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The magnet effect of price limits: evidence from high-frequency data on Taiwan Stock Exchange

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Abstract

Many financial markets impose limits on the amount asset prices can change within a trading day to prevent the market from overreacting and, hence, to dampen volatility. Using intraday data from Taiwan Stock Exchange (TSE), we document a statistically and economically significant tendency for stock prices to accelerate toward the upper bound and weak evidence of acceleration toward the lower bound as the price approaches the bounds. Previous research has referred to this phenomenon as the magnet effect of daily price limits, but to the best of our knowledge, the results presented here are the first empirical verification of such an effect. The magnet effect continues to hold even after controlling for possible momentum effects. The economic significance is established by simulated trading strategies. In addition, the effect is further confirmed by data from different sample period.
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Keywords: Magnet effect; Taiwan Stock Exchange; High-frequency data; Daily price limits

1. Introduction

Many stock markets, especially the emerging markets, implement price limits on daily price movement; see, for example, the markets in Austria, Belgium, France, Italy, Japan, Korea, Malaysia, Mexico, the Netherlands, Spain, Switzerland, Taiwan and Thailand. Some financial markets other than stock markets also impose daily price limits. For example, price limits exist in the US futures markets. Brennan (1986) provides a convincing argument for the rationale for price limits in the US futures market, arguing that the limits serve as a substitute to margin requirements to reduce the total cost of trading for market participants. However, the margin requirements and credibility issues of the futures market do not exist in the stock markets. A natural question arises: why do emerging stock markets impose price limits?

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Advocates of stock price limits claim that the limits have two attributes to decrease the price volatility. First, the limits literally set a ceiling and a floor for the price to move within a trading day. Second, price limits provide a cooling off period. Other proponents claim that the limits counter overreaction, but do not interfere with trading activity. Critics argue that the limits can have several adverse effects on the stock market. First, the volatility spillover hypothesis says price limits will increase the volatility on the subsequent trading days because the limits prevent large 1-day price changes and immediate corrections in order imbalance. Fama (1989) argues that inciting trading in anticipation of circuit breakers will increase the volatility. Price limits do not halt the trading, but they prevent immediate corrections in order imbalances so that it will have the same volatility spillover effects as the circuit breakers. The volatility spillover hypothesis is empirically supported by Kuhn et al. (1991) who found that stock volatility was not moderated by circuit breakers during the 1989 US mini-crash. Kim and Rhee (1997) used Tokyo Stock Exchange data to conclude that volatility does not return to the normal level after reaching the price limits.

A second potential problem with price limits is a delay in price discovery. The delayed price discovery hypothesis suggests that price constraints prevent price from reacting to new information and reaching the new equilibrium level. The delayed price discovery hypothesis was proposed in Fama (1989) and was supported by Lehmann (1989) and Lee et al. (1994).

Third, the trading interference hypothesis suggests that price limits can interfere with trading. If the stock price hits a limits, then the stock becomes less liquid and the trading will be heavier on the following days. For example, see Fama (1989), Telser (1989) and Lehmann (1989). Lee et al. (1994) found that trading halts increase both the volume and volatility for the New York Stock Exchange. They found that volume and volatility after a trading halt are higher than on normal days.

Fourth, the magnet effect suggests that the asset price accelerates toward the limits as it gets closer to the limits. There are two reasons proposed for the magnet effect: illiquidity and behavioral investors. First, the traders, for fear of illiquidity, would involve in active trading that pulls the price closer to the limit. Subrahmanyam (1994) showed in an intertemporal one-market model that if the price is close to the limits, the limits can increase ex ante price variability and the probability of the price crossing the limits. Similarly, Lehmann (1989) contends that order imbalances and the consequent lack of trading induce prices to reach the limits. Arak and Cook (1997) argued that the behavioral investors who believe in the price trends can act in a way that produces a magnet effect. In order to avoid being shut out of a trend, traders who think that the ceiling will be reached might buy sooner. This behavior will accelerate price changes as price gets closer to the ceiling. The cool off effect is the opposite of magnet effect, and it is claimed to be one of the major benefits of price limits by the advocates. Price limits may cause a trading halt, once the price reaches its limit. The market will then have time to reassess the fundamental value to counter the overreaction, if there is any in the market.

The empirical literature on the price limits concentrated on the first three hypotheses: volatility spillover, delayed price discovery and trading interference hypotheses. These studies typically use daily prices such as the close and open prices to test the hypotheses. To test the magnet effect, however, we cannot use daily prices. We must examine intraday price changes to see how the price reacts as it gets closer to the limits. Arak and Cook (1997) used intraday price changes, but actually only used the first 5-min return of the day and ignored the rest of the 5-min return series. In this paper, we used returns sampled at 5-min intervals to test the magnet effect.

The paper is organized as follows. Section 2 provides a brief description of the Taiwan Stock Exchange (TSE) and the data used in our empirical work. In Section 3, we propose an econometric model for the 5-min return series and propose a test for the magnet effect. We find statistically significant evidence for the magnet effect for the upper price limit (ceiling magnet effect). We also use intraday data from the trades and quotes (TAQ) database for 90 randomly chosen S&P 500 stocks and show that the magnet effect does not exist for this market without price limits. Furthermore, the detected magnet effect in the Taiwan Stock Exchange continues to hold when the data are extended 1 year to April 29, 2000. In Section 4, we analyze the economic significance of the magnet effect using several trading strategies. The ceiling magnet effect is found to be of economic significance even after adjusting for transaction costs. Finally, we conclude the paper in Section 5.

2. Data description

Daily price limits are currently used in many stock exchanges. However, in most stock exchanges, the daily price limits are set so high that the stock price rarely reaches the limits. For example, the Tokyo Stock Exchange implements daily price limits set, on average, at 20%, so that the limits are rarely reached. An ideal stock exchange to study magnet effects is a market with tight daily price limits and high volatility. The Taiwan Stock Exchange implements a daily price limit of 7% and the volatility is relatively high, making it suitable for studying magnet effect.

We begin with a brief description of the Taiwan Stock Exchange (TSE). It is an order-driven call market that does not utilize designated market makers. Investors issue orders, and the market uses a periodic batch process mode to match the order and to determine the market clearing price that maximizes the trading volume. Specifically, the batch process takes place every minute for inactive stocks. For an active stock, there is a callback design. Normally, a transaction of an active stock is executed every 50 s. However, immediately following the execution, there will be an automatic callback after 6 s so that the entered orders during the 6 s can be executed again. Thus, the minimum possible duration between transactions for an active stock is 6 s.

The trading hours are from 9:00 am to 12:00 noon on weekdays and the first and third Saturdays of each month from 9:00 to 11:00 am until March 1998. Starting April 1998, the trading hours for these two Saturdays were extended to 3 h from 9:00 am to 12:00 noon.

The TSE imposes a 7% price limits for all traded stocks. Within a trading day, the price for a single stock cannot move more than 7% from the previous price after adjusting for dividend and stock splits. Therefore, the maximum close to close 1-day return is 7% and the minimum return is -7%. There are, however, some extraordinary price movements outside the limits on certain days. For example, the stock of Taiwan Semiconductor

Manufacturing Company (TSCM) closed at New Taiwan Dollar (NTD) 130.5 on June 11, 1997, but opened at NTD 91 on June 12, 1997. This is seemingly impossible under the 7% limits. Once adjusted for dividend payment and stock split, the price remained within the 7% limits. All the returns in our analysis are adjusted for dividends and splits.

The primary data set used in the paper consists of 5-min return series on all the listed companies in the TSE from January 3, 1998 to March 20, 1999. The total market capitalization of TSE at the end of 1998 was NTD 8,392,697 million, which was worth US$ 258,234 million. Trading volume in 1998 was 612,009 million shares, or NTD 29,518,969 million (US$ 911,353 million). A total of 59.65% of the market capitalization is held by individual investors, 37.59% by institutional investors and only 2.76% by investment funds. Individual investors are the major contributors of capital.

There were 473 companies listed on TSE as of March 1999, out of which, 345 companies had at least one transaction for every 5-min bin (excluding periods of no trading at the price limits) to generate a reliable 5-min return series. Since the batch process takes place every 50 s or less for frequently traded stocks, the 5-min interval is sufficiently long to generate a reliable time series for the 345 stocks. In summary, we dropped 128 infrequently traded companies from the data set and used the remaining 345 companies in the empirical analysis.

Table 1
Summary statistics for the frequency of hitting the price limits

Industry			Ceiling				Floor			
Code	Name	Number of firms	A	B	C	D	E	F	G	H
11	cement	7	9.0	7.0	1.9	37.0	6.0	2.4	1.1	43.9
12	food	24	14.5	12.0	4.6	48.5	14.9	9.6	6.7	46.6
13	plastics	16	17.9	14.9	4.6	51.0	11.5	7.8	2.8	46.1
14	textiles	48	15.0	11.7	3.5	55.3	12.0	7.1	4.3	41.7
15	electrical machinery	19	14.0	10.9	3.6	52.0	12.6	8.4	4.9	54.6
16	electrical appliance	12	10.3	8.1	2.1	45.1	11.3	7.3	4.4	50.5
17	chemicals	16	12.8	10.0	3.2	48.0	11.4	7.1	3.7	38.8
18	glass	6	10.3	9.0	2.5	59.9	8.5	4.0	2.5	41.6
19	paper pulp	6	13.0	10.5	3.7	57.6	8.2	5.0	1.8	38.3
20	iron steel	25	16.4	12.6	5.4	53.6	16.6	11.4	8.9	49.7
21	rubber	8	17.4	14.4	5.4	60.0	9.9	6.1	2.0	46.0
22	automobile	4	2.8	2.5	0	57.6	4.0	1.8	1.0	47.0
23	electronics	66	21.1	16.5	5.0	49.4	15.7	10.6	3.4	49.1
25	construction	31	15.4	12.3	4.6	45.7	15.7	10.5	6.6	51.1
26	shipping	14	10.5	8.6	2.2	49.6	8.1	4.6	1.9	28.0
27	tourist	5	13.3	10.0	3.3	49.7	7.0	3.5	1.8	29.6
28	bank	34	12.9	10.4	4.0	52.1	5.6	3.2	1.1	30.2
99	others	4	10.8	8.3	2.5	52.0	10.0	5.5	3.3	29.5
All		345	15.3	12.1	4.0	50.9	12.3	7.8	4.1	44.1

A: Number of days reaching the ceiling, industry average, out of possible 324 days. B: Number of days closing at the ceiling, industry average. C: Average number of consecutive days closing at the ceiling, industry average. D: Duration of staying at the ceiling, industry average (units in minutes). E: Number of days reaching the floor, industry average. F: Number of days closing at the floor, industry average. G: Average number of consecutive days closing at the floor, industry average. H: Duration of staying at the floor, industry average (units in minutes).

The TSE categorizes the companies into 19 industrial sectors. These sectors and the number of firms used in our study are as follows: cement (7), food (24), plastics (16), textiles (48), electrical machinery (19), electrical appliances (12), chemicals (16), glass (6), paper and pulp (6), iron and steel (25), rubber (8), automobile (4), electronics (66), construction (31), shipping (14), tourist (5), bank (34), department stores (0) and others (4). Finally, the sample period is extended by 1 year to April 29, 2000 in Section 3.6 to validate the findings of the paper out of sample.

Table 1 presents summary statistics for how often the price limits were reached classified by the industrial sectors. For the sample period from January 3, 1998 to March 20, 1999, a stock price reached the ceiling, on average, 15.3 days out of the 324 trading days, which is about 4.7% of the sample period. The stock price reached the floor 12.3 days on average. The average number of days when a stock closed at the ceiling is 12.1 days and it is 7.8 days for the floor. This implies that once the limits are reached in a trading day, it is more likely to close at the limits. Table 1 also summarizes how long the price stays at the limits. On average, the price stays at the ceiling for 52 min once it reaches the ceiling, and it stays at the floor for 42 min. This implies that the stock stays at the limits roughly one-third of the trading hours once it reaches the limits. Thus, within a trading day, the stocks tend to stay at the limits for quite a long time. It is also interesting to see whether TSE stocks reach the limits for consecutive trading days. Among the 324 trading days, there are, on average, four cases when the stock reached the ceiling on two consecutive days. In other words, this is roughly a quarter of the 15.3 days when the price hits the ceiling. A similar phenomenon appears in the floor case. In summary, the stock prices in TSE often reached and closed at the limits due to the tight daily price limits. Therefore, the Taiwan Stock Exchange data are a natural candidate to study the intraday effect of the daily price limits.

3. Analysis based on econometric models

3.1. The model

In this section, we develop an econometric model to assess the magnet effect of daily price limits. The trading at TSE takes place from 9:00 am to 12:00 noon. For US stocks, it is well known that the volatility is higher when the market opens and closes than during the middle of trading day. Fig. 1 plots the intraday volatility pattern for the 345 TSE stocks. The volatility is defined as the standard deviation of the 5-min returns. Fig. 1 shows a clear U-shaped pattern of intraday volatility. Volatility is at the peak when the market opens and declines rapidly till 9:30 am. Volatility remains low most of the day, but it jumps at the end of the trading day. This figure clearly shows a deterministic pattern in the standard deviation of the 5-min returns. There are two ways to handle the deterministic volatility pattern. First, one can specify a multiplicative deterministic function in the conditional variance equation as in Andersen and Bollerslev (1997). Second, one can standardize the 5-min returns by its standard deviations. For simplicity, we use the second approach. For each stock, we first compute the standard deviation of the returns for each 5-min bin. Since there are 324 trading days, there are 324 observations to compute the

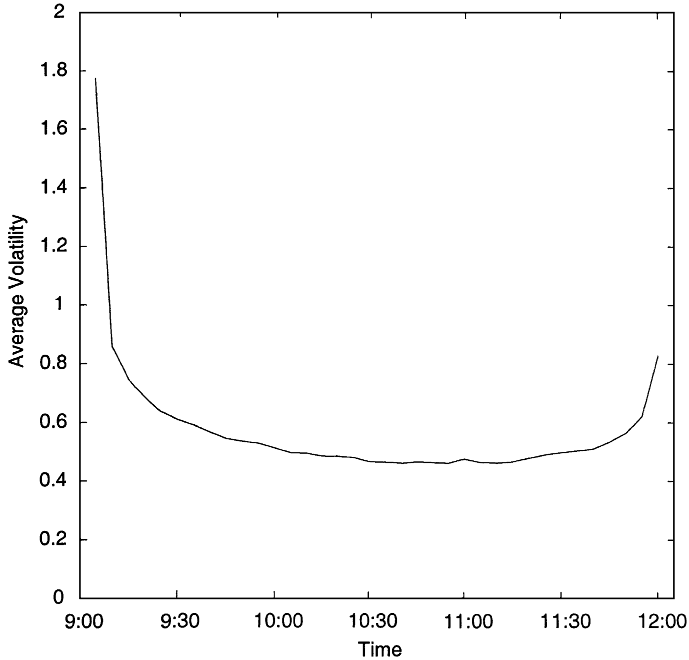

Fig. 1. Intraday volatility pattern. This figure plots the average intraday volatility pattern. Volatility is defined as the standard deviation of the 5-min returns. TSE market opens at 9:00 and closes at 12:00 to make 36 5-min time bins. For every stock, the standard deviation of the returns are calculated for 36 time bins. Then, the standard deviations for each bin are averaged over 345 stocks to create average intraday volatility pattern.

standard deviation for each 5-min bin. We then divide each 5-min return by its corresponding standard deviation. For example, we calculate the standard deviation of the 324 returns of a stock between 11:00 am and 11:05 am to obtain the standard deviation for the 11:00–11:05 am bin. Then, all 324 5-min returns of the stock between 11:00 am and 11:05 am is divided by this standard deviation. After standardizing the return series, the U-shaped intraday volatility pattern is removed.

Specifically, for a given stock, let $r_{\tau,k}$ be the 5-min return at day τ for the kth bin, and let

$$\delta_k = \sqrt{\frac{\sum_{i=1}^{324}(r_{i,k} - \bar{r}_k)^2}{323}}$$

be the sample standard deviation of the return, where $\bar{r}_k = \sum_{i=1}^{324} r_{i,k}/324$. The standardized 5-min return of the stock is defined as

$$\mathrm{RET}_{\tau,k} = \frac{r_{\tau,k}}{\delta_k}.$$

For simplicity, we will refer to RET_t as the dependent variable in our study, where t indexes the 5-min intervals.

We exclude the overnight returns and the returns at the price limits for the following reasons. The market opens at 9:00 am with the closing price of the previous trading day as its beginning price. As such, the return from 9:00 am to 9:05 am is the overnight return, not the actual 5-min return.[1] These overnight returns are excluded from the econometric analysis because they behave differently from the intraday 5-min returns. Typically, these overnight returns are very volatile as shown in Fig. 1. We also exclude the stock returns at the price limits because once the price reaches the limits, it can stay at the limits or move only in one direction, hence, exhibiting unusual dynamics. Once the price departs from the limits, the next return is included in the analysis.[2]

High-frequency stock returns normally exhibit negative serial correlations. The TSE 5-min returns typically exhibit strong negative serial correlations up to the third lag. We use an AR (3) process as the baseline model for the stock return process.[3]

To investigate the magnet effect, we define the dummy variables D(ceiling) and D(floor) as

$$D(\text{ceiling})_t = \begin{cases} 1, & \text{if the price } P_t \text{ is within 3\% of the ceiling} \\ 0, & \text{otherwise} \end{cases}$$

$$D(\text{floor})_t = \begin{cases} 1, & \text{if the price } P_t \text{ is within 3\% of the floor} \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

These two magnet variables[4] are included in the conditional mean equation of the return, and the model becomes

$$\begin{aligned} \text{RET}_t = {} & \alpha_0 + \alpha_1 \text{RET}_{t-1} + \alpha_2 \text{RET}_{t-2} + \alpha_3 \text{RET}_{t-3} + \gamma_1 D(\text{ceiling})_{t-1} \\ & + \gamma_2 D(\text{floor})_{t-1} + \varepsilon_t. \end{aligned} \tag{2}$$

In the finance literature, it has been repeatedly shown that high-frequency stock returns have heavy tails and exhibit volatility clustering; see Andersen and Bollerslev (1998) for more details. The generalized autoregressive conditional heteroskedasticity (GARCH) model is often used to capture heavy tails and volatility clusterings. In this paper, we use a

[1] The average number of observations excluded from the estimation is less than 3% of the total number of observations. A simulation study not reported in the paper shows the data truncation does not induce any spurious effects.

[2] Excluding the overnight returns and returns at the limits may cause a problem in time series analysis because the intervals between the observations may not be equally spaced. Thus, the estimation should reinitialize whenever a new returns series starts. We have also done the analysis based on reinitializing and found the results do not change significantly.

[3] We also implemented an MA (3) process instead of AR (3) and found similar results. AR (3) estimation is used throughout this paper for computational simplicity.

[4] We set the threshold at 3% in the definition of D(ceiling) and D(floor). However, we tried other specifications and found the results are not sensitive to the threshold. We also tried some monotonic function measuring the distance of the transaction price from the price limits and the results are consistent. Using dummy variables has a simple interpretation of the coefficients because it measures the magnitude of a level shift in the return series.

Table 2
Summary of the AR(3), GARCH(2,2) estimation results

Industry		Conditional mean					
Code	Firms	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\alpha}_2$	$\hat{\alpha}_3$	$\hat{\gamma}_1$	$\hat{\gamma}_2$
11	7	− 0.032 (− 5.610)	− 0.281 (− 25.397)	− 0.144 (− 13.979)	− 0.078 (− 7.395)	0.052 (0.558)	− 0.027 (− 0.698)
12	24	− 0.021 (− 4.455)	− 0.297 (− 26.011)	− 0.153 (− 13.337)	− 0.076 (− 7.385)	0.036 (0.641)	0.046 (0.957)
13	16	− 0.033 (− 5.774)	− 0.262 (− 24.715)	− 0.138 (− 13.942)	− 0.079 (− 7.827)	0.113 (2.209)	− 0.024 (− 0.430)
14	48	− 0.031 (− 5.814)	− 0.272 (− 24.427)	− 0.132 (− 11.724)	− 0.070 (− 7.010)	0.053 (0.858)	0.038 (0.246)
15	19	− 0.023 (− 4.011)	− 0.280 (− 25.338)	− 0.125 (− 11.836)	− 0.060 (− 6.100)	0.055 (1.249)	0.039 (0.971)
16	12	− 0.028 (− 5.369)	− 0.312 (− 28.385)	− 0.152 (− 14.667)	− 0.077 (− 7.359)	0.042 (0.840)	0.024 (− 0.974)
17	16	− 0.027 (− 4.983)	− 0.265 (− 23.692)	− 0.132 (− 11.572)	− 0.071 (− 7.011)	0.050 (0.553)	0.008 (− 0.212)
18	6	− 0.027 (− 4.979)	− 0.273 (− 25.747)	− 0.131 (− 13.851)	− 0.076 (− 7.075)	0.047 (1.372)	0.099 (1.409)
19	6	− 0.032 (− 5.649)	− 0.324 (− 30.036)	− 0.150 (− 13.623)	− 0.073 (− 7.441)	0.004 (− 0.323)	− 0.010 (− 0.668)
20	25	− 0.029 (− 6.216)	− 0.316 (− 27.715)	− 0.150 (− 13.588)	− 0.073 (− 7.205)	0.054 (0.934)	0.028 (0.427)
21	8	− 0.027 (− 4.899)	− 0.255 (− 21.995)	− 0.124 (− 11.105)	− 0.071 (− 7.030)	0.025 (0.262)	0.025 (0.940)
22	4	− 0.021 (− 4.260)	− 0.304 (− 27.823)	− 0.150 (− 13.722)	− 0.078 (− 7.295)	− 0.062 (− 0.505)	0.102 (0.583)
23	66	− 0.014 (− 2.299)	− 0.234 (− 20.429)	− 0.154 (− 15.417)	− 0.085 (− 8.679)	0.058 (1.367)	− 0.034 (− 1.072)
25	31	− 0.033 (− 5.859)	− 0.288 (− 24.820)	− 0.136 (− 12.012)	− 0.069 (− 6.754)	0.049 (1.004)	0.026 (0.035)
26	14	− 0.025 (− 4.335)	− 0.276 (− 25.055)	− 0.144 (− 13.075)	− 0.074 (− 7.606)	0.005 (0.372)	− 0.013 (− 0.662)
27	5	− 0.026 (− 4.221)	− 0.256 (− 22.754)	− 0.131 (− 13.171)	− 0.067 (− 6.062)	0.003 (0.210)	0.062 (1.403)
28	34	− 0.035 (− 6.942)	− 0.329 (− 28.558)	− 0.175 (− 15.780)	− 0.090 (− 9.044)	0.126 (2.411)	− 0.019 (− 0.554)
99	4	− 0.029 (− 5.422)	− 0.295 (− 27.015)	− 0.147 (− 13.795)	− 0.077 (− 7.624)	0.038 (0.782)	0.036 (0.266)
All	345	− 0.026 (− 5.030)	− 0.279 (− 24.946)	− 0.145 (− 13.767)	− 0.076 (− 7.672)	0.056 (1.115)	0.010 (− 0.263)

Industry		Conditional variance						
Code	Firms	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$	$\hat{\gamma}_3$	$\hat{\gamma}_4$
11	7	0.031 (7.797)	0.125 (19.246)	− 0.090 (− 16.782)	1.210 (29.949)	− 0.279 (− 9.258)	0.074 (5.981)	0.001 (0.879)
12	24	0.028 (8.498)	0.151 (20.623)	− 0.117 (− 18.831)	1.236 (42.056)	− 0.302 (− 13.097)	0.047 (5.171)	0.002 (2.427)
13	16	0.005 (6.928)	0.137 (16.330)	− 0.123 (− 14.879)	1.365 (31.701)	− 0.385 (− 8.992)	0.014 (4.351)	0.000 (0.331)
14	48	0.023 (7.599)	0.142 (19.081)	− 0.111 (− 16.520)	1.235 (43.393)	− 0.294 (− 14.580)	0.041 (4.758)	0.002 (1.540)
15	19	0.028 (7.067)	0.153 (18.751)	− 0.111 (− 17.823)	1.168 (29.502)	− 0.242 (− 7.392)	0.027 (3.122)	0.002 (1.329)
16	12	0.066 (7.508)	0.142 (17.811)	− 0.067 (− 13.770)	0.843 (22.409)	0.007 (− 3.798)	0.162 (3.919)	0.004 (1.458)
17	16	0.037 (7.221)	0.137 (19.980)	− 0.098 (− 17.320)	1.137 (34.269)	− 0.217 (− 9.416)	0.106 (3.553)	0.003 (2.198)
18	6	0.014 (9.716)	0.162 (24.455)	− 0.140 (− 20.713)	1.217 (39.244)	− 0.255 (− 11.187)	0.047 (5.577)	0.004 (1.126)
19	6	0.003 (6.460)	0.141 (18.812)	− 0.134 (− 18.556)	1.464 (40.887)	− 0.475 (− 13.499)	0.009 (4.228)	0.000 (0.667)
20	25	0.015 (7.823)	0.171 (21.578)	− 0.144 (− 18.543)	1.279 (48.158)	− 0.323 (− 15.116)	0.026 (4.142)	0.002 (2.697)
21	8	0.038 (7.373)	0.157 (22.273)	− 0.098 (− 19.544)	0.982 (29.510)	− 0.082 (− 6.780)	0.056 (2.099)	0.001 (1.202)
22	4	0.033 (6.195)	0.101 (17.272)	− 0.052 (− 11.370)	1.135 (33.407)	− 0.220 (− 13.339)	0.436 (2.703)	0.003 (0.314)
23	66	0.013 (5.725)	0.124 (13.560)	− 0.097 (− 11.161)	1.152 17.275)	− 0.193 (− 2.679)	0.012 (2.872)	0.001 (1.976)
25	31	0.013 (7.069)	0.159 (19.586)	− 0.136 (− 18.089)	1.327 (54.277)	− 0.366 (− 14.362)	0.040 (4.707)	0.001 (0.962)
26	14	0.033 (8.582)	0.157 (21.572)	− 0.119 (− 17.890)	1.220 (45.241)	− 0.295 (− 14.937)	0.116 (4.031)	0.003 (1.080)
27	5	0.003 (7.032)	0.120 (20.140)	− 0.115 (− 20.041)	1.518 (58.993)	− 0.526 (− 19.498)	0.009 (5.986)	0.000 (0.368)
28	34	0.005 (6.898)	0.141 (18.817)	− 0.125 (− 17.549)	1.343 (37.861)	− 0.364 (− 12.596)	0.011 (2.577)	0.001 (2.151)
99	4	0.006 (6.527)	0.159 (20.431)	− 0.146 (− 20.142)	1.332 (44.098)	− 0.352 (− 10.303)	0.016 (4.565)	0.000 (1.763)
All	345	0.020 (7.032)	0.143 (18.370)	− 0.113 (− 16.725)	1.226 (34.411)	− 0.278 (− 10.161)	0.044 (3.800)	0.001 (1.547)

$\mathrm{RET}_t=\alpha_0+\alpha_1\mathrm{RET}_{t-1}+\alpha_2\mathrm{RET}_{t-2}+\alpha_3\mathrm{RET}_{t-3}+\gamma_1 D(\text{ceiling})_{t-1}+\gamma_2 D(\text{floor})_{t-1}+\varepsilon_t$. $h_t=\beta_0+\beta_1 h_{t-1}+\beta_2 h_{t-2}+\beta_3\varepsilon^2_{t-1}+\beta_4\varepsilon^2_{t-2}+\gamma_3\{D(\text{ceiling})_{t-1}+D(\text{floor})_{t-1}\}+\gamma_4\mathrm{DLIM}_t$. The parameter estimates are averaged within each industry. The medians of the t-ratios are reported in the parenthesis.

GARCH(2,2) process as the baseline model for the conditional variance of the returns. Furthermore, we also include some factors in the conditional variance, leading to the following conditional variance equation for the TSE stocks:

$$h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 h_{t-2} + \beta_3 \varepsilon_{t-1}^2 + \beta_4 \varepsilon_{t-2}^2 + \gamma_3 \{D(\text{ceiling})_{t-1} + D(\text{floor})_{t-1}\} + \gamma_4 \text{DLIM}_t. \quad (3)$$

In Eq. (3), DLIM is the duration the price remained at the limit on the previous trading day, if the price closed at the limits. This variable is used to capture the volatility spillover effect.

In the proposed AR(3)–GARCH (2,2) model, there are four coefficients (γ_1, γ_2, γ_3 and γ_4) related to the price limits with different interpretations. First, γ_1 captures the magnet effect toward the ceiling. A positive γ_1 implies that the expected return increases as the price gets closer to the ceiling after controlling for deterministic volatility pattern, serial correlation and conditional heteroskedasticity. In other words, the price accelerates to the limit as it gets closer to the ceiling. Similarly, γ_2 captures the magnet effect of the floor. A negative γ_2 implies that the price accelerates to the floor as it gets closer to the floor. These two coefficients are of the most interest in this paper.

The coefficient γ_3 allows the volatility to change as the boundary is approached. A positive γ_3 implies that the volatility increases as the price gets closer to the limits. An increased volatility will increase the chance to draw a large absolute return so that it increases the probability that the price will reach the limits. The coefficient γ_4 captures the volatility spillover effect. Suppose the price closed at the ceiling on the previous trading day. The volatility spillover effect implies that the price limits prohibit the price to reach the equilibrium level yesterday and the effect will carry over to the volatility today. A positive γ_4 says that the volatility is larger after the price closed at the limits and supports the volatility spillover hypothesis.

3.2. Estimation results

We applied Eq. (2) and Eq. (3) to the 345 TSE stocks using the E-views program. Table 2 summarizes the estimation results. It reports the average estimated coefficients and the median of *t*-ratios in the parenthesis for each industry. As mentioned before, the return series have significant autocorrelations up to the third lag and the fitted GARCH(2,2) process is persistent.

Of particular interest among the results are γ_1, γ_2, γ_3 and γ_4, which are the coefficients of D(ceiling), D(floor), $\{D(\text{ceiling})+D(\text{floor})\}$ and *DLIM*, respectively. First, the median *t*-ratios for γ_1, the coefficient of D(ceiling) in the conditional mean equation, are all positive except for the paper pulp (19) and automobile industry (22) sectors. Since we look at the median *t*-ratios, we cannot conclude the significance directly by comparing it with the critical values. We introduce a formal joint test for all 345 estimations in the next section. The median value for the *t*-ratios heuristically gives an idea how many coefficients are significant. For example, bank industry (28) has a median value of 2.411. This implies that more than half of the bank stocks have significant γ_1. Plastics industry (13) also has similar results with a median *t*-ratio 2.209.

The magnet effect towards the floor limit can be captured by γ_2, the coefficient of D(floor). Industrial average γ_2 does not reveal any consistent sign. In addition, none of the median t-ratios are significant at the 5% level.

Instead of looking at the industrial averages, scatterplots of the estimates and the t-ratios may give a better understanding on individual stock behavior. Fig. 2 shows scatterplots of

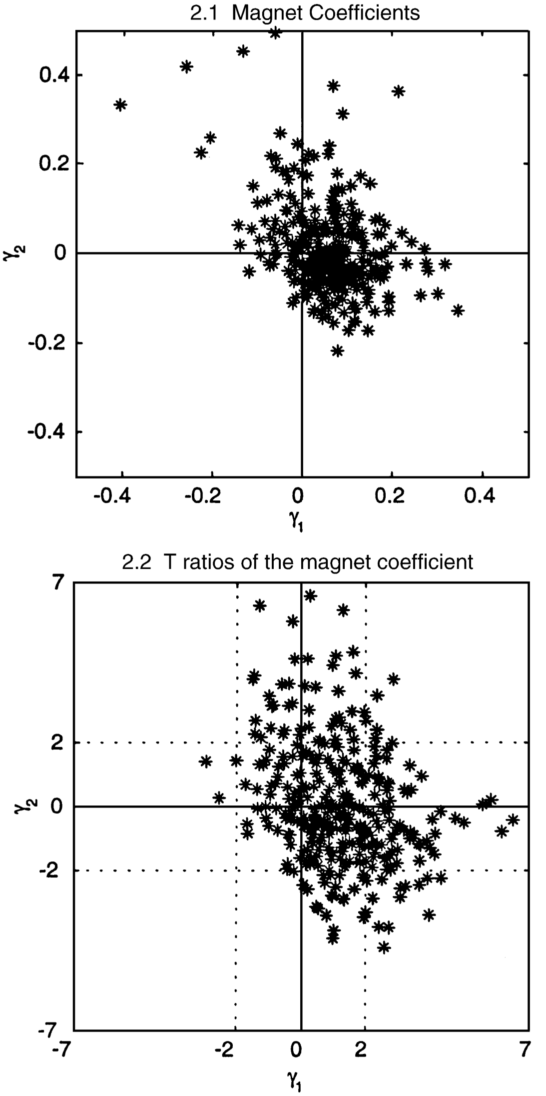

Fig. 2. Scatterplots of the magnet coefficients (January 3, 1998–March 20, 1999). (2.1) scatter plots ($\hat{\gamma}_1$, $\hat{\gamma}_2$) from the following AR(3)-GARCH(2,2) estimation and (2.2) scatter plots the t-ratios associated with ($\hat{\gamma}_1$, $\hat{\gamma}_2$). The same model is applied for 345 TSE firms to make 345 pairwise plots (see Eq. (2)).

the estimates and the *t*-ratios of the coefficients of *D*(ceiling) and *D*(floor) for the 345 stocks. The *x*-axis (horizontal) corresponds to the ceiling magnet effect and the *y*-axis (vertical) corresponds to the floor magnet effect. If there are magnet effects in both limits, the points should lie in the fourth (South–East) quadrant. Most points in the scatterplots are indeed in the right-hand side of the *y*-axis, implying that the magnet effect toward the ceiling is strong. There is less evidence for the floor magnet effect as only 191 of the 345 stocks produce a negative γ_2. Even though there are more negative γ_2 than positive, Fig. 2 shows that the floor magnet effect is relatively weak. In summary, we conclude that the magnet effect is present in the TSE. The effect is strong toward the ceiling but weak toward the floor.

Fig. 3 plots the industry average estimates from Table 2. Again, all the industries except 22 (automobiles) and 27 (tour) exhibit estimates consistent with the magnet effect towards the ceiling. Note that industries 23 (electronics), 13 (plastics), and 28 (banking) have the strongest magnet effects. The strong magnet effect of these three industries and the erroneous direction of the automobile and tourist industries are confirmed in Section 4 using a different approach.

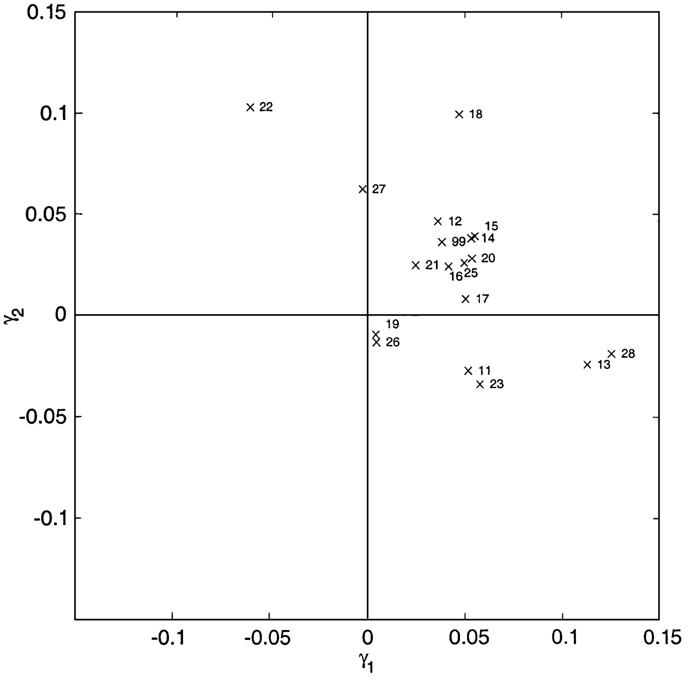

Fig. 3. Industry average magnet coefficients. The figure scatter plots 18 industry average coefficients. The industry code is associated with the plots. Industry codes: 11 = cement, 12 = food, 13 = plastics, 14 = textiles, 15 = electrical machinery, 16 = electrical appliances, 17 = chemicals, 18 = glass, 19 = paper and pulp, 20 = iron and steel, 21 = rubber, 22 = automobile, 23 = electronics, 25 = construction, 26 = shipping, 27 = tourist, 28 = bank and 99 = others.

We now turn to the results of the conditional variance equation in Table 2. The coefficients of interest are γ_3 and γ_4. The median t-ratios for γ_3 implies that the volatility increases as the price gets closer to the limits, hence, increasing the probability of reaching the price limits. The median t-ratios for the γ_3 parameter are greater than 2 for all industrial sectors.

To detect the volatility spillover effect, we test the null hypothesis that $\gamma_4 = 0$. A positive γ_4 implies that the conditional variance increases the longer the time spent at the limit. The median t-ratios for γ_4 is 1.547, which is not significant. However, many industries have median t-ratios greater than 2. Fig. 4 gives a better description on these two coefficients by showing the scatterplot of their t-ratios. It shows that most points lie in the first quadrant. The plot clearly shows that most γ_3 are positive and significant. Regarding γ_4, most points lie above 0. Even though less than half of the points lie above 2, it is clear that most γ_4 are positive. In short, we find some evidence for the volatility spillover hypothesis in TSE.

3.3. Test of magnet effect in TSE using GMM

The analysis in the previous section is exploratory in nature. In this section, we aggregate the cross-sectional results to provide a formal test. If the returns are not cor-

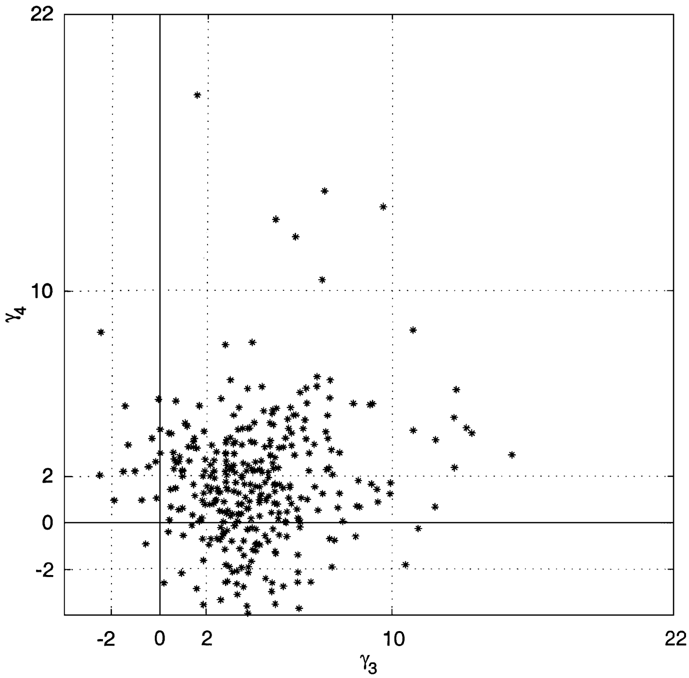

Fig. 4. Scatter plots of t-ratios in the conditional variance equation. The plots are the t-ratio pairs of ($\hat{\gamma}_3$, $\hat{\gamma}_4$) from the following AR(3), GARCH(2,2) regression (see Eq. (3)).

related from one stock to another, we can derive a simple joint test statistic for the magnet coefficients. Unfortunately, returns across stocks are likely to be correlated thereby complicating our testing strategy. One way to allow for cross- and serial correlations is to adopt a GMM methodology. We stack all 345 returns together in GMM estimation to derive the joint distribution of the estimates. To get closed form moments, we drop the conditional variance equation and concentrate on the conditional mean equation. Thus, the model becomes

$$\mathrm{RET}_t = \alpha + X_t\beta + Z_t\gamma + \varepsilon_t, \qquad \varepsilon_t \sim (0, \Sigma) \tag{4}$$

where RET_t: stacked standardized 5-min returns (345 by 1), X_t: AR(3) or three lagged variable (345 by 1035), Z_t: stacked $D(\mathrm{ceiling})_{t-1}$ and $D(\mathrm{floor})_{t-1}$ (345 by 690), β: AR coefficient (1035 by 1), γ: magnet effect coefficients (690 by 1). Since each equation of the stacked returns in Eq. (4) is identical to Eq. (2), we can use the usual OLS moments for the GMM estimation. Advantages of using OLS moments include the following: that it is consistent and the estimation process can be done stock by stock. Nevertheless, to calculate the proper standard errors for the estimates, we must pool all 345 stocks. The disadvantage of using OLS moments is that the estimate may not be efficient. The moments for the GMM estimation are

$$g_T(b) = E_T(f_t) = \begin{bmatrix} E_T(\mathrm{RET}_t - \alpha - X_t\beta - Z_t\gamma) \\ E_T[X_t'(\mathrm{RET}_t - \alpha - X_t\beta - Z_t\gamma)] \\ E_T[Z_t'(\mathrm{RET}_t - \alpha - X_t\beta - Z_t\gamma)] \end{bmatrix} = E_T\begin{bmatrix} \varepsilon_t \\ X_t'\varepsilon_t \\ Z_t'\varepsilon_t \end{bmatrix} = 0$$

The solution to the above moments is simply the OLS estimators for each individual regression. Fig. 5.1 scatterplots the magnet coefficients from the OLS estimations. The plots look strikingly similar to Fig. 2.1 where we used GARCH(2,2) as well as the conditional mean equation. γ_1 is positive for most stocks but γ_2 does not have a consistent sign. GMM provides a sampling distribution of the estimates,

$$\mathrm{cov}(b) = \mathrm{cov}\left(\begin{bmatrix} \hat{\alpha} \\ \hat{\beta} \\ \hat{\gamma} \end{bmatrix}\right) = \frac{1}{T} d^{-1} S d^{-1'}, \tag{5}$$

where

$$d \equiv \frac{\partial g_T(b)}{\partial b'}$$

$$S \equiv \sum_{j=-\infty}^{\infty} E(f_t f_{t-j}').$$

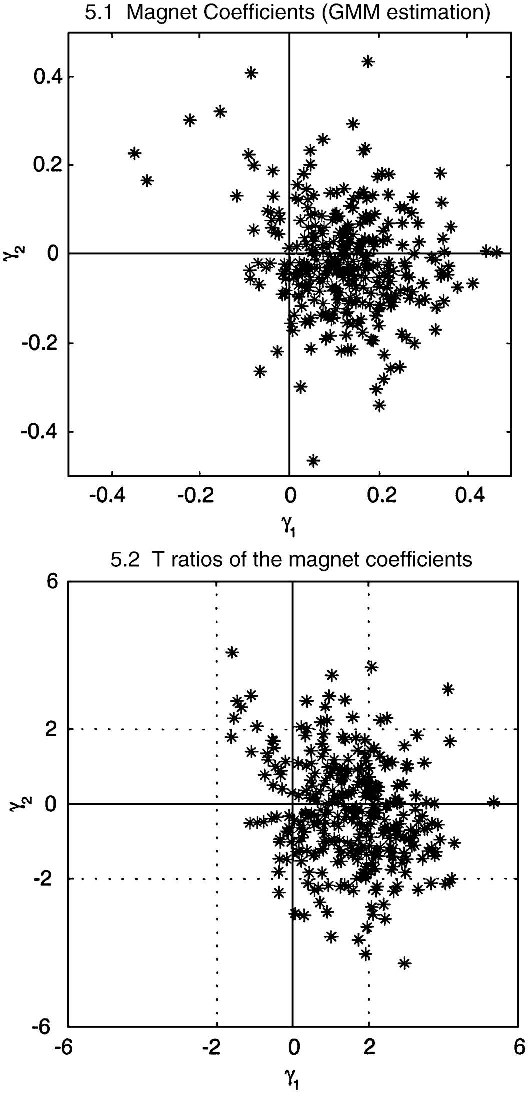

Fig. 5. Magnet coefficients from GMM estimation (January 3, 1998 – March 20, 1999). The figure scatter plots the magnet coefficients from GMM estimation. Standards errors are adjusted for the serial correlation and the cross-correlation using the GMM method (see Eq. (4)).

In our setup, the d and S matrices can be estimated by

$$d \equiv \frac{\partial g_T(b)}{\partial b'} = -\begin{bmatrix} I_N & E(X_t) & E(Z_t) \\ E(X_t') & E(X_t'X_t) & E(X_t'Z_t) \\ E(Z_t') & E(Z_t'X_t) & E(Z_t'Z_t) \end{bmatrix}$$

$$\hat{d} = -\begin{bmatrix} I_N & \frac{1}{T}\Sigma(X_t) & \frac{1}{T}\Sigma(Z_t) \\ \frac{1}{T}\Sigma(X_t') & \frac{1}{T}\Sigma(X_t'X_t) & \frac{1}{T}\Sigma(X_t'Z_t) \\ \frac{1}{T}\Sigma(Z_t') & \frac{1}{T}\Sigma(Z_t'X_t) & \frac{1}{T}\Sigma(Z_t'Z_t) \end{bmatrix}, \tag{6}$$

and

$$S \equiv \sum_{j=-\infty}^{\infty} E(f_t f_{t-j}')$$

$$= \sum_{j=-\infty}^{\infty} \begin{bmatrix} E(\varepsilon_t\varepsilon_{t-j}') & E(\varepsilon_t\varepsilon_{t-j}'X_{t-j}) & E(\varepsilon_t\varepsilon_{t-j}'Z_{t-j}) \\ E(X_t'\varepsilon_t\varepsilon_{t-j}') & E(X_t'\varepsilon_t\varepsilon_{t-j}'X_{t-j}) & E(X_t'\varepsilon_t\varepsilon_{t-j}'Z_{t-j}) \\ E(Z_t'\varepsilon_t\varepsilon_{t-j}') & E(Z_t'\varepsilon_t\varepsilon_{t-j}'X_{t-j}) & E(Z_t'\varepsilon_t\varepsilon_{t-j}'Z_{t-j}) \end{bmatrix}$$

$$\hat{S} = \sum_{j=-\infty}^{\infty} \begin{bmatrix} \frac{1}{T}\Sigma(\hat{\varepsilon}_t\hat{\varepsilon}_{t-j}') & \frac{1}{T}\Sigma(\hat{\varepsilon}_t\hat{\varepsilon}_{t-j}'X_{t-j}) & \frac{1}{T}\Sigma(\hat{\varepsilon}_t\hat{\varepsilon}_{t-j}'Z_{t-j}) \\ \frac{1}{T}\Sigma(X_t'\hat{\varepsilon}_t\hat{\varepsilon}_{t-j}') & \frac{1}{T}\Sigma(X_t'\hat{\varepsilon}_t\hat{\varepsilon}_{t-j}'X_{t-j}) & \frac{1}{T}\Sigma(X_t'\hat{\varepsilon}_t\hat{\varepsilon}_{t-j}'Z_{t-j}) \\ \frac{1}{T}\Sigma(Z_t'\hat{\varepsilon}_t\hat{\varepsilon}_{t-j}') & \frac{1}{T}\Sigma(Z_t'\hat{\varepsilon}_t\hat{\varepsilon}_{t-j}'X_{t-j}) & \frac{1}{T}\Sigma(Z_t'\hat{\varepsilon}_t\hat{\varepsilon}_{t-j}'Z_{t-j}) \end{bmatrix}. \tag{7}$$

There are two potential problems in estimating the d and S matrices. First, we need to invert the 2070×2070 d matrix. Since each block in the d matrix is a diagonal matrix; however, there is no problem obtaining the inverse matrix of d. Second, to estimate the S matrix, one must truncate the lag at some point because j runs from negative infinity to positive infinity. To choose an appropriate truncation point, we checked the cross-correlations of the residuals of the 345 estimations. Fig. 6.1 shows the box plots of the serial correlations of these residuals. The plots show virtually no serial correlations in the residuals. This implies that the AR(3) model can adequately capture the serial correlation in the returns. Fig. 6.2 shows the box plots of residual cross-correlations. There are not only significant contemporaneous cross-correlations among the residuals but also large cross-correlations at lags 1 and 2. Thus, we must compute contemporaneous cross-correlations and lagged cross-correlations. In this analysis, we truncate the lag at ± 6 and check the sensitivity of the results to the truncation lag. We find results stable when the truncation lag is around 6.

Once the d and S matrices are estimated, we can calculate the covariance matrix for the 2070 estimates. This covariance matrix accounts for not only the serial correlations but also the cross-correlations of the stock returns. We form a joint test of the ceiling magnet effect by testing if the cross-section mean of γ_1 is equal to 0. One can also test whether the 345 γ_1s are jointly equal to zero. However, the problem of the second joint test is that testing zero is misleading. The test may be rejected because some γ_1 are negative. We want

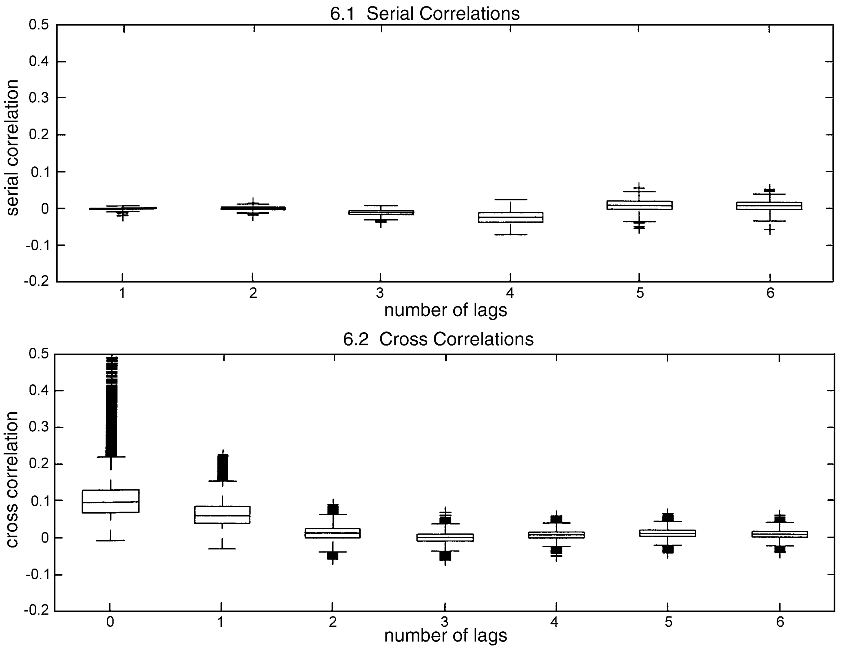

Fig. 6. Serial and cross-correlation of the residuals from GMM estimation. (6.1) box plots the serial correlations for the individuals residuals from the GMM estimation. (6.2) box plots the cross-correlations of the 345 residuals.

to test whether the γ_1 is positive. Thus, testing whether the mean of γ_1 is zero or positive is the correct test for the magnet effect. The standard error for the mean of γ_1 can be computed by

$$\mathrm{SE}\left(\frac{1}{345}\sum_{i=1}^{345}\hat{\gamma}_{1i}\right) = \sqrt{a\,\mathrm{cov}\,(b)a'}, \tag{8}$$

where a=[0 0...0 1/(345) 1/(345)...1/(345) 0 0...0] (1 by 2070).

We use the same procedure to obtain the appropriate standard errors for γ_2 and test the floor magnet effect. Table 3 reports the results for the ceiling and floor magnet effects. The average $\hat{\gamma}_1$ is 0.124 and the standard error of the mean is 0.011, which gives a t-ratio of 11.134. Therefore, the ceiling magnet effect clearly exists in the TSE. However, for the floor magnet effect, we cannot reject that mean of γ_2 is zero. The results of the GMM estimation are consistent with the heuristic analysis of the scatterplots and median t-ratios in the previous section. The industrial analyses are also consistent with the results of the previous section. Industries 23, 13 and 28, which produced the largest ceiling magnet effects in the previous section, have t-ratios greater than 6. On the other hand, industries 22 and 27, where we could not find any ceiling magnet effect, have t-ratios less than 1.65, which is equal to the critical value for the one-sided test.

Table 3
GMM estimation results

Industry		Ceiling			Floor		
Code	Firms	Average $\hat{\gamma}_1$	SE (average $\hat{\gamma}_1$)	t (average $\hat{\gamma}_1$)	Average $\hat{\gamma}_2$	SE (average $\hat{\gamma}_2$)	t (average $\hat{\gamma}_2$)
11	7	0.102	0.061	1.656	−0.098	0.052	−1.871
12	24	0.120	0.026	4.580	0.028	0.027	1.034
13	16	0.162	0.026	6.148	−0.039	0.036	−1.099
14	48	0.100	0.019	5.197	0.025	0.024	1.023
15	19	0.143	0.022	6.443	−0.002	0.022	−0.096
16	12	0.143	0.038	3.770	−0.044	0.055	−0.809
17	16	0.141	0.028	5.123	−0.023	0.029	−0.789
18	6	0.144	0.081	1.771	0.060	0.049	1.235
19	6	0.057	0.041	1.391	0.010	0.046	0.214
20	25	0.133	0.026	5.167	−0.014	0.030	−0.471
21	8	0.091	0.028	3.275	−0.008	0.032	−0.255
22	4	0.198	0.130	1.522	0.020	0.116	0.174
23	66	0.083	0.012	7.082	−0.041	0.017	−2.356
25	31	0.145	0.027	5.365	0.006	0.025	0.245
26	14	0.088	0.035	2.555	−0.021	0.041	−0.517
27	5	0.045	0.039	1.147	0.059	0.038	1.571
28	34	0.215	0.030	7.240	−0.052	0.030	−1.750
99	4	0.125	0.044	2.836	−0.031	0.039	−0.794
All	345	0.124	0.011	11.134	−0.014	0.017	−0.783

$\mathrm{RET}_t = \alpha_0 + \alpha_1 \mathrm{RET}_{t-1} + \alpha_2 \mathrm{RET}_{t-2} + \alpha_3 \mathrm{RET}_{t-3} + \gamma_1 D(\mathrm{ceiling})_{t-1} + \gamma_2 D(\mathrm{floor})_{t-1} + \varepsilon_t$.

3.4. Magnet vs. Momentum effects

From the estimation results of Eq. (2) and Eq. (3), we argue that the conditional mean return is higher as the price gets closer to the ceiling after controlling for deterministic volatility pattern, serial correlations and conditional heteroskedasticity. In other words, the expected price continues to move upward after exceeding the threshold. These results provide evidence that TSE stocks have a strong ceiling magnet effect. Another possible explanation for this finding is momentum as first documented in Jagadeesh and Titman (1993). Momentum is the name given to the observation that stocks that have done unusually well in the recent past are more likely to do unusually well in the near future and vice versa. While the presence of these characteristics in US stocks is still being debated, it is clear that the results of Section 3.2 could also be due to a high-frequency version of momentum in the TSE stocks. That is, stocks that have risen over the first part of the day and crossed the threshold are more likely to continue rising over the remaining portion of the day.

In this section, we seek to differentiate between a pure price continuation (or momentum effect) and a magnet effect. Toward this end, we construct variables which are designed to capture purely short-term trends in the price movements that are not perfectly correlated with the asset price's proximity to the price limits as the magnet variables of the previous sections were. We are not aware of any studies that attempt to quantify momentum effect in high-frequency data, so we propose two measures here, both of which are designed to capture short-run trends in the price. However, given no precise definition of momentum effect in high-frequency data, we acknowledge that the proposed methods may not be effective in distinguishing the two effects since the two effects are highly correlated. The first measure is constructed using dummy variables based upon the changes from the opening price:

$$\mathrm{Day}(\mathrm{up})_t = \begin{cases} 1, & \text{if } \frac{P_t - P_{\mathrm{open}}}{P_{\mathrm{open}}} > 4\% \\ 0, & \text{otherwise} \end{cases}$$

$$\mathrm{Day}(\mathrm{down})_t = \begin{cases} 1, & \text{if } \frac{P_t - P_{\mathrm{open}}}{P_{\mathrm{open}}} < -4\% \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

where P_{open} is the price at 9:05 am. Notice that the key difference between this measure and the magnet variable is that the latter is defined relative to the previous closing price. Hence, while both variables are indicative of the general movement in price level over the course of the day, only the magnet variable is a direct indicator of how close the price is to the limit.

The second measure is designed to capture very high-frequency trends in the price. It is defined as

$$5\ \mathrm{min}(\mathrm{up})_t = \begin{cases} 1, & \text{if the previous four 5-min returns are positive} \\ 0, & \text{otherwise} \end{cases}$$

$$5\ \mathrm{min}(\mathrm{down})_t = \begin{cases} 1, & \text{if the previous four 5-min returns are negative} \\ 0, & \text{otherwise} \end{cases} . \tag{10}$$

Both of these momentum variables characterize intraday price continuations that are not perfectly correlated with the magnet variable. We proceed to include each set of momentum variables separately in the conditional mean Eq. (2). The remainder of the specification (the volatility structure) is left unchanged. That is,

$$\begin{aligned} \mathrm{RET}_t = {} & \alpha_0 + \alpha_1 \mathrm{RET}_{t-1} + \alpha_2 \mathrm{RET}_{t-2} + \alpha_3 \mathrm{RET}_{t-3} + \gamma_1 D(\mathrm{ceiling})_{t-1} \\ & + \gamma_2 D(\mathrm{floor})_{t-1} + \gamma_5 M(\mathrm{up})_{t-1} + \gamma_6 M(\mathrm{down})_{t-1} + \varepsilon_t, \end{aligned} \tag{11}$$

and

$$\begin{aligned} h_t = {} & \beta_0 + \beta_1 h_{t-1} + \beta_2 h_{t-2} + \beta_3 \varepsilon_{t-1}^2 + \beta_4 \varepsilon_{t-2}^2 + \gamma_3 \{D(\mathrm{ceiling})_{t-1} + D(\mathrm{floor})_{t-1}\} \\ & + \gamma_4 \mathrm{DLIM}_t \end{aligned} \tag{12}$$

where $M(\mathrm{up})_{t-1}$ and $M(\mathrm{down})_{t-1}$ are the momentum dummy variables given in Eq. (9) or Eq. (10).

If the magnet effect was purely a manifestation of a momentum effect, then we should expect that including either of these local trend variables should dilute or eliminate the significance of the magnet variables. On the other hand, if the inclusion of these momentum variables has little or no impact on the magnet coefficients, then the analysis strengthens the conclusion of a magnet effect.

Fig. 7.1 shows the scatterplot of t-ratios of γ_1 and γ_2 after reestimating the model for all 345 stocks with the momentum variables given in Eq. (9). The plot is very close to Fig. 2.2, suggesting that t-ratios associated with the magnet variable coefficients are virtually unchanged. The ceiling magnet effect continues to be strong but the floor magnet effect is weak. Calculating the correlation coefficient of t-ratios for γ_1 between the two econometric models gives 0.93406 and that for γ_2 gives 0.9383. These correlations show that the momentum variables do not affect the estimation results. Fig. 7.2 shows the scatterplot of the t-ratios of γ_6 and γ_7. It shows that the momentum effect is not strong in TSE stocks.

Fig. 7.3 contains the scatterplot for the 345 t-statistics for γ_1 and γ_2 using the momentum variables defined in Eq. (10). The difference between Eqs. (9) and (10) is that Eq. (10) uses shorter horizons by considering the most recent four price movements only. The plot of the t-ratios associated with the magnet variables is again virtually unchanged with most t-ratio points lying in the right hand side implying a strong ceiling magnet effect. However, the floor magnet effect is not conclusive. Though there are more negative γ_2 than positive, it is

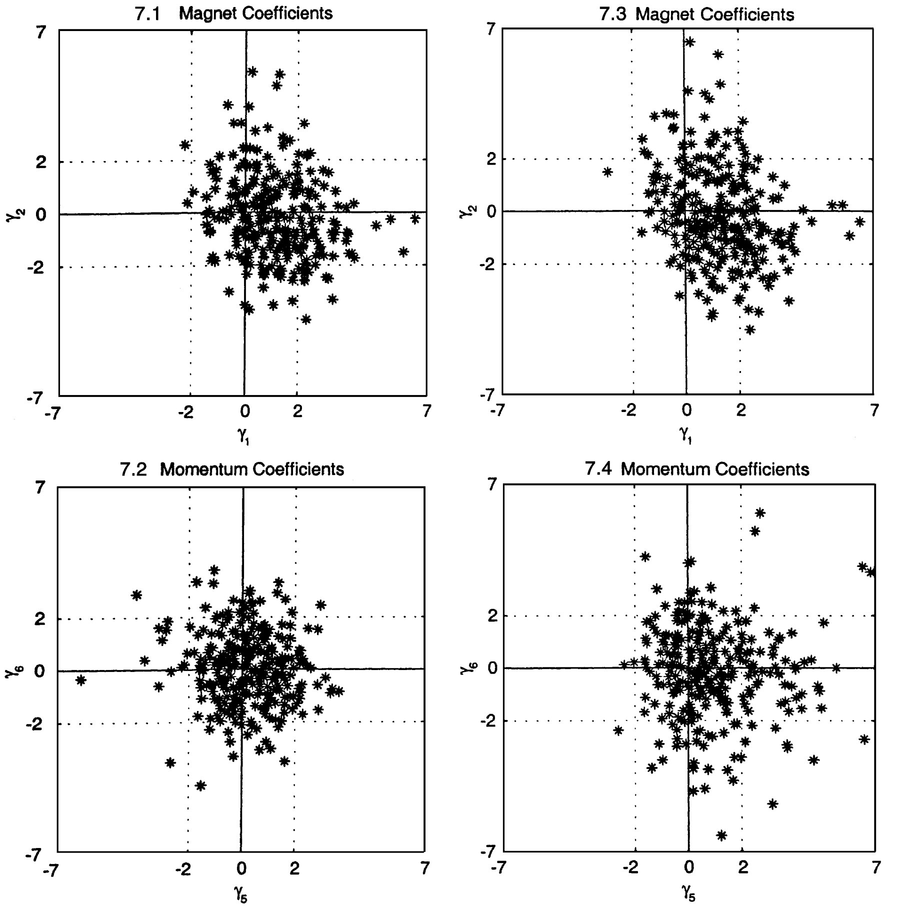

Fig. 7. T-ratios of magnet coefficients and momentum coefficients. The conditional mean equation includes two sets of additional variables M(up) and M(down) to control possible momentum effects.

still hard to find any strong floor magnet effect. Fig. 7.4 plots the t-ratios for the new momentum variables defined in Eq. (10). Unlike Fig. 7.2, Fig. 7.4 shows a tendency for positive γ_5 with many being positive and significant. Thus, for some stocks, if the price moved upward for four consecutive times, then the expected price will move upward.

We find the t-ratio plots associated with the magnet variables are virtually unchanged after adding two sets of variables specifically designed to capture short-run trends or momentum effects indicating that the magnet coefficients are robust. The results of this section point to the direction of magnet effects and not to spurious effects unaccounted for in momentum.

3.5. Stocks markets without daily price limits

To further confirm the detected magnet of price limits, we apply the econometric model to a data set without daily price limits. We randomly choose 90 stocks from the S&P 500 firms of the US market and use the Trades and Quotes (TAQ) data set, which provides the tic-by-tic data of the US stock market, from January 1, 1997 to June 30, 1997. We interpolate the 5-min returns from the data to match the interval used for TSE. Although the sample period of the US market is only 6 months, the number of observations for 5-min return series is similar to that of TSE because the daily trading hour is longer in the US stock market.

Because there are no daily limits for the US data, we cannot define the magnet variables as those in Eq. (2) and Eq. (3). We modify the definitions of the magnet variables for both the TSE and US data sets as follows:

$$D(\text{ceiling})_t = \begin{cases} \left(\frac{P_t - P_{\text{close}}}{P_{\text{close}}}\right)^2, & \text{if } P_t > P_{\text{close}} \\ 0, & \text{otherwise,} \end{cases}$$

$$D(\text{floor})_t = \begin{cases} \left(\frac{P_t - P_{\text{close}}}{P_{\text{close}}}\right)^2, & \text{if } P_t < P_{\text{close}} \\ 0, & \text{otherwise} \end{cases}, \tag{13}$$

where P_{close} is the closing price of the previous trading day. We use a squared function in the definition of Eq. (13) to capture the characteristics that the magnet effects become stronger as the price gets closer to the limits. These new magnet variables differ from the step functions of Eq. (1) since they are continuous function of stock prices. However, as in Eq. (1), large D(ceiling) and D(floor) imply that the price is far away from the previous close price. We apply these two magnet variables to both TSE and US stocks returns.

The econometric model used in comparison becomes

$$\begin{aligned} \text{RET}_t &= \alpha_0 + \alpha_1 \text{RET}_{t-1} + \alpha_2 \text{RET}_{t-2} + \alpha_3 \text{RET}_{t-3} + \gamma_1 D(\text{ceiling})_{t-1} \\ &\quad + \gamma_2 D(\text{floor})_{t-1} + \varepsilon_t, \\ h_t &= \beta_0 + \beta_1 h_{t-1} + \beta_2 h_{t-2} + \beta_3 \varepsilon_{t-1}^2 + \beta_4 \varepsilon_{t-2}^2 + \gamma_3 \{D(\text{ceiling})_{t-1} \\ &\quad + D(\text{floor})_{t-1}\} + \gamma_4 \text{DLIM}_t. \end{aligned} \tag{14}$$

Notice that the DLIM variable is not used for the US return series because there are no daily price limits.

We fit the AR(3)−GARCH(2,2) model with the magnet variables defined in Eq. (13) to the return series of 345 TSE stocks and 90 randomly chosen S&P 500 firms. US stock

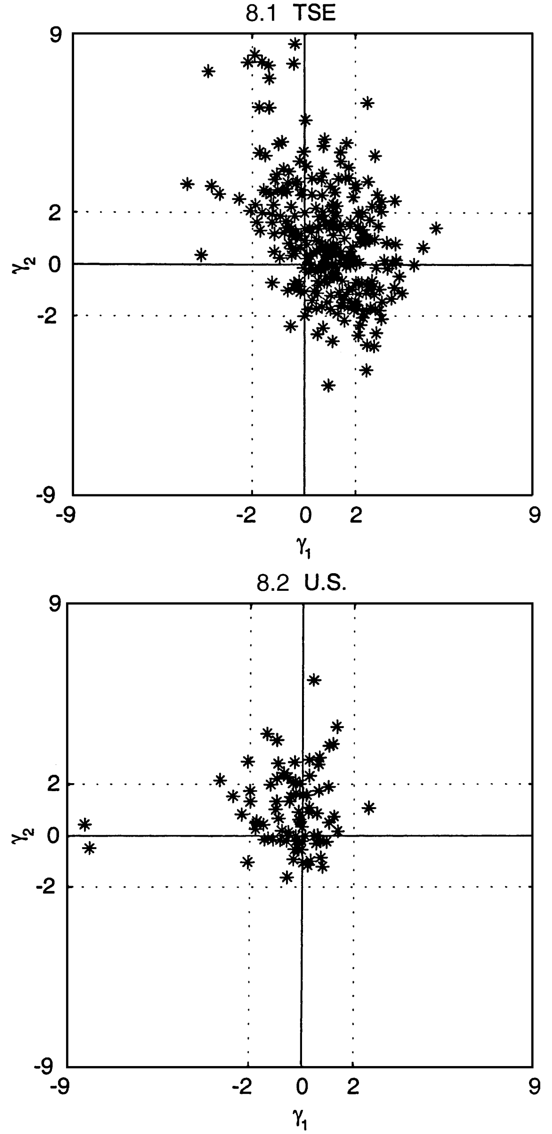

Fig. 8. *T*-ratios of magnet coefficients for TSE and US firms. The plots are *t*-ratio pairs for the magnet coefficients from the AR(3)-GARCH(2,2) estimation using the magnet variables defined in Eq. (13). (8.1) plots 300 converged results for TSE stocks and (8.2) plots 81 converged results from randomly chosen 90 S&P 500 firms.

returns are standardized since they also show a deterministic intraday volatility pattern. US stocks have no price limits and cannot exhibit a magnet effect. We therefore expect that the magnet coefficients for the US data should be insignificant.

Fig. 8 plots the *t*-ratios of the magnet coefficients. In Fig. 8.1, the TSE firms typically have positive ceiling magnet coefficients as in Fig. 2. Even using the new magnet variables

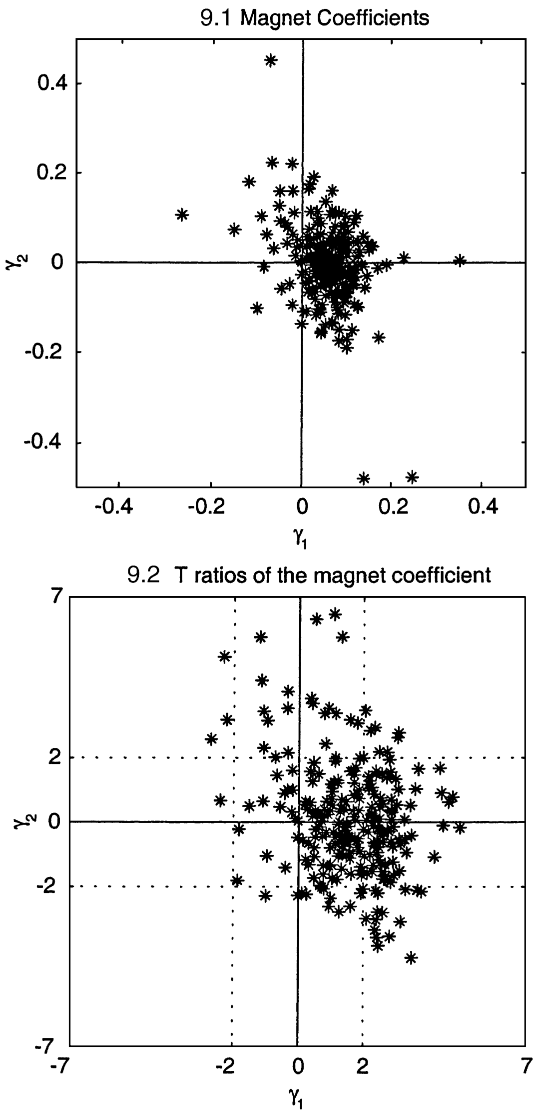

Fig. 9. Scatter plots of the magnet coefficients (March 21, 1999–April 29, 2000). (9.1) scatter plots ($\hat{\gamma}_1$,$\hat{\gamma}_2$) from the AR(3)-GARCH(2,2) estimation and (9.2) scatter plots the *t*-ratios associated with ($\hat{\gamma}_1$,$\hat{\gamma}_2$) using the data from March 21, 1999 to April 29, 2000.

in Eq. (13), we conclude that TSE stocks have a strong ceiling magnet effect. Fig. 8.2 shows that most, if not all, *t*-ratios for the US forms are inside the insignificant range, implying that as expected, there is no magnet effect for US firms. It is surprising to see that there are many positive and significant γ_2 for the US 500 firms, which implies a reverse magnet effect. Since US stocks do not have any price limits, this effect cannot be due to the price limits but due to some other factors.

3.6. Additional data

The sample period of the data analyzed so far is from January 3, 1998 to March 20, 1999. A natural question is whether the results obtained are sample period specific. In this section, we use more recent data for the sample period from March 21, 1999 to April 29, 2000 refitting Eq. (2) and Eq. (3) for the standardized 5-min return series. Fig. 9.1 shows the scatterplots of the estimates of the magnet coefficients, whereas Fig. 9.2 shows the scatterplot of the *t*-ratios for the new sample. The two plots are strikingly similar to Fig. 2.1 and 2.2, respectively, with most points being on the right-hand side of the *y*-axis and more than half of the points being in the fourth quadrant, supporting the magnet effect. Consequently, the detected magnet effect is not sample period specific. In summary, the detected magnet effect of the price limits in the TSE is statistically significant and persistent over time.

4. Analysis based on investment strategies

In Section 3, we found the presence of magnet effect using an econometric model. In this section, we use a different approach to find the same result and see whether the detected magnet effect is economically significant. Specifically, we introduce daily trading strategies designed to take advantage of the magnet effect. We find that the magnet effect is economically significant. Indeed, some strategies that take advantage of the magnet effect are economically meaningful even after adjusting for the transaction cost and taxes.

We introduce three simple strategies. Strategy A exploits the ceiling magnet effect. Here the investor buys the stock if the price reaches 4% and sells it at the following opening. The reason that the investor sells the stock at the following opening is due to the illiquidity problem. If the price reaches the limits, the stock remains illiquid so that the investor cannot trade it anymore. Sometimes, transactions occur at the price limits but the trading volume is very low. To make it economically sensible, the investor closes her position at the opening on the following trading day. Because the price can move freely up or down 7% from the previous closing price, the stocks are typically liquid at the opening and easy to trade. If the stock opens at the ceiling on the second day so the stock becomes illiquid, then the investor waits until the stock becomes liquid to close her position. For the same reason, the investor cannot invest in the stock, if its price is at the limits. For example, suppose the price of a stock increased 6% so that strategy A tells the investor to buy the stock. However, if the next price reaches the ceiling, then the investor cannot buy the stock. The analysis is done carefully so that no transaction takes place at the price limits when the stock is illiquid.

When the price of a stock reaches the threshold 4%, we assume that the investor can buy the stock at the next 5-min price by submitting an aggressive order (i.e., the equivalence of a market order). If the next 5-min price reaches the ceiling, then the investor waits until the stock becomes liquid to invest.

The investor must decide how to allocate her available fund (or capital). Since the investor has no knowledge about which stocks will reach 4% ex ante, she cannot allocate the fund to invest only in the stocks reaching 4% ex ante. We assume that the investor simply uses an equal-weighted portfolio. First, the investor allocated her available fund equally to all the stocks in the portfolio. The investor only buys Stock X if its price increases 4% over the previous close price. If the stock does not reach 4% during the trading hours, then the investor does not invest in the stock. Hence, the portfolio will always be equally weighted, but the amount invested will vary from day to day. For example, suppose there are 100 stocks in the portfolio and the investor starts out with \$100. The investor allocates \$1 to each stock and if a stock increases 4%, then she buys it at the next transaction price and sells it at the open of the following trading day. If all 100 stocks reached the 4% threshold in a trading day, then the investor invest \$100 fully. If none of the 100 stocks reached 4%, then she invests nothing and keeps the cash. In practice, the investor can invest in a risk-free asset when she holds cash. In our analysis, we take a conservative approach by assuming that the investor simply keeps the cash. This conservative approach allows the investor to invest in a stock immediately if its price reaches the threshold.

Strategy B exploits the floor magnet effect. The investor shorts the stock if the price reaches -4% and closes the position at the open of the next trading day in the same manner described for strategy A. Strategy C combines Strategies A and B. It is rare, but sometimes a stock can reach both 4% and -4% during a trading day. In such cases, strategy C tells the investor to use strategy A or strategy B depending on whichever comes first.

4.1. Industry portfolio comparison

Provided that there is a ceiling magnet effect, strategy A will work because the conditional mean return is higher if the price is above 4%. If there are both ceiling and floor magnet effects, then strategy C will work best. Performance of the three strategies is given in Table 4, which reports performance of the equally weighted industry portfolio without the transaction cost.

We use three benchmarks to evaluate the strategies. The first benchmark is buy and hold strategy for the Taiwan Stock Exchange Index TAIEX for the same sample period (January 1998–Marrch 1999). The average daily return of TAIEX during the sample period is -0.036% and the standard deviation of the daily returns is 1.564. To compute the Sharpe ratios, we used the annual risk-free rate equal to 3.5%. The resulting Sharpe ratio is -0.030. If an investor invest \$100 in TAIEX on January 3, 1998, then on March 20, 1999, the portfolio will have a value of \$85.47. Even though Taiwan was not among the countries hit by the Asian crisis, Taiwan stock market had a negative return over the

Table 4
Equally weighted industry portfolio performance (no transaction costs)

Benchmarks (buy and hold)	$\bar{r}$ (daily, %)	std	Sharpe	$100
TAIEX (January 1998–March 1999)	−0.036	1.564	−0.030	85.47
TAIEX (1989–1999)	0.034	1.949	0.012	

Panel A. Strategy A

Industry		Strategy A					Benchmark (cash–TAIEX)			
Code	Firms	$\bar{r}$ (daily, %)	std	Sharpe	$100	$ inv'd	$\bar{r}$ (daily, %)	std	Sharpe	$100
11	7	0.055	0.397	0.115	119.33	6.63	0.049	0.299	0.129	116.87
12	24	0.081	0.302	0.234	129.53	9.00	0.039	0.214	0.137	113.48
13	16	0.128	0.621	0.190	150.25	12.93	0.086	0.423	0.180	131.73
14	48	0.084	0.395	0.187	130.79	10.67	0.057	0.303	0.156	120.16
15	19	0.082	0.387	0.185	129.88	10.38	0.056	0.315	0.147	119.75
16	12	0.047	0.296	0.126	116.30	7.15	0.036	0.245	0.104	112.05
17	16	0.062	0.411	0.126	121.74	10.35	0.058	0.323	0.148	120.30
18	6	0.051	0.375	0.109	117.53	8.20	0.030	0.233	0.085	110.04
19	6	0.079	0.623	0.111	128.29	10.73	0.068	0.407	0.143	124.24
20	25	0.060	0.362	0.138	121.03	9.21	0.041	0.256	0.119	113.87
21	8	0.093	0.516	0.160	134.24	13.43	0.057	0.343	0.137	119.91
22	4	0.008	0.250	−0.010	102.37	4.57	0.010	0.214	0.000	103.21
23	66	0.112	0.536	0.191	143.05	16.60	0.077	0.395	0.169	127.73
25	31	0.077	0.478	0.141	127.83	10.31	0.057	0.355	0.133	120.09
26	14	0.054	0.318	0.138	118.82	9.16	0.042	0.264	0.123	114.55
27	5	0.037	0.620	0.043	111.85	11.70	0.058	0.410	0.118	120.42
28	34	0.061	0.463	0.111	121.47	8.71	0.059	0.365	0.135	120.90
99	4	0.091	0.505	0.161	133.70	10.76	0.056	0.323	0.143	119.73
All	345	0.080	0.300	0.235	129.46	11.13	0.058	0.275	0.173	120.32

Panel B. Strategy B

Industry		Strategy B					Benchmark (cash–TAIEX)			
Code	Firms	$\bar{r}$ (daily, %)	std	Sharpe	$100	$ inv'd	$\bar{r}$ (daily, %)	std	Sharpe	$100
11	7	−0.016	0.462	−0.057	94.49	5.84	−0.019	0.318	−0.091	93.97
12	24	0.017	0.392	0.017	105.32	9.88	−0.012	0.274	−0.080	96.11
13	16	0.038	0.620	0.045	112.37	9.25	−0.019	0.369	−0.077	93.99
14	48	0.022	0.431	0.028	107.04	9.84	−0.005	0.330	−0.046	98.14
15	19	0.010	0.354	0.001	103.19	9.27	−0.013	0.239	−0.097	95.77
16	12	0.029	0.459	0.041	109.43	6.86	−0.009	0.278	−0.066	97.17
17	16	0.045	0.483	0.072	115.10	9.04	−0.007	0.322	−0.053	97.62
18	6	0.036	0.437	0.059	111.87	7.02	−0.009	0.280	−0.066	97.17
19	6	0.046	0.398	0.092	115.91	7.53	0.005	0.292	−0.017	101.52
20	25	0.019	0.330	0.026	105.97	8.54	−0.012	0.233	−0.093	96.21
21	8	0.016	0.482	0.013	105.03	9.02	−0.008	0.312	−0.057	97.34
22	4	0.008	0.348	−0.007	102.33	4.95	−0.001	0.216	−0.049	99.72
23	66	0.017	0.564	0.012	105.09	13.70	−0.017	0.336	−0.081	94.37
25	31	0.022	0.495	0.023	106.79	10.24	−0.010	0.324	−0.063	96.57
26	14	0.009	0.369	−0.002	102.81	7.39	−0.012	0.261	−0.085	96.08
27	5	−0.016	0.603	−0.043	94.39	9.10	−0.023	0.377	−0.086	92.77
28	34	0.010	0.355	−0.000	103.05	5.56	−0.012	0.249	−0.090	95.95
99	4	0.023	0.555	0.023	107.05	8.20	−0.003	0.309	−0.043	98.78
All	345	0.019	0.340	0.027	106.17	9.53	−0.012	0.264	−0.082	96.23

Table 4 (*continued*)

Panel C. Strategy C

Industry		Strategy C					Benchmark (cash–TAIEX)			
Code	Firms	$\bar{r}$ (daily, %)	std	Sharpe	\$100	\$ inv'd	$\bar{r}$ (daily, %)	std	Sharpe	\$100
11	7	0.039	0.600	0.048	112.78	12.47	0.030	0.409	0.049	109.86
12	24	0.096	0.430	0.201	136.12	18.52	0.026	0.292	0.055	108.59
13	16	0.161	0.815	0.186	166.58	22.00	0.066	0.538	0.105	123.31
14	48	0.108	0.538	0.182	140.95	20.27	0.052	0.413	0.101	117.84
15	19	0.089	0.459	0.173	132.98	19.39	0.042	0.344	0.094	114.38
16	12	0.076	0.530	0.124	127.09	13.91	0.028	0.350	0.050	109.09
17	16	0.107	0.605	0.160	140.21	19.29	0.050	0.439	0.092	117.28
18	6	0.087	0.552	0.139	131.66	15.02	0.024	0.335	0.041	107.77
19	6	0.126	0.731	0.158	148.71	18.27	0.073	0.495	0.128	126.14
20	25	0.075	0.457	0.143	127.08	17.39	0.027	0.305	0.054	108.80
21	8	0.107	0.674	0.143	140.07	22.17	0.048	0.432	0.088	116.40
22	4	0.015	0.424	0.012	104.76	9.52	0.009	0.301	− 0.002	102.92
23	66	0.130	0.722	0.165	150.66	29.97	0.059	0.490	0.100	120.50
25	31	0.099	0.608	0.146	136.70	20.28	0.046	0.435	0.083	115.71
26	14	0.063	0.466	0.113	121.96	16.43	0.030	0.352	0.057	109.95
27	5	0.021	0.836	0.013	105.81	20.68	0.035	0.529	0.047	111.48
28	34	0.072	0.563	0.111	125.61	14.21	0.047	0.431	0.086	116.01
99	4	0.114	0.731	0.142	143.18	18.96	0.053	0.433	0.099	118.29
All	345	0.099	0.394	0.226	137.40	20.43	0.046	0.339	0.105	115.62

Strategy A: investor invests \$(available fund/number of firms in the portfolio) in the long position of a stock which reaches 4% during the day and closes the position when the trade opens on the following day. Strategy B invests \$(available fund/number of firms in the portfolio) in the short position of a stock which reaches −4% and closes the position on the following day. Strategy C combines Strategy A and Strategy B. The annual risk free rate is 3.5% for Taiwan. The benchmark portfolios are TAIEX and cash–TAIEX combination. $\bar{r}$ (daily, %) is average daily return in percentage for the sample period. std is standard deviation of the daily returns (%). Sharpe is Sharpe ratios and \$100 is the cumulative returns starting from \$100 initially. Units in $\bar{r}$(daily, %), std, Sharpe are in percentages and all the returns except for cumulative returns are daily returns.

sample period. The second benchmark is the buy and hold strategy for the TAIEX from 1989 to 1999. The average daily return from 1989 to 1999 is 0.034% and the standard deviation is 1.949, which gives a Sharpe ratio of 0.012.

The last benchmark is a cash–TAIEX mix that matches the equity allocation of the suggested trading strategy. For example, if the investor uses strategy A and if a stock reaches 4%, the investor will invest in the TAIEX instead of the individual stock. Since the proposed strategies involve market timing, the last benchmark will have similar exposures to risk factors. The performance of the last benchmark depends on the investment strategy portfolios. For example, the strategy portfolio is an equally weighted market portfolio of 345 firms, then the cash–TAIEX benchmark will have an average daily return of 0.058 and standard deviation of 0.275.

Table 4 reports the strategy performance of the 18 industry portfolios and the equally weighted TSE portfolio. Note that all the strategies performed better than the buy-and-hold TAIEX benchmark. Even though the overall Taiwan stock market went down during the same period, most of the strategies generated positive returns. One can conservatively evaluate the strategy against the risk-free returns. Positive Sharpe ratios imply that all the strategies beat the risk-free return. Using the cash–TAIEX mix as a benchmark may give a better challenge. Strategy A for the TSE of 345 firms had an average daily return of 0.080%, which is higher than the cash–TAIEX mix benchmark. Though the standard deviation is higher, the Sharpe ratio of 0.235 is higher than that of the cash–TAIEX mix. For all 345 firms, strategy A performed better than all the benchmarks. This is a surprising result since, on average, the investor only invest 11.13% of the fund in the stocks and leaves the rest in cash. There are several ways to increase the proportion to be invested in stocks, which will be introduced later. This impressive performance of strategy A is consistent with the empirical results in previous sections. We found that the magnet effect toward the ceiling in TSE was statistically significant and the same results in Table 4. Strategy A, which exploits the ceiling magnet effect, has an outstanding performance compared with the benchmarks.

Panel B reports the performances of strategy B, which capitalizes on the magnet effect toward the floor. The equal-weighted portfolio had a positive average daily return, but the performance is not as good as strategy A. Strategy B performed better than the buy-and-hold TAIEX benchmark for the sample period and cash–TAIEX mix, but the average daily return of 0.019% was lower than the 10-year buy-and-hold TAIEX benchmark. Due to the small standard deviation, the Sharpe ratio of 0.027 was higher than all the benchmarks. Strategy B was not as impressive as strategy A but exhibited a moderate success. Even though we could not document any statistically significant floor magnet effect, the investment strategy designed to exploit it still worked to some extent. Panel C reports strategy C, which combines both strategies A and B. Since both strategies had success, strategy C has an outstanding performance results. The average daily return is 0.099% with a Sharpe ratio of 0.226. The daily average return for the cash–TAIEX mix benchmark is 0.046%, higher than the other benchmarks. Both the average daily return and the Sharpe ratio of strategy C are much higher than those of the cash–TAIEX mix benchmark.

Fig. 10 plots the cumulative returns of strategy C, buy-and-hold TAIEX and cash–TAIEX mix benchmarks starting with \$100 on January 3, 1998. One interesting characteristic of the figure is the low volatility of the strategy returns. The low volatility magnifies the Sharpe ratios shown in Table 5. Fig. 10 also shows that strategy C worked even if the market (TAIEX) went down. Strategy C also uses strategy B, which short sells the stocks so that it can hedge against the downside.

Individual industry portfolio analysis gives a convincing support to the regression results in Section 3. The average daily returns for equally weighted portfolio of industries 22 (automobile) and 27 (tourist) are the lowest in Panel A of Table 4. In addition, these two industries are the only industries with average daily return lower than the cash–TAIEX benchmark. Investment strategy analysis implies that industries 22 and 27 failed to capitalize on the ceiling magnet effect. We found identical results in the previous analysis. Table 2 and Fig. 3 report the industry analysis using the econometric approach and they show that industries 22 and 27 are the only ones with the wrong sign for the ceiling magnet effect. Note that industries 22 and 27 are the only points in the left-hand side in Fig. 3. It is reassuring as the two approaches are fundamentally different yet yield the same results. We also find consistent results in industries with strong magnet effect. Panel C of Table 4 reports that industry 23 (electronics) and 13 (plastics) have the highest daily mean

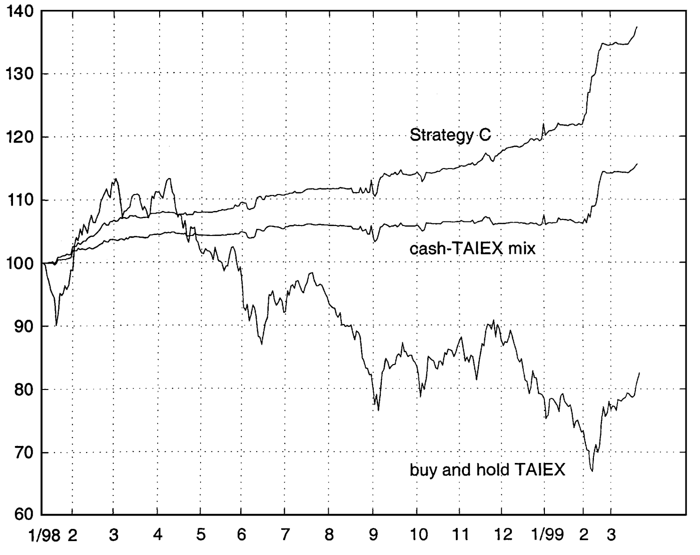

Fig. 10. Strategy C cumulative returns without transaction costs. The figure plots the cumulative returns of Strategy C and the benchmarks. The initial wealth is \$100. Strategy C combines the following Strategy A and Strategy B. Strategy A: investor allocates equal amount of available fund to all 345 stocks. If a stock reaches 4% during the day, he/she invests allocated fund in the long position and closes the position when the trade opens on the following day. Strategy B invests allocated fund in the short position if a stock reaches − 4% and closes the position on the following day.

return for strategy C. Fig. 3 shows that these two industries have strong magnet effects, which are consistent with the results in Table 4. Even though the two approaches came from different perspectives, the regression result and the investment result support each other.

4.2. Strategies with different thresholds

An investor may choose different thresholds other than 4% to implement the strategies. Table 5 reports the performance of all portfolio using five different thresholds, specifically, 2%, 3%, 4% and 6%. Strategies A, B and C are defined as previously except for the changes in the thresholds. The 6% strategy needs some explanation. TSE imposes tic size restrictions in price movement. With the tic size restrictions, the price typically reaches the ceiling at slightly less than 7%. Suppose the price closed 70 yesterday. The price can move between 65.1 and 74.9 today, which is the 7% window. However, the relevant tic size for this price range is 0.5 so that the price will reach the ceiling at 74.5, or 6.43% return. If the price is 74 (one tic smaller than 74.5), the return is 5.71%. Thus, the 6% threshold will be reached only when the price is 74.5. We assumed that the investor cannot transact at the price limits because of the illiquidity problem. If an investor uses 6% threshold, she may not be able to buy the stock because the price that exceeds the threshold is the limit price. On the other hand, we do not use any

Table 5
Strategy performances using different thresholds (no transaction costs)

Benchmarks (buy and hold)	$\bar{r}$ (daily, %)	std	Sharpe	$100
TAIEX (January 1998 – March 1999)	− 0.036	1.564	− 0.030	85.47
TAIEX (1989 – 1999)	0.034	1.949	0.012	

Panel A. Strategy A

Strategy A						Benchmark (cash – TAIEX)			
Thresholds (%)	$\bar{r}$ (daily, %)	std ret	Sharpe	$100	$ inv'd	$\bar{r}$ (daily, %)	std ret	Sharpe	$100
2	0.158	0.632	0.234	165.41	31.86	0.106	0.602	0.160	140.09
3	0.119	0.435	0.250	146.32	18.79	0.082	0.403	0.178	129.85
4	0.080	0.300	0.235	129.46	11.13	0.058	0.275	0.173	120.32
5	0.052	0.206	0.206	118.36	6.59	0.036	0.182	0.142	112.19
6	0.029	0.128	0.149	109.80	3.40	0.019	0.100	0.088	106.26

Panel B. Strategy B

Strategy B						Benchmark (cash – TAIEX)			
Thresholds (%)	$\bar{r}$ (daily, %)	std ret	Sharpe	$100	$ inv'd	$\bar{r}$ (daily, %)	std ret	Sharpe	$100
2	0.064	0.681	0.079	122.05	29.08	− 0.002	0.575	− 0.021	98.79
3	0.042	0.466	0.068	113.98	16.03	− 0.005	0.371	− 0.042	98.06
4	0.019	0.340	0.027	106.17	9.53	− 0.012	0.264	− 0.082	96.23
5	0.006	0.255	− 0.014	102.01	5.97	− 0.014	0.198	− 0.120	95.58
6	0.005	0.182	− 0.026	101.65	3.53	− 0.011	0.135	− 0.153	96.57

Panel C. Strategy C

Strategy C						Benchmark (cash – TAIEX)			
Thresholds (%)	$\bar{r}$ (daily, %)	std ret	Sharpe	$100	$ inv'd	$\bar{r}$ (daily, %)	std ret	Sharpe	$100
2	0.214	0.684	0.298	197.79	58.42	0.098	0.611	0.143	136.23
3	0.160	0.520	0.288	166.65	34.20	0.075	0.456	0.142	126.94
4	0.099	0.394	0.226	137.40	20.43	0.046	0.339	0.105	115.62
5	0.058	0.297	0.162	120.44	12.48	0.022	0.249	0.047	107.14
6	0.034	0.203	0.119	111.59	6.90	0.008	0.158	− 0.012	102.60

The benchmarks and the risk-free rates are the same as Table 4. The strategies are evaluated using five different thresholds from 2% to 6%. Strategy A: Long ($ fund)/(345) in the stock which reaches the threshold, and don't invest, otherwise. Strategy B: Short ($ fund)/(345) in the stock which reaches the threshold, and don't invest, otherwise. Strategy C combines A and B.

threshold values less than 2% because the strategy becomes similar to the buy-and-hold strategy.

Consider Table 5. Panel A shows the performance of strategy A. The mean return, Sharpe ratios and the $100 investment decrease as the threshold increases. Among the five thresholds, 2% seems to work best. The reason why 2% works best can be found in the average $ invested column in Panel A. The average amount invested out of $100 is $31.86 for the 2% threshold but just $3.40 for 6%. If the investor uses a lower threshold, the investor will invest more in stocks and leave less money as cash. Under the 2% threshold, the investor will invest the most and, if the magnet effect is present at such small threshold, receive a better return than leaving the money in cash. Recall that the investor cannot optimally allocate her funds to the stocks ex ante because she does not know which stocks to invest in ex ante. Mean returns and the $100 investment for 2% and 3% thresholds in Panel A are greater than the cash–TAIEX mix benchmark. Sharpe ratios are all higher than the corresponding benchmarks. Strategy B performs worse than strategy A. However, combining Strategies A and B in Panel C performs the best among all the strategies. Sharpe ratios are also the highest. Note that since strategy C combines two strategies, the average amount invested increases. For example, if an investor uses strategy C with 2% threshold, then on average, she will invest 58.42% in stocks and 41.58% in cash. According to Table 5, it seems that using lower threshold will be the optimal choice. However, this is not true as we will see in the following section, where we introduce the transaction costs. Intuitively, 2% threshold performed better than other thresholds because the investor invests the most using the lower threshold.

4.3. Transaction costs

The transaction cost in TSE is 0.1425% for buying and selling, which is a fixed commission fee. Selling a stock involves additional transaction tax at 0.3%. Since the strategies involve buying and selling, the investor must pay 0.585% of the amount invested. Since the above investor uses day trading strategies, the transaction cost will likely have a big impact on profits. Table 6 reports the same portfolio performance as in Table 5 when the transaction cost and tax are taken into consideration.

All the portfolios performed better than the cash–TAIEX mix benchmark, as in Table 5. This is not surprising because the transaction affects the cash–TAIEX mix benchmark the same way as the strategy portfolios. Since cash–TAIEX mix benchmark uses the same market timing as the strategies, the amount to be paid for transaction cost will be identical to that for the strategies. Therefore, the cash–TAIEX mix benchmark will not be affected by the transaction cost and we will not make any comparison.

Several portfolios now perform worse than the buy-and-hold TAIEX benchmark. The strategies' performances are not as good as in Table 5 since they incur heavy transaction costs while the buy-and-hold benchmark does not involve any transaction cost. In particular, most portfolios using strategy B have lower daily average return than the buy-and-hold TAIEX benchmark. We argue that the reason for this is because the magnet effect toward the floor is not very strong, so the strategies designed to capitalize on this weak effect will be wiped out by the transaction costs.

Strategy A in Panel A does fairly well for thresholds greater than 2%. The investment strategy that exploits the strong magnet effect survives even after the transaction cost. Strategy C does not outperform strategy A because of the poor performance of strategy B. All the strategies in Panel C give negative returns and the 2% strategy underperforms the TAIEX benchmark. Thus, once the transaction costs are considered, the investor that tries to exploit the magnet effect should use strategy A that capitalizes on only the strong ceiling magnet effect. Once adjusted for the transaction cost, we now have the identical result obtained in Section 3 using an econometric approach. The two approaches jointly conclude that the magnet effect toward the ceiling is both statistically and economically significant.

Table 6
Strategy performances using different thresholds with transaction costs

Benchmarks (buy and hold)	$\bar{r}$ (daily, %)	std	Sharpe	\$100
TAIEX (January 1998–March 1999)	−0.036	1.564	−0.030	85.47
TAIEX (1989–1999)	0.034	1.949	0.012	

Panel A. Strategy A

Strategy A						Benchmark (cash–TAIEX)			
Thresholds (%)	$\bar{r}$ (daily, %)	std ret	Sharpe	\$100	\$ inv'd	$\bar{r}$ (daily, %)	std ret	Sharpe	\$100
2	−0.028	0.577	−0.067	90.72	31.86	−0.080	0.552	−0.163	76.80
3	0.009	0.387	0.003	102.67	18.79	−0.028	0.357	−0.107	91.10
4	0.015	0.261	0.020	104.95	11.13	−0.007	0.235	−0.074	97.53
5	0.014	0.179	0.022	104.52	6.59	−0.003	0.153	−0.084	99.07
6	0.009	0.110	−0.008	102.97	3.40	−0.001	0.083	−0.133	99.64

Panel B. Strategy B

Strategy B						Benchmark (cash–TAIEX)			
Thresholds (%)	$\bar{r}$ (daily, %)	std ret	Sharpe	\$100	\$ inv'd	$\bar{r}$ (daily, %)	std ret	Sharpe	\$100
2	−0.106	0.650	−0.179	70.49	29.08	−0.172	0.563	−0.324	57.01
3	−0.052	0.448	−0.139	84.22	16.03	−0.099	0.373	−0.293	72.42
4	−0.037	0.340	−0.137	88.68	9.53	−0.067	0.281	−0.276	80.36
5	−0.028	0.264	−0.146	91.11	5.97	−0.049	0.220	−0.267	85.36
6	−0.015	0.187	−0.136	95.09	3.53	−0.031	0.152	−0.272	90.33

Panel C. Strategy C

Strategy C						Benchmark (cash–TAIEX)			
Thresholds (%)	$\bar{r}$ (daily, %)	std ret	Sharpe	\$100	\$ inv'd	$\bar{r}$ (daily, %)	std ret	Sharpe	\$100
2	−0.128	0.661	−0.209	65.64	58.42	−0.244	0.596	−0.426	45.14
3	−0.040	0.498	−0.101	87.39	34.20	−0.125	0.443	−0.305	66.52
4	−0.020	0.384	−0.079	93.42	20.43	−0.074	0.335	−0.251	78.59
5	−0.015	0.296	−0.085	95.15	12.48	−0.051	0.254	−0.241	84.63
6	−0.006	0.202	−0.080	97.94	6.90	−0.032	0.166	−0.255	90.05

The benchmarks and the risk-free rates are the same as Table 4. The strategies are evaluated using five different thresholds from 2% to 6%. Strategy A: Long (\$ fund)/(345) in the stock which reaches the threshold, and don't invest, otherwise. Strategy B: Short (\$ fund)/(345) in the stock which reaches the threshold, and don't invest, otherwise. Strategy C combines A and B. Transaction cost is 0.1425% for buying and 0.4425% for selling.

Comparing the performance of strategy A for different thresholds gives some insights for an optimal trading strategy. After adjusting for transaction costs, the threshold with the highest mean return is 4%. Using a threshold higher than 4% can capitalize on the magnet effect, but it also encounters illiquidity and less investment opportunities. Even if the magnet effect may be strongest at 6%, there are few periods of investment, so the investor cannot invest frequently enough to make high profits. The average amount invested for the 6% strategy is \$3.40, leaving \$96.60 as cash. Due to the trade off between transaction cost and advantage of exploiting the magnet effect, the optimal threshold is 4%. Nevertheless, even the strategy A using 4% threshold has lower daily average return than the 10-year

TAIEX. This is due to the fact that the investor does not invest enough to capitalize the magnet effect.

One possible way to increase the amount to invest is to restrict the maximum number of stocks to invest. For example, suppose the investor decides to invest 100 stocks, instead of investing all the stocks. The investor's strategy will be that she invests $1 each to the first 100 stocks that reach the threshold. If only 50 stocks reach the threshold, then the investor invest $50 to the 50 stocks and leave $50 as cash. If 200 stocks reach the threshold, then the investor invest $100 in the first 100 stocks that reach the threshold. Now, the investor has two choice variables when she adopts this new

Table 7
Performance of strategy A using different thresholds with different maximum number of firms to invest

Threshold (%)	Maximum number of firms to invest									
	10	20	30	40	50	60	70	100	200	345
Panel A. Mean return (daily, %)										
2	− 0.128	− 0.158	− 0.144	− 0.166	− 0.160	− 0.137	− 0.123	− 0.088	− 0.052	− 0.028
3	− 0.033	− 0.070	− 0.067	− 0.051	− 0.054	− 0.032	0.001	0.017	0.016	0.009
4	− 0.064	− 0.014	0.006	0.017	0.037	0.044	0.048	0.034	0.026	0.015
5	0.031	0.047	0.065	0.071	0.069	0.059	0.045	0.031	0.024	0.014
6	0.024	0.059	0.055	0.048	0.048	0.040	0.030	0.021	0.016	0.009
Panel B. Standard deviation of the returns (daily, %)										
2	2.098	1.906	1.848	1.759	1.693	1.565	1.402	1.154	0.952	0.576
3	2.061	1.814	1.654	1.550	1.460	1.291	1.064	0.808	0.646	0.386
4	1.917	1.594	1.451	1.305	1.181	0.962	0.758	0.558	0.439	0.260
5	1.756	1.393	1.186	1.010	0.873	0.707	0.539	0.389	0.308	0.178
6	1.440	1.046	0.828	0.689	0.598	0.470	0.357	0.253	0.190	0.110
Panel C. Sharpe ratios (daily)										
2	− 0.066	− 0.088	− 0.083	− 0.100	− 0.100	− 0.094	− 0.095	− 0.085	− 0.065	− 0.067
3	− 0.021	− 0.044	− 0.047	− 0.040	− 0.044	− 0.033	− 0.008	0.009	− 0.010	− 0.003
4	− 0.039	− 0.015	− 0.003	0.005	0.023	0.035	0.050	0.044	0.036	0.020
5	0.012	0.026	0.047	0.060	0.068	0.069	0.066	0.055	0.045	0.022
6	0.010	0.047	0.054	0.055	0.064	0.065	0.055	0.044	0.031	− 0.008
Panel D. Cumulative returns from $100										
2	61.50	56.66	59.36	55.64	56.96	61.71	65.04	73.77	83.38	90.75
3	83.94	75.64	76.96	81.48	81.20	87.66	98.67	104.58	104.71	102.70
4	76.69	91.75	98.41	102.81	110.09	113.54	115.59	111.23	108.35	104.93
5	105.00	112.67	120.75	123.74	123.47	120.04	115.27	110.38	107.86	104.52
6	104.46	119.05	117.95	115.87	116.22	113.56	109.87	106.94	105.18	102.98
Panel E. Average $ invested										
2	99.60	98.45	97.14	94.78	91.77	85.83	77.20	63.52	52.23	31.81
3	97.83	93.00	86.05	79.95	74.34	65.37	53.89	40.41	31.65	18.76
4	90.56	77.93	68.88	61.76	55.51	45.25	34.56	24.60	19.03	11.12
5	77.71	62.85	52.36	44.09	37.53	28.90	21.36	14.89	11.38	6.58
6	60.22	42.72	32.19	25.70	21.19	15.91	11.62	7.85	5.89	3.40

Example: Strategy (threshold = 4%, number to invest = 50 firms): invest ($ fund)/(50) in the first 50 stocks which reach 4% threshold.

strategy. The investor can choose the threshold value and also the maximum number of stocks to invest.

Table 7 presents the performance result of strategy A for different combinations of thresholds and maximum number of stocks in the portfolio. We used the same threshold as before, 2–6%. The maximum number of stocks considered are 10, 20, 30, 40, 50, 60, 70, 100, 300 and 345. Panel E reports the average amount invested in a day. Half of the portfolios considered invest more than half of the available fund on average. Using a lower number of stocks in the portfolio will allow to invest more, but on the other hand, the investor may increase the risk due to lack of portfolio diversification. Thus, there is a trade off between using different maximum number of stocks in the portfolio. As mentioned before, there is also a trade off between using different thresholds. These two tradeoffs induce an optimal choice of investing strategy.

Panel A reports the mean return. The maximum return is achieved by using 5% threshold and 40 stocks in the portfolio. The cumulative returns decrease as it moves away from 5% threshold and 40 firms. If we evaluate the strategies against the 10-year buy-and-hold TAIEX, many strategies have higher mean returns than 10-year TAIEX benchmark. Since the TAIEX during the sample period has a negative mean return, it may be more meaningful to evaluate against the risk-free return. More than half of the considered strategies outperform the risk-free return. Taking into account the high transaction costs involved in these strategies, the results are outstanding.

Panel C reports the Sharpe ratios. Most Sharpe ratios are positive, implying that most combinations outperform the risk-free return. The optimal choice between the threshold and the number to invest is 5% and 60 firms. This combination gives a Sharpe ratio of 0.069. This strategy is economically sensible because it capitalizes on the magnet effect efficiently by trying to invest optimally. To summarize, we found an interior optimal pairs of choice variables for the Sharpe ratio. The ceiling magnet effect can be capitalized by the proposed optimal strategy and it can be economically significant.

5. Conclusion

We used high-frequency data on Taiwan Stock Exchange (TSE) stocks to conduct an empirical study on the effects of daily price limits. High-frequency data enable us to investigate the effects of price limits better than empirical studies using daily prices only. Four effects on the price limits have been suggested in theory: volatility spillover effect, delayed price discovery effect, trading interference effect and the magnet effect. The price limits literature concentrated on the first three effects using the daily prices. Because magnet effect involves intraday price movements, daily prices are not useful. High-frequency data on the TSE provides a perfect environment to analyze the intraday price movement and test the magnet effect. The TSE imposes tighter daily price limits than other market, and the stock prices reach the limits frequently. Thus, the TSE is an ideal candidate for testing the magnet effect.

The magnet effect suggests the asset price accelerates toward the limits as it approaches the limit. We used two different methodologies to analyze the magnet effect. First, we fit an AR(3)–GARCH(2,2) model for the 5-min returns of each individual stock. From the estimation results, we found that the conditional mean return increases as the price gets closer to the ceiling. We conducted a formal test of overall magnet effect in the TSE and found that the ceiling magnet effect is statistically significant but the floor magnet effect is not. To distinguish the magnet effect from the momentum effect, we included two momentum variables in the regression and concluded that the strong ceiling magnet effects are robust. For S&P 500 stocks, which have no price limits, we could not find any evidence of the magnet effect. The coefficients for S&P 500 stocks are mostly insignificant with no conclusive directions. For the TSE data, the magnet effect is stable for different sample periods. Using the 1999–2000 data, we found similar results as the 1998–1999 data.

Second, we used the performance of investment strategies to investigate the magnet effect. We developed strategies that take advantage of the magnet effect. Implementing the investment strategies for the same period as the regression analysis supports the regression results. Strategy for ceiling magnet effect works better that the strategy for floor magnet effect, which is in good agreement with the regression results that the ceiling magnet effect is stronger that the floor magnet effect. The consistent results between the two methodologies can also be found in the industry analysis. The best performing industry portfolios generally had the highest *t*-ratios for the magnet coefficients. The worst performing industry had erroneous sign of magnet coefficients. The two approaches yielded the similar conclusions on the presence of magnet effects. Taking the transaction costs into account, simple strategies did not outperform the 10-year TAIEX benchmark. Because of the heavy trading, the strategies suffered from heavy transaction costs. We introduced two choice variables, threshold and maximum number of stocks in portfolio, to optimally allocate the funds. We found an interior optimal combination of threshold and number to invest. The performance of the optimal strategy is better than all the benchmarks considered.

Advocates of daily price limits claim that the price limits avoid the overreaction in the stock market by giving the market time to reassess the value of the stock (cool off effect). However, we find empirical evidence for the magnet effect, which is an opposite effect to the cool off effect. Rather than preventing the overreaction in the stock market, the daily price limits cause the stock price to accelerate towards the limit. We conclude that the daily price limits in the TSE are ineffective in preventing overreaction.

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