculators who just bought the shares) might sell their shares upon a sudden and dramatic increase in price; second, short sellers can also provide additional supply to the market; moreover, if price and volume of a stock increase dramatically, the firm

[1]Table 1 provides a partial list of "Nobel Prize Concept" stocks that experience abnormal return and volume exactly after the prize announcements in 2012.

[2]10% increase is the daily upper price limit for listed stocks in the two stock exchanges in mainland China, the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE).

[3]Another typical case of this phenomenon, the case of Zhejiang Dongri, is discussed in Appendix A.

can also offer a large quantity of new shares in the market via secondary equity offerings (SEO).

We construct an equilibrium model of bubble-creating attacks based on the assumption that these previous forces can be impaired. In our model, the short-term limit of stock supply (due to existing shareholders' reluctance to sell, short-sale constraint, and SEO restriction) makes the attack equilibrium possible. There are two types of existing investors: "behavioral-biased" and "unbiased". The inflated price after attack is maintained in equilibrium by investors who suffer the extrapolative bias and believe that the stock price would continue to rise, and by a subset of existing investors who are reluctant to sell due to the disposition effect. Existing investors who are unbiased and trade according to the fundamental value of a company sell their shares to speculators. As long as there are enough speculators (or enough speculative capital) who can coordinate to attack and absorb the selling orders of existing fundamental investors, the attack equilibrium can be possibly achieved. The likelihood of an attack, therefore, depends on the relative ratio between the aggregate capital of speculators whose attentions are attracted to a given stock and the amount of existing shares held by the unbiased investors. The higher the latter, the less likely is an attack. The likelihood of an attack also depends on how many biased investors are under loss with the stock investment. Based on these intuitions, we propose two characteristics of stocks that are prone to coordinated attacks: low mutual fund ownership and high average purchase cost of existing shareholders.

Our model generates three main predictions. First, coordinated attacks are more likely to occur to stocks with low mutual fund holding and high average purchase cost of existing shareholders. Second, stocks that are more likely to be under attack tend to experience low subsequent returns after a period of sudden extreme increase in price and volume. Third, speculators are the net buyers on the event days of extreme increase in price and volume, and the net sellers after the events. Investors with behavioral biases are the net buyers after the events.

The Chinese stock market, being neither free nor mature, serves as a natural laboratory where the mitigating forces for stock attacks are severely limited. First of all, retail investors, who are more likely to exhibit behavioral biases, constitute a large proportion of the trading activity and stock ownership in China.[4] Short selling is only allowed after 2010 and is limited to small subset

[4] According to the yearbook published by the SHSE, individual investors account for 86.01% of the total trading volume and hold 48.29% of the total market capital in the SHSE at the end of 2007.

of stocks at a very high cost.[5] Moreover, SEO in China is strictly regulated and requires a lengthy approval process that could last for months, preventing companies from taking advantage of the instantaneous bubble via SEO. In addition, the stock market in China adopts the "T+1" trading rule, which prevents any investor from selling the stocks they bought on the same trading day. Given these unique rules and conditions, the Chinese stock market provides an ideal setting to test our predictions from the model.

Using market data and a unique trading dataset from a brokerage firm, we document empirical evidence that is consistent with all three predictions. First of all, we find that stocks with low mutual fund holding level and stocks with high average purchase costs among shareholders are more likely to experience events of extreme increase in price and volume. Moreover, after the initial run-up in price, low mutual fund holding stocks and high average purchase costs stocks experience reversals, whereas stocks with high mutual fund holding and low average purchase cost remain at the new price after the initial increase. To be precise, stocks with low mutual fund holding value underperform stocks with high mutual fund holding value by 2.73% in the 30 days after the event days of extreme increase in price and volume. Stocks with high average purchase cost of existing shareholders underperform stocks with high gains by 1.99% in the 30 days after the event days.

Using a unique trading dataset from a brokerage firm, we also provide direct evidence that speculators conduct coordinated attack on stock prices to exploit individual investors' predictable trading behavior. Individual accounts with over five million RMB in stocks, which we suspect to be held by speculators, purchase shares to pump the stock price initially and dump them after the significant rise in price. Moreover, these accounts realize abnormally high return during the event days of extreme increase in price and volume. On the other hand, small individual accounts with less than 100,000 RMB, which we expect to be held investors with behavioral biases, exhibit the opposite trading direction and suffer an immediate paper loss on low fund holding and low gains stocks after events.

Our study contributes to the understanding of the potentially destabilizing role of rational investors both theoretically and empirically. Starting from DeLong, Shleifer, Summers, and Wald-

[5]The cost for borrowing shares in China is around 10% per annum. As measured in D'Avolio (2002), the value-weighted cost to borrow a sample portfolio is 0.24% per annum in the U.S.

mann (1990), several theoretical studies have suggested various ways in which rational arbitrageurs can drive price away from fundamental value. We adopt similar assumptions on the trading behavior of investors as in DeLong et al. (1990). However, we do not rely on the assumption that speculators have better information about the fundamental value of the stock. More recently, Stein (2009) and Di Maggio (2013) propose other theoretical settings in which speculators can destabilize prices. We propose a new mechanism in which investors' behavioral biases induce speculators to coordinately attack prices and create mispricing.

On the empirical side, Brunnermeier and Nagel (2004) and Griffin, Harris, Shu, and Topaloglu (2011) also question the view that sophisticated investors consistently trade against bubbles. These studies find that hedge funds as well as other institutional investors drive both the run-up and the crash of technology stocks during the tech bubble. Both papers are consistent with the model in Abreu and Brunnermeier (2003) that rational investors fail to burst the bubble until a coordinated selling effort occurs. We contribute to this strand of literature by providing direct evidence in the Chinese stock market suggesting that speculators initiate bubbles and gain from doing so by exploiting behavioral-biased investors.

Our study is also closely linked to previous literature on the predictable and suboptimal trading patterns of individual investors. The behavioral biases of individual investors we assume in this paper are well-documented across various financial markets in the literature[6]. The disposition effect that investors are more likely to recognize gains than to recognize losses is documented in Odean (1998). Feng and Seasholes (2005) and Chen, Kim, Nofsinger, and Rui (2007) find that Chinese investors exhibit similar behaviors. Previous literature also provides ample evidence that individual investors make purchase decisions based on previous returns. Barber and Odean (2008) find that individual investors are the net buyers for stocks with extreme high return. Seasholes and Wu (2007) extend the study to upper price limit events in the Chinese stock market and confirm this trading pattern for Chinese individual investors.

Since the trading patterns of individual investors are predictable, an important question is whether these biases affect asset prices. Grinblatt and Han (2005) and Frazzini (2006) examine whether the disposition effect drives the momentum and the post-earning-announcement drift anomalies, respectively. Seasholes and Wu (2007) find that, in the Chinese stock market, individ-

[6] Barber and Odean (2013) provide a comprehensive review on this literature

ual investors buy after observing upper price limit events. The attention-driven buying results in further increases in price after the events.

Our paper adds on to this strand of literature from a different angle. While behavioral biases drive the mispricing *directly* in previous literature, we study an *indirect* channel of the existence of behavioral-biased investors on stock prices. We explore the possibility that speculators, through coordinated attacks, *create* some events of extreme increase in price and volume to attract behavioral-biased investors. The initiation of bubbles by speculators distinguishes our study from Seasholes and Wu (2007). Our empirical results support the active role of speculators in creating mispricing for stocks prone to attacks.

Our study has general implication on phenomena in other stock markets as well.Huberman and Regev (2001) document a single case in the U.S. stock market similar to the "Nobel Prizes Concept" stocks in our paper. Our study sheds light on this puzzling phenomenon by characterizing the stocks that likely to be picked by speculators. With individual trading data, we also identify the investors who trade aggressively during the extreme increase in price and volume.

Broadly speaking, the bubble-creating attacks we study and document can be considered as a new type of trade-based manipulation, in which speculators try to manipulate price simply by buying and selling, as in Allen and Gale (1992) and Mei, Wu, and Zhou (2004). Although our model shares some similar features with the model in Mei et al. (2004), there is a crucial difference. Mei et al. (2004) envision a large manipulator who can set prices in the market, whereas we assume a large number of price-taking speculators who coordinately act upon a public signal. This coordination has important implication on the pervasiveness of this mechanism. A single investor or a group of cooperative investors who try to manipulate price by trading is subject to surveillance and can be considered as illegal. The coordination in our study is implicit. Since a large number of speculators can participate in the attack a legitimate way, the mechanism we study is likely to be widespread, difficult to eliminate, and have a large potential impact on market efficiency.

The rest of the paper is organized as follows: In the next section, we present our model of bubble-creating stock price attack. In particular, we derive testable hypotheses from the model in section 1.3. In section 2, we describe the data used in this paper. Section 3 describes the empirical methodology and documents key predictions of our model. Section 4 concludes.

1 The Model

1.1 Model description

Assumptions

We consider a model of four periods – 0, 1, 2 and 3 – and two assets, cash and a single stock. Cash pays no net return. Stock is in Φ of net supply. Stock is liquidated and each share of stock pays a certain dividend of V in period 3. There is no short sale of the stock and no leverage on the stock.

The model includes four types of investors. Two types suffer from different kinds of behavioral biases. Type 1: positive feedback investors, a group of individual investors endowed with only cash, present in a measure of one; Type 2: loss aversion investors, a group of individual investors, who are endowed with only stock, and who will sell the stock if and only if the price is above their purchase cost; Type 3: fundamental investors, whose demand of a stock depends only on the price relative to its fundamental value, *i.e.*, the expected value of dividend; Type 4: a large number of speculators, each endowed with only cash of amount c, who maximize his/her wealth at period 3. All investors are risk neutral.

The timeline of the model is described as follows:

Period 0

The public expectation of dividend payoff of the stock is V, and the stock price in period 0, P_0, equals V. In period 0, the stock has total floating shares Φ, of which θ fraction is held by loss aversion investors, and $1 - \theta$ fraction is held by fundamental investors. All loss aversion investors have suffered losses on the stock previously. That is, their purchase cost is above P_0. Loss aversion investors will sell the stock if and only if the price exceeds their purchase cost, which has a distribution function $F(P)$. A public news signal is revealed in period 0. The signal implies that the dividend in period 3 is $V + \epsilon$, where ϵ is positive, but infinitesimal. The signal generates varying degrees of attention: n represents how many speculators observe the signal. n is common knowledge among the speculators.

Period 1

After observing the public signal and n, each speculator choose his/her strategy. The equilibrium of the model depends on the realization of n. For any $P_1 > V$, fundamental investors' supply of stock is $(1-\theta)\Phi$ and loss aversion investors' supply of stock is $F(P_1)\theta\Phi$. If the event does not attract enough attention among speculators, *i.e.*, $nc \leq \Phi(1-\theta)V$, then each speculator buy zero share is the unique equilibrium. In this case, $P_0 = P_1 = P_2 = P_3 = V$ and trading volume for each period is zero. If $nc > \Phi(1-\theta)V$, then each speculator spends c to buy the stock is an attack equilibrium for certain parameter values, which is derived in section 1.2. In this attack equilibrium, P_1 is determined by $nc = P_1[(1-\theta) + \theta F(P_1)]\Phi$. The trading volume in terms of stock value is nc in period 1 in the attack equilibrium.

Period 2

The total demand from all positive feedback investors in period 2 is $\beta(P_1 - P_0)$, where β is the positive feedback coefficient. This demand function is the same as the one in DeLong et al. (1990). Positive feedback investors' demand in period 2 responses to the price change between period 0 and 1, and is invariant to P_2. The trading volume in terms of stock value is $\beta(P_1 - P_0)P_2$ at period 2.

Period 3

In period 3, dividend is realized and stock is liquidated. Investors who hold the stock in period 3 are paid the public known dividend $V + \epsilon$ for each share. There is no trading and the price of the stock is pinned down to the dividend value in period 3.

1.2 Solution of the model

We derive the condition for the existence of an attack equilibrium. As long as the positive feedback trading demand is sufficiently high, P_2 will be greater than P_1. Speculators can sell in period 2 with profit. At the same time, loss aversion investors whose purchase cost lie between P_1 and P_2 also sell at time 2. P_2 is determined by the following condition:

$$[F(P_2) - F(P_1)]\theta\Phi + \frac{nc}{P_1} = \beta(P_1 - P_0) \tag{1}$$

Coordinated attack is an equilibrium if $P_2^* > P_1^*$, *i.e.*, $F^{-1}(\frac{1}{\theta}[\frac{\beta}{\Phi}(P_1^* - V) - (1-\theta)]) > P_1^*$. Derivation for the parameter range is shown in Appendix B. The profit for each speculator is $c(\frac{P_2^*}{P_1^*} - 1)$. When the condition for the existence of an attack equilibrium is satisfied, the model has two symmetric equilibria, no attack and attack. Figure 1 illustrates the determination of price in period 1 and

2, and Table 2 summarizes the demand from each type of investors in each period in an attack equilibrium.

1.3 Testable hypotheses from the model

Ideally, we would conduct empirical analysis on all events of successful attacks. However, unlike news events studied in the previous literature, the news signal in our model can be related to the stock in a very subtle way. As described in the "Nobel Prize Concept" stocks example, it takes some detailed knowledge on the stocks to establish the linkage between the Nobel Prize award and the affected stocks. Even after we identify this linkage, it is still difficult to measure the exact informational value of the triggering news on a one-to-one basis. To address these issues, we consider the trading days (events) in which a stock experience extreme increase in price and trading volume simultaneously. We derive our testable hypotheses on the occurrence of these events, on the subsequent stock returns after the extreme increase in price and trading volume, and on the trading patterns of different types of investors during these events.

Extreme increases in price and trading volume can either be the result of unexpected shocks to stock value or the result of coordinated attacks. Assuming that extreme unexpected shocks to stock value happen with the same likelihood for all stocks, we can generate the following hypotheses on the occurrence of these events.

Hypothesis 1*: Stocks with more fundamental investor holdings are less likely to be attacked.*

Attack is an equilibrium only if speculators can drive up the price significantly in period 1. In that case, speculators' total capital has to exceed the value of shares held by fundamental investors ($nc > (1-\theta)\Phi V$) in period 1. Given n and c, it is less likely for speculators' total capital to exceed a stock with high fundamental investor holding value than a stock with low fundamental investor holding value.

Hypothesis 2*: Stocks with high average purchase cost of existing shareholders are more likely to be attacked.*

Loss aversion investors will not sell if speculators have not bid the price above their purchase cost. When the purchase cost for loss aversion investors are high, it is easy for the speculators to pump up the price in period 1. An illustration of Hypothesis 2 is shown in Appendix B.

Extreme increase in price and trading volume can either be the result of unexpected shock to stock value or the result of coordinated attack. When the initial increase in price and volume is due to rational reaction to unexpected shock to stock value, we expect the new price to sustain after the shock. However, when the initial increase in price and volume is due to coordinated attacks, we expect stock price to reverse after the attack. In addition, as stated in Hypothesis 1 and 2, stocks with less fundamental investor holdings and stocks that with high average purchase cost of existing shareholders are more likely to be attacked, we expect attacks to constitute a larger fraction of the events for stocks with these two characteristics. As a result, we expect to see more price reversal subsequently for stocks with these two characteristics.

Formally, we obtain two cross-sectional predictions on subsequent stock returns as follows:

Hypothesis 3*: After sudden and extreme increases in price and trading volume, stocks with high fundamental investor holdings will outperform those with low fundamental investor holdings.*

Hypothesis 4*: After sudden and extreme increases in price and trading volume, stocks with low average purchase cost among existing shareholders will outperform those with high average purchase cost among existing shareholders.*

Demand from each type of investors during each period generates predictions on the trading pattern and profitability of each type of investors. In the pump stage of the attack equilibrium, speculators buy the stock, whereas fundamental investors and loss aversion investors sell the stock. In the dump stage of the attack equilibrium, speculators sell the stock, whereas positive feedback investors buy the stock.

Hypothesis 5*: Speculators are the net buyers on the event days of extreme increase in price and volume, and the net sellers after the event days. Individual investors tend to be the net sellers on the event days, and the net buyers after the event days.*

Moreover, coordinated attack is an equilibrium only if the attack is profitable. We predict that speculators obtain superior return on their account. As a zero-sum game, behavioral-biased individual investors suffer a loss.

Hypothesis 6*: Speculators obtain superior returns, while behavioral-biased investors are exploited.*

We will test each of the above hypotheses in section 3.

2 Data Description

In this paper, we combine several different data sources in the empirical analysis. Stock price data and mutual fund holding data are obtained from China Security Market and Accounting Research (CSMAR). Stock price data include price, volume, total shares outstanding and floating shares information for all stocks traded in Shanghai Stock Exchange (SHSE) and Shenzhen Stock Exchange (SZSE) from January 1, 2007 to March 31, 2013 on a daily basis. In this paper, we consider all Chinese A-share stocks traded on the two exchanges.

The mutual fund holding data contains the number of shares held by each mutual fund on a semi-annual basis, at the end of June and December respectively. Table 3 summarizes the mutual fund holding for stocks in the two exchanges. The third column shows the number of stocks with fund holding data at the end of each year from 2007 to 2012. The last two columns show the average percentage of mutual fund holding and the average number of distinct mutual funds for each stock with fund holding data, respectively.

Our individual trading and daily portfolio holding data come from a top five brokerage company in China. The trading data contains 1.8 million investors' trading records from January 2007 to October 2009. The dataset contains investors trading records of common stocks, funds, treasury notes, and warrants. We focus on their trading records of common stocks, which is about 80% of all trading records. To trade on the SHSE and the SZSE, investors can open one and only one permanent stock account with each exchange. Even after they decide to close their accounts with the exchanges, their stock accounts identifier will not be recycled for future investors. Following the fact book published by the SHSE annually, we classify all trading accounts in our dataset according to the equity value of each trading account in the sample period. We define accounts with less than 100,000 RMB at any time as small accounts, those exceed 100,000 RMB at least once but never exceed 1,000,000 RMB as medium accounts, those exceed 1,000,000 RMB at least once but never exceed 5,000,000 RMB as large accounts, and those exceed 5,000,000 RMB at least once as super accounts. Table 4 shows the distribution of all accounts in our sample. Total accounts represent all accounts in our dataset, whereas active accounts are accounts with more than 20 times of transactions during our sample period. To eliminate the bias caused by inactive investors in our sample, we exclude the inactive accounts in our empirical analysis. We also provide the account distribution in the SHSE for comparison in Table 4. It appears that accounts with high equity value constitute a larger fraction in our sample than those in the SHSE.

In addition, to measure the abnormal return around the events we identify, we use abnormal return data provided by one of the largest fund management companies in China. Abnormal return is the daily return adjusted by a Barra style risk model with style factors including market, size, value, momentum, volatility, liquidity, and 29 industry factors for the Chinese stock market.

3 Empirical Analysis

To carry out empirical tests based on our hypotheses, it is essential to identify events that are likely to result from attacks. We propose our method of identifying events of attack based on prediction from our model. After identifying the events, we examine the likelihood of the occurence of events and the abnormal returns after the events for stocks with different characteristics. In section 3.4, we further study trading pattern of speculators and behavioral investors using investors' trading records from a large brokerage company in China.

3.1 Description of events and key explanatory variables

Identification of events

To attract positive feedback trading investors, speculators need to pump up the price. Therefore, successful attack should cause extreme positive returns. Moreover, according to the theory, to pump up the price, speculators purchase the stock aggressive from fundamental investors and loss aversion investors, which generates abnormally high trading volume compared to the everyday trading volume of the stock. The two exchanges in mainland China both have a ± 10% daily price limit for stocks.[7] Therefore, the highest return for a stock in normal circumstances is 10%. To identify events that are likely to due to attacks, we look for stocks that hit the upper price limit of 10% at the end of trading day and simultaneously have daily trading volume that is more than twice of the average daily trading volume of that stock in the previous 120 trading days.

Since the pumping phase of a typical attack can last for several days, as described in the case

[7] For some special treatment stocks, the daily price limit is ± 5%. The daily price limit is not imposed on stocks in some special situations, e.g., initial public offering, secondary equity offering, after long period of trading suspension, and so on.

of ZJDR in Appendix A, we identify each event as the first time in the last six months that a stock has a 10% daily return with simultaneous abnormally high trading volume (more than twice of the average daily trading volume of that stock in the previous 120 trading days). For example, if a stock has 10% return and abnormally high trading volume on both January 3 and January 5, we count this as one event on January 3, and we define this day with 10% return as event day 0.

We consider all such events between January 1, 2007 and December 31, 2012. This gives us a total of 5962 events, with 2033 unique stocks and 1294 unique dates of event. The description of the occurrence of events in each year is summarized in Table 5.

After we identify these events, we sort all events into quartiles by the two criteria discussed in the testable hypotheses in section 1.3.

Total mutual fund holding value

According to Hypothesis 1, stocks with low fundamental investor holding are more likely to be the victim of attacks than stocks with high fundamental investor holding. We use the total value of mutual fund holding as a proxy for fundamental investors holding. Mutual fund holding data are only available at a semi-annual frequency, which is on June 30 and December 31 of each year. We calculate total mutual fund holding value as the product of the total percentage shares held by all mutual funds and the market capital of the stock at the end of the half year. At the end of each half year, we sort all stocks in the SHSE and the SZSE into quartiles based on mutual fund holding value, and match the fund holding value of each stock to events that occurred in the subsequent six months. Since for most years in our sample, stocks with no fund holding data constitute more than 25% of the whole sample, we assign all stocks with no fund holding data to quartile 1 and sort the remaining sample into three groups based on mutual fund holding value.

Gains

To capture the intuition in Hypothesis 2, we first develop a proxy for the purchase cost of existing shareholders. We calculate the average purchase cost for current shareholders as follows:

$$AverageCost_i = \frac{\sum_{t=1}^{T} P_{it} V_{it}}{\sum_{t=1}^{T} V_{it}} \tag{2}$$

, where P_{it} and V_{it} are the price and share volume t days before the last trading day in each half year of stock i, and T is the total number of trading days of stock i during that half year.

We calculated the average cost for each stock in each half year on the last trading day of this half year. The price and volume used to calculate average cost are adjusted by stock splits and dividend payout. This measure proxies for the average price current shareholders paid for the stock, assuming that current investors purchase the stock in the last six months and have not sold the shares yet. Although this is a rough measure of the average purchase cost among current individual investors holding the stock, we prefer this measure to the actual average purchase cost obtained from the brokerage company. First, the data from the brokerage company contains only a fraction of all individual investors and is not available for the later part of our sample period. Second, and more importantly, we need a measure that proxies for the average purchase cost perceived by speculators. In our model, speculators rely on a public observable distribution of loss aversion investors' purchase cost to estimate the difficulty of pumping up the price of a certain stock. Coordinated attacks arise as an equilibrium when it is common knowledge among speculators that coordinated attacks can cause significant price increases due to limited supply from loss aversion investors. Consistent with the intuition from our model, volume-weighted average price is easily obtained by speculators. However, the actual average purchase cost is not observable for speculators, and we do not expect speculators to coordinate on that.

Since the average purchase costs defined above are not directly comparable across different stocks, we use the closing price on the last trading day of each half year to scale the average purchase cost during that half year. Specifically, we calculate the *Gains* of each stock in each half year as

$$Gains_i = \frac{P_{i0} - AverageCost_i}{P_{i0}} \tag{3}$$

, where P_{i0} is the closing price on the last trading day in each half year for stock i.

Gains stands for the gain or loss position for an average shareholder in this stock. A positive value of *Gains* means that the average shareholder of this stock is having a paper gain on his/her position of this stock, while a negative value of *Gains* means that the average shareholder of this stock is having a paper loss. *Gains* is a measure for the willingness of current shareholders to sell the stock. When the average shareholder is having a large loss on the position of this stock, he/she is less willing to sell his/her stock upon increase in price, because the inflated price is still below his/her purchase cost. The reluctance of individual investors to sell their shares creates a limited supply of the stock, which makes it easier for speculators to generate extreme increase in price without depleting their capital.

On each June 30 and December 31, we sort all stocks in the SHSE and the SZSE into quartiles based on the gains in the past half year and matched the gains quartiles of each stock to events in the subsequent six months.

Table 6 exhibits the descriptive statistics for events in each quartile sorted by total mutual fund holding value and gains. Panel A of Table 6 shows the average characteristics of stocks that are involved in identified events, sorted by fund holding value. As expected, stocks with high fund holding value are larger in total capital and float than stocks with low fund holding value. Stocks in fund holding value quartile 4, *i.e.*,stocks with the highest fund holding value, also tend to have lower average turnover rate and higher gains before the events. Stocks in the four quartiles sorted by fund holding value are similar in other dimensions.

Panel B of Table 6 shows the average characteristics of stocks that are involved in identified events, sorted by gains. Average turnover rate is slightly higher for high gains quartiles. Stocks in high gains quartile have higher fund holding value, as well as higher total fund holding percentage. As expected, stocks in high gains quartiles are also slightly higher in price, total capital and floating capital. Stocks in the four quartiles sorted by gains are similar in other dimensions.

3.2 Occurrence of events

To confirm Hypothesis 1 and 2, we perform logistic regressions on the occurrence of events. We count each half year of each stock in the SHSE and the SZSE as one observation. If an event occurs during a half year for a certain stock, we set occurrence to one. Otherwise, occurrence equals zero. Since we identify each event as the first extreme increase in the last six months, there will be at most one event during each half year. Table 7 exhibits the logistic regression results with occurrence of events as the dependent variable, and total fund holding value and gains quartile as explanatory variables.

In the baseline specification in the first column, only total mutual fund holding value and gains quartile are included. We use quartile numbers for gains in previous half year as an explanatory variable to avoid direct comparison in gains between different half years. Since the Chinese stock market overall experienced extreme positive and negative return over the sample years, the actual level of gains would primarily capture the gain or loss in stock values over the years, instead of a cross-sectional difference between stocks. Since we are trying to measure the reluctance of loss aversion investors to sell the stock, we use the quartile number to compare this reluctance across different stocks at a certain point in time.

Results from the base model suggest that events are less likely to occur for stocks with high fund holding value than stocks with low fund holding value. Also, events are more likely to occur for stocks with low gains than stocks that experienced high gains. As shown in the second column, this effect is still significant after controlling for half-year fixed effect. One alternative explanation would be stocks with low liquidity tend to coincide with low fund holding, and extreme return events tend to occur to low liquidity stocks. In the third regression, we show that the effect of fund holding value and gains still exist after controlling for average turnover and the Amihud illiquidity measure of each stock in the previous half year.

The results from three model specifications are all consistent with Hypothesis 1 and 2. Events of extreme increase in price and volume are more likely to occur for stocks with low fund holding value and stocks with low previous gains.

3.3 Cross-sectional analysis on CAR

Hypothesis 3 and 4 are predictions on the difference in return after the events for stocks with different characteristics. To study the cross-sectional return after events, we adopt the standard event study method in MacKinlay (1997). Cumulative abnormal return (CAR) of stock i on event day t is defined as:

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{i,t} \tag{4}$$

, where $AR_{i,t}$ is the daily return adjusted by a Barra style risk model with style factors including market, size, value, momentum, volatility, liquidity, and 29 industry factors for the Chinese stock market.

Since Hypothesis 3 and 4 are predictions on return after the events, we need to define the ending of attack empirically. As described in the case of ZJDR in Appendix A, for some events, the pumping stage can last for almost a month. Yet, the pumping stage for other events can be shorter, as in the "Nobel Prize Concept" stocks example. Due to the difference in the length of pumping stage, defining event days after attack relative to event day 0 (the initial day with extreme high return and volume) is not appropriate in our study. To address this issue, we define event day +1 as the first day after event day 0 in which the daily turnover is below the turnover on event day 0. Figure 2 and Figure 3 display the cumulative abnormal return from event day +1 to event day +60 for events in each quartile sorted by fund holding value and gains, respectively. The results confirm our Hypothesis 3 and 4. As shown in Figure 2, after the initial run up in price (daily return of 10% on event day 0), stocks with low fund holding value gradually decline in price within the subsequent 60 trading days, yet stocks with high fund holding value remain at a value similar to the value on event day +1. Similarly, stocks with low gains for an average shareholder underperform stocks with high gains for an average shareholder substantially, as shown in Figure 3.

Table 8 summarizes the cumulative abnormal return after the event (from event day +1 to event day +60). After the events, stocks in the high fund holding value group have a cumulative return of -0.279% that is not significantly different from zero. Yet, low fund holding value stocks have an average CAR of -3.00% between event day +1 and event day +30. The difference in CAR between the two quartiles is -2.73% and significant at 1% level for the same horizon. Moreover, the difference between the low fund holding quartile and high fund holding quartile is significant for cumulative abnormal return after 5 to 60 event days.

Similarly, stocks with high gains have a cumulative return of 0.699% that is not significantly different from zero. Yet, stocks with low gains have an average CAR of -2.964% between event day +1 and event day +30. The difference in CAR between the two groups is -1.99% and significant at 1% level for the same horizon. Moreover, the difference between the low gains quartile and high gains quartile is significant for cumulative abnormal return in the subsequent 5 to 60 trading days.

Following the same argument for Hypothesis 3 and 4, we expect the low float (measured as the value of tradable shares) and low percentage of mutual fund holding can both predict low subsequent return of the stock. The last two panels of Table 8 compare the CAR for stocks with high or low floating capital value, and for stocks with high or low fund holding quartiles sorted by percentage of shares held by mutual funds. Consistent with the prediction from the model, low float stocks and low fund holding percentage stocks both decline in price, whereas large stocks and high fund holding percentage stocks do not decline in price after the same extreme increase in price and trading volume.

In previous analyses, the significant reversals in stock price are consistent with the hypotheses that, for some of the events in our sample, the initial run-up of price is due to attack, as opposed to unexpected shocks to the stock value.

Cross-sectional regression results for CAR on total fund holding values and gains quartiles are shown in Table 9. The baseline regression includes total fund holding values and gains quartile as explanatory variables. Coefficients on both of the two variables are significant with the expected signs for all horizons.

To further control for the change in stock market condition through time, we include event half-year dummies in the regressions in panel B. The coefficients on total fund holding value and gains quartile are still significantly positive for all horizons.

In Panel C of Table 9, average turnover before events and Amihud illiquidity measure are included as additional controls for stock liquidity. Abnormal volume, defined as event day trading volume divided by average trading volume in the 120 trading days prior to the event day, is included as an additional explanatory variable. CAR after event is negatively related to abnormal turnover on the event day. This is consistent with our model, because events with high abnormal turnover are more likely to be events caused by attacks.

As a robust check, we perform all previous analyses using the next trading day as event day +1, as in conventional event studies, and obtain the same result qualitatively for long period (over event day +30) after the event day. The results for short period are generally less significant due to the uncertainty of the length of each attack. Figure 4 and 5 display the cross-sectional differences of CAR with the conventional definition of event days, starting from event day 0. Except for the further increase in price during the next trading day, the figures have similar patterns as Figure 2 and 3 for CAR after event day 0. Since our definition of event day is a more appropriate representation of the stock performance after attack, regression results from the conventional definition of event days are omitted here for abbreviation.

3.4 Trading pattern of different types of investors

Trading direction of speculators and individual investors

We now focus on the trading behavior of speculators and behavioral investors during events. Anecdotal evidence suggests that wealthy individuals frequently participate in this type of attacks.

Unlike mutual funds, they are subject to little regulation on their trading. To the contrary, previous literature shows that small individual investors tend to exhibit the behavioral biases in our model. We suspect small individual investors are exploited in the coordinated attacks. Following the annual fact book published by the SHSE, we treat individual accounts with more than five million RMB in equity as speculators' accounts, and individual accounts with less than 100,000 RMB in equity as behavioral investors' accounts.

We compute a buy and sell imbalance measure based on the amounts (in shares) bought and sold by each type of investors on event day 0 and the next trading day after event day 0. For each investor type, we sum the buys (B) and sells (S) of stocks on day t and calculate the buy and sell imbalance following the imbalance measure in Seasholes and Wu (2007)

$$BSI_{it}^{InvestorType} = \frac{(Buy_{it}^{InvestorType} - Sell_{it}^{InvestorType})}{(Buy_{it}^{InvestorType} + Sell_{it}^{InvestorType})} \tag{5}$$

, where $Buy_{it}^{InvestorType}$ is the number of shares of stock i purchased on day t by a certain type of investors, and $Sell_{it}^{InvestorType}$ is the number of shares of stock i sold at time t by a certain type of investors. Buy and sell imbalance is calculated for speculators and behavioral investors separately, and for each event day 0 and the next trading day after event day 0, respectively.

The results in Table 10 confirm Hypothesis 5 on the trading direction of investors. Panel A of Table 10 shows the BSI of each investor type on the event day. The second column shows the BSI for low fund holding and low gains stocks, whereas the third column shows the BSI for high fund holding and high gains stocks. For both groups of stocks, speculators are net buyers on event day 0. On the other hand, small individual investors are net sellers on event day 0. The direction flips for both types of investors on the first trading day after the initial increase in price and trading volume. Panel B of Table 10 shows the BSI of each investor type on the next trading day. Consistent with Hypothesis 5, speculators are on average dumping the stock, whereas small individual investors are buying the stock.

We also examine the difference of BSI across stocks with different characteristics. The second column shows the BSI for low fund holding and low gains stocks, whereas the third column shows the BSI for high fund holding and high gains stocks. The last column in Panel B of Table 10 shows the difference between the groups of stocks. The result in the last column suggests that speculators sell more aggressively on stocks with low fund holding and low gains than stocks with high fund holding and high gains on the next trading day. The difference is significant at 10% level.

Combined with the previous results of negative CAR for low fund holding and low gains stocks, speculators' active selling on low fund holding and low gains stocks further confirms the speculators role in these events. It suggests that speculators understand the initial increase in prices for low fund holding and low gains stocks are created by attack, and is not likely to sustain subsequently. The difference is reversed for behavioral investors. They purchase significantly more shares of stocks with low fund holding and low gains than stocks with high fund holding and high gains. The difference between the two groups is significant for the behavioral investors at 5% level.

Speculators' realized profit and potential losses for behavioral biased investors

Coordinated attacks are supposed to be profitable. Indeed, speculators realize significant gains by trading stocks with low fund holding and low gains between the trading day before the event day and the trading day after the event, the round trip return earned by speculators is 2.95% (t-stat=3.30).[8]

On the other hand, positive feedback investors are expected to lose after the events. Our analysis of trading imbalance for behavioral investors shows that they are net buyers of stocks on the next trading day following the event day. They immediately suffer an unrealized loss of 1.89% (t-stat=4.54) two days after the events. If they hold on losing stocks, their unrealized loss will reach 2.52% (t-stat=3.52) on the 10th day after the events. [9]

4 Conclusion

In this paper, we study a novel form of bubble-*creating* attack in the stock market, in which speculators implicitly coordinate to pump up the stock price and exploit the behavioral-biased investors. We derive testable hypotheses on the likelihood of the occurrences of attacks, on the cross-sectional differences in stock returns after the initial increase in price and trading volume, as well as on the trading direction for each types of investors at each stage of the attack events. Using market data and a unique dataset from a top brokerage company in China, we provide consistent

[8]Our trading data contains the weighted average cost of stocks held by each investor on a daily basis. The realized gains of speculators are calculated as the difference between selling prices and average costs over average costs.

[9]The unrealized gains/losses of behavioral investors are calculated as the difference between closing prices and average costs over average costs.

empirical evidence for all hypotheses from the model.

Our study is of both theoretical and empirical importance. From the theorectical perspective, we propose a new theory on the creation of bubbles by rational speculators in the stock market. Our paper illustrates how rational speculators can be a destablizing force even without any superior information on stock fundamentals, if the market is largely populated by individual investors with behavioral biases. We also provide insight on how the presence of fundamental investors in a stock can alleviate this problem.

From the empirically perspective, our study provide compelling evidence that speculators create bubbles in the Chinese stock market. Consistent with our model, stocks with low mutual fund holding, high average purchase cost among existing shareholders are more likely to be experience events of extreme increase in price and volume. After the initial run-up of price, stocks with these characteristics experience reversals. To the contrary, stocks with high mutual fund holding and low average purchase cost remain at the new price after the initial increase. To be precise, stocks with low mutual fund holding value underperform stocks with high mutual fund holding value by 2.73% in the 30 days after the identified events. Stocks with low gains (,*i.e.*, high average purchase cost of existing shareholders) underperform stocks with high gains by 1.99% in the 30 days after the events.

We also provide direct evidence that speculators conduct coordinated attack on stock prices to exploit individual investors' predictable trading behavior. With a unique dataset from a large brokerage company in China, we are able to observe the trading direction of each type of investors during the identified events. Individual accounts with over five million RMB in equity, which we suspect to be held by speculators, purchase shares to pump the stock price initially and dump them after the significant rise in price. Moreover, these accounts realize abnormally high return during the event days. To the contrary, small individual accounts with less than 100,000 RMB exhibit the opposite trading direction and suffer an immediate paper loss in low fund holding and low gains stocks after events.

Appendix A: The case of Zhejiang Dongri

In this appendix, we present another typical case of bubble-create attacks, the case of Zhejiang Dongri (hereafter ZJDR), a real estate firm incorporated in Wenzhou, China. The firm has 78 million shares (5.17%) of Bank of Wenzhou, a small local bank in Wenzhou. The total value of this holding is small compared to the market capital of ZJDR. As of March 28 2012, ZJDR's market capital is 1.74 billion RMB. However, estimated at 4.11 RMB per share, the total value of ZJDR's holding of Bank of Wenzhou is only 0.32 billion RMB. (The per share value of 4.11 RMB comes from the transaction price in an auction of Bank of Wenzhou in June 2012.)

On March 28, 2012, Chinese State Council assigned the city of Wenzhou to the status of a "Comprehensive Pilot Financial Reform Zone". This is the only zone of this kind in China. As one of the large shareholders of Bank of Wenzhou, ZJDR fits the "Financial Liberalization Concept". Therefore, when the news reached the market, it drew collective attention of investors to speculate on ZJDR.

Right after the policy announcement, ZJDR's price rises from 6.6 RMB to 17.41 RMB at the end of April, a 160% monthly return, which is equivalent to 3.4 billion RMB increase in value. The averager daily turnover is 16% during this period. In comparison, the A-share market had a monthly return of 7% and the average trading volume as a fraction of total market value is 2.3% during April 2012. Figure 6 presents the price and trading volume (as a percentage of total outstanding share value) of ZJDR in April 2012.

The month long roar of price and trading volume drew attention from the China Securities Regulatory Commission (hereafter CSRC), which is the securities authority in China playing a similar role as the Securities and Exchange Commission (SEC) in the US. CSRC halted ZJDR's trading for three days at the end of April and requested the board of ZJDR to announce any information that might cause the abnormal activities of its stock. The board of ZJDR issued a statement on the last trading day of April 2012, clarifying that there is no undisclosed information. Specifically, the management team has no plan to undertake asset reorganization, secondary equity offering, or merger and acquisition in the foreseeable future.

The price and trading volume slided down after the board's clarification. ZJDR closes at 11.62 RMB as of June 29, 2012. In other words, those who bought ZJDR in April and held on to the stock suffer a loss of 33% in two months.

Appendix B:

Condition for the existence of an attack equilibrium

$[F(P_2) - F(P_1)]\theta\Phi + \frac{nc}{P_1} = \beta(P_1 - P_0)$ is the equilibrium condition at period 2 and $nc = P_1[(1 - \theta) + \theta F(P_1)]\Phi$ is the equilibrium condition at period 1. Therefore, $[F(P_2) - F(P_1)]\theta\Phi + [(1-\theta) + \theta F(P_1)]\Phi = \beta(P_1 - P_0)$ at period 2, and we have $P_2 = F^{-1}(\frac{1}{\theta}[\frac{\beta}{\Phi}(P_1 - V) - (1-\theta)])$

The parameter values for the existence of an attack equilibrium is $P_2^* > P_1^*$. That is,

$$F^{-1}(\frac{1}{\theta}[\frac{\beta}{\Phi}(P_1^* - V) - (1-\theta)]) > P_1^*$$

, where P_1^* is the solution to $nc = P_1[(1-\theta) + \theta F(P_1)]\Phi$

Illustration of Hypothesis 2

Let the purchase cost for loss aversion investors of two stocks, a and b, follow uniform distributions with cumulative distribution functions $F^a(P) = \dfrac{P - V}{P^a - V}$ and $F^b(P) = \dfrac{P - V}{P^b - V}$, respectively. $P^a > P^b$. that is, loss aversion investors holding stock a have higher average purchase cost than the ones holding stock b.

At period 1, for both P_1^a and P_1^b to satisfy $nc = P_1[(1-\theta) + \theta F(P_1)]\Phi$, $P_1^a > P_1^b$.

At period 2, for attack to be an equilibrium, $P_2 > P_1$ has to hold. Thus,

$$P_2 - V = [\beta(P_1 - V) - (1-\theta)\Phi]\frac{P^a - V}{\theta\Phi} > P_1 - V$$

If attack is an equilibrium for stock b, then $[\beta - \dfrac{\theta\Phi}{P^b - V}](P_1^b - V) > (1-\theta)\Phi$. Since $P_1^a > P_1^b$ and $P^a > P^b$, $[\beta - \dfrac{\theta\Phi}{P^a - V}](P_1^a - V) > (1-\theta)\Phi$ is satisfied. Therefore, attack is also an equilibrium for stock a.

The previous derivation shows that, given the same level of attention triggered by the event (n) and the amount of capital held by each speculator (c), the parameter range in which an attack equilibrium exists for stock a contains that of the parameter range for stock b. (Stocks with high average purchase cost of loss aversion investors are more likely to be attacked.)

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Table 1. A partial list of "Nobel Prize Concept" stocks in 2012

Date	Nobel Prize in	Contributions in	Affected Stocks	Related Businesses
10/8/2012	Physiology /Medicine	Stem Cell	VcanBio (600645): 16% increase in price between 10/9/2012 and 10/10/2012, and an average increase of 1660% in trading volume	Detection and storage of stem cell sources in China
10/9/2012	Physics	Quantum Systems (with applications in laser science)	HansLaser (002008): 10% increase in price and 120% increase in trading volume on 10/10/2012	Laser processing equipment manufacturing
10/10/2012	Chemistry	G-protein-coupled receptors (with applications in bio-pharmaceuticals manufacturing)	ChangchunHiTech (000661): 10% increase in price and 480% increase in trading volume on 10/11/2012	Bio-pharmaceuticals manufacturing

Table 2. Demand for the stock by investor types (Total supply = Φ for all periods)

Period	Description	Price	Total demand from: Positive feedback investors	Loss aversion investors	Fundamental investors	Speculators
0	Public announcement of signal	$P_0^* = V$	0	$\theta\Phi$	$(1-\theta)\Phi$	0
1	Speculators buy from fundamental investors and loss aversion investors	P_1^*	0	$[1 - F(P_1^*)]\theta\Phi$	0	$\frac{nc}{P_1^*}$
2	Speculators sell to positive feedback investors	P_2^*	$\beta(P_1 - P_0)$	$[1 - F(P_2^*)]\theta\Phi$	0	0
3	Dividend payoff	$P_3^* = V + \epsilon$	$\beta(P_1 - P_0)$	$[1 - F(P_2^*)]\theta\Phi$	0	0

Table 3. Summary on mutual fund holding of A-share stocks

This table summarizes mutual fund holding of each stock at the end of each year. The second and third column show the total number of A-share stocks traded on the SHSE and the SZSE and the number of stocks with mutual fund holding data, respectively. Column four is the average percentage mutual fund holding for stocks. (Stocks with no mutual fund holding data in CSMAR are exclude from the calculation.) The last column is the average number of mutual funds that invest in each stock in each year.

Year	# of stocks	# of stocks with holding data	Avg holding (%)	Avg # of funds
2007	1517	956	8.89	24.43
2008	1577	940	8.57	23.43
2009	1680	1278	6.20	22.17
2010	2020	1662	7.04	26.77
2011	2301	2060	5.56	27.54
2012	2456	2124	5.03	35.51

Table 4. Account distribution

This table compares the distribution of accounts in the dataset from the brokerage company and that of all accounts in the SHSE. Following the fact book published by the SHSE annually, we classify trading accounts in our dataset according to the equity value of each trading account in the sample period. We define accounts with less than 100,000 RMB at any time as small accounts, those exceed 100,000 RMB at least once but never exceed 1,000,000 RMB as medium accounts, those exceed 1,000,000 RMB at least once but never exceed 5,000,000 RMB as large accounts, and those exceed 5,000,000 RMB at least once as super accounts. Active accounts are defined as accounts with more than 20 trades in the brokerage company dataset. Active (%) denotes the fraction of a specific type of accounts in all active accounts (in percentage) in the brokerage company dataset. Total (%) denotes the fraction of a specific type of account in all accounts (in percentage) in the brokerage company dataset. The last two columns are the account distributions of all accounts in the SHSE in 2008 and 2009, respectively.

Account distribution in the brokerage dataset					**Account distribution in the SHSE**	
Account Type	Active	Active (%)	Total	Total (%)	SHSE in 2008 (%)	SHSE in 2009 (%)
Small	529,970	52.98	1,104,325	65.96	91.97	82.78
Medium	419,975	41.98	519,476	31.03	7.62	15.99
Large	44,353	4.43	44,353	2.65	0.36	1.10
Super	6,028	0.60	6,028	0.36	0.05	0.12

Table 5. Summary on the occurrence of events

This table exhibits the distribution of events across different stocks and trading days in each year. # of stocks denotes the total number of A-share stocks traded on the SHSE and the SZSE. Distinct stocks with events denotes the number of stocks that experienced at least one event during that year. # of trading days is the number of official trading days for the SHSE and the SZSE in each year. Distinct trading days with events denotes the number of distinct trading days in which at least one event occurs for some stock. Total # of events denotes total number of events in each year.

Year	# of stocks	Distinct stocks with events	# of trading days	Distinct trading days with events	Total # of events
2007	1517	861	242	194	932
2008	1577	1159	246	211	1350
2009	1680	700	244	209	758
2010	2020	888	242	213	946
2011	2301	716	244	214	733
2012	2456	1151	243	233	1243
2007-2012	2491	2033	1461	1274	5962

Table 6. Summary statistics of stock characteristics

This table presents summary statistics of the stocks with events between 2007 and 2012. Holding (%) is the total percentage of shares held by mutual funds. Holding Value (bil) is the mutual fund holding value in billions of RMB calculated with the market capital of the stock at the end of the last half year. $Gains_i = \frac{P_{i0} - AvgCost_i}{P_{i0}}$, where P_{i0} is the closing price on the last trading day in each half year for stock i, and $AvgCost_i = \frac{\sum_{t=1}^{T} P_{it} V_{it}}{\sum_{t=1}^{T} V_{it}}$, where P_{it} and V_{it} are the price and share volume t days before the last trading day in each half year of stock i, and T is the total number of trading days of stock i during that half year. Total Cap is the market capital of equity in billions of RMB at the end of last half year. Float is value of tradable shares at the end of last half year in billions of RMB. Avg Vol(%) is the average turnover in the last 120 trading days before the event, where turnover is the ratio between trading volume in shares and number of tradable shares. Event Vol(%) is the turnover on event day 0. Abnormal Vol is the ratio between Event Vol(%) and Avg Vol(%). Mean and median are reported for each group.

Quartile	Stat	Close Price	Holding (%)	Holding Value (bil)	Gains (%)	Total Cap (bil)	Float (Bil)	Avg Vol(%)	Event Vol(%)	Abnormal Vol
Panel A: Sorted by Total Mutual Fund Holding Value										
1	Mean	9.9	0.00	0.00	-10.3	2.64	1.58	3.1	10.83	3.79
(Low)	Median	8.92	0.00	0.00	-9.6	2.09	1.29	2.69	9.37	3.26
	N	1325	1325	1325	1310	1325	1325	1325	1325	1325
2	Mean	11.03	0.38	0.05	-11.9	8.84	2.93	2.78	9.91	4.02
	Median	8.95	0.21	0.01	-10.0	2.9	1.72	2.48	8.83	3.36
	N	1822	1822	1822	1820	1822	1822	1822	1822	1822
3	Mean	13.77	3.11	0.3	-10.1	10.53	5.08	2.57	9.05	4.01
	Median	10.94	2.66	0.1	-10.8	4.21	2.58	2.2	7.75	3.32
	N	1499	1499	1499	1496	1499	1499	1499	1499	1499
4	Mean	19.82	15.18	1.86	-3.3	12.46	8	2.04	7.11	3.8
(High)	Median	15.93	12.4	0.77	-4.8	6.25	4.02	1.82	5.97	3.17
	N	1316	1316	1316	1314	1316	1316	1316	1316	1316
Panel B: Sorted by Gains										
1	Mean	11.31	2.82	0.27	-21.6	6.59	3.79	2.55	9.22	3.99
(Low)	Median	9.23	0.65	0.02	-19.2	3.04	1.94	2.16	7.91	3.4
	N	1879	1879	1879	1879	1879	1879	1879	1879	1879
2	Mean	11.39	3.05	0.32	-12.3	8.13	4.01	2.58	9.35	4.03
	Median	9.37	0.39	0.01	-10.2	3	1.98	2.21	8.07	3.45
	N	1590	1590	1590	1590	1590	1590	1590	1590	1590
3	Mean	13.46	4.04	0.53	-5.51	10.14	4.48	2.69	9.25	3.86
	Median	10.69	0.89	0.03	-3.52	3.35	2.09	2.36	7.99	3.25
	N	1396	1396	1396	1396	1396	1396	1396	1396	1396
4	Mean	19.97	8.84	1.12	12.3	11.21	5.38	2.78	9.15	3.65
(High)	Median	15.08	4.48	0.18	12.0	4.41	2.65	2.38	7.53	2.98
	N	1075	1075	1075	1075	1075	1075	1075	1075	1075

Table 7. Logistic regression on the occurrence of events

This table presents the logistic regression of occurrence of events on mutual fund holding value and gains quartile. An event is defined as a stock increases 10 % in price in one day and experiences abnormal high trading volume simultaneously. Each half year of each stock traded in the SHSE and the SZSE between 2007 and 2012 is counted as one observation. Occurrence equals one if at least one event occurs in this half year for a certain stock. Total fund holding value is the mutual fund holding value in billions of RMB calculated with the market capital of the stock at the end of the last half year. Gains quartile is the quartile number for gains (quartile 1 contains stocks with the lowest gains), where $Gains_i = \frac{P_{i0} - AvgCost_i}{P_{i0}}$, where P_{i0} is the closing price on the last trading day in each half year for stock i, and $AvgCost_i = \frac{\sum_{t=1}^{T} P_{it} V_{it}}{\sum_{t=1}^{T} V_{it}}$, where P_{it} and V_{it} are the price and share volume t days before the last trading day in each half year of stock i, and T is the total number of trading days of stock i during that half year. Average volume is the average daily turnover in the previous 120 trading days. Amihud illiquidity measure $= average(|\frac{Daily\ return}{Daily\ trading\ volume}|) \cdot 10^6$ in the previous half year. White-robust t-stats are presented in parentheses.

	Base Model		Control for Half-Year Fixed Effect		Control for Liquidity	
Total Fund Holding Value	-0.068	***	-0.053	***	-0.074	***
	(-3.785)		(-3.388)		(-3.914)	
Gains Quartile	-0.23	***	-0.25	***	-0.242	***
	(-16.286)		(-17.037)		(-16.338)	
Average Volume					-0.052	***
					(-8.996)	
Amihud Illiquidity Measure					-0.02	
					(-1.101)	
Half-year Fixed Effect	No		Yes		Yes	
Intercept	-0.592	***	0.49	***	0.648	***
	(-24.108)		-8.29		-10.607	
Pseudo R-squared	0.0137		0.0677		0.0718	
Number of Observations	21257		21257		21257	

*** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.

Table 8. Cumulative abnormal returns after attack

This table presents the mean cumulative abnormal returns of stocks after events for various horizons. Abnormal returns are daily returns adjusted by a Barra style risk model with style factors including market, size, value, momentum, volatility, liquidity, and 29 industry factors for the Chinese stock market. Event day +1 is defined as the first day after event day 0 in which the daily turnover is below the turnover on event day 0. Stocks are sorted into quartiles based on fund holding value, gains, asset float, and percentage shares held by mutual funds. Fund holding value is the product between percentage of shares held by mutual funds and the market capital of the stock at the end of the previous half year; $Gains_i = \frac{P_{i0} - AvgCost_i}{P_{i0}}$, where P_{i0} is the closing price on the last trading day in each half year for stock i, and $AvgCost_i = \frac{\sum_{t=1}^{T} P_{it} V_{it}}{\sum_{t=1}^{T} V_{it}}$, where P_{it} and V_{it} are the price and share volume t days before the last trading day in each half year of stock i, and T is the total number of trading days of stock i during that half year. Float is value of tradable shares at the end of the previous half year. CAR of stocks in bottom quartiles and top quartiles, and difference between the two quartiles are reported in this table. P-values are presented in parentheses.

		5 Days	10 Days	20 Days	30 Days	60 Days
	Low Fund Holding Value					
By Fund Holding Value	Mean	-1.116 ***	-2.299 ***	-2.769 ***	-3.002 ***	-2.021 ***
	P-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	High Fund Holding Value					
	Mean	-0.04	-0.125	0.191	-0.279	-0.029
	P-value	(0.713)	(0.526)	(0.496)	(0.422)	(0.952)
	Difference in Mean					
	Difference	-1.077 ***	-2.174 ***	-2.96 ***	-2.723 ***	-1.993 ***
	P-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
	Low Gains					
By Gains	Mean	-0.921 ***	-1.514 ***	-2.128 ***	-2.694 ***	-2.689 ***
	P-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	High Gains					
	Mean	-0.412 ***	-0.637 **	-0.632 *	-0.699	0.285
	P-value	(0.006)	(0.017)	(0.091)	(0.133)	(0.644)
	Difference in Mean					
	Difference	-0.509 ***	-0.876 ***	-1.496 ***	-1.994 ***	-2.974 ***
	P-value	(0.006)	(0.006)	(0.001)	(0.000)	(0.000)
	Low Float					
By Float	Mean	-1.264 ***	-2.268 ***	-2.683 ***	-3.241 ***	-2.185 ***
	P-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	High Float					
	Mean	-0.075	-0.254	-0.249	-0.418	0.476
	P-value	(0.513)	(0.223)	(0.393)	(0.252)	(0.343)
	Difference in Mean					
	Difference	-1.19 ***	-2.014 ***	-2.434 ***	-2.822 ***	-2.661 ***
	P-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Low Percentage Share Holding by Funds					
By Percentage Fund Holding	Mean	-1.246 ***	-2.408 ***	-2.725 ***	-2.984 ***	-1.719 ***
	P-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
	High Percentage Share Holding by Funds					
	Mean	-0.059	-0.111	0.094	-0.548	-0.226
	P-value	(0.620)	(0.609)	(0.764)	(0.151)	(0.663)
	Difference in Mean					
	Difference	-1.187 ***	-2.297 ***	-2.819 ***	-2.435 ***	-1.493 **
	P-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.042)

*** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.

Table 9. Cross-sectional regression results of CAR

This table represents the cross-sectional regression results of CAR on fund holding value and gains quartiles. Panel A is the base model with total fund holding value and gains quartile as explanatory variables. Panel B controls for fixed effect of each half year. Panel C controls for stock liquidity and includes abnormal turnover on the event day as an additional explanatory variable. Average volume is the average daily turnover in the previous 120 trading days. Abnormal volume is the ratio between turnover on event day 0 and the average turnover in the previous 120 trading days. Amihud illiquidity measure = $average(|\frac{Daily\ return}{Daily\ trading\ volume}|)\cdot 10^6$ in the previous half year. White-robust t-stats are presented in parentheses.

Independent Variables	5 Days	10 Days	20 Days	30 Days	60 Days
Panel A: Base Model					
Total Fund Holding Value	0.151***	0.267***	0.387***	0.441***	0.609***
	(4.988)	(5.043)	(5.707)	(6.063)	(4.547)
Gains Quartile	0.123**	0.221**	0.445***	0.590***	0.826***
	(2.151)	(2.275)	(3.210)	(3.539)	(3.718)
Intercept	-0.981***	-1.750***	-2.312***	-2.822***	-2.605***
	(-10.440)	(-11.272)	(-10.665)	(-11.124)	(-7.451)
Half-year Fixed Effect	No	No	No	No	No
Adj. R-Square	0.005	0.005	0.007	0.007	0.007
Number of Observations	5939	5938	5937	5937	5921
Panel B: Control for Half-year Fixed Effect					
Total Fund Holding Value	0.150***	0.277***	0.392***	0.428***	0.560***
	(4.979)	(5.203)	(5.780)	(5.946)	(4.208)
Gains Quartile	0.130**	0.228**	0.438***	0.580***	0.833***
	(2.272)	(2.331)	(3.141)	(3.462)	(3.729)
Intercept	-0.990***	-1.764***	-2.305***	-2.803***	-2.589***
	(-10.422)	(-11.203)	(-10.480)	(-10.912)	(-7.344)
Half-year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Adj. R-Square	0.011	0.010	0.011	0.010	0.015
Number of Observations	5939	5938	5937	5937	5921
Panel C: Control for Liquidity					
Independent Variables	5 Days	10 Days	20 Days	30 Days	60 Days
Total Fund Holding Value	0.134***	0.248***	0.355***	0.395***	0.535***
	(4.663)	(4.918)	(5.313)	(5.560)	(3.997)
Gains Quartile	0.132**	0.221**	0.421***	0.553***	0.805***
	(2.307)	(2.252)	(2.998)	(3.272)	(3.586)
Abnormal Volume	-0.095**	-0.282***	-0.469***	-0.518***	-0.476***
	(-2.546)	(-4.978)	(-5.693)	(-5.611)	(-4.191)
Average Volume	-0.101**	-0.175**	-0.200*	-0.165	-0.083
	(-2.260)	(-2.328)	(-1.757)	(-1.100)	(-0.468)
Amihud Illiquidity Measure	0.025	0.111	-0.032	0.154	-0.044
	(0.310)	(0.701)	(-0.206)	(0.601)	(-0.185)
Intercept	-0.348	-0.195	0.101	-0.314	-0.457
	(-1.582)	(-0.552)	(0.189)	(-0.495)	(-0.601)
Half-year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Adj. R-Square	0.013	0.015	0.016	0.015	0.017
Number of Observations	5939	5938	5937	5937	5921

*** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.

Table 10. Investors' trading direction

This table captures investors' trading direction of stocks on event day 0 and on the day after event day 0. The second column shows the buy and sell imbalance (BSI) for stocks with both low fund holding value and low gains. The third column shows the BSI for stocks with both high fund holding value and high gains. The last column shows the difference of BSI between the two groups of stocks by the same type of investors. Speculators are the holders of super individual accounts with over five million RMB in equity value. Behavioral investors are the holders of small individual accounts with less than 100,000 RMB in equity value. BSI for each investor type for stock i on date t is defined as

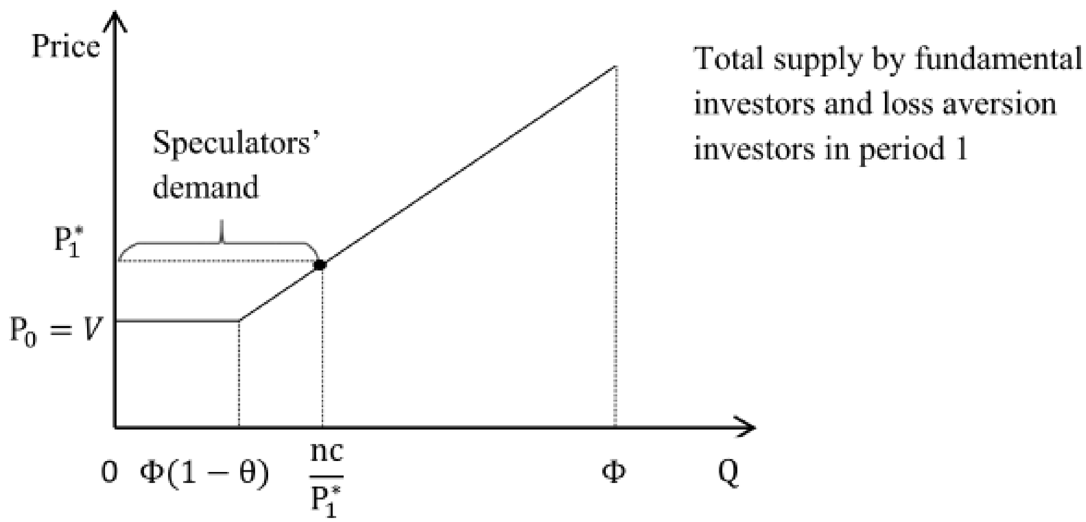
$$BSI_{it}^{InvestorType} = \frac{(Buy_{it}^{InvestorType} - Sell_{it}^{InvestorType})}{(Buy_{it}^{InvestorType} + Sell_{it}^{InvestorType})}$$

, where $Buy_{it}^{InvestorType}$ is the number of shares of stock i purchased on day t by a certain type of investors, and $Sell_{it}^{InvestorType}$ is the number of shares of stock i sold at time t by a certain type of investors. Mean and median are reported for each investor type on event day 0 and the next trading day after event day 0 respectively. P-values are reported in parenthesis under the mean value. Diff in rows denotes the difference between the mean BSI of two types of investors.

	Low Fund Holding & Low Gains Stocks		High Fund Holding & High Gains Stocks		Diff between Stock Groups	
Panel A: Event day 0						
Speculators						
Mean	0.265	***	0.167	***	0.098	
	(0.000)		(0.000)		(0.170)	
Median	0.719		0.332			
Behavioral Investors						
Mean	-0.173	***	-0.151	***	-0.021	
	(0.000)		(0.000)		(0.487)	
Median	-0.173		-0.196			
Diff	0.438	***	0.318	***		
	(0.000)		(0.000)			
Panel B: The next trading day after event day 0						
Speculators						
Mean	-0.226	***	-0.094	**	-0.132	*
	(0.000)		(0.028)		(0.054)	
Median	-0.585		-0.113			
Behavioral Investors						
Mean	0.139	***	0.079	***	0.060	**
	(0.000)		(0.000)		(0.012)	
Median	0.147		0.107			
Diff	-0.367	***	-0.173	***		
	(0.000)		(0.000)			

*** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.

Figure 1. Determination of prices in period 1 and 2



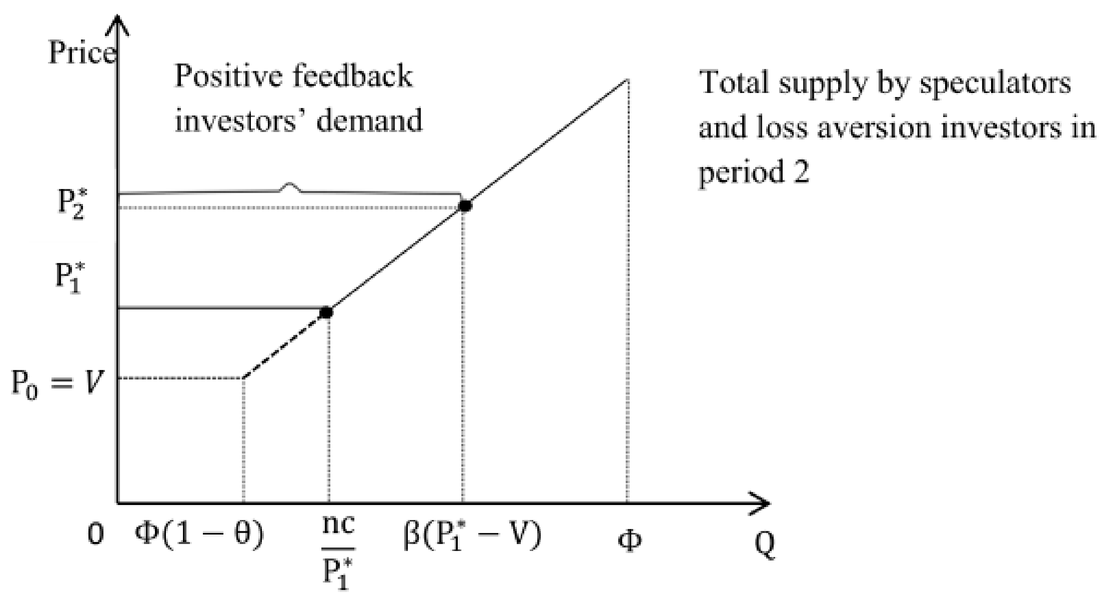


Figure 2. CAR: By total mutual fund holding value quartiles (Event day +1 is the first day after event day 0 in which the daily turnover is below the turnover on event day 0)

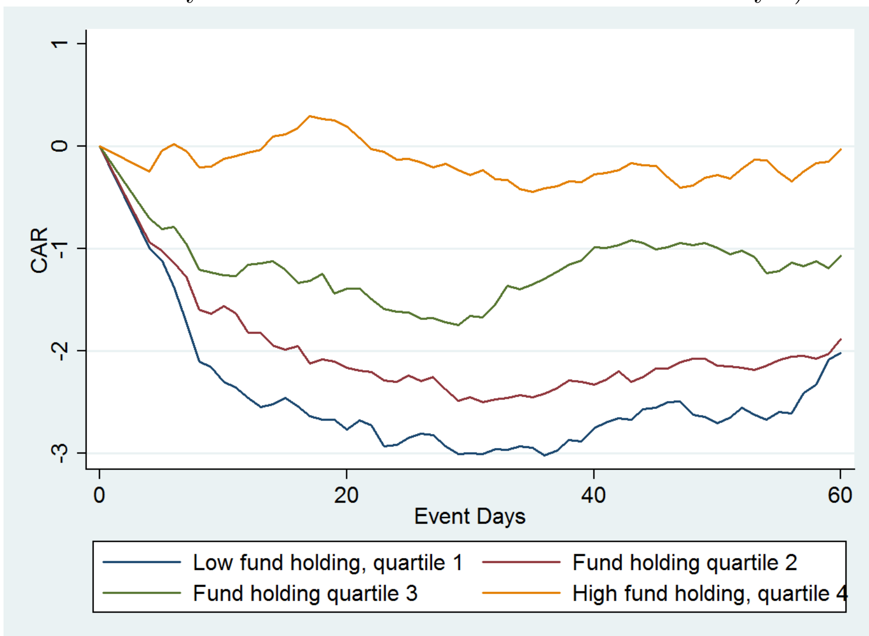


Figure 3. CAR: By gains quartiles (Event day +1 is the first day after event day 0 in which the daily turnover is below the turnover on event day 0)

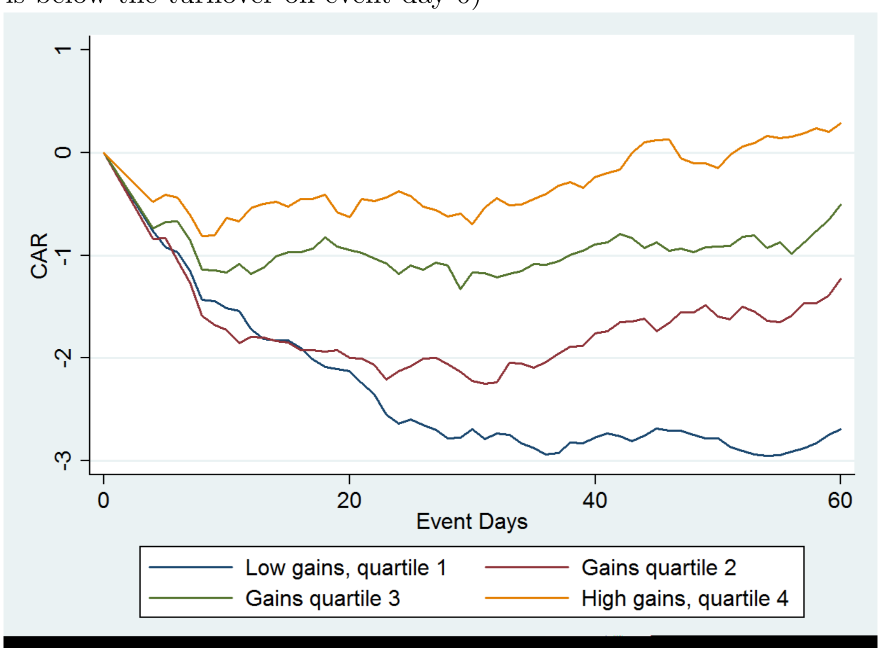


Figure 4. CAR: By total mutual fund holding value quartiles (The next trading day after event day 0 is defined as event day +1.)

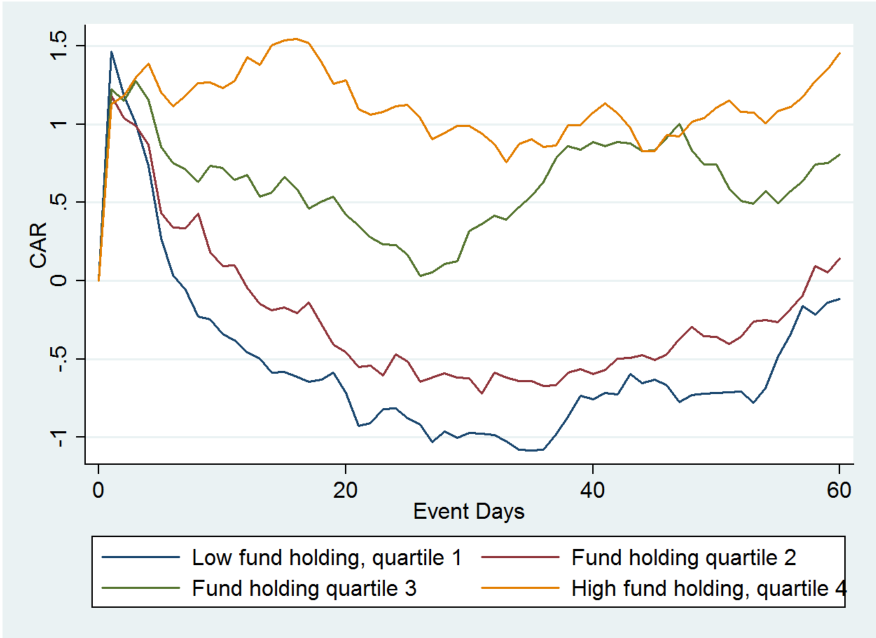


Figure 5. CAR: By pervious gains quartiles (The next trading day after event day 0 is defined as event day +1.)

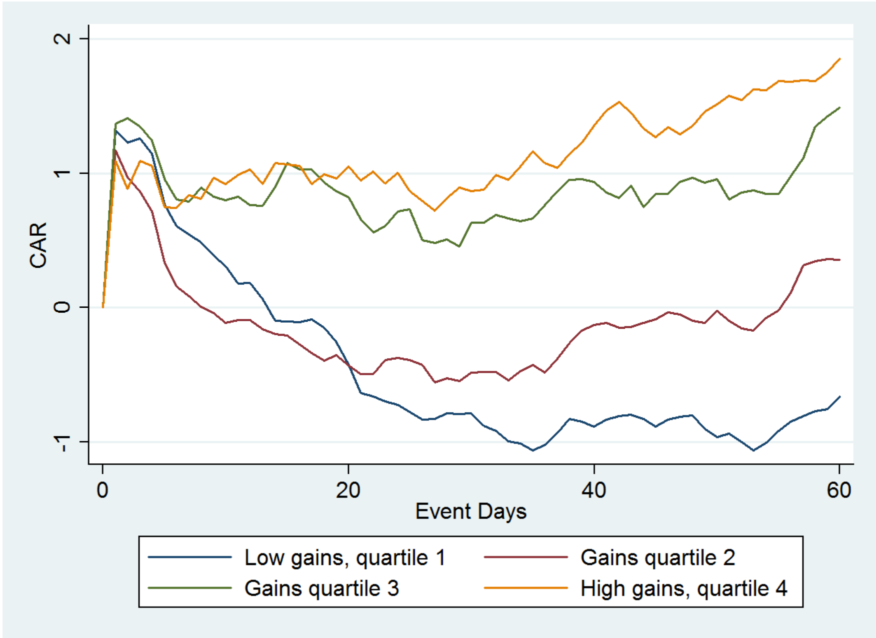


Figure 6. Price and trading volume of ZJDR around the policy announcement