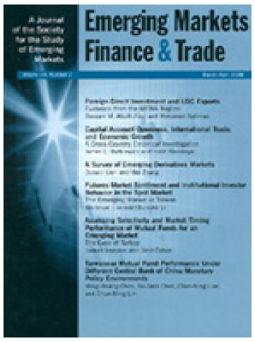

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Price Limits and Asymmetry of Price Dynamics—High Frequency Evidence from the Chinese Stock Market

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ABSTRACT: Our article employs the high frequency intraday data from the Shanghai Stock Exchange to analyze the impacts of the price limit mechanism on the stock price dynamics and their determinants. We document significant volatility spillover effects and downward magnet effects for individual stocks and for the market index. Finally, our empirical results suggest that timing and trading volumes are two determinants of price limit effects.

KEY WORDS: magnet effect, price limits, volatility spillover effect

1. Introduction

Price limits system is widely adopted, especially in emerging countries, in order to maintain a stable stock market. Its main purpose is to reduce market volatility, curb speculation, and ensure the stable operation of the stock market. However, according to the vast literature on price limits, the role of the system is still in dispute. From a theoretical point of view, these restrictions are proposed to reduce the market's volatility. For example, the price limits are to avoid the stock price fluctuation caused by panic and speculation. The circuit breaker attempts to give investors time to calm down, allowing them to fully assimilate market information and avoid extreme changes in market prices. However, many empirical studies provide the opposite answers. As Fama (1989) pointed out that if the price discovery process is constrained, the volatility of stocks will increase accordingly. Kuhn, Kurserk, and Locke (1991) found that the circuit breaker in the 1989 crash did not play a role in reducing volatility. In addition, trading restrictions will also bring a magnet effect, accelerating the market to reach the price limits.

The literature on the consequences of price limit policies on the market performance is still in dispute. One strand of literature documents that the price limits mechanism prevents investors from panicking and possible overreaction and helps reduce the price fluctuations and therefore mitigates market risks. It includes Aşçıoğlu, Karahan, and Yılmaz (2015), Bildik and Elekdag (2004), Chou, Lin, and Yu (2006), Liao, Lin, and Wang (2011) and etc. 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 2-h break between two daily conversations reduces volatility, which helps spread valuable information, thereby preventing serious overreactions to news events. Chou, Lin, and Yu (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,

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margin requirements after price limits are imposed may be lower than those without price limits. Liao, Lin, and Wang (2011) selected the daily stock price data for the Taiwan stock market from January 1, 2001 to August 31, 2007, the research indicates 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. Fama's (1989) study found that the implementation of the price limits system would increase the volatility of the stock price. Once the transaction is hindered, the volatility will inevitably increase in the next few trading days. Kim and Rhee (1997) used Tokyo market transaction data for analysis. They used the stocks that 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 Tokyo and Taiwan's stock market volatility, and even can produce an adverse effect on normal trading behavior. This is because the price limit system leads to the volatility spillover effect and causes the delay in the 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 summary, the role of the price limits system is still in dispute. Our article employs the daily data and high frequency data of the Shanghai Stock Exchange to explore if the price limit mechanism plays an important role in affecting price dynamics, and what are the determinant factors. Using high frequency intraday data, we document significant volatility spillover effects and downward magnet effects for individual stocks and for the market index. Our empirical results also suggest that timing and trading volumes are two determinants of price limit effects.

The remainder of this study is organized as follows. Section 2 describes the price limit mechanism in the major markets and the data description. Section 3 discusses the hypothesis developments and the statisitcal evidence. Section 4 represents the econometric model and empirical results. Section 5 concludes.

2. Trading Restrictions and Data Description

2.1. Trading Restrictions

In practice, stock markets, especially those in emerging countries, have adopted various restrictions. The restrictions mainly include the following three categories: the first type is the price limit mechanism, that is, the stock price is restricted to fluctuate within a specific interval. The second type is the share suspension of a single stock, which is mostly implemented by an exchange or a regulatory agency. The third category is the market-wide circuit breaker. Specifically, when the market index hits a certain threshold, the entire market stops trading. Table 1 describes price limit mechanisms of major markets around the world.

With regard to the setting of the thresholds of price limit mechanism, different markets have different measures. The price limit interval extends a wide range from 2% to 60%. In addition, many countries constantly change the threshold setting. For example, South Korea's price limit boundary has been increased from less than 5–30%; their fusing mechanism has also been modified from the previous 10% to the current hierarchic circuit breaker thresholds. Since the United States introduced the circuit breaker in 1987, it has also undergone several changes. The fuse threshold has evolved from the initial absolute index point to the current percentage change.

Table 1. Price limit mechanism in the major markets.

Countries	Limit (±)	Note
Austria, Luxembourg	5%	
Belgium,Mexico, Turkey	10%	
Finland, Peru, Romanian	15%	
France	About 20%	The top limitation is 21.25% and the bottom is 18.75%
Greece	4% and 8%	After August 1992, the 8% price limit was imposed on stocks with large trading volumes.
Italy	10%–20%	
Japan	10%–60%	Use different restrictions depending on the stock prices
Korea	30%	
Malaysia	30%	
South Africa	2%–6%	Use different restrictions depending on the stock prices
Spain	15%	
China	10%	The price limit has imposed since 1996
Thailand	30%	

Source: Collected from various exchange websites.

2.2. Data Description

Our data are compromised of the daily data and one-minute and five-minute data from the Shanghai Stock Exchange. The daily data cover from January 1, 2006 to June 22, 2016, including a total of 814 stocks. Our sample excludes stocks with short trading hours, and special treated (ST) shares. The high frequency data include 748 stocks in total and range from the first minute at the opening of January 4, 2016 to the last minute on the closing of July 14, 2016. The high frequency data also exclude stocks with short trading hours, stocks with little volatility and ST shares.[1]

Figure 1 shows a histogram of the daily returns of all stocks. From the histogram we can see that the average rates of return of all the stocks display thick tail characteristics, and a large number of observations are truncated at the boundaries of upper and down price limits. Given the empirical return distribution, we have reasons to believe that price limits have impacts on the fluctuation of stock price.

In what follows, we divide the rates of return into different groups according to the variation in their daily returns. We define Z10 as the group that hit the upper price boundary, the maximum increase exceeds 9% but did not hit the price limits as Z9, and see the stock price that the maximum increase more than 8% but not reach 9% as Z8. Correspondingly, we also define D10 as the group that hit the down price limit boundary, the stock price that minimum fall more than −9% but did not reach the price limit as D9, and that the minimum decline more than −8% but not reach −9% as group D8. The number of stocks in each group is shown in Table 2:

In the total 1,778,004 observations, the number of stocks that have hit upper price limits is 46,184, and the number of stocks that hit down price limits is 41,433. Apparently, the price limit mechanism restricts more rises of stock prices than the declines. Comparing stocks in the group of Z10(D10) to stocks in group Z9(D10) will help us tease out the impacts of the price limits on stock prices. However, the comparison between Z9 (D9) and Z8 (D8) helps us to decompose the effects whether the differences between Z10 (D10) and Z9 (D9) are caused by a 1% gap, or they are caused by the price limits.

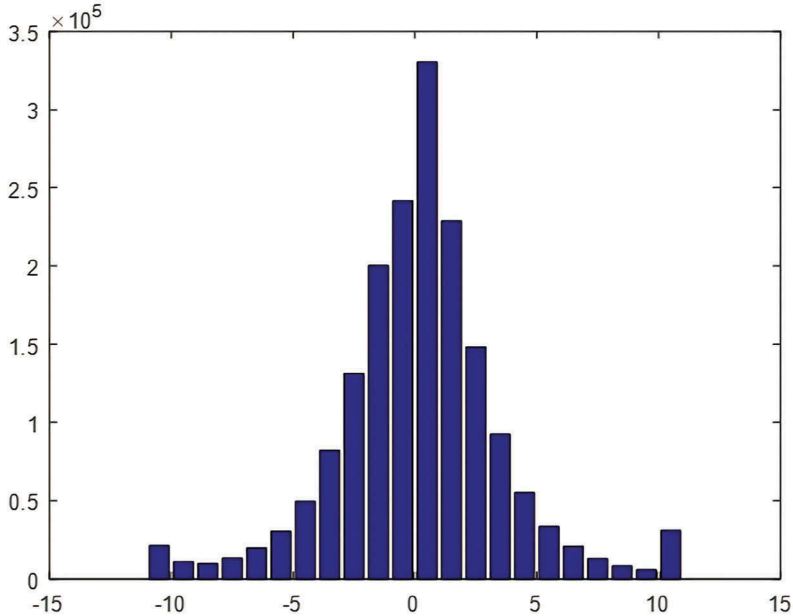

Figure 1. Shanghai stock return histogram.

Table 2. Data statistics.

	Observations (Price increases)	Observations (Price decreases)
	Z10 (n = 46184)	D10 (n = 41433)
Mean	0.0968	–0.0954
Median	0.0947	–0.096
S.D.	0.0015	0.0018
	Z9 (n = 19304)	D9 (n = 17001)
Mean	0.0849	–0.0831
Median	0.0832	–0.0845
S.D.	0.0021	0.0015
	Z8 (n = 21102)	D8 (n = 18735)
Mean	0.0764	–0.0755
Median	0.0771	–0.0742
S.D.	0.0017	0.0026

Note: S.D. refers to standard deviation. N denotes the numbers of observations in each group.

3. Hypothesis Development and Empirical Results

3.1. Volatility Spillover Hypothesis

3.1.1. Development of Volatility Spillover Hypothesis

The main function of the price limits is to restrain the abnormal fluctuation of stock, so as to reduce the volatility of the stock. However, the existing literature shows that when the price discovery process is constrained, the volatility of the stock increases. Price limits can have an spillover effect on stock volatility, that is, stock volatility will remain high for the next trading day (Fama 1989; Kuhn, Kurserk, and Locke 1991; Lehmann 1989, etc.). The volatility spillover hypothesis has been tested in many markets.[2] The validation method is based on the group comparison method presented by Kim and Rhee (1997).

3.1.2. Empirical Evidence

Referring to the practice of Fama (1989) and Kim and Rhee (1997), we define stock volatility as follows:

$$v_{i,t} = \left(r_{i,t}\right)^2 \tag{1}$$

where $r_{i,t}$ is the return rate of stock i on t day. For the group that hit the upper price limits (Z10), we define $t = 0$ as the limit-up day when stock price hit the upper price limits, $t = -n$ represents the nth day before the limit-up day, $t = n$ represents the nth day after the limit-up day. We calculate the daily volatility of each stock from $-n$th day to nth day, and then average all stocks to get the average volatility for each day, and record it in the table below. For comparison, we also calculated the average volatility of the Z9 (Z8) group in a similar way. The unique difference is that $t = -n$ is not a limit-up day, but it is the day that stock prices have reached the 9%(8%) boundary. We use $t - test$ to verify that the average volatility of the different groups is not significnatly different from each other. In order to avoid the deviation caused by the continuous daily price limits, we remove the data of consecutive 2-day or 3-day daily price limits. At the same time, in order to avoid the impact of the continuous close of stock transactions, we eliminated the data without transaction for more than three consecutive days. If the volatility spillover hypothesis is established, then for the next few days after $t = 0$, the volatility of Z10 will be significantly higher than that of Z9.

The asterisks on the estimates in Z10 column indicate the significant level of the differences between the estimated volatility in Z10 and their counterparts in Z9. Similarly, the asterisks on the estimates in Z9 column indicate the significant level of differences between Z9 estimates and Z8 estimates. Our results show a certain volatility spillover effect due to price limit mechanism. Although the data for the first day after the limit-up day showed no significant difference between the group Z10 and the group Z9, data from the following day but the third day confirmed the existence of the volatility spillover effect. In comparison between the Z9 Group and the Z8 Group, there is no volatility spillover effect in the first 3 days. Therefore, we can determine that the volatility spillover effect is not caused by the difference between the growth rate of 1%, but the price limits mechanism.

There is a noteworthy point in Table 3. It is how comes the volatility spillover effects are not significant on the first day after the day when shock prices hit the price limits. This observation is not quite intuitive because, intuitively, we think that the stock whose price hit limits will attract investors' attention, which will lead to an increase in the volatility of the next day. An important reason for our result is that we eliminated the data of consecutive limits-up and only retained the data of the daily increase of 9% and hit the price boundary of the next day, artificially reducing the volatility on the first day after the limit-up day. If we do not do the above process, the volatility of the group Z10 is significantly greater than the volatility of the group Z9 at t = 1.

There has been a controversy over whether the data that continuous hit the price limits should be eliminated (Kim 2001). Therefore, in order to obtain an uncontroversial conclusion, we use a GARCH model to further verify the volatility spillover effects, and the empirical results confirm the existence of the volatility spillover effects in the Shanghai market due to the price limit mechanism. The empirical analysis is given in the fourth section of high frequency data regression analysis.

The results of the comparison between the limit-down group and the control group are given in Table 4. The impact of the limit down on volatility is more pronounced, but it also makes the results more difficult to explain. Without exception, the obvious differences make it hard to resist the

Table 3. Hypothesis test of volatility spillover (limit-up).

	Z10	Z9	Z8
−9	19.4962 (***)	18.5058	18.7504
−8	20.0370	20.7354 (***)	19.5469
−7	19.3460 (**)	20.0785	19.6660
−6	20.2283	20.3378	20.5981
−5	18.8971	19.2776	19.2344
−4	19.1549 (**)	19.9454	20.5091
−3	19.8934	19.5248	19.3621
−2	22.6123	22.3370 (***)	21.0565
−1	22.1903 (***)	25.8448 (***)	23.9623
0	81.1195 (***)	45.7132 (***)	34.7659
1	18.2083	18.1654	17.8107
2	19.1505 (***)	18.0471	17.6090
3	19.9918 (**)	19.2580	18.7192
4	18.9179	18.6133 (***)	17.6289
5	18.0188	17.4188	16.9494
6	17.9693 (***)	18.7787	18.5736
7	19.1283	19.5176 (**)	18.6818
8	18.6847	18.7115	18.3715
9	17.9207	18.2423 (***)	17.1887
10	17.7056	18.1995 (***)	17.0373

NOTE:*** represents significant at the 1% level, and** represents significant at the 5% level.

Table 4. Hypothesis test of volatility spillover (limit-down).

	D10	D9	D8
−9	22.2360 (***)	19.6921 (***)	18.5540
−8	21.9976 (***)	19.5297 (***)	18.3765
−7	23.9026 (***)	21.1706 (***)	19.4901
−6	26.2328 (***)	22.2370 (***)	21.2457
−5	23.6653 (***)	22.3299 (***)	20.2419
−4	25.1981 (***)	22.3971 (***)	20.9839
−3	28.1796 (***)	23.6919 (***)	21.9131
−2	28.9359 (***)	24.7898 (***)	22.3523
−1	32.7239 (***)	29.3038 (***)	24.7783
0	78.1711 (***)	48.8027 (***)	38.9370
1	28.0766 (***)	23.7455 (***)	20.2522
2	31.2298 (***)	24.6005 (***)	21.2127
3	26.0250 (***)	22.3995 (***)	20.4826
4	28.2395 (***)	22.2202 (***)	18.9378
5	25.7816 (***)	20.2654 (***)	17.4354
6	25.4546 (***)	21.3236 (***)	18.9826
7	24.9902 (***)	23.1055 (***)	19.7577
8	26.5174 (***)	23.2479 (***)	19.4229
9	23.5195 (***)	20.4227 (***)	17.9448
10	24.1937 (***)	20.4695 (***)	18.1177

NOTE:*** represents significant at the 1% level, and** represents significant at the 5% level.

existence of other factors. Similarly, to make the results more convincing, we used the GARCH model to further validate the volatility spillover effects.

3.2. Liquidity Interference Hypothesis

3.2.1. Development of Liquidity Interference Hypothesis

According to the liquidity interference hypothesis, when the price reaches the price limit, the market liquidity will be exhausted and the transaction cannot be completed. When the price was no longer constraint on the following day, the volume of transactions that should have been completed on the previous trading day was finally realized, which results in a substantial increase in trading volume on the following day. However, in the control groups, there is no significant increase in trading volume on the next day due to the absence of price limits (Fama 1989). The effect of the liquidity interference hypothesis in the Japanese market is confirmed by the Kim and Rhee (1997). The Kim and Sweeney also found that in the Taiwanese market, informed investors would shift some of their trading behavior to the next day, proving a higher volume on the day after the price limit events.

3.2.2. Empirical Evidence

Given the different sizes of stock shares in the circulation, the stocks with less shares are more likely to hit the price limits. Our observations will be misleading if we simply compare the absolute trading volume data across different stocks. In order to overcome this problem, we instead use the index of turnover rates for our analysis. The turnover rate is defined as the daily volume/number of tradable shares in Equation (2).

$$\Delta TO = 100 * \left(\frac{TO_{i,t}}{TO_{i,t-1}} - 1 \right) \tag{2}$$

In Table 5, we report the average rate of change in turnover rate for each group,

At $t = 0$, the turn over ratio of Z10 group is significantly higher than that of the group whose stock prices did not hit the price limits, and its trading activities continued to rise on the following day. However, the trading volume of the control group fell on the following day. This finding confirms the liquidity interference hypothesis. The price limits mechanism imposes constraints on the daily transactions, and investors have to wait until the next trading day to trade the stocks that should have been traded in the previous day, which leads to an increase in trading volume the following day.

Table 6 shows the empirical results of the limit down, and the observations are similar to the limit up scenario. The trading volume of the limit-up group continued to rise on the following day. However, the trading volume of the control group decreased the next day. To sum up, we believe that the price limit mechanism has brought significant liquidity interference effects to the Shanghai stock market. Trading restrictions make it impossible for investors to complete transactions at the day when the price limits become effective, and have to wait for suboptimal trading opportunities.

3.3. Delayed Price Discovery Hypothesis

Because of the existence of the price limits, the process of price discovery is hindered. For example, when reaching the price limits, the stock price that should have continued to rise will have to wait for the next trading day to realize its market expectation, thus extending the time for price discovery. To test this hypothesis, we need to count the performance of stock prices on the following day. In general, the performance of the stock price in the following day can be divided into three cases: price continuation, price reversal and price unchanged. Referring to Kim and Rhee (1997), we categorize price movements by comparing the price changes between the benchmark day (t = 0) and the opening of the next day.

Table 5. Test of liquidity interference hypothesis (limit-up).

	Z10	Z9	Z8
−9	27.3722	24.9591	23.3036
−8	24.9579	23.2623	16.7551
−7	22.3098	17.8744	22.6948
−6	25.2800	29.3171	41.9429
−5	21.9229	21.4864	21.0286
−4	16.5708	16.2395	14.1937
−3	25.3078	27.6879	22.5193
−2	27.0810	27.8641***	16.8546
−1	20.2763***	32.3065	27.8934
0	169.9044***	95.8484***	87.2837
1	13.7844***	−15.5134**	−14.5249
2	−22.6946***	−9.1037	−5.9248
3	−1.5069***	4.6191	6.4610
4	2.9435**	5.2418	6.5657
5	3.5250	4.7565	5.9132
6	5.6247	6.9663	9.5214
7	12.2627	15.5886	10.9798
8	7.7929	9.3647	10.0357
9	10.7732	13.2683	12.7056
10	8.0147	8.0825**	14.8351

NOTE:*** represents significant at the 1% level, and** represents significant at the 5% level.

Table 6. Hypothesis test: liquidity interference (limit-down).

	D10	D9	D8
−9	38.4762	38.9621	24.8161
−8	54.6255***	19.1920	13.6628
−7	13.6824	14.8649	12.6393
−6	12.3676	10.8075	11.1031
−5	42.0515	27.4899	23.0732
−4	50.5802***	9.2400	11.4539
−3	19.9635	16.6116	15.4644
−2	14.2333	17.0530	17.0968
−1	16.8259**	29.5233	19.5580
0	73.6646***	23.7595***	17.7939
1	0.3752***	−10.2087***	−13.9685
2	−1.5065***	3.6802***	6.4209
3	10.1753	11.4686	13.5984
4	20.3137	10.3707	8.7057
5	14.1567	13.1236	11.3586
6	19.5177	19.8974	19.0328
7	44.9780***	14.9360	9.3138
8	12.1183	12.4495	15.4779
9	38.0477**	17.1828	13.6370
10	16.8094**	26.5783	16.6464

NOTE:*** represents significant at the 1% level, and** represents significant at the 5% level.

Specifically, the price change on the benchmark day is represented by the change rate of the closing price to the opening price,

$$r(Open_t, Close_t) = 100*\left(\frac{p_t^c}{p_t^o} - 1\right) \tag{3}$$

The price change on the following day is expressed as the ratio of the opening price on the following day to the closing price on the benchmark day.

$$r(Close_t, Open_{t+1}) = 100*\left(\frac{P_{t+1}^o}{p_t^c} - 1\right) \tag{4}$$

The price changes can be up (+), Down (-), and unchanged (0). According the changes of $r(O_tC_t)$ and $r(C_tO_{t+1})$, we can get nine different combinations: [+,+], [+, 0], [+,−], [0,+], [0, 0], [0, −], [−,+], [−, 0] and [], −]. When considering the influence of limit up, we classify [+,+] and [0,+] as price continuations, [+,−], [0,−], [−,+], [−, 0] and [−, −] are categorized as price reversal, [+, 0] and [0,0] are categorized as price unchanged. When considering the impact of limit down, we classify [−,−] and [0,−] as price continuations, [−,+], [0,+], [+,−], [+, 0], and [+,+] are the price reversal, [−, 0] and [0, 0] are the price unchanged.[3]

If the delayed price discovery hypothesis is established, then on the following day the stock price will continue the price trend that could not be completed in the previous trading day. On the contrary, if the hypothesis is not established, then the stock price will be reversed, which can either appear on the day when the price limits are hit, or the following day. As shown in Table 7, our statistics show that for the limit up the group, there are more than half of the stocks continued the previous price trend. For the control group (Z9, Z8), less than 30% of the stocks showed a trend of price continuation, while more than 60% of the stocks had a price reversal. Obviously, the price limit mechanism brings about the delayed price discovery effect.

Although the difference in the limit-down group is not as obvious as the limit-up group, there is still a difference of 10% between the limit-down group and the control group as shown in Table 8. Therefore, the delayed price discovery hypothesis still holds. The difference between the limit up and the limit down reflects the asymmetry of investors' reactions to good news and bad news. Bear markets are more likely to cause over-reactions in stocks, so there is a greater probability of a price reversal in a limit-down stock relative to a limit-up stock.

Table 7. Test of delayed price discovery hypothesis (limit-up).

	Z10	Z9	Z8
Price continuation	24910 (54%)	5273 (27%)	6095 (29%)
Price reversal	18836 (41%)	12893 (67%)	13611 (64%)
Price unchanged	2438 (5%)	1138 (6%)	1396 (7%)
Total	46184	19304	21102

Table 8. Hypothesis test: the delayed price discovery (limit-down).

	D10	D9	D8
Price continuation	24757 (60%)	8193 (48%)	9523 (51%)
Price reversal	14362 (35%)	7751 (46%)	7849 (42%)
Price unchanged	2314 (5%)	1057 (6%)	1363 (7%)
Total	41433	17001	18735

Similar research in other markets tends to be more in favor of delayed price discovery. These markets include the Japanese stock market (George and Hwang 1995, Kim and Rhee 1997) and the Korean market (Choi and Lee 2000).

4. Econometric Models and Empirical Results

The sample of daily stock data from January 1, 2006 to June 22, 2016 covers two major crashes due to the fusing mechanism implemented by the China's securities regulator in January 2016. In order to distinguish the impacts of the circuit breaker from those of the price limits, we use the following GARCH(2,2) models:

$$Return_t = c + \sum_{i=1}^{2} \alpha_i d_{i,t-1} + \sum_{j=1}^{3} \beta_j Return_{t-j} + \varepsilon_t \tag{5}$$

$$\varepsilon_t = \mu_t \sqrt{h_t},$$

$$where\ h_t = \gamma_0 + \gamma_1 h_{t-1} + \gamma_2 h_{t-2} + \gamma_3 \varepsilon_{t-1}^2 + \gamma_4 \varepsilon_{t-2}^2 \tag{6}$$

$Return_t$ is the volatility-adjusted 5 min return, and d_1 and d_2 are dummy variables used to capture the magnet effect in the up and the down directions, respectively. We define dummy variables in a standard way (see equation (A4) and (A5)).

$$d_3 = \begin{cases} 1, \text{if} \left(\frac{P_t - P_{close}}{P_{close}}\right) \geq p \\ 0, \text{otherwise} \end{cases} \tag{7}$$

$$d_4 = \begin{cases} 1, \text{if} \left(\frac{P_t - P_{close}}{P_{close}}\right) \leq q \\ 0, \text{otherwise} \end{cases} \tag{8}$$

Table 9 shows 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%. If we exclude the circuit breaker data and use a subsample from January 8, 2016 to the end, the magnet effect is no longer

Table 9. Magnet effects in the Chinese market.

	α_1	α_2
$p = 3\%, q = -3\%$	0.011	−0.007
	(0.09)	(-0.06)
$p = 3\%, q = -4\%$	0.011	−0.295
	(0.094)	(−1.602)
$p = 3\%, q = -5\%$	0.011	−0.638**
	(0.095)	(−1.995)
Exclude data of circuit-breaker halt:		
$p = 3\%, q = -5\%$	0.007	−0.399
	(0.061)	(-0.681)

Note: The t-statistics are in brackets. ** represents for significant at the 5% level. p and q refer to the thresholds in the up and down direction, respectively. we choose different combinations of p and q in order to bring the robustness problem of threshold selection. We set the threshold on the rising direction to 3% because there was only one day in the sample when the increase exceeded 4%.

significant. This suggests that the implementation of the circuit breaker mechanism has indeed brought a magnet effect to the Chinese market.

4.1. Hypothesis Test for Individual Stocks

In this section, we use the high frequency data of Shanghai Stocks to examine if the volatility spillover effects and the magnet effects are valid in individual stocks and in the market index. The magnet effects are also related to the liquidity interference effects and have been widely concerned. Specifically, investors know that when the price limits are touched, they will lose their trading opportunities. Therefore, when the stock price is about to hit the price limits, investors who follow the price movement are afraid to lose liquidity and trade preemptively. However, investors who want to trade against the direction of the price movements would wait for a better price and postpone the transaction. As a result, different actions ultimately lead to an acceleration of stock prices to reach the price limits.

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:

$$Return_t = c + \sum_{i=1}^{2} \alpha_i d_{i,t-1} + \sum_{j=1}^{3} \beta_j Return_{t-j} + \varepsilon_t \tag{9}$$

$$h_t = \gamma_0 + \gamma_1 h_{t-1} + \gamma_2 h_{t-2} + \gamma_3 \varepsilon_{t-1}^2 + \gamma_4 \varepsilon_{t-2}^2 + \gamma_5 d_{1,t-1} + d_{2,t-1} + \gamma_6 LIM_t \tag{10}$$

$$d_1 = \begin{cases} 1, \text{if priceincreases exceed the last close price by6\%} \\ 0, \text{otherwise} \end{cases} \tag{11}$$

$$d_2 = \begin{cases} 1, \text{if price decreases exceed the last close price by} - 6\% \\ 0, \text{otherwise} \end{cases} \tag{12}$$

where $Return_t$ is the 5min 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 that price limits, which will lead to a misleading result. In addition, when calculating the rate of return for the first 5 min of each trading day, we divide the price of 9:35 by the average auction prices 5 min prior to the opening of the market at 9:30 am instead of using the closing price of the previous trading day. In such a 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 limit-up, thenα_1 should be significantly greater than 0, indicating that when the stock price is close to the limitation of limit-up, there will be a continuous rise. Similarly, if there is a magnet effect in the direction of limit-down, α_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 γ_6 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 for at least one time. The estimated results are shown in Table 10.

Our statistical results show that the stock does not show a significant magnet effect, especially in the upward direction. Take α_1 as an example. If there is a magnet effect at price limits mechanism, the price should continue to rise when the stock price rises above a certain value. That is, α_1 should be greater than 0. In our sample, there are 170 stocks whose α_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

Table 10. Magnet effect test.

	α_1	α_2	γ_6
Number of shares with coefficient >0	170	210	496
Number of shares with coefficient <0	60	361	75
Coefficient(median)	–0.0772	–0.0431	0.0012
T statistics (median)	–0.5248	–0.4196	1.8842*

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

Table 11. Market impact of continued changes in stock prices.

	α_1	α_2	γ_6
Number of shares with coefficient >0	570	51	523
Number of shares with coefficient <0	2	521	49
Coefficient (median)	0.0128	–0.0092	0.0030
T statistics (median)	1.7222	–1.5681	2.1568**

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

decline in their price growth or even become negative price growth, which is not consistent with magnet effect. The magnetic effect in the direction of limit-down is more obvious, over half of the stocks have negative α_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 γ_6 is greater than 0, and the median value for the t statistics is 1.8842, meaning that the level of 10% is significant.

4.2. Hypothesis Test for the Market Index

Contrary to the conclusion that individual stocks do not have a 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 reflects market fluctuations.

$$d_1 = \begin{cases} \left(\frac{P_t^M - P_{close}}{P_{close}}\right)^2, & P_t^M > P_{close}^M \\ 0, & P_t^M \le P_{close}^M \end{cases} \tag{13}$$

$$d_2 = \begin{cases} \left(\frac{P_t^M - P_{close}}{P_{close}}\right)^2, & P_t^M < P_{close}^M \\ 0, & P_t^M \ge P_{close}^M \end{cases} \tag{14}$$

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

Table 11 shows that in the limit up scenario, other than two stocks, the α_1 of the rest stocks are all greater than 0 while in the limit down scenario, there are more than 90% stock α_2 is less than 0. The regression coefficients that confirm to 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 is positive and significant, which valid our volatility spillover hypothesis.

4.3. Determinant Factors in the Price Limit Mechanism

Our second question is about the stocks dynamics in half an hour prior to their reaching the price limits. We have documented these stocks have been accelerated to the price limits. In fact, besides the stocks who hit the price limits, there are many stocks that did not rise (fall) to the price limits. For example, at the 9% level of increase, we observe some stocks can finally accelerate to reach the price up-limits, while other stocks have a price reversal. What is the important factor causing such a different dynamic patterns?

We believe that the size of the trading volume determines whether stock prices can hit the up or down limits. The following analysis uses the 1 min rate of returns. We first look at whether we have observed large trading volumes at the time of reaching the limit-up. We divided the stock into two groups, the limit-up group and the control group whose maximum increase exceeds 9% but without reaching the limit-up. For the limit-up group, we record the moment of reaching the price limit as 0, 10 min before the limit-up as −10, and the 10 min after the limit-up as 10. We recorded the average volume of all the stocks in our sample from −10 to 10 per minute. In the same way, for the control group, we record the time at which the stock reached its highest point rather than the price limits as 0, the first 10 min and the next 10 min as −10 and 10, and draw the corresponding volumes. As shown in Figure 2, the trading volumes of the limit-up group have been higher than that of the control group. At t = 0, the average trading volumes of the limit-up group are 1.84 times as large as that of the control group.

Next, we analyze whether it is the high volumes lead to reaching the price limit-up. In order to test this idea, we conduct a simple regression analysis. We employ the minute trading volumes of all the stocks that had just reached the 9% level of price changes to check how many stock prices hit the price limits. In Equation (12), the variable, Hit = 0,1. If a stock price has reached the price limits, then we record *Hit* as 1, otherwise record *Hit* as 0.

$$Hit = a + b * volume \tag{12}$$

Our regression results show the value of b is positive and statistically significant. Therefore, high trading volumes cause the subsequent limit-ups. The findings of the limit-down are similar and will not be repeated here.

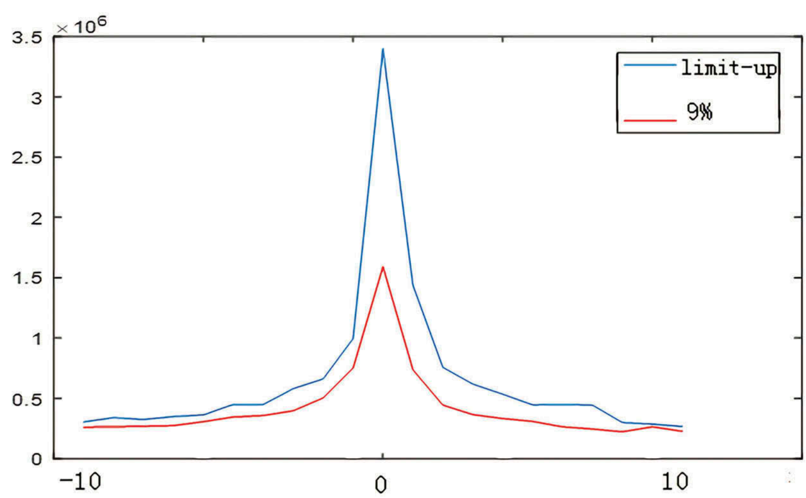

Figure 2. Volume comparison.

We have validated our hypotheses using high frequency data, namely the volatility spillover hypothesis, the delayed price discovery hypothesis and the liquidity interference hypothesis. We have affirmed the first three hypotheses in Shanghai stock exchange. Using high frequency intraday data, we also find that timing and trading volumes are two determinants of magnet effects. Such downward magnet effect is also widely confirmed in other markets, such as the Taiwan market (Cho et al. 2003), the Korean market (Du, Liu, and Rhee 2006), and so on. However, the Spanish market was an accident.

5. Conclusion

There are various trading restrictions in the world stock market. One of the main reasons for these trading restrictions is to reduce the stock market volatility. However, Fama (1989) points out that rational stock prices are not necessarily low volatility, and low volatility is not necessarily better than high volatility. If price fluctuations are a normal reaction to changes in fundamentals, then high volatility is not necessarily a bad thing. So reducing volatility should not be a reason to support trading restrictions. More importantly, various trading restrictions have not reduced the stock market volatility. Our estimated results indicate the price limit mechanism has significant volatility spillover effects in the Shanghai stock market.

In addition, our study also finds that trading restrictions will interfere with the market and hinder the price discovery of stocks. Our results indicate 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 the normal price discovery process and also induces magnet effect in special circumstances. Therefore, we should not place too much restraint on the market in order to better achieve the price discovery.

With regard to the magnetic effects of the trade impediment measures, we find that Chinese stocks have only a weak magnet effect in the downward direction. We find that the overall movement in the stock market is more likely to cause a single stock to continue to rise and fall. The empirical results show that market-wide variation is more likely to trigger a magnet effect than an individual stock's price limits.

Notes

1. The daily data comes from the Wind database, and the high frequency data comes from the Bloomberg database.
2. Many studies have examined the relationship between them from different angles. Chung (1991) studied data found in the South Korean market and there was no evidence that trading restrictions reduced the volatility of stocks. Chen (1993) has similar findings on the Taiwan market. Kim and .
3. To test the delayed price discovery hypothesis, we retain the data of continuous price limits-up/down.

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