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Can price limits help when the price is falling? Evidence from transactions data on the Shanghai Stock Exchange ☆

Woon K. WONG [a,*], Bo LIU [b], Yong ZENG [b]

[a] Investment Management Research Unit, Cardiff Business School, Aberconway Building, Colum Drive, Cardiff, CF10 3EU, United Kingdom
[b] School of Management and Economics, University of Electronic Science and Technology of China, No. 4, Section 2, North Jianshe Road, Chengdu 610054, Sichuan, P.R. China

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ABSTRACT

We use transactions data to explore the magnet effects of price limit rules on the Shanghai Stock Exchange (SHSE). When limit hits are imminent, stock prices are found to approach the price limits at faster rates, with higher trading intensity and larger price variation, supporting the magnet effect hypothesis of Subrahmanyam [Subrahmanyam, A., 1994. Circuit breakers and market volatility: A theoretical perspective. Journal of Finance, 49, 237–254.]. Moreover, when stock prices approach the floor limits, we observe lower than normal market conditions' trading volume and trade size but a wider spread. The panic selling psychology of individual investors for fear of illiquidity and the strategic trading decisions of discretionary traders during periods prior to price limit hits at the floors are conjectured as possible explanations for the observed price behaviors. Post-limit-hit analysis reveals evidence of delayed price discovery at the ceiling limit but price reversal at the floor.

1. Introduction

The design and evaluation of the market mechanism, especially the circuit breakers, is a core issue in the study of financial market microstructure and has attracted much attention from academics and practitioners alike. In particular, the price limit rules have been applied to many securities markets as a type of circuit breaker for individual securities. For example, both the Shanghai Stock Exchange (SHSE) and Shenzhen Stock Exchange (SZSE) have limit bounds of ±10% imposed on the fluctuations of stock prices from their previous day's closing prices. Other markets that impose similar limit bounds are, for example, Austria (5%), France (7%), Greece (4–8%), Korea (15%), Malaysia (30%) and Taiwan (7%).

In essene, the price limit rule is designed to provide a cooling off period and hence prevent excessive price movements. However, much theoretical and empirical research suggests, on the contrary, that it has four adverse effects. The first one is the volatility spillover effect documented by Kuhn, Kurserk and Locke (1991), Kim and Rhee (1997) and Kim (2001). It suggests that price limits will increase the volatility on the subsequent trading days since the limits prevent concurrent immediate corrections in the order imbalance. The delayed price discovery effect documented by Fama (1989), Lehmann (1989) and Lee, Ready and Seguin (1994) is the second adverse effect. Because limit bounds prevent prices from reaching the new equilibrium level, information

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* Corresponding author. Tel.: +44 29 20875079; fax: +44 29 20874419.
E-mail address: wongwk3@cardiff.ac.uk (W.K. Wong).

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revelation and price discovery are delayed. Thirdly, the trading interference effect documented by Fama (1989), Lehmann (1989) and Lee et al. (1994) suggest that price limits can interfere with trading activity by causing illiquidity. The extant literature on these three effects on the China stock markets is mixed. While Mu, Liu and Wu (2004) and Chen and Long (2003) find evidence of them using daily data, Wu and Xu (2002) reject them.

The fourth one, the magnet effect documented by Subrahmanyam (1994) and Cho, Russell, Tiao and Tsay (2003) refers to the phenomenon that the price limit acts as a magnet and further pulls the price even closer to the limit amidst high trading intensity and price volatility.[1] Such a phenomenon occurs when the traders, for fear of illiquidity and position lock caused by imminent price limit hits, are eager to protect themselves through aggressive trading, thereby inducing large price variation and heavy trading volume. Since the magnet effect is essentially a phenomenon that takes place at the intraday level, its study helps both investors and regulators to understand the mechanisms of how the market structure and the investors' trading behavior affect the price discovery process (O'Hara, 1995; Madhavan, 2000; Biais, Glosten & Spatt, 2005). For this reason, the magnet effect has been widely studied (e.g., Subrahmanyam, 1994, 1997; Kim and Rhee, 1997; Cho et al., 2003; Goldstein and Kavajecz, 2004; Chan, Kim & Rhee, 2005; Du, Liu & Rhee, 2005; Fernandes and Rocha, 2007; Wong, Chang & Tu, 2008).

While the evidence of the magnet effect is weak in the futures markets,[2] research on stock markets tends to find significant evidence of the magnet effect. For example, Chan et al. (2005) study the transactions data and limit order book from the Kuala Lumpur Stock Exchange. They find that price limits actually delay information revelation and worsen order imbalances, indicating the existence of the magnet effect. Du et al. (2005) use the transactions and order data of the Korea Stock Exchange and find that a narrower price limit features a stronger magnet effect and the ceiling provides a stronger magnet effect than the floor. For the Taiwan Stock Exchange, Cho et al. (2003) find statistically and economically significant magnet effects and Wong et al. (2008) reveal that the phenomenon is caused by individual investors.

One objective of our paper is to explore the intraday dynamics of the ceiling and floor magnet effects using transactions data from the SHSE in China. Our motivation for the study of magnet effects in the Chinese stock markets is twofold. First, Chinese stock markets have drawn a lot of attention from the world for their fast growth and China's economic development in recent years (see, e.g., Huang and Song, 2006; Girardin and Liu, 2007). Yet, trading on the SHSE is dominated by individual investors: according to the Chinese Securities Depository & Clearing Co. Ltd., 99.5% of the 68.8 million domestic investor accounts in 2002 were held by individual investors. Second, unlike most stock exchanges in the Asia–Pacific region, short selling is absolutely prohibited in the SHSE. Comerton-Forde and Rydge (2006) study the market design of the major stock exchanges of Australia, Hong Kong, Jakarta, Korea, Malaysia, Shanghai, Singapore, Taiwan, Thailand and Tokyo.[3] Out of these exchanges in the region, Bursa Malaysia is the only other stock exchange where short selling is disallowed; the authority is currently considering lifting the ban. Moreover, no stock index futures or other similar derivative instruments for holding short positions exist in the SHSE. While this rules out the risk of speculative selling that would cause excessive stock price volatility, it also means that investors in China have no means to hedge themselves against downside risk. Therefore, it is interesting to find out empirically if price limit rules do provide welfare for the investors (who are mostly individuals) in China.

The research methodology employed in this paper is similar to those of Du et al. (2005) and Wong et al. (2008). Specifically, we first examine the intraday dynamics of 5-min price returns, and return volatility and frequency of trades during the periods prior to limit hits. Consistent with the predictions of Subrahmanyam (1994), stock prices are found to approach limit bounds at faster rates with increased volatility and higher frequency of trades half an hour prior to the limit hits. Since Monte Carlo simulations show that stock prices approach the price limits at a seemingly quadratic rate of increasing speeds, we need to adjust for the sampling characteristics which arise from the fact that we are studying stocks with imminent limit hits half an hour later. Therefore, in order to confirm that stock prices do approach the limit bounds at faster rates, we subtract from the true pre-hit returns (at ±10% levels) the effects of quasi limit hits hypothetically set at ±6% levels and then carry out formal statistical tests. The empirical results show that there is at least a positive rate of magnetic pulls towards the limit bounds when the price limit hits are imminent.

In addition to the stylized magnet effects, our study also finds interesting asymmetry between ceiling and floor magnet effects. In particular, when the stock prices approach the floor limits, there is evidence that the bid-ask spreads are wider, trading volume is lower and trade size is smaller than they would have been during normal market conditions. This is in contrast to earlier literature such as Kim and Rhee (1997), who find that results for ceiling-hit and floor-hit events are qualitatively similar on the Tokyo Stock Exchange. To explain the above phenomenon, we first notice that Chinese stock markets are purely order driven with no market makers, short sale is strictly prohibited and the market for stock index futures or other similar derivative instruments does not exist. The implication is that the investors in China can have only long positions but have no means of hedging the downside risks of their equity portfolios.

Next, the study by Goldstein and Kavajecz (2004) on the trading behaviors of NYSE market participants during the turbulent October 1997 provides clues for us to explain the above findings of asymmetry between ceiling and floor limits.[4] Goldstein and Kavajecz find that, during this period of extreme market movements, the costs of supplying liquidity through an electronic limit

[1] The paper by Subrahmanyam (1994) provides an important theoretical study of the possible adverse effects of price limit as a form of circuit breaker. His two-period model indicates that as investors sub-optimally advance trades in time for fear of illiquidity when prices hit the limit bounds, the price variability, the trading volume and the probability of hitting the limits increase as prices approach the limits.

[2] Relevant literature includes, for example, Arak and Cook (1997), Berkman and Steenbeek (1998), Hall and Korfman (2001) and Fernandes and Rocha (2007).

[3] See also Bris, Goetzmann and Zhu (2007) for a world comparison.

[4] During the turbulent October 1997, the market-wide 'circuit breaker' provision of NYSE Rule 80B was triggered for the first time in the NYSE since the rule was adopted in 1988.

order book are so high that investors actually withdraw depth from the book, thus resulting in a wider spread and reduced liquidity. Thus, the market behaviors prior to the floor limit hits in the SHSE reveal signs of inefficiency of the electronic order book system during extreme price movements. Furthermore, the low trading volume and small trade size suggest that most of the market participants during the limit hits at the floor are individual investors. Being uninformed and risk averse, they are likely to sell frantically when stock prices fall towards the floor limits. Such a conjecture is supported by the results of our post-limit-hit analysis. Specifically, the event studies methodology of Patell (1976) and Henderson (1990) are carried out and we find significant price continuation during post-ceiling hits whereas after floor limit hits, significant price reversals are observed.

To sum up, the panic selling psychology of individual investors for fear of illiquidity and the strategic trading decisions of discretionary traders (to withdraw from the limit order book) during periods of extreme price movements prior to floor limit hits are conjectured as possible explanations for the observed price behaviors. Our findings are consistent with the analysis of Subrahmanyam (1997), which concludes that the *ex ante* behavior by informed traders in response to imminent limit hits can result in increased trading costs for precisely the individuals whom the price limit rules are intended to benefit. This is also in line with the results of Sun, Cao and Fei (2005), who carry out experimental research on the effectiveness of price limit rules. Based on Krahnen, Rieck and Theissen (1999) experiment design modified according to the trading mechanisms in Chinese stock markets, they find price limit rules weaken the flow of private information, causing large price variations which in turn lower the information efficiency and render traders myopic and irrational.

The remainder of the paper is organized as follows. Section 2 presents the institutional background of the SHSE and limit hit statistics. The research methodology is provided in Section 3 and the empirical results supporting the magnet effects are presented in Section 4. In Section 5, we conjecture that the thin volume and wide bid-ask spreads observed during floor limit hits are due to the panic selling psychology of individual investors, who are responsible for the bulk of the trading activities on Chinese stock markets. Finally, Section 6 concludes.

2. Institutional background of the SHSE and limit hit statistics

2.1. Institutional background of the SHSE

The Shanghai Stock Exchange (SHSE) is one of the most actively traded stock exchanges. Its annual share turnover reached 288.71% in 2004 with an average market capitalization of 2601 billion RMB. There were 837 listed companies and 881 listed issues on the SHSE by the end of 2004. We shall describe some of the Chinese market trading mechanisms below. Readers are referred to Xu (2000), Shenoy and Zhang (2007) and Tian and Guo (2007) for further details on the microstructure of Chinese stock markets.

The SHSE is a typical order-driven market without designated market makers. It runs an electronic automated trading system, opens from Monday to Friday and has three trading sessions: 9:15–9:25 for call auction, 9:30–11:30 and 13:00–15:00 for continuous double auction. Only limit orders, which will be stored in the limit order book, are allowed in the SHSE. Currently, the best five bid and ask prices and the corresponding depths of the book are revealed continuously to the public investors. The tick size (minimum price variation unit) is 0.01 RMB while the minimum trading quantities unit is 100 shares (one lot). The orders' period of validity is only one day. The call auction is conducted in the first session to generate the opening prices. In the call auction, all orders are submitted and executed at a single equilibrium price, i.e. opening price, which must satisfy the condition of maximizing the total trading volume. Then, a continuous double auction is used during the next two sessions in terms of the price and time priority rules for matching orders. In the continuous double auction, submitted buy and sell limit orders are matched continuously and trades occur when they are matched for sure. The unmatched orders will be cancelled or remain in the order queues in the limit order book, waiting for future executions. The transaction price of each trade mainly depends on the current prices and depths in the book. Short selling is absolutely prohibited in the SHSE.

To dampen extreme price movements and provide a cooling-off period in the events of overreaction in order to protect the public investors, the SHSE currently sets the daily price limit at 10%. For example, if the closing price of a stock on a trading day is 10.00 RMB, its allowable price changes on the next trading day will range from 9.00 RMB to 11.00 RMB.

2.2. Data and limit hit statistics

We use the transactions data of all the A-share stocks of the SHSE from CSMAR high-frequency tick database from 4 January 2002 to 31 December 2002, a total of 237 trading days. There are 705 companies in the database and, after adjustment for stock splits and some preliminary filters, we identify 463 companies that experience limit hits on a tick-to-tick basis in the year 2002.[5] Based on the direction of limit hits, we classify our sample of limit hits into two groups: ceiling and floor.

In this paper, analyses are carried out at 5-min frequency. Ideally, we would like to use highly liquid stocks in our study. However, due to possible missing data, if we consider only those stocks that have trading taking place every 5 min in the whole of the year 2002, we would be left with a sample too small to produce results that are representative of Chinese stock markets. We thus break each company's data into several time series separated by either limit hits or at least an hour of non-trading, so that the continuous zero trading records, if any, are less than an hour in each separated time series. From the separated time series, if there

[5] We exclude the following categories of data in our limit hits count: (1) stocks that are classified as ST and PT shares with a different price limit and trading mechanism from other stocks and (2) days when prices moved outside the allowed price fluctuation range, due to possible data collection error.

Table 1
The summary statistics of limit hits

		Ceiling	Floor
(1)	No. of limit hits (by tick)	3515	1186
(2)	Hits at market open	303	29
(3)	Hits remaining at market close	437	131
(4)	No. of companies	416	177
(5)	No. of hits per stock	1.55	1.48
(6)	No. of hits per trading day	2.71	1.11
(7)	Average duration of hits by tick (min.)	10.7	8.5

There are in total 4701 limit hits identified in 2002 for our sample of 317 companies. Out of these limit hits, we consider for the magnet effect study only those that take place 30 min after market open or, if it is a second or subsequent hit within a day, it must take place at least 60 min after the previous hit. There are 360 such limit hits suitable for the study of magnet effects.

are more than 10% of zero volume 5-min observations, we drop the company. Since this paper proposes to study the magnet effect in the half-hour interval prior to limit hits, we consider only those companies with first limit hits that take place 30 min after market open or, if there are two or more limit hits within a day, when the largest gap between two hits is more than 60 min.[6] Only those limit hits that satisfy these conditions are included in the study sample. After going through all the filtering processes, we are left with 317 companies, on which we carry out all the analyses from here onwards. We identify the limit hits on a tick-to-tick basis and the summary statistics of these limit hits are shown in Table 1.

The limit hits are classified into two groups: ceiling and floor. Items (1) to (7) present limit hits in 7 categories. We identify 3515 ceiling hits and 1186 floor hits by tick. The average number of daily limit hits is 2.71 for the ceiling group and 1.11 for the floor group. At the individual stock level, the average limit hits per stock are 1.55 and 1.48 for the ceiling and floor groups, respectively. Item (2) reports that there are more ceiling hits (303) than floor hits (29) at market open. At market close, similar patterns are observed. Short sale prohibition and no stock index futures or other similar derivative instruments for holding short positions on the Chinese stock markets may provide an explanation for this phenomenon: any investors can trade aggressively when the price moves upwards but only those investors holding the stocks can sell when the price falls. We also observe that there are more hits at market close (437 and 131) than at market open (303 and 29). This is consistent with Tian and Guo's (2007) findings on the Chinese stock markets that the return variance in the trading period (open-to-close) is larger than that in the non-trading hours (close-to-open); see also French and Roll (1986) on volatility generated from trading. Finally, we notice that most stocks hit the limits several times within one day. The duration of hits is measured from the time of the first hit to the time when the price is off the limit or market close. The average duration of hits is 10.7 min for the ceiling group and 8.5 min for the floor group.

3. Research methodology

Similar to Du et al. (2005) and Wong et al. (2008), we examine the effects of price limit rules by analysing 5-min returns half an hour prior to the limit hits. We follow Cho et al. (2003) to use an AR(3)-GARCH(2,2) model to remove time series autocorrelation and heteroscedasticity from our 5-min return time series. Monte Carlo simulations are used to illustrate the effect of magnetic pull on pre-hit returns and quasi limit hits are used to adjust for the sampling characteristics before formal statistical tests are carried out.

3.1. Return dynamics prior to limit hits

To construct the 5-min returns, the last price quote before the relevant time mark is used, and the 5-min returns are defined as the differences between successive log prices.[7] We drop out the overnight returns, as they behave very differently from the 'normal' ones, so we have 48 5-min returns in a day.

Generally speaking, intraday seasonal patterns consistent with the traditional market microstructure framework are observed for stock price return volatility, trading volume and bid-ask spread. Only the stock price return volatility is shown in Fig. 1 above. Consistent with Admati and Pfleiderer (1988) and Foster and Viswanathan (1993), existing asymmetric information causes the trading to cluster at the open and close of the trading day, thus establishing the L-shaped dynamics of the volatility. We remark that the study of Qu and Wu (2002) and Tian and Guo (2007) on the Chinese stock markets also obtain similar results.

This deterministic volatility component of the 5-min returns time series is removed in the same way as in Cho et al. (2003).[8] For each stock, the standard deviation of the returns for each 5-min interval is computed, and each 5-min return is divided by its

[6] Since we require at least 30 min of interval to study the magnet effect, limit hits at or too near to market open are ruled out. For subsequent limit hits on the day, if the subsequent limit hit takes place too soon, it will always have a quadratic price path. So, we required the subsequent hits to be at least an hour apart in order for them to be considered for the study of the magnet effect.

[7] Except for the opening prices at 9:30 and 13:00, and closing prices at 11:30 and 15:00, we use the first and last price quotes available to us.

[8] The other way of removing the intraday volatility pattern is to follow Anderson and Bollerslev (1998) by specifying a multiplicative deterministic function in the conditional variance equation.

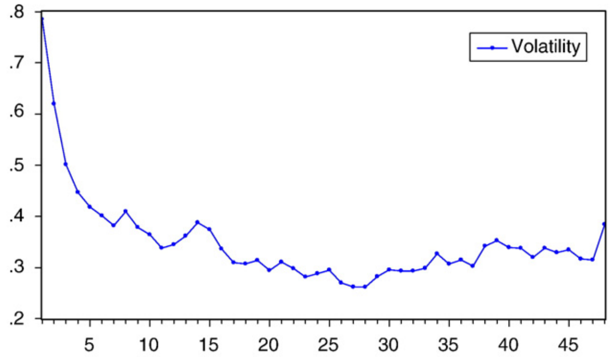

Fig. 1. Intraday pattern of return volatility. A typical intraday L-shape of return volatility is consistent with the market microstructure literature: existing asymmetric information causes trading, and thus higher volatility, to cluster at the market open.

corresponding standard deviations. To denote such standardized 5-min returns of stock i at time t by $r_{i,t}$, we fit the following AR(3)-GARCH(2,2) model:

$$r_{i,t} = \mu_i + a_{i,1} r_{i,t-1} + a_{i,2} r_{i,t-2} + a_{i,3} r_{t-3} + u_{i,t}, \tag{1}$$

where if $z_{i,t}$ is iid with zero mean and unit variance, $u_{i,t} = z_{i,t} h_{i,t}^{1/2}$ and

$$h_{i,t} = \alpha_{i,0} + \alpha_{i,1} u_{i,t-1}^2 + \alpha_{i,2} u_{i,t-2}^2 + \beta_{i,1} h_{i,t-1} + \beta_{i,2} h_{i,t-2}. \tag{2}$$

The above time series model is used to remove the autocorrelation and heteroscedasticity from the 5-min returns time series. We break the year's 5-min returns into several time series separated by either limit hits or more than 1 h of non-trading intervals. Thus, the AR(3)-GARCH(2,2) model estimation is reinitialized whenever a new time series starts.[9]

To focus on the half-hour of 5-min returns prior to limit hits, we carry out the following regression of filtered time series:

$$z_{i,t} = \delta_0 + \delta_1 \tau_{i,t} + \delta_2 \tau_{i,t}^2 + e_{i,t}, \tag{3}$$

where $e_{i,t}$ are regression errors and $t \in B$, the set of 5-min time points just half an hour before limit hits. For B to be a valid set in order to analyse the magnet effects, we require the time of limit hit at least half an hour after the market opens if it is the first hit of the day; in the case of second or subsequent limit hits, we require at least an hour of 'normal' returns between two successive limit hits on the same day. The variable $\tau_{i,t}$=1,…,6 indicates the integer distance of stock i at time t prior to the limit hit. For example, $\tau_{i,t}$=6 refers to the time mark just before the stock price hits limit bounds, whereas $\tau_{i,t}$=6 refers to the time mark that is furthest away.[10] In the case of the ceiling limit hit, Du et al. (2005) regard $\delta_0>0$ in Eq. (3) to mean that the stock price approaches the ceiling at a constantly faster speed during the half-hour before it hits the ceiling. Furthermore, he considers $\delta_1>0$ as evidence that the stock price approaches the ceiling at a speed increasing at a linear rate, and $\delta_2>0$ indicates that the speed is increasing at a quadratic rate. For a floor limit hit, the same interpretation applies if δ_0, δ_1 and δ_2 are negative. Though Du et al. (2005) describe the above quadratic rate of returns as evidence of the magnet effects of limit bounds, we cannot rule out the possibility that it is simply due to the pre-hit sampling characteristics. Since our sampled half-hour of 5-min returns are always followed by limit hits, it is not difficult to see that the closer we are to, say, a ceiling limit, the higher the probability of a positive 5-min return. Over a large collection of such 5-min returns prior to limit hits, the outcome is a series of returns approaching the limit bounds with speeds seemingly increasing at a quadratic rate. This conjecture is supported by the following Monte Carlo simulation study of random walks hitting quasi limit bounds.

3.2. Monte Carlo simulation

In order to study the sampling characteristics of returns prior to limit hits and the effects of magnetic pulls by limit bounds on pre-hit returns, we generate random walks that would hit the ceiling bounds in three scenarios:

(1) with zero drift hitting a true ceiling bound of 10%;
(2) with zero drift hitting a quasi ceiling bound of 6%; and
(3) with positive drift hitting a true ceiling bound of 10%.

Both scenarios (1) and (2) enable us to study the sampling characteristics of pre-hit returns under the assumption of no magnet effects but at different price limit levels. Scenario 3 corresponds to the effect of a (constant) positive drift due to the magnet effect

[9] Cho et al. (2003) remark that reinitializing does not change their results significantly. We nevertheless reinitialize our estimation as this overcomes the missing data problem.
[10] Since we are using ultra high-frequency tick data, most limit hits occur not at the 5-min marks but between them.

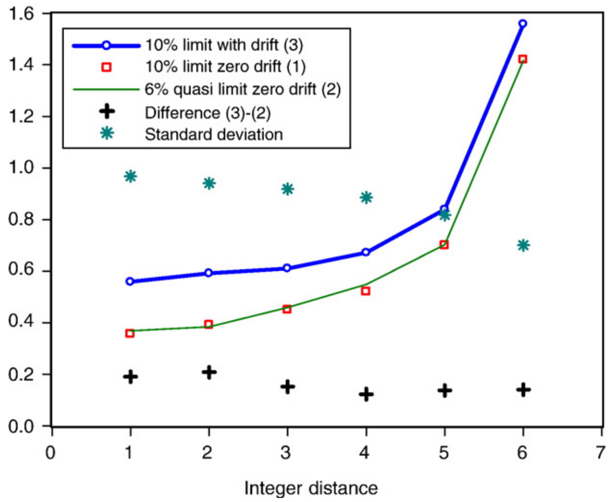

Fig. 2. Monte Carlo simulations of limit hits. When there is no drift, the rates of returns hitting true (10%) and quasi (6%) ceiling limits are nearly identical (graphs (1) and (2)). When there is a positive drift, stock prices hit the true limits (10%) at a faster rate of return across all the integer distances (graph (3)). The increase in the rate of return when there is a positive is roughly identical across all the integer distances (see the difference of (3) and (2)). In all three cases, standard deviations of returns decrease with integer distance.

of limit bounds. For all 3 scenarios, we use constant volatility of 0.35%, which is close to our average sample volatility. The positive drift is set at 0.175% in scenario 3. For all 3 scenarios, 10,000 ceiling hits are generated.

Fig. 2 depicts the sample averages and standard deviations at various integer distances of the three simulated pre-hit returns above. From scenarios (1) and (2), it is clear that the seemingly quadratic rate of returns prior to limit hits are due to the sampling characteristics, and the levels of limit bounds have literally no effect on the rates of pre-hit returns. We also note that the standard deviations show signs of decreasing magnitude. This is consistent with the fact that, the nearer the stock price is to the ceiling hit, the more likely a positive return is observed, thus resulting in a lower price variation.

Next, the constant magnetic pull is simulated by scenario (3) and its effects on the rates of pre-hit returns are contrasted with simulated quasi limit hits at 6%. Though the complexity of sampling characteristics of pre-hit returns are evident from the small declining difference between scenarios (2) and (3), it does suggest a methodology to test for the existence of magnetic pulls in the SHSE: subtracting the rates of returns at quasi limit hits from those at true limit hits would enable us to remove the effects due to possible momentum and sampling characteristics.

3.3. Test of magnet effects

Following the above Monte Carlo simulations study, we propose here a formal econometric test to see if there are magnetic pulls caused by price limits using quasi limit hits. In particular, we carry out the following modified regression:

$$\left(z_{\tau(it)} - m_{\tau(it)}\right) = \delta_0 + \delta_1 \tau_{i,t} + \delta_1 \tau_{i,t}^2 + e_{i,t}, \qquad (4)$$

where $m_{\tau(it)}$ is the rate of return at $\tau_{i,t}$ integer distance away from the quasi limit bounds set at ±6% price levels. The same interpretations of δ_0, δ_1 and δ_2 as above apply and their significance would imply the existence of magnet effects in the SHSE. Let $H_{\tau(i,t)}$ and $Q_{\tau(i,t)}$ be the sets of pre-hit returns at $\tau_{i,t}$ integer distance before the (true) ±10% and (quasi) ±6% limit hits, respectively. Because we consider those returns only when limit hits are imminent, the quadratic rates of returns implied by regression (3) may

Table 2
Returns, volatility and trade frequency

Integer distance	Ceiling (208 observations for each τ)			Floor (152 observations for each τ)		
τ	RET	VLTY	FREQ	RET	VLTY	FREQ
6	3.301**	2.654**	1.906**	−3.633**	3.047**	1.450**
5	1.690**	2.292**	1.805**	−1.684**	2.407**	1.096**
4	1.197**	2.050**	1.682**	−0.973**	2.172**	0.979**
3	1.118**	2.255**	1.622**	−1.218**	1.981**	0.941**
2	1.194**	2.398**	1.610**	−0.770**	2.000**	0.819**
1	0.624**	1.965**	1.463**	−0.698**	1.919**	0.736**

RET, *VLTY* and *FREQ* represent respectively the standardized return, volatility and trade frequency obtained using the same method as Lee et al. (1994) and Du et al. (2005). τ refers to the integer distance prior to the limit hits. ** indicates significance at 1%. * indicates significance at 5%.

Table 3
AR(3)-GARCH(2,2) models

	$r_{i,t}=\mu_i+a_{i,1}r_{i,t-1}+a_{i,2}r_{i,t-2}+a_{i,3}r_{t-3}+u_{i,t}$				
	μ		a_1	a_2	a_3
Coefficients	-0.021^{**}		-0.063^{**}	-0.124^{**}	-0.028^{**}
	$h_{i,t}=\alpha_{i,0}+\alpha_{i,1}u_{i,t-1}^2+\alpha_{i,2}u_{i,t-2}^2+\beta_{i,1}h_{i,t-1}+\beta_{i,2}h_{i,t-2}$				
	α_0	α_1	α_2	β_1	β_2
Coefficients	0.004^{*}	0.181^{**}	-0.160^{**}	1.357^{**}	-0.381^{**}

AR(3)-GARCH(2,2) models are fitted to the 5-min returns of 317 companies using the quasi maximum likelihood method. Similarly to Cho et al. (2003), we find the intraday returns are negatively autocorrelated and exhibit highly persistent heteroscedasticity. Both the coefficients and t-statistics given below are medians of the corresponding parameters of the 317 fitted models. ** indicates significance at 1%. * indicates significance at 5%.

be due to the way we sample our data. Thus, taking the difference of genuine and quasi limit pre-hit returns in Eq. (4) can remove the seemingly quadratic effects due to the sampling characteristics.

Unlike Du et al. (2005), where only one nearby day of each true limit hit is used to construct the quasi limit hit, we use all the days in our sampled period to construct our quasi pre-hit returns. As a result, the number $N_{\tau(i,t)}$ of such returns in $Q_{\tau(i,t)}$ is about five times that of $H_{\tau(i,t)}$. This enables us to simplify our econometric analyses by using

$$\hat{m}_{\tau(it)} = N_{\tau(it)}^{-1} \sum_{z \in Q_{\tau(it)}} z_{i,t}, \tag{5}$$

to substitute for $m_{\tau(i,t)}$ in (4) and apply the GMM technique of Hansen (1982) to estimate the regression model.

The AR(3)-GARCH(2,2) filter is set up in order to remove heteroscedasticity and autocorrelation from the 5-min returns. Stock returns, however, are known to be cross-correlated and thus an appropriate robust covariance matrix should be used. Now, if N refers to the number of observations in Eqs. (3) or (4), let y be the N vector of the LHS of (3) or (4), e the vector of $e_{i,t}$, X the appropriate data matrix and θ the corresponding parameters.[11] These equations have the following matrix form

$$y = X\theta + e. \tag{6}$$

We use the GMM technique of Hansen (1982) to estimate Eq. (6) and proceed as follows. Let y_i and e_i be the i-th element of y and e, respectively, and x_i be the i-th row of matrix X. If $\hat{\theta}$ is the GMM estimator, then we have the following empirical moment equations:

$$N^{-1} \sum_{i=1}^{N} x_i \left(y_i - x_i' \hat{\theta}\right) = N^{-1} X' \cdot \hat{e}\left(\hat{\theta}\right) = \bar{g}\left(\hat{\theta}\right) = 0. \tag{7}$$

The GMM estimator is given by

$$\hat{\theta} = \arg\min \bar{g}'\left(\hat{\theta}\right) \cdot \left\{ \lim_{N\to\infty} var\left(\sqrt{N}\bar{g}\left(\hat{\theta}\right)\right) \right\}^{-1} \cdot \bar{g}\left(\hat{\theta}\right). \tag{8}$$

Similar to the case of Cho et al. (2003), the above minimization is an exactly identified case, so the GMM estimator is simply the ordinary least squares estimator. It is straightforward that

$$\lim_{N\to\infty} \mathrm{var}\left(\sqrt{N}\bar{g}\left(\hat{\theta}\right)\right) = \sigma^2 (X'X)^{-1}(X'\Omega X)(X'X)^{-1}, \tag{9}$$

where $E(e'e)=\sigma^2\Omega$. Because the elements of y are not a complete time series but a piecewise one, the usual covariance matrix estimator of Newey and West (1987) cannot be applied. Let $l(i,j)$ be the integer distance between y_i and y_j.[12] Then, we use the following modified covariance matrix estimator:

$$\mathrm{var}\left(\hat{\theta}\right) = N^{-1} \left\{ \sum_{i=1}^{N} \hat{e}_i^2 x_i x_i' + \sum_{i=1}^{N} \sum_{j=1}^{N} w_l \hat{e}_i \hat{e}_j \left(x_i x_j' + x_j x_i'\right) \cdot I(|l| \le L) \right\}, \tag{10}$$

where $l=l(i,j)$, $w_l=l/(L+1)$ and $I(\backslash l \backslash \le L)$ is an indicator function equal to one if the condition is satisfied, and zero otherwise. The empirical results are not sensitive to the length of L and we set $L=12$ in Section 4. Finally, we remark that the covariance matrix given above is heteroscedasticity and autocorrelation consistent.

4. Empirical evidence of magnet effects

4.1. Standardized returns, volatility and trade frequency

The theoretical model of Subrahmanyam (1994) predicts that traders, for fear of illiquidity and position lock caused by imminent price limit hits, would trade aggressively, thereby causing a higher chance of hitting the limit bounds, high trading

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[11] For Eqs. (3) and (4), X is the $N\times3$ matrix with row $\begin{pmatrix}1 & \tau_{i,t} & \tau_{i,t}^2\end{pmatrix}$ and $\theta = (\delta_0 \;\; \delta_1 \;\; \delta_2)'$.

[12] For example, if y_i and y_i are the adjusted returns at time marks 14:55 on 7 January 2002 and 09:40 on 8 January 2002, respectively, then $l(i,j)=3$.

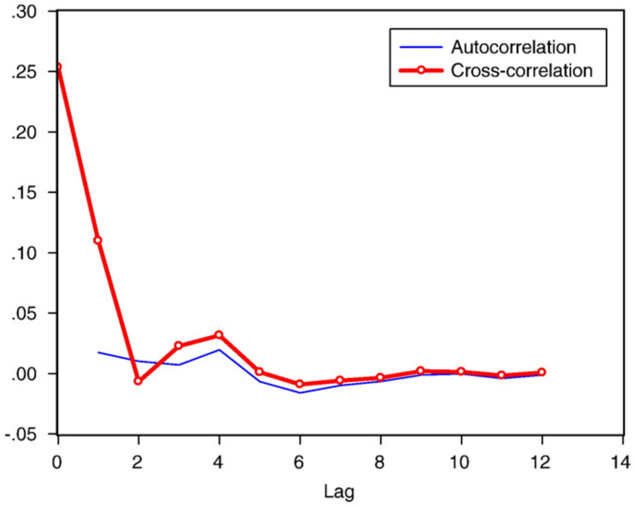

Fig. 3. Auto- and cross-correlations of standardized residuals. The auto- and cross-correlations are similar to those of Cho et al. (2003). Significant cross-correlations exist between returns of different stocks.

intensity and price volatility. We therefore, in this section, first explore the intraday dynamics of price returns, volatility and frequency of trades half an hour prior to limit hits. Price returns and volatility are measured at 5-min frequency and trade frequency refers to the frequency of reported trades observed at each 5-min interval in the database. In order to remove any deterministic intraday patterns, we adopt the same method as in Lee et al. (1994) and Du et al. (2005) by standardizing all the market variables in the following way. Specifically, let *ave* and *sd* at a 5-min time mark *m* be respectively the sample mean and standard deviation of the 237 raw returns of the same time mark *m* across all the days in the sample period. Then, the standardized returns at time mark *m* are obtained by first deducting away the *ave* and then dividing by the *sd* of the same time mark *m*.

In Table 2, the standardized statistics reveal that the price returns approach the limit bounds at faster rates with higher than normal return volatilities and trade frequencies, indicating the existence of magnet effects in the SHSE. We notice in particular the standardized returns' volatilities are significantly larger than one, which is in sharp contrast to the declining volatilities of random walks observed in Fig. 2.

4.2. Regression tests

To test formally whether the price limit mechanism in the SHSE has a magnet effect on stock prices, we first fit the AR(3)-GARCH(2,2) to all 317 stocks in order to remove autocorrelation and heteroscedasticity. The estimation is reinitialized whenever a limit hit or a zero trading session is encountered. The estimation results are given in Table 3. Similarly to Cho et al. (2003), we find that intraday returns exhibit negative autocorrelations (the autoregressive coefficients in Eq. (1) are all negative), and are highly persistent in heteroscedasticity ($\beta_1+\beta_2=0.976$).

Next, we collect all the standardized residuals 30 min prior to limit hits and construct the regression models given by Eqs. (3) and (4). Similarly to Du et al. (2005), we use integer distances prior to limit hits from 1, 2 … 6 to mean respectively 30-min, 25-min, down to 5-min time points just before the limit hits. We also calculate the correlations of all standardized residuals and plot them in Fig. 3.

Table 4
Regression results

		Ceiling $N=1272$			Floor $N=918$		
		δ_0	δ_1	δ_2	δ_0	δ_1	δ_2
Panel A: $z_{i,t}=\delta_0+\delta_1\tau_{i,t}+\delta_2\tau_{i,t}^2+e_{i,t}$							
Quadratic model	Coeff.	0.925^{**}	-0.270^{*}	0.0687^{**}	-1.043^{**}	0.432^{**}	-0.096^{**}
Panel B: $(z_{\tau(it)}-m_{\tau(it)})=\delta_0+\delta_1\tau_{i,t}+\delta_1\tau_{i,t}^2+e_{i,t}$							
Quadratic model	Coeff.	0.065	0.189	−0.032	0.013	−0.069	−0.00011
Linear model	Coeff.	0.359^{**}	−0.032		0.014	-0.070^{**}	
Constant model	Coeff.	0.248^{**}			-0.230^{**}		

The speeds of 5-min returns, seemingly increasing at quadratic rates prior to limit hits, are given by Eq. (3) in Section 3, namely $z_{i,t}=\delta_0+\delta_1\tau_{i,t}+\delta_2\tau_{i,t}^2+e_{i,t}$, where $z_{i,t}$ is the standardized residual and $\tau_{i,t}=1,\ldots,6$ indicates the integer distance prior to the limit hit. Magnet effects after adjustment using quasi limit hits are given by Eq. (4) in Section 3, that is, $(z_{\tau(it)}-m_{\tau(it)})=\delta_0+\delta_1\tau_{i,t}+\delta_1\tau_{i,t}^2+e_{i,t}$. Subtracting $m_{\tau(it)}$ from $z_{i,t}$ has the same effects of removing from $z_{i,t}$ the sampling characteristics of varying speeds dependent on the integer distances prior to limit hits. ** indicates significance at 1%. * indicates significance at 5%.

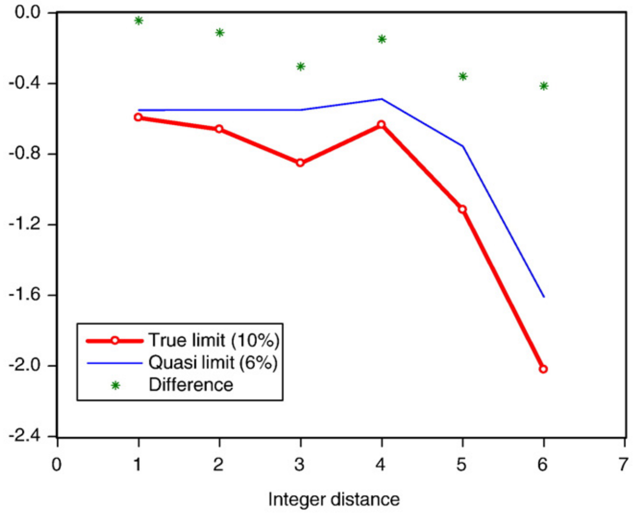

Fig. 4. Pre-hit returns at floor limits. Seemingly quadratic rates of returns are observed for both true (10% level) and quasi (6% level) limit hits at floor bounds. Pre-hit returns prior to true floor limit hits are higher than those of quasi limit hits for almost all integer distances.

We can see that the cross-correlations are significantly different from zero at lags up to 4, but are nearly zero for lags >9.[13] For the calculation of the robust covariance matrix given by Eq. (10), we include all the correlation calculations at lags smaller or equal to 12 to account for possible auto- and cross-correlations. The regression results are presented in Table 4.

As predicted by the Monte Carlo simulations in Section 3, we can see from Panel A in Table 4 that not only does the stock price approach the limit bounds at a faster rate, but the rate at which the speed is increasing is significantly quadratic. This seemingly quadratic rate of increasing speed does not, however, confirm the existence of the magnet effect. A plot of the rates of pre-hit returns for both the true and quasi floor limit bounds is shown in Fig. 4.[14] Clearly, stock prices approach both true and quasi limit bounds at quadratic rates, but with the former case doing so at faster rates. The results in Panel B confirm that, after adjusting for sampling characteristics, there is a statistically significant pulling force at stock prices towards the true limit bounds. Though the ceiling regression indicates a significant quadratic model, a caveat is needed as the Monte Carlo study shows that the sampling characteristics can be quite complicated. Nevertheless, it is clear that there exists at least a positive pull on stock prices towards the price limits.

5. Panic selling by uninformed individual investors?

5.1. Spread, volume and trade size

Having confirmed the magnet effect, we go on to explore the associated intraday market dynamics of three other market variables, namely volume, trade size and bid-ask spread prior to limit hits. Volume refers to the total shares traded in each 5-min interval and trade size is defined as volume divided by frequency of trades at each 5-min interval. We use depth-weighted bid-ask spread, which is defined as follows. Let B_1, B_2, B_3 (S_1, S_2, S_3) denote the best three bids (asks) and D_1, D_2, D_3 (E_1, E_2, E_3) the corresponding depth in each 5-min interval. Then, the depth-weighted spread[15] is defined as

$$\text{Spread} = \frac{\sum_{i=1}^{3} E_i S_i}{\sum_{i=1}^{3} E_i} - \frac{\sum_{i=1}^{3} D_i B_i}{\sum_{i=1}^{3} D_i}. \tag{11}$$

The three market variables are standardized in the same way as in Lee et al. (1994) and Du et al. (2005) and are reported in Table 5. Asymmetric patterns are observed during periods prior to ceiling and floor limit hits. This is contrary to earlier literature that suggests that both the upper and lower price limits have similar effects on stock (see, for example, Kim and Rhee, 1997). Specifically, when the stock prices approach the floor limits, we find that the spread is wider than it would have been during normal market conditions, but with lower trading intensity as measured by trading volume and trade size.[16]

To provide possible explanations for our empirical findings, we first look at the trading mechanisms and market structures that are unique to Chinese stock markets. Specifically, Chinese stock markets are purely order driven without market makers, short-sale constraint is imposed and the market for stock index futures or other similar derivative instruments that can be used to hedge

[13] We note that the AR(3)-GARCH(2,2) filters do not remove the autocorrelation structure from the 5-min returns time series completely. This, however, does not affect our inference as our correlation adjusted *t*-statistics take into account all the auto- and cross-correlations up to lag 12.

[14] We depict only the rates of pre-hit returns at floor limits. The graphs at ceiling hits are qualitatively similar.

[15] The simple spread given by $S_1 - B_1$ and relative spreads (simple spread divided by price) are also considered, but the results are qualitatively the same, so we only report the depth-weighted spread here.

[16] Since the standardized statistics are demeaned, negative values imply that they are smaller than their normal market average.

Table 5
Volume, trade size and spread

Integer distance	Ceiling (208 observations for each τ)			Floor (152 observations for each τ)		
τ	*VOL*	*TSZE*	*SPR*	*VOL*	*TSZE*	*SPR*
6	1.178**	0.922**	0.166	0.085	−0.001	0.956**
5	0.812**	0.607**	0.027	−0.033	−0.095	0.764**
4	0.754**	0.556**	−0.030	−0.058	−0.125**	0.600**
3	0.757**	0.587**	0.008	−0.034	−0.104	0.630**
2	0.690**	0.487**	−0.117	−0.051	−0.095	0.604**
1	0.545**	0.378**	−0.036	−0.097*	−0.137**	0.731**

VOL, *TSZE* and *SPR* denote respectively the standardized volume, trade size and spread of stock i prior to limit hits at integer distance τ. The three market variables are standardized using the same method as Lee et al. (1994) and Du et al. (2005). ** indicates significance at 1%. * indicates significance at 5%.

downside risks are absent. This leads to investors in China having only long positions but being unable to hedge the downside risks of their equity portfolios. Next, the study by Goldstein and Kavajecz (2004) on the trading strategies of NYSE market participants during the turbulent October 1997 period helps to explain our findings. Goldstein and Kavajecz find that, during this period of extreme market movements, the adverse selection risk of placing limit orders and thus the costs of supplying liquidity through an electronic limit order book are so high that many limit order traders may become liquidity demanders instead of liquidity suppliers. Therefore, depth is withdrawn from the book, resulting in a wider spread and reduced liquidity. Given the price limit rules and other market imperfections in Chinese stock markets, the trading behaviors noted by Goldstein and Kavajecz are likely to happen in the SHSE when stock prices fall towards their floor limits. This implies the electronic limit order book system is inefficient in providing liquidity, at least during periods prior to stock prices hitting the floor limits, which is in contrast to the predictions of Glosten (1994).[17]

In addition, since the trade size is an effective proxy for individual investors (e.g., Lee and Radhakrishna, 2000; Shanthikumar, 2003, 2005; Hvidkjaer, 2004), the low trading volume and small trade size suggest that the market is dominated by individual investors[18] prior to the limit hits at the floor. They are uninformed (Dennis and Weston, 2001), risk averse and likely to sell frantically when stock prices fall towards the floor limits. As a summary of the above arguments, the panic selling psychology of individual investors for fear of illiquidity and the strategic trading decisions of discretionary traders prior to floor limit hits are conjectured as possible explanations for the observed price behaviors.

The primary purpose of designing a price limit mechanism is to protect individual investors from excessive price movements. Ironically, the evidence from our study suggests that, on the contrary, at least at the microstructural level, it is the individual investors who have to bear with a wider spread and a higher risk of illiquidity.

5.2. Post-limit-hit analysis

Our analysis thus far has focused on intraday dynamics. The adverse effects of price limit rules at the microstructural level may not imply the failure of price limit rules from a longer horizon day-to-day viewpoint. Berkman and Lee (2002) investigate the effects of a revision in the price limit rules on the Korean Stock Exchange. Their results illustrate the benefits of price limit rules in reducing volatility.

On the other hand, Kim and Rhee (1997) find evidence of post-limit-hits price continuation for the Tokyo Stock Exchange. If stock prices continue to fall after limit hits at the floors, our findings of wider spread and illiquidity born by individual investors may be justified after all, since they would have sold the stocks at a higher price. Here, we employ the event study methodology of Patell (1976) and Henderson (1990) to examine the post-limit-hits analysis on stock price performance. Specifically, we define the limit hit date as the event date and select 80 to 20 trading days before each limit hit date to be the estimation period (or the pre-event window) and 60 trading days after each limit hit date to be the post-event window. Let R_{it} and R_{mt} be the daily log returns of individual stock i and market on day t, respectively. Then, the abnormal return can be calculated using the estimated index model as $AR_{it}=R_{it}-(\hat{\alpha}_i+\beta_i R_{mt})$. Cumulative abnormal returns (CAR) and their associated Z-statistics for post-limit-hit dates are calculated as follows:

$$\mathrm{CAR}_t = N^{-1}\sum_{\tau=1}^{t}\sum_{i=1}^{N}\mathrm{AR}_{i\tau}, \tag{12}$$

$$Z_t = \frac{1}{\sqrt{N}}\sum_{i=1}^{N}\sum_{\tau=1}^{t}\frac{\mathrm{AR}_{i\tau}}{\sqrt{t\sigma_i^2}}, \tag{13}$$

where N is the number of stocks and, if T is the length of estimation interval,

$$\sigma_{it}^2 = \frac{\sum_{\tau=1}^{T}\left(R_{i\tau}-\hat{\alpha}_i-\hat{\beta}_i R_{m\tau}\right)^2}{T-2}\left[1+\frac{1}{T}+\frac{\left(R_{mt}-\overline{R}_m\right)^2}{\sum_{\tau=1}^{T}\left(R_{m\tau}-\overline{R}_m\right)^2}\right]. \tag{14}$$

[17] Glosten (1994) predicted that an electronic limit order book could well supply liquidity in extreme adverse selection environments.
[18] The proportion of individual investors in China stock markets has been as high as 90%.

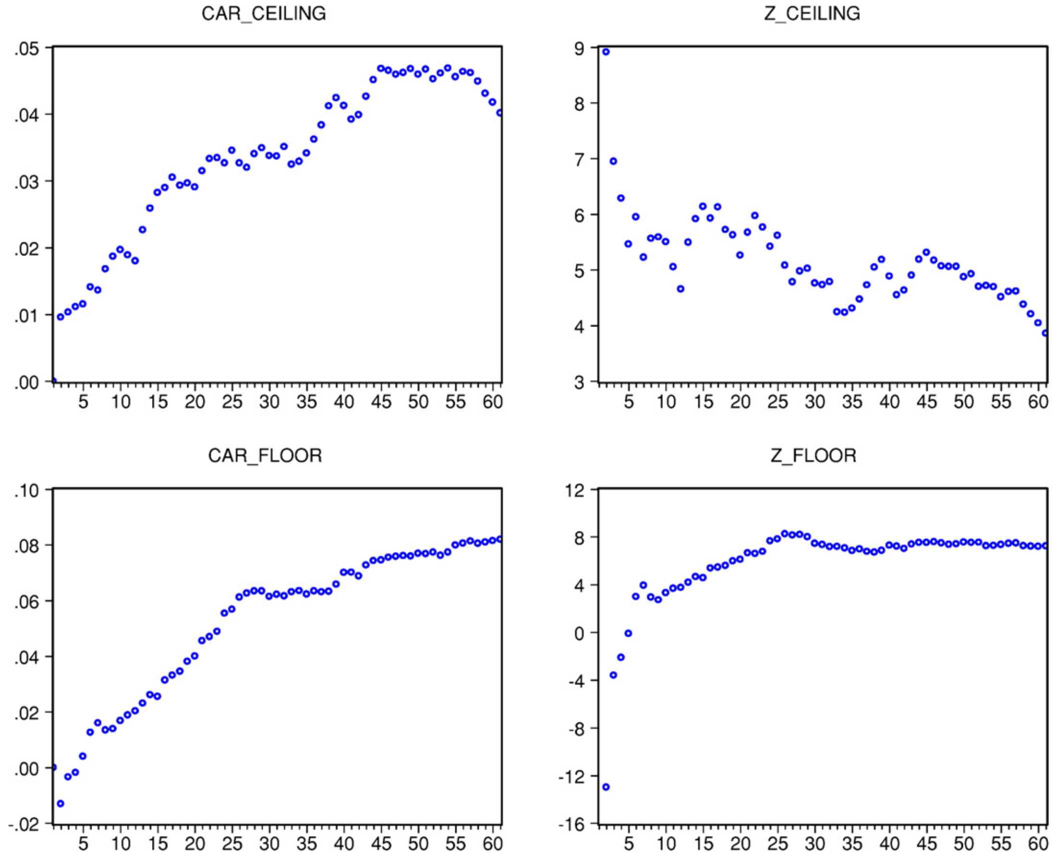

Fig. 5. Post-limit-hit analysis. The graphs above depict the CAR and associated *Z*-statistics during the post-ceiling and floor hit periods. Stock prices exhibit significant price continuation during the post-ceiling-hit period and price reversal during the post-floor-hit period.

Under the null hypothesis of zero abnormal returns, Z_t is approximately standard normal for large T. Fig. 5 depicts the post-limit-hits stock price performance at both ceiling and floor limits. Clearly, stock prices exhibit significant price continuation after hitting ceiling limits, consistent with the so-called delayed price discovery effects in Chinese stock markets reported by Chen and Long (2003) and Mu et al. (2004). The stock price performance after floor limit hits, however, indicates essentially a price reversal. After floor limit hits, prices continue to fall only for one day by an average of 1.3%. From the second day onwards, stock prices bounce back by about 1% and, from the fifth day onwards, the stock return becomes significantly positive for the rest of the post-event window of 60 days.

The observed price reversal rejects the delayed price discovery hypothesis but lends further support to our conjecture on the panic selling psychology of individual investors for falling stock prices. Finally, we remark that, though stock prices continue to fall for one day after floor limit hits, it is difficult for investors to benefit from a trading strategy of selling on floor-hitting day and buying back on the next day since there will be transaction costs involved. So, our analysis suggests that investors would be better off not selling stocks frantically when stock prices fall towards the floor limits.

6. Conclusions

The performance of price limit rules is always the focus of policy making and academic research. This paper makes use of transactions data to study the market dynamics and the stylized facts that accompany the magnet effects of the price limit system in the Shanghai Stock Exchange.

Consistent with Subrahmanyam (1994), when limit hits are imminent, we find stock prices approach limit bounds at faster rates and with increased volatility and higher trade frequency. A formal regression analysis on the AR(3)-GARCH(2,2) filtered time series returns with sampling characteristic adjustment confirms our findings.

We also observe asymmetry effects between limit hits at the ceiling and floor bounds. Specifically, we find that, as stock prices approach the floor limits, the volume and trade size are lower than normal market conditions but the bid-ask spread is wider. We conjecture that this is due to the panic selling activities of uninformed and risk-averse individual investors when stock prices falls towards the floor limits. This is supported by our post-limit-hit analysis at the floor limits, where we find price reversal. Evidence of price reversal indicates that aggressive selling at floor limit hits is irrational and sub-optimal.

Finally, we remark that our research makes an interesting and relevant contribution to the arguments for launching new equity index futures and options markets in Chinese stock markets this year. These new derivatives should at least in theory provide the investors with effective tools to hedge the downside risks of their equity portfolios, thus reducing the tendency to sell frantically as stock prices fall towards lower limit bounds.

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