The Impacts of Trading Restrictions on the Stock Market in China  
- An investigation of Circuit Breaker Mechanism

Abstract

Since circuit breakers are rarely triggered, thus, it is challenging to test their efficacy with a high degree of reliability. In this paper, we employ unique high-frequency intraday data to investigate the impacts of the circuit breaker mechanism installed in the Shanghai Stock Exchange. Using high-frequency intraday data, we find that trading restrictions have liquidity effects. Contrary to conventional wisdom, in the presence of circuit breakers, investors’ behavior will accelerate the arrival of price limits. We also document significant downward magnet effects for individual stocks and for the market index but find no significant volatility spillover effects.

Key words: Circuit breaker, trading restrictions, price limit mechanism, magnet effects
1. Introduction

In January 2016, the Chinese stock market tumbled, leading to a loss of 7.4 trillion yuan (US$1.56 trillion). Widespread panic ensued, and the stock market continued its downward descent until March 2016. The spectacular market crashes led to great speculation on what had caused it. Some have posited that the Chinese economy was going into a recession, while most market participants attributed it to the regulators, who had made a measure of installing market-wide circuit breakers into the Chinese stock markets, inciting widespread panic selling. The Chinese regulator suspended the market circuit breaker mechanism after the market crashed on January 8, 2016. However, one objective of circuit breakers is to allow a cool-down period for market-clearing participants to halt trading in a security or market to avoid extreme changes in market prices and to prevent fear and panic selling from collapsing prices too quickly without a fundamental basis. Thus, they prevent spurring more panic selling in the process. Furthermore, a second purpose for breakers is to prevent extreme order imbalances during rapid market movements that might create disruption, and letting orders accumulate and then batching them may lead to better quality execution prices and thus lower volatility. Therefore, which factors make the circuit breaker mechanism a dis-stabilizer in China’s stock markets?

Since circuit breakers are rarely triggered, it is challenging to test their efficacy with a great degree of reliability. To our best knowledge, there are very limited empirical studies on the impacts of circuit breakers, and the empirical evidence is also mixed. The models of Greenwald and Stein (1991) and Kodres and O’Brien (1994) address the possible benefits of circuit breakers. These authors argue that, when noise trades affect prices in panic, informed traders become concerned about execution price uncertainty and tend to withdraw. Circuit breakers improve market performance and pricing efficiency by facilitating the batching of orders and improving liquidity. A breaker may also lead to greater liquidity and decrease volatility, because it provides traders more time to react. However, Fama (1989) points out the obvious point that rational pricing does not imply lower volatility, and thus pricing processes with lower volatility are
not necessarily superior to pricing processes with higher volatility. Fama (1989) found that price limits might serve no purpose other than to delay the discovery of the true price. Even though price limits can prevent large rises or drops on a given day, on subsequent days, the price will inevitably converge to true values, albeit more slowly. Kuhn et al. (1991) found that the fusing mechanism in the 1989 crash did not play a role in reducing volatility. Santoni and Liu (1993) tested for changes in volatility following the adoption of circuit breakers using an ARCH model. Using data from the inception of the breakers through 1991, they found no significant effects on volatility. Thus, they conclude that the imposition of circuit breakers has had no discernible impact on volatility.

Another important issue to consider is that circuit breaker may affect prices even if they are not trigged. That is, the existence of a circuit breaker may affect decisions of investors prior to the triggering of the breaker. Subrahmanyam (1994) demonstrates the “magnet effect.” Thus, as the price nears the price limit, investors anxious about being denied the opportunity to trade will advance their trades in time, thus increasing price volatility and accelerating the market to reach the limit. Ackert, Church, and Jayaraman (2001) used an experimental approach to investigate the likely impacts of these impediments to trade. They conducted an experiment to focus on the effects of NYSE-type market-wide circuit breakers. They found that circuit breakers cause agents to speed up their trading activity as the price approaches a trigger, therefore supporting a magnet effect.

With regard to the order flow and liquidity effects of trading restrictions, Subrahmanyam (1997) argued that, in the presence of a circuit breaker, informed investors might be concerned that their large trades might trigger the breaker. In this case, they would simply reduce their order sizes that would increase the bid-ask spread for small orders. This might end up harming retail investors, who typically submit smaller orders than large institutions do. Similarly, Goldstein and Kavajecz (2004) investigated an episode during which circuit breakers were triggered on October 27, 1997. They found that the circuit breakers cause a shortage of liquidity on the day following the circuit breaker, because limit order traders were reluctant to resubmit the previous days’ expired orders. This
causes a lack of depth in the limit order book. This evidence is at odds with the notion that circuit breakers calm down markets and increase market liquidity.

There is also a large body of literature on the efficacy of the traditional impediment to trade, namely, price limits. One strand of literature documents that the price limits mechanism prevents investors from panicking, helps reduce the price fluctuations, and therefore mitigates market risks. For instance, Bildik and Elekdag (2004) examined the impact of price restrictions on the volatility of stock returns by examining the over-reaction and information assumptions of the Istanbul Stock Exchange. They implemented structural break tests as well as a comprehensive GARCH framework to estimate the impact of price limits on volatility, controlling for structural breaks, financial and economic crises, trading activity, and business cycle fluctuations. They found that, by acting as a circuit breaker, the two-hour break between two daily conversations reduces volatility, which helps spread valuable information, thereby preventing serious overreactions to news events. Chou et al. (2006) investigated the cost-minimizing combination of spot limits, futures limits, and margins for stock and index futures in the Taiwan market. The results indicate that, because price limits can lower price volatility and default probability, margin requirements after price limits are imposed may be lower than those without price limits. Liao et al. (2011) selected the daily stock price data for the Taiwan stock market from January 1, 2001 to August 31, 2007. The findings indicate that removing price limits can significantly reduce the level of returns, and hence the market becomes effective. In addition, the liquidities in the trading of IPOs, which were prevented by price limits, increased significantly after removing price limits. Furthermore, the price discovery process was delayed by price limits.

Many studies also find that the price limits system stops the trading in the stock market, reduces the effectiveness of the stock market, and increases the stock price volatility in the following trading days. Kim and Rhee (1997) used Tokyo market transaction data for analysis. They used the stocks that are close to the price limits as the traded group and the stocks that have reached the price limits as the controlled group and then compared the fluctuation direction, the volatility of the returns, and the volume of transactions of the two groups of
stocks when they both hit the price limits. They found that the price limits system does not help reduce the stock market volatility of Tokyo and Taiwan and can even produce an adverse effect on normal trading behavior. This is because the price limit system leads to the volatility spillover effect and causes a delay in stock price discovery process. Chou and Wu (1998) used Taiwan stocks as a sample to explore the impact of the price limits system of the Taiwan stock market and found that the expected payout after the suspension of the stock market was not significantly affected and the stock price fluctuated. Choi and Lee (2000) conducted an empirical analysis of the Korean stock market and found that, when prices rise or fall beyond certain thresholds, they will move in a faster speed to the price limits. That is, there are magnetic effects that will accelerate the completion of the transaction and thus increase the price volatility.

In sum, the bulk of the literature has not found consistently compelling and solid evidence that circuit breakers or price limits reduce volatility or enhance price discovery. The benefits or disadvantages of trading restrictions such as breakers may exist as informal arguments but do not receive much support in the data.

In this paper, we employ the daily data and high frequency intraday data of the Shanghai Stock Exchange to investigate the efficacy and impacts of the circuit breaker mechanism. Using unique high frequency intraday data, we find that trading restrictions have liquidity effects. In the presence of circuit breakers, investors’ behavior will accelerate the arrival of the price limits. We also document significant downward magnet effects for individual stocks and for the market index but find no significant volatility spillover effects.

The remainder of this study is organised as follows. Section 2 describes the stylized facts of circuit breakers and the data description. Section 3 discusses the hypothesis developments and the statistical evidence. Section 4 represents the econometric model and empirical results. Section 5 concludes.

2. Stylized facts of circuit breakers in China’s stock markets

On December 4, 2015, the Shanghai Stock Exchange (henceforth SHSE), the
Shenzhen Stock Exchange (henceforth SZSE), and the China Financial Futures Exchange issued the relevant regulations for the circuit breaker of the CSI 300 Index. The Chinese version of the index fusing mechanism was formally implemented on January 1, 2016. The mechanism is shown in Table 1.

Table 1  Overview of Fusing Mechanism of A-shares in China

<table>
<thead>
<tr>
<th>Benchmark Index</th>
<th>CSI 300 Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Objects of Fusing mechanism</td>
<td>A-shares, B-shares, Funds, Convertible corporate bonds, Index Futures</td>
</tr>
<tr>
<td>Thresholds</td>
<td>5% and 7%, both increase and decline can trigger the halt</td>
</tr>
<tr>
<td>Trading Halt Time</td>
<td>Trigger 5% threshold and suspend trading for 15 minutes. After 14:45, if the circuit breaker is triggered or 7% of the threshold is triggered, close trading for the day.</td>
</tr>
</tbody>
</table>

Under China's circuit breaker system, if CSI 300 index rises or drops by five percent, trading would halt for 15 minutes. A seven percent drop would put an end to the day’s trading. Critics of the circuit breaker system said Chinese regulators had made a blunder by setting limits on the circuit breaker that were too tight which drain the market liquidity significantly. As China already imposes daily price limits on its stocks – stock prices cannot fall more than 10 percent in a day, the introduction of circuit breakers could have been perceived by the market as a repetitive and, not surprisingly, frightening move.¹ However, at the beginning of 2016, after the Shanghai Stock Exchange first implemented a market-wide circuit breaker mechanism, the circuit breakers were triggered twice in a short period of time. On January 4, 2016, on the first trading day after the fusing mechanism was implemented, the A-share market hit a -5% threshold shortly after the opening in the afternoon. After the trades halt, the stock market once again triggered -7% of the fuse threshold, causing the market to be suspended. By then, a total 1,984 stocks in the Shanghai and Shenzhen Stock

¹ Tables 1A and 2A describe the circuit breaker and the price limit mechanism in major markets around the world, respectively. (See Appendix A)
Exchanges fell more than 9%. Affected by the circuit breakers, on January 5, the opening price of Shanghai Stock Exchange Index was 3% lower than the last closing price, but it rebounded for the remainder of the day. The index continued to rise on January 6. On January 7, the stock markets crashed again. Within 13 minutes of opening, it triggered a first-level halt. After the reopening of trading, it triggered the second threshold in 3 minutes. Trading for the entire day was only half an hour. As of the market closure, nearly 2,000 stocks fell. On the evening of the 7th, the regulator issued a notice stating that the implementation of the circuit breaker mechanism was suspended from January 8. However, the SHSE Index reached its lowest point – 2638.30 points – from the 5178.19 points in the next 14 trading days.

Due to the frequent triggering of the circuit breakers and the resulted market crashes, the Chinese regulator suspended the market circuit breaker mechanism on January 8, 2016. These extreme reactions have led researchers to focus on the volatility of the Chinese stock market. Market participants have questioned the circuit breaker mechanism. Does the fuse mechanism hinder the price discovery of stocks? Does it increase the volatility of the stock market? Does the magnet effect really exist? Next, we will answer these questions with specific data.

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2 The circuit breakers were triggered twice in four days while the NYSE only had experienced a single trading impediment due to the circuit breakers in the last 30 years.
2.1 Data description

Our data comprise the daily data and one-minute and five-minute data from the Shanghai Stock Exchange. The daily data cover the period from January 1, 2006 to June 22, 2016, including a total of 836 stocks, of which 166 are from CSI 300 Index constituents, accounting for 19.86%; 670 are non-CSI 300 Index constituents, accounting for 80.14%. Our sample excludes stocks with short trading hours and special treated (ST) shares. The high-frequency data include the same 836 stocks and range from the first minute at opening on January 4, 2016 to the last minute at closing on July 14, 2016. The high-frequency data also exclude stocks with short trading hours, stocks with little volatility, and ST shares.3

2.2 Do the circuit breakers hinder the price discovery of stocks?

In order to eliminate other factors that can influence the price change, we do not simply compare the returns on the fusing days with the returns on the non-fusing dates. Instead, we compare the returns on the fusing dates with those on non-fusing dates when the circuit breakers should have been triggered if the fusing mechanism had not been suspended. Specifically, we choose January 11, January 26, and February 25, 2016 as dates for the control group, which have similar declines as the dates when circuit breakers were triggered. The index fluctuations on these three days are not affected by the circuit breaker, but the declines exceed -5%. The specific data is shown in Table 2.

<table>
<thead>
<tr>
<th>Fusing Date</th>
<th>January 4</th>
<th>January 7</th>
<th>January 11</th>
<th>January 26</th>
<th>February 25</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Daily return in %</td>
<td>-6.86%</td>
<td>-7.04%</td>
<td>-5.33%</td>
<td>-6.42%</td>
<td>-6.41%</td>
</tr>
<tr>
<td>The number of stocks whose prices were at the lowest point</td>
<td>429 (9.32%)</td>
<td>529 (8.32%)</td>
<td>382 (6.228%)</td>
<td>388 (12.89%)</td>
<td>535 (11.03%)</td>
</tr>
</tbody>
</table>

3 The daily data comes from the Wind database, and the high-frequency data comes from the Bloomberg database.
<table>
<thead>
<tr>
<th>(Percentage of stocks of CSI 300 Index)</th>
<th>316 (8.23%)</th>
<th>323 (5.88%)</th>
<th>306 (5.88%)</th>
<th>207 (11.59%)</th>
<th>369 (7.59%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>The number of stocks that limit down at the closing price</td>
<td>15 (20%)</td>
<td>808 (20.54%)</td>
<td>504 (26.39%)</td>
<td>526 (23.19%)</td>
<td>687 (23.00%)</td>
</tr>
<tr>
<td>(Percentage of CSI 300 Index)</td>
<td>324 (5.88%)</td>
<td>388 (11.59%)</td>
<td>369 (7.59%)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Although the reference index for the circuit breaker was the CSI 300 Index, on the day of fusing, we did not find that the CSI 300 Index constituents performed significantly differently from the non-component stocks. Therefore, we rule out the possibility that speculators intentionally shorted the CSI 300 Index constituents to manipulate the markets.

Our data suggest that the fusing mechanism has hindered the price discovery of stocks. As we can see from the opening prices on the following days, the re-opening prices after the two “Full Circuit Breakings” both showed extreme trends. After the first “full breaking,” only 1.79% of stocks rose at the opening on the following day, while after the second “full breaking,” 96.65% of stocks opened at better prices. However, the proportion of the control group’s stocks that rose on the next day is on average not so extreme, to the percentages of 60.29%, 62.92%, and 82.18%, respectively.

In order to test whether the proportions of 1.79% and 96.65% are abnormal, we use the daily data of all the stocks from January 2006 to June 2016 to analyze the impacts of the market crashes on the opening prices on the following day.
Figure 1 shows the ups and downs of stocks' open prices without any constraints. On average, the stocks that opened higher accounted for approximately 37.31% of all stocks in each trading day. In the whole sample, there exist extreme cases in which all of the stocks opened higher and all of the stocks opened, but both extremes had nothing to do with the circuit breakers.

Next, we narrowed our sample from all trading days to the trading days when the market index of previous day fell by more than 5%. With the subsample, the proportion of stocks that opened higher on the following day is shown in Figure 2. By comparing the two histograms, we find that, compared to the full sample, the subsample data have much fewer observations of the days when a big proportion of stocks opened higher on the next day, and the distribution has a stronger positive skewness, which suggests that the re-opening prices have a greater probability of continuing to decline in accordance with a big drop of the market index. Within the whole sample, there are a total of 116 cases in which the proportion of stocks that opened higher is only 4.56% of the total sample. For a trading day that fell more than 5%, this proportion exceeds 16% (7/43). Taking into account the price limit in China, this phenomenon is not difficult to understand, because the floor limit has blocked the further decline of stocks, and
the falling demand can only be realized by the next day.

Figure 2 The proportion of open high (lost more than -5% in the previous trading day)

In the sample with a decline of more than -5% the day before, after the first “full breaking,” opening on January 5 (only 1.79% of stocks opened higher on the following day) was not unusual. However, we still believe that the circuit breaker on January 4 hindered the price discovery of stocks because the fusing mechanism prevented the price from falling further. Our statistics indicate that 316 out of the 836 stocks hit the floor limit at the market closure, and more than half of the stocks still had room to fall. The failure to fully release the downside momentum was also the reason why the vast majority of stocks opened lower on the following day. In order to verify this idea, we find cases in which the stock index had fallen by more than 6%, and the proportion of stocks that opened higher on the following day was less than 2% on average. There have been four such cases in our sample: three times in 2015 when the financial crisis occurred, and the first time when the circuit breaker was triggered on January 4, 2016.

Table 3: The next day’s opening after a drop of more than 6%
<table>
<thead>
<tr>
<th>Date</th>
<th>2015.7.27</th>
<th>2015.8.18</th>
<th>2015.8.24</th>
<th>2016.01.04</th>
</tr>
</thead>
<tbody>
<tr>
<td>The decline on that day in %</td>
<td>-8.4834</td>
<td>-6.1473</td>
<td>-8.4909</td>
<td>-6.8638</td>
</tr>
<tr>
<td>The proportion of stocks hitting the floor limit at the market closure</td>
<td>0.7831</td>
<td>0.7226</td>
<td>0.8841</td>
<td>0.4146</td>
</tr>
<tr>
<td>The proportion of stocks opening higher on the next day</td>
<td>0.0015</td>
<td>0.0107</td>
<td>0</td>
<td>0.0129</td>
</tr>
</tbody>
</table>

Table 3 shows that the proportions of stocks that hit floor limit at market closure on July 27, August 18, and August 24, 2015 are all above 70%, of which the proportion on August 24 even reached 88.41%. On these days, stocks had no room to fall further and could only wait until the resumption on the next day. On January 4, however, only 41.46% of the stocks reached the floor limit, and many stocks still had room to fall. Apparently, the circuit breaker had suspended the transaction and thus hindered price discovery.

The situation is completely different for the second “Full Breaker” day of January 7, 2016, after which 96.65% of stocks opened higher on January 8. This is the single date in China’s stock history on which the market index fell by more than 6%, but on the following day, more than 95% of the stocks opened higher. If we expand the scope to a day when the stock index falls by more than 5% and more than 95% of the stocks open higher on the following day, we have one more observation. During the market crash, the stock index fell 5.77% on July 3, 2015, but 98.75% of the stocks opened higher on the following trading day. However, this case is very special. July 3, 2015 was the last trading day of the first week of July. This week, due to rapid falling prices and the exacerbated panic amongst investors, the state issued a series of good news on the evening of July, 3, including: 1. Confirmation that Central Huijin Investment Co.\(^4\) would intervene and stabilize the market, 2. A statement by the China Securities Regulatory Commission that the number of IPOs and the amount of funds raised would be

\(^4\) A state-owned investment company.
reduced, 3. Notification that China Securities Finance Co., Ltd. would substantially increase capital and expand shares to maintain the stability of the capital market, and 4. Notification that the China Financial Futures Exchange (CFFE) decided to raise transaction fees and restrict the speculative short positions on the index futures. In addition, Premier Li Keqiang presided over the rescue of the market on the weekend. With a number of positive announcements, the stock prices rose on the next Monday, caused by a significant change in market sentiment.

On January 7, after experiencing the first “Full Breaking,” rapidly falling prices exacerbated panic amongst investors and caused irrational overreactions in the market. After a Level 1 circuit-breaker halt (-5% threshold), the market triggered a “Full Breaking” (-7% threshold) three minutes later. The market officially closed at 9:59 am. Considering the 15 minutes of trade suspension, there were only 15 minutes to trade throughout the day. Due to the “Full Breaking,” impediment to trade lets orders accumulate, and then they are batched upon the re-opening, which may lead to better quality execution prices.

Through the above analysis, we suggest that the implementation of the circuit breaker mechanism will cause the market that should have fallen further to fall insufficiently (e.g. January 4, 2016). Quick impediment to trade will also cause overreaction in markets that should not have fallen sharply (e.g. January 7, 2016). The first situation is easier to understand, because the cessation of the transaction prevents further decline but results in a lack of liquidity and an increase in execution uncertainty. In order to better understand the second scenario, we need to study the impact of impediment to trade on investors.

2.3 Impacts of Trading Stop on Investors

In addition to the lack of opportunity of trade caused by the circuit breaker, the normal opening and closing of the market will also bring a halt to transactions. We firstly examine the effect of the suspension of trading on investors’ behavior by studying the normal trading situation after the opening and before the closing.
Figure 3 shows the trading volume of the CSI 500 Index every half hour. From the chart we find that the trading volume shows a clear "U-shaped" pattern. That is, in the half hour after opening and the half hour before closing, the trade volume is higher than that of the rest of the day. Given that information disclosed after the market closure on the previous day would affect the opening volume on the following day, being denied opportunity to trade caused by the closing is another factor (Amihud and Mendelson 1987, 1991, Gerety and Mulherin 1992, etc.). Investors are unwilling to bear the uncertainty caused by the closing, and therefore they advance their trade in time and buy it again after the resumption of trade on the next day.

![Average trading volume every half an hour in a day](chart.png)

*Figure 3 Average trading volume every half an hour in a day*

Note: The vertical axis represents trading volume, and the horizontal axis represents the $n^{th}$ half an hour.

To formally test this view statistically, we refer to Schwert (1989, 1990) and

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5 Intraday data comes from the Bloomberg database. Because Bloomberg does not provide the trading volume of the Shanghai Stock Exchange Index and Shenzhen Stock Exchange Index, we use the CSI 300 Index and the CSI 500 Index as research objects. The conclusions obtained from both are similar, so only the results from CSI 500 Index are reported. The data sample is from the period of January 4, 2016 to July 15, 2016.

6 In addition to the volume of transactions, other indicators such as volatility and bid-ask spreads also exhibit a "U-shape."
Gerety and Mulherin (1992), who decomposed the overnight volatility of stocks into predictable and unpredictable parts. In light of their approach, we examine the impacts of these two parts on the trading volume before closing and after opening on the following day. We use the following model to decompose the volatility:

\[
\text{Return}_t = \sum_{i=1}^{n} \alpha_i \text{d}_i + \sum_{j=1}^{p} \beta_i \text{Return}_{t-j} + \varepsilon_t \tag{1}
\]

\[
|\varepsilon_t| = \sum_{i=1}^{n} \gamma_i \text{d}_i + \sum_{j=1}^{q} \delta_j |\varepsilon_{t-j}| + \mu_t \tag{2}
\]

In the formula (1), \(\text{Return}_t\) is the return for each half hour of the CSI 500 Index, and \(\text{d}_i\) denotes a dummy variable for each half hour of the day. The dummy variable is used to reflect the characteristics of the return in different time slots, and the lags of the returns reflect the persistency of the returns. In addition to the four trading hours (i.e. 8 half an hour) in the SHSE, we add the prices of the pre-market call auctions, in total nine returns per day. The first return is derived from the closing price of the previous day and the price of the pre-market auctions. The second return is derived from the price of the pre-market auction and the price of the first half an hour, and so on until market closure. The purpose of adding pre-market auction data is to effectively identify overnight volatility. Finally, we exclude the data related to the circuit breaker, and the sample includes 1,170 half hour observation in total.

In formula (2), \(|\varepsilon_t|\) is the absolute value of the residuals from formula (1). The absolute terms are similar to the standard deviation reflecting the stock volatility (Schwartz 1989). Given the regression of (2), we obtain the fitted value of \(|\varepsilon_t|\), the expectable volatility denoted as \(\sigma_{exp}\), and the residuals of (2), \(\mu_t\), with the unpredictable volatility denoted as \(\sigma_{unexp}\).

Then we use the decomposed volatility to study the trading behavior of investors. We calculate the values of \(\sigma_{exp}\) and \(\sigma_{unexp}\) for all pre-market auction periods, where \(\sigma_{exp}\) can be thought of as the expectable overnight volatility and \(\sigma_{unexp}\) is the unpredictable overnight volatility. We regress the trading volume on these volatility variables to test whether investors have a tendency to avoid overnight uncertainty. The specific model is given by equations (3) and (4).

\[
\text{Volume}_{c,t} = \alpha_0 + \alpha_1 \sigma_{exp,t} + \alpha_2 \sigma_{unexp,t} + \omega_{c,t} \tag{3}
\]

\[
\text{Volume}_{o,t+1} = \beta_0 + \beta_1 \sigma_{exp,t} + \beta_2 \sigma_{unexp,t} + \omega_{o,t+1} \tag{4}
\]

Among them, \(\text{Volume}_{c,t}\) is the trading volume for half an hour prior to
closing, and $Volume_{o,t+1}$ is the trading volume for half an hour after the opening of the next day. $\sigma_{exp}$ and $\sigma_{unexp}$ are the expectable overnight volatility and the unpredictable overnight volatility. The regression results are shown in Table 4.

<table>
<thead>
<tr>
<th>$\alpha_1$</th>
<th>$\alpha_2$</th>
<th>$\beta_1$</th>
<th>$\beta_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.0369<em>10^6</em>**</td>
<td>-0.0719*10^6</td>
<td>0.9627<em>10^6</em>**</td>
<td>0.1643*10^6**</td>
</tr>
<tr>
<td>(6.6101)</td>
<td>(-1.4531)</td>
<td>(3.6391)</td>
<td>(1.9693)</td>
</tr>
</tbody>
</table>

Note: The t-statistics are in the parentheses. ***,** represent significance at the 1% and 5% levels, respectively.

Table 4 shows that the expectable overnight volatility, $\sigma_{exp,t}$, has a significant positive effect on the trading volume before the market closure, i.e., $\alpha_1$ is significantly positive. Given the expectable volatility, investors will adjust their portfolios as expected before closing. The unpredictable overnight volatility $\sigma_{unexp,t}$ should not have a significant effect on the trading volume before closing, so $\alpha_2$ is not significant.

In terms of the trading volume after opening on the next day, the regression results show that both $\sigma_{exp,t}$ and $\sigma_{unexp,t}$ have significant positive impacts on $Volume_{o,t+1}$. The positive impacts of $\sigma_{unexp,t}$ on $Volume_{o,t+1}$ are as expected. At the closing of the previous day, investors are unable to observe $\sigma_{unexp,t}$, so they can not adjust their portfolio based on this variable. After the opening of the next day, $\sigma_{unexp,t}$ can be observed, and the updated overnight information leads investors to trade after the resumption of trade. We are concerned about the effects of $\sigma_{exp,t}$ on trading volume at the next day opening. Since $\sigma_{exp,t}$ is a variable that investors can observe before the previous day’s closing, investors can actually make portfolio adjustments before market closure. $\sigma_{exp,t}$ still affects the opening volume on the following day of trading, because investors resort to intraday trading in order to avoid overnight risks. They transfer risks of holding exposures during the closure of the market by selling their stocks and buying stocks that they should have held at the next opening. The positions that are supposed to be held are affected by $\sigma_{exp,t}$, so the opening volume on the next
day would be affected.

In order to further prove that investors’ incentives to avoid market risks lead to overlapping parts of $Volume_{ct}$ and $Volume_{o,t+1}$, and this kind of overlap makes the trading volume at the opening on the next day affected by the expectable volatility of the previous day, $\sigma_{exp,t}$, we examine the differences between $Volume_{o,t+1} - Volume_{c,t}$, $\sigma_{exp,t}$, and $\sigma_{unexp,t}$. If our speculation is established, then subtracting the two volumes eliminates the part that is sold before the first day’s closing and bought back after the next day’s opening. The remaining part should be unrelated to $\sigma_{exp,t}$ and only related to $\sigma_{unexp,t}$. The regression results confirm our judgment. In formula (5), the coefficient of expectable volatility is not significant, and it is negative, while the coefficient of the unpredictable volatility is significantly positive.

$$Volume_{o,t+1} - Volume_{c,t} = 10^5 \left(4.688 - 0.74 \times \sigma_{exp,t} + 2.36 \times \sigma_{unexp,t}\right) \quad (5)$$

$t$ statistics

$$\left(3.82 \right) \left(-0.35\right) \left(3.51\right)$$

By analyzing the relationship between the volume differences and volatility, we find that investors are anxious about being denied opportunities to trade and advance their trading before the market suspension. Based on our finding, we speculate that the trading volume before and after the circuit-breaker halt should also increase rapidly. The high-frequency data confirms our hypothesis. Figure 4 shows the number of transactions per minute before and after the fusing in the afternoon of January 4th and in the morning of January 7th. The gaps between the histograms are the 15-minute break after the Level 1 halt. Regardless of Level 1 halt (5% decline) or the subsequent Level 2 halt (7% decline), the volume of transactions increases significantly before the circuit breaker. 7

---

7 Due to the circuit breaker, the time interval is less than 1 minute, so there is a reduction in the amount of trading before the circuit-breaker halt.
Figure 4 Trading volume per minute before and after circuit-breaker halt

Under normal circumstances, investors who intend to avoid market risks know the closure time of the market, so they will choose to adjust their portfolio before market closure. However, the halt brought by the circuit breakers cannot be accurately predicted. This uncertainty will prevent traders from making effective position adjustments. That is, the existence of a circuit breaker may affect the decisions of investors prior to the trigger of the breaker. In addition, this uncertainty can also lead to circuit-breaker self-realization. Investors can only preemptively trade, and this behavior will accelerate the arrival of the circuit-breaker halt. This phenomenon is also known as the magnet effect. We will conduct formal statistical tests on the magnet effect in the following section.

4 Econometric models and empirical tests on the magnet effect

The magnet effect refers to the phenomenon that occurs when, as the price nears the limit, investors become anxious about being denied the opportunity to trade and advance their trades in time and thus increase the price volatility.

We refer to the model of Cho et al. (2002) to verify the magnet effect of the fusing mechanism. Since the circuit breaker in China was only implemented for a week, we obtained the limited observation from the short period of installment
of circuit breakers. However, we have a large sample of high-frequency data across the market. For comparison, we also employ the high-frequency data of the Korean Kosdaq Index provided by the Bloomberg database with the sample ranging from January 28, 2016 to July 29, 2016.  

We will take the volatility-adjusted 5-minute return as our explanatory variable. Similar to trading volume, stock volatility becomes higher after opening and before closing. The volatility-adjusted return excludes the influence of the different time slots on the return (Cho et al. 2002). The specific adjustment is as follows: First, we calculate every 5-minute return for each trading day, such as 9:30~9:35, 9:35~9:40, and so forth. We have N days of transaction data for each fixed time slot; for example, there are N returns in the 5-minute time slot (9:30~9:35). We calculate the standard deviation of the N returns for each time slot and use the calculated standard deviation to standardize the 5-minute returns for each 9:30 to 9:35 time slot. The same method is used to adjust the returns for other time slots. The standardized returns are used in the following GARCH(2,2) model as follows:

\[
\text{Return}_t = c + \sum_{i=1}^{2} \alpha_i \text{Return}_{t-i} + \sum_{j=1}^{3} \beta_j \text{Return}_{t-j} + \epsilon_t \\
\epsilon_t = \mu_t \sqrt{\text{h}_t}, \text{h}_t = \gamma_0 + \gamma_1 \text{h}_{t-1} + \gamma_2 \text{h}_{t-2} + \gamma_3 \epsilon_{t-1}^2 + \gamma_4 \epsilon_{t-2}^2
\]  

(6)

(7)

In this AR(3)-GARCH(2,2) model, Return$_t$ is the volatility-adjusted 5-minute return, and $d_1$ and $d_2$ are used to capture the magnet effect in the up and the down directions, respectively. Since it is difficult to determine which critical values will trigger the magnet effect (e.g., 5% or 6% or otherwise), we prefer to make $d_1$ and $d_2$ more general in order to bring the robustness problem of threshold selection:

\[
d_{1,t} = \begin{cases} 
\left( \frac{P_t-P_{\text{close}}}{P_{\text{close}}} \right)^2, & P_t > P_{\text{close}} \\
0, & P_t \leq P_{\text{close}} 
\end{cases}
\]  

(8)

\[
d_{2,t} = \begin{cases} 
\left( \frac{P_t-P_{\text{close}}}{P_{\text{close}}} \right)^2, & P_t < P_{\text{close}} \\
0, & P_t \geq P_{\text{close}} 
\end{cases}
\]  

(9)

In (8) and (9), $P_t$ is the price of the market index every 5 minutes, and
$P_{\text{close}}$ is the close price of the market index on the previous trading day. $d_1$ and $d_2$ are quasi dummy variables. This truncated setting has two advantages over the traditional dummy variables that use a specific threshold: first, because we avoid the selection of the thresholds, the result is more robust. Second, the values of $d_1$ and $d_2$ are not simply 0 and 1, but increase with the increase in price, which helps us to test the accelerated impacts on the magnet effect.

Table 5 Magnet Effects: Korea and China

<table>
<thead>
<tr>
<th></th>
<th>$\alpha_1$</th>
<th>$\alpha_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>South Korea</td>
<td>0.013*</td>
<td>-0.018***</td>
</tr>
<tr>
<td></td>
<td>(1.833)</td>
<td>(-3.917)</td>
</tr>
<tr>
<td>China</td>
<td>0.008</td>
<td>-0.0004</td>
</tr>
<tr>
<td></td>
<td>(1.261)</td>
<td>(-0.071)</td>
</tr>
</tbody>
</table>

Note: The t-statistics are in parentheses. *** and * represent significance of 1% and 10%, respectively.

The estimated results in Table 5 confirm the existence of magnet effects in the Korean market. $\alpha_1$ is significantly positive at the 10% level, meaning that, when there is a sharp increase in prices, the subsequent increases become greater at a faster speed. Similarly, $\alpha_2$ is significantly negative at the 1% level, indicating that the market also has a magnet effect in the downward direction. The more the price drops below the previous day’s closing price, the greater and faster the subsequent fall will be.

Magnet effects move the price in its current direction at a faster rate. This finding is similar to the momentum effect (Jegadeesh and Titman, 1993). In order to distinguish between magnet effects and momentum effects, we add dummy variables that reflect short-term trends in the regression model (6) to capture the momentum effect in price changes.

$$
\text{Return}_t = c + \sum_{i=1}^{2} \alpha_i d_{i,t-1} + \sum_{i=1}^{2} \rho_i m_{i,t-1} + \sum_{j=1}^{3} \beta_i \text{Return}_{t-j} + \epsilon_t \quad (10)
$$

$$
m_{1,t} = \begin{cases} 
1, & \text{If returns of the previous four periods are positive.} \\
0, & \text{otherwise.}
\end{cases}
$$

(11)

$$
m_{2,t} = \begin{cases} 
1, & \text{If returns of the previous four periods are negative.} \\
0, & \text{otherwise}
\end{cases}
$$

(12)
\( m_1 \) and \( m_2 \) are used to capture positive and negative momentum effects, respectively, indicating whether the price will keep moving in its current direction. The regression results after considering the momentum effect are shown in Table 6.

Table 6 Magnet Effect vs. Momentum Effect

<table>
<thead>
<tr>
<th>Regression Coefficients (t statistics)</th>
<th>( \alpha_1 )</th>
<th>( \alpha_2 )</th>
<th>( \rho_1 )</th>
<th>( \rho_2 )</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression Coefficients</td>
<td>0.0122*</td>
<td>-0.017***</td>
<td>0.045*</td>
<td>-0.065***</td>
<td>0.044</td>
</tr>
<tr>
<td>(t statistics)</td>
<td>(1.713)</td>
<td>(-3.738)</td>
<td>(1.665)</td>
<td>(-2.982)</td>
<td></td>
</tr>
</tbody>
</table>

Note: The t-statistics are in parentheses. *** and * represent significance at 1% and 10%, respectively.

The regression coefficients of \( m_1 \) and \( m_2 \) are consistent with the expectation that changes in prices have momentum effects. It is worth noting that, even if we control for the momentum effect, the magnet effect still exists, especially the magnet effect in the downward direction. \( \alpha_2 \) is still significantly negative at the 1% level. Therefore, empirical results indicate that the fusing mechanism will bring a magnet effect to the Korean stock market.

Since circuit breaker mechanism in China was only implemented for a week, the magnet effect of the index might not be as pronounced as in the Korean market. We used the 5-minute SHSE Index to re-do the above regressions. We select the sample from January 4, 2016 to July 14, 2016, which covers the two “Full Breaking” experienced by the Chinese stock market. The regression results show that, if we use (8) and (9) to define the quasi dummy variables, there is no significant magnet effect in the Chinese market, as shown in Table 8. However, if we define dummy variables in a standard way (see equations (13) and (14)), then there exists a magnet effect in the downward direction in the Chinese market, and the effect is statistically significant only when the threshold is set to -5%, as shown in Table 7. If we exclude the circuit breaker data and use a subsample from January 8, 2016 to the end, the magnet effect is no longer significant. This suggests that the implementation of the circuit breaker mechanism has indeed brought a magnet effect to the Chinese market.
\[ d_3 = \begin{cases} 
1, & \text{if } \left( \frac{P_t - P_{\text{close}}}{P_{\text{close}}} \right) \geq p \\
0, & \text{otherwise}
\end{cases} \quad (13) \\
\]

\[ d_4 = \begin{cases} 
1, & \text{if } \left( \frac{P_t - P_{\text{close}}}{P_{\text{close}}} \right) \leq q \\
0, & \text{otherwise}
\end{cases} \quad (14) \\
\]

Table 7 Magnet effects in the Chinese market

<table>
<thead>
<tr>
<th>( p = 3% ), ( q = -3% )</th>
<th>( \alpha_1 )</th>
<th>( \alpha_2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.011</td>
<td>-0.007</td>
</tr>
<tr>
<td></td>
<td>(0.09)</td>
<td>(-0.06)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>( p = 3% ), ( q = -4% )</th>
<th>( \alpha_1 )</th>
<th>( \alpha_2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.011</td>
<td>-0.295</td>
</tr>
<tr>
<td></td>
<td>(0.094)</td>
<td>(-1.602)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>( p = 3% ), ( q = -5% )</th>
<th>( \alpha_1 )</th>
<th>( \alpha_2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.011</td>
<td>-0.638**</td>
</tr>
<tr>
<td></td>
<td>(0.095)</td>
<td>(-1.995)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>( p = 3% ), ( q = -5% )</th>
<th>( \alpha_1 )</th>
<th>( \alpha_2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exclude data of circuit-breaker halt.</td>
<td>0.007</td>
<td>-0.399</td>
</tr>
<tr>
<td></td>
<td>(0.061)</td>
<td>(-0.681)</td>
</tr>
</tbody>
</table>

Note: The t-statistics are in brackets. ** represents significance at the 5% level.

We set the threshold on the rising direction to 3% because there was only one day in the sample when the increase exceeded 4%.

By comparing the data between China and South Korea, we find that the fusing mechanism has a significant impact on the stock market. The purpose of the fusing mechanism is to give the market a cooling-off period, allowing investors to fully assimilating market information and prevent irrational fluctuations in the market (Greenwald and Stein 1988, 1991). Goldman and Sosin (1979, p. 55) believe that, given sufficient uncertainty, the fusing mechanism can increase the efficiency of the market. However, our findings are more inclined to the following point: the risk of being denied to trade encourages traders to preempt trading, which leads to a magnet effect on prices.
4.2 Magnet effects in the standard price limit mechanism

Given the fact that the circuit breaker is different from the traditional price limit mechanism, in this section, we examine if magnet effects are still valid in the standard price limit mechanism.

4.2.1 Hypothesis test for individual stocks

To test the effects of the price limits, we used the previous GARCH(2,2) model to test whether stock prices continued to rise or fall after reaching a certain range of price fluctuations. In order to further study the volatility spillover hypothesis, we add a new variable, LIM, to the variance equation to capture the volatility spillover effects of the price limits. The specific model is set as follows:

\[
\begin{align*}
\text{Return}_t &= c + \sum_{i=1}^{2} \alpha_i d_{i,t-1} + \sum_{j=1}^{3} \beta_j \text{Return}_{t-j} + \epsilon_t \\
\text{Vol}_t &= \gamma_0 + \gamma_1 \text{Vol}_{t-1} + \gamma_2 \epsilon_{t-2}^2 + \gamma_3 \epsilon_{t-1}^2 + \gamma_4 \epsilon_{t-2}^2 + \gamma_5 \left( d_{1,t-1} + d_{2,t-1} \right) + \gamma_6 \text{LIM}_t
\end{align*}
\]

(15) (16)

where \text{Return}_t is the five-minute rates of return after adjusting for each stock’s volatility. We eliminate the stocks that hit the price limits. This is because the price can only move in the opposite direction once it reaches the price limits, which will produce a misleading result. In addition, when calculating the rate of return for the first 5 minutes of each trading day, we divide the price of 9:35 by the average auction price 5 minutes prior to the opening of the market at 9:30am instead of using the closing price of the previous trading day. In such way, we can eliminate the effects of overnight earning jumps. \( d_1 \) and \( d_2 \) are dummy variables related to the price fluctuations. We use \( \pm 6\% \) as the threshold.

If there is a magnet effect in the direction of the limit-up, then \( \alpha_1 \) should be significantly greater than 0, indicating that, when the stock price is close to the limitation of the limit-up, there will be a continuous rise. Similarly, if there is a magnet effect in the direction of the limit-down, \( \alpha_2 \) should be significantly less
than 0. The $LIM_t$ in the variance equation represents the timing of hitting the price limits of the previous trading day. If there is a volatility spillover effect, then the longer the time of hitting price limits, the greater the volatility on the next day. Therefore, we expect $\gamma_6$ to be significantly greater than 0 if the volatility spillover effects hold.

For the validity of $LIM_t$, we use the same GARCH model to apply to all stocks whose prices have hit the price limits at least one time. The estimated results are shown in Table 8.

<table>
<thead>
<tr>
<th>Table 8 Magnet effect test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>Number of shares with</td>
</tr>
<tr>
<td>coefficient &gt;0</td>
</tr>
<tr>
<td>Number of shares with</td>
</tr>
<tr>
<td>coefficient &lt;0</td>
</tr>
<tr>
<td>Coefficient (median)</td>
</tr>
<tr>
<td>T statistics (median)</td>
</tr>
</tbody>
</table>

Our statistical results show that the stock does not show a significant magnet effect, especially in the upward direction. Take $\alpha_1$ as an example. If there is a magnet effect on the price limits mechanism, the price should continue to rise when the stock price rises above a certain value. That is, $\alpha_1$ should be greater than 0. In our sample, there are 170 stocks whose $\alpha_1$ is greater than 0, which accounts for about 30% of total stocks. After reaching a certain positive growth rate, the remaining 70% of stocks decline in their price growth or even become negative price growth, which is not consistent with the magnet effect. The magnetic effect in the direction of limit-down is more obvious; over half of the stocks have a negative $\alpha_2$, and the median value of the t statistic is -0.4196.

Although the magnet effects are not very obvious, the volatility spillover effect is well validated. The statistical results show that the median value of $\gamma_6$ is greater than 0, and the median value for the t statistics is 1.8842, meaning that it demonstrates significance at the 10% level.
4.2.2 Hypothesis test for the market index

Contrary to the conclusion that individual stocks do not have significant magnet effects, we have found that the overall rise and fall of the stock market is more likely to cause a single stock to continue to rise and fall. We replace the dummy variables that reflect the rise and fall of a single stock in equation 5, with truncated variables that reflect market fluctuations.

\[ d_1 = \begin{cases} \left( \frac{P_t^M - P_{close}}{P_{close}} \right)^2, & \quad P_t^M > P_{close}^M \\ 0, & \quad P_t^M \leq P_{close}^M \end{cases} \] (19)

\[ d_2 = \begin{cases} \left( \frac{P_t^M - P_{close}}{P_{close}} \right)^2, & \quad P_t^M < P_{close}^M \\ 0, & \quad P_t^M \geq P_{close}^M \end{cases} \] (20)

where \( P_t^M \) is the price of the Shanghai Composite Index at the time \( t \), and \( P_{close}^M \) is the closing price of the Shanghai Composite Index on the previous trade day.

Table 9 shows that, in the limit-up scenario, except for two stocks, the \( \alpha_1 \) of the rest of the stocks are all greater than 0, while in the limit-down scenario, there are more than 90% stocks in which \( \alpha_2 \) is less than 0. The regression coefficients that confirm the sign expectations and the t statistics suggest that the impacts of stock market index fluctuations on the continued rises or falls of stock prices are more obvious than the impacts of individual stocks on themselves. This evidence further points out that the market-wide fuse is more likely to trigger a magnet effect than an individual stock's price limits. In addition, the coefficient of volatility spillover effect are positive and significant, which validate our volatility spillover hypothesis.

<table>
<thead>
<tr>
<th></th>
<th>( \alpha_1 )</th>
<th>( \alpha_2 )</th>
<th>( \gamma_6 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of shares with coefficient &gt;0</td>
<td>570</td>
<td>51</td>
<td>523</td>
</tr>
<tr>
<td>Number of shares with coefficient &lt;0</td>
<td>2</td>
<td>521</td>
<td>49</td>
</tr>
<tr>
<td>Coefficient (median)</td>
<td>0.0128</td>
<td>-0.0092</td>
<td>0.0030</td>
</tr>
<tr>
<td>T statistics (median)</td>
<td>1.7222</td>
<td>-1.5681</td>
<td>2.1568</td>
</tr>
</tbody>
</table>
5 Circuit-breaker Halt and Volatility at the Next Opening

In this section, we examine the consequences of the circuit breaker mechanism on the market volatility by analyzing the volatility of the opening price of the market index on the following trading day after the circuit breaker has been triggered. The reason for choosing volatility at the market opening is to exclude other factors that may affect the market volatility. We define the volatility at the opening as follows:

$$\text{volatility}_t^o = \left( \frac{p_{t+1}^o - p_{t}^c}{p_t^c} \right)^2$$  \hspace{1cm} (21)

Where $p_{t+1}^o$ is the next day's opening price, and $p_t^c$ is the previous day's closing price.

We do not examine the effect of the impediment to trade on the market volatility by simply comparing the volatility before and after the circuit breaker, because it is difficult to identify the changes in volatility caused by the circuit breaker from the changes caused by some other factors that lead to circuit-breaker halts and affects the volatility at the same time. To answer this tricky question, we compared the market volatility of the next day opening within a group of observations that have a similar drop in index prices.

Our sample includes all of the trading days between January 2006 and July 2016. We select a subsample in which the intraday price of the Shanghai Composite Index fell by more than -5%. Based on our sample, in the past 10 years, the Shanghai Composite Index has experienced a total of 63 days during which the lowest intraday price fell below -5%. We further select the dates when the close prices dropped below -5%. Thus, 63 trading days are divided into two groups. In group A, the intraday prices fell below -5%, but not the closing price. Group A includes 20 trading days. In group B, both the intraday prices and the close price exceeded -5%. The B group includes 43 trading days. Figures 5 and 6 display the histograms of average market volatility of the next day opening for group A and group B, respectively.
The mean volatility of the next-day opening for group A was 7.98, while the mean value for group B was only 4.69. The t-test shows no significant difference between the means of the two groups (p value=0.391). Therefore, according to our test, even if we admit that the circuit breaker has caused the Level 2 break (as in the case of January 7, 2016), the fusing had an impact on the closing price of the day at most, and it would not affect the volatility of the next day. These findings are consistent with previous studies (Kuhn et al., 1991; Lauterbach and Ben-Zion, 1993). In summary, the empirical results suggest that the circuit
breaker mechanism has no significant effects on the volatility of the next day’s opening.

In order to conduct formal tests on whether the volatility of the next-day opening in both groups A and B is not significantly different, we employ the following regression model.

First, we define the proportion of stocks that hit the down-limit at the market closure as $DL_{close}$ to denote the daily drop in the index. The larger the value of $DL_{close}$, the smaller the space for the market index to fall.

Second, we then calculate the differences between the proportion of stocks that hit the down-limit at the market closure and the proportion of stocks that hit the down-limit at their lowest intraday price, $\frac{DL_{low}-DL_{close}}{DL_{low}}$, to indicate the degree of the market index rebound. The larger the value of this ratio, the greater the degree of index rebound.  

Finally, we use these two variables to regress on volatility$^{\theta}_{t+1}$. The sample includes 63 trading days with a -5% decline. The regression results are as follows:

$$volatility^{\theta}_{t+1} = -0.01 + 0.03 \times DL_{close} + 0.02 \times \frac{DL_{low}-DL_{close}}{DL_{low}}$$

$t$ statistics (-1.56) (2.73) (1.85) (22)

The regression coefficients of these two variables are all positive. The variable representing the falling space is significant at the 1% level, and the variable representing the degree of rebound is significant at the 10% level.

The economic meaning of $DL_{close}$ is not difficult to understand because the down limit prevents the market index from falling further, and the decline needs to be realized on the next trading day. The more stocks that reach the down-limit in the previous trading day, the greater the probability that the price will continue to fall the following day. However, the coefficient of $\frac{DL_{low}-DL_{close}}{DL_{low}}$ indicates that the greater the recovery after the fall, the higher the volatility of the next-day opening.

---

9 Use $S_{dietinglow} - S_{dietingclose}$ instead of $S_{dietingclose} - S_{dietinglow}$ as a numerator is to ensure that the variable is positive.
The classification of group B is somewhat too general, because the threshold of the Level 2 breaker will prevent the market index from falling further below the threshold. In order to exclude the influence of the second threshold on the closing price, we divide the B group into different subsets. We divide the 43 trading days of Group B into the following ranges. B1: [-10%, -7.5%], B2: [-7.5%, -6.5%], B3: [-6.5%, -5%]. Among them, there are 7 observations in the B1 interval, 9 observations in the B2 interval, and 27 observations in the B3 interval. We then use the t-test to verify whether the average values of the volatility of the next-day opening in different sub-groups are equal. The test results for the B group are shown in Table 10:

Table 10 Test of volatility of the next-day opening

<table>
<thead>
<tr>
<th>$H_0$</th>
<th>The average volatility of Group B1 is not significantly different from Group B2.</th>
<th>The average volatility of Group B1 is not significantly different from Group B3.</th>
<th>The average volatility of Group B2 is not significantly different from Group B3.</th>
</tr>
</thead>
<tbody>
<tr>
<td>P value</td>
<td>0.197</td>
<td>0.267</td>
<td>0.814</td>
</tr>
<tr>
<td>Conclusion</td>
<td>Do not reject $H_0$</td>
<td>Do not reject $H_0$</td>
<td>Do not reject $H_0$</td>
</tr>
</tbody>
</table>

Through the further division of Group B, we confirm the previous view that the fusing mechanism has no significant effect on the volatility at the opening of the next day.

5. Concluding remarks and policy discussion on the circuit breaker

Some researchers assert that the launch of the fusing mechanism is intended to prevent extreme market reactions, but the 5% and 7% rises or falls are not as extreme in the Chinese stock market. Based on the historical performance of the Shanghai-Shenzhen 300 Index, since the index was released on April 8, 2005, consideration of the largest increase and decrease revealed 70 days when intraday increase or decline exceeded 5%, of which 24 times were increases and 46 times were declines. There were 33 days when intraday increase or decline exceeded 7%, of which 11 times were increases and 22 times were declines. The
time distribution indicates that 30 of the 70 thresholds (5% increase or decrease) occurred in 2008 and 12 in 2015. 13 of the 33 thresholds (7% increase or decrease) occurred in 2008 and 11 in 2015.

In addition, we calculated the daily volatility of the US S&P Index, South Korea’s KOSPI Index, and the CSI 300 Index and found that, between January 2000 and September 2016, the average volatility of the S&P 500 and KOSPI Index was 1.569 and 2.468, respectively, while the average volatility of the CSI 300 index was 3.122, which was significantly higher than the other two indices. As the volatility of the CSI 300 Index itself is too large, it is easy to trigger frequent circuit breakers. Due to the small volatility of the S&P Index, the U.S. stock market has only experienced one circuit breaker in 1997 since the implementation of the fusing mechanism. The South Korean index has a volatility between that of S&P 500 and CSI 300, and frequent circuit breakers have been triggered in Korea. The Korean stock market once suffered three consecutive circuit-breaker halts between 2000 and 2001. During that time, the volatility of the Korean stock market was 6.387. Given the fact that the volatility of the Chinese stock market is significantly higher than that of the other two markets and the threshold setting is much lower than that of other markets, this will result in more frequent circuit-breaker halts. Note that, even if all stocks in the Chinese market fell to the price limit, the market index will decline by 8.5% instead of 10%, because there are the stocks in suspension and the ST stocks. Therefore, the circuit breaker threshold of 7% is justified more or less. However, the 5% threshold appears to be restrictive, because the historical data has shown that it has been quite frequently reached. Most importantly, we document that the magnet effects of the circuit breaker will exacerbate investors’ panic and therefore limit the market liquidity and increase the execution uncertainty.

In addition, our study also finds that trading restrictions interfere with the market and hinder the price discovery of stocks. Our research finds that, in order to avoid the risk of not being able to trade, investors will sell stocks before the closing and buy them again after the next opening. This behavior interferes with

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10 The starting time of the CSI 300 Index in the Bloomberg database is January 2002.

11 China has a price limit of 10% while the United States has no price limit, and South Korea’s price limit is 30%.
the normal price discovery process and also induces magnet effects in special circumstances.

Finally, on the issue of magnet effects, we find that the fusing mechanism has brought about a strong magnet effect through the data of the Korean stock market. There was a certain magnet effect in the downward direction in Chinese stock market due to the two “Full Breaking” instances. After the elimination of the fusing mechanism, however, there is no magnet effect in Chinese stock market. With regard to the magnet effects of the price limiting mechanism, we find that, according to our high-frequency data, Chinese stock market has a magnet effect in the downward direction, and more than half of the stocks will continue to fall after reaching a certain level of decline.

References


Fama, E., 1989, Perspectives on October 1987, or, what did we learn from the


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Appendix I

Tables 1A and 2A describe the circuit breaker and the price limit mechanism in major markets around the world. With regard to the setting of the thresholds of price limit and the circuit breaker mechanism, different countries have different restrictions. For example, the price limit interval extends with a wide range from 2% to 60%. In addition, many countries constantly change the threshold setting. For example, South Korea’s price limits have been increased from less than 5% to 30%, and its market-wide circuit breakers have also been modified from the previous 10% to the current various thresholds, as shown in Table A1. The NYSE firstly implemented the fusing mechanism in 1987, and it has also undergone several changes. The fuse threshold has evolved from the initial absolute index point to the current percentage change.

Table A1: The circuit breaker systems of the major markets across the world

<table>
<thead>
<tr>
<th>Country</th>
<th>Fuse Threshold</th>
<th>Trading Halt Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>US</td>
<td>S&amp;P 7%</td>
<td>15 minutes</td>
</tr>
<tr>
<td></td>
<td>13%</td>
<td>15 minutes</td>
</tr>
<tr>
<td>Country</td>
<td>Threshold</td>
<td>Note</td>
</tr>
<tr>
<td>-------------</td>
<td>-----------------</td>
<td>-----------------------------</td>
</tr>
<tr>
<td>Canada</td>
<td>10% 20% 30%</td>
<td>30 minutes 1 hour 2 hours</td>
</tr>
<tr>
<td>South Korea</td>
<td>8% 15% 20%</td>
<td>20 minutes 20 minutes Close trading for the day.</td>
</tr>
<tr>
<td>Japan</td>
<td>8%, 12%, 16%</td>
<td>15 minutes</td>
</tr>
<tr>
<td>France</td>
<td>Decline by 10%</td>
<td>15 minutes</td>
</tr>
<tr>
<td>Singapore</td>
<td>Decline by 10%</td>
<td>5 minutes</td>
</tr>
<tr>
<td>Israel</td>
<td>5% 8% 12%</td>
<td>45 minutes 45 minutes Close trading for the day.</td>
</tr>
<tr>
<td>Brazil</td>
<td>10% 15% 20%</td>
<td>30 minutes 1 hour Determined by the exchange.</td>
</tr>
<tr>
<td>India</td>
<td>10% Before 13:00</td>
<td>45 minutes 15 minutes Not stop.</td>
</tr>
<tr>
<td></td>
<td>13:00-14:30</td>
<td>15 minutes</td>
</tr>
<tr>
<td></td>
<td>After 14:30</td>
<td>45 minutes</td>
</tr>
<tr>
<td></td>
<td>15% Before 13:00</td>
<td>1 hour and 45 minutes Close trading for the day.</td>
</tr>
<tr>
<td></td>
<td>13:00-14:30</td>
<td>45 minutes</td>
</tr>
<tr>
<td></td>
<td>After 14:30</td>
<td>Close trading for the day.</td>
</tr>
<tr>
<td></td>
<td>20% Any trading time</td>
<td>Close trading for the day.</td>
</tr>
</tbody>
</table>

Source: obtained from exchange websites.
<table>
<thead>
<tr>
<th>Country</th>
<th>Percentage</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Romania</td>
<td></td>
<td>21.25% limit up and 18.75% limit down.</td>
</tr>
<tr>
<td>France</td>
<td>About 20%</td>
<td></td>
</tr>
<tr>
<td>Greece</td>
<td>4% and 8%</td>
<td>After August 1992, the 8% limit was imposed on stocks with large trading volume.</td>
</tr>
<tr>
<td>Italy</td>
<td>10%-20%</td>
<td></td>
</tr>
<tr>
<td>Japan</td>
<td>10%-60%</td>
<td>Use different limits depending on the stock price.</td>
</tr>
<tr>
<td>South Korea</td>
<td>30%</td>
<td>Since 1995, the threshold of limit up and limit down has continued to increase, initially only 6%.</td>
</tr>
<tr>
<td>Malaysia</td>
<td>30%</td>
<td></td>
</tr>
<tr>
<td>South Africa</td>
<td>2%-6%</td>
<td>Use different limits depending on the stock price.</td>
</tr>
<tr>
<td>Spain</td>
<td>15%</td>
<td></td>
</tr>
<tr>
<td>Taiwan region</td>
<td>10%</td>
<td>By June 2015 it was 7%.</td>
</tr>
<tr>
<td>Thailand</td>
<td>30%</td>
<td></td>
</tr>
</tbody>
</table>

Source: from exchange websites.