Price Limits Are Not Always Bad

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Abstract

Regulators impose price limit on daily price movement to protect investors from excessive volatility, but several empirical studies so far have cast serious doubt on benefits of such mechanism. This paper provides fresh evidence of price limit performance on market volatility and informational efficiency on Tokyo Stock Exchange which is a good platform for this research due to a large cross-sectional sample and its elaborated market microstructure. We find evidences that partially supports conventional criticisms that price limits spread out volatility, delay price discovery and interrupt trading activities. However, the analysis based on transaction data reveals that price limit helps to reduce order imbalance and improve information asymmetry, justifying the existence of the price limits on the Tokyo Stock Exchange.

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1. Introduction

The increasingly volatile market, along with the huge loss that investors have suffered from market crashes in the 80's, Asian financial crisis in year 1997, and high-tech stocks bubble bursting in 2000, calls for a market mechanism that can cool down fanatic trading and prevent market crash. Since 1987, market 'circuit breakers' have been introduced and widely used in over 12 stock exchanges. Price limit is adopted as a most common way to prevent excessive market volatility and, more specifically, to restrict daily price movement in a certain range.

By using price limits, market regulators expect to put the brake on the trading activities when designed price boundary is exceeded, and regulators revise the limit when their perceptions of market or macroeconomic environment change[1]. Not surprisingly, research interest is well stimulated as price limit appears to be an "arbitrary way" to intervene the self functioning of securities market, which is against most classic economics theory. The previous studies mainly focus on testing the effectiveness by using price limit to control price volatility and the consequent affect on trading activities (Kim & Rhee, 1997; Kim, 2001; Chen, Rui & Wang, 2005). The overall empirical results from those studies suggest that price limit is not beneficial to stock market and investors and its performance does not meet regulators' expectation. Therefore it is natural to question the rationales of implementing price limit on stock exchanges, when price limit exists ubiquitously in many countries across Europe to

[1] For example, Stock Exchange of Thailand increased price limit from 10 percent to 30 percent in December 1997; the Korea Stock Exchange has raised price limit from 4.6 percent to 15 percent within four steps since year 1995.

Asia. Are price limits always bad?

TSE is chosen as the object in this paper to investigate the influence of price limit for four reasons. Firstly, TSE is the second largest stock exchange in the world, with sufficient size to provide sample magnitude, hence bias can be reasonably reduced and the test result can be more persuasive. Secondly, with no designated dealer or market maker, limit-order traders provide most of market liquidity in TSE; this main difference along with its elaborate microstructure distinguishes TSE from other major stock exchanges, which includes disseminating special quote as warnings of order imbalance, using maximum variation rule and price limit to hinder trading when necessary. Thus it is interesting to seek whether price limit hazards market efficiency and protect the uniformed traders in this "well-functioning financial market" (Lehmann & Modest, 1994, p. 982). It is also worth noting that in the most recent study on price limit of TSE, Kim and Rhee (1997), the sample period is restricted between 1989 and 1992. Despite of their forerunning methodology, it is necessary to re-examine TSE with more recent data, so that the test results can be more relevant to present regulators, since the stock market has become more volatile in the past 15 years and the price limit range has changed on TSE. Lastly, among many research papers about price limit, few of them study its influence on intraday trading activities (i.e., order flow, informed trading, and information content of prices). Chan, Kim and Rhee (2005) use intraday data from the Kuala Lumpur Stock Exchange (KLSE), but their sample size is fairly limited and only up-side events data are tested.[2] However, regulators are concerned about down-side events as much as, if not more, about up-side events, since the large decrement on stock price is always followed by low trading volume on the subsequent trading days, and it also largely affects rational investment decision.

This paper aims to explore any empirical benefits that price limits bring to stock markets and investors by performing an extensive investigation in two parts. Firstly, daily price variation, price behaviour and trading volume are examined on the daily data of all the stocks listed in the First section of Tokyo Stock Exchange (TSE) during the period from year 1996 to year 2005. In the second part, trade-by-trade data of stocks that are actively traded on TSE from year 1999 to 2000 is adopted to test how price limit affects intraday trading activities and degree of information asymmetry, which is a particularly important factor for maintaining equilibrium spread in an order-driven market (Harris, 2003, p. 311).

The primary findings are as follows. 1. Volatility is spread out to subsequent trading days, which is heavily contributed by stocks with price variation restricted within ±15% of the previous day closing price. 2. Price continuation occurs more frequently to stocks of which prices hit the limits in previous trading days, especially when upper price limits are hit; we find investors' under-reaction (momentum strategy) partially

[2] Here, up-side events refer to the events when upper bound of price limit is hit by daily price movement; down-side events occur when the lower bound of price limit is hit. In Chan, Kim and Rhee (2005), only 98 up-side sample events are eventually included in the testing procedure.

contributes to price continuation when price is moving upward; however, the proposition of Kim and Sweeney (2002) is not supported with sample data that informed traders are inclined to delay trades after limit being hit. 3. Trading volume of stocks with prices hitting limits is found to decrease at a lower speed compared with other stocks that also experience large price variation without hitting price limits. 4. Inconsistent with previous literature (e.g. Chan et al., 2005), we find order imbalance is improved in the post limit-hit period, and the result from cross-section regression shows no particular "magnet" effect is found on stocks with prices hitting limit; Price limits also improves information asymmetry, providing the market with cooling-off periods to transmit information and absorb one-side orders.

The rest of this paper is organized as follows. Section 2 reviews the previous literature on price limit. Section 3 firstly introduces some background information and relevant market microstructure of TSE, and then describes the sample data, the process of data filtering, and summary statistics of the sample. In Section 4, daily data is tested on three hypotheses: volatility spill-over, delayed price discovery, and trading interference. Section 5 further analyzes the intraday data, aiming to provide some possible explanations for the test results from Section 4, and more importantly to explore the influence of price limit on order flows and information asymmetry. Conclusions and future research suggestions are presented in Section 6.

2. Literature review

According to Harris (1998), there are four concepts of power that regulators need to concern about circuit breakers: Economic power, psychological power, political power, and statistical power. Although so influential as circuit breakers are, there are no clear answers to the questions yet that whether security markets are efficiently protected by this mechanism or as some scholars believe volatility is controlled by price limit with the cost of lower market efficiency.

2.1 Volatility

The previous researches have addressed possible influence from price limit from three main perspectives. The affect on stock price volatility is the first focus of many studies. The mechanism of price limits can literally prevent prices from rising or dropping out of a certain range, which, as regulators of many exchanges would anticipate, means price limits may help to stabilize prices change and hence reduce the volatility. However, many studies affirm that after stock prices hit the limit, the market volatility would simply be spread out to the subsequent trading days till the new equilibrium price is formed. Therefore the imposition of price limits is argued to induce volatility spill-over effect, which is firstly proposed by Fama (1989); he makes a guess that circuit breakers stop prices from being adjusted promptly when fundamental values experience large changes.

This hypothesis is advocated by Kyle (1988) and Lehmann (1989), and the empirical evidences support this notion by and large. Chung (1991) finds no evidence in Korean

Stock market that restrictive price limit (4.6% before year 1995) decrease price volatility, Chen (1993) reaches the similar result in Taiwan Stock Exchange. Kim and Rhee (1997) have reported that "volatility does not return to normal levels" at the same speed as the stocks that experience large price variation but do not yet reach price after investigating price limit performance on Tokyo Stock Exchange (TSE). Other studies use different approaches and data resource to test this hypothesis: Phylaktis, Kavussanos, and Manalis (1999) use ARCH/GARCH methodology on data before and after the price limit was imposed in Athens Stock Exchange in 1992; Gan and Li (2001) compare the stocks traded on Tokyo Stock Exchange and U.S. market in the forms of ADRs, as price limit is not used in U.S. market. Neither of them finds price limits exerting significant effect on the stock price volatility. Controversy on the effectiveness of price limits in stock markets still exists. In the finding of Lee and Kim (1995), price limits moderate price volatility based on the comparison of the volatilities between two portfolios with different levels of price limit. Berkman and Lee (2002) reach the similar result after examining the Korean Stock Exchange. They find the weekly volatility increases after the price limits being widened by 30% to 6%, and they propose a size-effect on small stocks with relatively higher volatility in emerging markets.

Many researches have attempted to test volatility spill-over in the last 15 years, but the result is still inconclusive. If the volatility is caused by trading of uninformed traders, price limit can help to moderate market fluctuation from noise trading and protect uninformed traders from suffering trading loss. Nevertheless, when the volatility is induced by fundamental value changes, it is suspected that temporary low volatility is achieved with low market efficiency. Interestingly, Chen et al., (2005) find asymmetric influence from price limit during different periods on China A shares market that price limits only effectively reduce volatility of downward price movement in the bull market and of upward price movement in the bearish market. This, to some extent, suggests that price limit may not successfully control volatility and diminish over-reaction when most investors believe that fundamental value is changing. However an accurate debate can only be drawn upon a more specific study in this regards.

2.2 Market Efficiency

From the second perspective, market efficiency, since market price may not reach the equilibrium level when it is restricted by the constraint on price movement, price limit is argued to delay price discovery process. Fama further points out rational prices are not necessarily less volatile than irrational prices. (Fama, 1989; Lehmann, 1989) Following this logic, prevailing prices on the market may not reflect all the available information, which consequently may affect allocation of the capital resource; hence the semi-strong form of market efficiency is reduced. Empirical studies, including Chen (1993), Kim and Rhee (1997), Shen and Wang (1998), and Chan, Kim and Rhee (2001), examine serial correlations of stock returns or price continuation behaviour and conclude that price discovery process is delayed with the imposition of price limit.

Choi and Lee (2001) further find the asymmetric price activities towards the upper and lower bound of price limits and they suggest it may help to reduce market volatility and improve market efficiency to set the upper price limit wider than the lower limit. Similar asymmetry is discovered by Chen et al. (2005) in China A shares market.

Another influence on market efficiency from price limit is that trading at the price outside the pre-assigned price range is prohibited, consequently it “amounts to reducing the supply of commodity, liquidity” (Fama, 1989, p.80). It is particularly distinctive when there is strong demand on trading during market fluctuation. Lauterbach and Ben-Zion (1993) specifically refer this interference in trading process as “obvious cost”.[3] Kim and Rhee (1997) test *trading interference hypothesis* in Tokyo Stock Exchange by observing changes on trading volumes of event stocks between pre limit-hit period and post limit-hit period. Their test result supports the notion that price limits interfere trading. However, the consensus on this issue has not been reached so far. Nath (2005) find the effect of price limit is asymmetric in the Indian market —the interference is only observed from the stocks that hit the upper bound but not from those hitting the lower bound. Chen et al. (2005) reject the hypothesis that trading is interfered in the Chinese A shares market during the sample period from December 1996 to December 2003. Nevertheless, none of these studies have tried to distinguish informed trading activities from noise trading by only

[3] More specifically, investors with long position find it costly to cash the asset when the market goes down, and investors with short positions have the similar problem, due to the in-continuous trading.

observing trading volume, it is still pre-mature to tell if price limit is any beneficial to market at this stage.

Apart from trading volume, the order imbalance between buyer- and seller-initiated orders is also a useful measurement for liquidity and price movement between trades, as developed by Stoll (1978a) and Spiegel and Subrahmanyam (1995). From perspective of regulators, price limit is partially designed for providing time to market investors to react to news and absorb one-side heavy trading orders. However as early noted in Lehmann (1989) that price limits "create a systematic order imbalance between patient and impatient traders" before and after the limits being hit, Chan et al. (2005) propose that price limit would cause the magnet effect before limit hitting and do not help to correct order imbalance afterward. One major weakness of their conclusion is that it is drawn upon a small sample pool and only from the aspect of upper limit-hit events. It is of importance to investigate how price limit affects order imbalance via more observations on both directions of price movement, which may also provide some explanation for volatility spill-over effect, considering the close relationship between volatility and order imbalance.

2.3 Order Flows and Informed Trading

Lastly, some recent papers, such as Chan et al. (2005), examine price limits from perspective of order flows, information content of stock prices, and trading behaviours of informed traders. By extracting information content from trade-by-trade price data, it implicitly gives the inspiration of the extent how price limits influence informed trading and informed traders. One of the rationales for advocating price limit is that it can offer uninformed investors time to receive information, reassess asset value, and get a good estimation of new equilibrium prices. French and Roll (1986) point out that the degree of information asymmetry is positively related to uninformed trading (noise) in the market, but the assumption that price limits could reduce noise trading and achieve lower information asymmetry faces the criticism that equilibrium price can only be realized during continuous trading (Amihud & Mendelson, 1991; Gerety & Mulherin, 1992). French and Roll (1986) also contend it is more likely for private information to induce price variation when market is open. Therefore price limit possibly holds back the rational trading from informed traders rather than the noise trading that increases the transitory volatility (Harris 1998).

Kim and Sweeney (2002) argue that informed traders with private information would put off their orders during the session when price hitting limit until price ranges been revised in the subsequent trading days, so that informed traders can obtain higher profit from trading. They study the distribution of closing prices, price continuations and reversals in Taiwan Stock Exchange, and their argument is supported by test result. However, as limit order traders are assumed to be liquidity providers in an order-driven market (Ahn, Cai, Hamao, and Ho, 2002), the caveat of their study is that they fail to consider the adverse selection component in bid-ask spread, which affects liquidity providers' decision. Chan et al. (2005) test this hypothesis on KLSE by using trade-by-trade data, and draw the conclusion that price limits do no improve information asymmetry and delay the information resolution. But as mentioned before, the applicability of their conclusion is restricted by the small sample size, and also only events related to upward price movement are studied.

3. Tokyo Stock Exchange and Descriptions of Sample Data

3.1 Tokyo Stock Exchange

Tokyo Stock Exchange was established on May 15, 1878, and then developed to the second largest stock exchange – next to New York Stock Exchange – with 2323 listed companies and over 4.5 billion U.S. dollars of total market capitalization. The market for domestic stocks is divided into three sections: First Section, Second Section and Mothers. Assignment rules among sections are applied to listed stocks based on trading volume, number of shares listed, and market capitalization et cetera. The sample stocks in this paper are from First section, where the most actively traded stocks are listed.

TSE is a pure order-driven market with no designated market maker, where all liquidity is provided through a limit order book and also some mechanism, such as special quote and price limit, to slow down the trading process when large order imbalance is expected or present. Special quotes are disseminated by a *saitori* exchange member on her own discretion of market, who is supervising trading process on TSE, taking the responsibilities of logging and matching orders, and maintaining the limit order book. Price limit is set on TSE to prevent "wild swings" in daily price movement and provide investors with "time-out" period and when big fluctuations occur to stock prices (TSE, Fact book, 2006). Stocks are grouped by different price ranges, on which the exchange imposes the different limits in absolute yen value[4]. When trading at price outside the limits, trading within the price limit is still allowed to carry on. Price limit also applies to special quotes.

There are two trading sessions in TSE: morning session that starts from 9:00am to 11:00am, and the afternoon session from 12:30pm to 3:00pm. Two transaction methods are used in off-hours trading and trading sessions respectively: *itayose* and *zaraba* methods. The *itayose* is applied to decide opening and closing prices, by pooling all the orders placed without time priority rule. The *zaraba* method is used in the continuous trading, under which pairs of buy and sell orders are matched following both of the time priority and price priority principles. All observations in the off-hours trading, thus trades under *itayose* method, are excluded from the sample of my study.

3.2 Data Description

For testing the three hypotheses[5] in section 4, we adopt the historical daily data of 1695 stocks in the first section of Tokyo Stock Exchange from year 1996 to year 2005 collected from Datastream. The raw data include daily high, low, closing prices of

4 This feature is different from that price limit is set in a certain percentage in most exchanges that adopt this mechanism. I list the detailed price limit table in appendix.
5 Here, the hypotheses refer to volatility spill-over, delayed price discovery, and trading interference hypothesis.

each stock, as well as some relevant information such as daily trading volumes and the market capitalization. It is worth noting that during the sample period, both tick size and price limit on TSE have been changed, as shown in the Table *1* & *2* in Appendices. Despite the large range of stock prices on TSE, by and large, 90% of sample stocks are priced under ¥5000, and about 40% of stocks are priced under ¥500. Price limit for stocks with price between ¥100 and ¥500 varies proximately from 16% to 50%, with price between ¥500 and ¥5000 varies from 10% to 20%. The percentile statistics of year end closing price is listed in Table *3* in Appendices.

The events are identified as the occurrences of the limits being hit by comparing the daily high, low and closing prices. There are in total 8390 events of the upper limits being hit and 3355 events of the lower limits being hit during the ten years, which construct the initial sample events. The summary statistics is shown in the Table *4* in Appendix. As we can see from the statistics, TSE apparently experienced the most downward price movements in year 2000 when the high-tech bubble burst after the first quarter, which caused about 30% loss on Nikkei index. In the previous year, stock market rose about 50% in Japan along with the booming of technology companies, therefore the market saw the most upwards price movements.

Due to the pattern that events happen densely in year 1999 and year 2000, we use the trade-by-trade data of these two years in Section 5, where the intraday order imbalance and degree of information asymmetry are examined. The data is obtained from SIRCA, including trading price, bid and ask quotes and trading volume. With no dealer or market maker in TSE, the buy and sell orders are classified by the following rules: if the mid-point of bid-ask spread is greater than the trading price, the trade is indicated as seller-initiated, otherwise the trade is indicated as buyer-initiated; if the mid quote is equal to the trading price, then a trade is identified as buyer-initiated if there is an up-tick from the previous trade, or seller-initiated order otherwise.

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

4.1 Volatility Spill-over Hypothesis

We apply the methodology in Kim and Rhee (1997) to test the volatility spill-over hypothesis on the sample $Stock_{hit}$. Two other groups are chosen for comparison, which are identified as $Stock_{0.90}$ of which the stock price change over 90% of limits but do not hit limits and $Stock_{0.80}$ of which prices change between 80% and 90% of limits. We construct a 21-day event window: Day 0 represents the day that price limit is hit or 90% of limit is reached for $Stock_{0.90}$. This applies to $Stock_{0.80}$ in the similar way. Day-1 is indicated as the day before Day 0, and Day+1 is the day after Day 0 and so on. Squared logarithm of daily return, $V_{t,j} = (r_{t,j})^2$ is used as the volatility measurement. Before computing the volatilities, we screen off the events when stock prices hit their limits for the second or third consecutive day, in order to avoid the high volatility bias during the pre-limit days. In other words, there are no consecutive observations in each 5-day event window (from Day-2 to Day+2) in the sample that we eventually implement the test. Due to this filtering process, the sample size is shrank to including 6660 upper hits and 2754 lower hits. It is hoped to examine this hypothesis by comparing the volatility of Stock_{hit} and other subgroups during post limit-hit days.

As expected, all subgroups have the highest volatilities on Day 0 and then experience a large drop on Day 1. The symbols > and >> in the Table 1 are used to indicate the left side is greater than the right side at significance level with 5% and 1% respectively. The comparison between the groups Stock_{hit} and $\text{Stock}_{0.90}$ shows the volatility of Stock_{hit} price is significantly larger since Day 0, especially for the stocks that hit the upper limit, which also implies that price limit may not be efficient to mitigate investors' over-reaction to new information. The table also shows a confusing trend that stocks in group $\text{Stock}_{0.90}$ has significantly higher volatility than in group $\text{Stock}_{0.80}$ through most part of event windows.

In order to make the result more robust, we divide the entire sample into three groups with different levels of price limit in percentages, lower than 15%, higher than 25%, and between 15% and 25% respectively. The test result from Table *2* is not surprising that most spill-over effect is contributed by stocks that fall into the lower range of price limit, which implies that the narrower the limit, the longer and stronger spill-over effect turns to be.

4.2 Delayed Price Discovery Hypothesis

In this part, this paper tries to find how price limit affects price discovery hypothesis by testing price continuations and price reversals. In the first step, we follow Kim and Rhee (1997) methodology 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 $\ln(O_1C_0)$, where C_0 and O_0 denote stock closing price and opening price of the event day when the price limit is hit, O_1 denotes the opening price of the subsequent day. This calculation is performed on all three groups that are already defined when examining volatility spill-over hypothesis in the previous part. The objective is to find if there is any unique pattern of stock price behaviour of the group Stock_{hit}, by comparing these two return series among all groups.

For simplicity, positive, negative, and zero returns are denoted by the symbol [+], [-], and [0], hence with the order of return series as $[r(C_0O_0), r(O_1C_0)]$, and there are nine possible series: [+, +], [+, 0], [+, −], [−, +], [−, −], [−, 0], [0, −], [0, +], and [0, 0]. For upward price movement, WE identify price continuation by the series [+, +] and [0, +]; price reversal by the series [+, −], [−, +], [−, −], [−, 0], and [0, −]; no change in prices by [+, 0] and [0, 0][6]. Alternatively, for downward price movement, price continuation is identified by return series [−, −] and [0, −]; price reversal is identified by [+, +], [+, 0], [+, −], [0, +], and [−, +]; no change in prices by [−, 0] and [0, 0].

[6] For the upward price movement, I classify [0, +] as price continuation because price experiences the overnight increase; [−, +], [−, −], and [−, 0] are classified as price continuation because price reversal already happens before the market close on Day 0. The similar reason applies to the rule of classifying downward price movement.

Table 7 shows the classified price behaviour for all three stock categories that is presented in the frequencies of price continuation, price reversal and no change in the prices of the sample. We use the full sample in block a, which includes all the consecutive price limit hit events in order to avoid underestimating the frequency that price continuation occurs. It can be observed from the table that the price continuation for Stock_{hit} happens more often than for other two groups. Although the frequency of price continuation in the downward price movement for Stock_{hit} is 2% lower than price reversal, it is still clearly higher than that of $\text{Stock}_{0.90}$ and $\text{Stock}_{0.80}$. There is hardly any difference between price behaviours of group $\text{Stock}_{0.90}$ and $\text{Stock}_{0.80}$, if only observing the frequency data from the table.

In order to filter the influence that maximum price variation rules in TSE in the early years may have on price discovery process[7], in part b of Table *3*, for upper (lower) price movement, WE only include the stocks whose closing price equals to the daily high (low) price, so that the result would only be affected by the price limit. This filtering process shrinks the sample size by 30% to 40%, but does not change the substantial feature of price movement for all three stock groups. WE perform the same tests on another two groups $\text{Stock}_{0.70}$ and $\text{Stock}_{0.60}$, of which daily prices changes between 70% ~ 80% and between 60%~70% of the price limit, for the purpose of comparing $\text{Stock}_{0.90}$ with the rest non-hit groups. The sample sizes of all the stock groups are presented in Figure 1 to provide a basic idea. The test result,

[7] Maximum price variation rule is the mechanism TSE used to restrict transaction by transaction price change into certain ranges. This regulation can not be seen in the TSE fact book of recent years. Kim and Rhee (1997) considered this in their research. I follow their methodology in the light of the long sample period in this paper.

shown in Figure 2a and 2b, is inconsistent with what Kim and Sweeney (2002) find in their research on Taiwan Stock Exchange. They observe a significantly higher price continuation on $Stock_{0.90}$ compared with other groups, based on which they believe when the new equilibrium price is greater than price limit and the closing price is close to limit, informed traders may choose to delay the transaction to the next day, whereas, such pattern can not be found in Figure *2a* and *2b*. This inconsistency suggests further intraday data analysis about the effect of price limit on informed traders' behaviours.

Before concluding the discussion on the delayed price discovery hypothesis, one other factor needs to be considered: investors' under-reaction and the consequent momentum strategy (Chan et al., 1996; Chan, Hameed, & Tong, 2000). If under-reaction effect holds for investors after new information comes out in the market, then it is likely that either investors would keep assuming a new equilibrium price and trading on a certain stock until the value change is fully revealed by the stock price, or investor are inclined to believe momentum strategy would make profit from the past experience . This factor can also induce price continuation, if its influence is significant in the short term.

The methodology to identify its influence on price continuations is as follows. Based on the 6-month moving average return (the calculation period is moved forward by day), we classify all the sample stocks into three groups: winners, neutrals, and losers for every day during the ten-year sample period (except for the first observing 6-month period). Winners are selected from the stocks that have top 30% return, and the loser stocks have the bottom 30% return, the rest is grouped into neutral stocks. Then WE identify four daily time series: 1. The proportion of winners that hit upper limit over the total upper limit hit events; 2. The proportion of losers that hit upper limit over the total upper limit hit events; 3. The proportion of losers that hit lower limit over the total lower limit hit events; 4. The proportion of winners that hit lower limit over the total lower limit hit events. By doing so, it facilitates to statistically test whether there are significant difference on means and medians between series 1 and 2, and also between series 3 and 4. The null hypothesis (H_0) is there is no difference between means and medians of the two groups that defined above – or there is no difference on the frequency of limit-hitting events that occur to winners and losers with respect to price limit of the same side. If winner stocks are found more likely to hit the upper price limit or the loser stocks more likely to hit the lower price limit, we can reasonably assume under-reaction may partly contribute to price continuation, vice versa.

Test results are separated into two parts for upper limit-hit and lower limit-hit events respectively, as shown in Table *4*. H_0 is strongly rejected for both of mean and median test on upper limit hit events with level of significance at 1%. In other word, the difference between the proportion of winners that hit upper limit and the proportion of losers that hit upper limit over the total upper events is statistically significant, which suggests under-reaction proposition may also cause price continuation. However, this argument can not hold for the lower limit hit events, for which H_0 can not be rejected with level of significance at 5% (One tail test suggest to reject H_0 at 10% significance level).

In summary, the combined result is consistent with the delayed price discovery hypothesis, which is more distinctive when price is moving upward. The methodology that Kim and Sweeney (2002) use to prove that informed traders delay transaction to the subsequent day fails to give the same result on TSE. Also, the asymmetric result after testing investor's under-reaction suggests the possible reason for the more significant price continuation on upper limit-hit events than the lower limit-hit events. However, it may not be useful to set the upper price limit wider, since not only price limit but also under-reaction or investors' momentum trading strategy affects the efficient price discovery process[8].

4.3 Trading Interference Hypothesis

To test whether price limit interferes with trading activities and hence reduces market liquidity, WE observe the change on trading volumes during the 11-day event window from Day -5 to Day +5. Turnover ratio $TA_{t,j}$ for stock j on day t is measured by $TVOL_{t,j}$ / $SOUT_{t,j}$, where $TVOL_{t,j}$ denotes the trading volume of stock j on Day t, and SOUT denotes the total outstanding shares for stock j on Day t. By comparing the

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

logarithmic change in turnover ratio from the previous day, ln ($TA_{j,t}/TA_{j,t-1}$), WE expect to test the hypothesis that trading activities do not increase for Stock$_{hit}$ after limit hitting days. Following the methodology in Kim and Rhee (1997), the consecutive events are not included in this sample testing, which is consistent with the volatility spill-over hypothesis test.

From the test result shown in the Table *5*, it is observed that all groups experience highest positive logarithmic change on event day, and large decrease on trading volume occurs on the next day. On Day +1, the day subsequent to the event day, the decrement of trading volume on Stock$_{hit}$ is significantly lower than all other groups, but on the following days from Day +2 to Day +4, the decrement on Stock$_{hit}$ is getting much larger compared with other groups. Despite that the overall pattern in the post limit-hit days is not clear, it can be concluded that the trading activities of Stock$_{hit}$ do not experience the decrement on trading volume as large as other groups after event days, which is consistent with trading interference hypothesis. Nevertheless, it is beyond the scope of this test to give more details about the disappearing volume after limit-hit days, which makes it necessary to further investigate the trade-by-trade data.

5. The Influence on Intraday Trading Activities and Information Asymmetry

5.1 Order Imbalance

Following the same methodology in Chan at al. (2005), two sample groups, Stock$_{hit}$ and Stock$_{90\%,}$ which are identified with the same rule as in the previous section, are tested on this hypothesis. For the events of prices hitting the upper limit, the order imbalance is measured by the ratio of buyer-initiated orders over the total orders; for the events of prices hitting the lower limit, it is measured by the ratio of seller-initiated orders over the total orders. We identify the pre-hit period and post-hit period for each event for comparison purpose: firstly the event session S_0 is defined as the trading session when price limit being hit, then the pre period S_{-1} starts from the previous trading session of S_0 to when the limit is firstly hit in S_0; the post period S_{+1} starts from the trade next to the limit-hitting trade in S_0 to the end of the next session after S_0, in order that no trade data would be excluded and comparison can be more complete and hence more accurate[9].

The order imbalance ratio in the pre-period is calculated by dividing the sum of buyer (seller) orders by total trading volumes in that period for the upper (lower) limit-hit events, the same for the ratio in the post-period. In order to avoid the bias caused in the circumstance when there are only few observations, we filter the events, to which there are less than 5 trades happening in either period S_{-1} or period S_{+1}. After this filtering process, the entire sample of upper limit-hit events Stock$_{hit}$ shrinks from 2084 to 1747 and the sample of Stock$_{0.90,}$ shrinks from 980 to 906 with price moving

[9] This classification is slightly different from Chan, Kim and Rhee, where they define the post-period as starting from the end of event session S_0 to the end of the subsequent session S_{+1}, consequently the trading between limit-hitting trade and the last trade in S_0 is excluded in the test.

upwards; the sample of lower limit-hit events $Stock_{hit}$ shrinks from 925 to 681 and $Stock_{0.90,}$ shrinks from 507 to 448 with price moving downwards.

The mean and median of order imbalance ratio are summarized below for both stock groups. As we can see from Table *6*, both $Stock_{hit}$ and $Stock_{0.90,}$ have a fairly significant order imbalance in the pre-hit period, well above 50% where demand equals to supply in the market. With upper events, the ratio of both groups decreased with a large extent in the post-hit period, approximately 14% for $Stock_{hit}$ and 19% for $Stock_{0.90}$, however with $Stock_{hit}$, the order imbalance stands by around 57% in post-hit period, which means the one-side order flows still exist; the imbalance seems to be better alleviated for $Stock_{0.90}$ with the ratio slightly over 50% in the post-hit period. With the lower events, the decrement on order imbalance ratio appears to be larger compared with upper events, about 19% and 23% for $Stock_{hit}$ and $Stock_{0.90}$ respectively; the ratio is lower than 50% for both groups in the post-hit period.

It can be concluded that no particular "magnet" effect exists for group $Stock_{hit}$, If comparing $Stock_{hit}$ and $Stock_{0.90}$, the order imbalance ratios of both groups experience reversal from pre-hit period to post-hit period with lower limit-hit events; both of them stay above 0.50 in the post-hit period with upper events. Hence there is no substantial difference between $Stock_{hit}$ and $Stock_{0.90}$. Apart from that, although it is assumed that part of the prevailing orders cannot be executed after stock prices hit limits because of the price constraints, different from $Stock_{0.90}$ that all trading orders are executed from pre- to post period, Table *6* clearly shows order imbalance ratio decreases largely for $Stock_{hit}$ in the post-hit period with both upper and lower events. It can be concluded that price limit effectively lowers the order imbalance ratio after limit-hitting, which is more significant with lower limit-hit events.

This result also provides some possible explanation for the volatility spill-over effect and delayed price discovery effect that we confirm to exist in the previous section, the continuously high volatility and price continuation can be partly caused by the high order imbalance in the post-hit period – the ratio is still very close to 50% even when it drops below 50% on the lower limit-hit events.

To incorporate the influence of other factors on order imbalance observation and examine if it is specifically related to limit-hit, WE use the similar cross-section regression in Chan et al. (2005), apart from using some different variables. The dependent variable, the change on order imbalance ratio is defined as $\Delta IMBAL_j$ = $IMBAL_{i,post}$ - $IMBAL_{i,pre,}$ where $IMBAL_{i,post}$ stands for the order imbalance ratio in the post-hit period and $IMBAL_{i,pre}$ for the ratio in the pre-hit period for a certain event *j*. The regression function is constructed as follows:

$$\Delta IMBAL_j = \beta_0 + \beta_1 * LHG_j + \beta_2 * MktCap_j + \beta_3 * \Delta Volume_j + \beta_4 * Weekday_j + \beta_5 * Month_j + \beta_6 * Volatility_j + \varepsilon_j, \qquad (1)$$

where LHG is the dummy variable that equals to 1 if stock *j* comes from $Stock_{hit}$ and 0 if stock *j* comes from $Stock_{90\%}$; MktCap denotes the logarithm of stock's market capitalization; ΔVolume_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 post-hit period and the opening price of pre-hit period; Weekday_j and Month_j refer to the weekday and the month when the event j happens; lastly ε_j is the error term, on which heteroskedasticity is taken into consideration if there is pattern in the error term.

As presented in the Table *7*, the coefficients for the dummy variable LHG of both upper events and down events are significantly positive, which does not indicate that the limit-hit is entirely associated with the reversal on order imbalance ratio from pre-hit to post-hit period. This result is inconsistent with what Chan et al.(2005) find in their research on Kuala Lumpur Stock Exchange that the coefficient for variable LHG is significantly negative to the dependent variable "ΔIMBAL" that is defined in the same way as in this paper. It shows clearly in Table *7* that price limit does not create a distinctive "magnet effect" by comparing Stock_{hit} and $\text{Stock}_{90\%}$.

5.2 Information Asymmetry Hypothesis

This part further examines the degree of information asymmetry surrounding limit-hit events. Ahn et al. (2002) propose that it is possible that price limit "would reduce the amount of information asymmetry" in the market when it slows down price discovery process. The result from the previous test on order imbalance ratio is not sufficient to explain if or to what extent price limit also affects price transmission at the same time when part of one-side orders is suppressed. Therefore, it is necessary to further investigate order arrival sequences via decomposing the bid-ask spread before and after limits being hit.

To test the null hypothesis that information asymmetry is not improved (i.e., decreased) after limit-hit, WE start with the decomposition model in Glosten and Harris (1998) (GH88 model) to estimate the adverse selection cost. The model is designed as follows:

$$\Delta P_t = \mu + c_0\Delta Q_t + c_1\Delta(q_tQ_t) + z_0Q_t + z_1q_tQ_t + \varepsilon_t, \qquad (2)$$

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 order and -1 otherwise; q_t is the trading size that is uniformly measured in the minimum trading units, 1000 shares one unit[10]. The adverse selection component in GH88 model is defined as $z_0 + z_1q_t$; and the adverse selection cost, SYMM, is measured as the ratio $(z_0 + z_1q_t) / (z_0 + z_1q_t + c_0 + c_1q_t)$. WE calculate the coefficients z_0, z_1, c_0, and c_1 of GH88 model by using the price, trading volume and indicator serials in both pre-hit period and post-hit period of each event. SYMM ratios for pre- and post period are then computed based on the coefficients and q_t, which is set to be the median trading volumes of pre- and post period. In order to avoid the influence on estimation from the extreme trading sizes, the trades with volumes larger than 99 percentile or smaller than 1 percentile are excluded from the actual computation in each period.

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

The mean and median of SYMM ratios in pre- and post-hit period are presented below in Table *8*. For the events with price moving up, the mean SYMM ratios of Stock_{hit} and $\text{Stock}_{0.90}$ in the pre-hit period are 0.4244 and 0.4314 respectively, higher than 0.3691 and 0.4199 correspondingly in the post-hit period, and the reduction for Stock_{hit} is slightly larger than for $\text{Stock}_{0.90}$; for the events with price decreasing, the mean SYMM of Stock_{hit} drops from 0.4336 before limit-hit to 0.4087 in the post-hit period, but the ratio increase on $\text{Stock}_{0.90}$, from 0.4039 to 0.4440. (Medians of SYMM ratios for both groups show the similar pattern.) The proposition of Ahn et al. (2002) that price limit reduces information asymmetry on TSE is therefore supported.

To assure that the decrement in information asymmetry is specifically associated with limit-hit events, regression analysis is constructed as:

$$\Delta\text{SYMM}_j = \beta_0 + \beta_1\text{* LHG}_j + \beta_2\text{*MktCap}_j + \beta_3\text{*}\Delta\text{Volume}_j + \beta_4\text{*Weekday}_j + \beta_5\text{*Month}_j + \beta_6\text{*Volatility}_j + \varepsilon_j, \quad (3)$$

where ΔSYMM_j denotes the change on SYMM ratio between pre- and post-hit period for event j, with all other variables defined in the same way as in equation (1). If the coefficient of variable LHG is shown to be negative, we can assume that information asymmetry ratio changes in light of price limit.

The regression result is summarized in the Table *9*. The coefficients of variable LHG for both upper and lower events are -0.0373 and -0.0612, both negative at 5% and 1%

level of significance respectively. Again, this result is inconsistent with what Chan et al. (2002) find on KLSE, and it suggests that price limit in TSE contributes to the improvement on information asymmetry. The coefficients of variable ΔVolume are significantly positive for both upper and lower events, which shows that degree of information asymmetry changes oppositely with the direction of trading volume changing, in other words that degree of information asymmetry increases (decreases) along with trading volume decreasing (increasing). This is consistent with the finding of Ahn et al. (2002) on Tokyo Stock Exchange that adverse selection component increases with larger trade size.

6. Conclusion

After experiencing market crashes and huge market fluctuations, investors' discomfort with excessive volatility has more or less put exchange regulators on the roles of stabilising prices. Under the psychological power and political power that circuit breakers (Harris, 1998), a number of order-driven exchanges start using price limit to meet this demand, which is considerably facilitated by electronic trading systems. However, the understanding about this interference mechanism is still ambiguous. This study set out to seek any positive extent of price limit performance, by which the ubiquitous adoption of price limit can be justified.

This study has found that on Tokyo Stock Exchange, price limits restrict volatility in certain range and spread it out into subsequent trading days, price continuation occurs more frequently and trading volume decreases slowly when price limits being hit. On the other hand, market efficiency is not hazarded since price limits effectively reduce order imbalance and improve information asymmetry. Therefore, on the whole, test results show that although price limit cannot powerfully diminish volatility after limits being hit, this mechanism still benefits market by calming noise traders from panic order-submission and providing market participants with a time period for absorbing information as well. The current finding adds to a growing body of literature about price limit on its influence on trading activities, order flows and informative prices.

However due to the absentness of appropriate methodology, this paper has not proceeded into investigating the behaviours of informed traders[11], which may potentially provide strong evidence to separate transitory volatility from fundamental volatility and better explains price limits' affect on price resolution process. If the debate on price limit is to be move forward, further research on the arrival rate of informed traders would be of great help. More broadly, future research might also be done in establishing the rationales for the magnitudes of price limits that are used on stock exchanges in different microeconomic environments

[11] Chan et al. (2002) test arrival rate of informed traders and conclude that informed traders arrive after limit-hit, therefore price limits delay the arrival of information. Nevertheless this result is challenged by the inaccurate application of Easley, Kiefer, O'Hara, and Paperman (1996) model in this specific circumstance, since it would be apparently naïve to assume the arrival of news is independent for each 2-minute interval in their study, and consequently the estimation of PIN based on that would be biased.

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Table 1. 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	2.2186	2.4792	1.6699	2.0468	1.9217	1.7779
-9	1.8341	1.8964 >	1.6050	2.1747	2.2629	1.8272
-8	1.9505	2.4017 >	1.6880	1.9690	2.0352 >	1.7316
-7	1.9709	2.1041 >	1.9038	2.1133	2.1058 >	1.7609
-6	2.1811 >	2.0825	1.8751	2.1226	2.3602 >	1.9842
-5	2.1789	2.3416	1.9977	2.6668	2.7030	2.0626
-4	2.4805	2.2113 >	2.0082	2.5244	2.6012	2.1920
-3	2.5078	2.7018 >>	2.2954	2.6157	3.1135	2.5899
-2	2.6416 <	3.4523 >	3.0203	2.8911	3.1604 >>	3.1539
-1	3.8064 <<	5.2837 >>	4.0875	3.3586	4.3095 >>	3.8137
0	20.7594 >>	13.2210 >>	11.2288	19.2173 >>	13.3783 >>	11.4712
+1	5.3171 >>	3.2679 >>	2.7337	5.7292 >>	3.7114	3.2926
+2	3.4438 >>	2.4878 >>	2.1742	4.7018 >>	3.2993 >>	2.6530
+3	2.7805 >>	2.2276 >>	1.9709	3.4076 >>	2.9094 >>	2.2688
+4	2.4348 >>	2.0167 >	1.8938	3.0802 >	3.0776 >>	2.4373
+5	2.3817 >>	2.1416 >>	1.7629	2.8974	2.8585 >	2.3075
+6	2.2264 >>	1.9802 >>	1.7476	2.5028 >	2.4984 >	2.1471
+7	2.2279 >>	1.8340	1.7366	2.3250	2.4354 >>	1.9770
+8	2.1490 >>	1.8348 >	1.7066	2.0742	2.0832 >>	1.8895
+9	2.0401 >	1.8754 >>	1.6726	2.1229	2.0777 >>	1.7591
+10	1.9679 >>	1.7584 >	1.6103	2.2883 >>	2.0035>	1.7558

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, using the Wilcoxon rank-sum test.

Table 2 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	$Stock_{hit}$		$Stock_{0.90}$	$Stock_{hit}$		$Stock_{0.90}$	$Stock_{hit}$		$Stock_{0.90}$
-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

The categories are classified by the magnitude of their price movement on the event day. Upper events refer to the sample events with upwards 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, using the Wilcoxon rank-sum test. Since there is no substantial difference for the lower events, the detailed table is not presented in the paper, but can be provided upon request.

Table 3. Test on Delayed Price Discovery Hypothesis.

Price Behaviour	$Stock_{hit}$	$Stock_{0.90}$	$Stock_{0.80}$	$Stock_{hit}$ – $Stock_{0.90}$	z-value[12]	Sample [13]size for $Stock_{hit}$
a. Full sample						
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
b. Price behaviour 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

[12] This z-value is the z-statistic for a standard nonparametric binomial test. Null hypothesis in this case is there are more price continuations happen to the sample group $Stock_{hit}$ than $Stock_{90\%}$. According to Olkin, Gleser, and Derman (1980, p. 244-253), the z-statistic has normal distribution when the sample sizes are both sufficiently large. The calculation for z-statistics is: $z = (CON_{hit} – PrCON_{0.90}Nhit)/(PrCON_{0.90}(1 – PrCON_{0.90})N_{hit})_{0.5}$, where CON_{hit} denotes the number of price continuations for $Stock_{hit}$, $PrCON_{0.90}$ denotes the frequency of price continuations that occur to $Stock_{0.90}$. Nhit represents the sample size of $Stock_{hit}$.

[13] The full sample size here is slightly smaller than the sample size mentioned in the data description section, where there are 8390 upper limit hit events and 3355 upper limit hit events in total. This is due to the opening price data error and missing observations on some event days, which is neglected in this hypothesis testing.

Table 4. Test on Under-reaction Factor

A. Upper limit-hit events		
t-Test: Paired Two Sample for Means	*Group 1*	*Group 2*
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		
Median	0	0
Hypothesized Median Difference	0	
p = 6.50E-20 (Reject H_0)		

B. Lower limit-hit events		
t-Test: Paired Two Sample for Means	*Group 3*	*Group 4*
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		
Median	0	0
Hypothesized Median Difference	0	
p = 0.4161 (Do not reject H_0)		

Group 1 refers to the time serial of the proportion of winners that hit upper limit over the total upper limit hit events; group 2 refers to the time serial of the proportion of losers that hit upper limit over the total upper limit hit events. Either mean test or median test shows that the null hypothesis should be rejected, in other words, winner stocks are more likely to hit upper limits than the loser stocks.

Group 3 refers to the time serial of the proportion of losers that hit lower limit over the total lower limit hit events; group 4 refers to the time serial of the proportion of winners that hit lower limit over the total lower limit hit events. Both mean and median tests suggest not rejecting the null hypothesis, which means winner stocks and loser stocks are equally likely to hit lower limits.

Table 5. 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

For all stock groups, the percentage change on trading volume during the 11-day period is calculated and compared in this test. >> and > indicate that the percentage on the right hand side is greater than the left hand side at 0.01 and 0.05 significance level respectively.

Table 6. 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

Means and medians of order imbalance ratios for $Stock_{hit}$ and $Stock_{0.90}$ are presented separately in pre- and post hit period for comparison purpose. Stock groups are defined by the same rule as in the previous tests.

Table 7. Regression of the Change on Order Imbalance Ratio between Pre and Post-hit Period

A. Summary Statistics of ∆IMBAL

	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

Summarized below is the result 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
∆Volume	-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	

The symbols * and *** in front of the t-statistics indicate that coefficients are significant at 5% and 1% significance level. Due to the missing observation during data processing, sample sizes vary from the initial sample.

Table 8. Test on Information Asymmetry.

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

In this table, the adverse selection cost computed in 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 model regression and also events with small amount of trades (less than 10) in either pre- or post-hit period. $Stock_{hit}$ and $Stock_{0.90}$ are defined by the same rule as in the previous tests.

Table 9. Regression of the Change on Information Asymmetry Ratio between Pre and Post-hit Period

A. Summary Statistics of ∆SYMM

	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

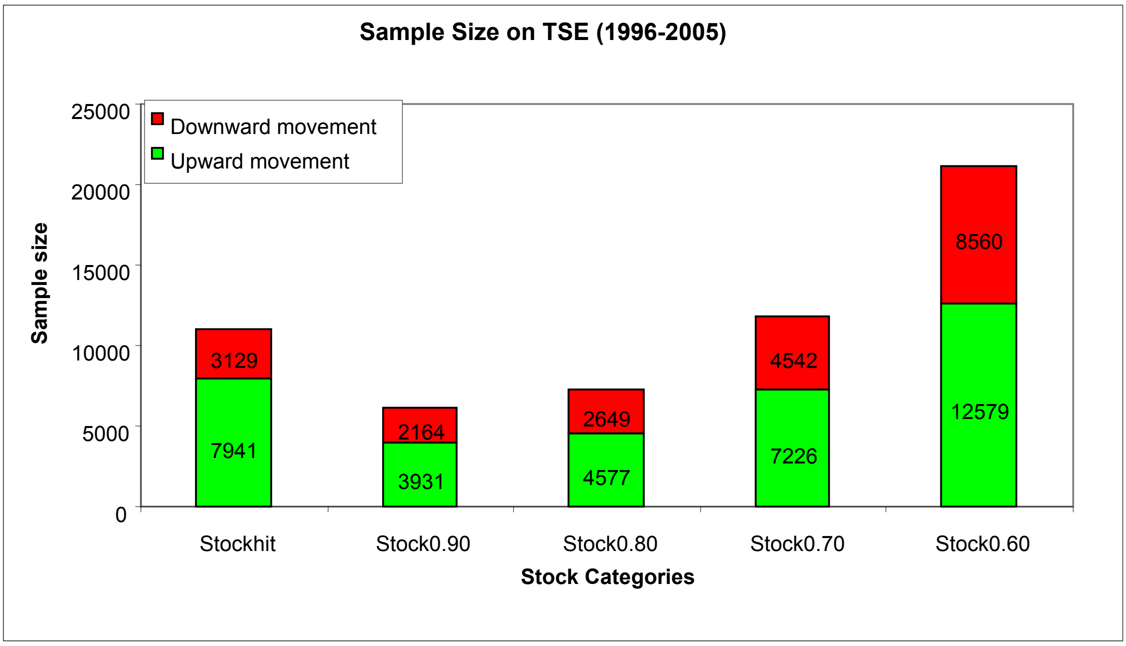
Summarized below is the result from the following regression :

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

	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
∆Volume	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	

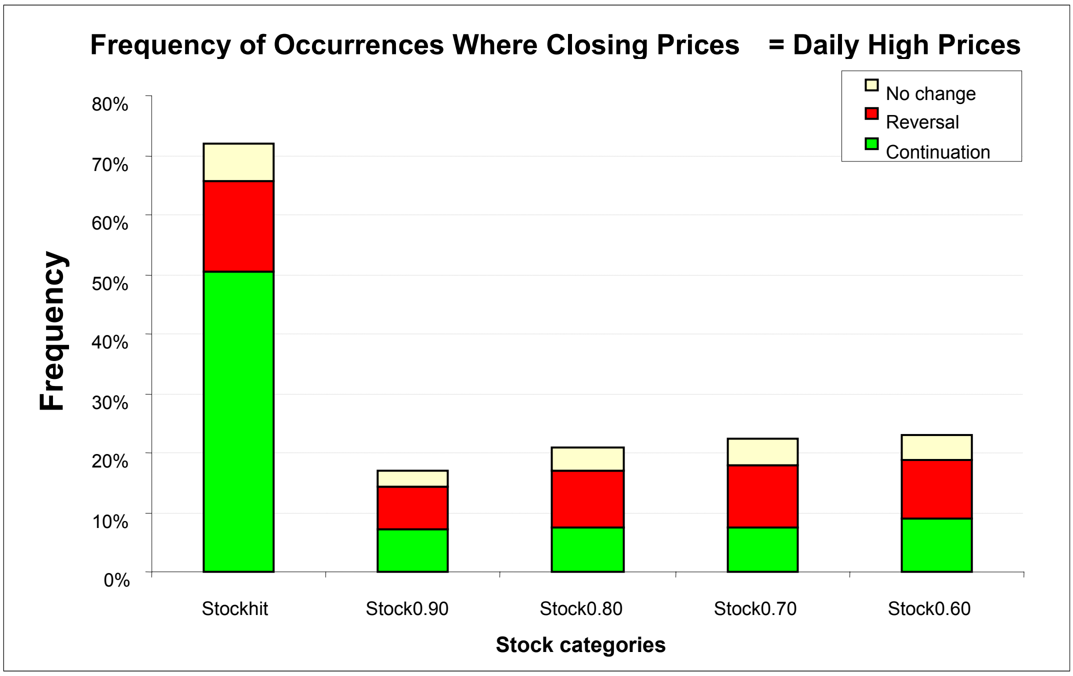
The symbols * and *** in front of the t-statistics indicate that coefficients are significant at 5% and 1% significance level. Due to the missing observations during data processing, sample sizes vary from the sample used in GH88 model computation.

Figure 1. Sample Size For All Stock Categories



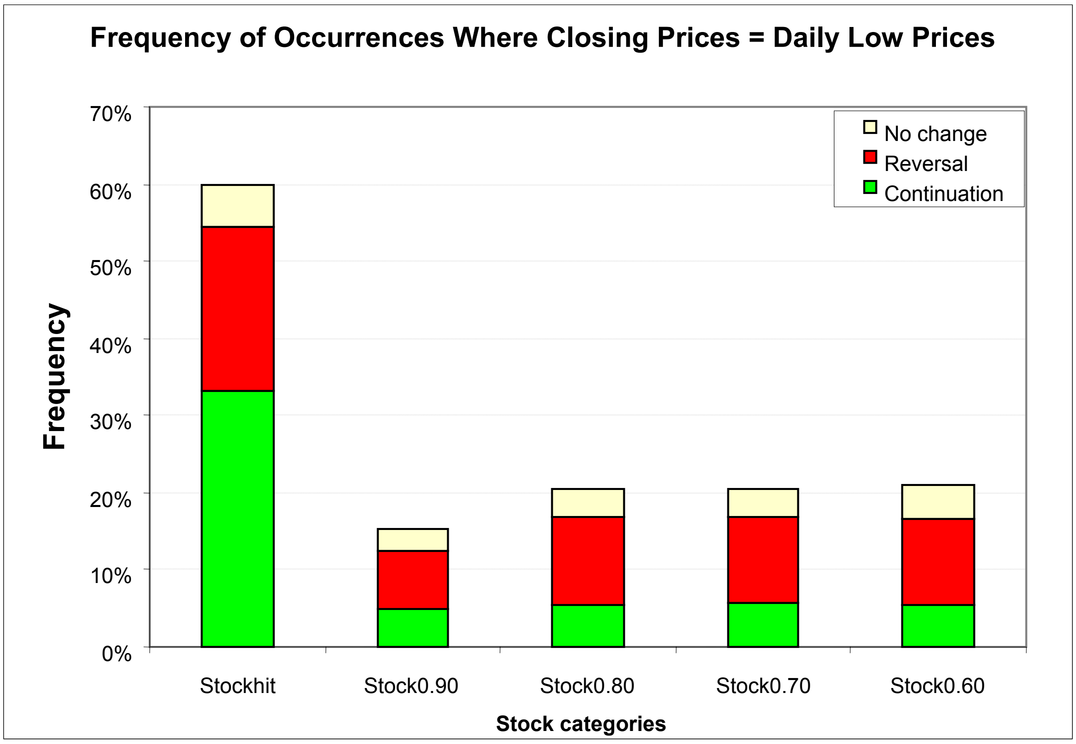
The red area indicates the sample size for events with downward price movement, and the green area indicates the sample size for events with upward price movement. Samples of all groups are filtered to exclude maximum price variation rule.

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 not obvious difference between Stock$_{0.90}$ and other groups with large price variation but no limit-hitting.

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 not obvious difference between Stock$_{0.90}$ and other groups with large price variation but no limit-hitting.

Appendices

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

Tick Size on TSE		
Previous Day's Closing Price or Special Quote[14]	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

[14] Special quotes are also called special bid & asked quotes, which are disseminated to the TSE market through information system when there is a major imbalance in orders. The quotes are either matched by the following orders or revised up or down according to the imbalance within 5 minutes intervals until the imbalance is resolved.

Table *A2*. Price Limits Used on 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
$100 \le p < 200$	¥50	¥50
$200 \le p < 500$	¥80	¥80
$500 \le p < 1000$	¥100	¥100
$1,000 \le p < 1,500$	¥200	¥200
$1,500 \le p < 2,000$	¥300	¥300
$2,000 \le p < 3,000$	¥400	¥400
$3,000 \le p < 5,000$	¥500	¥500
$5,000 \le p < 10,000$	¥1,000	¥1,000
$10,000 \le p < 20,000$	¥2,000	¥2,000
$20,000 \le p < 30,000$	¥3,000	¥2,000
$30,000 \le p < 50,000$	¥4,000	¥3,000
$50,000 \le p < 70,000$	¥5,000	¥5,000
$70,000 \le p < 100,000$	¥10,000	¥5,000
$100,000 \le p < 150,000$	¥20,000	¥50,000
$150,000 \le p < 200,000$	¥30,000	¥50,000
$200,000 \le p < 300,000$	¥40,000	¥80,000
$300,000 \le p < 500,000$	¥50,000	¥80,000
$500,000 \le p < 1,000,000$	¥100,000	¥100,000
$1,000,000 \le p < 1,500,000$	¥200,000	¥200,000
$1,500,000 \le p < 2,000,000$	¥300,000	¥300,000
$2,000,000 \le p < 3,000,000$	¥400,000	¥400,000
$3,000,000 \le p < 5,000,000$	¥500,000	¥500,000
$5,000,000 \le p < 10,000,000$	¥1,000,000	¥1,000,000
$10,000,000 \le p < 15,000,000$	¥2,000,000	¥2,000,000
$15,000,000 \le p < 20,000,000$	¥3,000,000	¥2,000,000
$20,000,000 \le p < 30,000,000$	¥4,000,000	¥2,000,000
$30,000,000 \le p < 50,000,000$	¥5,000,000	¥2,000,000
$P \ge 50,000,000$	¥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	1406	1222	1537	9194	2023	2528	1347	2133	1883	2454

* P_i refers to the *i*th 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 is slightly over ¥1,000. 90% of the sample stocks are priced under ¥5,000 with an exception in 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 more volatile than high priced stocks. Additionally, mean prices appear much higher than medians, which suggests that the price distribution is largely left skewed on TSE.

Table A4. Summary Statistics of All Limits Hit Events on 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 list 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 Halloween effect, however, there is no apparent seasonal pattern for the downwards limit hits. (The same features also appear on 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, however, is out of the scope of this research.