Journal of Empirical Finance 16 (2009) 830–837

Contents lists available at ScienceDirect

Journal of Empirical Finance

journal homepage: www.elsevier.com/locate/jempfin

The magnet effect of price limits: A logit approach☆

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ARTICLE INFO

Article history:
Received 23 January 2009
Received in revised form 4 June 2009
Accepted 10 June 2009
Available online 21 June 2009

JEL classification:
G14
G15
G18

Keywords:
Price limits
Magnet effect
Transaction data
Logit model

ABSTRACT

We investigate the magnet effect of price limits using transaction data from the Taiwan Stock Exchange. A logit model incorporates explanatory variables from microstructure literature and reveals that the conditional probability of a price increase (decrease) increases significantly when the price approaches the upper (lower) price limit, in support of the magnet effect. Our approach recognizes when the magnet effect starts to emerge and identifies possible determinants of magnet effect. The probability of information-based trading has a significant impact on the magnet effect for lower price limits.

1. Introduction

The magnet effect of price limits describes the ex ante trading decisions of market participants in response to impediments to trade. Subrahmanyam (1994) develops a model in which traders place a higher value on their desire to trade and thus advance trades to ensure their ability to trade, even if doing so means a departure from their optimal trading strategy. This magnet effect may increase price variability and the probability that the price reaches the limit if the price comes very close to the limit. Although price limits exist in many financial markets, understanding of this particular market stabilization mechanism remains limited[3]. We therefore investigate the magnet effect using transaction data from one of the most active stock markets in Asia, namely, the Taiwan Stock Exchange (TWSE).

Existing studies suffer from several issues that we address to provide clearer evidence of the magnet effect. First, we investigate transaction data for all listed firms on the TWSE to capture intra-day trading behavior and thus avoid potential sample selection biases. Second, because the TWSE is one of the most active markets in the world, thin trading issues are not a concern. Third, our logit model not only captures price behavior but also controls for documented microstructure variables that might affect price

☆ Earlier versions of this paper have been circulated under the title "The Magnet Effect of Price Limits: Evidence from Transactions Data". This paper has benefited from comments by Dong-Hyun Ahn, Richard Baillie (the editor), Brian Hatch, Joon-Seok Kim, Ken Kim, Eun Jung Lee, Steve Slezak, Dennis Steele, Ruoyun Zhao, and seminar participants at the Joint Conference of the Korea-America Finance Association, Korean Finance Association, Korean Securities Association, Korean Financial Management Association, and Korea Derivatives Association 2006, the Joint Conference of Korea Economic Association and Korea-America Economic Association 2006, the Financial Management Association Meeting 2006, the Joint Statistical Meetings 2006, the Joint Conference of Korea-America Finance Association and Korea Securities Research Institute 2007, and the Asian Finance Association Conference 2007. Hsieh and Kim acknowledge financial support from the 2006 Vivian Bales Research Fellowship and the University of Cincinnati Foundation, respectively.
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doi:10.1016/j.jempfin.2009.06.002

movements. Fourth, we investigate all transactions that occur prior to reaching the limits, not just some transactions before actual limit hits, so our results are not biased in support of the magnet effect. Fifth, our results are robust to various estimation methods.

Several researchers attempt to test the existence of the magnet effect indirectly. For example, Gerety and Mulherin (1992) observe investors' desire to trade prior to daily market closings, in line with the magnet effect. However, whereas a price limit closure typically is associated with large market movements and high volatility, a regular closing may not be. A regular closure also is certain, whereas a price limit closure is uncertain. In their experimental study, Ackert et al. (2001) find that mandated market closures accelerate trading activity when the interruption is imminent, which implies the existence of the magnet effect.

Studies that test directly for this effect generally use relatively small data sets and reach various conclusions. In futures markets, Arak and Cook (1997), Berkman and Steenbeek (1998), and Hall and Kofman (2001) find no magnet effect, whereas Holder et al. (2002) and Belcher et al. (2003) find evidence of it. Results from stock markets also conflict: Cho et al. (2003) and Nath (2003) find support for the magnet effect, but they cannot explain theoretically why it occurs only when the price approaches the upper limit (Cho et al., 2003) or the lower limit (Nath 2003).

Some studies also suffer from methodological issues. Instead of studying all transactions prior to the limits, Du et al. (2005) and Wong et al. (2009) focus on the transactions before the actual limit hits, which creates a selection bias in support of the magnet effect. If there were no magnet effect, a priori, the price would not accelerate to reach the limit when it approaches this limit. This observation, which implies the rejection of the magnet effect, cannot appear in these samples, because the price limit never arrives. In contrast, it is not surprising that Abad and Pascual (2007) find no magnet effects in the Spanish Stock Exchange (SSE) where limit hits trigger five-minute trading halts, followed by continuous trading with revised price limits. In the SSE, investors know that they may trade after limit hits and trading halts, which creates little incentive for them to advance their trades.

In support of the magnet effect, our logit model shows that the conditional probability of a price increase (decrease) increases significantly when the price approaches the upper (lower) price limit. To the best of our knowledge, we provide the first evidence of when magnet effects start to emerge. Specifically, our results show that the magnet effect initiates when the price falls within nine ticks of the upper price limits and approximately four ticks of the lower price limits. The magnet effect receives support from not only the greater conditional probability but also the increasing price limit moves when the price approaches the limits. Furthermore, we find that the probability of information-based trading has a significant impact on the magnet effect for the lower price limit.

In turn, this research makes several contributions. First, we take into account market participants' demand for liquidity when prices approach the limit. Prior studies either fail to investigate this important factor or use selective data that create biased results. Second, our finding may contribute to momentum literature (e.g., Jegadeesh and Titman, 1993), in the sense that the magnet effect may represent a special case of intra-day momentum. However, a momentum strategy in an intra-day context faces a challenging implementation, in that orders might not get executed at the price limits. Third, our findings are relevant for limits-of-arbitrage literature (e.g., Shliefer and Vishny, 1997). If the magnet effect drives the stock price away from its fundamental value, arbitrageurs may step in and move the price back to its equilibrium level. This action, if well executed, could mitigate the magnet effect, and our finding of strong magnet effects suggests limits to arbitrage. The price limit regulation itself might have been one of the limits. Fourth, the magnet effect of the upper and lower price limits provides a potentially interesting connection to the concept of attractors in nonlinear dynamic modeling (e.g., Devaney, 1989). Our results suggest that when the price level is within nine ticks of the upper price limit or four ticks of the lower limit, it appears in the neighborhood of an attractor, toward which it should move.

We organize the remainder of this paper as follows: In the next section, we provide the institutional background of the TWSE. In Section 3, we discuss our hypotheses and establish our research design. Finally, we present the empirical findings in Section 4 and then conclude in Section 5.

2. Institutional background

At the end of 2000, the TWSE listed 531 stocks, and its total market value was approximately US$248.5 billion. The average daily trading volume reached US$3.4 billion, making the TWSE one of the most active stock markets in the world in terms of annual turnover. The TWSE is an order-driven market with no market makers or specialists. Bid and ask quotations represent the best prices in the limit order book. Following the opening auction, the TWSE matches orders on a periodic basis until the closing. The actual time interval of each round of clearing may vary slightly, according to the trading intensity. In our sample, 39% of the firms have an average time interval of less than a minute, and 65% exhibit an average time interval of less two minutes. The mean (median) time interval is 2.10 (1.28) minutes, and the minimum (maximum) time interval is 0.26 (18.96) minutes.

The TWSE has imposed daily price limits since its inception in 1962 and sets both upward and downward daily price limits at a predetermined rate on the basis of the previous day's closing price. In 2000, the price limit rate was 7%, but the downward limit moved down to 3.5% four times, in accordance with the market conditions. Therefore, we test our hypothesis with different price limit rates. In addition, the clearing price in each matching round cannot go beyond two ticks of the clearing price in the preceding round. Tick sizes, set by the TWSE, vary with market prices.[4]

The TWSE price limits are boundaries, not triggers for trading halts[5]. Stocks that hit their price limits can be traded as long as the transaction prices remain within the allowable ranges. Although price limits do not trigger trading halts, a trade might not be executed

[4] The tick size is NT$0.01 for Price < NT$5, NT$0.05 for NT$5 ≤ Price < NT$15, NT$0.1 for NT$15 ≤ Price < NT$50, NT$0.5 for NT$50 ≤ Price < NT$150, NT$1 for NT$150 ≤ P < NT$1,000, and NT$5 for NT$1,000 ≤ Price. The NT$ symbol denotes the unit of Taiwanese currency.

[5] For conceptual differences and similarities between price limits and trading halts, as well as empirical evidence of their relative performance, see Kim et al. (2008).

past the price limits. The rationale for the magnet effect therefore should hold in this market. Furthermore, our observance of strong evidence for the magnet effect in this market indicates that a mandatory trading halt is not necessary to generate the magnet effect.

3. Hypothesis and methodology

3.1. Magnet hypothesis

Our magnet hypothesis emphasizes the ex ante effect of price limits. According to the theoretical support that Subrahmanyam (1994) provides for the magnet effect, investors may rush to submit orders when prices approach the limits, even if these orders do not meet investors' optimal trading strategy. The traders must greatly value the ability to trade, which makes them willing to alter their trading strategy and execute these trades. In other words, the opportunity cost of not trading should be greater than the cost of deviating from an optimal trading strategy.

The likelihood of triggering an impediment to trade relates inversely to the distance from the limits. If the magnet effect holds, we should observe a higher probability that the price moves toward and eventually hits the limits when that price approaches the limit. That is, the closer the price gets to its upper (lower) limit, the greater is the probability that the price will move up (down) to reach the limit.

3.2. Methodology

Because the magnet effect is an ex ante effect, we focus on investors' trading behavior prior to the limits. To test the magnet hypothesis, we must find a price that is close enough to the limits to induce a magnet effect. Theoretical literature does not provide any plausible threshold for the circumstances in which price limits likely generate the magnet effect. Unlike existing studies that rely on arbitrarily selected trigger points, we employ an indicator variable that captures all plausible threshold possibilities and allow it to generate a recognizable pattern of when magnet effects may start to emerge.

To investigate the relation between the distance from price limits and the probability of price increases or decreases, we use logit regressions to estimate the probabilities. These regressions include control variables that microstructure research identifies as potential determinants of price movements[6]. If a magnet effect exists, the conditional probability of a price increase (decrease) would increase significantly when the price approaches the upper (lower) price limit. In its generic form, we express the logit model as follows:

$$log\left(\frac{P(Y_k=1|X_k)}{1-P(Y_k=1|X_k)}\right)=X_k^{'}B. \tag{1}$$

In turn, an UP (DOWN) model enables us to examine the magnet effect of the upper (lower) limit. For an UP (DOWN) model, $Y_k=1$ if the price of the kth transaction is greater (less) than that of the $(k-1)$th transaction.

To capture some features of the transaction price changes, we follow Hausman et al. (1992) and carefully select our explanatory variables X. Specifically, we try to incorporate the trade duration effect, the effects of bid–ask bounces, the size of the transaction, and the impact of systematic movements on the conditional distribution of an individual stock's price changes. We specify $X_k'B$ in the following expression:

$$\begin{aligned}X_k^{'}B &= \beta_0+\beta_1\Delta T_k+\beta_2 V_{k-1}+\beta_3 V_{k-2}+\beta_4 V_{k-3}+\beta_5 DIST_{k-1}+\beta_6 IDIST_{k-1}^{m}\times DIST_{K-1}+\beta_7 ISPREAD_{k-1}\\ &\quad+\beta_8 IBID_{k-1}+\beta_9 IASK_{k-1}+\beta_{10} IBS_{k-1}+\beta_{11} IBS_{k-2}+\beta_{12} IBS_{k-3}+\beta_{13} V_{k-1}\times IBS_{k-1}\\ &\quad+\beta_{14} V_{k-2}\times IBS_{k-2}+\beta_{15} V_{k-3}\times IBS_{k-3}+\beta_{16} MKT_{k-1}+\beta_{17} MKT_{k-2}+\beta_{18} MKT_{k-3}\end{aligned} \tag{2}$$

In Panel A of Table 1, we describe each independent variable in the logit model. The variable ΔT_k appears in X_k to capture the trade duration effect. Easley and O'Hara (1992) show that longer durations should decrease the price impact of trades, whereas if the prices are stable over the transaction period, the coefficient should be zero. Karpoff (1987) reviews research into the relationship between price changes and trading volume and concludes that volume relates positively to the magnitude of the price change. Therefore, to control for the price impact of trading volume, we include three lags of the log-transformed dollar volume, V_{k-l}. The variable $DIST_{k-1}$ equals the distance from the $(k-1)$th transaction price to the limit price, measured as the number of ticks. The indicator variable $IDIST_{k-1}^{m}$ separates the transaction prices that fall within m ticks of the limit from the overall sample. The parameter β_5 measures the impact of the distance from the limit on the odds of hitting that limit; β_6 measures the additional impact of this subgroup of prices. A

[6] We know the total volume assigned at the clearing price at the clearing of each auction, but we do not have information about how many trades are completed and the average transaction size. Thus, we do not include the potenial impact pf the stealth trading hypothesis (e.g., Barclay and Warner, 1993) in our model.

Table 1
Logit regression: variable description and sign of estimates.

Panel A: Variable description

ΔT_k	Time elapsed between transactions $k-1$ and k, in minutes.
V_{k-l}	Three lags ($l=1, 2, 3$) of the log-transformed dollar volume of the $(k-l)$th transaction, defined as the price of the $(k-l)$th transaction (in dollars) times the number of shares traded (in thousands of shares).
$DIST_{k-1}$	Distance of the $(k-1)$th transaction price from the limit, in ticks.
$IDIST^m_{k-1}$	Indicator variable equals to 1 if the $(k-1)$th transaction price is within m ticks of the upper (lower) limit for an UP (DOWN) model, and 0 otherwise.
$ISPREAD_{k-1}$	The bid–ask spread prevailing prior to transaction k, in ticks. If either the bid or ask price is not available, the spread is set to 0.
$IBID_{k-1}$	Indicator variable that takes the value of 1 if the bid price immediately prior to transaction k is not available, and 0 otherwise.
$IASK_{k-1}$	Indicator variable that takes the value of 1 if the ask price immediately prior to transaction k is not available, and 0 otherwise.
IBS_{k-l}	Three lags ($l=1, 2, 3$) of an indicator variable that takes the value of $+1$ (-1) if the $(k-l)$th transaction price is greater (less) than the average of the quoted bid and ask prices at time T_{k-l}, and 0 otherwise.
MKT_{k-l}	Three lags ($l=1, 2, 3$) of one-minute continuously compounded returns of the TWSE Capitalization Weighted Price Index (TAIEX).

Panel B: Signs of estimates

Model ($m=2$)		β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	β_{10}	β_{11}	β_{12}	β_{13}	β_{14}	β_{15}	β_{16}	β_{17}	β_{18}
UP	+	0	312	10	108	40	200	2	354	0	435	22	30	246	53	193	46	389	320	355
	−	429	11	349	52	227	100	315	10	430	0	325	145	12	229	26	93	1	13	0
	Zero	10	116	80	279	172	139	122	75	9	4	92	264	181	157	220	300	49	106	84
	Sign	−	+	−	Zero	−	+	−	+	−	+	−	Zero	+	−	Zero	Zero	+	+	+
DOWN	+	7	354	2	6	9	345	1	414	435	0	411	315	25	147	3	19	0	7	2
	−	391	4	409	303	294	25	308	1	0	435	1	2	88	181	301	100	373	280	320
	Zero	41	81	28	130	136	69	130	24	4	4	27	122	326	111	135	320	66	152	117
	Sign	−	+	−	−	−	+	−	+	+	−	+	+	Zero	−	−	Zero	−	−	−

Panel A provides detailed descriptions of each explanatory variable in the logit regression. For the UP (DOWN) model, the dependent variable is a dummy that equals 1 if the price of the kth transaction is higher (lower) than that of the $(k-1)$th transaction and 0 otherwise.

$$X_k'B = \beta_0 + \beta_1 \Delta T_k + \beta_2 V_{k-1} + \beta_3 V_{k-2} + \beta_4 V_{k-3} + \beta_5 DIST_{k-1} + \beta_6 IDIST^m_{k-1} \times DIST_{k-1} + \beta_7 ISPREAD_{k-1} + \beta_8 IBID_{k-1} + \beta_9 IASK_{k-1} + \beta_{10} IBS_{k-1} + \beta_{11} IBS_{k-2} + \beta_{12} IBS_{k-3} + \beta_{13} V_{k-1} \times IBS_{k-1} + \beta_{14} V_{k-2} + IBS_{k-2}$$
$$+ \beta_{15} V_{k-3} \times IBS_{k-3} + \beta_{16} MKT_{k-1} + \beta_{17} MKT_{k-2} + \beta_{18} MKT_{k-3}$$

We run 14 logit regressions for each of the 439 firms in our sample, with the m of the indicator variable $IDIST^m_{k-1}$ ranging from 2 to 15 ticks from the price limits. Panel B reports the numbers of estimates that are significantly positive (+), significantly negative (−), and insignificant (Zero) at the 5% level when $m=2$. The sign is determined by the largest number of estimates.

negative $\beta_5+\beta_6$ value implies that the odds of hitting the limit increase exponentially as the price gets closer to the limit and thus supports the magnet effect.

Furthermore, $ISPREAD_{k-1}$ captures the effect of bid–ask bounces and the liquidity effect (Brockman and Chung, 1999). If the magnet effect holds, market participants who anticipate decreased liquidity when the price approaches the limit should exhibit increased demand for liquidity, which should increase the cost of liquidity. The variables $IBID_{k-1}$ and $IASK_{k-1}$ capture the effects when the bid or ask price is unavailable immediately prior to a transaction. Another important issue related to the magnet effect is the potential imbalance between demand and supply. When the price approaches the upper (lower) limit, there may be more buy (sell) orders than sell (buy) orders in the market, and the resulting order imbalance in an order-driven market could lead to a temporary situation in which bid or ask prices are not immediately available. The indicator IBS_{k-l} indicates whether the trade is buyer-initiated, seller-initiated, or indeterminate. The interaction term $V_{k-l}\times IBS_{k-l}$ measures the per-unit volume impact of the buyer or seller initiation effect. Finally, we use the variable MKT_{k-l} to account for market-wide effects on price changes.

4. Results

4.1. Logit model

We obtain transaction data from the Taiwan Economic Journal Data Bank. These data record the trading volume, trading price, and time for each transaction, as well as the bid and ask prices. We investigate all transactions from the opening till the price limits are hit on a daily basis for 439 firms that traded during the year. We run 14 logit regressions for each firm, in which the m of the indicator variable $IDIST^m_{k-1}$ ranges from 2 to 15 ticks. We therefore run a total of 6146 logit regressions. We also examine the ratio of the residual deviance of each logit regression to its residual degrees of freedom; the maximum ratio of residual deviance to the degrees of freedom is 1.055 (1.007) for the UP (DOWN) model, which indicates no evidence of systematic deficiencies in the model or overdispersion.

In Panel B of Table 1, we report the number of significantly positive, negative, and insignificant estimates at the 5% level when $m=2$[7]. Although we include microstructure factors mainly to control for possible determinants, several parameter estimates also are worth discussing. Specifically, β_8 (β_9) is negative (positive) for the UP model and positive (negative) for the DOWN model. When no buy (sell) orders appear in the market, the price should move down (up), because investors are selling (buying) shares. In addition, β_{10} is negative for the UP model and positive for the DOWN model, which indicates reversals due to the effect of bid–ask bounces. We also find that β_{16}, β_{17}, and β_{18} are all positive (negative) for the UP (DOWN) model, such that when the market is moving up (down), the probability of a price increase (decrease) also increases.

When we control for the documented explanatory variables for price movements, we find that the mean estimate of $\beta_5+\beta_6$ is -0.4318 when m equals 2. The magnitude of the estimates of $\beta_5+\beta_6$ derives primarily from β_6, because β_5 is very close to zero. We calculate the translated odds to measure any changes in conditional probabilities when the price moves one tick closer to the limit. When $m=2$, the mean (median) $\beta_5+\beta_6$ translated odds is 54% (42.05%); that is, when the price is within two ticks of the upper price limit, the conditional probability that the price will move up increases approximately 54% (42.05%) for each tick closer to the limit, according to the mean (median) estimate. The mean (median) translated odds decrease monotonically from 54% to 2.11% (42.05% to 0.27%) when we increase m from 2 to 9. When m is equal to or greater than 10, the median translated odds equal zero, which suggests that the magnet effect starts to emerge when the price is nine ticks below the upper price limit. The effect appears to get stronger when the price approaches the limit.

We also find support for the magnet effect in the DOWN model, though it is not as strong as in the UP model (see Table 2). When the price is within two ticks of the lower price limit, the conditional probability that the price will move down increases approximately 25.21% (23.54%) for each additional tick, according to the mean (median) estimate. The mean translated odds decrease monotonically from 25.21% to 1.26% when we increase m from 2 to 5. When m is greater than 4, the median translated odds become zero. Thus, our overall evidence suggests that the magnet effect starts to emerge when the price is within nine ticks of the upper price limits and four ticks of the lower price limits. The magnet effect also is stronger when the price is within two and three ticks of the upper and lower price limits, respectively.

4.2. Price limit moves

If price limits generate the magnet effect, stock prices should keep moving toward the price limits until they eventually hit those limits. We expect to see more price limit moves when the price comes closer to the limits, consistent with the magnet effect. To test this conjecture, we examine our trading data to determine the percentage of price limit moves that occur when the price approaches the limits.

The results in Table 3 support our supposition: When the price is within one tick of the upper price limits, the mean (median) percentage of price limit moves equals 79% (80%). The mean percentage of price limit moves drops to 64%, 52%, 43%, and 35%, when the price moves to within two, three, four, and five ticks of the upper price limits, respectively. We obtain similar results for the lower price limits and the weighted average percentage of price limit moves. With regard to the difference of the mean percentage of price limit moves between adjacent cases, we find that the difference between one and two ticks is 15%. It drops to 11% between

[7] We also run our analysis using transactions during periods with 3.5% downward price limits. The results are similar, so we only report the transactions in all periods. Results for other periods and $m = 3–15$ are available on request.

Table 2
Logit regression results: conditional probability.

m	β_5		β_6		$\beta_5+\beta_6$		Mean $\beta_5+\beta_6$ translated odds (%)	Median $\beta_5+\beta_6$ translated odds (%)
	Mean	Median	Mean	Median	Mean	Median		
Panel A: UP model								
2	−0.0021	0.0000	−0.3199	−0.3212	−0.4318	−0.3510	54.00	42.05
3	−0.0020	0.0000	−0.1002	−0.0974	−0.1501	−0.1125	16.20	11.91
4	−0.0021	0.0000	−0.0511	−0.0313	−0.0764	−0.0514	7.93	5.27
5	−0.0022	0.0000	−0.0285	0.0000	−0.0529	−0.0303	5.43	3.08
6	0.0029	0.0000	−0.0196	0.0000	−0.0374	−0.0195	3.81	1.97
7	0.0027	0.0000	−0.0126	0.0000	−0.0305	−0.0108	3.10	1.08
8	0.0030	0.0000	−0.0070	0.0000	−0.0239	−0.0047	2.42	0.47
9	0.0031	0.0000	−0.0047	0.0000	−0.0209	−0.0027	2.11	0.27
10	0.0035	0.0000	−0.0020	0.0000	−0.0176	0.0000	1.77	0.00
11	0.0117	0.0043	0.0000	0.0000	−0.0157	0.0000	1.58	0.00
12	0.0128	0.0049	0.0000	0.0026	−0.0143	0.0000	1.44	0.00
13	0.0123	0.0053	0.0078	0.0034	−0.0132	0.0000	1.33	0.00
14	0.0135	0.0061	0.0084	0.0038	−0.0025	0.0000	0.25	0.00
15	0.0143	0.0066	0.0117	0.0056	−0.0024	0.0000	0.24	0.00
Panel B: DOWN model								
2	0.0145	0.0150	−0.2189	−0.2424	−0.2248	−0.2114	25.21	23.54
3	0.0148	0.0154	−0.0417	0.0000	−0.0599	−0.0282	6.18	2.86
4	0.0151	0.0157	−0.0156	0.0000	−0.0219	0.0000	2.21	0.00
5	0.0153	0.0160	−0.0065	0.0000	−0.0125	0.0000	1.26	0.00
6	0.0158	0.0159	−0.0005	0.0000	−0.0083	0.0000	0.83	0.00
7	0.0159	0.0153	0.0013	0.0000	−0.0067	0.0000	0.67	0.00
8	0.0153	0.0161	0.0015	0.0000	−0.0050	0.0000	0.51	0.00
9	0.0153	0.0159	0.0007	0.0000	−0.0036	0.0000	0.37	0.00
10	0.0153	0.0164	0.0015	0.0000	−0.0024	0.0000	0.24	0.00
11	0.0156	0.0166	0.0014	0.0000	−0.0015	0.0000	0.15	0.00
12	0.0155	0.0166	0.0015	0.0000	−0.0010	0.0000	0.10	0.00
13	0.0159	0.0171	0.0021	0.0000	−0.0005	0.0000	0.05	0.00
14	0.0162	0.0177	0.0027	0.0000	−0.0005	0.0000	0.05	0.00
15	0.0170	0.0179	0.0052	0.0000	−0.0004	0.0000	0.04	0.00

This table presents the logit regression results for the variables of interest. The dependent variable is a dummy variable equal to 1 if the price of the kth transaction is higher (lower) than that of the $(k-1)$th transaction, and 0 otherwise, in the UP (DOWN) model. For the detailed description of independent variables, see Table 1. We run a separate logit regression for each of the 439 firms in our sample and report the cross-sectional means and medians of the estimates. The m of the indicator variable $IDIST_{k-1}^{m}$ is 2 to 15 ticks from the price limits. The estimate is equal to 0 if the p-value of the estimate is greater than 5%, because the estimate is not significantly different from 0. Translated odds are the changes in conditional probabilities derived from the mean and median of the $\beta_5+\beta_6$ estimates when the price moves one tick closer to the limit, calculated as $e^{-(\beta_5+\beta_6)}-1$.

Table 3
Percentage of price limit moves.

Panel A:	Number of ticks to upper price limits				
	1	2	3	4	5
Maximum	100%	95%	90%	74%	66%
Minimum	33%	30%	0%	0%	0%
Median	80%	64%	53%	44%	36%
Mean	79%	64%	52%	43%	35%
Weighted average	80%	66%	56%	46%	38%
Difference	15% >	11% >	9% >	8%	
Panel B:	**Number of ticks to lower price limits**				
	1	2	3	4	5
Maximum	100%	84%	80%	73%	69%
Minimum	14%	5%	0%	0%	0%
Median	73%	59%	50%	42%	36%
Mean	71%	58%	49%	42%	36%
Weighted average	74%	61%	53%	45%	39%
Difference	13% >	9% >	7% >	6%	

This table reports the percentage of price limit moves when the price is within one to five ticks from the limits. Price limit moves describe the situation in which the price reaches the limits. The percentage of price limit moves is equal to the number of days that feature price limit moves, divided by the number of days on which the price reaches the reported number of ticks from the price limits. There are 439 firms in our sample. We calculate the percentage of price limit moves for each firm and report the maximum, minimum, median, and mean across the 439 firms. Weighted average is the average percentage of price limit moves, weighted by the total number of price limit moves by each firm. Difference is the difference of the mean between adjacent ticks near the price limits. The symbol > indicates that the left-hand figure is significantly greater than the right-hand figure at a 1% significance level, based on a t-test.

the two and three tick cases and then grows monotonically smaller as the price moves away from the limits. The increasing percentage of price limit moves thus provides ex post evidence of the magnet effect.

4.3. Informed trading and the magnet effect

Informed trading might affect the magnet effect. In Subrahmanyam's (1997) framework, an informed trader who knows that trading large quantities will cause a limit crossover will scale back his or her trading to avoid a possible market closure, which contrasts with the magnet effect. Similarly, Kim and Sweeney (2001) develop a model to show that an informed investor delays profit-motivated trades when the price is near the limit. These two studies therefore suggest the magnet effect should be less prominent among firms that possess a greater probability of informed trading. To examine the relation between informed trading and the magnet effect, we adopt the measure of the probability of information-based trading (PIN) proposed by Easley et al. (1996) and employed by Easley et al. (2002), among others.

Because the degree of the magnet effect varies across firms, we control for firm characteristics that might explain cross-sectional variations in this effect. In line with Kim and Limpaphayom (2000), we identify firm volatility, size, trading activity, and the book-to-market ratio as potential explanatory variables. To study the relation between PIN and the magnet effect, we run the following regression:

$$ME = \alpha + \beta_1 Beta + \beta_2 RR + \beta_3 Volume + \beta_4 Size + \beta_5 BTM + \beta_6 PIN + \varepsilon, \tag{3}$$

where *ME* is the degree of the magnet effect obtained from the standardized estimates of $\beta_5+\beta_6$ in our logit model, multiplied by (-1); Beta is from the standard market model calculated with daily stock returns and value-weighted market returns; RR is the residual standard deviation of the market model; Volume is daily trading volume divided by total shares outstanding; Size is the natural logarithm of market capitalization; and BTM is the book-to-market ratio.

In Table 4, we report the results of our PIN estimations. The mean (median) PIN is 0.2133 (0.2090), and the maximum PIN is 0.4566. As we show in Panel B, PIN correlates negatively with *ME*, such that firms with higher PIN are less associated with the magnet effect. However, the correlation coefficients are significant only in the DOWN model. The ordinary least squares (OLS) regression results in Panel C of Table 4 also show that PIN is significantly negative only in the DOWN model. The coefficients of Beta, Volume, Size, and BTM are mostly significant and positive, consistent with Lauterbach and Ben-Zion's (1993) finding that

Table 4
Informed trading and magnet effect.

Panel A: PIN					
Variable	Mean	Median	Std. dev.	Minimum	Maximum
PIN	0.2133	0.2090	0.0554	0.0000	0.4566

Panel B: Correlation	UP model		Down model	
	ME $(m=2)$	ME $(m=3)$	ME $(m=2)$	ME $(m=3)$
PIN	-0.0279	-0.06299	-0.1777**	-0.13224*
	$(p=0.5994)$	$(p=0.2358)$	$(p=0.0008)$	$(p=0.0125)$

Panel C	UP model		DOWN model	
	$m=2$	$m=3$	$m=2$	$m=3$
Intercept	-1.7386	-2.8837**	-2.0440	-4.2733**
Beta	1.2164**	1.3438**	1.0940**	1.0547**
RR	16.3676	32.9329	32.4432	29.9542
Volume	43.0505**	28.4879	57.0046**	24.7612
Size	0.2292**	0.2809**	0.3283**	0.4357**
BTM	0.4162**	0.3537*	0.4878**	0.3214*
PIN	1.2338	0.5742	-3.3627*	-0.6841
Adj. R^2	0.1458	0.1406	0.2078	0.1552
F value	10.98**	10.57**	16.35**	11.75**

Panel A reports the probability of information-based trading (PIN), estimated with Easley et al.'s (2002) approach. Panel B reports the correlation coefficients between ME and PIN for various models; ME is the degree of the magnet effect obtained from the standardized estimates of $\beta_5+\beta_6$, multiplied by (-1), from our logit model. When $m=2$ and $m=3$, the ME comes from the logit model in which the m of the indicator variable $IDIST^m_{k-1}$ equals 2 and 3, respectively. Panel C reports the ordinary least squares regression results for the following model:

$$ME = \alpha + \beta_1 Beta + \beta_2 RR + \beta_3 Volume + \beta_4 Size + \beta_5 BTM + \beta_6 PIN + \varepsilon$$

The significant levels are based on White's heteroskedasticity-consistent x^2 test. We calculate Beta from the standard market model, using daily stock returns and the value-weighted market returns; RR is the residual standard deviation of the market model from which we calculate Beta; Volume is the daily trading volume divided by total shares outstanding; Size is the natural logarithm of market capitalization; and BTM is the book-to-market value of equity.

** Significant at 1%.

* Significant at 5%.

during the 1987 market crash, sell pressures concentrated in higher beta, larger company, and lower leverage stocks. Goldstein and Kavajecz (2004) also find that high volume stocks suffer the most dramatic liquidity drains during extreme market movements.

4.4. Robustness check

As a robustness check, we execute probit regressions for the same models and data; the results are qualitatively similar to those from the logit regression models. We also use the Lee and Ready's (1991) method to identify buyer- and seller-initiated trades for the IBS_{k-l} variable, and again, the results are similar. For our Eq. (3), we employ the generalized method of moments approach to obtain estimates. The results are similar to our OLS estimates. Overall then, our results are robust across different estimation methods and model specifications.

5. Conclusion

Using a logit model, we find evidence of the magnet effect of price limits, a finding with important regulatory implications. To the extent that the magnet effect exists, price limits may increase short-run conditional volatility rather than reducing it. Policymakers therefore should evaluate their specific objectives for imposing price limits.

Further empirical research should study the magnet effect by investigating the change in liquidity when the price comes near the limits and providing evidence from other markets. Liquidity represents an important factor in asset pricing (e.g., Amihud and Mendelson, 1986; O'Hara, 2003), so it would be interesting to determine changes in liquidity near price limits. Although we include the trading volume and the bid–ask spread in our model, we do not have access to order submission data, which would offer insight into the demand for liquidity and order flow when the price approaches the limits. In recent years, limit order books have become available in Taiwan, so a follow-up study that uses such information might enhance our understanding of the magnet effect. Furthermore, in Taiwan, the price limits do not trigger trading halts, because trading continues as long as the price remains within the limits. We expect the magnet effect might be even stronger in markets in which price limits trigger trading halts, such as in the U.S. futures markets. Our methodology therefore should be implemented in such settings to test the magnet effect and identify the trigger point, if there is any.

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