

Price Limit Performance: Evidence from the Tokyo Stock Exchange

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ABSTRACT

Price limit advocates claim that price limits decrease stock price volatility, counter overreaction, and do not interfere with trading activity. Conversely, price limit critics claim that price limits cause higher volatility levels on subsequent days (volatility spillover hypothesis), prevent prices from efficiently reaching their equilibrium level (delayed price discovery hypothesis), and interfere with trading due to limitations imposed by price limits (trading interference hypothesis). Empirical research does not provide conclusive support for either positions. We examine the Tokyo Stock Exchange price limit system to test these hypotheses. Our evidence supports all three hypotheses suggesting that price limits may be ineffective.

DAILY PRICE LIMITS SUPPOSEDLY have two attributes to control volatility: first, they establish price constraints; second, they provide time for rational reassessment during times of panic trading. Price limits literally limit, or prevent, stock prices from rising above or falling below predetermined price levels. It is posited that such limits would have prevented the price freefall during the 1987 crash. Price limits are also supposed to give frenzied traders time to cool off. Many researchers and market participants blame panic behavior for the excessive volatility that led to the October 1987 crash (Blume, MacKinlay, and Terker (1989) and Greenwald and Stein (1991)). For these reasons, many of the Asian stock exchanges have already adopted daily price limits (Rhee and Chang (1993)). In fact, the Tokyo Stock Exchange (TSE) justifies its price limit system by stating that “it prevent(s) day-to-day wild swings in stock prices,” and that it also provides a “time-out” period (Tokyo Stock Exchange Fact Book (1994)).

Despite the appealing rationale to price limits, research confirming these beneficial aspects is lacking. Ma, Rao, and Sears (1989a) find evidence of price reversals after limits are reached, indicating overreaction and subsequent correction. They also find that volatility subsides after limits were hit. In referring to the study of Ma *et al.* (1989a), however, Lehmann (1989) and

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Miller (1989) both question the knowledge gained from examining volatility after limit days since postlimit prices will undoubtedly experience less volatility.

Price limit critics, on the other hand, contend that there are at least three problems with price limits: volatility spillover, delayed price discovery, and trading interference. Fama (1989) reasons that if the price discovery process is interfered with, underlying volatility may increase as a consequence. This notion is supported by Kyle (1988) and Kuhn, Kurserk, and Locke (1991). Kuhn *et al.* (1991), for example, find that limits were ineffective in reducing volatility during the 1989 U.S. mini-crash. Lehmann (1989) also suggests that supply and demand imbalances for trading actually induce prices to reach their limits, which implies a transfer of transactions to subsequent days. Therefore, rather than reducing volatility, price limits may cause volatility to spread out over a longer period of time because limits prevent large one-day price changes and prevent immediate corrections in order imbalance.¹ This spillover to subsequent trading days is consistent with the volatility spillover hypothesis.²

The delayed price discovery is another costly problem induced by price limits. As price limits represent upper and lower bounds on stock prices, trading usually stops (when limit-hits occur) until the limits are revised creating an interference with the price discovery process, as previously suggested by Fama (1989), Lehmann (1989), and Lee, Ready, and Seguin (1994). By putting constraints on price movements, stocks may be prevented from reaching their equilibrium prices for that day. If limits block prices, then stocks have to wait until a subsequent trading period, usually the next day, to continue toward their true price. This notion is consistent with the delayed price discovery hypothesis.

Lauterbach and Ben-Zion (1993) cite the interference of liquidity (trading) as the "obvious cost" to circuit breakers. This problem is also noted by Fama (1989) and Telser (1989). If price limits prevent trading, then stocks become less liquid, which may cause intensified trading activity on following days. An alternative interpretation is offered by Lehmann (1989). He contends that order imbalances, and the consequent lack of trading, induce prices to reach their limits. The implication is that on subsequent days, impatient investors will buy or sell at unfavorable prices or patient investors will wait for prices to reach their equilibrium levels so order imbalances can be corrected. In both cases, this implies that trading volume will be higher on the days following limit-days. These activities are consistent with the trading interference hypothesis.

¹ Roll (1989) succinctly states, "Most investors would see little difference between a market that went down 20 percent in one day than a market that hit a 5 percent down limit four days in a row. Indeed, the former might very well be preferable."

² In studying NYSE-imposed trading halts, Lee, Ready, and Seguin (1994) find increased trading volume and volatility on days following trading halts.

We empirically test three hypotheses: the volatility spillover hypothesis, the delayed price discovery hypothesis, and the trading interference hypothesis. For our study, we employ a new design to examine price limit performance. Lehmann (1989) and Miller (1989) both criticize the argument of Ma *et al.* (1989a) that volatility declines on days following limit days provide favorable evidence for price limits. They feel that such a finding is inevitable and trivial because volatility is biased (inclined) to decrease on days after high volatility. Furthermore, Lehmann (1989) states that it is difficult to interpret price behavior around limit moves without considering the supply and demand for liquidity. In direct response to their contentions, we compare the behavior of stocks that reach a price limit to stocks that almost reach their daily limit. By examining the postlimit day behavior between both stock categories, we are able to conduct an analysis that is superior to studies that merely compare postlimit days to limit days of stocks that hit limits. Since the former group of stocks experience restraints in their price movement while the latter group of stocks do not, any significant difference in postlimit day behavior can be associated with the price limit.

This study is the first to provide empirical evidence against price limit effectiveness. We study the TSE price limit system because a daily price limit system does not exist on the New York Stock Exchange (NYSE). Furthermore, the TSE is the second largest stock exchange in the world in terms of market capitalization and its price limit system has remained unchanged since 1973. The rest of this article is organized as follows: in Section I, we discuss our methods for appraising TSE price limits; in Section II, we present and discuss our findings; and finally, in Section III we conclude.

I. The Approach

We use daily stock price data from 1989 to 1992 of the First Section of the Tokyo Stock Exchange compiled by the Sandra Ann Morsilli Pacific-Basin Capital Markets (PACAP) Research Center of the University of Rhode Island. In this database, the daily opening, closing, high, and low prices are reported. We adjust our price data to reflect capital distributions that include stock splits, reduction of capital, rights offerings, and stock dividends. Information on capital distributions is also obtained from the PACAP databases.

Table I shows the daily price limits utilized by the TSE. Tick sizes and maximum price variation for successive transactions are also reported. As reflected in the table, the size of the daily price limit depends on the individual stock price. The price limit range for individual securities is based on the previous day's closing price and is reestablished each day.

To find occurrences of prices reaching their limits, we identify days where the high price matches its previous day's closing price plus its price limit. In other words, we assume upward limits are reached for a specific stock when $H_t \geq C_{t-1} + \text{LIMIT}_t$, where H_t represents Day t 's high price, C_{t-1} represents the previous day's closing price, and LIMIT_t is the maximum allowable upward price movement for each Day t . Similarly, we assume downward limits are

Table I

Tick Size, Maximum Price Variation, and Daily Price Limit

The Tokyo Stock Exchange (TSE) utilizes three price stabilization mechanisms: tick size, maximum price variation, and daily price limit. Tick size is the minimum allowable unit that stock price may deviate; maximum price variation is the maximum allowable trade-to-trade price change; and daily price limit is the maximum allowable price change per day. The stock price determines these three values: the last sale price is used to determine tick size and maximum price variation, while the previous day's closing price is used to determine the daily price limits.

Price Range in Yen	Tick Size	Maximum Price Variation	Daily Price Limit
$0 < p < 100$	1	5	30
$100 \leq p < 200$	1	5	50
$200 \leq p < 500$	1	5	80
$500 \leq p < 1,000$	1	10	100
$1,000 \leq p < 1,500$	10	20	200
$1,500 \leq p < 2,000$	10	30	300
$2,000 \leq p < 3,000$	10	40	400
$3,000 \leq p < 5,000$	10	50	500
$5,000 \leq p < 10,000$	10	100	1,000
$10,000 \leq p < 30,000$	100	200	2,000
$30,000 \leq p < 50,000$	100	300	3,000
$50,000 \leq p < 100,000$	100	500	5,000

(Source: TSE Fact Book, 1994)

reached when $L_t \leq C_{t-1} - \text{LIMIT}_t$, where L_t represents Day t 's low price, and LIMIT_t represents the maximum allowable downward price movement.³

On days when price limits are reached, we classify stocks that did not reach the price limit into two subgroups: stocks that came within at least $0.90(\text{LIMIT}_t)$ of reaching the daily limit; and stocks that came within at least $0.80(\text{LIMIT}_t)$, but less than $0.90(\text{LIMIT}_t)$ of reaching the daily limit. In the rest of the article, our stock categories for those stocks that did not hit price limits are referred to as $\text{stocks}_{0.90}$ and $\text{stocks}_{0.80}$, where the subscripts denote the mag-

³ In using this approach, we discover occurrences where high (low) prices are greater (lesser) than their allowed price fluctuation, where prices move beyond their limits. This is caused by (i) stocks priced between ¥1000 and ¥10,000 using a tick size of ¥10, which often results in high or low prices being a few yen over or under their allowed price level and (ii) using a base price to determine the next day's price limits rather than the closing price when order imbalances occur. A special quote, *tokubetsu kehai*, is used as the base price in these circumstances (We thank Masao Takamori and Eitaro Nakagawa of the TSE for this information.). In the TSE, successive transactions must be executed within the maximum price variation range. If successive orders on the same side of the market arrive that exceed this maximum price variation, then a special quote is issued (current stock price plus the maximum price variation). Lehmann and Modest (1994a) provide an excellent description of the special quote process. Also, we have communicated with TSE officials to ensure clean samples, however, because price limits are enforced by the *saitori*, there may be occasions where limits were neglected inadvertently. Nevertheless, there is a very slim chance of this happening and more importantly, if $\text{stocks}_{\text{hit}}$ do contain nonhits, then the empirical findings would be biased against us.

Table II
Summary Statistics

Stocks are categorized into three groups based on the magnitude of their price movement on Day 0 (the event day). $Stocks_{hit}$ denotes stocks that reach their daily price limit. $Stocks_{0.90}$ denote stocks that experience a price change of at least $0.90(LIMIT_t)$ from the previous day's close, but do not reach a price limit; where $LIMIT_t$ denotes the maximum allowable daily price movement on Day t . $Stocks_{0.80}$ denote stocks that experience a price change between $0.80(LIMIT_t)$ and $0.90(LIMIT_t)$. The sample size of each of these three categories during the study period 1989 to 1992 are presented below, for both upward price movements and downward price movements.

Upward Price Movements		Downward Price Movements	
$Stocks_{hit}$	($n = 1,915$)	$Stocks_{hit}$	($n = 528$)
1989	$n = 346$	1989	$n = 15$
1990	$n = 936$	1990	$n = 369$
1991	$n = 286$	1991	$n = 56$
1992	$n = 347$	1992	$n = 88$
$Stocks_{0.90}$	$n = 762$	$Stocks_{0.90}$	$n = 342$
$Stocks_{0.80}$	$n = 1,125$	$Stocks_{0.80}$	$n = 575$

nitude of a stock's price movement on Day 0, the limit-hit-day.⁴ $Stocks_{hit}$ refer to those stocks that reach their daily price limit.

Stocks that reach their limit are prevented from correcting their order imbalance, while stocks that almost hit their limit are not. For example, assuming that the supply for immediacy in these two samples is identical, any differences on postlimit days may be associated with differences in the demand composition for immediacy. Under these conditions, limit up (down) days are days where there is a larger imbalance of motivated buyers over sellers (sellers over buyers). If we assume that the supply of immediacy is not identical between the two categories, then it is plausible to suppose that liquidity suppliers become active less quickly with stocks in the $stocks_{hit}$ sample. Liquidity suppliers may fear the information content of the larger imbalance of motivated buyers over sellers (sellers over buyers) on limit up (down) days, and less likely to supply immediacy. Therefore, $stocks_{hit}$ are more likely to experience order imbalances for liquidity.⁵ Finally, we utilize the $stocks_{0.80}$ sample to show that differences between $stocks_{hit}$ and $stocks_{0.90}$ are not due to the difference in price movement on Day 0 by showing that differences do not exist between $stocks_{0.90}$ and $stocks_{0.80}$.

Table II reports the yearly breakdown of price-limit-hit occurrences and shows the number of occurrences for each of the three stock categories for both upper and lower price movements. For our final samples, we identify 1,915

⁴ We also examined a $stocks_{0.70}$ group and a $stocks_{0.60}$ group. The empirical findings are qualitatively similar to the $stocks_{0.90}$ and $stocks_{0.80}$ results, so we do not report these results for the sake of space and lack of additional insight. Complete empirical results are available from the authors.

⁵ We thank an anonymous referee for his discussion on the demand and supply of immediacy and its potential effect on limit performance.

occurrences where upper daily price limits are reached and 528 occurrences where lower price limits are hit. Interestingly, this implies that limits prevent more stock price increases than decreases.

II. Empirical Findings

A. *The Volatility Spillover Hypothesis*

To test the volatility spillover hypothesis, we utilize a 21-day event window: Day -10 to $+10$. For stocks_{hit}, Day 0 represents the limit-hit-day, for stocks_{0.90}, Day 0 represents the day the stocks experienced their 0.90(LIMIT_{*t*}) price movement and this similarly applies to stocks_{0.80}. Day -1 represents the day before Day 0, and Day 1 is the day after Day 0, and so forth.

Daily price volatility is measured by $V_{t,j} = (r_{t,j})^2$, where $r_{t,j}$ represents close-to-close returns using Day $t - 1$ closing price and Day t closing price for each stock j .⁶ We calculate this measure for each stock in all three stock categories and find averages for each Day t . If the stocks_{hit} group experiences greater volatility during postlimit days than the other subgroups, then this finding supports the volatility spillover hypothesis. We examine the effects of upper price-limit-hits in the next section.⁷

A.1. *Empirical Results: Upper Limits*

Table III contains the V_t data of price increases for stocks_{hit}, stocks_{0.90}, and stocks_{0.80} with multiple limit day observations excluded from the sample.⁸ Excluding observations when stocks hit their limit for the second or third consecutive day eliminates the high prelimit-day volatility bias that occurs when we categorize these consecutive hits as independent events. Consequently, this reduces the sample size for the stocks_{hit} group from 1,915 to 1,653.

Of course, all stock categories experience their highest level of volatility on Day 0. This is the day when stocks_{hit} reach their upper daily price limits and

⁶ Since our database contains daily high and low stock prices, we could have employed Parkinson's (1980) extreme value method to measure volatility. However, Lehmann (1989) correctly points out that variance measures that use extreme values, such as Parkinson's, are subject to measurement error and that, "measurement errors are more probable on high volume days like limit price days." In response to Lehmann's acumen, we therefore use a simple measure of volatility that does not incorporate extreme values.

⁷ We do not report our volatility results for the lower limit-hit cases since the lower limit-hit findings are qualitatively the same as the upper limit-hit findings. The lower limit-hit results can be obtained from the authors upon request.

⁸ We first considered using a sample that included each limit hit as a separate event even though it may have been a second or third consecutive limit day. Since these days would also be considered Day 0, this would bias the pre-event volatility upwards, while its affect on postevent volatility is ambiguous. Using the complete sample, we find that stocks_{hit} experience larger volatility preceding the limit day. However, regardless of whether these multiple hits are included or excluded, the postlimit results remain virtually the same for both samples. Therefore, we only report results without using consecutive limit day stocks as separate events.

Table III
Volatility Spillover: Upper Limit Reaches

For all three stock categories: $stocks_{hit}$, $stocks_{0.90}$, and $stocks_{0.80}$, we calculate volatility for each day for the 21-day period surrounding the event Day 0. The stock categories are based on the magnitude of their price movement on Day 0. $stocks_{hit}$ denotes stocks that reach their daily price limit. $stocks_{0.90}$ denote stocks that experience a price change of at least $0.90(LIMIT_t)$ from the previous day's close, but do not reach a price limit; where $LIMIT_t$ denotes the maximum allowable daily price movement on Day t . $stocks_{0.80}$ denote stocks that experience a price change between $0.80(LIMIT_t)$ and $0.90(LIMIT_t)$. Day 0 denotes the day $stocks_{hit}$ reach their upper-limit-hits. Day -1 represents the day before Day 0. We use daily returns-squared as our volatility measure, which is calculated as follows:

$$V_{t,j} = (r_{t,j})^2,$$

where $r_{t,j}$ denotes the daily return for each stock j on Day t . Here, $V_{t,j}$ is multiplied by 10^3 . \gg and $>$ indicate that the left-hand figure is greater than the right-hand figure at the 0.01 and 0.05 levels of significance, respectively, using the Wilcoxon signed-rank test.

Day	$stocks_{hit}$		$stocks_{0.90}$		$stocks_{0.80}$
-10	1.564		1.508		1.338
-9	1.676		1.506		1.442
-8	1.576		1.620		1.363
-7	1.598		1.624		1.595
-6	1.730		1.862		1.633
-5	2.022		2.214		1.798
-4	2.929	\gg	2.202		2.152
-3	2.452		2.467		2.198
-2	3.346	$>$	2.793		2.576
-1	3.476		4.076		3.656
0	18.234	\gg	12.690	\gg	9.990
1	4.194	\gg	2.333		2.197
2	3.333	\gg	2.553		2.130
3	2.311	\gg	1.745		1.665
4	2.355	\gg	1.856		1.736
5	1.753		1.784		1.486
6	1.783	\gg	1.745		1.466
7	1.576		1.645		1.188
8	1.658		1.661		1.304
9	1.742		1.667		1.354
10	1.419		1.354		1.068

when $stocks_{0.90}$ and $stocks_{0.80}$ experience their extreme price increases. For each day, we compare volatility levels between stock categories by using the nonparametric Wilcoxon signed-rank test. The symbols " \gg " and " $>$ " signify that the left hand volatility measure is greater than the right hand measure at the 0.01 and 0.05 levels of significance, respectively. From Table III, we note differences in Day 0 volatility among stock subgroups, but this observation merely reflects the different degrees of price movement that occur on Day 0, and no significance should be associated with this result because it exists by design.

On Day 1, we observe a large drop in volatility for stocks_{hit} (from 18.234 on Day 0 to 4.194 on Day 1). Researchers may be tempted to conclude that price limits have effectively reduced volatility citing volatility decreases after upper price limits were reached. In fact, Ma *et al.* (1989a) cite this phenomenon as proof that price limits reduce volatility. However, this interpretation is overly simplified because volatility will naturally decline after extremely large volatility days. When we examine Day 1 volatility for the other two stock groups, we again see the same large drop in volatility despite the absence of limit reaches on Day 0. This finding supports Lehmann's (1989) and Miller's (1989) insight. Consequently, we interpret our results differently from Ma *et al.* (1989a); specifically, we note that the volatility of stocks_{hit} during the post-limit-day period does not drop as much as the volatility of the other stock categories. On Day 1, the volatility of stocks_{hit} is almost twice as large as the volatility of stocks_{0,90}. In fact, stocks_{hit} continue to experience greater volatility than stocks_{0,90} for up to four days after the limit-day. Additionally, we observe that the ordering of the estimated day zero volatilities across subgroups is preserved without exception in Days 1 to 4. Similarly, the ordering in Days -1 to -4 is preserved with only two exceptions. Apparently, all three stock categories experience high volatility, ARCH-like episodes, but stocks_{hit} is the only group with a materially different time path after Day 0, consistent with the volatility spillover hypothesis.⁹

We feel that stocks_{hit} experience greater volatility on Days 1 to 4 because stocks that reach their daily price limit may be prevented from correcting their order imbalance. This persisting volatility does not exist for stocks_{0,90} and stocks_{0,80} and there are no postlimit-day differences between stocks_{0,90} and stocks_{0,80}. In fact, for stocks_{hit}, we see that volatility on Day 1 is greater than volatility on Day -1 (further reflecting evidence of volatility spillovers), whereas for the other stock groups volatility is lower on Day 1 than on Day -1 (This is verified with the Wilcoxon signed-rank test where all differences are significant at the 0.01 level.)

We interpret our findings as evidence that price limits cause stocks_{hit} to have volatility spillovers. Stocks that reach their limit are prevented from experiencing larger price changes on Day 0. Price movement, in essence, becomes pent-up on limit days, which leads to volatility spillovers in subsequent days. This interpretation implies that limits do not decrease volatility, but only spread volatility out over a longer period of time.¹⁰ This finding suggests that price limits are not useful in mitigating volatility. In a related

⁹ We are grateful to an anonymous referee for pointing out this important observation.

¹⁰ We also considered reporting the day-to-day change in volatility for all stock subgroups. If price limits were not causing volatility spillovers, then the change in volatility on Day 1, from Day 0, for stocks_{hit} is the most biased among all stocks groups since they, by construction, experience the greatest volatility on Day 0. However, our results find that the magnitude of change for stocks_{0,90} is statistically higher than the magnitude of change for stocks_{hit} on Day 1, indicating volatility spillovers. For the remaining postlimit-days, the day-to-day change in volatility is the same across all stock subgroups because, in general, volatility is known to be serially dependent. For the sake of space, we do not report these results.

study, Lee *et al.* (1994) observe greater volatility in the post-trading-halt period at the NYSE, which indicates that trading halts impede the price adjustment process. Their results are consistent with our findings. Trading halts are like price limits except that they are determined subjectively by exchange officials.

B. The Delayed Price Discovery Hypothesis

To examine price limits' effects on efficient price discovery, we look at the following two returns series for each of the three stock categories: $r(O_0C_0)$ and $r(C_0O_1)$. The first measure represents open-to-close returns on the limit day measured by $\ln(C_0/O_0)$ and the second represents close-to-open returns measured by $\ln(O_1/C_0)$. \ln denotes the natural logarithm operator; O and C denote opening and closing prices, respectively; and subscripts denote the day. Stock returns can be positive, negative, or zero and are denoted as (+), (-), and (0), respectively. Consequently, nine returns series are possible: [+ , +], [+ , -], [+ , 0], [0 , +], [0 , -], [0 , 0], [- , +], [- , -], and [- , 0], where the first return symbol represents $r(O_0C_0)$ and the second return symbol represents $r(C_0O_1)$.

We examine this particular return series to observe the immediate stock price movement subsequent to price-limit-hits on Day 0. By comparing the return series results among all stock groups, we may be able to identify stock return behavior unique to the $stocks_{hit}$ sample. The delayed price discovery hypothesis posits that we will see positive (negative) overnight returns for stocks that reach their upper (lower) limit. Of course, stocks always experience price continuations and reversals, so the price continuation behavior of $stocks_{hit}$ would have to be greater than normal to conclude that limits are delaying the efficient price discovery process. Therefore, we use the price return behavior of stocks that do not reach a price limit to represent normal behavior. These stocks also experience large price changes similar to $stocks_{hit}$, but without limit hits. If $stocks_{hit}$ experience greater price continuation than the other subgroups, then the implication is that price limits prevent stock prices from reaching their equilibrium prices during event Day 0, thereby delaying the efficient price discovery process. This price continuation behavior implies that price limits prevent rational or informed trading (Roll (1989)), otherwise we would observe price reversals in the context of overreactive behavior (Ma *et al.* (1989a, 1989b)). We do not exclude consecutive limit days from our sample since this would only underestimate the frequency of price continuation.

For upper limit hits, we classify [+ , +] and [0 , +] as price continuations. We include the latter as a price continuation since it represents stocks that open at the upper limit, remain unchanged on Day 0, and then experience price increases overnight. Also, for upper limit hits, we classify [+ , -], [0 , -], [- , +], [- , 0], and [- , -] as price reversals. The last three return series are considered reversals because the first negative sign indicates reversals before trading closes on the limit day. Return series [+ , 0] and [0 , 0] represent no change in prices. For lower limit hits, we classify the return sequences [- , -] and [0 , -]

as price continuations and the return sequences $[-, +]$, $[0, +]$, $[+, -]$, $[+, 0]$, and $[+, +]$ as price reversals. Return series $[-, 0]$ and $[0, 0]$ represent no change in prices.

Table IV, Panel A, presents the frequency of price continuations, price reversals, and no changes. For stocks that hit their upper limit, price continuations occur 65 percent of the time and price reversals occur 25 percent of the time. In contrast, for stocks that almost hit the upper limit ($\text{stocks}_{0.90}$), price continuations occur 50 percent of the time and price reversals occur 36 percent of the time. $\text{stocks}_{0.80}$ experience nearly identical return patterns as $\text{stocks}_{0.90}$. For lower limits, $\text{stocks}_{\text{hit}}$ experienced price continuations 49 percent of the time compared to 32 percent for $\text{stocks}_{0.90}$. Also, $\text{stocks}_{\text{hit}}$ experience reversals 44 percent of the time compared to 61 percent for $\text{stocks}_{0.90}$.

Overall, price continuations occur more often for $\text{stocks}_{\text{hit}}$ than for $\text{stocks}_{0.90}$, even though both stock categories experience nearly identical price changes on Day 0.¹¹ This implies that price limits delay the price discovery process, thus supporting the delayed price discovery hypothesis. In addition, limits do not seem to prevent overreactive behavior since price reversal behavior is not predominant for $\text{stocks}_{\text{hit}}$. Although reversals do occur after limit days, they occur more frequently in the absence of limits. From these results, we conclude that price limits seem to be preventing prices from continuing toward their equilibrium prices on Day 0, without curbing overreactive behavior.

Before concluding our discussion on the delayed price discovery results, we must determine whether the delay in price discovery found in the $\text{stocks}_{\text{hit}}$ sample could be due to maximum price variation rules rather than price limit rules.¹² George and Hwang (1995) and Lehmann and Modest (1994a,b) observe that maximum price variation rules slow the price discovery process and that consecutive transactions must be made within prespecified maximum price ranges that lead to order breakup in the TSE. To test for this possibility, we identify stocks whose closing prices match their high (low) prices on Day 0. For the $\text{stocks}_{\text{hit}}$ sample, this identifies those stocks that closed at their price limit. Table IV, Panel B, reports the results. For both upper and lower price movements, stocks that close at their limit experience more continuations and fewer reversals. This evidence indicates that price limits prevent efficient price discovery for the $\text{stocks}_{\text{hit}}$ sample. This is not to say, however, that maximum price variation rules do not contribute to inefficient price discovery, but the

¹¹ To test for statistically significant differences, we use a standard nonparametric binomial test. The following z -statistic is used to answer the question "Do the $\text{stocks}_{\text{hit}}$ sample experience more price continuations than the $\text{stocks}_{0.90}$ sample?": $z = (\text{CON}_{\text{hit}} - \text{PrCON}_{0.90}N_{\text{hit}}) / (\text{PrCON}_{0.90}(1 - \text{PrCON}_{0.90})N_{\text{hit}})^{0.5}$. CON_{hit} denotes the number of price continuations that $\text{stocks}_{\text{hit}}$ experience; $\text{PrCON}_{0.90}$ represents the proportion of price continuations that occur for the $\text{stocks}_{0.90}$ sample and is calculated as $\text{CON}_{0.90}/N_{0.90}$, where $\text{CON}_{0.90}$ denotes the number of price continuations that $\text{stocks}_{0.90}$ experience and $N_{0.90}$ represents the $\text{stocks}_{0.90}$ sample size; and finally, N_{hit} represents the $\text{stocks}_{\text{hit}}$ sample size. The z -statistic is distributed normally since sample sizes are all sufficiently large (See Olkin, Gleser, and Derman (1980, pp. 244–253)).

¹² We are grateful to the referee who motivated this portion of our article.

Table IV

Delayed Price Discovery: Price Continuations and Reversals

To identify price continuations and reversals, we look at the following two returns series: $r(O_t C_t)$ and $r(C_t O_{t+1})$. The first measure represents open-to-close returns measured by $\ln(C_t/O_t)$ and the latter represents close-to-open returns measured by $\ln(O_{t+1}/C_t)$, where O and C denote opening and closing prices respectively and t represents the day. Specifically, we examine $r(O_0 C_0)$ and $r(C_0 O_1)$ for all stocks subgroups, where the first measure looks at the open-to-close returns for Day 0 and the latter measure looks at the immediate following overnight returns. Stock return can either be positive, negative, or zero, and is denoted as (+), (-), and (0), respectively. Consequently, nine returns series are possible: [+ , +], [+ , 0], [+ , -], [0 , +], [0 , 0], [0 , -], [- , +], [- , 0], and [- , -], where the first return represents $r(O_0 C_0)$ and the second return represents $r(C_0 O_1)$. For upper limit hits, we classify [+ , +] and [0 , +] as price continuations, we classify [+ , -], [0 , -], [- , +], [- , 0], and [- , -] as price reversals, and we classify [+ , 0] and [0 , 0] as no change. For lower limit hits, we classify [- , -] and [0 , -] as price continuations, we classify [- , +], [0 , +], [+ , -], [+ , 0], and [+ , +] as price reversals, and we classify [- , 0] and [0 , 0] as no change. We present the total proportions of continuations, reversals, and no change for each stock subgroup. Stocks are categorized into five categories based on the magnitude of their price movement on Day 0 (the event day). S_{hit} denotes stocks that reached their daily price limit. $S_{0.90}$ denote stocks that experience a price change of at least 0.90(LIMIT_{*t*}) from the previous day's close, but do not reach a price limit; where LIMIT_{*t*} denotes the maximum allowable daily price movement on Day *t*. $S_{0.80}$ denote stocks that experience a price change between 0.80(LIMIT_{*t*}) and 0.90(LIMIT_{*t*}). Day 0 denotes the day S_{hit} experience their limit-hits. For the sake of space, we use the abbreviation "S" for each stock group. For each stock group, the proportions may not add to 1.00 due to rounding. The last column reports the difference between S_{hit} and $S_{0.90}$. Z-values based on a binomial test statistic is given in parenthesis. We do not report z-values for other pairwise comparisons. Panel A reports the results for the entire sample. Panel B reports the results only for stocks that closed on Day 0 at its high (low) price for stocks that experienced extreme upward (downward) price movement. Panel B sample sizes for Upward Price Movement stocks are as follows: S_{hit} : $n = 1518$; $S_{0.90}$: $n = 293$; $S_{0.80}$: $n = 425$. Panel B sample sizes for Downward Price Movement stocks are as follows: S_{hit} : $n = 377$; $S_{0.90}$: $n = 124$; $S_{0.80}$: $n = 195$.

Price Behavior	S_{hit}	$S_{0.90}$	$S_{0.80}$	$S_{hit} - S_{0.90}$ (z-value)
Panel A: Entire Sample				
Upward Price Movements				
Continuation	0.65	0.50	0.53	0.15 (13.13)
Reversal	0.25	0.36	0.34	-0.11 (-10.03)
No change	0.09	0.14	0.12	-0.05 (-5.42)
Downward Price Movements				
Continuation	0.49	0.32	0.36	0.17 (8.37)
Reversal	0.44	0.61	0.57	-0.17 (-8.01)
No change	0.07	0.08	0.08	-0.01 (-0.84)
Panel B: Price Behavior for Stocks that Closed at Their High or Low Price on Day 0				
Upward Price Movements				
Continuation	0.70	0.50	0.47	0.20 (15.38)
Reversal	0.21	0.33	0.36	-0.12 (-9.99)
No change	0.09	0.17	0.17	-0.08 (-6.30)
Downward Price Movements				
Continuation	0.59	0.45	0.39	0.14 (5.36)
Reversal	0.35	0.46	0.50	-0.11 (-4.37)
No change	0.06	0.09	0.11	-0.03 (-1.70)

evidence does provide consistent support for the delayed price discovery hypothesis.

C. The Trading Interference Hypothesis

To test the trading interference hypothesis, we only present results for the 10-day period from Day -4 to Day $+5$ because days outside this shorter event period yield no additional insight. To support the trading interference hypothesis, we expect to find trading volume increases for the $\text{stocks}_{\text{hit}}$ group on the day after a limit-hit-day indicating continued intense trading. With increased trading on subsequent days, the implication is that price limits prevent rational trading on the event day, suggesting a harmful interference to liquidity. For other stock subgroups, we expect to see decreased or stabilized trading activity on subsequent days because price limits do not interfere with their trading on Day 0.

To examine the trading activity behavior around limit-days, we use the following turnover ratio as our measure for trading activity: $\text{TA}_{t,j} = \text{TVOL}_{t,j} / \text{SOUT}_{t,j}$, where $\text{TVOL}_{t,j}$ represents trading volume for each stock j on Day t and $\text{SOUT}_{t,j}$ represents the total number of shares outstanding for stock j on Day t . We calculate this ratio for each stock in all three stock categories and then find averages for each Day t . Because the liquidity interference hypothesis is interested in the day-to-day change in trading activity, we calculate a percentage change from the previous day as follows: $\ln(\text{TA}_{j,t} / \text{TA}_{j,t-1}) * 100$. In this analysis, we present results using samples that exclude consecutive limit-days to be consistent with our volatility analysis.¹³ Upper limit hits are examined in the next section.¹⁴

C.1. Empirical Results: Upper Limits

Table V presents the day-to-day trading activity changes for each of our three stock categories that show an overall pattern of trading increases as Day 0 approaches. Not surprisingly, our results reveal increases in trading activity on Day 0 that are much larger than the changes on previous days. However, the most striking result is that $\text{stocks}_{\text{hit}}$ experience an increase in trading activity on Day 1, the day after the limit day. For $\text{stocks}_{0.90}$ and $\text{stocks}_{0.80}$, trading decreases significantly on Day 1. This result is especially striking because $\text{stocks}_{0.90}$ and $\text{stocks}_{\text{hit}}$ both experience nearly identical upward price movements on Day 0.

The overall decline in trading for stocks with no limit hits indicates that traders, for the most part, obtain their desired positions on Day 0 in the absence of price limits. In contrast, because price limits interfere with trading for $\text{stocks}_{\text{hit}}$ on Day 0, traders wait for the subsequent day to obtain their

¹³ While we do not report them, we also conducted our study using complete samples and find very similar results, thus reflecting the robustness of our trading interference findings.

¹⁴ Again, we do not report the results for the lower limit cases since the results are qualitatively the same as the upper limit-hit findings.

Table V
Trading Interference: Upper Limit Reaches

For all three stock categories: stocks_{hit}, stocks_{0.90}, and stocks_{0.80}, we calculate trading activity for each day for the 11-day period surrounding the event Day 0. The stock categories are based on the magnitude of their price movement on Day 0. Stocks_{hit} denotes stocks that reach their daily price limit. Stocks_{0.90} denote stocks that experience a price change of at least 0.90(LIMIT_t) from the previous day's close, but do not reach a price limit; where LIMIT_t denotes the maximum allowable daily price movement on Day *t*. Stocks_{0.80} denote stocks that experience a price change between 0.80(LIMIT_t) and 0.90(LIMIT_t). Day 0 denotes the day stocks_{hit} experience their upper-limit-hits. Day -1 represents the day before Day 0. Trading activity (TA) is measured by a turnover ratio where for each company *j* on Day *t*, we divide daily trading volume by daily total shares outstanding. For each day, we report the percentage change in trading activity from the previous day: $\ln(TA_{j,t}/TA_{j,t-1}) * 100$, where \ln represents the natural log operator. We calculate this percentage change for each stock *j* and report the daily means. >> and > indicate that the left-hand figure is greater than the right-hand figure at the 0.01 and 0.05 levels of significance, respectively, using the Wilcoxon signed-rank test.

Day	Stocks _{hit}		Stocks _{0.90}		Stocks _{0.80}
-4	12.70%		7.05%		8.09%
-3	10.52%		9.86%		9.78%
-2	9.50%		8.04%		7.68%
-1	20.60%		25.33%		15.13%
0	72.54%	<	82.48%	>	74.01%
1	21.07%	>>	-23.94%		-21.82%
2	-54.34%	<	-45.20%	<<	-33.77%
3	-14.97%		-15.60%		-11.76%
4	-11.56%	<	-4.43%		-9.41%
5	-10.11%		-9.05%		-5.60%

desired position. As posited by Lehmann (1989), on the days after prices reach their limits, impatient investors will buy or sell at unfavorable prices or patient investors will wait for prices to be allowed to reach their equilibrium levels so that order imbalances can be corrected. As a result, we observe higher trading activity on the days following limit-days, indicating order imbalances for liquidity. Our results indicate that, for the stocks_{hit} sample, investors are forced to wait until the next trading day to continue to transact.

C.2. The Relation between Volatility and Trading Volume

French and Roll (1986), Harris (1986), Karpoff (1987), Schwert (1989), and Stoll and Whaley (1990), among others, document a positive relation between volatility and trading volume. So far, we have shown that price limits interfere with trading activity. In this section, we investigate the effect that trading interference may have on the volatility to further support the trading interference hypothesis. To examine this issue, we employ the following cross-sectional regression:

$$V_j = a + b(TA)_j + c(\text{Hit-Dummy})_j + d_j, \tag{1}$$

where V_j is our previously discussed volatility measure for each stock j , TA_j is the previously introduced turnover ratio for each stock j , and Hit-Dummy represents a dummy variable that equals 1 for stocks that reach an upper or lower price limit ($\text{stocks}_{\text{hit}}$) and 0 otherwise. The above regression is run for each day of our 21-day event period. We conduct two separate analyses for upper and lower price movements, where each sample includes two groups of stocks that experience nearly identical upward (downward) price movement on Day 0: $\text{stocks}_{\text{hit}}$ and $\text{stocks}_{0,90}$. We use samples that exclude consecutive limit-hit-days to be consistent with our previous analyses.

Naturally, we expect the trading activity variable to be significantly positive on all prelimit days during our 21-day event period, consistent with previous literature. On the event Day 0, we doubt that the typical positive relation between volatility and trading activity can prevail because of the trading constraints imposed by price limits. This, therefore, would imply that on Day 0, the Hit-Dummy variable will become significantly positive. We also expect the Hit-Dummy variable to remain significant on Days 1 to 4 because price limits, as we found earlier, cause volatility spillovers that last for four days.

Table VI reports the regression results for our upper limit analyses.¹⁵ As expected, Table VI presents a positive significant relation between trading volume and volatility during the prelimit-day period, Days -10 to -1 , and the positive relation disappears on the event Day 0 due to the trading interference that price limits cause. This finding is further supported by the significantly positive Hit-Dummy variable on Day 0. More importantly, on Day 1, the positive Hit-Dummy variable indicates that the Day 0 price-limit-hits continue to explain the high volatility, while the trading activity variable does not. Furthermore, consistent with our volatility spillover results and consistent with our expectations, the dummy variable continues to remain significant until Day 4.

These findings have two very important implications: one, the trading interference caused by price limits disturbs the normal positive relation between volatility and trading volume; and two, price limits, not high trading volume, directly cause the volatility spillovers on Day 1. On Days 2 to 4, price limits continue to explain the volatility spillovers.

III. Conclusion

We find evidence to support the position of price limit critics who question the effectiveness of price limits in the stock markets. Using three categories of stocks based on the magnitude of a one day price movement, we examine the TSE price limit system to compare volatility levels, price continuation and reversal activity, and trading activity patterns. For stocks that experience limit-hits, we document the following results: volatility does not return to normal levels as quickly as the stocks that did not reach price limits (volatility spillover hypothesis); price continuations occur more frequently than for stocks

¹⁵ The lower limit results (not reported) are qualitatively the same as the upper limit findings.

Table VI

Trading Interference: Regression Results for Upper Limit Reaches

The following cross-sectional ordinary least squares regressions are run to examine the relation between trading activity (TA) as measured by trading volume/shares outstanding and volatility (V):

$$V_j = a + b(TA)_j + c(\text{Hit-Dummy})_j + d_j,$$

where Hit-Dummy equals 1 for stocks that reached an upper price limit ($\text{stocks}_{\text{hit}}$) and 0 otherwise. V_j is measured by the daily returns-squared for each stock j and $(TA)_j$ is measured by a turnover ratio where for each company j , we divide daily trading volume by daily total shares outstanding. For each day, the percentage change in trading activity from the previous day is calculated as follows: $\ln(TA_{j,t}/TA_{j,t-1}) * 100$, where \ln represents the natural log operator. The above regression is run for each day for our 21-day event period. Our sample includes two groups of stocks that experience nearly identical upward price movement on Day 0: $\text{Stocks}_{\text{hit}}$ and $\text{Stocks}_{0.90}$. $\text{Stocks}_{\text{hit}}$ denotes stocks that reach their daily price limit. $\text{Stocks}_{0.90}$ denote stocks that experience a price change of at least 0.90(LIMIT) _{t} , from the previous day's close, but do not reach a price limit; where LIMIT_t denotes the maximum allowable daily price movement on Day t . Day 0 denotes the day $\text{stocks}_{\text{hit}}$ experience their upper-limit-hits. Consistent with previous volatility data, we multiply V_j by 10^3 .

Day	Intercept	Trading Activity	Hit-Dummy	Adj. R ²	F-Value
-10	1.102**	0.129**	0.014	0.084	106.25**
-9	1.242**	0.083**	0.141	0.034	41.20**
-8	1.230**	0.110**	-0.087	0.062	77.49**
-7	1.265**	0.093**	-0.003	0.057	71.43**
-6	1.489**	0.077**	-0.063	0.022	27.73**
-5	1.722**	0.098**	-0.116	0.088	113.90**
-4	1.819**	0.075**	0.797**	0.039	47.89**
-3	2.088**	0.068**	0.019	0.029	35.53**
-2	2.643**	0.058**	0.397	0.013	16.33**
-1	3.694**	0.058**	-0.552	0.024	29.88**
0	12.610**	0.002	5.588**	0.066	83.57**
1	2.296**	0.007	1.816**	0.017	21.09**
2	2.238**	0.032**	0.762**	0.015	18.76**
3	1.350**	0.055**	0.443*	0.042	52.78**
4	1.378**	0.066**	0.426*	0.056	70.76**
5	1.385**	0.058**	-0.085	0.061	76.46**
6	1.440**	0.053**	-0.003	0.038	47.26**
7	1.229**	0.066**	-0.067	0.067	84.60**
8	1.380**	0.058**	-0.068	0.038	46.41**
9	1.342**	0.058**	0.072	0.028	34.02**
10	1.041**	0.064**	0.031	0.054	66.75**

** and * denote statistical significance at the 0.01 and 0.05 levels, respectively.

that did not reach limits (delayed price discovery hypothesis); and trading activity increases on the day after the limit day, while all other stock sub-groups experience drastic trading activity declines (trading interference hypothesis). We attribute these findings to price limits.

Based on our results, we question the effectiveness of price limits in countering overreaction and in reducing volatility. Furthermore, price limits seem

to cause delays in equilibrium price discovery and desired trading activity. We concede, however, that our small sample sizes are a weakness in our study. TSE price limits are set wide enough so that limit reaches are rare events. Nonetheless, based on our sample and analysis, the evidence against price limits appears to be significant.

REFERENCES

- Blume, Marshall E., A. Craig MacKinlay, and Bruce Terker, 1989, Order imbalances and stock price movements on October 19 and 20, 1987, *Journal of Finance* 44, 827–848.
- Fama, Eugene F., 1989, Perspectives on October 1987, or What did we learn from the crash?, in Robert W. Kamphuis, Jr., Roger C. Kormendi, and J. W. Henry Watson, Eds.: *Black Monday and the Future of the Financial Markets* (Irwin, Homewood, Ill.).
- French, Kenneth, and Richard Roll, 1986, Stock return variances: The arrival of information and the reaction of traders, *Journal of Financial Economics* 7, 5–26.
- George, Thomas J., and Chuan-Yang Hwang, 1995, Transitory price changes and price-limit rules: Evidence from the Tokyo Stock Exchange, *Journal of Financial and Quantitative Analysis* 30, 313–327.
- Greenwald, Bruce C., and Jeremy C. Stein, 1991, Transactional risk, market crashes, and the role of circuit breakers, *Journal of Business* 64, 443–462.
- Harris, Lawrence, 1986, A transaction data study of weekly and intradaily patterns in stock returns, *Journal of Financial Economics* 16, 99–117.
- Karpoff, Jonathan M., 1987, The relation between price changes and trading volume: A survey, *Journal of Financial and Quantitative Analysis* 22, 109–126.
- Kuhn, Betsy A., Gregory J. Kurserk, and Peter Locke, 1991, Do circuit breakers moderate volatility? Evidence from October 1989, *The Review of Futures Markets* 10, 136–175.
- Kyle, Albert S., 1988, Trading halts and price limits, *The Review of Futures Markets* 7, 426–434.
- Lauterbach, Beni, and Uri Ben-Zion, 1993, Stock market crashes and the performance of circuit breakers: Empirical evidence, *Journal of Finance* 48, 1909–1925.
- Lee, Charles M. C., Mark J. Ready, and Paul J. Seguin, 1994, Volume, volatility, and New York Stock Exchange trading halts, *Journal of Finance* 49, 183–214.
- Lehmann, Bruce N., 1989, Commentary: Volatility, price resolution, and the effectiveness of price limits, *Journal of Financial Services Research* 3, 205–209.
- Lehmann, Bruce N., and David M. Modest, 1994a, Market structure and liquidity on the Tokyo Stock Exchange, Finance Working paper No. 235, University of California-Berkeley.
- Lehmann, Bruce N., and David M. Modest, 1994b, Liquidity on the Tokyo Stock Exchange: A bird's eye view, *Journal of Finance* 49, 183–214.
- Ma, Christopher K., Ramesh, P. Rao, and R. Stephen Sears, 1989a, Volatility, price resolution, and the effectiveness of price limits, *Journal of Financial Services Research* 3, 165–199.
- Ma, Christopher K., Ramesh P. Rao, and R. Stephen Sears, 1989b, Limit moves and price resolution: The case of the Treasury Bond futures market, *Journal of Futures Market* 9, 321–335.
- Miller, Merton H., 1989, Commentary: Volatility, price resolution, and the effectiveness of price limits, *Journal of Financial Services Research* 3, 201–203.
- Olkin, Ingram, Leon J. Gleser, and Cyrus Derman, 1980, *Probability Models and Applications* (MacMillan, New York).
- Parkinson, Michael, 1980, The extreme value method for estimating the variance of the rate of return, *Journal of Business* 53, 61–65.
- Rhee, S. Ghon, and Rosita P. Chang, 1993, The microstructure of Asian equity markets, *Journal of Financial Services Research* 6, 437–454.
- Roll, Richard, 1989, Price volatility, international market links, and their implications for regulatory policies, *Journal of Financial Services Research* 3, 211–246.
- Schwert, William G., 1989, Why does stock market volatility change over time? *Journal of Finance* 44, 1115–1153.

- Stoll, Hans, and Robert Whaley, 1990, Stock market structure and volatility, *Review of Financial Studies* 3, 37–71.
- Telser, Lester G., 1989, October 1987 and the structure of financial markets: An exorcism of demons, in Robert W. Kamphuis, Jr., Roger C. Kormendi, and J. W. Henry Watson, Eds.: *Black Monday and the Future of the Financial Markets* (Irwin, Homewood, Ill.).
- Tokyo Stock Exchange, 1994, *Tokyo Stock Exchange Fact Book*, (Tokyo Stock Exchange, Tokyo, Japan).