The Causal Effect of Investor Attention

Abstract

We examine the *casual* effect of investor attention on asset pricing dynamics. Our empirical investigation relies on repeated natural experiments in which investor attention difference does not contain any information related to stock fundamentals, nor is a rational decision of investors. We find higher investor attention causes higher return volatility, higher trading volume, higher stock liquidity, and higher short-term stock returns which largely reverse in two weeks. We also find that these are due to higher noise trader participation after the attention grabbing events, as evidenced by positive order imbalance for small orders, increased return comovement with small stocks, and decreased price efficiency.

JEL Code: G12, G14, D03

Keywords: attention; asset pricing dynamics; noise trader; volatility

1. Introduction

Attention, as a scarce cognitive resource (Kahneman, 1973), can affect asset pricing. In theoretical works, there are two prominent ways for attention to affect asset pricing. First, attention is treated as a necessary device for rational Bayesian learning (Hirshleifer and Teoh, 2003; Sims, 2003; Peng, 2005; Peng and Xiong, 2006; Huang and Liu, 2007; Andrei and Hasler, 2015a, 2015b). Higher attention leads to better price efficiency. Second, attention attracts noise traders (Barber and Odean, 2008). Barber and Odean (2008) find that individual investors are net buyers of attention-grabbing stocks. They argue that this is because an investor has to search through thousands of stocks when making a buy decision but only through the limited number of stocks he/she already holds when making a sell decision. Together with the fact that attention is scarce and searching thousands of stocks is costly, investors are more likely to buy attention-grabbing stocks than to sell them. In the framework of Barber and Odean (2008), higher attention predict higher stock prices in the short term and price reversals in the long run.

When testing theories of attention, empiricists face substantial challenges: attention is typically endogenously allocated by investors based on the specific situations they face and attention-grabbing events typically coincide with the release of useful information. Both the attention allocation criteria used by investors and the contemporaneously released information are typically only partially observable to econometricians, preventing us from measuring the *causal* effect of attention.

To address these issues, we rely on repeated natural experiments in which investor attention difference is purely affected by institutional idiosyncrasies which do not contain any information related to stock fundamentals: 10% upper price limit events on the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE). The two Chinese stock exchanges established the price limit rule on December 16, 1996. For most of the stocks, daily absolute stock price movement is restricted to 10% of the previous trading day's close price. The minimum tick size for stocks is RMB 1 cent. Therefore, in cases where 10% price change is not an integral number of cents, daily price limit is rounded to the nearest cent. This leads to differences of maximum daily return movements. For example, the maximum daily price increases for stocks priced at 9.99RMB, 10.00RMB, and 10.01RMB are all 1.00RMB. But the maximum return limits are 10.01%, 10.00%, and 9.99%, respectively.[1]

The small difference in returns makes a large difference in attracting investor attention. First, after the market closes for the day, a stock that has hit its 10% daily price limit is featured on social media such as investment-related television programs, finance websites and traditional newspapers. Investors pay attention to these media channels at the end of the trading day in order to get information before the next trading day. In many cases, they will list these stocks based on their daily returns, which makes the ones with higher returns more salient. Second, most investors use trading software to submit orders. For most trading software, the quickest way for investors to get the list of stocks which hit daily price limit is to rank them by returns. This will also rank the ones with higher returns on the top, which makes them more salient and attract higher attention. Empirically, we find that, among the stocks which hit daily upper price limit, the ones with larger returns attract significantly more attention than others with lower returns.

Conditional on stocks hitting their upper price limits, the differences in their daily returns are small and are purely determined by the rounding effect which is unlikely to contain any information about firm fundamentals. The difficulty of acquiring information on these stocks does not depend on their daily return limits, and it is unlikely that the attention difference is rationally allocated by investors. Lou (2014) find that firms have incentives to manage investor

[1] See the Institutional Background and Empirical Design section for more details.

attention opportunistically by adjusting firm advertising activities to exploit the temporary return effect of investor attention. Corporate opportunistic activity may matter whether a stock hits its daily price limit or not, but we think that it is unlikely to differ between limit hitting stocks with different daily returns. In order for a firm to do this, they need to manage its stock price deliberately to close at some specific number and make sure that the stock will hit the upper price limit the next trading day, which is a small probability event to begin with. In addition, as we document, the price effect is temporary, it is unclear how firms can benefit from it. Empirically we do not find any significant difference between upper limit hitting stocks with different daily returns. Therefore we argue that the upper price limit events provide us quasi-random attention differences.

Our empirical strategy relies on comparing the 10% upper price limit hitting stocks with different daily returns on the same day. We focus on the days with at least five 10% upper price limit hitting stocks. For each event day, we sort them into two groups based on the median daily returns: High group contains the stocks with equal or higher than median daily returns, and Low group contains all other 10% upper price limit hitting stocks. We find that, relative to stocks in the Low group, stocks in the High group attract significantly more investor attention. In the days after the price hitting day, relative to stocks in the Low group, the ones in the High group have significantly higher trading volume, better liquidity and higher return volatility. Consistent with Barber and Odean (2008), we also find that High group stocks' returns on the day after they hit price limit is significant higher, and the difference reverses at least partially in two weeks.

The economic magnitudes are large. At day t (the event day) and also t+1, relative to stocks in the Low group, the attention for stocks in the High group increases by more than 60% of their normal time level. On t+1, relative to stocks in the Low group, trading volume of stocks in the High group increases by more than 19.8% of their normal time level, return volatility increases by more than 21.0% of their normal time level, and abnormal return of stocks' in the High group is around 40 basis points larger.

The literature has proposed two channels for investor attention to affect asset prices: First, rational investor learning enhances price discovery and reduces information asymmetry, which can lead to higher trading volume and better liquidity. Enhanced price discovery can also make price more reactive to fundamental information and increase volatility (Amihud and Mendelson, 1987; Andrei and Hasler, 2015a). Second, attention can lead to more participation of noise traders. This can lead to increased volume, and better liquidity (Kyle, 1985), and also higher volatility (De Long, Shleifer, Summers, and Waldmann, 1989, 1990; Foucault, Sraer, and Thesmar, 2011). Empirically, we find that, relative to the Low group stocks, the High group stocks attract more individual investors buying, and their return comovement with the small stocks increases. Also importantly, we also find that relative to the Low group stocks, the High group stocks price efficiency decreases. Overall, the evidence is consistent with the second view that attention attracts noise trader trading, which lowers market quality.

To further rule out the possibility that stocks in the High group and the Low group are inherently different and the differences may affect the asset pricing dynamics in the period after they hit upper price limit, we conduct a placebo test. Between May 21, 1992 and December 15, 1996 (both inclusive), there was no limit for daily stock price movement. We construct *hypothetical* 10% price limit events for this period by applying the price limit rule that is only effective after this period, and conduct analysis by comparing *hypothetical* High and *hypothetical* Low. If stocks in the High and the Low group are inherently different, we should expect the hypothetical price limit events will deliver similar findings as the real price limit events in the post-December 16, 1996 period. If attention is the driving force, we expect no significant difference between the hypothetical High and hypothetical Low, because there is no priori that attention between the hypothetical High and the hypothetical Low is different. Empirically we do not find any significant difference between the hypothetical High and hypothetical Low, providing further evidence on the importance of attention.

On the two Chinese stock exchanges, there are also other daily price limit events. First, there are -10% lower price limit. Second, there are upper and lower limits for a group of “special treatment” stocks (“ST” stocks), which are ±5%. The same as the upper price limit events for “normal” stocks, conditional on a particular group of stocks hitting their upper/lower limits, their maximum or minimum daily return differences do not contain much information. However, we do *not* expect that they will attract significantly different investor attention. First, given short selling is not allowed in most of our sample period and is very costly in the end of our sample period, together with the fact that prices of stocks hitting lower limit tend to continue to decrease, only investors who already hold the stocks have incentive to pay attention to stocks hitting lower price limits. Given that selling decision is much less sensitive to attention than buying decision (Barber and Odean, 2008), investor trading is unlikely to be different between lower price limit hitting stocks. Second, “ST” stocks’ return limits are much narrower than that of “normal” stocks. ±5% returns are typically not the most extreme returns. In trading software, ranking by daily returns typically does not put them in the most salient positions. In practice, media coverage of “ST” stocks is also lower. Empirically, consistent with these predictions, we find no significant differences in attention or other characteristics between price limit hitting stocks with different daily returns for lower price limits of “normal” stocks, upper or lower price limits of “ST” stocks.

Our study belongs to the growing literature on how investor attention affects investor trading behavior and asset prices. A large body of theoretical studies have examined how attention constraints affect investors' trading behavior and portfolio choice (Abel, Eberly, and Panageas, 2007; Van Niewerburgh and Veldkamp, 2010; Hendershott, Li, Menkveld, and Seasholes, 2014), price informativeness (Peng, 2005), return comovement (Peng and Xiong, 2006; Mondria, 2010), return volatility (Andrei and Hasler, 2015a), asset price levels (Barber and Odean, 2008; Andrei and Hasler, 2015a), and corporate policy (Hirshleifer and Teoh, 2003).

There is also a large body of empirical literature on attention. The empirical literature has proposed various proxies for attention, such as extreme returns (Barber and Odean, 2008; Seasholes and Wu, 2007), trading volume (Gervais, Kaniel, and Mingelgrin, 2001; Barber and Odean, 2008; and Hou, Peng, and Xiong, 2009), news and headlines (Huberman and Regev, 2001; Barber and Odean, 2008; Tetlock, 2011; Yuan, 2015), advertising spending (Chemmanur and Yan, 2009; Grullon, Kanatas, and Weston, 2004; Lou, 2014; Madsen and Niessner, 2015), Google Search Volume Index (Da, Engelberg, and Gao, 2011), Retweeted Twitter news (Chawla, Da, Xu, and Ye, 2015), release of stale information (Huberman and Regev, 2001; Tetlock, 2011; Gilbert, Kogan, Lochstoer, and Ozyildirim, 2012), and distraction by weekends or contemporaneous events (DellaVigna and Pollet, 2009; Hirshleifer, Lim, and Teoh, 2009; Louis and Sun, 2010).

We extend the literature on attention in two ways. First, we develop an empirical strategy in which we can identify the causal effect of exogenously attracted attention, while the existing empirical studies have struggled to do.[2] Second, existing studies almost exclusively focus on the

[2] For example, as argued by Da, Engelberg, and Gao (2011, p.1462), some of these proxies "…make the critical assumption that if a stock's return or turnover was extreme or its name was mentioned in the new media, then investors should have paid attention to it. However, return or turnover can be driven by factors unrelated to investor attention and a news article in the *Wall Street Journal* does not guarantee attention unless investors actually read it."

effect of attention on stock returns. Studies on how attention affects other important aspects of the financial markets such as trading volume, liquidity, volatility, return comovement, and price efficiency are limited. Notable exceptions are Hirshleifer, Lim, and Teoh (2009) and Chawla, Da, Xu, and Ye (2015). Hirshleifer, Lim, and Teoh (2009) study how attention affects volume reaction to earnings announcement and find lower attention is associated with lower volume reaction.[3] Chawla, Da, Xu, and Ye (2015) document that retail attention leads to lower bid-ask spread. However, to our best knowledge, no studies have examined returns, return volatility, trading volume, pricing efficiency, and return comovement altogether and in a systematic way.

We also contribute to the literature on noise trader (Black, 1986; De Long, Shleifer, Summers, and Waldmann, 1990; Shleifer and Summers, 1990). Systematically correlated noise is a necessary condition for noise to have effect on asset prices (Shleifer and Summers, 1990). Many studies have documented that noise trading is indeed correlated (Kumar and Lee, 2006; Barber, Odean, and Zhu, 2009b). Shleifer and Summers (1990) argue that investor behavior biases can lead to correlated noise trading. The findings of this study suggest that attention is also one mechanism to cause correlated noise trading.

It is worth pointing out that our findings do *not* imply that attention always causes price inefficiency. The consequences of attention are likely to depend on the nature of attention and also the nature of the focal assets. First, in this study, the attention difference across price limit

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Both DellaVigna and Pollet (2009) and Hirshleifer, Lim, and Teoh (2009) have extensive discussions and smart tests on the endogeneity of their measures of attention. But both admit that they cannot exclude all the possible endogeneity possibilities. Liu and Peng (2015) document strong evidence that investor allocate their attention. They find that investor attention (proxied by Google Search Volume Index) is lower on Fridays and in the summer months, investors actively allocate their attention in response to information shocks (such as firm earnings announcement) and prioritize their information processing to large firms and systematic shocks. These results suggest that it is important to control for the endogeneity of investor attention.

[3] Some studies use abnormal volume (Gervais, Kaniel, and Mingelgrin, 2000; Barber and Odean, 2008; Hou, Peng, and Xiong, 2009; Da, Engelberg, and Gao, 2011) as a measure of attention, and Da, Engelberg, and Gao (2011) find the trading volume and their attention measure – Google Search Volume – are positively correlated, but they do not examine the causal relationship between attention and trading volume.

hitting stocks with small different returns is unlikely to be a rational decision of investors. Therefore, our finding may not be applicable to settings where attention is predominantly rationally allocated. Distinguishing rationally allocated and exogenously caused attention may help reconcile why the previous literature document that higher attention is associated with worse price efficiency in some situations (Barber and Odean, 2008) and is associated with better price efficiency in others (DellaVigna and Pollet, 2009; Hirshleifer, Lim, and Teoh, 2009). Second, for assets like stocks, their prices are noisy and their valuations are subjective in nature, which leaves space for noise traders. But for assets that are not as speculative (e.g., Treasury securities), even exogenously attracted attention may have limited effect.

We are not the first paper to use price limit events of Chinese stocks to measure investor attention. Seasholes and Wu (2007) is an important predecessor. However, there is a critical difference between their methodology and ours. They investigate investor behavior and return patterns of *all* upper price limit events, while we compare the differences *across* the stocks which hit price limits. While Seasholes and Wu (2007)'s findings are inspiring and in spirit also consistent with our findings, the endogeneity of price limit events constrains their ability to make causal inferences, especially on volatility, volume, liquidity, price efficiency and return comovement.

The paper proceeds as follows. In Section 2, we discuss relevant institutional background of the Chinese stock markets. We also discuss why we focus on the 10% upper price limit events of "normal" stocks but not other price limit events. In Section 3, we discuss our data and report summary statistics. Section 4 reports the empirical results, including a placebo test and robustness tests. Conclusion is in Section 5.

2. Institutional Background

China's two stock exchanges, the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE), were established in December 1990 and July 1991, respectively. The number of listed stocks increases from less than 20 in 1991 to around 2,500 in early 2015. Total market capitalization increases from RMB10 billion to RMB40 trillion.[4] Both exchanges are pure limit order book market. Short selling was prohibited in China before the implementation of a pilot scheme in March 2010 and the number of shortable stocks was expanded later on. However, even among the shortable stocks, short selling is costly and short selling volume is typically less than 1% of daily trading volume.

At the very beginning when the two exchanges were established, both had daily price limit rules. The major purpose was to restrict excess speculative trading and excess volatility. The daily limits varied in different time periods from 0.5% to 5%, were frequently adjusted, and could also be different for different stocks even they were listed in the same exchange. In this early period, there were only dozens of listed stocks. The demand for stocks was very high. The price limits were so frequently hit that trading volume was extremely low. On May 21, 1992, the price limit rule was completely lifted.

SSE and SZSE re-established the price limit rule on December 16, 1996 and the rule largely keeps unchanged until today. For most of the stocks ("normal" stocks), daily absolute stock price movement is restricted to 10% of the previous trading day's close price. On April 22, 1998, SSE and SZSE started to label a group of stocks as "special treatment" stocks (or "ST" stocks). These stocks have a narrower daily price limit of ±5%. A stock is labelled as an "ST" stock if its accounting profits are negative for two consecutive years or if the net asset value per share is lower than the par value of the stock. For both "normal" stocks and "ST" stocks, trading

[4] The exchange rate between RMB and USD is in the range of 5.3RMB/USD to 8.6RMB/USD.

can continue to take place after its stock price hits the upper (lower) price limit, but the trading price cannot take place out of the range of the daily price limits.[5] However, price limits are lifted on the first trading day of IPO stocks or when a stock is emerging from long trading suspension.

In both SSE and SZSE, the minimum tick size for stocks is RMB 1 cent. Therefore, in cases where ±10% (or ±5% in case of "ST" stocks) price change is not an integral number of cents, daily price limit is rounded to the nearest cent. Consider the following example. Suppose there are three stocks: A, B, and C. Their close prices at the previous trading day are 9.99RMB, 10.00RMB, and 10.01RMB, respectively. Rounded to the nearest cent, their 10% price movement are all 1.00RMB. Though they all have the same dollar value for daily price movement, their return limits are different. Returns at upper (lower) limits are 10.01% (-10.01%), 10.00% (-10.00%), and 9.99% (-9.99%), for A, B, and C, respectively.

As we discussed in the Introduction, stocks with the higher daily returns are more likely to be in a more salient places and attract higher attention. In the previous example, if the three stocks all hit upper price limits, the differences in their returns determine their relative salience, with A attracts the most attention, C the least, and B in the middle. However, this is less applicable to lower price limit events. Because of short selling constraint, only the investors who already hold the stocks have incentive to pay attention to stocks hitting lower price limits. Given that selling decision is much less sensitive to attention than buying decision, investor trading is unlikely to be different between lower price limit hitting stocks. This is also less applicable to "ST" firms. Because their daily return range is around 5%, they are very unlikely to be ranked the highest or lowest among all the stocks. Overall, stocks hitting ±5% or -10% price limits but with different returns are unlikely to attract significantly different investor attention. Our empirical analysis confirms this. In our empirical analysis, we therefore focus on the upper price

[5] This is different from trading halt we typically see in the U.S. In trading halt, trading of a security is suspended.

limit events of “normal” stocks.

3. Data and Summary Statistics

We restrict our sample to China’s A-shares (i.e., shares that are quoted and traded in Chinese yuan).[6] Our daily stock return, price, volume, and number of shares outstanding data, and annual firm-level accounting data are from the China Stock Market & Accounting Research (CSMAR) Database. We also collect the intraday data from CSMAR. Both SSE and SZSE adopt a centralized computerized order-matching system without market makers. The intraday database includes data items of intraday transactions, such as stock code, trade size, price, and trade time. The database also provides an indicator on whether the trade is buyer initiated or seller initiated. Thus we do not need to infer it. Our sample period of price limit events starts from December 16, 1996, as that was when SSE and SZSE established the current price limit rule. Our sample stops at March 31, 2015. This was the latest data we have when we started this project. In this sample period, the number of listed firms increases from around 500 to around 2,500. The availability of the intraday data is slightly different. Our sample for the intraday data is from January 2000 to October 2014. CSMAR does not cover intraday before 2000 and post-October 2014 intraday data was not available when we started this project.

In our sample period, there are 4,910 trading days. Out of them, 3,773 days have at least 1 upper price limit event for “normal” stocks (i.e., 10% upper price limit event). Because we compare 10% upper price limit stocks with different daily returns on the same day, we require

[6] There are two types of shares in China: A shares and B shares. A-shares are restricted to domestic investors, and B-shares were restricted to foreign investors before February 2001 when domestic individual investors were allowed to participate in the B-share market. A-shares are quoted and traded in Chinese local currency (Chinese yuan), Shanghai B-shares are quoted and traded in US dollar, and Shenzhen B-shares are quoted and traded in Hong Kong dollar. In the end of our sample period, there are around 2,500 A share companies, but only around 100 B share companies. The B share market liquidity is also much worse than the A share market.

that there are at least 5 such stocks for a day. Out of the 3,773 days with at least 1 upper price limit event for "normal" stocks, 2,505 have at least 5 such stocks. In total, we have 54,706 price limit events. Figure 1 shows the distribution of number of upper price limit events for "normal" stocks. The number of days with 5 events is 170. This number of days decreases gradually when number of events increases. The day with the largest number of such events is September 19, 2008, which has 1,234 "normal" stocks hitting 10% limit. On that day, the market index increases by 9.45%. Days like this are unusual. There are only 66 days with more than 70 upper price limit "normal" stocks. The mean (median) number of such stocks in a day is 21.8 (14). In our empirical analysis, we weight each event day equally rather than weighting each event stock equally. Therefore, our results are not affected by these unusual days.

Our measure of investor attention is from *hexun.com*. In China, *hexun.com* is one of the largest websites specializing providing financial information. They provide real time trading data and the latest accounting data for all the Chinese stocks. Each stock has its own web page. Starting from July 10, 2009, it started to provide, stock by stock, the number of viewers via its website. Viewers are identified based on their IP address. Relative to Google Trends data, there is no ambiguity on identifying stocks. It is also reasonable to assume that all views are for trading purposes, and viewer data rather than views/searches data avoids double counting of views/searches done by the same person. In addition, the coverage of *hexun.com* is much better than Google Trends which does not return valid data for many stocks in our sample.[7] We manually collected viewer data until March 31, 2012, when the website changed its reporting format, which makes the data collection too costly to collect.[8] Across all the stocks with

[7] Google was never the biggest search engine in China, even before it exited China in 2010.
[8] After the change, hexun.com started to report cumulative intraday number of viewers, and the updating frequency is 15 minutes. This does not make data collection completely impossible, but it does increase the collection difficulty significantly. The only way we can collect the aggregated daily data is to wait until mid-night and collect

available data, the mean (median) number of daily viewers is 3,459.28 (1,512). The 1st percentile and the 99th percentile are 134 and 30,557, respectively. The large average number of viewers per stock confirms that *hexun.com* is a widely used website for financial information.

Our empirical strategy relies on comparing 10% upper price limit stocks with different daily returns on the same day. For days with at least 5 such stocks, we sort them into two groups: High group contains the stocks with above median returns, and Low group contains others. In case of ties at the cutoff between Low and High, we classify them into the High group. The tie cases are mostly stocks with exactly 10% daily returns. Classifying them into the Low or High group makes little change of the final results.

Table 1 reports the summary statistics of the 10% upper price limit stocks, for High and Low groups separately. For each variable, we first calculate the daily average for High, Low, and High minus Low, and then calculate the averages across different event days. By doing this, we weight each event day (rather than each event stock) equally. In order to mitigate the effect of outliers, we winsorize all continuous variables at 1% level for both tails except returns which does not seem to have extremely values. For High-Low, we report its mean, median, t-test testing whether the mean is statistically different from zero, and the p-value of Wilcoxon signed-rank test. The Wilcoxon signed-rank test is a nonparametric alternative to the t-test, but it is solely based on the order in which the observations fall, and therefore is not very sensitive to extreme values.

On average, there are 12.36 stocks in the High group and 9.51 stocks in the Low group. The difference is because we classify ties (mostly stocks with exactly 10% return) into the High group. Day *t* is the day of the price limit day. The means of $Return_t$ are 10.032% and 9.974% for

the data before the next update which is in 15 minutes. While, before this, the updating frequency was 24 hours and we had 24 hours to collect the data. We contacted data service staff at hexun.com and they refused to share or sell.

High and Low, respectively. By the construction of the sample, the high statistical significance is not surprising. However, the difference is only around 5 basis points which are economically small. We also report firm size (logged market capitalization), logged price and price at t-1. None of the three variables show any statistically or economically significant difference.

In the end, we report a few other stock characteristics. Turnover is daily trading volume scaled by the number of tradable shares.[9] We use relative bid-ask spread to measure liquidity and realized variance to measure return variation. We calculate both measures from intraday data. Relative spread is defined as bid-ask spread divided by the average of bid and ask. Daily relative spread is averaged across all the prevailing quotes for all the trades within a day. Realized variance for stock i is defined in a "model-free" fashion by

$$\mathrm{RV}_i^t \overset{\text{def}}{=} \sum_{i=1}^{n} [p_j^i - p_{j-1}^i]^2, \tag{1}$$

where p_j^i denotes the logarithmic price (midpoint of bid and ask) of stock i at the end of the jth 10-minutes interval in day t. This model-free realized volatility based on high-frequency intraday data is more accurate than the realized volatility based on daily returns (Andersen, Bollerslev, Diebold, and Labys, 2001a, 2001b). It also provides us a daily measure of volatility, making us able to compare return variations day by day around price limit events.

For all the three variables, we calculate them for two periods: one from t-125 to t-21 and the other from t-20 to t-1. We do the calculation for these two periods separately because the period shortly before the price limit events (t-20 to t-1) may be different from the normal time (t-125 to t-21). We want to make sure that the High and Low groups of stocks are not different in

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[9] Originally because the government did not want to lose control of the state owned enterprises, most of the shares owned by the government were not allowed to trade in the public market. These nontradable shares accounted for around two thirds of the total market capitalization. Starting from 2005, via the split share structure reform, most of these shares gradually became tradable. We measure turnover as trading volume divided by the number of tradable shares to reflect this feature. However, if we dividing trading volume by total number of shares outstanding, the results are similar.

both periods. For each variable, we first calculate its daily value and then calculate its time series mean. The results in Table 1 shows that turnover and volatility in the *t*-20 to *t*-1 period is higher than in the *t*-125 to *t*-21 period, and relative spread keeps constant. The increase of turnover and volatility suggests that stock trading in the month leading to price limit events is different from normal times. However, the changes of these variables are similar for both the High group and the Low group, and we do not find any significant difference between them in any of the three variables or in any period. To further compare the High group and the Low group, in later analysis, we also report these firm characteristics from *t*-5 to *t*-1 on a daily basis. We do not find any significant difference between the High group and the Low group either.[10] Overall, these results confirm that the High group stocks and the Low group stocks are comparable to each other in the periods *before* they hit the 10% upper price limits, at least for the observable characteristics we examine.

4. Empirical Results

4.1 Methodology

In this section, we compare the differences between the High group and the Low group. First, we show direct evidence that the High group and the Low group attract significantly different investor attention. Then, we compare whether they are different in terms of average returns, trading volume, liquidity and return volatility in the periods *after* they hit the 10% upper price limits. In the end, we compare their differences in price efficiency and investor trading behavior to shed light on the mechanism of the effects of investor attention.

As before, turnover is defined as trading volume divided by the number of total tradable

[10] Please see Table 2 to Table 7 for details.

shares. Liquidity is defined as relative spread which is bid-ask spread divided by the bid ask midpoint. Return volatility is measured as realized variance as in equation (1). We use the standard event study method to gauge the difference between the High group and the Low group, for both returns and other variables. For a given variable *X*, we do the following:

(1) We first calculate the abnormal change of *X* (denoted as *AbnX*) for each price limit stock.

(2) For a given day with at least 5 upper price limit "normal" stocks, we calculate the average *AbnX* for the High group and the Low group separately.

(3) We calculate the time series average of the daily mean *AbnX* from (2) and also the difference of it between the High group and the Low group. We also calculate the statistical significance for High-Low, based on the time series data.

For all these variables, we calculate and report the statistics for these window periods: every day from *t*-5 to *t*+5, (*t*+6, *t*+10), and (*t*+11, *t*+20).

In step (1), we adjust different variables differently. For return, we calculate the abnormal return as the difference between raw return and the contemporaneous value weighted size decile portfolio return to make the adjustment. Size deciles are formed at the end of June of each year and rebalanced annually. For investor attention, turnover, relative spread, and realized variance, we calculate their abnormal changes as

$$AbnX_{i,t-j} = \frac{X_{i,t-j} - \sum_{j=-125}^{-21} X_{i,t-j}}{\sum_{j=-125}^{-21} X_{i,t-j}}. \qquad (2)$$

This adjustment can help us control for the cross sectional differences in the unconditional levels of these variables. In order to include a stock into our sample, we require that there are at least 60 data points in the *t*-125 to *t*-21 window.

4.2 Main Results

4.2.1 Investor Attention

Table 2 shows the results on investor attention using the viewer data from *hexun.com*. We have the viewer data for 249 days with enough number of upper price limit events of "normal" stocks. On *t*-5, the average abnormal investor attention is 0.471 and 0.485 for High and Low, respectively. This means that relative to normal times, number of viewers increases by around 50% on *t*-5. It continues to increase, reaches the highest at the event day, and gradually decreases. For the five days before the event day, we do not see any significant difference between High and Low. But starting from the event day, the divergence appears. On day *t* and *t*+1, High-Low is 0.603 and 0.610, respectively. This means the difference in attention is more than 60% of normal time attention level. Both are statistically significant and economically large. High-Low then gradually decreases. But even in the period from *t*+11 to *t*+20, the mean of High-Low is still 0.149 and the median is 0.130, both of which are statistically significant though the mean is only marginally so. For the 20 days from *t*+1 to *t*+20, the mean (median) of High-Low is 0.215 (0.175) and both are statistically and economically large. Overall, the results in Table 2 confirm that the small difference in daily return limits between High and Low leads to large differences of investor attention allocation, and therefore validate our empirical strategy.

4.2.2 Average stock returns

Table 3 shows the results on stock returns adjusted by size decile portfolios. The results show that, for both High and Low, their stock prices start to increase at least 5 days before the event days. It also shows an increasing pattern. At *t*-1, the average size-decile adjusted returns are 1.533% and 1.579% for High and Low, respectively. Not surprisingly, day *t* shows the largest adjusted returns. From Table 1, the average raw returns are 10.032% and 9.974% for High and

Low, respectively. Size-decile adjustment reduces them to 9.258% and 9.210%, suggesting that on the days with at least 5 price limit events, the contemporaneous market returns are also likely to be high. Abnormal returns continue to be positive for day t+1 to t+3 and then start to decrease. This is consistent with Seasholes and Wu (2007) who also document a similar pattern.

For the 5 days before the event day, we only see significant difference between High and Low for t-4, which is only marginally significant. For the other four days, we do not see any significant difference. We also conduct a test (but unreported) for the difference between the cumulative returns from t-5 to t-1 and find no statistical significance. On day 0, the mean and median of High-Low are both around 0.05%, which are similar to the unadjusted return as shown in Table 1. On t+1, the mean and median of High-Low are 0.396% and 0.500%, both of which are economically large and highly statistically significant. From t+2, High-Low becomes negative (except for t+3 when High-Low is almost exactly 0) and is statistically significant for t+5. In unreported results, we investigate the difference between the cumulative returns from t+2 to t+10 and find that the average High-Low is -0.332% which is significant at 1% level. The difference in cumulative returns from t+1 to t+10 is 0.065%, which is insignificant. This suggests that the initial difference between High-Low largely reverses by t+10. From t+11 to t+20, the average of High-Low is only 0.070% and is not significant anymore.

Overall, these results provide strong support to Barber and Odean (2008) that attention causes price increase in the short-run and eventual price reversal.

4.2.3 Trading volume, liquidity, and volatility

Table 4, Table 5, and Table 6 report the results on trading volume, liquidity, and return volatility. We find that from t-5 to t-1, both trading volume and return volatility are at higher levels than normal times, and increase from t-5 to t-1. However, from t-5 to t-1, relative spread is slightly lower than that of normal times and shows a much weaker upward trend. All the three variables reach their highest levels either at day *t* or *t*+1. In the post event period, all three variables show decreasing trend. The decrease of relative spread is consistent with that private information is gradually incorporated into stock price.

For the three variables in the pre-event windows, occasionally we find significant difference between High and Low: the *t*-test of volume at *t*-1, the Wilcoxon test of liquidity at *t*-4, and the Wilcoxon test of volatility at *t*-2. However, none of the test is strong (one is significant at 5% level, and the other two are only significant at 10% level), no single change are significant for both the *t*-test and the Wilcoxon test, and their economic magnitudes are also quite small. Given that in total we have 30 statistical tests, it is not surprising to have a few cases which show statistical significance just by chance. Overall, the difference between High and Low in the pre-event windows is very small.

In contrast, the post-event windows show large differences between High and Low. The volume difference between High and Low becomes positive from *t*+1 and is almost always so until *t*+20. The magnitude is also large. On *t*+1, the difference is 19.7% of a stock's unconditional daily trading volume. Even in the period from *t*+11 to *t*+20, the difference is still 4.1%. The difference of relative spread between High and Low also starts to be significant from *t*+1, and is also significant at *t*+3 and *t*+4. However, the economic magnitude seems small: only 0.9% of the level of relative spread of normal times. From Table 1, we know that relative spread in normal times is around 0.22%. This means that the attention difference between High and Low only causes 0.002% (0.22%*0.9%) difference in relative spread. Similar to the other two measures, the difference of volatility between High and Low starts to be different from *t*+1. The difference becomes highest at *t*+1 and then gradually decreases. At *t*+1, the volatility difference between High and Low is 0.214 of the level of volatility of normal times and gradually decreases to 0.023 in the period between t+11 and t+20.

Overall, the results on trading volume, liquidity, and return volatility show a few interest patterns. First, in the post-event period, relative to the Low group, the High group stocks have larger trading volume, better liquidity and higher volatility. Second, the effect of trading volume and volatility is larger and persists longer, but the effect of liquidity is smaller and only lasts for a few days.

4.2.4 Price efficiency

There are two channels for investor attention to affect asset prices: First, rational investor learning enhances price discovery and reduce information asymmetry, which can lead to higher trading volume and better liquidity. Enhanced price discovery can also make price more reactive to fundamental information and increase volatility (Amihud and Mendelson, 1987; Andrei and Hasler, 2015a). Second, attention can lead to more participation of noise traders. This can lead to increased volume, and better liquidity (Kyle, 1985), and also higher volatility (De Long, Shleifer, Summers, and Waldmann, 1989, 1990; Foucault, Sraer, and Thesmar, 2011).

The two channels are both consistent with the findings of trading volume, liquidity, and volatility. But we are not aware of any existing rational learning attention models that can explain the findings on returns, while the increased noise trader participation channel can (Barber and Odean, 2008). In this part, we conduct more analysis on the mechanism by testing another key difference between these two channels: rational learning predicts better information efficiency, but increased noise trading participation predicts the opposite.

We measure price efficiency using variance ratio. We follow the methodology in O'Hara and Ye (2011) and use intraday data to compute the variance ratio as the absolute value of one minus the variance of 10-minute log returns divided by two times the variance of 5-minute log returns. To mitigate the effect of bid ask bounce, returns are calculated based on the midpoint of bid and ask. A ratio of zero is consistent with stocks following a random walk. Hence, a smaller number is better in terms of price efficiency (Lo and MacKinlay, 1988).

Table 7 reports the results on price efficiency. Similar to other variables, we also make adjustment based on equation (2) to calculate abnormal level variance ratio. The abnormal variance ratio of High at *t*-5 is -0.006, which means that variance ratio of High at *t*-5 is 99.4% of its normal time average. We find that, from *t*-5 to *t*-1, variance ratio is close to normal times and increases marginally from *t*-5 to *t*-1. On day *t*, adjusted variance ratio decreases to -0.072 and -0.059 for High and Low, respectively.[11] Starting from *t*+1, adjusted variance ratio increases to be higher than 1 and gradually decreases to -0.017 and -0.016 for High and Low, respectively, in the period from *t*+11 and *t*+20. The difference between High and Low is significant for both *t*+1 and *t*+2, but insignificant for other days. These results suggest that price efficiency of High decreases more than Low, but the relative decrease is a short term phenomenon.

The relative larger decrease of price efficiency of High than Low provides further evidence for the increased noise trader participation channel. In the next section, we show more direct tests whether attention attracts more small investors than large investors.

4.2.5 Investor trading behavior

The noise trader channel predicts that noise traders are more likely to be affected by attention and they buy more than other investors after the attention-grabbing events. As we do not directly observe investors' trading, we infer it in two ways. First, we infer it from order

[11] The change may be due to the special trading arrangements of price limit events. When a stock hits upper price limit, though trading may continue, but price hardly moves. New information stops being incorporated into price. Both 5-minute returns and 10-minute returns all become zero and variance ratio will be close to zero. However, in this case, smaller variance ratio may not indicate higher efficiency.

imbalances of trades of different size. Many studies have documented that less sophisticated investors are more likely to make small trades than more sophisticated investors (Lee and Radhakrishna, 2000; Hvidjaer, 2008; Barber, Odean, and Zhu, 2009b). Following these studies, we use trade size to proxy for investor sophistication. We expect that the High group stocks should attract more small buy orders than the Low group. Second, we infer increased individual investor participation from the change of stock return comovement with small stocks. Small stocks tend to be held by individual investors. Individual investors are more likely to be affected by sentiment (Lee, Shleifer, and Thaler, 1991; Kumar and Lee, 2006). If the High group stocks attract more individual investor participation than the Low group, we should expect that, relative to the Low group stocks, the High group stocks' return comovement with small stocks will increase more.

Order imbalance. We sort all the trades into three groups: small trades are the trades with value equal to or lower than 20,000RMB, medium trades are the trades with value equal to or lower than 100,000RMB, and large trades are the trades with value larger than 100,000RMB. 20,000RMB is roughly the median trade size of all the trades across all the stocks for the sample we have intraday data, and 100,000RMB is roughly the 83rd percentile.[12]

We measure order imbalance as the value of buyer-initiated trades minus the value of seller-initiated trades divided by the total value of trades. We calculate its abnormal level as $AbnX_{i,t-j} = X_{i,t-j} - \sum_{j=-125}^{-21} X_{i,t-j}$. We do not divide it by its unconditional mean as we do for trading volume, liquidity and volatility, because for many stocks, the unconditional mean of order imbalance in the period between *t*-125 and *t*-21is negative or near to zero.

[12] The choice of cutoffs is inherently arbitrary. Therefore we also check the results by changing the cutoffs. Our results are robust if we set the maximum small trade size cutoff from 20,000RMB to 10,00RMB, 30,000RMB, 40,000RMB, or 50,000RMB, or if we set the maximum medium trade size cutoff from 100,000RMB to 200,000RMB or 500,000RMB.

Table 9 reports the results on order imbalance analysis. Panel A, Panel B, and Panel C report the results for small trades, medium trades, and large trades, respectively. A few interesting observations emerge. First, leading to the price limit events, large trade order imbalance is positive and increasing, but small trade order imbalance is negative and decreasing, and medium trade order imbalance decreases from being positive to negative. On the event day, large trades have large positive order imbalance, but the other two groups have large negative order imbalance. One possibility is that large trade traders have better information. But before the event day, there is no significant difference between the High group and the Low group.

Second, on t+1, the difference in order imbalance between High and Low is significantly positive for both small trades and medium trades, but not for large trades. This is consistent with the conjecture that smaller investors are more likely to be affected by attention, and large investors are insensitive to attention. On day t+2, the difference is still positive for small trades, but insignificant for medium trades. Interestingly, large trade traders start to sell more of the High group. Large trade traders continue to be net seller for t+3 and t+4. This suggests that large trade traders trade against the short-term mispricing induced by attention difference. From t+5 to t+20, we do not see any statistically significant differences between High and Low for any of the three groups.

Return comovement with small stocks. We measure a stock's return comovement with small stocks by its loading on the small-minus-big (SMB) factor. For each event day, we calculate equally-weighted daily portfolio returns for both High and Low, and then estimate β_{SMB} by running daily portfolio excess returns (raw return minus risk-free rate) on market excess return (MktRf), SMB, the value factor (HML) and the momentum factor (UMD). We do the estimation separately for the pre-event window and post-event window. We construct the China version of the Fama-French-Carhart four-factor model by following Fama and French (1993) and Carhart (1997). Risk free rate is bank deposit rate of China. We define the pre-event period as *t*-40 to *t*-6 and the post-event period as *t*+1 to *t*-40. We exclude the period from *t*-5 to *t*-1 because as we learn from previous results, they are different from normal times. Our results also hold if we also exclude *t*+1 to *t*+5 from the post-event window, or if we change the pre-event window to be between *t*-60 to *t*-21.

For each event day, we get estimates of β_{SMB} for High and Low, and for both pre- and post-event windows. Based on these estimates, we calculate the time series means across all the event days. For completeness, we also report factor loadings of other factors. Table 9 reports the results. Panel A reports the statistics for High, Low, and Panel B reports the statistics for High-Low.

From Panel A, we find that β_{SMB} of the High group does not show significant change between the pre- and post-event windows. However, β_{SMB} of the Low group decreases significantly. The decrease of β_{SMB} of the Low group is not surprising, because price limit events are associated with large positive returns which increase firms' size. It is the difference between the change of the High group and the Low group that captures the effect of attention. Panel B shows that the difference between the change of β_{SMB} of High and Low is 0.062, with *t*-stat of 2.57 which is statistically significant at 5% level.

Panel A also shows that price limit events also change event stocks' loadings on other factors: β_{MktRf}, β_{HML}, and β_{UMD} all increase relative to the pre-event window. However, the increases of β_{HML}, and β_{UMD} are not different between the High group and the Low group. We do find that the increase of β_{MktRf} is significantly larger for the High group. The increase in β_{MktRf} is also consistent with increased noise trader participation. In noise trader models (De Long, Shleifer, Summers, and Waldmann, 1990), the stock market return is partially affected by noise traders. Higher noise trader participation of the High group stocks increases their return comovement with the market more than that of the Low group stocks.

4.3 Placebo test

As we discuss, conditional on stocks hitting their upper price limits, the differences in their daily returns are small and are purely determined by the rounding effect specified by the exchanges. In Table 1, we show that on observable characteristics, the stocks in the High group and the Low group are not significantly different. To further rule out the possibility that stocks in the High group and the Low group are inherently different and the differences may affect the asset pricing dynamics in the period after they hit upper price limit, we conduct a placebo test.

Between May 21, 1992 and December 15, 1996 (both inclusive), there was no limit for daily stock price movement. We construct *hypothetical* 10% price limit events based on stocks' daily prices and returns for this period by applying the price limit rule that is only effective after this period, and conduct analysis by comparing *hypothetical* High and *hypothetical* Low. If stocks in the High and the Low group are inherently different, we should expect the hypothetical price limit events will deliver similar findings as the real price limit events in the post-December 16, 1996 period. If attention is the driving force, we expect no significant difference between the hypothetical High and hypothetical Low, because there is no priori that attention between the hypothetical High and the hypothetical Low is different.

In total, we have 212 days with at least 5 hypothetical 10% upper price limit events, and in total, we have 5,924 event stocks. At the event day, the raw returns for the hypothetical High and the hypothetical Low are 15.711% and 15.597%. Not surprisingly, both are well above 10%.

The difference is 0.114% which is statistically insignificant. This also suggests that, if we did not have price limit rule in the post-December 16, 1996 period, the stocks in the High group and the ones in the Low group may have similar daily returns on the event day. Table 10 reports the results. In this period, we do not have intraday data or the attention data from *hexun.com*. We thus focus on return, turnover, and return comovement. Panel A reports the results on returns (adjusted by size decile portfolios). Panel B reports the results on turnover (adjusted as in Equation (2)). Panel C reports the results on return comovement. None of the three measures show significant differences between the hypothetical High group and the hypothetical Low group.[13]

Overall, we find no evidence that the hypothetical High and the hypothetical Low are different in the period after the hypothetical price limit events. This further confirms that stocks classifying into High or Low are orthogonal to firm fundamentals.

4.4 Results for other price limit events

In this Section, we report the analysis for other three types of price limit events: (1) lower price limits of "normal" stocks, (2) upper price limits of "ST" stocks, and (3) lower price limits of "ST" stocks. Similar to the upper price limit events of "normal" stocks, in unreported results, we also find that, relative to normal times, the average investor attention at day 1 increases significantly. For (1), (2), and (3), the average investor attention at day 1 is around 290%, 200%,

[13] At the event day, the size decile portfolio adjusted returns for High and Low are 9.800% and 9.601%, respectively. The adjustment leads to a 6% decrease in returns. This is mainly due to the fact that in this sample period, the number of firms was small and return synchronicity was also higher. 1992-1996 was the very early stage of China's stock market. The number of listed firms in May 1992 was 28 and increased to 513 by the end of December 1996. In unreported results, we find qualitatively similar results for raw returns. Results are also similar if we "re-allocate" returns following the price limit rule. For example, if a stock had return of 15% and its hypothetical daily return is 10.01%, we "move" 4.99% into the next trading day.

and 170% of their respective levels of normal times. However, this is much lower than the investor attention increase for upper price limit events of “normal” stocks, for which investor attention at day 1 is near to 700% of their level of normal times. This also confirms our conjecture that upper price limit events make the largest increase of investor attention and is most suitable to for our econometric exercise.

Nevertheless, we repeat all the tests we did for upper price limit events of “normal” stocks (i.e., Table 2 to Table 9) for all these three different types of price limit events. The results are reported in Table 11. Panel A, Panel B, and Panel C are for (1), (2), and (3), respectively. In each panel, High indicates the group of stocks with the largest magnitude of daily returns. For upper limits, High includes the stocks with higher returns, but for lower limits, High includes the stocks with lower (more negative) returns. For sake of space, for β_{SMB}, we only report the difference between High and Low in the post-event period. For all other variables, we only report the mean and *t*-tests for High-Low from *t* to *t*+5. Analysis based on median show qualitatively similar results.

From Table 11, we find that, for all the three types of price limit event, High and Low do not attract significantly different investor attention. For other stock characteristics and investor trading variables, overall, we do not find a strong and consistent pattern, though some are occasionally statistically significant.

Overall, the results in Table 11 show that small return difference of daily return limits of these three types of price limit events do not lead to large differences in investor attention. Consistent with investor attention theories, they do not lead to significant differences in stock characteristics or investor trading. Combing the results for upper price limit events for “normal” stocks, these results show the importance of investor attention and its necessity for the price limit events to make differences.

4.5 Excluding stocks priced lower than 5RMB

Our identification relies on daily return limit differences caused by rounding. Though the maximum rounding effect is only half a cent, nevertheless, sometimes the return difference can be large, especially for low-priced stocks. In our sample, the average stock price is 13RMB (see Table 1). For stocks priced around 13RMB, 0.5 cent makes very small difference in their returns. However, we do have stocks priced as low as 2RMB. For them, 0.5 cent means 25 basis points. For daily returns, 25 basis points are economically large. We investigate whether our results are sensitive to the exclusion of them.

Table 12 presents the results. We exclude stocks priced lower than 5RMB and redo all the analysis. The same as before, we require at least 5 price limit events to include an event day into our sample. The 5RMB requirement reduces the number of event days from 2,505 to 2,293. The total number of price limit events decreases from 54,706 to 52,083.[14] Similar to the whole sample analysis, we find very similar results for this restricted sample, suggesting that our results are not driven by extremely low priced stocks.

5 Conclusion

In China, the price limit rule requires that, for most stocks, daily return limit is 10%. But rounding of prices leads to small return deviations from 10%. These small deviations are purely determined by a stock's previous closing price and are orthogonal to firm fundamentals. The difficulty to learn of these stocks does not depend on these small return deviations. However,

[14] Some stocks priced higher than 5RMB are excluded if the exclusion of 5RMB reduces an event day's total number of price limit stocks to be less than 5.

higher returns put stocks in more salient positions. Empirically, we find that the small return differences across upper price limit stocks lead to large differences in investor attention. Using this as natural experiments, we document that higher investor attention causes higher trading volume, better liquidity, higher return volatility, higher short-term returns which reverses at least partially in a few weeks. We also find that higher attention leads to worse price efficiency, more small sized purchases and higher return comovement with small stocks, all consistent with the view that attention attracts noise trader participation, which leads to lower price efficiency.

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Table 1. Summary statistics of price limit hitting events

This table reports the summary statistics of the High group, the Low group, and also their differences. For each day with at least 5 upper price limit events of "normal" stocks, we sort these stocks into two groups based on their daily returns: High includes the ones with above median daily returns and Low includes other. For all the variables, we first calculate the mean for High and Low separately at each day and also their difference: High-Low, and then calculate the time series means. For High-Low, we also calculate median, t-test for the mean, and the p-value of the Wilcoxon signed-rank test. Return_t is the return on day t which is the price limit hitting day. Firm size, log(price) and price are measured at the end of day t-1. Turnover is trading volume divided by the number of shares tradable. Relative spread is the bid-ask spread divided by the midpoint. Realized variance is defined as $\mathrm{RV}_i^t \stackrel{\text{def}}{=} \sum_{i=1}^{n}[p_j^i - p_{j-1}^i]^2$, where p_j^i denotes the logarithmic price of stock i at the end of the jth 10-minutes interval in day t. We scale both turnover and realized variance by 100. The sample period is from December 16, 1996 to March 31, 2015, except relative spread and realized variance for which we only have data from January 1, 2000 to October 2014.

	High	Low	High-Low			
	Mean	Mean	Mean	t-test	Median	Wilcoxon p-value
Number of stocks	12.364	9.508	2.856	(12.24)	1.000	<.0001
Return_t	10.032	9.974	0.058	(77.42)	0.050	<.0001
Firm Size_{t-1}	14.848	14.867	-0.019	(-1.16)	-0.030	0.214
$\mathrm{Log}(\mathrm{Price}_{t-1})$	2.311	2.329	-0.018	(-1.51)	-0.021	0.331
Price_{t-1}	12.958	13.225	-0.267	(-1.10)	-0.206	0.232
Turnover*100 (t-125,t-21)	3.647	3.645	0.002	(0.04)	0.012	0.637
Turnover*100 (t-20,t-1)	4.092	4.077	0.014	(0.49)	-0.004	0.688
Relative Spread (t-125,t-21)	0.221	0.219	0.001	(1.22)	0.002	0.364
Relative Spread (t-20,t-1)	0.215	0.224	-0.009	(-0.60)	0.002	0281
Realized variance*100 (t-125,t-21)	0.173	0.173	0.000	(0.01)	0.006	0.261
Realized variance*100 (t-20,t-1)	0.227	0.214	0.012	(0.79)	0.001	0.343

Table 2. Daily return limits and investor attention

This table reports the analysis on investor attention. Our measure of attention is number of viewers from *hexun.com*. Reported is abnormal investor attention. Abnormal investor attention for stock *i* at day *t+j* is calculated as attention for stock *i* at day *t+j* ($j \epsilon (-5, 20)$) divided by this stock's average attention from *t*-125 to *t*-21 and minus one. For each day with at least 5 upper price limit events of "normal" stocks, we sort these stocks into two groups based on their daily returns: High includes the ones with above median daily returns and Low includes other. For abnormal attention, we first calculate the mean for High and Low separately at each day and also their difference: High-Low, and then calculate the time series means. For High-Low, we also calculate median, t-test for the mean, and the p-value of the Wilcoxon signed-rank test. The sample period is from July 10, 2009 to March 31, 2012.

	High	Low	High-Low			
Window	Mean	Mean	Mean	t-test	Median	Wilcoxon p-value
-5	0.471	0.485	-0.015	(-0.13)	-0.030	0.323
-4	0.502	0.439	0.063	(0.62)	0.009	0.883
-3	0.636	0.546	0.090	(0.84)	0.006	0.579
-2	0.800	0.826	-0.026	(-0.18)	0.028	0.800
-1	1.352	1.303	0.050	(0.27)	0.084	0.533
0	5.989	5.386	0.603	(2.22)	0.419	0.005
1	5.699	5.089	0.610	(2.27)	0.619	0.001
2	3.634	3.099	0.538	(2.51)	0.454	0.001
3	2.836	2.352	0.484	(2.48)	0.284	0.002
4	2.248	2.113	0.136	(0.76)	0.103	0.221
5	1.990	1.807	0.183	(1.07)	0.090	0.243
6-10	1.446	1.325	0.122	(1.02)	0.238	0.048
11-20	0.909	0.760	0.149	(1.71)	0.130	0.009
1-20	1.633	1.418	0.215	(2.13)	0.175	0.004

Table 3. Daily price limits and stock returns

This table reports the analysis on stock returns (measured in percentage) around the price limit events. Returns are measured in percentage. Reported is abnormal stock return. Abnormal stock return for stock *i* at day *t* is calculated as the difference between its raw return and the contemporaneous return of the size decile portfolio the stock belongs to. For each day with at least 5 upper price limit events of “normal” stocks, we sort these stocks into two groups based on their daily returns: High includes the ones with above median daily returns and Low includes other. For abnormal returns, we first calculate the mean for High and Low separately at each day and also their difference: High-Low, and then calculate the time series means. For High-Low, we also calculate median, t-test for the mean, and the p-value of the Wilcoxon signed-rank test. The sample period is from December 16, 1996 to March 31, 2015.

	High	Low	High-Low			
Window	Mean	Mean	Mean	t-test	Median	Wilcoxon p-value
-5	0.162	0.210	-0.048	-1.18	0.009	0.677
-4	0.413	0.336	0.077	1.84	0.073	0.080
-3	0.498	0.549	-0.051	-1.13	-0.039	0.441
-2	0.661	0.736	-0.074	-1.60	-0.021	0.169
-1	1.533	1.579	-0.046	-0.81	-0.020	0.828
0	9.258	9.210	0.048	8.61	0.056	<.0001
1	1.920	1.524	0.396	6.96	0.500	<.0001
2	0.056	0.115	-0.059	-1.13	-0.052	0.354
3	0.036	0.035	0.000	0.01	-0.000	0.857
4	-0.133	-0.086	-0.047	-1.02	-0.043	0.412
5	-0.396	-0.305	-0.091	-2.09	-0.071	0.038
6-10	-0.335	-0.201	-0.134	-1.43	0.021	0.245
11-20	-0.532	-0.602	0.070	0.26	0.130	0.288
1-20	0.619	0.483	0.136	0.68	0.439	0.081

Table 4. Daily return limits and volume

This table reports the analysis on turnover (measured in percentage) around the price limit events. Reported is abnormal turnover. Turnover is defined as daily shares traded divided by a stock's number of tradable shares. Abnormal turnover for stock *i* at day *t+j* is calculated as turnover for stock *i* at day *t+j* (*j*∊(-5, 20)) divided by this stock's average turnover from *t*-125 to *t*-21 and minus one. For each day with at least 5 upper price limit events of "normal" stocks, we sort these stocks into two groups based on their daily returns: High includes the ones with above median daily returns and Low includes other. For abnormal turnover, we first calculate the mean for High and Low separately at each day and also their difference: High-Low, and then calculate the time series means. For High-Low, we also calculate median, t-test for the mean, and the p-value of the Wilcoxon signed-rank test. The sample period is from December 16, 1996 to March 31, 2015.

	High	Low	High-Low			
Window	Mean	Mean	Mean	t-test	Median	Wilcoxon p-value
-5	0.498	0.514	-0.016	-0.75	0.005	0.914
-4	0.562	0.581	-0.019	-0.85	-0.003	0.444
-3	0.656	0.640	0.016	0.69	0.010	0.723
-2	0.773	0.775	-0.002	-0.06	0.004	0.981
-1	1.021	1.084	-0.063	-2.08	-0.007	0.211
0	3.103	3.158	-0.054	-1.18	-0.001	0.578
1	4.173	3.977	0.197	3.81	0.131	<.0001
2	2.720	2.612	0.107	2.55	0.098	<.0001
3	2.248	2.150	0.098	2.47	0.075	0.0002
4	1.946	1.850	0.096	2.70	0.079	<.0001
5	1.690	1.604	0.087	2.65	0.073	0.0001
6-10	1.375	1.343	0.033	1.21	0.022	0.061
11-20	0.989	0.948	0.041	1.88	0.027	0.014
1-20	1.481	1.422	0.059	2.45	0.039	0.002

Table 5. Daily return limits and liquidity

This table reports the analysis on relative spread around the price limit events. Reported is abnormal relative spread. Relative spread is defined as bid-ask spread divided by the average of bid and ask. Daily relative spread is averaged across all the prevailing quotes for all the trades. Abnormal relative spread for stock *i* at day *t+j* is calculated as relative spread for stock *i* at day *t+j* (*j*ϵ(-5, 20)) divided by this stock's average relative spread from *t*-125 to *t*-21 and minus one. For each day with at least 5 upper price limit events of "normal" stocks, we sort these stocks into two groups based on their daily returns: High includes the ones with above median daily returns and Low includes other. For abnormal relative spread, we first calculate the mean for High and Low separately at each day and also their difference: High-Low, and then calculate the time series means. For High-Low, we also calculate median, t-test for the mean, and the p-value of the Wilcoxon signed-rank test. The sample period is from January 1, 2000 to October 31, 2014.

	High	Low	High-Low			
Window	Mean	Mean	Mean	t-test	Median	Wilcoxon p-value
-5	-0.009	-0.015	0.005	1.49	0.004	0.188
-4	-0.012	-0.016	0.004	1.13	0.006	0.088
-3	-0.016	-0.018	0.002	0.44	0.004	0.216
-2	-0.011	-0.011	-0.000	-0.02	0.002	0.488
-1	-0.002	-0.003	0.001	0.19	0.000	0.743
0	0.060	0.057	0.003	0.40	0.009	0.148
1	-0.104	-0.095	-0.009	-2.37	-0.005	0.014
2	-0.091	-0.090	-0.002	-0.47	0.000	0.500
3	-0.103	-0.095	-0.007	-2.22	-0.003	0.126
4	-0.107	-0.101	-0.006	-1.90	-0.002	0.162
5	-0.108	-0.104	-0.004	-1.23	-0.001	0.570
6-10	-0.110	-0.108	-0.002	-0.74	-0.003	0.361
11-20	-0.114	-0.111	-0.003	-1.10	-0.001	0.430
1-20	-0.110	-0.107	-0.003	-1.39	-0.002	0.164

Table 6. Daily return limits and volatility

This table reports the analysis on realized variance around the price limit events. Reported is abnormal realized variance. Realized variance is defined as $\mathrm{RV}_i^t \overset{\text{def}}{=} \sum_{i=1}^{n}[p_j^i - p_{j-1}^i]^2$, where p_j^i denotes the logarithmic price of stock i at the end of the jth 10-minutes interval in day t. Abnormal realized variance for stock i at day $t+j$ is calculated as realized variance for stock i at day $t+j$ ($j\epsilon(-5, 20)$) divided by this stock's average realized variance from t-125 to t-21 and minus one. For each day with at least 5 upper price limit events of "normal" stocks, we sort these stocks into two groups based on their daily returns: High includes the ones with above median daily returns and Low includes other. For abnormal realized variance, we first calculate the mean for High and Low separately at each day and also their difference: High-Low, and then calculate the time series means. For High-Low, we also calculate median, t-test for the mean, and the p-value of the Wilcoxon signed-rank test. The sample period is from January 1, 2000 to October 31, 2014.

	High	Low	High-Low			
Window	Mean	Mean	Mean	t-test	Median	Wilcoxon p-value
-5	0.370	0.381	-0.011	-0.50	-0.005	0.621
-4	0.459	0.474	-0.014	-0.54	-0.005	0.991
-3	0.563	0.552	0.011	0.37	-0.006	0.929
-2	0.758	0.804	-0.046	-1.45	-0.043	0.092
-1	1.255	1.292	-0.038	-0.87	0.024	0.785
0	2.611	2.603	0.008	1.05	0.029	0.222
1	2.784	2.570	0.214	4.64	0.200	<.0001
2	1.752	1.661	0.091	2.52	0.085	0.0005
3	1.349	1.261	0.088	2.69	0.078	0.0003
4	1.110	1.075	0.035	1.20	0.012	0.073
5	0.946	0.882	0.064	2.42	0.033	0.005
6-10	0.711	0.699	0.012	0.71	0.017	0.142
11-20	0.483	0.460	0.023	1.74	0.020	0.063
1-20	0.830	0.788	0.042	2.90	0.040	0.001

Table 7. Daily return limits and price efficiency

This table reports the analysis on variance ratio around the price limit events. Reported is abnormal variance ratio. Variance ratio is defined as the absolute value of one minus the variance of 10-minute log returns divided by two times the variance of 5-minute log returns. Log returns are calculated based on the midpoint of bid and ask. Abnormal variance ratio for stock *i* at day *t+j* is calculated as variance ratio for stock *i* at day *t+j* ($j\epsilon(-5, 20)$) divided by this stock's average variance ratio from *t*-125 to *t*-21 and minus one. For each day with at least 5 upper price limit events of "normal" stocks, we sort these stocks into two groups based on their daily returns: High includes the ones with above median daily returns and Low includes other. For abnormal variance ratio, we first calculate the mean for High and Low separately at each day and also their difference: High-Low, and then calculate the time series means. For High-Low, we also calculate median, t-test for the mean, and the p-value of the Wilcoxon signed-rank test. The sample period is from January 1, 2000 to October 31, 2014.

	High	Low	High-Low			
Window	Mean	Mean	Mean	t-test	Median	Wilcoxon p-value
-5	-0.006	-0.001	-0.004	-0.59	-0.007	0.336
-4	-0.006	-0.011	0.005	0.64	0.002	0.587
-3	-0.012	-0.006	-0.006	-0.75	-0.004	0.799
-2	-0.002	0.006	-0.009	-1.08	-0.008	0.185
-1	0.032	0.027	0.005	0.59	0.003	0.890
0	-0.072	-0.059	-0.013	-1.53	-0.006	0.191
1	0.210	0.196	0.014	1.88	0.012	0.089
2	0.140	0.118	0.021	2.91	0.016	0.003
3	0.044	0.045	-0.001	-0.15	0.000	0.950
4	0.019	0.015	0.004	0.58	0.008	0.521
5	0.016	0.018	-0.002	-0.25	0.000	0.675
6-10	-0.008	-0.011	0.003	0.85	0.001	0.444
11-20	-0.017	-0.016	-0.001	-0.40	-0.000	0.813
1-20	0.012	0.009	0.003	1.24	0.001	0.265

Table 8. Daily return limits and investor trading

This table reports the analysis on order imbalance (scaled up by 100 times) for different order size around the price limit events. Panel A, Panel B, and Panel C report the results on small orders, medium orders, and large orders, respectively. We sort all the trades into three groups: small trades are the trades with value equal to or lower than 20,000RMB, medium trades are the trades with value equal to or lower than 100,000RMB, and large trades are the trades with value larger than 100,000RMB. We measure order imbalance as the value of buyer-initiated trades minus the value of seller-initiated trades divided by the total value of trades. We calculate its abnormal level as $AbnX_{i,t-j} = X_{i,t-j} - \sum_{j=-125}^{-21} X_{i,t-j}$. For each day with at least 5 upper price limit events of "normal" stocks, we sort these stocks into two groups based on their daily returns: High includes the ones with above median daily returns and Low includes other. For abnormal order imbalance, we first calculate the mean for High and Low separately at each day and also their difference: High-Low, and then calculate the time series means. For High-Low, we also calculate median, t-test for the mean, and the p-value of the Wilcoxon signed-rank test. The sample period is from January 1, 2000 to October 31, 2014.

Panel A. Small orders

	High	Low	High-Low			
Window	Mean	Mean	Mean	t-test	Median	Wilcoxon p-value
-5	-0.306	-0.488	0.183	0.90	0.243	0.187
-4	-0.846	-0.911	0.064	0.30	0.150	0.840
-3	-1.157	-0.973	-0.185	-0.80	0.041	0.817
-2	-1.781	-1.984	0.204	0.83	-0.033	0.922
-1	-3.758	-4.035	0.277	0.91	-0.162	0.965
0	-34.561	-34.406	-0.155	-0.33	-0.068	0.712
1	3.659	2.565	1.094	3.57	0.484	0.005
2	-1.050	-1.593	0.542	2.50	0.445	0.016
3	0.105	0.230	-0.124	-0.64	-0.260	0.166
4	0.252	0.305	-0.053	-0.28	-0.349	0.161
5	0.175	-0.012	0.187	1.00	0.105	0.330
6-10	0.775	0.706	0.069	0.68	-0.109	0.866
11-20	0.944	1.008	-0.065	-0.78	-0.075	0.220
1-20	0.822	0.752	0.070	0.97	0.046	0.812

Panel B. Medium orders

	High	Low	High-Low			
Window	Mean	Mean	Mean	t-test	Median	Wilcoxon p-value
-5	0.637	0.574	0.063	0.26	-0.147	0.719
-4	0.498	0.844	-0.346	-1.45	-0.218	0.115
-3	0.686	0.439	0.247	0.98	-0.112	0.953
-2	-0.017	0.098	-0.114	-0.43	0.145	0.907
-1	-0.437	-0.266	-0.171	-0.60	-0.536	0.156
0	-18.955	-19.053	0.098	0.23	-0.293	0.664
1	6.465	5.916	0.549	2.27	0.488	0.051
2	1.528	1.492	0.035	0.18	-0.027	0.897
3	2.179	2.083	0.096	0.52	-0.054	0.868
4	1.810	2.019	-0.208	-1.13	-0.233	0.110
5	1.210	1.288	-0.078	-0.40	-0.078	0.947
6-10	1.730	1.705	0.025	0.24	-0.001	0.945
11-20	1.281	1.429	-0.148	-1.68	-0.203	0.036
1-20	1.734	1.754	-0.061	-0.85	-0.111	0.257

Panel C. Large orders

	High	Low	High-Low			
Window	Mean	Mean	Mean	t-test	Median	Wilcoxon p-value
-5	0.681	0.942	0.261	-0.62	-0.240	0.496
-4	1.612	1.745	-0.133	-0.31	-0.196	0.459
-3	1.994	2.246	-0.252	-0.61	-0.633	0.216
-2	1.651	1.888	-0.237	-0.56	-0.374	0.281
-1	2.915	2.406	0.508	1.22	0.303	0.276
0	4.424	4.055	0.370	0.90	0.398	0.412
1	6.052	5.893	0.159	0.63	0.017	0.758
2	1.686	2.236	-0.549	-2.13	-0.441	0.003
3	1.300	1.656	-0.356	-1.10	-0.270	0.176
4	0.536	1.133	-0.597	-2.00	-0.154	0.118
5	-0.145	-0.060	-0.085	-0.26	-0.220	0.778
6-10	0.891	1.001	-0.118	-0.66	-0.035	0.449
11-20	0.142	0.092	0.050	0.31	-0.041	0.763
1-20	0.777	0.891	-0.114	-0.92	-0.065	0.226

Table 9. Daily return limits and return comovement with SMB

We measure a stock's return comovement with small stocks by its loading on the small-minus-big (SMB) factor. For each event day, we calculate equally-weighted daily portfolio returns for both High and Low, and then estimate β_{SMB} by running daily portfolio excess returns (raw return minus risk-free rate) on market excess return (MktRf), SMB, the value factor (HML) and the momentum factor (UMD). We do the estimation separately for the pre-event window and post-event window. We construct the China version of the Fama-French-Carhart four-factor model by following Fama and French (1993) and Carhart (1997). Risk free rate is bank deposit rate of China. We define the pre-event period as t-40 to t-6 and the post-event period as t+1 to t-40. For each event day, we get estimates of β_{SMB} for High and Low, and for both pre- and post-event windows. Based on these estimates, we calculate the time series means across all the event days (Panel A). We also report the difference between the pre-event window and the post-event window (Panel A) and also the differences between High and Low (Panel B). The numbers reported below the mean are t-value and the numbers reported below the median are the p-value of Wilcoxon signed-rank tests. The sample period is from December 16, 1996 to March 31, 2015.

Panel A. Factor loadings of upper price limit stocks

	High				Low			
	MktRf	SMB	HML	UMD	MktRf	SMB	HML	UMD
Pre	1.047	0.741	0.127	-0.014	1.058	0.745	0.156	-0.030
	(220.18)	(52.04)	(7.20)	(-1.02)	(214.54)	(47.50)	(8.56)	(-2.04)
Post	1.098	0.757	0.219	0.060	1.088	0.700	0.226	0.047
	(233.34)	(52.76)	(13.08)	(4.44)	(216.51)	(46.50)	(12.49)	(3.28)
Dif	0.051	0.016	0.093	0.074	0.030	-0.045	0.071	0.077
	(8.15)	(0.87)	(4.59)	(4.06)	(4.58)	(-2.28)	(3.25)	(3.96)

Panel B. Differences between High and Low

	High-Low							
	MktRf		SMB		HML		UMD	
	Mean (t-test)	Median p-value	Mean (t-test)	Median p-value	Mean t-test	Median p-value	Mean t-test	Median p-value
Pre	-0.011	-0.005	-0.004	-0.001	-0.029	-0.029	0.014	0.007
	(-1.70)	0.050	(-0.23)	0.801	(-1.34)	0.223	(0.81)	0.526
Post	0.010	0.007	0.057	0.036	-0.005	0.012	0.012	-0.001
	(1.65)	0.114	(3.39)	0.002	(-0.28)	0.817	(0.71)	0.691
Dif	0.020	0.018	0.062	0.018	0.023	0.035	-0.003	0.003
	(2.49)	0.007	(2.57)	0.050	(0.86)	0.346	(-0.12)	0.768

Table 10. Placebo test

This table reports placebo test results. Between May 21, 1992 and December 15, 1996 (both inclusive), there was no limit for daily stock returns. We construct hypothetical price limit events based on the real returns of stocks, by applying the price limit rule which was only effective after December 16, 1996. We repeat the same analysis as we do for real price limit events for these hypothetical price limit events. For details, please see other tables. Due to the unavailability of the attention data from *hexun.com* and the unavailability of intraday data in this sample period, we focus on returns, turnover and return comovement. Panel A reports the results on returns (size decile adjusted), turnover (adjusted based on Equation (2)), and return comovement.

Panel A. Hypothetical price limits and stock returns

	High	Low	High-Low			
Window	Mean	Mean	Mean	t-test	Median	Wilcoxon p-value
-5	0.116	0.209	-0.093	(-0.55)	-0.141	0.380
-4	0.163	0.363	-0.200	(-1.05)	-0.007	0.348
-3	0.302	0.261	0.041	(0.19)	-0.056	0.744
-2	0.232	0.617	-0.385	(-1.69)	-0.132	0.311
-1	1.584	1.002	0.584	(1.46)	0.265	0.134
0	9.800	9.601	0.191	(0.63)	0.455	0.080
1	0.202	0.234	-0.032	(-0.10)	-0.115	0.986
2	-0.194	-0.227	0.033	(0.13)	0.041	0.921
3	0.194	-0.252	0.446	(1.77)	0.020	0.290
4	0.063	0.019	0.044	(0.22)	0.173	0.622
5	-0.088	-0.068	-0.020	(-0.11)	-0.053	0.820
6-10	-0.200	0.362	-0.562	(-1.22)	-0.008	0.594
11-20	0.067	-0.126	0.193	(0.41)	0.007	0.752
1-20	0.043	-0.055	0.098	(0.13)	0.426	0.449

Panel B. Hypothetical price limits and volume

	High	Low	High-Low			
Window	Mean	Mean	Mean	t-test	Median	Wilcoxon p-value
-5	1.396	1.374	0.023	0.15	0.068	0.129
-4	1.641	1.629	0.012	0.07	0.015	0.556
-3	1.767	1.778	-0.031	-0.17	-0.002	0.594
-2	1.778	1.942	-0.165	-0.97	0.064	0.394
-1	2.811	1.705	0.106	0.54	0.167	0.028
0	7.428	7.238	0.190	0.47	0.134	0.308
1	6.386	6.577	-0.190	-0.43	0.184	0.247
2	4.083	4.327	-0.243	-0.75	0.067	0.215
3	3.663	3.747	-0.084	-0.30	0.144	0.088
4	3.270	3.364	-0.093	-0.32	0.094	0.385
5	3.096	3.058	0.037	0.12	0.109	0.152
6-10	2.449	2.413	0.036	0.15	0.092	0.140
11-20	2.319	2.195	0.124	0.45	0.031	0.311
1-20	2.798	2.755	0.043	0.17	0.036	0.220

Panel C. Return comovement

Panel C1. Factor loadings of upper price limit stocks

	High				Low			
	MktRf	SMB	HML	UMD	MktRf	SMB	HML	UMD
Pre	1.042	0.305	-0.103	0.112	1.123	0.276	0.038	0.020
	(36.84)	(3.82)	(-1.86)	(2.16)	(22.10)	(2.68)	(0.63)	(0.32)
Post	1.050	0.391	-0.024	0.047	1.033	0.443	0.009	0.081
	(88.99)	(8.44)	(-0.67)	(1.71)	(85.84)	(8.69)	(0.24)	(2.88)
Dif	0.008	0.085	0.079	-0.066	-0.091	0.167	-0.029	-0.061
	(0.28)	(1.06)	(1.34)	(-1.18)	(-1.77)	(1.58)	(-0.47)	(-0.96)

Panel C2. Differences between High and Low

	High-Low							
	MktRf		SMB		HML		UMD	
	Mean (t-test)	Median p-value	Mean (t-test)	Median p-value	Mean t-test	Median p-value	Mean t-test	Median p-value
Pre	-0.084	0.000	0.033	0.014	-0.135	-0.022	0.076	0.033
	(-1.58)	0.943	(0.33)	0.704	(-1.86)	0.266	(1.00)	0.101
Post	0.026	0.006	-0.071	-0.025	-0.032	-0.037	-0.033	-0.033
	(1.90)	0.353	(-1.33)	0.420	(-0.86)	0.269	(-1.18)	0.179
Dif	0.110	0.005	-0.104	-0.041	0.103	-0.016	-0.109	-0.061
	(1.96)	0.444	(-0.98)	0.280	(1.40)	0.505	(-1.39)	0.037

Table 11. Results of other price limit events

This table reports the results of other three types of price limit events: Panel A for lower price limit events of “normal” stocks, Panel B for upper price limit events of “ST” stocks, and Panel C for lower price limit events of “ST” stocks. For sake of space, we only report the difference between High and Low and its t-test. All others are the same as in Table 2 to Table 9.

Panel A. Lower price limit events of “normal” stocks

Window	Mean	t-stat	Mean	t-stat	Mean	t-stat	Mean	t-stat	Mean	t-stat
	Attention		Average returns		Trading volume		Liquidity		Volatility	
0	-0.511	-1.31	-0.072	-4.39	0.048	0.68	0.021	1.43	0.018	0.16
1	0.102	0.31	-0.083	-0.69	-0.102	-1.15	-0.006	-0.67	-0.070	-0.65
2	0.174	0.94	0.207	1.98	-0.009	-0.11	0.001	0.18	-0.077	-1.41
3	-0.245	-1.01	0.069	0.71	0.143	1.66	-0.002	-0.19	-0.008	-0.17
4	-0.322	-1.35	-0.016	-0.15	0.052	0.63	-0.013	-1.59	0.028	0.57
5	-0.323	-1.26	0.024	0.36	0.076	0.93	-0.009	-1.12	0.035	0.89
	Price efficiency		Order Imbalance: small		Order Imbalance: medium		Order Imbalance: large		Return comovement	
0	0.009	0.54	-0.003	-0.56	0.000	-0.12	-0.010	-1.18	-0.033	-0.95
1	0.017	1.09	0.003	0.90	0.002	0.66	-0.007	-0.87		
2	-0.023	-1.40	-0.003	-1.20	-0.004	-1.85	-0.002	-0.24		
3	-0.000	-0.02	-0.001	-0.62	0.001	0.49	-0.003	-0.38		
4	0.005	0.31	-0.001	-0.29	-0.002	-1.02	0.003	0.40		
5	-0.033	-1.89	0.002	1.03	-0.001	-0.42	-0.013	-1.29		

Panel B. Upper price limit events of “ST” stocks

Window	Mean	t-stat	Mean	t-stat	Mean	t-stat	Mean	t-stat	Mean	t-stat
	Attention		Average returns		Trading volume		Liquidity		Volatility	
0	0.170	1.16	0.116	20.53	0.005	0.20	-0.003	-0.51	0.013	0.97
1	0.135	0.83	0.036	0.68	-0.014	-0.51	-0.002	-0.28	-0.016	-0.73
2	-0.109	-0.75	-0.088	-1.67	-0.010	-0.38	-0.014	-2.27	-0.049	-2.30
3	0.008	0.05	-0.032	-0.60	-0.004	-0.17	-0.006	-1.09	-0.009	-0.50
4	0.081	0.51	-0.013	-0.27	0.009	0.37	0.012	2.30	0.006	0.31
5	0.103	0.81	-0.025	-0.51	0.010	0.44	-0.005	-0.98	-0.013	-0.74
	Price efficiency		Order Imbalance: small		Order Imbalance: medium		Order Imbalance: large		Return comovement	
0	-0.004	-0.32	0.004	0.63	0.010	1.72	-0.001	-0.08	0.012	0.54
1	0.009	0.96	0.002	0.30	0.002	0.39	0.000	0.04		
2	-0.003	-0.27	0.006	1.46	0.003	0.68	-0.002	-0.22		
3	-0.005	-0.49	-0.003	-0.78	-0.007	-1.57	-0.012	-1.49		
4	0.011	1.03	-0.003	-0.69	-0.002	-0.42	-0.007	-0.94		
5	0.012	1.16	-0.006	-1.62	-0.003	-0.71	-0.010	-1.31		

Panel C. Lower price limit events of "ST" stocks

Window	Mean	t-stat	Mean	t-stat	Mean	t-stat	Mean	t-stat	Mean	t-stat
	Attention		Average returns		Trading volume		Liquidity		Volatility	
0	-0.008	-0.98	-0.046	-0.85	-0.056	-2.20	0.008	0.78	-0.022	-0.85
1	-0.005	-0.75	0.058	1.14	0.004	0.13	0.003	0.32	0.019	0.64
2	-0.004	-0.48	0.053	0.99	-0.022	-0.79	0.019	1.37	-0.041	-1.46
3	-0.005	-0.92	0.010	0.18	-0.020	-0.71	0.025	1.83	0.021	0.75
4	-0.006	-1.56	0.046	0.89	0.003	0.10	0.013	1.25	-0.056	-1.99
5	-0.007	-1.44	-0.027	-0.49	0.023	0.81	0.004	0.40	-0.025	-0.98
	Price efficiency		Order Imbalance: small		Order Imbalance: medium		Order Imbalance: large		Return comovement	
0	0.017	0.94	-0.007	-1.57	-0.006	-0.84	-0.007	-0.45	-0.022	-0.65
1	-0.017	-1.05	-0.003	-0.54	0.003	0.53	0.012	0.76		
2	0.015	0.95	-0.001	-0.27	-0.005	-0.65	-0.007	-0.48		
3	-0.036	-2.15	-0.001	-0.19	0.002	0.27	0.013	0.86		
4	-0.005	-0.31	-0.006	-1.14	-0.005	-0.72	-0.019	-1.32		
5	-0.021	-1.21	-0.007	-1.40	-0.001	-0.21	-0.030	-2.04		

Table 12. Robustness: excluding stocks priced lower than 5RMB

This table reports the results of upper price limit events of "normal" stocks after we exclude stocks priced below 5RMB at the previous close. For sake of space, we only report the difference between High and Low and its t-test. All others are the same as in Table 2 to Table 9.

Window	Mean	t-stat	Mean	t-stat	Mean	t-stat	Mean	t-stat	Mean	t-stat
	Attention		Average returns		Trading volume		Liquidity		Volatility	
0	0.644	2.35	0.036	5.90	0.014	0.32	-0.001	-0.08	0.020	0.49
1	0.555	2.05	0.303	4.90	0.147	2.93	-0.009	-2.13	0.162	3.76
2	0.422	1.95	-0.036	-0.64	0.100	2.50	-0.004	-1.03	0.081	2.40
3	0.387	1.91	0.019	0.35	0.081	2.12	-0.007	-2.05	0.056	1.89
4	0.043	0.23	-0.016	-0.32	0.092	2.59	-0.006	-1.85	0.039	1.41
5	0.082	0.49	-0.070	-1.47	0.094	2.93	-0.005	-1.42	0.042	1.70
	Price efficiency		Order Imbalance: small		Order Imbalance: medium		Order Imbalance: large		Return comovement	
0	0.010	1.30	0.001	0.19	0.001	0.25	0.002	0.46	0.036	1.68
1	0.023	2.62	0.011	3.11	0.003	1.14	0.000	0.10		
2	0.019	2.55	0.006	2.48	-0.001	-0.28	-0.007	-2.44		
3	-0.001	-0.19	-0.002	-0.90	-0.001	-0.42	-0.003	-0.98		
4	0.007	0.95	0.000	0.19	0.002	1.18	0.003	0.93		
5	0.003	0.32	0.002	0.99	0.002	0.91	-0.001	-0.26		

Figure 1. The distribution of number of upper price limit hitting stocks for "normal" stocks

This table reports the distribution of daily number of stocks hitting their 10% upper price limit. Days with less than 5 upper price limit "normal" stocks are excluded. Days with more than 70 event stocks is aggregated into one group and is labeled as ">=71". The sample period is from December 16, 1996 to March 31, 2015.