Massey University

Price Limits Are Not Always Bad

A thesis presented in partial fulfilment of the requirements for the degree of Masters of Business Studies in Finance

at Massey University, Albany,

New Zealand.

December 2006

Supervisor: Dr Nuttawat Visaltanachoti

Student: Haina Ding

Student ID: 03064530

Price Limits Are Not Always Bad

Abstract

Regulators impose price limits on daily price movements to protect investors from excessive volatility, but several empirical studies have cast serious doubt on the benefits of such mechanisms. Using a large cross-sectional sample combined with intraday data from the Tokyo Stock Exchange, this study finds evidence that partially supports conventional criticisms that price limits spread out volatility, delay price discovery, and interrupt trading activities. More importantly, the transaction data analysis reveals that price limits help to reduce order imbalance and improve information asymmetry, justifying the existence of price limits on the Tokyo Stock Exchange.

JEL Classification: G10; G14

Keywords: Price limit; Order imbalance; Information asymmetry; Tokyo Stock Exchange.

Acknowledgements

First of all, I would like to thank my supervisor, Dr Nuttawat Visaltanachoti for his continuous encouragement and support. This thesis could not have been completed without his patient instructions, invaluable suggestions and great enthusiasm. I would like to thank Professor Henk Berkman for the early discussions on this topic, and Nhut Nguyen for helping with the data collection and processing.

A special thanks goes to my dearest friend John Deverall, who was always there to talk about my ideas, to help with programming problems and proofread my drafts. I would also like to take this opportunity to give my gratitude to Grace Ooi, Simon Liao, and Steven Fan, my fellow students from Department of Commerce, Massey University, who have asked good questions, and offered encouragement and friendship.

During the course of this research, I was supported in part by a Massey Masterate Scholarship, awarded by the Graduate Research School, Massey University.

Table of Contents

List of Tables

List of Figures

1. Introduction

As one of the commonly used market circuit breakers, price limits are used by many securities markets to protect investors from excessive volatility while restricting daily price movements to within a certain range[1]. There is, however, controversy on price limit performance, which remains unsettled. This study examines the value of price limits, by performing an extensive investigation on the Tokyo Stock Exchange based on a sample pool constructed from intraday and daily data. We find price limits improve order imbalance in the post limit-hit period and, also, that no particular magnet effect occurs on stocks whose prices hit the limits. Furthermore, we find that the market absorbs one-side orders, while price limits provide cooling-off periods for alleviating information asymmetry in the market. Combining these results with our tests on daily data, we also conclude that price limits can mitigate the volatility caused by uninformed trading, although we find that price limits delay fundamental volatility by temporarily controlling the daily price variation.

The important motivation for adopting price limits, is to calm fanatic trading during turbulent periods in stock markets; such as 1987 Black Monday, the 1997 Asian financial crisis and the 2000 Dot-com mania. Price limits halt trading activities when a pre-specified price boundary is exceeded, but still allow trading between the boundaries

---

[1] In general, policy makers use circuit breakers to limit trading activities. These circuit breakers include price limits, trading halts, transaction taxes, collars, margin requirements and position limits. Stock exchanges that use price limits are those in Athens, Taiwan, Japan, China, Malaysia, Thailand, India, Korea and Paris, among others. Wide differences in percentages on price limits exist among the exchanges listed, from approximately 3.5% to 30% and, at times, even higher.

to continue. Regulators revise the limits when their perceptions of the market, or the macroeconomic environment change[2]. Also, advocators suggest that if excessive volatility is a result of uninformed trading, price limits provide uninformed traders with more time to reassess asset value and rationalise the estimation of new equilibrium prices before continuing their trades. An imperfect market suffers the problem of limited capacity when facing volume shocks, where informed value traders are concerned about price adjustments during the intervals between the time when an order is decided, submitted and executed. In this circumstance the benefit of price limits also comes from reducing the implementation risk caused by the massive volume, which encourages informed value traders to enter the market. (Greenwald and Stein, 1991; Kodres and O'Brien, 1994)

Nevertheless, early studies have raised criticisms regarding the relationships of price limit, volatility and market efficiency. Kyle (1988) and Fama (1989) both argue that circuit breakers stop prices from being adjusted promptly when fundamental values change greatly. Therefore, instead of mitigating large price fluctuations, price limits may induce a volatility spill-over. Furthermore, Fama (1989) points out that rational prices are not necessarily less volatile than irrational prices, and prevailing prices on the market may not reflect all the available information with the imposition of price limits. Thus, price limits may delay price discovery and reduce market efficiency in semi-strong form. Another proposition related to market efficiency is that the trading

[2] For example: the Stock Exchange of Thailand increased price limits from 10% to 30% in December 1997; and the Korean Stock Exchange has raised price limits from 4.6% to 15% in four steps since 1995.

process is interfered with when trades at prices outside the pre-assigned ranges are prohibited. The argument that price limits could reduce noise trading and achieve lower information asymmetry faces the criticism that equilibrium price can only be realised during continuous trading (Amihud and Mendelson, 1991; Gerety and Mulherin, 1992). Although French and Roll (1986) contend that the degree of information asymmetry is positively related to uninformed trading (noise) in the market, they also suggest it is more likely for private information to induce price variation when the market is open. Therefore, price limits possibly hold back rational trading from informed traders, however price limits do not stop the noise trading that increases transitory volatility (Harris 1998).

Based on the above discussions, most of the empirical studies on the impact of price limits on market economies show that price limits do not meet regulators' expectations on controlling volatility, but instead impose inefficiency issues on securities markets. For example, Kim and Rhee (1997) confirm volatility spill-over, delayed price discovery and trading interference hypotheses on the Tokyo Stock Exchange (TSE). The studies of Chung (1991) on the Korean stock market and Chen (1993) on the Taiwan Stock Exchange (TWSE) show that price limits do not bring significant benefit to markets. Nevertheless, most studies only look at the impact of price limits on total volatility, instead of separating transitory and fundamental volatility. It would be premature to draw conclusions on whether price limits are always bad for markets without further studying how informed decisions are affected (Harris, 1998).

Our study contributes to the existing literature by shedding light on the influence of price limits on intraday trading activities and the information content of prices. Chan, Kim, and Rhee (2005) conclude that price limits do not improve the price formation process and exacerbate order imbalance, based on the intraday data of the Kuala Lumpur Stock Exchange (KLSE). Nevertheless, the sample size for their paper is fairly small, with only upper limit-hit events included[3], which limits the applicability of their results. As a matter of fact, both regulators and investors are concerned with lower limit-hit events, as much as, if not more so, than they are concerned with upper events. This is because the large decrement on stock price often induces market panic, and also greatly affects rational investment decisions. Using transaction data of stocks that were actively traded on the TSE from 1999 to 2000, we test how price limits affect intraday activities, as well as the degree of information asymmetry; which is an important factor for maintaining equilibrium spread in an order-driven market (Harris, 2003).

This paper also fills a gap in the literature by conducting a recent investigation of price limit performance on volatility, price behaviours and trading volumes in the TSE during the last decade (1996 to 2005). The most recent study on TSE price limits (Kim and Rhee, 1997) uses a sample period of 1989 to 1992. It is necessary to re-examine this market and provide research which is more relevant to current regulators, as the economic environment of the stock market in Japan has changed since the Big Bang

[3] In Chan et al. (2005), only ninety-eight sample events with prices hitting upper limit (+30%) are included in the testing procedure, with six events with prices hitting lower limits being excluded from their tests.

reform[4]. The TSE also presents a very good platform, with sufficient sample magnitude and various price limit ranges, hence the test result can be more persuasive with lower bias. Compared with other major exchanges, the market liquidity in the TSE is mostly provided by limit-order traders, with no designated dealer or market maker. TSE also distinguishes itself with its elaborate market microstructure, including special quotes, maximum price variation rule and price limits. Thus, it is interesting to seek how price limits affect market efficiency and protect uninformed traders in this much regulated, but "...well-functioning financial market" (Lehmann and Modest, 1994, p. 982).

Our three findings on the daily data during the past decade are summarised below. Firstly, the volatility spill-over effect not only occurs with limit-hitting stocks, but also with stocks where the changes in price are within 90% of the limits. This result suggests that volatility spill-over may not be solely attributed to price limits. Secondly, price continuation occurs more frequently in stocks which hit the limits in previous trading days, especially when upper price limits are hit, which implies a delayed price-discovery effect. We find investors' under-reaction (momentum strategy) partially contributes to price continuation when the price is moving upward. Following the methodology of Kim and Sweeney (2002), however, our sample data does not lend support to the proposition that informed traders are inclined to delay trades after price limits are hit. Thirdly, the trading volume of stocks with prices hitting limits, decreases at a lower speed in comparison with other stocks which also experience large price

[4] After the rise and collapse of the economic bubble around 1990, a financial system reform was initiated in Japan in order to revitalise Japan's financial market. This reform, which has been in place since late 1996, is also known as the Japanese Big Bang.

variations without hitting limits. Unsurprisingly, these daily results confirm our findings based on transaction data about improved order imbalance and information asymmetry in the post limit-hit period.

The rest of this paper is organised as follows. The next section lays out institutional background information about the TSE, and then describes the sample data, our data filtering process, and the summary statistics of the sample. Section 3 outlines our empirical designs and presents the findings on the test of order imbalance and information asymmetry hypotheses on transaction data. In Section 4, three hypotheses are tested on daily data; volatility spill-over, delayed price discovery, and trading interference. Conclusions and future research suggestions are summarised in Section 5.

2. Tokyo Stock Exchange and Descriptions of Sample Data

2.1 Tokyo Stock Exchange

The Tokyo Stock Exchange was established on May 15, 1878, and is now the second largest stock exchange in the world. It has 2323 listed companies, and over US$4.5 billion in total market capitalisation. The exchange for domestic stocks is divided into three sections: First Section; Second Section; and Mothers. Assignment rules to place listed stocks in each section are based on trading volume, number of shares listed, market capitalisation, et cetera. The sample stocks investigated in this paper are from the First Section, where the most actively traded stocks are listed.

The Tokyo Stock Exchange is a pure order-driven market with no designated market maker, where all liquidity is provided through a limit order book. Market mechanisms, including special quotes, maximum variation rule and price limits, are designed to slow down the trading process when a large order imbalance is expected, or present. In the TSE, the full order book is not accessible for normal traders and the hidden orders are not presented to traders, either. Only the five best prices are presented by the exchange[5]. Special quotes, disseminated by a *saitori* exchange member at their own discretion, are often seen to be indicators of buying (selling) interest in the market, which compensates for the lack of transparency and improves market liquidity. In the TSE, a *saitori* member undertakes the responsibilities of supervising trading processes, logging and matching orders, and also maintaining the limit order book. The Tokyo Stock Exchange uses price limits to prevent "wild swings" in daily price movements, and provide investors with a "time-out" period when big fluctuations occur (Tokyo Stock Exchange, 2006). Price limits are set as the maximum daily price variation in absolute yen value, dependant on stock prices[6]. Price limits also apply to special quotes.

There are two trading sessions on the TSE: the morning session lasts from 9:00am until 11:00am, and the afternoon session lasts from 12:30pm until 3:00pm. Two transaction methods are used in off-hours trading and trading sessions; *itayose* and *zaraba*, respectively. The *itayose* method is used to decide opening and closing prices and

[5] Prior to June 2003, traders could only observe the three best trade prices.
[6] This feature is different from that where price limits are set at certain percentages in most exchanges that adopt this mechanism. We list the detailed price limits in Appendices; Table A2.

works by pooling all orders placed, without the time priority rule. The *zaraba* method is used in continuous trading, and works by matching pairs of buy and sell orders, following both of the time priority and price priority principles. All observations in the off-hours trading; that is, all trades under the *itayose* method; are excluded from our study sample.

2.2 Data Description

Firstly, we extract the historical daily data of 1695 stocks listed in the First Section of the TSE between 1996 and 2005 from Datastream. During this period, there are ups and downs in the market, but without extreme situations such as the 1990 market collapse, which was followed by severe stagnation[7]. This ten-year period provides a sample pool of sufficient magnitude to ensure the general applicability of our results. It is worth noting that during the sample period, both tick size and price limits on the TSE changed (see Table 1A and 2A for details).

The raw data includes the daily high, the daily low and the closing price of each stock, along with daily trading volumes and the market capitalisation. The percentile statistics of year end closing prices (presented in Table 3A) show that the mean prices are much higher than the medians, suggesting the left skewness of price distribution on the TSE. 90% of sample stocks are priced under ¥5000, and about 40% are priced under ¥500.

[7] We show the general trend in the market (1989 to 2005) by displaying the Nikkei 225 price index and its daily volatility, in monthly average (Figure 1A).

Price limits for stocks with a price between ¥100 and ¥500 vary from approximately 16% to 50%. With a stock price between ¥500 and ¥5000, the limits vary from 10% to 20%. This feature allows cheap stocks to be more volatile than high priced stocks.

We identify sample events as the occurrences of the limits being hit, by comparing the daily high, low and closing prices. There are 8390 occurrences of the upper limits being hit and 3355 occurrences of the lower limits being hit during the sample period, which construct our initial sample. As we can see from the summary statistics in Table 4A, downward price movements happen most frequently in the year 2000, due to the high-tech stock bubble burst after the first quarter, which caused a loss of approximately 30% on the Nikkei index. Overall, there are 1198 down-side events in that year. In the previous year, 1999, the Japanese stock market rose about 50%, due to booming of technology companies. As a result, the market saw the most upwards price movements in that year, with 2970 up-side events in total.

Due to events occurring densely in 1999 and 2000, we use the trade-by-trade data of these two years to test order imbalance and the degree of information asymmetry in Section 3, thus our study of the high frequency data can be applicable for either bull or bear market periods. We obtain this data, which includes trading price, bid and ask quotes, and trading volume of the 1399 stocks that were most actively traded from 1999 to 2000, from the Securities Industry Research Centre of Asia-Pacific (SIRCA). With no dealer or market maker in the TSE, we classify buy and sell orders according to the following rules: If the mid-point of the bid-ask spread is greater than the trading price, then the trade is indicated as being seller-initiated, otherwise the trade is indicated as being buyer-initiated; If the mid quote is equal to the trading price, and if there is an up-tick from the previous trade, then the trade is identified as being buyer-initiated, otherwise the trade is identified as being seller-initiated.

3. The Influence on Intraday Trading Activities and Information Asymmetry

3.1 Order Imbalance Hypothesis

From the perspective of regulators, price limits are partially designed to provide time for the market to absorb one-side heavy trading orders. However, as earlier noted by Lehmann (1989, p.207), price limits may "...create a systematic order imbalance between patient and impatient traders", before and after the limits are hit. Therefore, it is important to investigate how price limits affect order imbalance based on broad observations of both directions of price movement.

Following the methodology of Chan et al. (2005), we form two groups of stocks; the stocks with limit-hitting events into $Stock_{hit}$, and the stocks with prices changing over 90% of the limits but without actually hitting the limits into $Stock_{0.90}$, during the 1999 to 2000 period. We then identify the pre-hit period and the post-hit period of each event for the purpose of comparison. Based on the event session S_0 (defined as the trading session when the limit is hit), the pre limit-hit period S_{-1} starts from the previous trading session of S_0 and runs until when the limit is first hit in S_0; and the post period S_{+1} starts from the trade next to the limit-hitting trade in S_0 and runs until the end of the next session after S_0. This definition enables the inclusion of all the trade data, so that our comparison is more complete and, hence, more justifiable. We calculate the order imbalance ratio in the pre-hit period, by dividing the sum of buyer (seller) orders by the total trading volumes in that period for the upper (lower) limit-hit events. The same algorithm is then used for the post-period $Stock_{hit}$. We compute the order imbalance ratio for $Stock_{0.90}$ using the same procedure. In order to avoid the bias that occurs when there are only few observations, we filter events with less than five trades in either S_{-1} or S_{+1} from the sample. Due to this filtering, our sample of upper limit-hit events shrinks from 2084 to 1747, and the sample of $Stock_{0.90,}$ shrinks from 980 to 906, with the stock price moving upwards. In the circumstance that prices move downwards, the number of lower limit-hit events drops from 925 to 681, and from 507 to 448 for the events of $Stock_{0.90}$.

Table 1 summarises the mean and median statistics of the order imbalance ratio. As we can see from the table, both $Stock_{hit}$ and $Stock_{0.90}$ have fairly significant order imbalance in the pre-hit period, which is well above 50% where demand equals supply in the market. For upper events, the ratio of both groups decreases to a large extent in the post-hit period; approximately 14% for $Stock_{hit}$ and 19% for $Stock_{0.90}$. Nonetheless, the ratio of $Stock_{hit}$ stands at around 57% in the post-hit period, which means that order imbalance still exists for this group. The imbalance is better alleviated for $Stock_{0.90}$, with the ratio slightly over 50% in the post-hit period. The ratio reversal does not occur in either group. As for the lower events, the decrement on the order imbalance ratio is 19% for $Stock_{hit}$, and 23% for $Stock_{0.90}$, which are both larger than for the upper events. The ratio is lower than 50% for both groups in the post-hit period. The order imbalance ratios for both groups experience reversal from the pre-hit period to the post-hit period with lower limit-hit events, but stay above 0.50 in the post-hit period with upper events. Thus, no substantial difference exists between $Stock_{hit}$ and $Stock_{0.90}$ in this result, suggesting that no particular magnet effect exists for group $Stock_{hit}$, as found by Chan et al. (2005).

[Insert Table 1 here]

Apart from this result, because of the constraints from the price limits, some of the prevailing orders of the $Stock_{hit}$ group cannot be executed after limit-hit moments, which differs from the case where all trading orders of $Stock_{0.90}$ are executed from the pre-hit to the post-hit period. Table 1 shows, however, that the order imbalance ratio decreases largely for $Stock_{hit}$ in the post-hit period with both the upper and lower events. This suggests that price limits effectively lower the order imbalance ratio after limit-hitting, and that this effect is more significant in the case of lower limit-hit events.

In order to incorporate the influence from other factors on the order imbalance ratio and examine whether the decrement is specifically related to limit-hit, we use a similar cross-section regression to that used by Chan et al. (2005), with some different variables. The dependent variable (the change in the order imbalance ratio) is defined as:

$$\Delta \mathrm{IMBAL}_j = \mathrm{IMBAL}_{j,post} - \mathrm{IMBAL}_{j,pre},$$

where $\mathrm{IMBAL}_{j,post}$ stands for the order imbalance ratio in the post-hit period and $\mathrm{IMBAL}_{j,pre}$ stands for the ratio in the pre-hit period for a certain event *j*. The regression function is constructed as follows:

$$\Delta \mathrm{IMBAL}_j = \beta_0 + \beta_1 * \mathrm{LHG}_j + \beta_2 * \mathrm{MktCap}_j + \beta_3 * \Delta \mathrm{Volume}_j + \beta_4 * \mathrm{Weekday}_j + \beta_5 * \mathrm{Month}_j + \beta_6 * \mathrm{Volatility}_j + \varepsilon_j, \qquad (1)$$

where: LHG is the dummy variable, and equals 1 if stock *j* comes from the Stock_{hit} group and 0 if stock *j* comes from the $\mathrm{Stock}_{0.90}$ group; MktCap_j denotes the logarithm of stock *j*'s market capitalisation; $\Delta \mathrm{Volume}_j$ is computed as the logarithm change on the trading volume from the pre-hit period to the post-hit period with stock *j*; $\mathrm{Volatility}_j$ is computed as the squared logarithm return between the closing price of the post-hit period and the opening price of the pre-hit period; $\mathrm{Weekday}_j$ and Month_j refer to the day of the week and the month when event j happens; and ε_j is the error term, on which heteroskedasticity is taken into consideration if there is some pattern in the error term.

[Insert Table 2 here]

Table 2 presents the results from the cross-section regression. The coefficients for the dummy variable LHG, of both upper events and lower events, are significantly positive, which implies that the change in the order imbalance ratio on $Stock_{hit}$ is not larger than for $Stock_{0.90}$. We can conclude that there is a smaller decrease in the order imbalance ratio for both upper and lower limit-hit events, and that the ratio reversal on lower events from the pre-hit to post-hit period is not entirely associated with price limits. This result is inconsistent with the findings of Chan et al. (2005) on the Kuala Lumpur Stock Exchange. In their study they discover that the coefficient for variable LHG is significantly negative to the dependent variable ΔIMBAL.

3.2 Information Asymmetry Hypothesis

Now we examine the degree of information asymmetry surrounding limit-hit events. Ahn, Cai, Hamao and Ho (2002, p.403 - p.404) argue that it is possible that price limits "...would reduce the amount of information asymmetry" in the market when the price discovery process is slowed down. The previous test on the order imbalance ratio is not able to explain to what extent price limits may also affect price transmission at the time when part of the one-side orders are suppressed. Therefore, it is necessary to extract information content from the transaction data by decomposing the bid-ask spread before and after the limit-hit moment, so that we can have an implicit understanding of the extent to which price limits influence informed trading.

Kim and Sweeney (2002), contend that informed traders with private information put off their orders during limit-hitting sessions until price ranges are revised in subsequent trading days, so that they may obtain higher profits from trading. Kim and Sweeney (2002) study the distribution of closing prices, price continuations and reversals. Their argument is supported by their test results, which are based on daily data from the Taiwan Stock Exchange. One caveat of their study, however, is that they fail to consider the adverse selection component of the bid-ask spread, which affects the decision of limit order traders who can be considered as liquidity providers in an order-driven market (Ahn et al., 2002). As noted by Ma, Rao and Sears (1989), it is difficult to evaluate price limit performance by only using daily data. It may be too early to imply the impact of price limits on informed traders without breaking down transaction price data.

Based on the transaction data, we begin by testing the degree of information asymmetry before, and after the limits are hit. This is done by estimating the adverse selection cost under the following decomposition model, which is provided by Glosten and Harris (1988) and, from here on is referred to as the GH88 model:

$$\Delta P_t = \mu + c_0 \Delta Q_t + c_1 \Delta(q_t Q_t) + z_0 Q_t + z_1 q_t Q_t + \varepsilon_t, \qquad (2)$$

where: P_t denotes the transaction price at time t; Q_t denotes the trading indicator of the trade at time t, which is valued at 1 with buyer-initiated orders and -1 otherwise; and q_t is the trading size, which is uniformly measured in thousands of shares, as per the minimum trading unit[8]. The GH88 model defines the adverse selection component as $z_0 + z_1 q_t$; and the adverse selection cost, SYMM, as $(z_0 + z_1 q_t) / (z_0 + z_1 q_t + c_0 + c_1 q_t)$. We calculate the coefficients z_0, z_1, c_0, and c_1 of the GH88 model by using the price, trading volume and indicator serials in both pre- and post-hit periods, for each event. Then we calculate SYMM ratios for the pre and post periods based on the corresponding coefficients and q_t, which is now defined as the median trading volume. In order to avoid influence on our estimation from the extreme trading size, we exclude trades with volumes larger than the 99th percentile, or smaller than the 1st percentile, from the actual computation of each event during the pre- and post-hit periods.

The means and medians of the SYMM ratio from the pre- and post-hit periods are presented in Table *3*. For events with prices moving up, the mean SYMM ratios of Stock$_{hit}$ and Stock$_{0.90}$ in the pre-hit period are 0.4244 and 0.4314, respectively, correspondingly higher than 0.3691 and 0.4199, respectively, in the post-hit period. The reduction for Stock$_{hit}$ is slightly larger than that for Stock$_{0.90}$. As for events with decreasing prices, the mean SYMM of Stock$_{hit}$ is 0.4336 in the pre limit-hit period, dropping to 0.4087 in the post-hit period, while the ratio increases on Stock$_{0.90}$, from

[8] In the TSE, the trading unit varies between different companies, but over half of listed companies in the First Section use a trading unit of 1000 shares (e.g., 917 of a total 1595 companies in the First Section use 1000 shares as a trading unit by the end of 2004 (Tokyo Stock Exchange, April 22, 2005).

0.4039 to 0.4440. Medians of SYMM ratios for both groups show a similar pattern. Therefore, this result supports the proposition of Ahn et al. (2002), that price limits reduce information asymmetry on the TSE.

[Insert Table 3 here]

To confirm that the decrement in information asymmetry is specifically associated with limit-hit events, we construct the cross-section regression below:

$$\Delta SYMM_j = \beta_0 + \beta_1 * LHG_j + \beta_2 * MktCap_j + \beta_3 * \Delta Volume_j + \beta_4 * Weekday_j + \beta_5 * Month_j + \beta_6 * Volatility_j + \varepsilon_j, \quad (3)$$

where $\Delta SYMM_j$ denotes the change on the SYMM ratio between the pre- and post-hit period for event j ($\Delta SYMM_j = SYMM_{j,post} - SYMM_{j,pre}$), with all other variables being defined as in Equation (1). If the coefficient of variable LHG is shown to be negative, we can assume that the improvement on information asymmetry is more significant with the imposition of price limits.

Table *4* summarises the regression results. The coefficients of variable LHG for the upper and lower events are -0.0373 and -0.0612, respectively; which are both negative at the 5% and 1% levels of significance, respectively. The result suggests that price limits in the TSE contribute to the improvement of information asymmetry, which is again inconsistent with the conclusion of Chan et al. (2005) on the KLSE. Table 4 also shows that the coefficients of variable ΔVolume are significantly positive for both upper and lower events. This implies that the magnitude of the change in the degree of information asymmetry is negatively related to the change on trading volume. The decrement in information asymmetry increases when the change in trading volume decreases, and vice versa. This is consistent with the finding of Ahn et al. (2002), that the adverse selection component increases with larger trade sizes on the TSE.

[Insert Table 4 here]

So far, we discover that price limits help to correct order imbalance and lower the adverse selection component of the bid-ask spread. Price variations are strongly associated with the order imbalance between buyer- and seller-initiated orders (Kyle, 1985; Spiegel and Subrahmanyam, 1995). Also, considering the close relationship between information transmission and the price discovery process, it is necessary to examine the daily volatility and price behaviours, which may also provide a good foundation to compare our findings with other studies which also focus on daily data.

4. The Influence on the Daily Price Volatility and Trading Activities

4.1 Volatility Spill-over Hypothesis

Based on daily data from 1996 to 2005, we apply the methodology of Kim and Rhee (1997), in order to test the volatility spill-over hypothesis on the limit-hit events. We identify Stock_{hit} and $\text{Stock}_{0.90}$ in the same way as in the previous section, and also identify a new group. This group is $\text{Stock}_{0.80}$, which is defined by a change in prices between 80% and 90% of the limits. We construct a 21-day event window to compare the volatility before and after limits being hit: Day 0 represents the day when a price hits the limit, or reaches 90% or 80% of the limit for the $\text{Stock}_{0.90}$ or $\text{Stock}_{0.80}$ group, respectively. Day-1 indicates the day before Day 0, and Day+1 is the day after Day 0, and so on. The squared logarithm of the daily return; $V_{t,j} = (r_{t,j})^2$; is used as the volatility measurement. In order to reduce the high volatility bias during the pre-limit period, we screen out events where stock prices hit limits on the second or third consecutive day before computation. In other words, there are no consecutive observations in each 5-day event window (from Day-2 to Day+2) in the test sample. After the filtering process, the sample size shrinks to 6660 upper limit hits and 2754 lower limit hits. We intend to examine the volatility spill-over hypothesis by comparing price volatility of Stock_{hit} and other stock groups with large price variations.

The volatilities of the three stock groups on each day of the 21-day event window are reported in Table 5. The symbols > and >> indicate that the left side is greater than the right side at the 5% and 1% levels of significance, respectively. As expected, all stock groups have the highest volatility on the event day, Day 0, and the magnitude decreases from Stock_{hit} to $\text{Stock}_{0.80}$, which is not associated with the current hypothesis. On Day +1, volatilities for all groups experience a large decrement, which follows the proposition that volatility naturally decreases after a large price fluctuation (Lehmann, 1989). Nevertheless, Table 5 shows that for stocks with prices moving up, the volatility of Stock_{hit} is significantly greater than the volatility for $\text{Stock}_{0.90}$ from Day 1 to Day 10. As for the lower events, volatilities of Stock_{hit} remain consistently higher than $\text{Stock}_{0.90}$ until Day 6.

[Insert Table 5 here]

In order to find how different limit ranges affect price volatility, we divide the entire sample into three groups restricted by different levels of price limits; lower than 15%, higher than 25%, and between 15% and 25%. The test result for upper events in Table *6a* shows that, for events with limits higher than 25%, the spill-over effect remains on Day 1, 3, 4 and 5. For Stock_{hit} group stocks with limits between 15% and 25%, volatility only spreads to Day 3, but for Stock_{hit} group stocks with limits under 15%, volatility remains higher than for $\text{Stock}_{0.90}$ group stocks from Day 1 until Day 9. Therefore most of the spill-over effect on upper events, is contributed by stocks that fall into the lower range of the price limits, which implies that the narrower the limit is, the longer and stronger the spill-over effect tends to be. The pattern in Table 6b for the lower events is similar, but not so strong and it is consistent with the overall feature that the spill-over effect is more significant for upper events.

[Insert Table 6a and 6b here]

We notice a confusing trend in Table 5: The upper events of Stock$_{0.90}$ have significantly higher volatilities than for Stock$_{0.80}$ from Day 1 to Day 10 of the event windows. The pattern exists for lower events as well, even when the volatility of Stock$_{hit}$ is not significantly higher than Stock$_{0.90}$. This implies that the volatility spill-over effect may not be solely associated with price limits, and also that price limits control volatility effectively during later trading days for lower events. Upon observing the test result of Kim and Rhee (1997), we find that the average volatility of Stock$_{0.90}$ is higher than for Stock$_{0.80}$, although this is not signalled as being statistically significant in their paper. The feature is also found to be partially significant in the papers of Chen, Rui, and Wang (2005) and Nath (2005). We use the Wilcoxon rank-sum test to compare the median volatility among the stock groups on each day. For the purpose of comparison with the studies of Kim and Rhee (1997), Chen et al. (2005) and Nath (2005), we present the mean volatility for each stock group in Table 5A.

Related to our findings of Section 3, that price limits do not exacerbate order imbalance but rather improve information asymmetry, the test results in this section imply that price limits induce a volatility spill-over to subsequent trading days, if caused by fundamental value changes. On the other hand, price limits may help to moderate volatility and protect uninformed traders from suffering trading losses from transitory volatility. Interestingly, our results seem to correspond with the findings of Chen et al. (2005) in regards to the asymmetric influence of price limits during different periods on the China A shares market. They find that price limits only effectively reduce the volatility of downward price movements in a bull market and the volatility of upward price movement in a bear market. This implies that price limits may not successfully control volatility when most investors believe that fundamental value is changing. On the other hand, price limits function effectively when market expectation is not uniform.

4.2 Delayed Price Discovery Hypothesis

In this sub-section, we test delayed price discovery hypothesis by observing whether there are any unique patterns in the price behaviour of stocks with limit-hitting events. In the first step, we follow Kim and Rhee's (1997) methodology in order to calculate the logarithm open-to-close return $r(C_0O_0)$ and close-to-open return $r(O_1C_0)$ as $\ln(C_0O_0)$ and $\ln(O_1C_0)$. Here, C_0 and O_0 denote stock closing price and opening price of the event day, and O_1 denotes the opening price of the subsequent day. Then, we compare the return serials among stock groups $Stock_{hit}$, $Stock_{0.90}$ and $Stock_{0.80}$; which are defined in the same way as in the volatility spill-over test.

For simplicity, positive, negative, and zero returns are denoted by the symbol [+], [-], and [0] respectively. Hence there are nine possible return series with the order $[r(C_0O_0), r(O_1C_0)]$: [+, +]; [+, 0]; [+, −]; [−, +]; [−, −] [−, 0]; [0, −]; [0, +]; and [0, 0]. For upward price movement, we classify price continuation by the series [+, +] and [0, +], price reversal by the series [+, −], [−, +], [−, −], [−, 0], and [0, −], and the behaviour no change in prices, by [+, 0] and [0, 0][9]. Alternatively, for downward price movement, price continuation is identified by the return series [−, −] and [0, −]; price reversal is identified by [+, +], [+, 0], [+, −], [0, +], and [−, +]; and no change in prices is identified by [−, 0] and [0, 0].

[Insert Table 7 here]

In Table 7 we list the classified price behaviours for all three stock groups as the proportions of price continuation, price reversal and no change in prices, over the entire sample. We use the full sample, which includes all the consecutive limit-hit events, to avoid underestimating the frequency of price continuation. The table shows that when stock prices are moving upward, the price continuation for $Stock_{hit}$ (61%) occurs more often than for the other two groups; 43% for $Stock_{0.90}$ and 42% for $Stock_{0.80}$. As for downward price movement, the proportion of price continuation for $Stock_{hit}$ is 45%, which is 2% lower than for price reversal, but still higher than $Stock_{0.90}$ and $Stock_{0.80}$; 31% and 30%, respectively. Price behaviours do not appear to be largely different between $Stock_{0.90}$ and $Stock_{0.80}$.

We then select another two groups, $Stock_{0.70}$ and $Stock_{0.60}$, in which daily prices change 70% ~ 80% and 60% ~ 70% of the price limits. The same test is performed on their

[9] For the upward price movement, we classify [0, +] as price continuation, because the price experiences an overnight increase; and [−, +], [−, −] and [−, 0] are classified as price continuation, because the price reversal has already happened before the market closes on Day 0. Similar reasoning applies to the rule of classifying downward price movements.

return series. The purpose of doing this is to compare Stock$_{0.90}$ with other stocks that have relatively lower price variations than Stock$_{0.90}$. We provide the sample sizes of all the stock groups in Figure 1. This methodology follows the investigation of Kim and Sweeney (2002) on the Taiwan Stock Exchange. They discover a significantly higher price continuation on Stock$_{0.90}$ compared with other none limit-hit groups. As presented in Figure 2a and 2b, however, our result shows there is no significant difference in the frequency of price continuation among Stock$_{0.90}$, and other non-hit groups. The interpretation from Kim and Sweeney (2002); that informed traders may choose to delay transactions when the new equilibrium price is greater than the price limits and the closing price is close to the limits; cannot be applied to the TSE. Our result from this test further confirms the robustness of our conclusion on the improved information asymmetry in Section 3.

Before drawing any conclusions on the delayed price discovery hypothesis, there is another factor that needs to be considered: investors' under-reaction and the consequent momentum trading strategy. If the under-reaction effect holds when news arrives in the market, then information dissolves gradually into stock price, until the stock price fully reveals the value change. Meanwhile, momentum traders try to make profit by operating in the same direction as historical stock returns. This factor can also induce price continuation, if the influence is significant in the short term. (Chan, Jegadeesh, and Lakonishok, 1996; Chan, Hameed, and Tong, 2000)

We use the following methodology to identify under-reaction effect. Based on the 6-month moving average return (the calculation period is moved forward by day), we classify all of the sample stocks into three groups: winners; neutrals; and losers: for each day during the ten-year sample period (except for the first 6-month observing period). Winners are selected from the stocks with the top 30% of returns, and losers are selected from the stocks with the bottom 30% of returns. The remaining stocks are classified into a neutral group. We then generate two daily time series to indicate, for each day, the percentage of winner stocks that hit the upper limits over the total upper events, and also the percentage of loser stocks that hit the upper limits over the total upper events. We also generate another two series in the same way for the lower limit-hit events. By comparing these time series, we are able to test the null hypothesis (H_0) that winner and loser stocks hit the upper, or lower, price limits with equal likeliness. If winner (loser) stocks are found to hit the upper (lower) price limits more frequently, we can assume that under reaction exists and partially contributes to price continuation when prices are increasing (decreasing).

[Insert Table 8 here]

We present the test result for upper limit-hit and lower limit-hit events separately in Table 8. H_0 is strongly rejected for both the mean and the median tests on upper events, with a 1% level of significance. The proportion of winners that hit the upper limit is significantly higher than the proportion of losers which hit the upper limit over the total number of upper events. This suggests that an under-reaction effect exists, and that it may also cause upward price continuation. Nevertheless, for the lower limit hit events, H_0 can not be rejected at the 5% level of significance (the one tail test suggests that H_0 should be rejected at the 10% level of significance), which means that winners and losers are equally likely to hit the lower price limits. Therefore, we exclude under-reaction from the factors that may cause downward price continuation. The asymmetric result from testing the under-reaction effect suggests a possible reason for the fact that there is more significant price continuation for upper limit-hit events than for the lower limit-hit events. Therefore, it may not be effective to set the upper price limits wider, since not only price limits, but also under-reaction or momentum trading strategy, affects the efficient price discovery process[10]. This conclusion is not contradictory to our result in Section 3, that price limits improve information asymmetry in the post-hit period, as we test the possibility of prices under-reacting to news among all the sample stocks by using the daily data during the whole sample period. In this sense, testing is only carried out if there is a momentum trend in the market generally, instead of comparing information transmission specifically between the pre and post limit-hit periods, which is the approach we use to investigate information asymmetry.

[10] Choi and Lee (2001) find asymmetric price activities towards the upper and lower bound of price limits. They suggest that it may help to reduce market volatility and improve market efficiency to set the upper price limit wider than the lower limit.

4.3 Trading Interference Hypothesis

Kim and Rhee (1997) test trading interference hypothesis in the TSE by observing the day-to-day change on trading volume in an event window. Their test result shows that, compared to $\text{Stock}_{0.90}$, higher trading activities occur for Stock_{hit} on the subsequent days after limits are hit. Recent studies on other stock exchanges provide different evidence. Nath (2005) finds that the effect of price limits is asymmetric in the Indian market, with the interference only being observed in the stocks which hit upper price limits, not in those stocks hitting lower limits. Chen et al. (2005) reject this hypothesis in the China A shares market during the period from December 1996 to December 2003.

Following the methodology from Kim and Rhee (1997), we observe the change on trading volumes during the 11-day event window from Day -5 to Day +5. Turnover ratio $\text{TA}_{t,j}$ for stock j on day t is measured by $\text{TVOL}_{t,j}$ / $\text{SOUT}_{t,j}$, where $\text{TVOL}_{t,j}$ denotes the trading volume of stock j on Day t, and $\text{SOUT}_{t,j}$ denotes the total outstanding shares for stock j on Day t. By comparing the logarithmic change in turnover ratio; ln $(TA_{j,t} / TA_{j,t-1})$; we expect to test the null hypothesis that trading activities for Stock_{hit} do not rise significantly after event days. The consecutive events on Day +2 and Day +3 are not included in this test, so that the sample here is consistent with the sample we use to test the volatility spill-over hypothesis.

As shown in the Table 9, all groups experience their highest positive logarithmic changes in trading volume on the event day; Day 0; with a large decrease occurring on the next day. The decrement of trading volume on $Stock_{hit}$ is 7.85% on Day +1, which is significantly lower than 44.67% for $Stock_{0.90}$, and 41.62% for $Stock_{0.80}$. This pattern is also found for the lower events. The table also shows that the decrement on $Stock_{hit}$ becomes much larger compared with other groups on the days following; from Day +2 to Day +4. The trading activities of $Stock_{hit}$ do not increase after the limit-hit day, but the magnitude of decrement on trading volume is not as large as for the other groups, which partially supports trading interference hypothesis. Relating to our investigation on the transaction data in Section 3, we believe that the disappearing volume is partially contributed to by the lower order imbalance ratio and improved information asymmetry in the post limit-hit period. Nevertheless, the order imbalance ratio in the post-hit period still remains relatively high; 0.5715 for the upper limit-hit events and 0.4915 for the lower events (still very close to 50%), and this provides some possible explanation for the continuously high volatility and price continuations.

[Insert Table 9 here]

5. Conclusion

After suffering from market crashes and huge market fluctuations, investors' discomfort with excessive volatility more or less puts exchange regulators in the role of stabilising prices. A number of order-driven exchanges use price limits to meet this demand, which is considerably facilitated by electronic trading systems. The understanding of this mechanism, however, is still incomplete. Most previous studies show that price limits have a negative influence on market efficiency without effectively mitigating volatility. This study sets out to discuss any positive extent to which the adoption of price limits may be justified on the basis of price limit performance.

We find that volatility in the Tokyo Stock Exchange is temporarily restricted by price limits, but then spreads out into the subsequent trading days. We also find a similar pattern in $Stock_{0.90}$: stocks with prices changing over 90% of the price limits. We suspect that the spill-over effect is not solely connected with price limits, as the test results of the order imbalance ratio and the degree of information asymmetry show that $Stock_{0.90}$ often shares the same features as the limit-hit stocks. Our study also confirms that, in the post limit-hit period, price continuation occurs more frequently and trading seems to be more active for the limit-hit stocks, in comparison to the other sample groups. On the other hand, we find price limits effectively reduce order imbalance and improve information asymmetry, thus market efficiency is not reduced from these perspectives. Therefore, on the whole, we conclude that although price limits cannot powerfully diminish volatility especially when the volatility is caused by a fundamental value change; this mechanism still benefits the market by slowing panic order-submission and providing market participants with a period of time in which to absorb new information.

Harris (1998) considers the political power of price limits. He argues that policy makers may adopt this mechanism, either to avoid being blamed for not reacting promptly to market panic, or to achieve regulators' own welfare, even when the policy is of little to no effectiveness. Nevertheless, our study provides evidence to justify the adoption of price limits in the Tokyo Stock Exchange. This paper improves the understanding of price limits and adds to a growing body of literature about the influence of price limits on trading activities, order flows and price formation.

Due to the absence of appropriate methodology, this paper does not proceed into the behaviours of informed and uninformed traders[11], the study of which may potentially help to separate transitory volatility from fundamental volatility and better explain the impact of price limits on the price resolution process. If the debate on price limits is to be moved forward, further research on the arrival rate of informed traders would be valuable. More broadly, we also suggest future research be carried out in establishing rationales to set suitable price limit magnitudes for stock exchanges in different microeconomic environments.

[11] Chan et al. (2005) test the arrival rate of informed traders and conclude that informed traders arrive after the limit-hit moments, therefore, price limits delay the arrival of information. Nevertheless, when they apply the model developed by Easley, Kiefer, O'Hara, and Paperman (1996) to estimate the probability of information-based trading, they assume that the news arrival rate is independent for each 2-minute interval during the day. This ignores the well-documented U-shape pattern of intraday information arrival, which may consequently bias their PIN estimation.

Tables and Figures

Table 1. Test on Order Imbalance Hypothesis

Upper Limit-Hit Events		$Stock_{hit}$	$Stock_{0.90}$
Pre-Hit Period	Mean	0.7098	0.6982
	Median	0.7304	0.7152
Post-Hit Period	Mean	0.5715	0.5095
	Median	0.5818	0.5170
Sample Size		1747	906
Lower Limit-Hit Events		$Stock_{hit}$	$Stock_{0.90}$
Pre-Hit Period	Mean	0.6838	0.6715
	Median	0.7216	0.6984
Post-Hit Period	Mean	0.4915	0.4376
	Median	0.4755	0.4292
Sample Size		681	448

$Stock_{hit}$ refers to the group of events where prices hit the price limits, and $Stock_{0.90}$ refers to the group where stock prices change over 90% of the limits but do not reach the limits. The event session S_0 is defined as the trading session when the limit is hit. The pre-hit period starts from the previous trading session of S_0 and runs until when the limit is first hit in S_0; and the post-hit period starts from the trade next to the limit-hitting trade in S_0, and runs until the end of the next session after S_0. We calculate the order imbalance ratio by dividing the sum of the buyer (seller) orders by the total trading volumes in that period for the upper (lower) limit-hit events. The same algorithm is applied on $Stock_{0.90}$. If the ratio is equal to 0.50, market demand and supply reach equilibrium.

Table 2. Regression of the Change on Order Imbalance Ratio between the Pre- and Post-hit Periods

A. Summary Statistics of ΔIMBAL

	Upper events		Lower events	
	Mean	*Median*	*Mean*	*Median*
$Stock_{hit}$	-0.1372	-0.1337	-0.19182	-0.21345
$Stock_{0.90}$	-0.1880	-0.1848	-0.23432	-0.24156

B. Regression Results

Summarised below are the results from the following regression :

$\Delta IMBAL_j = \beta_0 + \beta_1 * LHG_j + \beta_2 * MktCap_j + \beta_3 * \Delta Volume_j + \beta_4 * Weekday_j + \beta_5 * Month_j + \beta_6 * Volatility_j + \varepsilon_j,$

	Upper events		Lower events	
	Coefficients	*t-statistics*	*Coefficients*	*t-statistics*
Intercept	-0.189**	-6.13	-0.3432**	-6.61
LHG	0.0421**	4.95	0.0502**	3.64
MktCap	-0.0001	-0.04	0.0050	1.20
ΔVolume	-0.0080	-1.15	-0.0560**	-4.15
Weekday	-0.0028	-0.95	0.0081	1.72
Month	-0.0003	-0.29	0.0018	0.91
Volatility	1.0519**	5.38	0.0285	0.19
R-square	2.4%		3.6%	
F-statistic	10.69**		6.89**	
Sample size	2601		1106	

LHG is the dummy variable, that equals to 1 if stock *j* comes from $Stock_{hit}$ group, and 0 if stock *j* comes from $Stock_{0.90}$; $MktCap_j$ denotes the logarithm of stock *j*'s market capitalisation; $\Delta Volume_j$ is computed as the logarithm change on the trading volume from the pre-hit period to the post-hit period with stock *j*; $Volatility_j$ is computed as the squared logarithm return between the closing price of the post-hit period and the opening price of the pre-hit period; $Weekday_j$ and $Month_j$ refer to the day of the week and the month when event *j* happens; and ε_j is the error term, on which heteroskedasticity is taken into consideration if there is some pattern in the error term. The symbols * and ** after the coefficients indicate that coefficients are significant at the 5% and 1% levels of significance, respectively. Due to the missing observations for the regression variables, the sample size varies from the initial sample.

Table 3. Test on Information Asymmetry Hypothesis

Upper Limit-Hit Events		$Stock_{hit}$	$Stock_{0.90}$
Pre-Hit Period	Mean	0.4244	0.4314
	Median	0.4430	0.4560
Post-Hit Period	Mean	0.3691	0.4199
	Median	0.4057	0.4462
Sample Size		1425	754
Lower Limit-Hit Events		$Stock_{hit}$	$Stock_{0.90}$
Pre-Hit Period	Mean	0.4336	0.4039
	Median	0.4656	0.4397
Post-Hit Period	Mean	0.4087	0.4440
	Median	0.4507	0.4631
Sample Size		526	346

$Stock_{hit}$ refers to the group of events where prices hit the price limits, and $Stock_{0.90}$ refers to the group where stock prices change by over 90% of the limits but do not reach the limits. The event session S_0 is defined as the trading session when the limit is hit. The pre-hit period starts from the previous trading session of S_0 and runs until the limit is first hit in S_0 and the post-hit period starts from the trade next to the limit-hitting trade in S_0, and runs until the end of the next session after S_0. In this table, the adverse selection cost computed by the GH88 model is used to indicate information asymmetry in the market. Sample size varies due to the process of excluding events with extreme estimations from the model regression, and also events with small amount of trades (less than ten) in either the pre- or post-hit period.

Table 4. Regression of the Change on Information Asymmetry Ratio between the Pre- and Post-hit Periods

A. Summary Statistics of ΔSYMM

	Upper events		Lower events	
	Mean	*Median*	*Mean*	*Median*
$Stock_{hit}$	-0.0479	-0.0040	-0.0145	0
$Stock_{0.90}$	-0.0104	0	0.0416	0.0059

B. Regression Results

Summarised below are the results from the following regression :

$\Delta SYMM_j = \beta_0 + \beta_1 * LHG_j + \beta_2 * MktCap_j + \beta_3 * \Delta Volume_j + \beta_4 * Weekday_j + \beta_5 * Month_j + \beta_6 * Volatility_j + \varepsilon_j,$

	Upper events		Lower events	
	Coefficients	*t-statistics*	*Coefficients*	*t-statistics*
Intercept	-0.0059	-0.1022	0.0707	0.9628
LHG	-0.0373*	-2.2752	-0.0612**	-2.4136
MktCap	0.0005	0.1082	0.0047	0.8299
ΔVolume	0.0418**	3.8129	0.0512*	2.5003
Weekday	0.0030	0.5635	-0.0144	-1.6752
Month	0.0001	0.0668	-0.0016	-0.4505
Volatility	-0.5561	-1.5864	-0.5241	-1.4941
R-square	1.0%		2.0%	
F-statistic	3.47**		2.85*	
Sample size	2150		865	

LHG is the dummy variable that equals to 1 if stock *j* comes from $Stock_{hit}$ group, and 0 if stock *j* comes from $Stock_{0.90}$; $MktCap_j$ denotes the logarithm of stock *j*'s market capitalisation; $\Delta Volume_j$ is computed as the logarithm change in the trading volume from the pre-hit period to the post-hit period with stock *j*; $Volatility_j$ is computed as the squared logarithm return between the closing price of the post-hit period and the opening price of the pre-hit period; $Weekday_j$ and $Month_j$ refer to the day of the week and the month when the event *j* happens; and ε_j is the error term, on which heteroskedasticity is taken into consideration if there is some pattern in the error term. The symbols * and ** after the coefficients indicate that the coefficients are significant at the 5% and 1% levels of significance, respectively. Due to the missing observations for the regression variables, sample sizes vary from the sample used in the GH88 model computation.

Table 5. Test on Volatility Spill-over Hypothesis.

	Upper events			Lower events		
Day	Stock_{hit}	$Stock_{0.90}$	$Stock_{0.80}$	Stock_{hit}	$Stock_{0.90}$	$Stock_{0.80}$
-10	0.3044	0.2735	0.2554	0.3736	0.2922	0.2885
-9	0.2987	0.2917 >>	0.2281	0.3568	0.3133	0.2873
-8	0.3266	0.3367 >	0.2735	0.3755	0.3247 >	0.2566
-7	0.2825	0.3181 >	0.2805	0.3386	0.3321 >	0.2587
-6	0.3494 >	0.3002	0.3025	0.3451	0.3844 >	0.2921
-5	0.3693	0.3574	0.2956	0.4082	0.3857 >	0.3094
-4	0.4164 >	0.3734 >	0.2986	0.4026	0.3735	0.3227
-3	0.3952	0.4586 >>	0.3560	0.4620	0.4291	0.4082
-2	0.4675 <	0.4832 >	0.4346	0.5361	0.4789 >>	0.4082
-1	0.6562 <<	0.8943 >>	0.6749	0.7266	0.7507 >>	0.6314
0	15.8725	10.3360	8.5020	14.5515 >>	10.0550	8.4029
+1	1.6496 >>	0.9469 >>	0.7260	1.6664 >>	0.9854	0.8722
+2	0.8822 >>	0.6230 >>	0.5239	1.4498 >>	0.7936 >>	0.6410
+3	0.6739 >>	0.5222 >>	0.4344	0.8255 >>	0.5436 >>	0.4706
+4	0.6158 >>	0.4527 >	0.3994	0.7347 >	0.5654 >>	0.4682
+5	0.5556 >>	0.4431 >>	0.3628	0.5892	0.4764 >	0.4234
+6	0.4913 >>	0.4000 >>	0.3588	0.5285 >	0.4352 >	0.3876
+7	0.505 >>	0.4027	0.3746	0.4993	0.4586 >>	0.3332
+8	0.4677 >>	0.3921 >	0.3367	0.4427	0.3821 >>	0.3220
+9	0.4492 >>	0.3734 >>	0.3216	0.4259	0.3699 >>	0.2825
+10	0.3976 >>	0.3541 >	0.2973	0.4704 >>	0.3525 >	0.3038

Stock_{hit}, $\text{Stock}_{0.90}$ and $\text{Stock}_{0.80}$ are classified by the magnitude of their price movement on the event day, as mentioned in the previous text. Upper events and Lower events refer to the sample events with upwards price movements and downwards price movements, respectively. The squared logarithm of the daily return, $V_{t,j} = (r_{t,j})^2$, is used as the volatility measurement. Here, $V_{t,j}$ is multiplied by 1000 for the purpose of presentation. The signs >> and > indicate that the left-hand figure is greater than the right-hand figure at the 1% and 5% levels of significance, respectively, using the Wilcoxon rank-sum test.

Table 6a. Volatility Spill-over Effect Shown in Different Price Limit Ranges (Upper limit-hit Events)

	Upper Events					
	Price limit > 25%		*25% > price limit >15%*		*Price limit < 15%*	
Day	Stock_{hit}	$\textit{Stock}_{0.90}$	Stock_{hit}	$\textit{Stock}_{0.90}$	Stock_{hit}	$\textit{Stock}_{0.90}$
-10	0.2228	0.2070	0.2625	0.2416	0.3589	0.2999
-9	0.2644	0.3096	0.2644	0.2989	0.3367	0.2785
-8	0.2857	0.2506	0.2693	0.3084	0.3845	0.3646
-7	0.2825	0.3133	0.2602	0.2860	0.2934	0.3367
-6	0.3367	0.3025	0.3241	0.3065	0.3719 >	0.2973
-5	0.3974	0.2560	0.3367	0.3367	0.3972	0.3832
-4	0.4082	0.4194	0.3494	0.3357	0.4564 >	0.3908
-3	0.3398	0.4252	0.3699	0.4035	0.4294	0.4769
-2	0.4252	0.5225	0.3648 <<	0.4860	0.5179	0.4831
-1	0.6410 <	0.9922	0.6575 <<	1.2316	0.6564 <<	0.7452
0	66.0470 >>	41.1495	23.3900 >>	17.3830	11.1010 >>	8.0303
+1	4.9688 >>	3.3246	1.6396 >>	1.0732	1.4267 >>	0.8146
+2	1.7943	1.6092	1.0009 >>	0.6690	0.7492 >>	0.5632
+3	1.4154 >>	0.7394	0.6632 >	0.5349	0.6097 >>	0.4939
+4	1.0456	0.8267	0.5870	0.4991	0.5656 >>	0.4082
+5	0.9899 >	0.6576	0.4892	0.4597	0.5537 >>	0.4175
+6	0.8087	0.5882	0.4371	0.3673	0.4913 >>	0.4009
+7	0.6410	0.8695	0.4829 >	0.3468	0.4929 >>	0.3984
+8	0.6747	0.5255	0.4266	0.4092	0.4667 >>	0.3722
+9	0.5127	0.5374	0.4185	0.4082	0.4589 >>	0.3486
+10	0.4665	0.5168	0.4093	0.3306	0.3842 >	0.3490

We divide both Stock_{hit} and $\text{Stock}_{0.90}$ into three sub-groups according to the magnitude of the price limits that constrain the price movement on the event day. Upper events refer to the sample events with upwards price movements. The signs >> and > indicate that the left-hand figure is greater than the right hand figure at the 1% and 5% levels of significance, respectively, using the Wilcoxon rank-sum test.

Table 6b. Volatility Spill-over Effect Shown in Different Price Limit Ranges (Lower limit-hit Events)

	Lower Events								
	Price limit > 25%			*25% > price limit >15%*			*Price limit < 15%*		
Day	$Stock_{hit}$		$Stock_{0.90}$	$Stock_{hit}$		$Stock_{0.90}$	$Stock_{hit}$		$Stock_{0.90}$
-10	0.7507		0.7306	0.2812		0.2659	0.3921		0.2936
-9	0.6357		0.4726	0.3247		0.2811	0.3628		0.3323
-8	0.7431		0.4123	0.3225		0.3493	0.4009	>	0.3172
-7	0.7889		0.4027	0.3078		0.3274	0.3482		0.3313
-6	0.4998		0.4433	0.2741		0.3470	0.3780		0.3911
-5	0.6918		0.2085	0.3665		0.2825	0.4137		0.4102
-4	0.3883		0.4296	0.3589		0.3365	0.4243		0.3841
-3	1.0080		0.6747	0.3118		0.3149	0.5010		0.4473
-2	0.6003		0.4726	0.5000		0.4393	0.5591		0.4974
-1	0.8888		1.8910	0.5231		0.7056	0.8042		0.7304
0	96.957	>>	56.6240	29.964	>>	20.8795	12.100	>>	8.6706
+1	9.3905	>	3.1936	1.8876	>>	1.1891	1.4885	>>	0.8791
+2	1.6019		2.5263	1.6533	>>	0.8403	1.3762	>>	0.7439
+3	1.7668		1.8638	0.8023	>>	0.5331	0.8211	>>	0.5285
+4	1.6508		1.6664	0.6987	>>	0.4999	0.7445		0.5680
+5	1.4703		1.8541	0.4810		0.3098	0.5970		0.5088
+6	0.6886		0.8601	0.5184	>	0.3295	0.5285		0.4579
+7	0.8500		0.6251	0.4996		0.3392	0.4957		0.4744
+8	0.7430	>	0.2480	0.3918		0.3753	0.4578		0.3921
+9	0.6525		0.1010	0.3352		0.2885	0.4662		0.4009
+10	0.4342		0.5409	0.4296	>	0.2977	0.4831	>>	0.3813

We divide both $Stock_{hit}$ and $Stock_{0.90}$ into three sub-groups, according to the magnitude of the price limits that constrain the price movement on the event day. Lower events refer to the sample events with downwards price movements. The signs >> and > indicate that the left-hand figure is greater than the right-hand figure at the 1% and 5% levels of significance, respectively, using the Wilcoxon rank-sum test.

Table 7. Test on Delayed Price Discovery Hypothesis.

Price Behaviour	$Stock_{hit}$	$Stock_{0.90}$	$Stock_{0.80}$	$Stock_{hit} - Stock_{0.90}$	z-value	Sample size for $Stock_{hit}$
Upward Price Movement						
Continuation	61%	43%	42%	18%	32.60	4835
Reversal	31%	47%	47%	-16%	-29.21	2440
No Change	8%	10%	11%	-2%	-5.13	666
Total						7941
Downward Price Movement						
Continuation	45%	31%	30%	14%	17.01	1412
Reversal	47%	60%	59%	-12%	-14.22	1472
No Change	8%	9%	11%	-2%	-3.06	245
Total						3129

We follow Kim and Rhee (1997)'s methodology, and present the price behaviour of all three groups as in the proportion of price continuation, price reversal and no change in price. The sample size of $Stock_{hit}$ here is smaller than the sample size mentioned in the data description section, where there are 8390 upper limit hit events and 3355 lower limit hit events in total. This is due to the opening price data error and missing observations on some event days, with these data figures not being included in this hypothesis testing.

This z-value is the z-statistic for a standard nonparametric binomial test. The null hypothesis in this case is that there are more price continuations happening in the sample group $Stock_{hit}$, than for the group of $Stock_{0.90}$. According to Olkin, Gleser, and Derman (1980), the z-statistic has a normal distribution when the sample sizes are both sufficiently large. The calculation for the z-statistics is:

$$z = (CON_{hit} - PrCON_{0.90} * Nhit) / (PrCON_{0.90} * (1 - PrCON_{0.90}) * Nhit) * 0.5$$

where CON_{hit} denotes the number of price continuations for $Stock_{hit}$ and $PrCON_{0.90}$ denotes the frequency of price continuations that occur to Stock0.90. Nhit represents the sample size of $Stock_{hit}$.

Table 8. Test on the Under-reaction Factor.

A. Upper limit-hit events		
t-Test: Paired Two Sample for	*Group 1 (winners)*	*Group 2 (losers)*
Mean (proportion of total upper hit)	0.298	0.191
Sample size (days)	2480	2480
Hypothesized Mean Difference	0	
t Stat	9.978	
P(T<=t) one-tail	0	
Sign rank test for Medians	P value < 0.001	
B. Lower limit-hit events		
t-Test: Paired Two Sample for	*Group 3 (losers)*	*Group 4 (winners)*
Mean	0.151	0.165
Sample Size (days)	2480	2480
Hypothesized Mean Difference	0	
t Stat	-1.457	
P(T<=t) one-tail	0.0727	
Sign rank test for Medians	P value = 0.4161	

Group 1 refers to the time series of the proportion of winners that hit the upper limit over the total upper limit hit events; and Group 2 refers to the time series of the proportion of losers that hit the upper limit over the total upper limit hit events. Either the mean test, or the median test, shows that the null hypothesis should be rejected, which means that winner stocks are more likely to hit upper limits than are loser stocks. Hence, we believe that the under-reaction factor is significant during upward price movements.

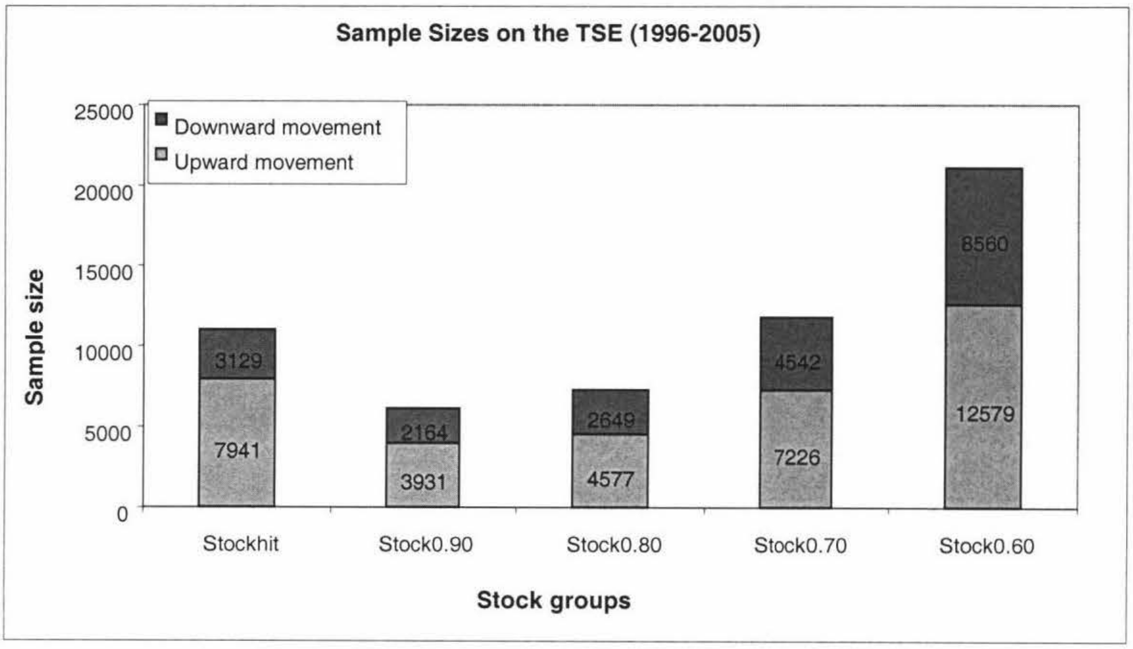
Group 3 refers to the time series of the proportion of losers that hit the lower limit over the total lower limit hit events; and Group 4 refers to the time series of the proportion of winners that hit the lower limit over the total lower limit hit events. Both the mean and median tests suggest that the null hypothesis should not be rejected, which means that winner stocks and loser stocks are equally likely to hit lower limits. The under-reaction factor is not significant when stock prices decrease.

Table 9. Test on Trading Interference Hypothesis

	Upper events					Lower events				
Day	$Stock_{hit}$		$Stock_{0.90}$		$Stock_{0.80}$	$Stock_{hit}$		$Stock_{0.90}$		$Stock_{0.80}$
-5	0.00		0.00		0.00	-2.30		0.00		0.00
-4	0.00		0.00		0.00	0.00		0.00		-2.17
-3	0.00		0.00		1.42	-1.29		0.00		0.00
-2	3.96	<	7.29	>>	1.98	0.00		1.80		0.00
-1	17.67		16.10		16.89	6.57		2.42		3.12
0	88.86	>>	79.70	>>	73.09	36.77		40.30	>	34.04
+1	-7.85	>>	-44.67	<	-41.62	-3.57	>>	-31.79	<	-26.24
+2	-55.79	<<	-40.69		-36.88	-32.29	<<	-22.26		-21.10
+3	-28.07	<<	-19.07		-15.10	-14.31	<	-10.18		-7.09
+4	-16.32	<<	-9.50		-10.11	-10.74		-5.86		-5.61
+5	-8.75		-8.59	<	-6.28	-9.09		-3.27		-5.62

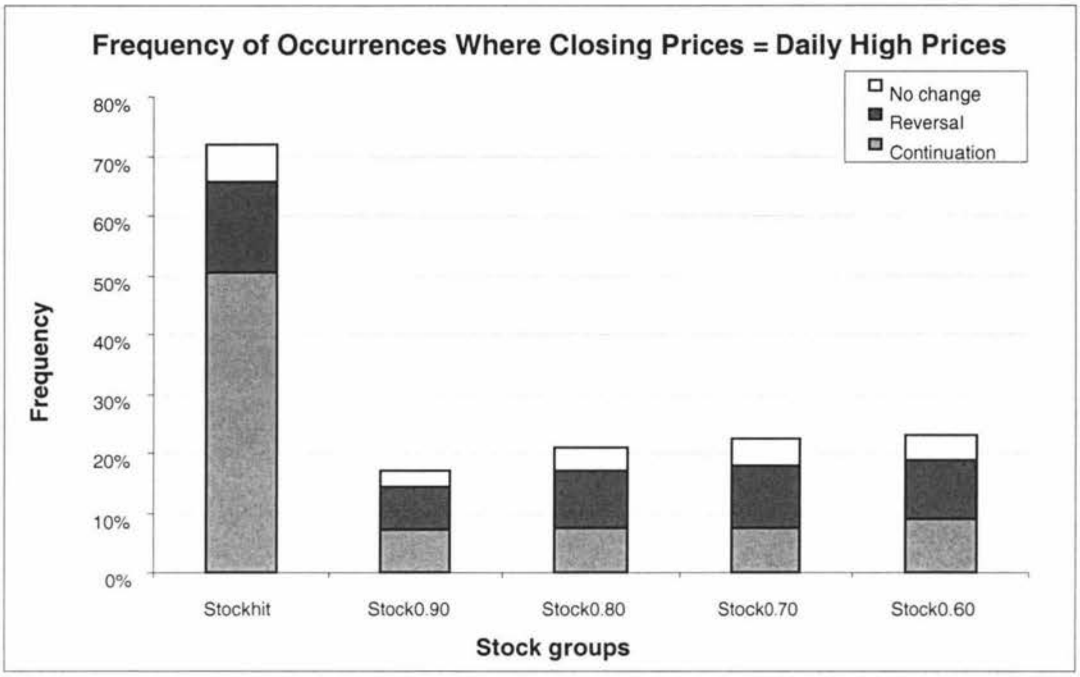
We measure the turnover ratio $TA_{t,j}$ for stock j on day t by dividing the total outstanding shares by the trading volume of stock j on Day t. In this table, the logarithmic change in the turnover ratio, $\ln(TA_{j,t}/TA_{j,t-1}) * 100$, is compared among stock groups by using the Wilcoxon rank-sum test. The symbols >> and > indicate that the percentage on the right-hand side is greater than that on the left-hand side at the 0.01 and 0.05 levels of significance, respectively.

Figure 1. Sample Sizes for All Stock groups on the TSE



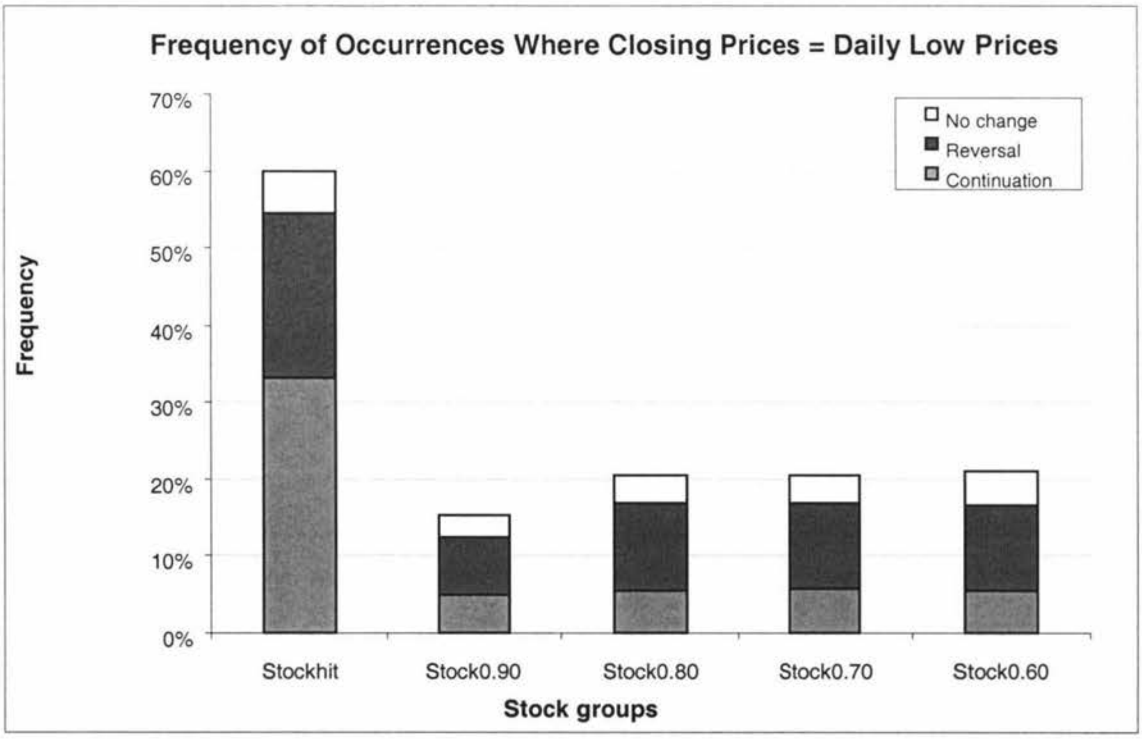
The red area indicates the sample size for events with downward price movement, and the green area indicates the sample size for events with upward price movement. Samples of all groups are filtered to exclude the influence from the maximum price variation rule.

Figure 2a. Frequency of Different Price Behaviours When Price is Moving Upward



The frequency of price continuation occurring to Stock$_{hit}$ is significantly higher than all other groups. There is no obvious difference between Stock$_{0.90}$ and other groups with large price variation without limit-hit.

Figure 2b. Frequency of Different Price Behaviours When Price is Moving Downward.



The frequency of price continuation occurring to Stock$_{hit}$ is significantly higher than all other groups. There is no obvious difference between Stock$_{0.90}$ and other groups with large price variations without limit-hit.

References

Ahn, H.J., Cai, J., Hamao, Y. and Ho, R. (2002). The components of the bid-ask spreads in a limit-order market: Evidence from the Tokyo Stock Exchange. *Journal of Empirical Finance*, 9, 399-430.

Amihud, Y. and Mendelson, H. (1991). Volatility, efficiency and trading: Evidence from the Japanese stock market. *Journal of Finance*, 46, 1765– 1791.

Chan, K., Hameed, A. and Tong, W. (2000). Profitability of momentum strategies in the international equity markets. *Journal of Financial and Quantitative Analysis*, 35, 153-172.

Chan, L.K.C., Jegadeesh, N. and Lakonishok, J. (1996). Momentum strategies. *The Journal of Finance*, 51, (5), 1681-1713.

Chan, S.H., Kim, K.A. and Rhee, G. (2005). Price limit performance: Evidence from transactions data and the limit order book. *Journal of Empirical Finance*, 12, (2), 269-290.

Chen, G., Rui, O.M. and Wang, S.S. (2005). The effectiveness of price limits and stock characteristics: Evidence from the Shanghai and Shenzhen Stock Exchanges. *Review of Quantitative Finance and Accounting*, 25, (2), 159-182.

Chen Y.M. (1993). Price limits and stock market volatility in Taiwan. *Pacific Basin Finance Journal*, 1, 139-153

Choi, W.S. and Lee, S.B. (2001). *A transitory and asymmetric properties in price limits: Korean evidence with intra-day data.* Working paper, Hanyang University.

Chung, J.R. (1991). Price limit system and volatility of Korean stock market. In Rhee, S.G. and Chung, R.P. (Eds.), *Pacific basin capital market research, Vol. II*, (pp 283-294). Amsterdam: North Holland.

Easley, D., Kiefer, N.M., O'Hara, M. and Paperman, J.B. (1996). Liquidity, information, and infrequently traded stocks. *Journal of Finance,* 51, (4), 1405-1436.

Fama, E.F. (1989). Perspectives on October 1987, or what did we learn from the crash. In Barro, R.J., Kamphuis, R.W.Jr., Kormendi, R.C. and Watson, J.W.H. (Eds.), *Black Monday and the Future of Financial Markets,* (pp 71-82). Homewood, IL: Dow Jones-Irwin.

French, K. and Roll, R. (1986). Stock return variances: The arrival of information and the reaction of traders. *Journal of Financial Economics*, 17, 5-26.

Gerety, M.S. and Mulherin, H.J. (1992). Trading halts and market activity: An analysis of volume at open and close. *Journal of Finance*, 47, 1765– 1784.

Glosten, L.R. and Harris, L. (1988). Estimating the components of the bid-ask spread. *Journal of Financial Economics*, 21, 123-142.

Greenwald, B.C. and Stein, J.C. (1991). Transaction risk, market crashes, and the role of circuit breakers. *Journal of Business*, 64, (4), 442-462.

Harris, L. (1998). Circuit breakers and program trading limits: What have we learned? In Litan, R.E. and Santomero, A.M. (Eds.), *Brookings-Wharton Papers on Financial Services*. (pp. 17–63). Washington DC: Brookings Institutions Press.

Harris, L. (2003). *Trading and exchanges: Market microstructure for practitioners.* New York: Oxford University Express.

Kim, K.A. and Rhee, S.G. (1997). Price limit performance from the Tokyo Stock Exchange. *Journal of Finance,* 52, 885–901.

Kim, K.A. and Sweeney, R.J. (2002). *Effects of price limits on information revelation: theory and empirical evidence.* Working paper, Georgetown University.

Kodres, L.E. and O'Brien, D.P. (1994). The existence of Pareto superior price limits. *American Economic Review,* 84, 919-932.

Kyle, A.S. (1985). Continuous auctions and insider trading. *Econometrica*, 53, 1315–1335.

Kyle, A.S. (1988). Trading halts and price limits. *The Reviews of Futures Markets*, 7, 426-434.

Lehmann, B.N. (1989). Commentary: Volatility, price resolution, and the effectiveness of price limits. *Journal of Financial Services Research,* 3, 205–209.

Lehmann, B.N. and Modest, D.M. (1994). Trading and liquidity on the Tokyo Stock Exchange: A bird's eye view. *Journal of Finance,* 49, 951-984.

Ma, C.K., Rao, R.P. and Sears, S.R. (1989). Volatility, price resolution, and the effectiveness of price limits. *Journal of Financial Services Research*, 3, 165-199.

Nath, P. (2005). Are price limits always bad? *Journal of Emerging Market Finance*, 4, (3), 281-313.

Olkin, I., Gleser, L.J., and Derman, C. (1980). *Probability models and applications.* New York: Macmillan.

Spiegel, M. and Subrahmanyam, A. (1995). On intraday risk premia. *Journal of Finance*, 50, 319-339.

Tokyo Stock Exchange. (2005). *General FAQ – What is a trading unit?* Retrieved September 10, 2006, from http://www.tse.or.jp/english/faq/t_e.html

Tokyo Stock Exchange. (2006). *Tokyo Stock Exchange Fact book 2006.* Retrieved September 10, 2006, from http://www.tse.or.jp/english/data/factbook/index.html

Bibliography

Berkman, H. and Lee, J.B. (2002). The effectiveness of price limits in an emerging market: Evidence from the Korean Stock Exchange. *Pacific-Basin Finance Journal*, 10, 517–530.

Gan, L. and Li, D. (2001). *Using American Depository Receipts to Identify the Effect of Price Limits.* Working paper, University of Texas.

Kim, K.A. (2001). Price limits and stock market volatility. *Economics Letters,* 71, 131–136.

Lauterbach, B. and Ben-Zion, U. (1993). Stock market crashes and the performance of circuit breakers: Empirical evidence. *Journal of Finance*, 48, 1909–1925.

Phylaktis, K., Kavussanos, M. and Manalis, G. (1999). Price limits and stock market volatility in the Athens Stock Exchange. *European Financial Management*, 5, 69-84.

Seasholes, M. and Wu, G. (2004). *Profiting from predictability: Smart traders, daily price limits, and investor attention.* Working paper, University of California, Berkeley.

Shen, CH. and Wang, LR. (1998). Daily serial correlation, trading volume and price limits: Evidence from the Taiwan stock market. *Pacific-Basin Finance Journal*, 6, (3), 251-273.

Stoll, H. (1978). The supply of dealer services in securities markets. *Journal of Finance*, 33, 1133-1151.

Appendices

Table A1. Tick Size Used on the Tokyo Stock Exchange (TSE Fact Book, 2006)

Tick Size on the TSE		
Previous Day's Closing Price or Special Quote[12]	Tick Size (after change in April 13 1998)	Tick Size (before change in April 13 1998)
$0 < p < 100$	¥1	¥1
$100 \leq p < 200$	¥1	¥1
$200 \leq p < 500$	¥1	¥1
$500 \leq p < 1000$	¥1	¥1
$1{,}000 \leq p < 1{,}500$	¥1	¥10
$1{,}500 \leq p < 2{,}000$	¥1	¥10
$2{,}000 \leq p < 3{,}000$	¥5	¥10
$3{,}000 \leq p < 5{,}000$	¥10	¥10
$5{,}000 \leq p < 10{,}000$	¥10	¥10
$10{,}000 \leq p < 20{,}000$	¥10	¥100
$20{,}000 \leq p < 30{,}000$	¥10	¥100
$30{,}000 \leq p < 50{,}000$	¥50	¥100
$50{,}000 \leq p < 70{,}000$	¥100	¥100
$70{,}000 \leq p < 100{,}000$	¥100	¥100
$100{,}000 \leq p < 150{,}000$	¥1,000	¥1,000
$150{,}000 \leq p < 200{,}000$	¥1,000	¥1,000
$200{,}000 \leq p < 300{,}000$	¥1,000	¥1,000
$300{,}000 \leq p < 500{,}000$	¥1,000	¥1,000
$500{,}000 \leq p < 1{,}000{,}000$	¥1,000	¥1,000
$1{,}000{,}000 \leq p < 20{,}000{,}000$	¥10,000	¥10,000
$20{,}000{,}000 \leq p < 30{,}000{,}000$	¥50,000	¥10,000
$30{,}000{,}000 \leq p < 50{,}000{,}000$	¥100,000	¥10,000
$P \geq 50{,}000{,}000$	¥100,000	¥10,000

[12] Special quotes are also called special bid and asked quotes, which are disseminated to the market through information systems when there is a major order imbalance. The quotes are either matched by the following orders, or revised up or down, according to the imbalance within five minutes intervals, until the imbalance is resolved.

Table A2. Price Limits Used on the Tokyo Stock Exchange (TSE Fact Book, 2006)

	Daily Price Limits	
Previous Day's Closing Price or Special Quote	Daily Price Limits (±) (after change on July 17, 2000)	Daily Price Limits (±) (before change on July 17, 2000)
$0 < p < 100$	¥30	¥30
$100 \leq p < 200$	¥50	¥50
$200 \leq p < 500$	¥80	¥80
$500 \leq p < 1000$	¥100	¥100
$1,000 \leq p < 1,500$	¥200	¥200
$1,500 \leq p < 2,000$	¥300	¥300
$2,000 \leq p < 3,000$	¥400	¥400
$3,000 \leq p < 5,000$	¥500	¥500
$5,000 \leq p < 10,000$	¥1,000	¥1,000
$10,000 \leq p < 20,000$	¥2,000	¥2,000
$20,000 \leq p < 30,000$	¥3,000	¥2,000
$30,000 \leq p < 50,000$	¥4,000	¥3,000
$50,000 \leq p < 70,000$	¥5,000	¥5,000
$70,000 \leq p < 100,000$	¥10,000	¥5,000
$100,000 \leq p < 150,000$	¥20,000	¥50,000
$150,000 \leq p < 200,000$	¥30,000	¥50,000
$200,000 \leq p < 300,000$	¥40,000	¥80,000
$300,000 \leq p < 500,000$	¥50,000	¥80,000
$500,000 \leq p < 1,000,000$	¥100,000	¥100,000
$1,000,000 \leq p < 1,500,000$	¥200,000	¥200,000
$1,500,000 \leq p < 2,000,000$	¥300,000	¥300,000
$2,000,000 \leq p < 3,000,000$	¥400,000	¥400,000
$3,000,000 \leq p < 5,000,000$	¥500,000	¥500,000
$5,000,000 \leq p < 10,000,000$	¥1,000,000	¥1,000,000
$10,000,000 \leq p < 15,000,000$	¥2,000,000	¥2,000,000
$15,000,000 \leq p < 20,000,000$	¥3,000,000	¥2,000,000
$20,000,000 \leq p < 30,000,000$	¥4,000,000	¥2,000,000
$30,000,000 \leq p < 50,000,000$	¥5,000,000	¥2,000,000
$P \geq 50,000,000$	¥10,000,000	¥2,000,000

Table A3. Percentile Statistics of Year End Closing Price from Year 1996 to 2005

$*P_i$	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
P10	396	154	161	148	137	111	97	176	229	354
P20	468	210	217	205	210	191	174	255	328	482
P30	560	293	290	294	302	291	264	358	441	656
P40	680	375	375	385	395	386	361	463	580	852
P50	816	480	480	512	540	517	476	646	763	1130
P60	989	620	608	721	776	705	657	886	1040	1568
P70	1310	825	851	1180	1081	1020	931	1239	1494	2130
P80	1800	1270	1300	2000	1700	1620	1441	1849	2160	3040
P90	2690	2120	2360	4500	3380	3400	2820	3620	4200	6000
Mean	14069	12226	15371	91945	20238	25282	13478	21330	18836	24543

* P_i refers to the ith percentile of the stock prices in the sample. P50 equals to the median. It is shown in the table that over half of the listed stocks are priced under ¥1,000, except for the year 2005 when the median was slightly over ¥1,000. Ninety percent of the sample stocks are priced under ¥5,000, with the exception of year 2005. The price limit for stocks that fall into the range from ¥500 to ¥5,000 is approximately between 10% and 20%, and the limit is between 16% and 50% for the price range from ¥100 to ¥500. This feature allows cheap stock to behave with more volatility than high priced stocks. Additionally, mean prices appear much higher than medians, which suggests that the price distribution is left skewed in the TSE.

Table A4. Summary Statistics of All Limit-hit Events on the TSE from 1996 to 2005

	All	Upper	%	Lower	%
By Year					
1996	333	270	3%	63	2%
1997	530	217	3%	313	9%
1998	673	446	5%	227	7%
1999	2930	2350	28%	580	17%
2000	2970	1772	21%	1198	36%
2001	1027	762	9%	265	8%
2002	583	408	5%	175	5%
2003	1111	896	11%	215	6%
2004	980	724	9%	256	8%
2005	608	545	6%	63	2%
Total	*11745*	*8390*	*100%*	*3355*	*100%*
By Month					
January	1096	864	10%	232	7%
February	926	749	9%	177	5%
March	1168	856	10%	312	9%
April	1319	885	11%	434	13%
May	937	568	7%	369	11%
June	640	558	7%	82	2%
July	701	546	7%	155	5%
August	591	433	5%	158	5%
September	937	609	7%	328	10%
October	1180	806	10%	374	11%
November	1260	863	10%	397	12%
December	990	653	8%	337	10%
Total	*11745*	*8390*	*100%*	*3355*	*100%*
By Weekday					
Monday	2813	1761	63%	1052	37%
Tuesday	2192	1523	69%	669	31%
Wednesday	2322	1789	77%	533	23%
Thursday	2318	1746	75%	572	25%
Friday	2100	1571	75%	529	25%
Total	*11745*	*8390*		*3355*	

This table reports the total number of price limit hit events, and lists the events by the year and also by the month. In the columns *Upper* and *Lower*, the sub-samples with upper limits hitting and lower limits hitting are listed separately. When the events are sorted by month, the distribution of upwards limit-hit events seems to imply the Halloween effect, however, there is no apparent seasonal pattern for the downwards limit hits. (The same features also appear in the subgroups $Stock_{0.90}$ and $Stock_{0.80}$.) It is also shown that most downwards limit-hit events happen on Monday, almost twice as frequently as on other weekdays, while the pattern is not so obvious for the upwards limit-hit events. The reason for this pattern is out of the scope of this research, however.

Table A5. Test result of Volatility Spill-over Hypothesis presented in mean volatility.

	Upper events			Lower events		
Day	Stock$_{hit}$	*Stock$_{0.90}$*	*Stock$_{0.80}$*	Stock$_{hit}$	*Stock$_{0.90}$*	*Stock$_{0.80}$*
-10	2.2186	2.4361	1.6699	2.0461	1.9046	1.7779
-9	1.8341	1.8599 >>	1.6050	2.1739	2.2608	1.8272
-8	1.9505	2.4084 >	1.6880	1.9683	2.0118 >	1.7316
-7	1.9709	2.0404 >	1.9038	2.1125	2.0372 >	1.7609
-6	2.1811 >	2.0424	1.8751	2.1219	2.275 >	1.9842
-5	2.1789	2.2892	1.9977	2.6658	2.6053 >	2.0626
-4	2.4805 >	2.1691 >	2.0082	2.5235	2.5234	2.1920
-3	2.5078	2.6026 >>	2.2954	2.6147	3.0358	2.5899
-2	2.6416 <	3.2768 >	3.0203	2.89	3.0219 >>	3.1539
-1	3.8064 <<	5.1432 >>	4.0875	3.3574	4.1618 >>	3.8137
0	20.759 >>	13.37 >>	11.2288	19.21 >>	13.558 >>	11.4712
+1	5.3171 >>	3.2293 >>	2.7337	5.7271 >>	3.6744	3.2926
+2	3.4438 >>	2.4421 >>	2.1742	4.7001 >>	3.2594 >>	2.6530
+3	2.7805 >>	2.1794 >>	1.9709	3.4063 >>	2.8499 >>	2.2688
+4	2.4348 >>	1.9927 >	1.8938	3.0791 >	3.0466 >>	2.4373
+5	2.3817 >>	2.0914 >>	1.7629	2.8964	2.8292 >	2.3075
+6	2.2264 >>	1.9631 >>	1.7476	2.5018 >	2.4525 >	2.1471
+7	2.2279 >>	1.8179	1.7366	2.3241	2.4122 >>	1.9770
+8	2.149 >>	1.789 >	1.7066	2.0734	2.0385 >>	1.8895
+9	2.0401 >>	1.8582 >>	1.6726	2.1221	2.0248 >>	1.7591
+10	1.9679 >>	1.7017 >	1.6103	2.2874 >>	1.9666 >	1.7558

For comparing with other relevant studies (i.e. Kim and Rhee, 1997; Chan et al. 2005), we present the mean volatility for all stocks groups on each day during the event window in this table. Stock$_{hit}$, Stock$_{0.90}$ and Stock$_{0.80}$ are classified by the magnitude of their price movement on the event day, as mentioned in the previous text. Upper events and Lower events refer to the sample events with upwards price movement and downwards price movement. The signs >> and > indicate that the left-hand figure is greater than the right-hand figure at the 1% and 5% levels of significance, respectively, using the Wilcoxon rank-sum test.

Table A6. Test on Delayed Price Discovery Hypothesis (considering the maximum price variation rule)

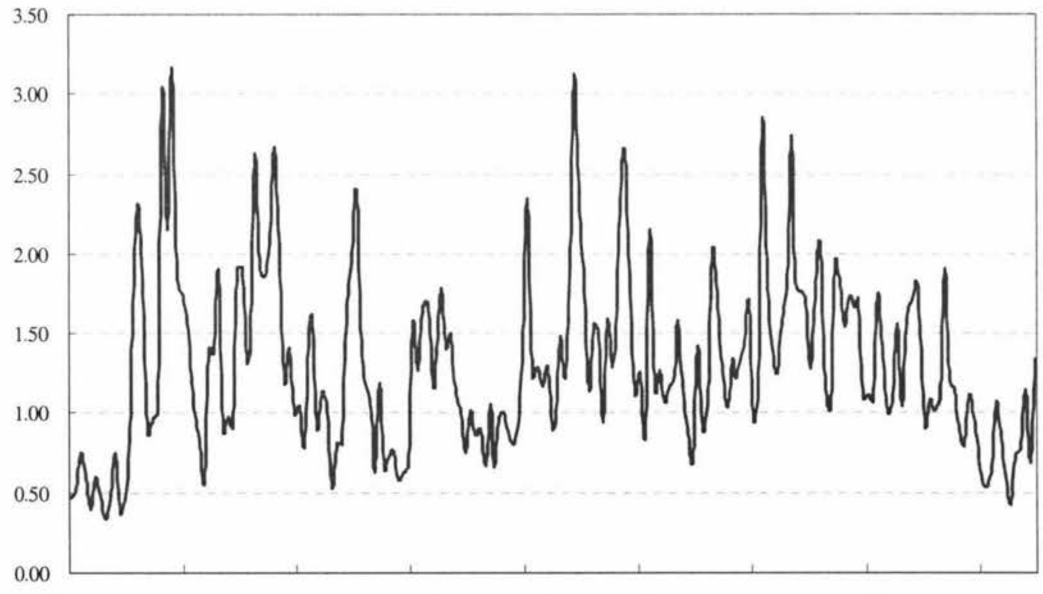
Price Behaviour	$Stock_{hit}$	$Stock_{0.90}$	$Stock_{0.80}$	$Stock_{hit} - Stock_{0.90}$	z-value	Sample size for $Stock_{hit}$
Price behaviours for stocks that close at daily high or low price on Day 0						
Upward Price Movement (price closes at daily high)						
Continuation	70%	41%	36%	29%	43.93	4000
Reversal	21%	42%	46%	-21%	-32.03	1221
No Change	9%	16%	18%	-8%	-15.78	486
Total						5707
Downward Price Movement (price closes at daily low)						
Continuation	55%	31%	26%	24%	22.54	1040
Reversal	35%	51%	56%	-15%	-13.20	663
No Change	9%	18%	17%	-9%	-10.01	172
Total						1875

In Table A6, we only include the stocks whose closing prices are equal to the daily high (low) prices for upper (lower) price movements. As a result, our result of price discovery process may not be influenced by the maximum price variation rule used in the early years in the TSE. The maximum price variation rule is used to restrict the maximum transaction price. This regulation can not be seen in the TSE fact books of recent financial years. Due to the long sample period in this paper, we follow the methodology of Kim and Rhee (1997) and filter the possible impact from the mechanism. This filtering process shrinks the sample size by 30% to 40%, but does not change the substantial feature of price behaviours from what we find before in Table 7, thus confirms the robustness of the result. The proportion of price continuation for $Stock_{hit}$ is largely greater than other groups in relation to both price moving directions.

Figure 1A. Nikkei225 price index and daily volatility averaged by month.

Nikkei225 Price Index

Daily Volatility Averaged by Month



Here, we calculate the daily volatility of the Nikkei 225 index for the period 1989 to 2005, and then multiple the volatility by 1000. The average value of daily volatility for each month is presented in the above graph.