# Chapter 6.

# Empirical Findings

Based on the reasoning suggested in Chapter 4, we examine how the existence of circuit breakers affects price behavior using Korean stock market data. After providing descriptive statistics, we test the price overshooting hypothesis and also volatility implications due to circuit breakers.

In the interest of brevity, we report the results for 8 firms whose names are shown in bold characters in Table 4.2 although all 30 individual firms have been analyzed.[44] They include 1 from mining, 3 from manufacturing (including 1 administrative issue), 1 from construction and 3 from financial and other services.

## 6.1. Descriptive Statistics

### 6.1.1. Frequency of Limit Triggering

To see how frequently price limits were triggered, we first calculated the number of trading days that price limits were triggered for each individual firm during the sample period. Table 6.1 summarizes the proportion of trading days that the upper and lower limit were triggered. Due to the narrowness of price limits, the proportion of limit-triggered events for the normal issues averages out to 13.4 percent, ranging from 7.9 to 16.9 percent of 1761 daily observations. For the administrative issue (I.D.:

[44]We obtained similar results for all 30 firms although there are minor differences between industries. The results for the firms which are not reported here are available upon request.

42010), the proportion amounts to 60 percent, most of which were triggered consecutively. This indicates that price movements were severely restricted due to price limits for more than half of the sample period.

Among those limit-triggered events, the upper limits were triggered roughly twice as much as the lower limits were. This can partly be explained by the fact that the Korean stock market experienced upward price movements during the sample period with large price swings. The Korean Stock Index which was 277 on Dec. 15, 1986 ended up at 669 at the end of 1992 after reaching its highest point of 1007 on April 1989.

Certain industries such as construction (75100) and securities (88010) show a higher percentage of limit-triggered events. They are often called *leading issues* by investors in the sense that they move faster than others in response to a marketwide shock. As a result, their price movements are more volatile than others as shown later in Table 6.3 and 6.4. In order to see how the frequency of limit-triggering is related to the responsiveness to a marketwide shock, we report the market beta at the bottom of the table. Betas are frequently used to measure the sensitivity of stock prices to overall fluctuations in the market portfolio.[45] Figure 6.1 plots the proportion of the limit-triggered events and beta values for all sample firms excluding the administrative issues. As expected, the firms with bigger beta values show the higher percentage of the limit-triggered events.

We also examined whether the frequency of limit-triggering is affected by stock prices. As a stock price becomes higher, a greater proportion of limit-triggering is expected since price limits become narrower in percentage terms. Figure 6.2 shows

[45]Due to difficulties in obtaining beta estimates of each firm, I used as a proxy the industry betas to which each firm belongs from the U.S. stock market. Data are from the Value Line Industry Review which releases betas monthly estimated using the weekly data over a period of 5 years. Since changes over time are minor, I used betas released in Dec., 1993.

the stock prices and the proportion of the limit-triggered events. The administrative issues are excluded since their high percentage of limit-triggering is due to narrowly specified price limits. The result shows that the proportion of limit-triggering tends to increase as stock prices become higher, although they are dispersed.

### 6.1.2. Price Overshooting

In order to examine the price overshooting hypothesis, successive price changes after the limit-triggered events are calculated and compared to events where limits were not triggered. We calculated sample means of successive price changes defined in (4.6) for three events: *UPLIM, LOLIM* and *NO* (the event that price limits were not triggered). Table 6.2 shows how much price overshoots its equilibrium level after price limits were triggered. Significant differences in sample means between the limit-triggered events and the other events indicate that a substantial price overshooting has occurred. In the case when price limits were not triggered, sample means of successive price changes take values which are close to zero. On the other hand, the mean of successive price changes shows a significant negative bias after the upper limits were triggered and a positive bias after the lower limits were triggered. In most cases, the magnitude of price overshooting ranges from 1 to 3 percent which is substantial considering that average maximum price change is 4.6 percent. Among the limit-triggered events, the magnitude of overshooting turned out to be greater for the lower limit-triggered events than for the upper limit-triggered events.

Compared to normal issues, the administrative issue (42010) shows a smaller amount of overshooting. However, it is partly due to the more restrictive nature of price limits applied to the administrative issue. Considering that the maximum daily price change for the administrative issue is 1~2 percent for most cases, the overshooting magnitude of 0.5 percent for the daily return cannot be said to be small.

We also examined how responsiveness to a marketwide shock affects the magnitude of price overshooting. Figure 6.3 plots the sample mean of the intraday return after the limit-triggered events and market betas for each firm except the administrative issues. Greater price overshooting is observed for stocks with high betas, suggesting that prices tend to overshoot more when due to a marketwide shock.

### 6.1.3. Increased Volatility

To examine how the existence of price limits affects price volatility, we calculated the conditional standard deviation defined in (4.7) and the average dispersion in (4.8) after the limit-triggered events and compared those with the events where price limits were not triggered. We found the increased volatility in both measures, which suggests that volatility has substantially increased after price limits were triggered.

Table 6.3 reports the conditional standard deviation of successive price changes after each event. Reflecting the fact that variances are an increasing function of time intervals, the conditional standard deviation was shown to be greater with longer time interval.[46] In all cases except the administrative issue, standard deviations of intraday, daily and weekly returns are greater after the limit triggered events. Roughly speaking, price volatility increased more than 20 percent after price limits were triggered. One exception is the administrative issue (42010), for which volatility

[46] When a discrete-time process $\{X_t\}$ follows a random walk (with drift), its variance is an increasing function of time intervals. That is, $Var(X_t) = t \cdot \sigma^2$ where $\sigma^2$ is the variance of random errors. The best-known examples of time series which behave like random walks are share prices on successive days, as is the case for this study.

becomes smaller in the case of the daily and weekly return. However, less volatility for the administrative issue after the limit-triggered events is mainly due to the fact that price limits are consecutively triggered in most cases as shown in Table 6.1. The very restrictive nature of price limits for the administrative issues dictates successive price movements in the same direction, which brings a decrease in volatility.[47]

Among the limit-triggered events, the lower limit-triggered events are found to be associated with greater volatility than the upper limit-triggered events. This indicates that people become more worried when they are confronted with a negative shock. Alternatively, we can interpret it as being due to the gravitational effect. When price approaches the lower limit, those who are liquidity-constrained will be afraid of being locked into their position and expedite their selling activities. Such an increase in noise-based trading will bring additional uncertainty since value traders find it more difficult to disentangle signal from noise, resulting in greater volatility after the lower limit-triggered events.

Average dispersion for intraday, daily and weekly returns is reported in Table 6.4. In order to exclude bias due to price overshooting, we deducted the bias reported in Table 6.2 from the original successive price change series and calculated the mean absolute error for the adjusted series.[48] Similar patterns to those of the conditional standard deviation are exhibited. Average dispersion for the limit-triggered events are more than 30 percent greater than the case when price limits were not triggered. And also, lower limit-triggered events showed greater dispersion than upper limit-triggered events.

[47]For example, consider the extreme case when a maximum price change is close to zero. Price limits will be triggered in most trading days and one can observe decreased volatility after the limit-triggered event.

[48]By doing this, we can guarantee a zero mean for a successive price change series. We also calculated the average absolute value for the original price difference series. Reflecting the bias due to price overshooting, the dispersion was slightly greater in all events than the one reported in Table 4.6.

We plot the conditional standard deviations and market betas to see how the responsiveness to a marketwide shock affects price volatility. The vertical axis represents the ratio of the conditional standard deviations of the limit-triggered events compared to those of non-limit triggered events for the intraday return. Figure 6.4 tells us that price volatility has no clear relation to betas.[49] Although the absolute magnitude of conditional volatility is greater for limit-triggered events, its relative magnitude compared with non-triggered events is not affected by betas. Also, it can be easily confirmed from the figure that price volatility for lower limit-triggered events is greater than that for upper limit-triggered events.

### 6.1.4. Distribution of Price Changes

The above evidence of increased volatility together with price overshooting can be more clearly identified by relying on the figure. We chose three firms which represent different industries, one from manufacturing (28550), one from construction (75100) and one from financial services sector (88010). Figure 6.5a, 6.5b and 6.5c exhibit the distribution of daily returns after each event for three firms. When price limits were not triggered, daily returns are distributed symmetrically around zero. However, a significant negative (positive) bias in mean is observed in all three cases after the upper (lower) limit-triggered events. Also, it can be easily observed that the limit-triggered events are associated with greater volatility.

[49]When the conditional volatility itself rather than the ratio is plotted on the vertical axis, a positive relation between volatility and beta is observed.

### 6.2. Estimation Method and Results

6.2.1. Test of Price Overshooting

To test the empirical validity of the price overshooting hypothesis more formally, we run several regressions based on (4.5). It follows from (4.5) that

$$R_t = \beta_0 + \beta_1 \cdot UPLIM_{t-1} + \beta_2 \cdot LOLIM_{t-1} + \varepsilon_t \tag{6.1}$$

where $R_t$ denotes successive price changes in percentage terms. If price overshooting has occurred, the coefficient on the *UPLIM* dummy will take a significant negative sign while the coefficient will be positive for the *LOLIM* dummy.

Several explanatory variables are included in (6.1) to control for other effects besides circuit breakers. The dummy variables indicating the consecutive limit triggered events and the events where price limits do not apply (*UPLIM2, LOLIM2* and *BAD*) are included. We included lagged return variables considering the empirical evidence that short-horizon returns for individual securities are negatively autocorrelated. (Lo and MacKinlay (1988) and Conrad, Kaul and Nimalendran (1991)) Trading volume is included to control for its possible effect on returns. The expanded equation is given as follows:

$$\begin{aligned} R_t = \beta_0 &+ \beta_1 \cdot UPLIM_{t-1} + \beta_2 \cdot LOLIM_{t-1} + \beta_3 \cdot UPLIM2_{t-1} + \beta_4 \cdot LOLIM2_{t-1} \\ &+ \beta_5 \cdot BAD_t + \beta_6 \cdot VOL_t + \sum_{j=1} \gamma_{t-j} R_{t-j} + \varepsilon_t \end{aligned} \tag{6.2}$$

Based on (6.2), the intraday, daily and weekly returns are regressed on the above set of explanatory variables, which generates three separate equations. The same explanatory variables are used except for some minor changes in the lagged return and volume series. In a regression with *IR* (Intraday Return) as a regressed variable, lagged return variables include *OR* (Overnight Return) which is the immediate past return and $IR_{t-1}$. For equations with *DR* (Daily Return) and *WR* (Weekly Return) as dependent variables, we included the first lag of the dependent variable.[50] Whereas daily trading volume series (*VOL*) are included in the regression of *IR* and *DR*, the weekly moving average of trading volume series (*WVOL*) is used in the regression for weekly return. The three regression equations being run for the test of price overshooting are given as follows:

$$\begin{aligned} IR_t = \beta_0 + \beta_1 \cdot UPLIM_{t-1} + \beta_2 \cdot LOLIM_{t-1} + \beta_3 \cdot UPLIM2_{t-1} + \beta_4 \cdot LOLIM2_{t-1} \\ + \beta_5 \cdot BAD_t + \beta_6 \cdot IR_{t-1} + \beta_7 \cdot OR_{t-1} + \beta_8 \cdot VOL_t + \varepsilon_t \end{aligned} \tag{6.3a}$$

$$\begin{aligned} DR_t = \beta_0 + \beta_1 \cdot UPLIM_{t-1} + \beta_2 \cdot LOLIM_{t-1} + \beta_3 \cdot UPLIM2_{t-1} + \beta_4 \cdot LOLIM2_{t-1} \\ + \beta_5 \cdot BAD_t + \beta_6 \cdot DR_{t-1} + \beta_7 \cdot VOL_t + \varepsilon_t \end{aligned} \tag{6.3b}$$

$$\begin{aligned} WR_t = \beta_0 + \beta_1 \cdot UPLIM_{t-1} + \beta_2 \cdot LOLIM_{t-1} + \beta_3 \cdot UPLIM2_{t-1} + \beta_4 \cdot LOLIM2_{t-1} \\ + \beta_5 \cdot BAD_t + \beta_6 \cdot WR_{t-6} + \beta_7 \cdot WVOL_t + \varepsilon_t \end{aligned} \tag{6.3c}$$

where $OR_t = (OPEN_{t+1} - CLOSE_t) / CLOSE_t$ and $WVOL_t = \sum_{i=0}^{5} VOL_{t+j}$.

If the price overshooting hypothesis is true, *UPLIM* and *LOLIM* will have significant negative and positive coefficient in all of the above equations. Since *UPLIM2* (*LOLIM2*) are dummies indicating the events that the upper (lower) limits

[50]It is possible that returns are autocorrelated with lags of order higher than one. However, in the estimated equations, coefficients at higher lags than one turn out to be insignificant in most cases. Although there are cases where coefficients at higher lags are significant, those lags are different for each individual firm. Since omission of higher lags did not change the results significantly, only the first lag of the dependent variable is included in the regression equation.

are triggered both today and the next day, their coefficients will be positive (negative). The coefficients on the past return variables are expected to have a negative sign if negative autocorrelation in short-horizon return exists.

Tables 6.5a, 6.5b and 6.5c report the regression results for the equations (6.3a) to (6.3c). Whereas (6.3a) and (6.3b) are estimated by OLS, the regression equation for weekly return, (6.3c), is estimated by Cochrane and Orcutt's iterative procedure.[51] Since we used daily data for individual stock, $R^2$ is relatively small in the intraday and daily returns. However, the better fit is obtained in the regression of weekly returns.

Similar to the results shown in the descriptive statistics, coefficients on *UPLIM* and *LOLIM* have the expected and significant signs in all equations. Although the magnitude of price overshooting differs for individual firms, it does range from one to two percent in most cases, which is a substantial amount. Even for the administrative issues where price limits are narrowly specified, the price overshooting phenomenon is observed to hold although its magnitude is smaller.

The coefficients for *UPLIM2 (LOLIM2)* for the intraday and daily returns also have positive (negative) sign, which is dictated by its nature, and all of them are statistically significant. On the other hand, it can be observed that the coefficients for weekly returns have the opposite sign compared to those for intraday and daily returns. Note that *UPLIM2* (*LOLIM2*) is a dummy indicating the event that the upper (lower) limit is consecutively triggered for two days or more. Consecutive triggering of the price limit may cause people to hold more optimistic beliefs than for the single limit-triggered event and the magnitude of overshooting may be greater. Although the *UPLIM2* (*LOLIM2*) dummy dictates the *next day's* price to move in the same

[51]We conducted the Lagrange multiplier test suggested by Breusch-Godfrey (1978) to detect the possible autocorrelation. Whereas we could not reject the null hypothesis of no autocorrelation for Eq. (6.3a) and (6.3b), severe first order autocorrelation was found for Eq. (6.3c).

direction, greater overshooting for the successive limit-triggered events dominates the first day's effect as time passes, which causes the above reversion in signs.

The negative coefficients of the contemporaneous dummy *BAD* for intraday and daily return indicate that price declines due to issuance of new shares or payoff of dividends are not completely reflected in the daily opening price, but those coefficients are not significant for daily returns. For weekly returns, it takes on a positive sign indicating there was a tendency for price change due to those events to move toward the initial prices as time passes.

The negative significant coefficients of the immediate past returns suggest the possibility of mean reversion in short-horizon expected returns. This is consistent with the empirical findings by Lo and MacKinley (1988) and Conrad, Kaul and Nimalendran (1991). These authors find that whereas the weekly and monthly *portfolio* returns are strongly positively autocorrelated, *individual security* returns are negatively autocorrelated.[52]

Trading volume is found to have a positive correlation with successive price changes in all equations. This indicates that price tends to rise when trading volume is heavy.

### 6.2.2. Convergence Pattern

We also examined how rapidly the overshot price converges to an equilibrium by employing an unrestricted, finite distributed lag model. Lagged values of the *UPLIM* and *LOLIM* dummies are included in (6.3b), the regression equation for daily

[52]To explain the different time-series properties of portfolio and individual securities, Lo and MacKinley (1988) suggest that idiosyncratic market microstructure effects causing a negative autocorrelation are diversified away and dominated by a positively autocorrelated common component in the case of portfolios.

returns. Appropriate lag length is chosen to be 7 for both dummies, which shows how the overshot price converges over about one week.[53]

$$
\begin{aligned}
DR_t = \beta_0 + \sum_{i=1}^{7} \beta_i \cdot UPLIM_{t-i} + \sum_{j=1}^{7} \gamma_j \cdot LOLIM_{t-j} + \lambda_1 \cdot UPLIM2_{t-1} \\
+ \lambda_2 \cdot LOLIM2_{t-1} + \lambda_3 \cdot BAD_t + \lambda_4 \cdot DR_{t-1} + \lambda_5 \cdot VOL_t + \varepsilon_t
\end{aligned}
\tag{6.4}
$$

Table 6.6 summarizes the regression results based on OLS. The results including the first lag of *UPLIM* and *LOLIM* are almost the same as those reported in Table 6.5b. Regarding the distribution of lag coefficients for *UPLIM* and *LOLIM*, the coefficients of lags higher than 2 are statistically insignificant in most cases. This suggests that the overshot price nearly approaches its equilibrium level within one or two days. Also, it is found that the overshot prices converges more rapidly for the lower limit-triggered event than for the upper limit-triggered event.

In order to compare convergence patterns of the upper and lower limit-triggered events, we averaged the coefficients of 8 individual firms at each lag. Figure 6.6 presents the distribution of lag coefficients for the upper and lower limit-triggered events. The vertical axis refers to the average coefficients for each lag of *UPLIM* and *LOLIM* dummies. In the case of the upper limit-triggered events, price converges smoothly to the equilibrium level but it takes almost one week. On the other hand, the lower limit-triggered events converges relatively quickly but with fluctuation. Although the convergence patterns shown in Figure 6.6 are based on the average value of 8 individual firms, they are representative of individual stocks shown in Table 6.6.

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[53]We applied Akaike's information criterion (AIC) and also the Schwarz criterion to determine the appropriate lag length. Although it turned out to be 2 to 3 in many cases, it differs for each individual firm. Since we have a large number of observations, we chose a lag length of 7, which allows us to see the convergence pattern over about a week.

### 6.2.3. Volatility Test

A variant of the Autoregressive Conditional Heteroscedastic (ARCH) model is employed to examine how the existence of price limits affects price volatility. It has long been recognized that speculative asset prices have the characteristic of time-varying volatility.[54] For example, large and small forecast errors appear to occur in clusters, suggesting a form of heteroscedasticity where the variance of the forecast errors depends on the size of the preceding disturbances. The ARCH model introduced in Engle (1982) explicitly recognizes this type of temporal dependence. According to the ARCH model, the conditional error distribution is normal, but with conditional variance equal to a linear function of past squared errors. Thus, there is a tendency for extreme values to be followed by other extreme values, but of unpredictable sign.

To analyze the volatility effect of circuit breakers, we first introduce a simple version of the ARCH model which is given as follows:[55]

$$\begin{aligned} R_t &= \beta' X_t + \varepsilon_t \\ E[\varepsilon_t^2 \mid \Phi_{t-1}] &= \alpha_0 + \alpha_1 \cdot \varepsilon_{t-1}^2 \end{aligned} \qquad (6.5)$$

where the first equation in (6.5) is a replication of (6.3a) to (6.3c). Equation (6.5) says that *conditional on an information set* $\Phi_{t-1}$, $\varepsilon_t$ is heteroscedastic.

In addition to the preceding disturbances, limit-triggered events would be another source of heteroscedasticity if circuit breakers affect price volatility. That is, if

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[54] For an application of an ARCH model to analyze speculative asset prices, see Bollerslev (1987).

[55] To guarantee positivity of conditional variances, the second equation of (6.5) can be modelled as an exponential function, that is, $E[\varepsilon_t^2 \mid \Phi_{t-1}] = e^{\alpha_0 + \alpha_1 \cdot \varepsilon_{t-1}^2}$. Considering the estimation results shown in Table 6.7a to 6.7c, positive conditional variances are achieved also by the specification in (6.5).

price volatility has increased after price limits were triggered, then the conditional variance will have a positive correlation with the dummy variables indicating limit-triggered events. The systematic difference in conditional variances due to triggering the price limit can be captured by including the dummy variables indicating limit-triggered events into the second equation in (6.5).

$$E[\varepsilon_t^2|\Phi_{t-1}] = \alpha_0 + \alpha_1 \cdot UPLIM_{t-1} + \alpha_2 \cdot LOLIM_{t-1} + \alpha_3 \cdot \varepsilon_{t-1}^2 \tag{6.6}$$

Both the *UPLIM* and *LOLIM* dummies are included since price volatility after the upper limit-triggered events may differ from price volatility after lower limit-triggered events. Equation (6.6) gives the following regression equation.

$$e_t^2 = \alpha_0 + \alpha_1 \cdot UPLIM_{t-1} + \alpha_2 \cdot LOLIM_{t-1} + \alpha_3 \cdot e_{t-1}^2 + u_t \tag{6.7}$$

where $u_t$ is white noise and $e_t^2$ is the squared residual from the regressions of (6.3a) to (6.3c).

We run equation (6.7) for intraday, daily and weekly returns.[56] The regression results are reported in Table 6.7a, 6.7b and 6.7c. First of all, the ARCH effect is detected in all three equations. The coefficient on the previous squared residuals is positive and significant for most individual firms, suggesting that large forecast errors tend to be followed by other large forecast errors. This result is consistent with other empirical findings based on ARCH models. For example, Bollerslev (1987), using several stock price indices and foreign exchange rate data, also found a significant positive coefficient of the previous squared residuals.

[56]In estimating Eq. (6.7) for weekly return, we used $e_{t-6}^2$ instead of $e_{t-1}^2$ since $e_{t-6}^2$ corresponds to the squared residual of the previous disturbance in the case of weekly return.

Regarding the effect of price limits on price volatility, the results show that price volatility has increased after either price limit was triggered. Almost all the coefficients on the *UPLIM* and *LOLIM* dummies turned out to be positive although there are cases where they were insignificant. The exception is for the administrative issue (42010). The coefficients on the limit-triggered events for the administrative issue take a negative sign for the case of daily and weekly volatility. However, they are all insignificant.[57]

Also, it is found that price movements become more volatile after lower limit-triggered events than upper limit-triggered events. This is possibly due to the gravitational effect caused by the existence of circuit breakers. Or it may be caused by the selling activities of traders who need to meet margin requirements. Compared to upward price movements where there would be no "involuntary" counterparts, price declines are inevitably associated with more noise-based trading, thereby adding uncertainty to the market.

We conducted an F-test for the following hypothesis that price limits do not affect price volatility.

$$H_0\colon \alpha_1 = \alpha_2 = 0$$

The 5% critical value from the F-table with 2 and 1750 degrees of freedom is about 3.0 and the observed F is higher than 3 in about half of all the cases. This indicates that the existence of price limits impairs the price discovery process rather than facilitating it. Additionally, *t*-tests reveal that at least one of two dummies is significant in most of the cases.

[57]This result is consistent with what we observe in the descriptive statistics.

In sum, we conclude that price limits do not moderate price volatility. On the contrary, the above evidence of increased volatility together with price overshooting suggests that price limits introduce another source of uncertainty and confusion to the market, casting doubt on the presumed role and rationale of circuit breakers.

### 6.3. Discussion

We examined how the existence of circuit breakers affects price behavior based on Korean stock market data. The results indicate that price behavior after circuit breakers were triggered is systematically different from price behavior when circuit breakers were not triggered. Significant negative (positive) bias in price movements are detected after the upper (lower) circuit breaker bound was triggered, which is consistent with the price overshooting hypothesis suggested in Chapter 3. We also found that price volatility increased after circuit breakers were triggered. In sum, the existence of circuit breakers aimed at reducing price volatility destabilizes price movements, which contrasts with intentions of this type of regulation.

The evidence of increased volatility after limit-triggered events is consistent with the findings made by McMillan (1990) and Kuhn, Kuserk and Locke (1990). Using an episodic event of the mini-market crash in October 1989, both studies find that price volatility increased after circuit breakers were triggered. Compared to their studies, our findings provide more general evidence on the effect of circuit breakers. Whereas they analyzed a single historical event, this study has the advantage of being based on a large number of limit-triggered observations. Also, the price overshooting phenomenon was identified, which was not suggested by other existing studies.

Moreover, Korean stock market data allows us to examine the effect of circuit breakers not only for the lower limit-triggered event but also for the upper limit-triggered one. It is observed that the former is associated with greater overshooting and volatility than the latter, suggesting that the lower limit-triggered event may bring about further uncertainty.

The Korean stock market is different from other stock exchanges in its institutional characteristics. First, the Korean stock exchange does not have market makers. It may be possible that market makers with superior access to market information can stabilize price movements from an unexpected large shock by invoking circuit breakers. However, if people hold more optimistic (pessimistic) beliefs owing to the triggering of circuit breakers and submit orders based on such beliefs, it inevitably causes large price changes. Not only can market makers indistinguish noise trading from information-based trading, but also any attempt to maintain stable prices in such a situation may exhaust their capital.

Empirical evidence reported by Roll (1989) indicates that it makes no difference whether or not there are market makers. He investigates whether institutional market characteristics, including the existence of official specialists, affected market performance during the international market crash in 1987 and found that none of the institutional market characteristics remains even marginally significant. Also, note that the findings made by McMillan (1990) and Kuhn, Kuserk and Locke (1990) are based on a market where market makers exist. Their findings of increased volatility after the triggering of circuit breakers are consistent with the results of this study.

Another important difference is that the price limits in the Korean stock market are applied to each individual stock whereas circuit breakers in other exchanges such as the NYSE are triggered upon the prespecified change in the overall market index. However, the triggering of circuit breakers in the latter case may cause more uncertainty in the market since people may become more skittish when large price declines are observed for all other stocks as well as stocks they hold. Since large price changes of the market portfolio are more likely due to a marketwide shock, we examined whether a marketwide shock makes a difference in price behavior after the limit-triggered events by comparing each firm's "beta" to its performance. Our results show that greater price overshooting occurs with higher "beta" stocks. Although this evidence is only indirect, it suggests that the adverse effect of circuit breakers found in this study also applies to the case where their triggering depends on changes in the market index.