The Magnet Effect of Price Limits: Evidence from Transactions Data

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Abstract

We investigate the magnet effect of price limits using transactions data from the Taiwan Stock Exchange. Using a logit model that incorporates explanatory variables documented in the microstructure literature to capture transaction price changes, we find that the conditional probability of price going up (down) increases significantly when the price is approaching the upper (lower) price limit, supporting the magnet effect. We find that the magnet effect starts to emerge when the price is within 10 ticks from the upper price limits and about 5 ticks from the lower price limits. We also examine firm characteristics to identify possible determinants of magnet effect and find that beta, trading volume, market capitalization, and book-to-market are positively related to the degree of magnet effect. Our overall results generate important policy implications.

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Abstract

We investigate the magnet effect of price limits using transactions data from the Taiwan Stock Exchange. Using a logit model that incorporates explanatory variables documented in the microstructure literature to capture transaction price changes, we find that the conditional probability of price going up (down) increases significantly when the price is approaching the upper (lower) price limit, supporting the magnet effect. We find that the magnet effect starts to emerge when the price is within 10 ticks from the upper price limits and about 5 ticks from the lower price limits. We also examine firm characteristics to identify possible determinants of magnet effect and find that beta, trading volume, market capitalization, and book-to-market are positively related to the degree of magnet effect. Our overall results generate important policy implications.

I. Introduction

Price limits exist in many financial markets, but it is very unfortunate that our understanding of this particular market stabilization mechanism is limited.[1] By definition, price limits regulate the magnitude of the change in price that can occur for a given asset during a single trading session. From their proponents' point of view, price limits provide a cooling-off period that allows investors to reevaluate market information and make more rational decisions during periods of extreme price changes,[2] thereby reducing traders' overreaction and diminishing price volatility. However, opponents of price limits argue that they serve no purpose other than to slow or delay the price discovery process (see, e.g., Fama (1989) and Kim and Rhee (1997)). Although price limits can stop the price of a share from falling or rising beyond the limit on a given trading day, opponents argue that the price will continue to move toward equilibrium when new trading limits are established on subsequent trading day(s). Furthermore,

[1] Countries with price limits include Austria, Belgium, France, Greece, Italy, the Netherlands, Spain, Switzerland, and Turkey in Europe and China, India, Japan, Korea, Malaysia, Taiwan, and Thailand in Asia. For a survey of market stabilization mechanisms, see Kim and Yang (2004).

rather than generating a stabilizing effect that calms market movements, price limits may have a magnet effect that pulls prices toward the limit (Subrahmanyam (1994)). When prices move toward the limits, traders may rush to trade, for fear that their orders might not be executed if the limit is hit. We investigate the magnet effect of price limits using transactions data from the Taiwan Stock Exchange (TSE), one of the major stock markets in Asia.

The magnet effect of price limits describes the ex ante trading decisions of market participants in response to the impediments to trade. In Subrahmanyam's (1994) model, traders place a high value on their desire to trade and thus may advance their trades to ensure their ability to trade even though that means the departure from their optimal trading strategy. Although the description of the magnet effect sounds behavioral, the paper adopts an optimizing model to generate the magnet effect. In the intertemporal, one-market model, Subrahmanyam shows that the magnet effect may increase price variability and the probability of the price reaching the limit if the price is very close to the limit. Gerety and Mulherin (1992) investigate how the daily closing of financial markets affects trading volume and observe the desire of investors to trade prior to market closings, in line with the magnet effect.[3] Ackert, Church, and Jayaraman (2001) conduct an experimental study to examine the effects of mandated market closures and temporary halts on market behavior. Their analysis of trading volume indicates that mandated market closures accelerate trading activity when an interruption is imminent.

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[2] Brennan (1986) also shows that price limits can act as partial substitutes for margin requirements, in that they ensure contract performance without the need for costly litigation.

[3] There is difference between a regular and a price limit closure, though. For example, a price limit closure is associated with large market movements and high volatility, but a regular closing may not.

On the other hand, Subrahmanyam (1997) explores the ex ante response of strategic informed traders to closure boundaries and, thus, the ex ante effect of closures on market liquidity. Whereas most prior theoretical models have assumed that all traders are competitive and do not react to the closure strategically, Subrahmanyam (1997) uses an informed trader who knows that trading large quantities will cause the limit to be crossed, which will cause him or her to lose profit potential. Therefore, the strategic action would be to scale back his or her trading in response to the closure, contrary to the magnet effect.

Empirical literature does not definitively answer whether price limits generate a magnet effect. Studies that test directly for the effect of price limits generally use relatively small data sets and reach different conclusions. Arak and Cook (1997) examine the price behavior in the U.S. Treasury bond futures market to test whether behavior is affected by proximity to a price limit. By analyzing behavior after large overnight price moves, they find that proximity to the limit tends to cause a small price reversal, which rejects the magnet effect. Berkman and Steenbeek (1998) examine the price formation of the Nikkei 225 stock index futures contracts traded on both the Osaka Securities Exchange (OSE), a market with strict price limits, and the more lenient Singapore International Monetary Exchange (SIMEX) to test the magnet effect of price limits. Using the Nikkei futures contract on SIMEX as a benchmark, they find that Nikkei futures on the OSE do not trade at a relatively low (high) price near the lower (upper) price limit. That is, no magnet effect is found. Hall and Kofman (2001) also reject the magnet hypothesis in their study of five agricultural futures contracts. However, Holder, Ma, and Mallett (2002) and Belcher, Ma, and Mallett (2003) study the Treasury bond futures market and find supports for the magnet effect.

Earlier studies on the magnet effect have focused on the futures markets, but recently several studies have investigated the stock market to test the magnet effect. However, again, the results are conflicting. Cho et al. (2003) use intraday data from the TSE to test the magnet effect and find 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 limits. However, their study is limited to the return-generating process and leaves other important trading variables uninvestigated. Furthermore, similar results from different thresholds of proximity to the limits cloud the magnet effect. Contrary to Cho et al. (2003), Nath (2003) finds that trading activity accelerates as stock prices approach their lower, but not upper, price limits on the National Stock Exchange of India.

Osler and Tooma (2004) study the Egyptian Stock Exchange, where trading is halted frequently under the five percent price limits imposed in 1997, to test the magnet effect and find supporting evidence. Similar to our study, they employ a logit model to obtain the conditional probability of reaching a limit. However, instead of studying the intraday trading behavior, they focus only on the daily close-to-close and the overnight returns. Furthermore, the results are from a sample of five firms in a market with 1,151 listed companies. Du, Liu, and Rhee (2005) examine the magnet effect using the limit order book and transactions data from the Korea Stock Exchange. They find evidence of a significant magnet effect as investors place more orders and frequently reposition quotes to advance transactions prior to the limit hits. Although the use of limit order book provides an insight into traders' behavior, the use of only limit hit observations in the study creates a selection bias toward supporting the magnet effect. For instance, suppose there is no magnet effect. When the price is very close to the limit, it does not accelerate to reach the limit. This observation, which would help reject the magnet effect, is not in the sample because the price limit is not hit. Thus, the results from the study are biased.

We overcome the problems and difficulties exhibited by existing studies and provide a clear evidence of magnet effect. First of all, we investigate the transactions data of all listed firms on the TSE to capture the intraday trading behavior and thus avoid potential biases that may be introduced by sample selection. Second, the TSE is one of the most active markets in the world so the thin trading issue that may exist in other markets is not a concern. Third, we use a logit model that incorporates explanatory variables documented in the microstructure literature to capture the transaction price changes. Thus, we not only examine the price behavior, but also control for the clock-time effects, the effects of bid-ask bounce, the size of the transaction, and the impact of systematic or market-wide movements. Last, we investigate all transactions occurred prior to limit hits to examine the ex ante effect of price limits, so our results are not biased toward supporting the magnet effect.

We find that the conditional probability of price going up (down) increases significantly when the price is approaching the upper (lower) price limit, supporting the magnet effect. For instance, when the price is within 2 ticks from the upper price limit, the conditional probability of the price to move up increases about 31 percent for each tick closer to the limit. To the best of our knowledge, we provide the first evidence to show when the magnet effect starts to emerge for both upper and lower price limits. Our results show that the magnet effect starts to emerge when the price is within 10 ticks from the upper price limits and about 5 ticks from the lower price limits. We also examine firm characteristics to identify possible determinants of magnet effect and find that beta, trading volume, market capitalization, and book-to-market are positively related to the degree of magnet effect. Our overall results generate important policy implications.

Our paper makes several contributions to the literature. First, we take into account the market participants' demand for liquidity when prices approach the limit and show that price limits have a magnet effect. Prior studies that attempted to test the magnet effect have either failed to investigate this important factor or used daily data that have limited information about investors' intraday behavior. Second, our findings have important regulatory implications. Price limits can potentially generate the magnet effect on top of an apparent cost of impeding trading. Because of the magnet effect, price limits may increase short-run conditional volatility rather than reducing it. Policymakers need to evaluate the specific objective they hope to achieve by imposing price limits and set rules to optimize their net advantage.

We organize the remainder of this paper as follows: In the next section, we provide the institutional background of the TSE. In Section III, we describe our data and present the summary statistics. Then in Section IV, we discuss our hypotheses and establish the research design. Finally, we present the empirical findings in Section V and conclude in Section VI.

II. Institutional Background

According to the Monthly Bulletin of Statistics of the Republic of China (March 2001), 531 stocks were listed on the TSE at the end of 2000. The total market value is New Taiwanese Dollar (NT$) 8,191,170 million (or approximately US$248.5 billion at the exchange rate of NT$32.96/US$1). The average daily trading volume is NT$112,640 million (US$3.4 billion).

The TSE is an order-driven market with no market makers or specialists in which investors can submit either market or limit orders. The automated central limit order book accumulates and matches orders against one another. Because there are no official market makers, the bid and ask quotations represent the best prices, provided by various traders, in the limit order book. According to the Taiwan Stock Exchange Corporation (TSEC), since August 1985, the open outcry system gradually has been replaced by a computer-aided trading system and was upgraded to a fully automated securities trading system in 1993. The trading session of the centralized market lasts from 9:00 a.m. to 12:00 p.m., Monday through Friday. On the first, third, and fifth (if there is one) Saturdays of each month, trading also takes place from 9:00 a.m. to 12:00 p.m. Thirty minutes before the market opens, orders can be submitted through security firms and are ranked on the basis of their price–time priority. The opening price is the one that maximizes the trading volume. Following the opening, the system matches orders on a periodic basis until the closing; each round of clearing takes approximately one minute. The actual time interval of each round of clearing may vary slightly according to the trading intensity.

The TSE has imposed daily price limits since its inception in 1962. According to the TSEC, the purpose of price limits is to avoid excessive volatility and protect investors by limiting their potential daily losses. The TSE sets both its upward and its downward daily price limits at a predetermined rate on the basis of the previous day's closing price. The price limit rate has been adjusted up or down several times in accordance with the market conditions. For example, Panel A of Table 1 provides the price limit rates during different periods of 2000. For stocks listed on the TSE, tick sizes (i.e., the minimum allowable unit that a stock price may change) vary with the market prices, as we illustrate in Panel B of Table 1 for each price range. In addition to the daily price limits, the clearing price in each round of matching cannot go beyond two tick sizes from the clearing price in the preceding round. Stocks that hit their price limits can be traded as long as the transaction prices are within the limits. Thus, the TSE price limits are simply boundaries, not triggers for trading halts.

[Insert Table 1 about Here]

III. Data and Summary Statistics

A. Data Description

We obtained transactions data for all TSE-listed stocks in 2000 from the Taiwan Economic Journal Data Bank. The data contain time-stamped records of all transactions on the TSE. In 2000, 541 stocks traded on the TSE, but only 439 traded during the entire year; the remainder were either delisted or initial public offerings (IPOs). The data record the trading volume, trading price, and time for each transaction, as well as the bid and ask prices.

The year 2000 is an ideal period for examining price limit effects for at least two reasons. First, the stock market was relatively volatile in 2000; the index rose from 8756.55 at the beginning of the year to 10202.20 on February 17, and then dropped to 4743.94 at the end of the year. Because of this high volatility, the chance for stocks to hit their limits is high, and we probably can obtain more observations of limit hits. Thus, our data alleviate the concern of small sample sizes, as has been noted in previous studies. Second, some important events, such as a presidential election and the resignation of the prime minister, occurred in 2000, so the lower limit rate was adjusted down from 7% to 3.5% four times during the year, though the upper limit rate remained unchanged at 7% (see Panel A of Table 1). Therefore, we are able to test our hypothesis on the basis of these different price limit rates during different periods.

B. Summary Statistics

In Panel A of Table 2, we report the number of observations and ratios for limit hits during two periods for all 439 stocks traded throuout the year 2000 on the TSE. Period 1 represents all times during which 7% upward and 7% downward price limits were applied, whereas Period 2 represents all times with 7% upward and 3.5% downward price limits. During Period 1, 17,188,194 transactions occurred, and 3,539,160 transactions took place during Period 2. We define upper (lower) limit hits as those that occur when the transaction prices hit the upward (downward) price limits. Ratios, as we display in Panel A of Table 2, represent the number of observations divided by the number of transactions in each period. The tick size, set by the TSE, effectively limits the number of stocks that can hit the exact 7% price limit. For example, at a closing price of NT$80, the price of a stock on the next trading day may go up to NT$85.6 or down to NT$74.4. However, the tick size for the price range NT$50–$150 is NT$0.5; therefore, a limit hit occurs when the price rises to NT$85.5 or declines to NT$74.5, even though the return is only 6.875% or –6.875%, respectively.

[Insert Table 2 about Here]

During Period 1, there are more upper limit hits than lower limit hits, and the overall limit-hit ratio is approximately 4%. That is, for every 100 transactions, 4 hit the price limits. In contrast, there are more lower limit hits than upper limit hits during Period 2, largely because of the 3.5% downward price limits. Furthermore, Period 2 is more volatile than Period 1, probably because of several important events that occurred then, such as the presidential election and the resignation of the prime minister. In Period 2, the overall limit-hit ratio is approximately 10%, and 7% are lower limit hits.

In Panel B of Table 2, we report the summary statistics of the daily market returns during Periods 1 and 2, which are based on the TSE Capitalization Weighted Price Index (TAIEX), the most frequently quoted index of the many stock indices published by TSE. Because the standard deviation (SD) of daily market returns in Period 2 is higher than that in Period 1, Period 2 is more volatile than Period 1. We also perform the Wilcoxon rank sum test to determine if the median in Period 1 is significantly different from that in Period 2, but we find no significant difference between them with a *p*-value of 0.4104. Because the stock market is more volatile in Period 2, we expect to find higher limit-hit ratios in Period 2. Furthermore, given the asymmetric price limit rates during Period 2, we also expect to find more lower limit hits than upper limit hits. The results we report in Panel A of Table 2 are consistent with our expectations. All ratios in Period 2 are significantly higher than those in Period 1, and there are more lower limit hits than upper limit hits in Period 2.

IV. Hypothesis and Methodology

A. Magnet Hypothesis

The magnet hypothesis emphasizes the ex ante effect of price limits. Theoretical support for the magnet hypothesis has been modeled by Subrahmanyam (1994) to suggest that investors may rush to submit orders when prices approach the limits, even if these orders do not meet investors' optimal trading strategy. If the magnet effect holds, we will observe higher probability of the price hitting the limits when a price approaches the limit. More specifically, the closer the price gets to its upper (lower) limit, the greater is the probability of price moving up (down) to reach its limit.

B. Methodology

Because the magnet effect is the ex ante effect, we focus on investors' trading behavior prior to hitting the limits. To test the magnet hypothesis, the most challenging task is to find a price that is so close to the price limits that the magnet effect is likely to occur. Theoretical models do not provide a clear threshold as to under what circumstances do price limits generate the magnet effect. Instead of selecting the trigger point arbitrarily, we use an indicator variable that captures all possibilities and provides us a clear picture as to when the magnet effects start to emerge.

To investigate the relation between the distance to price limits and the probability for prices to go up and down, we use the logit regressions to estimate the probabilities. These regressions include control variables that are documented in the microstructure literature as potential determinants of price movements. Examples are the clock-time effects, the effects of bid-ask bounce, the size of the transaction, and the impact of systematic or market-wide movements. If there is a magnet effect, the conditional probability of price going up (down) increases significantly when the price is approaching the upper (lower) price limit.

If the magnet effect holds, market participants who anticipate a drying up of liquidity when the price is approaching the limit should have an increased demand for liquidity, and accordingly, the cost of liquidity should rise. In an order-driven market, liquidity is provided by the traders who submit limit orders. The difference between the price of the lowest sell limit order and that of the highest buy limit order determines the effective bid–ask spread, which represents the compensation they expect in return for supplying immediacy. Brockman and Chung (1999) examine an order-driven market, the Stock Exchange of Hong Kong, and find that the bid–ask spread is positively related to the liquidity costs. Because the TSE is also an order-driven market, we expect to observe increasing spreads as prices approach the limits. Therefore, we include the bid–ask spread in our model.

Another important issue related to the magnet effect is the imbalance between demand and supply. When the price is approaching the upper limit, there may be more buy orders than sell orders in the market. On the other hand, when the price is approaching the lower limit, there may be more sell orders than buy orders. The order imbalance in an order-driven market may lead to a temporary situation where either no bid or ask prices are immediately available. This situation may impact the price movement and thus should be considered in our model. We use indicator variables to capture these cases when the bid price is unavailable and when the ask price is unavailable immediately prior to a transaction.

C. Model

We consider a logit model to capture the relation between the distance to price limits and the probability of price moving toward the limits. In its generic form, the model can be expressed as

$$\log\left(\frac{P(Y_k = 1 \mid \mathrm{X}_k)}{1 - P(Y_k = 1 \mid \mathrm{X}_k)}\right) = \mathrm{X}_k^{'}\mathrm{B}\,, \tag{1}$$

where $Y_k = 1$ if the price of the k^{th} transaction is closer to the price limit than that of the $(k\text{-}1)^{\text{th}}$ transaction. The model defined in (1) is called an UP (DOWN) model if it is used to examine the magnet effect of the upper (lower) limit. For an UP (DOWN) model, $Y_k = 1$ if the price of the k^{th} transaction is higher (lower) than that of the $(k\text{-}1)^{\text{th}}$ transaction.

To capture several aspects of transaction price changes, we follow the suggestions in Hausman, Lo, and MacKinlay (1992) and carefully selected the following explanatory variables X. Specifically, we try to incorporate the clock-time effects, the effects of bid-ask bounce, the size of the transaction, and the impact of systematic or market-wide movements on the conditional distribution of an individual stock's price changes. The following table describes each independent variable in our logit model.

ΔT_k	The time elapsed between transactions k – 1 and k, in seconds.
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.)

$DIST_{k-1}$	The distance of the (k – 1)th transaction price to the limit, in ticks.
$IDIST_{k-1}^{m}$	An indicator variable that takes the value of 1 if the (k – 1)th transaction price is within m ticks to 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 bid or ask price is not available, the spread is set to zero.
$IBID_{k-1}$	An indicator variable that takes the value of 1 if the bid price immediately prior to transaction k is not available, and 0 otherwise.
$IASK_{k-1}$	An 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 +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 zero otherwise. That is, $IBS_{k-l} = \begin{cases} +1, & \text{if } P_{k-l} > \frac{1}{2}(ask_{k-l} + bid_{k-l}) \\ 0, & \text{if } P_{k-l} = \frac{1}{2}(ask_{k-l} + bid_{k-l}) \\ -1, & \text{if } P_{k-l} < \frac{1}{2}(ask_{k-l} + bid_{k-l}) \end{cases}.$
MKT_{k-l}	Three lags (l =1, 2, 3) of one-minute continuously compounded returns of the TSE Capitalization Weighted Price Index (TAIEX).

The specification of $\mathrm{X}_k^{'}\mathrm{B}$ is thus given by the following expression:

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

The variable ΔT_k is included in X_k to capture the clock-time effects. If prices are stable in transaction time rather than clock time, the coefficient should be zero. The variable MKT_{k-l} is used to account for market-wide effects on price changes. The indicator IBS_{k-l} indicates whether the trade was buyer-initiated (= +1), seller-initiated (= –1), or indeterminate (= 0). The sign of the associated β parameters shows the effect of the buyer-seller initiation: a positive β implies that buyer-initiated trades tend to increase the odds of prices moving toward the limit and seller-initiated trades tend to decrease the odds. The magnitude of the β parameters associated with the interaction terms $V_{k-l} \times IBS_{k-l}$ measures the per-unit volume impact of the buyer-seller initiation effect on the conditional probability of observed price changes.

The parameter β_6 is of most importance for testing the magnet hypothesis. The indicator variable $IDIST_{k-1}^{m}$ separates the transaction prices that are within *m* ticks to the limit from the entire sample. The parameter β_6 measures the additional impact of this subgroup of prices on the odds of hitting the limit; whereas the parameter β_5 measures the impact of the prices that are more than *m* ticks away from the limit on the odds. A negative $\beta_5 + \beta_6$ implies that the odds of hitting the limit increase *exponentially* as price gets closer to the limit (i.e., within *m* ticks), and thus, demonstrates the magnet effect.

V. Results

A. Logit Model

Table 3 presents the logit regression results for the UP model and shows evidence that supports the magnet effect. We investigate all transactions from the opening till the price limits are hit on a daily basis for all publicly traded firms on the TSE in year 2000. We run a separate logit regression for each of the firms in our sample and report the summary statistics of the estimates of $\beta_5 + \beta_6$ from all regressions. We remove 10 firms from our original sample due to data unavailability, leaving 429 firms in the final sample. The *m* of the indicator variable $IDIST_{k-1}^{m}$ goes from 2 to 15 ticks away from the price limits. The estimate is equal to zero if the P-value of the estimate is higher than 5% as the estimate is not significantly different from zero. We also report the number of estimates whose P-value is less than 5%.

After controlling for documented explanatory variables for price movements, we find that the mean estimate of $\beta_5 + \beta_6$ is -0.3691, which translates to -30.86% odds, when the *m* of the indicator variable $IDIST_{k-1}^{m}$ is set at 2. That is, when the price is within 2 ticks from the upper price limit, the conditional probability of the price to move up increases about 31 percent for each tick closer to the limit. When the price is within 3 ticks from the upper price limit, the conditional probability of the price to move up increases only about 11.6 percent for each tick closer to the limit. The conditional probability decreases monotonically from 30.86% to 0.02% when we increase the *m* from 2 to 10. Once the *m* is at or above 11, the conditional probability of the price to move up actually decreases for each tick closer to the limit, though the probability is not large enough to be meaningful. Although not reported, we also remove the 1% and 5% outliers and the results are similar.

[Insert Table 3 about Here]

Table 4 reports the logit regression results for the DOWN model. The magnet effect is also supported by the DOWN model, though the effect is not as strong as that observed from the UP model. When the price is within 2 ticks from the lower price limit, the conditional probability of the price to move down increases about 21 percent for each tick closer to the limit. When the price is within 3 ticks from the lower price limit, the conditional probability of the price to move down increases only about 5 percent for each tick closer to the limit. Once the *m* is above 5, the conditional probability of the price to move down actually decreases for each tick closer to the limit. Results are similar when the 1% outliers are removed.

Overall, our result strongly supports the magnet effect that when the price is approaching the price limit, the probability of the price moving toward the limit increases. Our evidence suggests that the magnet effect starts to emerge when the price is within 10 ticks from the upper price limits and about 5 ticks from the lower price limits. The magnet effect is strong when the price is within 2 and 3 ticks from both the upper and lower price limits.

[Insert Table 4 about Here]

B. Firm Characteristics and Magnet Effect

As our evidence shows that the degree of the magnet effect varies across firms, an interesting question arises – what firm characteristics could explain the cross-sectional variations of the magnet effect? Kim and Limpaphayom (2000) study the characteristics of stocks that frequently hit price limits and find that volatile stocks, actively traded stocks, and small market capitalization stocks hit price limits more often than other stocks. On the basis of Kim and Limpaphayom, we identify firm volatility, size, trading activity, and the book-to-market ratio as potential explanatory variables. For volatility, we estimate beta from the standard market model using daily stock and both value- and equally-weighted market returns, both without dividends re-invested, in year 1999. We also use the market model residual standard deviation as the measure of residual risk. The trading activity is calculated as daily trading volume divided by the total shares outstanding. For size, we use the market capitalization.

To determine what firm characteristics could explain the degree of the magnet effect, we run the following regressions:

$$ME = \alpha + \beta_1 \text{V-Beta} + \beta_2 \text{V-RR} + \beta_3 \text{Volume} + \beta_4 \text{Size} + \beta_5 \text{BTM} + \varepsilon, \quad (3)$$

$$ME = \alpha + \beta_1 \text{E-Beta} + \beta_2 \text{E-RR} + \beta_3 \text{Volume} + \beta_4 \text{Size} + \beta_5 \text{BTM} + \varepsilon, \quad (4)$$

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); V-Beta is calculated from the standard market model using daily stock returns and the value-weighted market returns; V-RR is the residual standard deviation of the market model from which V-Beta is calculated; E-Beta is calculated from the standard market model using daily stock returns and the equally-weighted market returns; E-RR is the residual standard deviation of the market model from which E-Beta is calculated; Volume is the daily trading volume divided by total shares outstanding; Size is the natural logarithm of market capitalization; BTM is the book-to-market value of equity.

Table 5 presents the OLS regression results for equations (3) and (4) in Panel A and Panel B, respectively. Because the magnet effect is strong when the price is within 2 and 3 ticks from the upper and lower price limits, we only concentrate on these two cases. As shown in both Panels A and B, the coefficients of Beta, Volume, Size, and BTM are mostly significantly positive, with RR being the only insignificant variable. Because the dependent variable ME is obtained from the standardized estimates of $\beta_5 + \beta_6$ in our logit model multiplied by (-1), the higher the ME the higher the degree of magnet effect. Thus, our results suggest that Beta, Volume, Size, and BTM are all positively related to the degree of magnet effect. Although no apparent economic rationale exists to explain our results, our finding seem to be in line with Kim and Limpaphayom's (2000) finding that volatile stocks and actively traded stocks hit price limits more often than others as well as Lauterbach and Ben-Zion's (1993) finding during the 1987 market crash that sell pressures were concentrated in higher-beta, larger-company, and lower-leverage stocks. Their explanation is that traders may have concluded that less solid stocks had a good chance of selling at an inferior price. Goldstein and Kavajecz (2004) examine liquidity provision by limit order traders and floor members during extreme market movements and find that high volume stocks showed the most dramatic liquidity drain, consistent with our positive result from Volume.

[Insert Table 5 about Here]

C. Robustness Check

As a robustness check, we also execute probit regressions for the same models and data, and the results are qualitatively similar to the logit regression models. We also use the Lee and Ready (1991) method to identify the buyer- and seller-initiated trades for the IBS_{k-l} variable and again the results are similar.

For our equations (3) and (4), we also employ the generalized method of moments (GMM) approach to obtain estimates. Results are similar to our OLS estimates and thus are not reported. Overall, our results are robust to different estimation methods.

VI. Conclusion

Given the recent development of behavioral finance and its empirical evidence about market overreaction, we attempt to answer the question, "Will price limits, one form of circuit breakers, generate the magnet effect?" Although the most popular rationale for imposing price limits is to reduce market overreaction, opponents of price limits argue that they serve no purpose other than to slow or delay the price discovery process. Furthermore, they argue, rather than generating a stabilizing effect that calms market movements, price limits have a magnet effect that pulls prices toward the limit. We use transactions data from the TSE to examine this ex ante effect of price limits.

The magnet hypothesis suggests that investors may rush to submit orders when prices approach the limits. Using a logit model that incorporates explanatory variables documented in the microstructure literature to capture transaction price changes, we find that the conditional probability of price going up (down) increases significantly when the price is approaching the upper (lower) price limit, supporting the magnet effect. We find that the magnet effect starts to emerge when the price is within 10 ticks from the upper price limits and about 5 ticks from the lower price limits. We also examine firm characteristics to identify possible determinants of magnet effect and find that beta, trading volume, market capitalization, and book-to-market are positively related to the degree of magnet effect.

Our findings have important regulatory implications. Supporters of price limits argue that they provide a cooling-off period that allows investors to reevaluate market information and make more rational decisions during periods of extreme price changes, thereby reducing traders' overreaction and diminishing price volatility. However, we find that price limits not only create an apparent cost of impeding trading but also generate the magnet effect. Policymakers should evaluate the net effect of price limits and set rules to utilize their benefits optimally.

Further empirical research is encouraged to provide evidence from other markets and ultimately determine the net effect of price limits. In this connection, the magnet effect can be investigated further. For example, in some countries, e.g., Taiwan, the price limits do not trigger trading halts because trading is permitted as long as the price is within the limits. Other countries, e.g., Spain, have implemented price limit systems that lead to trading halts. One would expect the magnet effect to be stronger in markets where price limits also trigger trading halts. We leave the empirical verification of such a proposition to future studies.

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Table 1
Price Limit Rates and Tick Sizes

Panel A reports the price limit rates during different periods of 2000. Panel B reports the tick sizes for different price ranges on the Taiwan Stock Exchange. NT$ is the Taiwanese currency. Information from both panels was obtained from the Taiwan Stock Exchange Corporation.

Panel A: Price Limits in 2000

Periods	Price Limit Rates
01/01/2000 to 03/19/2000	7% upward and 7% downward
03/20/2000 to 03/26/2000	7% upward and 3.5% downward
03/27/2000 to 10/03/2000	7% upward and 7% downward
10/04/2000 to 10/11/2000	7% upward and 3.5% downward
10/12/2000 to 10/19/2000	7% upward and 7% downward
10/20/2000 to 11/07/2000	7% upward and 3.5% downward
11/08/2000 to 11/20/2000	7% upward and 7% downward
11/21/2000 to 12/31/2000	7% upward and 3.5% downward

Panel B: Tick Sizes

Price Range	Tick Size
P < NT$ 5.00	NT$ 0.01
NT$ 5.00 ≤ P < NT$ 15.00	NT$ 0.05
NT$ 15.00 ≤ P < NT$ 50.00	NT$ 0.10
NT$ 50.00 ≤ P < NT$ 150.00	NT$ 0.50
NT$ 150.00 ≤ P < NT$ 1,000.00	NT$ 1.00
NT$ 1,000.00 ≤ P	NT$ 5.00

Table 2
Summary Statistics

There were 439 stocks traded during the whole year 2000 on the Taiwan Stock Exchange. Panel A reports the number of observations and ratios for both upper and lower limit hits during Periods 1 and 2. Upper (lower) limit hits occur when the transaction prices hit the upward (downward) price limits. Period 1 represents all times with 7% upward and 7% downward price limits; Period 2 represents all times with 7% upward and 3.5% downward price limits. There are 17,188,194 transactions during Period 1 and 3,539,160 transactions during Period 2 for all 439 stocks. Ratios each are defined as the number of observations divided by the number of transactions in each period. $Ratio_2$-$Ratio_1$ is the ratio of Period 2 minus the ratio of Period 1. The Z-value of $Ratio_2$-$Ratio_1$ is based on the standard binomial test. Panel B reports the summary statistics of the daily market return during Periods 1 and 2 from the TSE Capitalization Weighted Price Index (TAIEX). S.D. represents the standard deviation.

Panel A: Observations and Ratios

	Period 1		Period 2		$Ratio_2$-$Ratio_1$	Z-value
	# of Observations	Ratios	# of Observations	Ratios		
Upper limit hits	399890	0.0233	104124	0.0294	0.0062	68.46
Lower limit hits	305466	0.0178	251757	0.0711	0.0534	565.21
Total limit hits	705356	0.0410	355881	0.1006	0.0595	462.62

Panel B: Daily Market Return

Period	N	Mean	S.D.	Min	Max	Median
1	213	-0.00375	0.01990	-0.06774	0.04483	-0.00292
2	57	0.00325	0.02518	-0.02757	0.06172	-0.00125

Table 3
Logit Regression Results: UP Model

This table presents the logit regression results for the UP model. The dependent variable is a dummy which equals to one if the price of the k^{th} transaction is higher than that of the $(k\text{-}1)^{th}$ transaction and zero otherwise. The independent variables are as follows.

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

For the detailed description of each variable, please see section IV part C. We run a separate logit regression for each of the 429 firms in our sample and report the summary statistics of the estimates of $\beta_5 + \beta_6$ from all regressions. The *m* of the indicator variable $IDIST_{k-1}^{m}$ goes from 2 to 15 ticks away from the price limits. The estimate is equal to zero if the P-value of the estimate is higher than 5% as the estimate is not significantly different from zero. We also report the number of estimates whose P-value is less than 5%. Odds are the conditional probabilities derived from the means of the $\beta_5 + \beta_6$ estimates.

# of Ticks to	# of estimates	$\beta_5 + \beta_6$ estimates							
Upper Limit	with P< 0.05	min	1Q	median	3Q	max	std	mean	odds
2	319	-2.9270	-0.5353	-0.3691	0.0000	0.0234	0.3251	-0.3691	-30.86%
3	264	-2.2840	-0.1907	-0.1149	0.0000	0.0000	0.1606	-0.1234	-11.61%
4	242	-2.2840	-0.1081	-0.0559	0.0000	0.2216	0.1333	-0.0673	-6.51%
5	237	-2.2840	-0.0679	-0.0290	0.0000	0.3084	0.1209	-0.0392	-3.85%
6	219	-0.1909	-0.0476	0.0000	0.0000	0.2444	0.0396	-0.0225	-2.23%
7	216	-0.1048	-0.0353	0.0000	0.0000	0.3182	0.0356	-0.0140	-1.39%
8	221	-0.0905	-0.0265	0.0000	0.0000	0.3487	0.0319	-0.0076	-0.76%
9	204	-0.1041	-0.0192	0.0000	0.0000	0.2180	0.0271	-0.0035	-0.35%
10	201	-0.0940	-0.0105	0.0000	0.0000	0.1622	0.0228	-0.0002	-0.02%
11	202	-0.0896	0.0000	0.0000	0.0139	0.1641	0.0208	0.0036	0.36%
12	220	-0.0446	0.0000	0.0000	0.0192	0.1822	0.0226	0.0078	0.78%
13	243	-0.1066	0.0000	0.0000	0.0217	0.1822	0.0202	0.0094	0.94%
14	258	-0.0943	0.0000	0.0107	0.0237	0.1822	0.0207	0.0119	1.19%
15	262	-0.0788	0.0000	0.0147	0.0265	0.1822	0.0199	0.0141	1.42%

Table 4

Logit Regression Results: DOWN Model

This table presents the logit regression results for the DOWN model. The dependent variable is a dummy which equals to one if the price of the k^{th} transaction is lower than that of the $(k\text{-}1)^{th}$ transaction and zero otherwise. The independent variables are as follows.

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

For the detailed description of each variable, please see section IV part C. We run a separate logit regression for each of the 429 firms in our sample and report the summary statistics of the estimates of $\beta_5 + \beta_6$ from all regressions. The m of the indicator variable $IDIST_{k-1}^{m}$ goes from 2 to 15 ticks away from the price limits. The estimate is equal to zero if the P-value of the estimate is higher than 5% as the estimate is not significantly different from zero. We also report the number of estimates whose P-value is less than 5%. Odds are the conditional probabilities derived from the means of the $\beta_5 + \beta_6$ estimates.

# of Ticks to	# of estimates	$\beta_5 + \beta_6$ estimates							
Lower Limit	**with P< 0.05**	**min**	**1Q**	**median**	**3Q**	**max**	**std**	**mean**	**odds**
2	319	-1.4510	-0.3813	-0.2720	0.0000	6.0790	0.3614	-0.2391	-21.27%
3	220	-0.4048	-0.1186	0.0000	0.0000	0.7517	0.0949	-0.0550	-5.35%
4	179	-0.3733	-0.0571	0.0000	0.0000	0.6481	0.0716	-0.0187	-1.85%
5	172	-0.6024	-0.0289	0.0000	0.0000	0.6538	0.0637	-0.0060	-0.60%
6	185	-0.1194	-0.0194	0.0000	0.0000	0.6538	0.0508	0.0009	0.09%
7	199	-0.1979	-0.0142	0.0000	0.0000	0.7190	0.0585	0.0039	0.39%
8	204	-0.9571	0.0000	0.0000	0.0099	0.7190	0.0707	0.0051	0.51%
9	196	-0.8972	0.0000	0.0000	0.0096	0.5500	0.0622	0.0050	0.50%
10	206	-0.8972	0.0000	0.0000	0.0177	0.7200	0.0624	0.0060	0.60%
11	233	-0.8972	0.0000	0.0000	0.0211	0.4862	0.0547	0.0073	0.74%
12	227	-0.8972	0.0000	0.0000	0.0201	0.2080	0.0484	0.0065	0.65%
13	248	-0.9019	0.0000	0.0000	0.0212	0.2345	0.0485	0.0077	0.78%
14	257	-0.8578	0.0000	0.0096	0.0212	0.1306	0.0456	0.0090	0.91%
15	260	-0.0639	0.0000	0.0114	0.0225	0.0713	0.0165	0.0119	1.20%

Table 5

Firm Characteristics and Magnet Effect

This table reports the OLS regression results for the following models. The significant levels are based on White's heteroskedasticity-consistent x^2 test.

Panel A: $ME = \alpha + \beta_1$ V-Beta $+ \beta_2$ V-RR $+ \beta_3$ Volume $+ \beta_4$ Size $+ \beta_5$ BTM $+ \varepsilon$,

Panel B: $ME = \alpha + \beta_1$ E-Beta $+ \beta_2$ E-RR $+ \beta_3$ Volume $+ \beta_4$ Size $+ \beta_5$ BTM $+ \varepsilon$,

where 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; V-Beta is calculated from the standard market model using daily stock returns and the value-weighted market returns; V-RR is the residual standard deviation of the market model from which V-Beta is calculated; E-Beta is calculated from the standard market model using daily stock returns and the equally-weighted market returns; E-RR is the residual standard deviation of the market model from which E-Beta is calculated; Volume is the daily trading volume divided by total shares outstanding; Size is the natural logarithm of market capitalization; BTM is the book-to-market value of equity. Dist=2 and Dist=3 mean that the ME is from the logit model where the *m* of the indicator variable $IDIST_{k-1}^{m}$ equals to 2 and 3, respectively.

Panel A	UP Model		DOWN Model		Panel B	UP Model		DOWN Model	
	Dist=2	Dist=3	Dist=2	Dist=3		Dist=2	Dist=3	Dist=2	Dist=3
Intercept	0.0536	-1.2430	*-1.5875	***-3.4489	Intercept	-0.4908	**-1.7273	***-2.0305	***-3.9654
	(0.7587)	(0.8144)	(0.8337)	(0.8570)		(0.7047)	(0.7509)	(0.7735)	(0.8006)
V-Beta	***1.1696	***1.3138	***1.0530	***0.9653	E-Beta	***0.9746	***1.2609	***1.0030	***0.7190
	(0.2777)	(0.2981)	(0.3052)	(0.3137)		(0.2116)	(0.2254)	(0.2322)	(0.2403)
V-RR	9.2093	22.8215	25.3783	23.1977	E-RR	-0.2291	7.0739	16.9631	24.0243
	(14.6223)	(15.6965)	(16.0678)	(16.5174)		(13.7925)	(14.6978)	(15.1396)	(15.6699)
Volume	***35.8558	**28.4517	***40.8284	*22.7665	Volume	***43.2492	***37.1468	***46.0503	**25.8144
	(10.5851)	(11.3627)	(11.6315)	(11.9570)		(10.4194)	(11.1033)	(11.4371)	(11.8377)
Size	0.0911	**0.1486	***0.2285	***0.3497	Size	***0.1765	***0.2292	***0.2909	***0.4161
	(0.0674)	(0.0723)	(0.0740)	(0.0761)		(0.0590)	(0.0629)	(0.0648)	(0.0671)
BTM	***0.3397	**0.2705	***0.4629	**0.3516	BTM	**0.2618	0.1638	***0.3823	**0.3130
	(0.1237)	(0.1328)	(0.1360)	(0.1398)		(0.1267)	(0.1350)	(0.1391)	(0.1440)
R^2	0.1312	0.1336	0.1564	0.1409	R^2	0.1391	0.1539	0.1658	0.1388
F value	***13.78	***14.04	***16.69	***14.87	F value	***14.66	***16.38	***17.82	***14.63

***significant at 1%, **significant at 5%, *significant at 10%