

# **Towards A Flexible Price Limit System**

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# **Towards A Flexible Price Limit System**

## ***Abstract***

This paper proposes an improvement to the existing price limit systems. Using price limit data from Tokyo Stock Exchange, this study shows that price limits are costly when they obstruct rational price movements. Observable events, such as volatility spillovers and consecutive price limit hits, associated to improper price limit imposition can be predicted using proxies of informed and uninformed trading, changes in order imbalance, number of trades hitting price limit, fraction of the trading day affected by limit hit and security characteristics such as size, growth and idiosyncratic risk. We propose a flexible price limit system based on the predicted likelihood of improper price limit imposition. We suggest that if exchange-officials decide on relaxing or continue imposing price limits for a trading day based on predicted probability of volatility spillover and consecutive hit then price limit rules could become effective.

## **I. Introduction**

Price limits for individual securities are present in many stock exchanges around the world. This study proposes a possible improvement for efficient implementation of these rules in equity markets.

Price limit rules are often criticized for being ad-hoc and non discretionary Subrahmanyam (1995). Market regulators and stock exchange authorities primarily adopt these rules to prevent wild volatility caused by speculative activity or overreaction of traders<sup>1</sup>. However by design these non discretionary rules can not differentiate between rational price movement and irrational exuberance of the traders. Thus, many academic researchers argue that price limit rules are more likely to make markets less efficient (Fama,1989; Lehman,1989; Miller,1989). Several costs such as volatility spillover, delayed price discovery and trading interference are associated with these rules. Empirical evidence provided by George and Hwang (1995), Kim and Rhee (1997) and many others supports this argument and suggests that use of price limit rules could be costly to the market.

However, on the other hand, the findings of Lee and Kim (1995), Berkman and Lee (2002) and Westerhoff (2003) show that price limit could be quite effective in reducing volatility and overreaction in the market. Though opinions of academic researchers are divided on the utility of these rules, in reality, quite a large number of equity markets prefer them. This paper explores the possibilities of improving the existing system of price limit rules by making it flexible enough to avoid the costs such as volatility spillover, delayed price discovery or trading interference.

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<sup>1</sup> Speculative trading and over reaction of the traders are the primary reasons for implementation of price limit rules cited in TSE (2005) and also in Report of The Presidential Task Force on Market Mechanisms compiled in Reams (1988).

In this paper, we argue that imposition of price limits is “improper” when they obstruct rational price movements. We also suggest that costs associated with these rules are various manifestations of obstruction to the information revelation process through trading. Various negative effects of price limit rules, for example, volatility spillover, delayed price discovery and trading interference are reflections of same cost measured in three different scales. We propose that price limit rules could be more effective and less costly if improper price limit impositions are avoided.

In this study, we hypothesize, that in general, consecutive price limit hits and volatility spillovers occur when price limits interfere with information based trading. Using data from Tokyo Stock Exchange (TSE) over a period of 2001 to 2005 this study provides empirical support to this hypothesis. The empirical evidence suggests that variables such as, trading volume, change in order imbalance, size of the trades, time of the price limit hit, number of trades that hit price limit, number of hours of the day affected by price limit hits, firm size, growth potential and idiosyncratic risk of a firm are important in identifying improper price limit impositions. Finally, we propose that a flexible price limit system based on the conditional probability of an improper limit hit could improve the efficacy of existing price limit rules.

This paper contributes to the sparse literature on improving efficacy price limit rules. To the best of my knowledge, this is the first study that analyses the determinants of volatility spillover and consecutive price limit hit events. Many existing studies such as Kim and Rhee (1997), Phylaktis, Kavussanos and Manalis (1999), Bildik and Elekdag (2004) document evidence of various costs related to price limit rules. However, In this study we show that obstruction to information based trading makes price limit costly. This study also contributes to the literature by

suggesting a flexible price limit system which could help exchange officials to avoid improper price limit impositions.

The remainder of the paper is organised as follows. Section II reviews relevant literature and discusses basic idea of this study. Section III describes development of hypotheses. Section IV discusses data and methodology used in the study. In Section V we report and analyse the empirical findings. Finally, Section VI concludes the paper.

## **II. Background Literature and the Idea of Flexible Price Limit**

### *Price Limits Pros and Cons:*

The history of rule based price stabilising mechanisms such as price limits in securities markets dates back to the early eighteenth century. However, a fresh debate on their usefulness is triggered by the recommendations of The Presidential Task Force on Market Mechanisms (1988) following the 1987 US market collapse. The task force under the leadership of Nicholas F. Brady proposed that Circuit Breakers such as price limits

“...cushion the impact of market movement, which would otherwise damage market infrastructures. They protect markets and investors.”<sup>2</sup>

The report identifies the benefit of such rules is that they restrict price movement in order to provide time for “frenetic trading” to settle up. These rules also facilitate price discovery as traders pause to re-evaluate security prices and *value* investors get time to enter into the market to reduce the order imbalance. The Brady Commission Report also points out that there are perceived disadvantages of these

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<sup>2</sup> The Report of The Presidential Task Force on Market Mechanism in Reams(1988), page 61.

rules, as they may hinder trading in the market but the report argues that these rules are necessary to avoid a disorderly market.

Academic literature on price limits rules primarily focuses on the rationale and efficacy of these rules. Many researchers have investigated cost and benefits of these rules. Brennan (1986) rationalises the use of price limit rules in commodity futures markets, as these rules along with margin requirement may contribute to the design of efficient futures contract by reducing the default risk. Kodres and O'Brian (1994) argue that price limit rules would assist in efficient risk sharing among market participants. Anshuman and Subrahmanmyam (1999) propose that optimal price limit is a trade off between liquidity and price discovery in the market.

Critics of price limit rules suggest that price limit rules are too costly for the market as they delay price discovery, interfere with market liquidity and spreads volatility over a longer period. Fama (1989) argues that rational prices can be volatile, so use of price limit to reduce price volatility may cause delay in the price discovery process. In the same line of argument, Lehmann (1989) suggests that if excess demand or supply forces the price to hit daily limits, then unexecuted orders will get transferred to the following trading days, and as a result, post price limit hit days could become more volatile. Lehmann (1989) also criticises price limits since these rules may force impatient investors to trade at an unfavourable price on the days of price limit hits. These arguments are commonly known as delayed price discovery hypothesis, volatility spillover hypothesis and trading interference hypothesis. These three hypotheses about the cost of price limit rules essentially centres around the argument that price limits cannot reduce volatility caused by arrival of information but they can make markets less efficient by restricting rational price movements.

On the other hand, Stein (1987), Greenwald and Stein (1988) support proposals of Brady commission on trading halt and suggest that due to the negative externality effect, speculative trading can make market prices less informative. If such externality effect is significant in the market then a temporary halt in trading makes all market participants better off. This argument maybe applicable for price limit rules too, as once price limit for the day is reached these rules impose a virtual trading halt unless traders revise their price. Deb, Kalev and Marisetty (2007) also support utility of these rules and conclude that price limit rules can be beneficial in markets that are prone to price manipulation and difficult to monitor.

Hence existing literature suggest that while price limit rules can be costly due to the fact that they hinder rational price movements, they can be also beneficial for a market affected by investor overreaction or speculative trading. Therefore, price limit rules could be more efficient if it is possible to avoid the costs associated with the improper impositions of price limit rules.

#### *Flexible Price Limit – The Idea*

Based on the existing literature discussed in previous subsection, we propose that if price limits of a specific trading day could be relaxed on the basis of the likelihood that the limit hit on that day is obstructing information revelation, then such a flexible price limit rule system would be more efficient than the existing system.

Though primarily adopted to curb price volatility due to overreaction of misguided traders, price limit rules are often accused of increasing or “spilling over” volatility on post price limit hit days. This is expected to happen if price limits interfere with trading interest generated by new fundamental information as discussed by Fama (1989). To avoid such situations stock exchanges keep various provisions to

relax price limits, for instance, the Tokyo Stock Exchange keeps the option of removing price limits for the days when stocks are expected to experience large price changes due to events such as bankruptcy and other fundamental reasons. These provisions are useful to make price limit rules more effective. However, there may be many occasions when information reaches market through private sources, long before its public announcement. In such cases, volatility spillover due to price limits would be inevitable as argued by Fama (1989) and Lehmann (1989).

In extreme cases such spill over of volatility could lead to price limit hits on consecutive trading days. In an active market, price volatility caused by misguided exuberance of uninformed traders should not persist long enough to cause price limit hits on several consecutive trading days. Therefore, on an average consecutive limit hit events may indicate obstruction to rational price movement through improper imposition of price limit rules. Stock exchange officials are also conscious of this fact; for example, the Tokyo Stock Exchange doubles its price limit rule on the fourth day if there are price limit hits with no trading over previous three consecutive days. Therefore, to make price limit rules more efficient, it is essential to know if the limit hit caused by a price movement driven by information or overreaction. In this paper, we argue that if exchange officials can predict whether a price limit hit is caused by arrival of new information then they could effectively avoid volatility spillovers and consecutive limit hits by relaxing price limit rules. This added flexibility will make price limit rules more efficient, as it would reduce costs associated with improper imposition of price limits.

This paper proposes a procedure to improve effectiveness of price limit rules although it does not aim to propose optimal price limits. In the literature of price limit rules there are several important papers such as Brennan (1986), Kodres and O'Brien



(1994) and Anshuman and Subrahmanyam (1999) that contribute towards designing optimal price limits for futures market. Deb et al. (2007) discusses optimal daily price limits in the presence of price manipulators. In contrast to these studies, here we argue that theoretically it may be possible to find out an optimal price limit for each security in the market, but in practice, it would be difficult to implement such an elaborate price limits system. In reality, stock exchanges assign a single price limit rule to a group of stocks. For example, price limit rules of the Tokyo Stock Exchange divides all the listed stocks in 29 groups based on their prices, the National Stock Exchange of India has three price bands and the Shanghai Stock Exchange prefers one uniform price limit for all listed stocks. It may not be theoretically optimal to put stocks in few price limit groups but this seems to be the best possible solution for the exchanges under the operational constrains as almost all stock exchanges with price limit rules follow similar practice.

The central hypothesis of this study is that volatility spill over and consecutive limit hit events occur when price limit rules become barriers to information dissemination process. Therefore, predicting the probability of a volatility spillover or consecutive limit hit will help in identifying an improper price limit imposition. The exchange officials ideally want to prevent volatility due to irrational price movements without hindering price discovery processes. Therefore market would be better off relaxing price limits for the day if a limit hit event on that day has high probability of being an improper one.

The price limit rules are easy to implement as they are predetermined and do not demand much resources, my suggestion of making price limit rules flexible does not take away these characteristics from price limit mechanism. We do not propose continuous monitoring of trading and information flow for individual stocks.

However, the methodology proposed in this paper focuses on finding the probability of a volatility spillover or consecutive limit hit using different variables related to informed-trading and firm specific characteristics.

In this study, two basic options are offered for modifying the existing price limit system to be a flexible one. These two options differ in terms of the time of the analyses and also on their demand for resources. Option one requires analysis at the end of the trading day and it is a relatively less demanding analysis. On the other hand, option two requires a more detailed, intraday analysis.

Option one proposes that at the end of a limit hit day exchange officials may determine the probability of a consecutive hit for the next day. They may take a decision about relaxing next day's price limit based on the outcome the analysis. This does not demand much resource as it is based on readily available information such as limit hit day's trading history and can be carried out at any time between limit hit day's close of trading to opening of next trading day. However, an issue with this option is that still volatility spillovers cannot be avoided.

In order to avoid volatility spillover price limits need to be relaxed on the limit hit day so that traders can execute their pending orders on that same day. Under option one exchange officials would determine the probability of an improper limit hit imposition only after the trading hours of the limit hit day. Therefore the officials will be unable to avoid volatility spillovers on next day. To avoid volatility spillovers as well as consecutive limit hits, exchange officials need to react soon after an improper limit hit event.

The second option discusses how exchange officials could determine the probability of an improper price limit hit within the same trading day using intraday trading history. This option will demand greater resources than the previous option as

there is less time to collect data and to carry out the analysis. Under option two, the probability of a consecutive hit or volatility spillover needs to be determined soon after the first transaction hits price limit of the day. Otherwise there may not be enough time for relaxing the price limit and for the order imbalance to adjust. At the same time, the exchange officials also need to wait long enough after the first hit to gather sufficient information about the hit event. In this study, we suggest that one should consider waiting period of one hour after the first trade hits the day's price limit. The intraday analysis could be carried out by using trading information of one hour before and one hour after the first limit hit. Finding the optimum waiting period is an empirical question, for this study, we assume one hour would be sufficient time for the investors to re-evaluate the security prices and to react if there is any mispricing due to investor over reaction. Henceforth we refer analysis associated with option one as "End of the Day Analysis" and option two as "One Hour Analysis". The predictive models used to find probability of volatility spillovers and consecutive hits under these two options are discussed at Section IV.

### **III. Hypotheses**

This section develops the hypotheses that are tested in this study. It defines and provides a detailed explanation of consecutive price limit hits, volatility spillovers and non-consecutive hits on the basis of informed trading and uninformed overreaction in the market.

We define that a price limit hit will be called consecutive limit hit event if it is followed by another daily price limit hit on the next trading day for the same stock. If on the first day after price limit hit the stock experiences abnormally higher volatility then such price limit hits are called non-consecutive hits with volatility spillover or

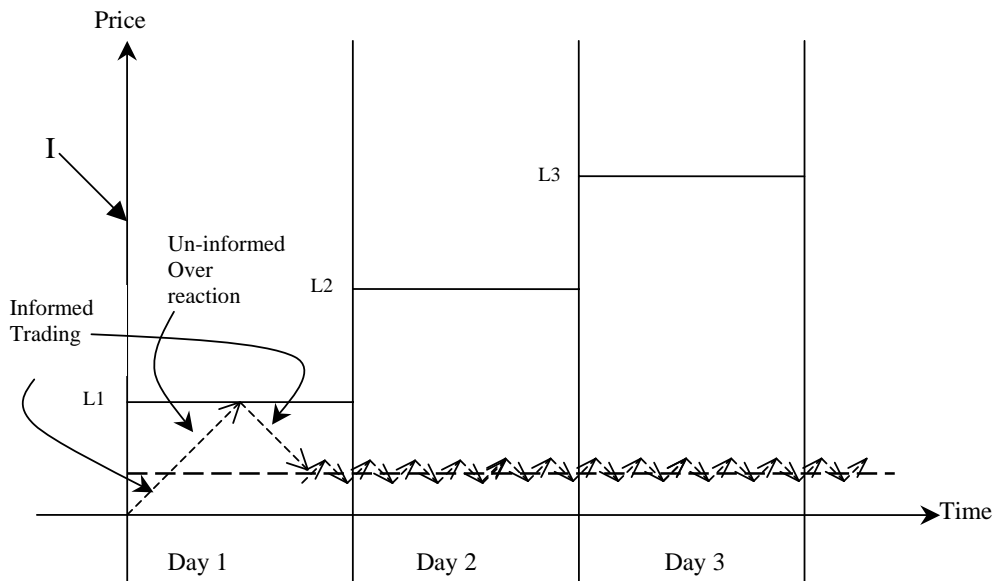
just volatility spillover for brevity. (in Section IV we discuss in detail about identifying volatility spillovers). Finally non-consecutive price limit hit events are limit hits that are neither followed by another price limit hit event or volatility spillover on the next trading day.

Rational price movements in the market occur when some unexpected information, which is not already incorporated in the prices, arrives. We assume that there are informed traders in the market who are aware of the true value of the security and they trade when the security is under-valued or over-valued. We also assume that there are uninformed traders who are either noise traders or trading for liquidity purposes.

Figure 1, 2 and 3 elaborate overreaction based explanation for non-consecutive price limit hits and information based explanation for consecutive price limit hits and volatility spillover on post price limit hits. Let us assume that at the beginning of any trading day,  $t$ , information,  $I_t$ , about the true value of a security reaches the market through private sources. Subsequently at some point of time this information may also get released through public sources too. The informed traders in the market trade to take advantage of their prior information and the informed trading activity pushes the price towards its intrinsic value.

Now, suppose the rational price impact of the information  $I_t$  is less than the price limit ( $LI$ ) for the day, i.e.  $\Delta p_t = v - p_{t-1} < LI$ . Where  $\Delta p_t$  is the rational price impact of the information  $I_t$  or rational change in security price due to the arrival of  $I_t$ ;  $p_{t-1}$  is the security price on day  $(t-1)$  and  $v$  is the intrinsic value of the security or can be assumed to be the efficient price in the sense of expected price of the security conditional to the information on day  $t$  i.e.  $E(p_t|I_t)$ .

In the above case informed trading would not force the price to hit the daily limits. Still, the daily price limit hit may occur if the uninformed investors overreact to the subsequent public release of the same information or if they overreact observing the informed traders' activity. This kind of price limit hits should not persist and trading in the market should not halt for long because when uniformed traders push the prices beyond the intrinsic value of the security then the informed traders will take the opportunity which will bring back the prices to their rational level.<sup>3</sup>

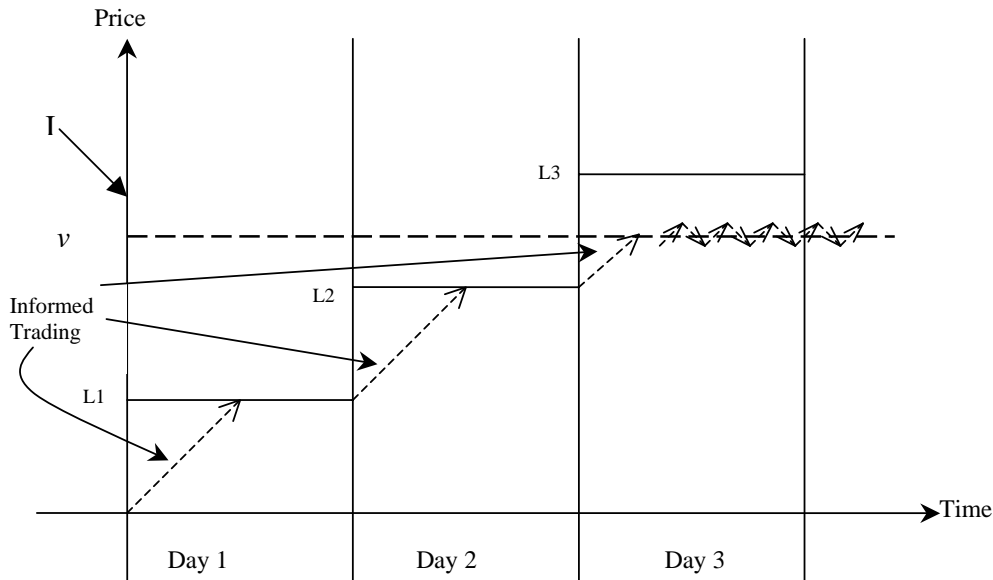


**Figure1-Non Consecutive Price Limit Hits:** This figure pictorially depicts the argument that non-consecutive price limit hits are caused by overreaction of the uninformed traders. Figure 1 describes the case of upper limit hit. This figure plots security price on vertical axis and time on the horizontal. With the arrival of information *I* on Day 1, informed trading brings the price to the rational level (*v*). Overreaction from uninformed traders may push the price to its daily limit L1 but in an active market informed selling will not allow price limit hit to persist.

<sup>3</sup> However there is a chance that in some occasions uninformed overreaction may persist over a few days but I argue that over a long period, on an average, uninformed overreaction will not be observed to persist for days.

Figure 1 graphically represents the explanation for non-consecutive limit hits. The expectations are that, in the case of non-consecutive price limit hit events, there will be more uninformed trading before and more informed trading after the price limit hit. In addition, in these hits we would expect more uninformed trades to hit daily limits. Informed traders will be active to bring the price back to the rational level after non-consecutive hits. One may observe this directly through the change in aggregate order imbalance sign after non-consecutive price limit hit.

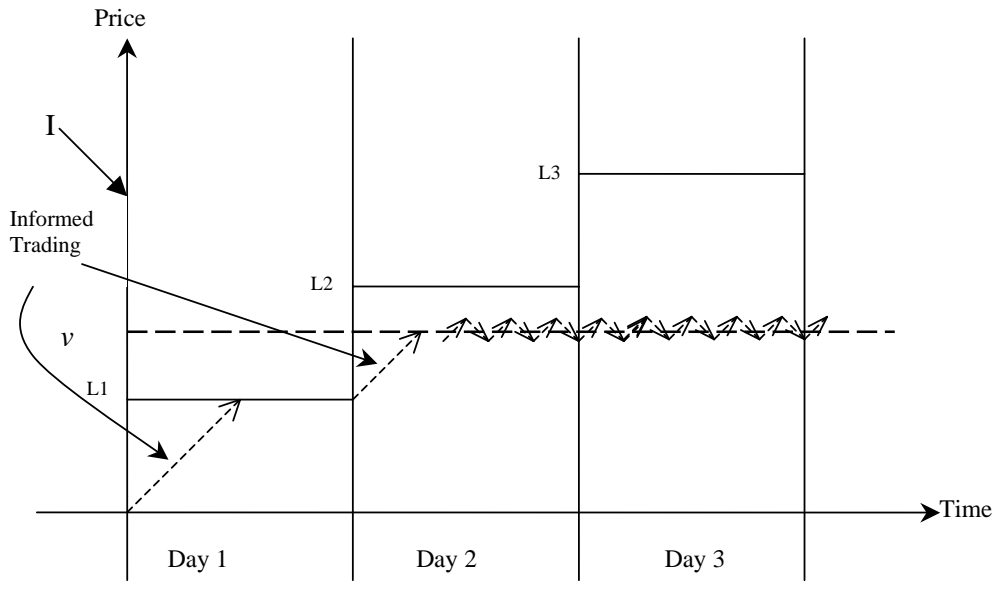
Now consider the situation when the rational price impact of the information  $I_t$  is greater than the price limit for the day, i.e.  $\Delta p_t = v - p_{t-1} > L1$ . We would focus on two specific scenarios to elaborate the explanation of consecutive price limit hits and volatility spillover due to obstruction to information revelation.



**Figure2-Consecutive Price Limit Hits:** This figure shows the argument that consecutive price limit hits are caused by information based traders. Figure 2 describes the case of upper limit hit. This figure plots security price on vertical axis and time on the horizontal. Information  $I$  arrives in the market on Day 1. Informed traders push the price towards the rational price level ( $v$ ). As rational price is beyond the price limits of Day 1 and Day 2 i.e.  $L1$  and  $L2$ , there will be consecutive price limit hit on these two days. Due to informed trading, on Day 3 price movement will continue its trend until it reaches the rational level.

First, let us consider,  $L3 > \Delta p_t = v - p_{t-1} > L2$ . This is the situation where the efficient price or intrinsic value  $v$  is beyond successive two days' price limit. Figure 2 provides a graphical description of this scenario. In this situation, informed traders would push the price towards its intrinsic value ( $v$ ) and as  $v$  is beyond the day's price limit, there will be a price limit hit on day 1 and this limit hit will persist throughout the day. There will be a virtual trading halt since informed traders will continue to offset any decrease in price due to erroneous uninformed trading. On the next day, again informed trading will take the price to the day's price limit as  $v$  is still above the price limit of day 2. Finally, on Day 3, prices will reach to their new equilibrium. There will be intense trading from the informed traders even on Day 3 till prices reach

their equilibrium value. As a result, Day 3 will experience some volatility spillover from the previous two days.



**Figure3-Volatility Spillover:** This figure describes volatility spillover in the market when price limits obstructs rational price movements. Figure 3 shows volatility spillover for upper limit hits. This figure plots security price on vertical axis and time on the horizontal. Information  $I$  arrives in the market on Day 1. Informed traders push the price towards the rational price level ( $v$ ). As rational price is beyond the price limit of Day 1, i.e.  $L1$ , prices will hit day's price limit hit. There will be a volatility spillover from Day1 to Day2 as informed traders will trade intensely on Day 2 till price reaches the rational level.

The second scenario is graphically represented in Figure 3. Following the above explanation, if price impact of new information is expected to be  $L2 > \Delta p_t = v - p_{t-1} > L1$  then we expect a price limit hit on day 1 and although there will not be any price limit hit on day 2, We still expect market to be quite volatile on day 2, as argued by Lehmann (1989).

As per the informed trading based explanation of consecutive hits and volatility spillover, We expect more informed trading before the price limit hit for consecutive limit hits and also for limit hits that cause volatility spillover during the subsequent days. We also expect that there will not be any price trend reversal after



limit hits that cause consecutive hits or volatility spillover. Further, we expect these limit hits to be contributed mainly by informed trades. In the cases of limit hits caused by rational price movements, price limit hits are expected to persist for a longer period causing a virtual trading halt in the market.

Following the arguments of Fama (1989) and Lehmann (1989) discussed in previous section and on the basis of our explanation provided above, the primary hypothesis that we propose is

*Consecutive price limit hits and volatility spillovers are observed when price limits obstruct information based trading while non consecutive price limit hits are observed when price limits restrain overreaction of uninformed traders.*

To test this hypothesis, we setup several secondary hypotheses that focus on the association of various observable aspects of informed trading and uninformed overreaction with consecutive hits, volatility spillovers and non consecutive price limit hits.

Kyle (1985), Admati and Pfleiderer (1988) argue that stock price movements are mainly caused by information based trading. Barclay and Warner (1993) and Chakravarty (2001), Anand and Chakravarty (2007) provide evidence that trade size could be a proxy for informed trading. In this study, we also find that medium size trades are more informed than the other trade sizes. Section IV discusses these findings in greater detail. Following these evidence, we use medium size trades as proxy for informed trading and small trades as proxy for uninformed trades. In line with explanation of consecutive and non-consecutive price limit hit provided above, my first two hypotheses are:

*H1: There are more informed trades before (after) consecutive (non consecutive) limit hit events.*

*H2: There are more uninformed trades before non consecutive limit hit events.*

The next two hypotheses are closely related to the previous hypotheses; The basic difference is previous hypotheses discuss about trades that happen before or after limit hit event where as following hypotheses are about the trades that hit price limit of the day. Based on the explanation of consecutive and non consecutive hits, We propose following hypotheses regarding the trades that hit price limits of the day:

*H3: For consecutive limit hit events informed trades constitute greater proportion of limit hitting trades.*

*H4: For non consecutive limit hit events uninformed trades constitute greater proportion of limit hitting trades.*

As we expect rational demand for the stocks causes consecutive limit hits, we would not expect a reversal in order imbalance after price limit hit. On the other hand, we argue that uninformed overreaction causes non-consecutive hits; therefore, we would expect a reversal in order imbalance after non-consecutive price limit hits.

*H5: Order imbalance sign reverses after non consecutive limit hit whereas after consecutive hits there is no reversal of order imbalance.*

We expect price limit hits will be more persistent if rational price movements cause them. Hence for consecutive limit hit days we expect more number of trades to hit price limit and also expect larger part of the trading day to be affect by price limit hits than non consecutive hit days.

*H6: Number of trades that hit price limits and number of trading hours affected by price limit hits is greater for consecutive hit days than non consecutive limit hit days.*

Pastor and Veronesi (2003) show that growth firms have greater volatility associated with their intrinsic value. Aslan et al. (2007) report that probability of

informed trading is higher for a smaller size , faster growing and higher volatility firm. Therefore we expect more informed trading on growth firms i.e. firms with high market to book value ratio, high firm specific risk and small size. So my final hypothesis is:

*H7: Growth firms i.e. small size firms with high market to book value ratio and high firm specific risk experience more consecutive hits.*

Following section discusses in detail about data and methodology for testing these hypotheses.

## **IV. Methodology, Data and Variables**

### *IV A. Univariate and Multivariate Tests*

We test the hypotheses proposed in previous section using both univariate and multivariate analysis. In univariate analysis, parametric t tests with equal and unequal variances as along with non parametric wilcoxon rank sum test. The objective of the analyses is to find out whether, on an average, there are any significant differences between the characteristics of consecutive and non-consecutive hits.

The multivariate analyses for hypotheses testing are also associated with the construction of models for predicting the probability of consecutive hits and volatility spillover. For this purpose binary Probit models and ordered Probit models are used. These models test various hypotheses stated in Section III in a multivariate setting by testing if identified proxies of informed trading and uninformed overreaction can predict a consecutive hit in the next trading day. A significant model specification will also work as a tool to improve price limit system as discussed in Section II.

Rest of this subsection discusses various details of the predictive models used for both End of the Day Analysis and One HourAnalysis. Following the

explanation on consecutive and non consecutive limit hit events in Section III, we assume that in a limit hit day, if unobservable information  $y^*$  crosses the threshold value  $\delta$  then consecutive hits ( $y = 1$ ) are observed. If the latent variable  $y^*$  can be modelled as

$$y^* = x' \beta + \varepsilon \quad (1)$$

where  $x$  is a vector of  $k$  independent variables comprise of various proxies for informed trading and uninformed overreaction and several control variables (Details regarding definition and construction of variables used is discussed in successive subsections) and  $\beta$  is the parameter vector with  $k$  elements. Then to design models for End of the Day Analysis estimates variations of binary Probit model described below,

$$\Pr(y = 1 | x) = \Phi(x' \beta) \quad (2)$$

where, variable  $y$  takes the value 1 for hits that cause consecutive hits on the next trading days and 0 for the other limit hit days.  $\Pr(\cdot | x)$  denotes conditional probability with respect to  $x$  and  $\Phi(\cdot)$  represents the cumulative normal distribution function.

In One Hour Analysis, we are interested in modelling probability of volatility spillovers along with probability of consecutive hits. Following my earlier argument, we assume, a consecutive price limit hit (i.e.  $y = 3$ ) occurs if the unobserved continuous information variable  $y^*$  for the day is greater than the threshold value  $\delta_2$ . Non consecutive hits with volatility spill over (i.e.  $y = 2$ ) is observed if  $\delta_1 < y^* \leq \delta_2$ , where  $\delta_1$  is another threshold value smaller than  $\delta_2$ . Non consecutive hits occur if  $y^*$  is less than  $\delta_1$ . Therefore, if  $y^*$  can be expressed as Equation (1) and the observed

discrete variables related to consecutive hits, volatility spillovers and non consecutive hit are expressed as

$$\left. \begin{aligned} y = 3 & \text{ if } y^* > \delta_2 \\ y = 2 & \text{ if } \delta_1 < y^* \leq \delta_2 \\ y = 1 & \text{ if } y^* \leq \delta_1 \end{aligned} \right\} \quad (3)$$

Then for the One Hour Analysis, we estimate an ordered probit model described below,

$$\left. \begin{aligned} \Pr(y = 1 | x) &= \Phi(\delta_1 - x' \beta) \\ \Pr(y = 2 | x) &= \Phi(\delta_2 - x' \beta) - \Phi(\delta_1 - x' \beta) \\ \Pr(y = 3 | x) &= 1 - \Phi(\delta_2 - x' \beta) \end{aligned} \right\} \quad (4)$$

where  $\delta_1$  and  $\delta_2$  are two unknown thresholds.  $\Phi(\cdot)$  is the cumulative standard normal distribution function.  $x$  is the vector of independent variables (details in following subsection) and  $\beta$  is the parameter vector as defined earlier.

For both analyses described above identification of consecutive limit hits, non consecutive limit hits and volatility spillover are required. Consecutive limit hits are easily identifiable in the data but the volatility spillovers events are not. To identify volatility spillovers we use *modified* Kim and Rhee (1997) methodology. Based on propensity score matching methodology, we compare the volatility of each limit hitting stock against a comparable stock (a stock that has closest propensity to hit daily price limit and also experienced a large price change (at least 90% of days price limit) but did not hit price limit on the previous day). If limit hitting stock has higher volatility on post limit hit day, relative to the comparable stock, then we classify that particular limit hit event as a volatility spillover causing limit hit. A detailed discussion on *modified* Kim and Rhee (1997) methodology, calculation of propensity scores and identifying comparable stocks is provided in the Appendix 1.

#### *IV B. Data and Variable Description*

This subsection describes data and variables along with interpretations of each variable and the ex-ante expectations about them. This study uses data from the Tokyo Stock Exchange (TSE). We use intra-day transaction level stock price data of TSE for a period five years from January 2001 to December 2005. Data for this study is supplied by Securities Industry Research Centre of Asia-Pacific (SIRCA) on behalf of Reuters. The firm level and daily data such as market capitalisation, market to book value, daily market index figures are obtained from Data-stream International database. Remainder of this subsection will provide details about the definition and construction of variables used in this study.

To test the hypotheses outlined in Section III, we construct ten independent variables as follows,

- a) Trade size related variables:  $\Delta \text{Medium} / \Delta \text{Medium1}$ ,  $\Delta \text{Small} / \Delta \text{Small1}$ ,  $\text{Hit-M} / \text{Hit-M1}$  and  $\text{Hit-S} / \text{Hit-S1}$  ;
- b) Order imbalance variables:  $\Delta \text{OI} / \Delta \text{OI-sign} / \Delta \text{OI-sign1}$ ;
- c) Variables related to hit characteristics: No-of-Hits / NHits and Hit Span;
- d) Firm characteristics - Market to book value (MB), firm specific risk (Rsd-Risk), and market capitalisation of a firm (Mcap / Size).

Other than above mentioned variable, this study also uses several control variables in the multivariate analysis, such as,

- a) Proxy of trading activity ( No-of-Trds / Trds)
- b) Time of the limit hit (Hit-to-Close)
- c) Market Volatility and
- d) Dummy variables for the months and days

A detail description of construction and interpretation of these variables are provided below.

Trade size related variables are used to identify informed trading in the market. According to trade fragmentation and stealth trading literature (Barclay and Warner (1993), Chakravarty (2001) and Anand and Chakravarty (2007)) medium size trades on an average represent fragmented trades from informed traders. To find out informed trade size in the sample, each trade is classified as small, medium or large size trade. We classify transactions of the limit hit days based on the distribution of the transaction volume of past one month for each limit hit event. We classify a transaction as small size if it is smaller than first quartile of the distribution, as medium size if it is equal to or greater than first quartile and less than or equal to the third quartile of the distribution. Any transaction with a size greater than third quartile of the trade size distribution is classified as large trades.

The methodology used in this study to classify trades into different size groups is different from the methodology of Barclay and Warner (1993) and Chakravarty (2001) who use absolute trade sizes. Absolute trade sizes cannot be used in our sample to classify trades because in TSE for each listed stock there is a minimum amount that may be traded. These minimum trade sizes are known as “trading units”. Trading units in TSE varies from 1 share to 3000 shares. Majority of stocks use a trading unit of 1000 stocks. Over the time the trading units for a stock may change at the discretion of the individual company. Details of trading units of companies listed in various segments of Tokyo Stock Exchange are given in Table 2. Presence of trading units does not allow use of absolute trade size ranges prescribed by Barclay and Warner (1993) to classify trade sizes.

The sample used for the study spans through different segments of TSE over a period of five years, 2001 to 2005. It is very difficult, if not impossible to track trading units of each stock at any day in the sample period as no available database provides such information. Therefore, a trade size classification based on distribution of individual stock's transaction volumes is quite appealing in this scenario. This methodology is quite appropriate as it allows trade size classifications to be different for each stock as they have different trading units. In this methodology trade size classifications for a stock can even differ over time to account for different market condition and changing trading unit.

We follow Barclay and Warner (1993) to test information content of different trade sizes. Table 3 reports percentage of cumulative price change and percentage of cumulative volume contribution of small, medium and large size trade over one month prior to each price limit hit. Table 3 shows that cumulative price change contributed by medium size trades is greater than their volume contribution. However, for small and large size trades volume contribution is greater than their cumulative price change. In the light of trade fragmentation literature, this evidence suggests that, on average, medium size trades are informed while the other trade sizes do not have much information content. Therefore we interpret medium size trades as transactions of informed traders and small size trades as trades generated by uninformed retail traders. On the other hand, large size trades may be interpreted as uninformed institutional/liquidity trading, though in this study large trades are not used in any analysis. For the purpose of this study, to test the Hypotheses *H1* to *H4* stated in Section III, we concentrate on small and medium trade sizes. Variables such as  $\Delta \text{Medium} / \Delta \text{Medium1}$ ,  $\Delta \text{Small} / \Delta \text{Small1}$ ,  $\text{Hit-M} / \text{Hit-M1}$ ,  $\text{Hit-S} / \text{Hit-S1}$  are constructed based on the above indicated trade classifications.



Variables  $\Delta \text{Medium}$  /  $\Delta \text{Medium1}$ ,  $\Delta \text{Small}$  /  $\Delta \text{Small1}$  are used to test influence of informed trading and effect of uninformed overreaction on consecutive and non-consecutive limit hits as discussed in hypothesis *H1* and *H2*.  $\Delta \text{Medium}$  refers to change in the proportion of medium size trades from *before to after* first limit hit of the day. This variable is measured by subtracting the proportion of medium size trades before first price limit hit of the day from the proportion of medium size trades after the limit hit.  $\Delta \text{Medium}$  is used as a proxy for change in informed trading in the market. Hence this variable represents change in the proportion of informed traders in the market after first price limit hit. Increase (decrease) in  $\Delta \text{Medium}$  infers higher proportion informed trading after (before) first limit hit. As per hypothesis *H1*  $\Delta \text{Medium}$  should be higher for non consecutive hit days. In One Hour Analysis, equivalent of  $\Delta \text{Medium}$  is  $\Delta \text{Medium1}$  which is calculated using trades from 1 hours before and after the first price limit hit.

$\Delta \text{Small}$  is defined as change in the proportion of small size trades from *before to after* first limit hit of the day. It is calculated by taking difference between the proportion of small size trades after and before first price limit hit of the day. Small size trades are proxy for the small and uninformed traders in the market. Hence this variable measures change in the proportion of small uninformed traders in the market from before to after first price limit hit. According to hypothesis *H2* expectation is that  $\Delta \text{Small}$  should be less for non consecutive hits as we expect non consecutive hits are caused by uninformed traders activity which reduces after the limit hit. For 1 hour after limit hit analysis, we use variable  $\Delta \text{Small1}$  that measures change in the proportion of small size trades from 1 hour before to 1 hour after first limit hit of the day. The interpretation of the variable remains similar to  $\Delta \text{Medium}$ .

For testing if more number of informed (uninformed) transactions hit consecutive (non-consecutive hits) as suggested in hypothesis *H3* and *H4*, we construct variables Hit-M / Hit-M1, Hit-S / Hit-S1. Hit-M measures the proportion of limit hits caused by medium size trades. As medium trades represent trade fragmentations by informed traders, higher proportion of hits from medium size trades may indicate limit hit due to flow of new information. My expectation is that Hit-M should be high for consecutive hits. Hit-M1 is the counter part of Hit-M in 1 hour analysis.

Hit-S measures the proportion of limit hits caused by small size trades. As small trades represent uninformed traders, higher proportion of hits from small trades may indicate limit hit is caused by overreaction from uninformed traders. We expect high values of Hit-S for non consecutive hits. In 1 hour analysis, Hit-S1 or the proportion of limit hits caused by small size trades within 1 hour after first limit is used instead of Hit-S.

Hypothesis *H5*, i.e. change in order imbalance around limit hit events, is tested using variables  $\Delta OI$  /  $\Delta OI\text{-sign}$  /  $\Delta OI\text{-sign1}$ . The variable  $\Delta OI$  refers to change in order imbalance after the first limit hit of the day. This variable is measured as the ratio of order imbalance after first limit hit *over* order imbalance before first limit hit of the day. Order imbalance is calculated from the difference of the value of seller and buyer initiated trades where Lee and Ready (1991) algorithm is used for the identification of trade direction. This variable reflects changes in buying and selling pressure in the market after first price limit hit of the day.  $\Delta OI$  greater than 1 shows continuation of buying (selling) for an upper (lower) limit hit, whereas negative  $\Delta OI$  represents a reversal of buying (selling) pressure to selling (buying) pressure,  $\Delta OI$  less than 1 and greater than 0 reflects continuation of buying or selling pressure at a

reduced magnitude. So we expect  $\Delta OI$  to be less in non consecutive hit days compared to consecutive hit days.  $\Delta OI1$  is the counterpart of  $\Delta OI$  in One Hour Analysis. For the purpose of multivariate analyses, we use dummy variable  $\Delta OI\text{-sign}$  ( $\Delta OI\text{-sign1}$ ) which takes the value 1 if  $\Delta OI$  ( $\Delta OI1$ ) is greater than 0 otherwise  $\Delta OI\text{-sign}$  ( $\Delta OI\text{-sign1}$ ) takes the value 0.

To test the relation between persistence of price limit hit and types of hit as discussed in hypothesis *H6*, variables such as No-of-Hits / NHits, Hit Span are used. No-of-Hits represents the total number of transactions that hit daily price limit on a limit hit day. For multivariate analysis we use variable NHits, which is natural logarithm of No-of-Hits.

Hit Span measures the time difference in hours between first and last price limit hit of the day. It reflects how many trading hours of the day are affected by price limit hits. Hit Span along with No-of-Hits quantifies intensity, seriousness and persistence of limit hits. Low No-of-Hits and small Hit Span might reflect momentary overreaction or erroneous order placement from the traders, where as if No-of-Hits as well as Hit Span is high than it may indicate that many traders in the market believe securities prices should be beyond the price limits of the day. Therefore we would expect low No-of-Hits and small Hit Span for non-consecutive hits.

Firm specific variables such as Mcap / Size, MB and Rsd-Risk are used to test the Influence of firm characteristics on consecutive and non-consecutive hits as specified in hypothesis *H7*. Mcap is the market capitalisation for a firm measured in 100mn Yen, represents size of the firm. The natural logarithm of Mcap – variable Size, is used as a proxy of firm size in multivariate analyses. MB or Market to Book value ratio measures growth opportunity of a firm. Residual risk (Rsd-Risk) is a

measure of idiosyncratic risk of the firm. Rsd-Risk is 100 times of the standard deviation of residuals obtained from the market model.

Aslan et al. (2007) report significant negative relationship between trading activity and probability of informed trading. Their study supports the notion that more active stocks attract greater uninformed order flow. In our multivariate analysis to control for cross sectional variation of liquidity and trading activity variable Trds is used. Trds is the natural logarithm of number of transactions in a limit hit day for a stock.

The variable Hit-to-Close is used to control intraday pattern of trading. This variable quantifies the time of the first price limit hit. It measures the time difference in hours between market closing and first price limit hit of the day. Higher values of the variable signify hits on earlier parts of the day.

We also control for effect of market wide volatility in our multivariate analysis. Market volatility of the limit hit days is calculated as squared daily returns of market index of TSE, the TOPIX.

Apart from these variables we also use dummy variables to control for months of the year and days of the week as there is a considerable amount of evidence in the literature that suggests seasonality of trading activity and concentration of trading on certain days of the week. Table 1 summarises my a-priori expectations from different variables based on the hypotheses and also provides explanations about those expectations.

## **V. Analysis of Results**

### *V.A Univariate Analysis*

Descriptive statistics of the variables used in the study are reported in Table 4. Statistics are provided for the entire sample of limit hit events and also for two sub samples of consecutive hits and non-consecutive hits. This table also presents the results of univariate analyses such as test for equality of mean and median between the consecutive and non-consecutive hit samples, using t tests and Wilcoxon Rank Sum test.

Table 4 shows that average value of  $\Delta$  Medium in non-consecutive hit sample is significantly greater than the consecutive sample. This may suggest that more informed trading occurs after first price limit hit on non-consecutive hit days than consecutive hit days. This is consistent with hypothesis *H1*.

At the univariate level, we do not find much support for hypothesis *H2*. Though average value of  $\Delta$  Small non-consecutive hits is smaller than that of consecutive hits but they are not significantly different. This suggests that change in the proportion of small uninformed trades after first limit hit of the day does not help in differentiating consecutive limit hits from non-consecutive ones.

Results of the univariate tests do not support Hypothesis *H3*. we find, Hit-M or proportion of hits due to medium size trades is not significantly different between consecutive or non-consecutive hits. So in univariate tests there is no evidence that more informed transactions hit price limits on consecutive limit hit days.

However, univariate analysis supports hypothesis *H4*. Hit-S or proportion of hits by small trades is significantly higher for non-consecutive hits than consecutive hits. This suggests that in the case of non consecutive hits more number of hits are caused by uninformed traders.

Average value of  $\Delta$  OI is significantly more negative for non consecutive limit hit days than for the consecutive hit days. This signifies that, on non-consecutive hit

day, after the first price limit hit, change in the direction of order imbalance occurs at a greater magnitude compared to the consecutive hits days. This result reflects that on non-consecutive hit days, after first upper (lower) limit hit, more sellers (buyers) are willing to transact more than the consecutive limit hit days. This is quite consistent with my expectation in Hypothesis *H5*. we expect a price trend reversal after a non consecutive hit than a consecutive one.

Results reported in Table 4 provide partial support to hypothesis *H6*. Univariate tests do not suggest any significant difference between consecutive and non-consecutive hits in terms of No-of -Hits. Though the average Hit Span, i.e. number of trading hours affected by limit hits, for consecutive hits is significantly higher than that of non consecutive hits. This suggests, that on consecutive hit days the limit hitting trades are more persistent and affect larger part of the trading day.

Consistent with hypothesis *H7*, we find average market capitalisations of stocks, that experience consecutive limit hits, are significantly smaller than the average market capitalisation of the firms that experience non-consecutive hits. Table 1 also reports that average market to book value (MB) and average idiosyncratic risk (Rsd-Risk) for the stocks with consecutive hits are significantly higher than the non-consecutive hit sample. This evidence may be interpreted as small stock, stocks with high growth opportunities and with high firm specific risk attract more informed traders as a result experience more consecutive limit hits.

The average liquidity of the stocks experiencing non-consecutive hits is significantly higher than the stocks that experience consecutive hits as mean and median values of No-of-Trds is significantly higher in non-consecutive hit sample compared to consecutive hits. This is consistent with our expectation that more uninformed trader trades in highly active stocks as mentioned by Aslan et al. (2007).

On average, consecutive hits occur earlier in the day than non-consecutive ones as the average Hit-to-Close values for consecutive hits are higher than the non-consecutive hits. However, this difference is not statistically significant.

Univariate analysis also shows that average Market Volatility for non-consecutive hit days is higher than that of consecutive hit days but the difference is again not statistically significant.

Though we do not find much evidence in favour of the hypotheses *H2*, *H3*, the results provided in Table 4 support my hypotheses *H1*, *H4*, *H5*, *H6* and *H7*. Therefore my findings from univariate analysis suggest that on an average consecutive limit hit events occurs when price limits restrict rational price movement due to new information flow where as overreaction of uninformed traders cause non-consecutive hits.

#### *V.B End of the Day Analysis*

Following the discussion in Section IV, we carry out the End of the Day Analysis using binary Probit models. Table 5 provide the results of End of the Day Analysis using four different model specifications. Panel A reports estimations from the entire sample, where as Panel B and C presents estimated coefficients from the subsample of upper and lower limit hits respectively. All the estimated models include following independent variables  $\Delta$ Medium,  $\Delta$ Small,  $\Delta$ OI-sign, Hit-M, Hit-S, Nhits, Hit Span, MB, Rsd-Risk, Size, Trds, Hit-to-Close and Market Volatility. Along with these variables, Model I, II and III also include dummy variables controlling for months of the year and days of the week.

Panel A of Table 5 shows that the probability of consecutive price limit hit is negatively related to  $\Delta$ Medium and the relationship is statistically significant in all

the models. This supports hypothesis *H1* that there is more informed trading after (before) non-consecutive (consecutive) hit events. Results in Panel B reports that this relationship is also significant at 1% level of significance for all the models estimated for the sub sample of upper limit hit events. However, for lower limit hit sample  $\Delta$ Medium is not a significant variable in determining probability of consecutive limit hits.

Similar to univariate analysis findings, we do not find any support for Hypothesis *H2* in the multivariate models too. Consistently in all the models and for all the samples,  $\Delta$ Small is insignificant which suggest change in uninformed traders activity may not help in determining the probability of consecutive limit hit events.

As indicated in the initial univariate analysis results also, we do not find proportion of medium size trades hitting day's price limit (Hit-M) as a significant variable in any of the models estimated in Panel A, Panel B or Panel C. However, Hit-S or proportion of small trades hitting price limit is negatively significant in all the models. These results reject the hypothesis *H3* that, on consecutive hit event, more informed trades hit price limits. On the other hand, we find support in favour of Hypothesis *H4* that, on non-consecutive limit hit days, more uninformed trades hit price limits.

Consistent with hypothesis *H5*,  $\Delta$ OI-sign has a significant negative relationship with consecutive hits at 1% level of significance in all the models estimated using the entire sample. Panel B results also support this findings from the sub sample of upper limit hits. But we do not find any significant relationship between  $\Delta$ OI-sign and consecutive hits in the sample of lower limit hit events.

Results of the estimated models from the entire sample fully support hypothesis *H6*, i.e. there is greater persistence of limit hitting trades on consecutive



limit hit days. Number of trades hitting daily limit and number of hours of the trading day affected by limit hit events are both, positive and significantly associated with consecutive limit hits at 5% and 1% level respectively. These results imply that trades that hit price limits are more persistent and they affect greater portion of the trading day in case of consecutive hits in comparison to non-consecutive hits. Though the results from upper and lower limit sub samples provide only partial evidence in support of this hypothesis. Panel B shows that, in upper limit sample NHits is not a significant variable in any of the models. However, the coefficient of Hit Span is positive and significant at 1% level. For lower limit hit sub sample NHits is positive and significant and Hit Span is not significant.

Market to book value ratio (MB) and firm specific risk (Rsd-Risk) are found to be positive and highly significant at 1% level in models estimated for entire sample as well as in the models estimated using sub samples of limit hit events. Size of a firm measure as natural logarithm of its market capitalisation is found to be negative and significant at 1% level in all the models across all the panels. These results provide evidence in favour of the hypothesis *H7* that growth firms experience more likely to experience consecutive hits.

The control variables such as Hit-to-Close and Market Volatility are not significant in most of the models. The proxy of trading activity, Trds, is found to be negative and significant in all the samples, though for the lower limit hit sub sample coefficients are weakly significant at 10% level only.

In all the panels Model I includes month of the year dummies as well as day of the week dummies whereas Model II and Model III include only month dummies and only day dummies respectively. For each model  $\chi^2(\text{Month})$  and  $\chi^2(\text{Day})$  provide the value and significance of the  $\chi^2$  statistics from Wald test to report joint significance

of all the month and day dummy variables. Table 5 results shows that in all the models these dummies are significant at 1% level of significance.

For overall significance of the models, Table 5 reports  $\chi^2$  statistics from the Wald test for the global null hypothesis that all the coefficients are equal to zero. Values and significance of  $\chi^2(\text{Global})$  reported for all the models suggest that the estimated models are significant at 1% level. Table 5 also report Pseudo -  $R^2$  for all the estimated models. Pseudo -  $R^2$  for the models estimated for the entire sample ranges from 13.1% to 15.2%. For the upper limit hit sub sample the Pseudo -  $R^2$  of the models varies from 11.7% to 14% and for the lower limit sub sample the range is from 21.8% to 28.3%. In all the panels Model I have greater Pseudo -  $R^2$  values compared to the other models.

The final row of Table 5 reports the  $\chi^2$  statistics from Hosmer-Lemeshow (H-L) test for goodness of fit described in Hosmer and Lemeshow (2000). The null hypothesis for this test is that the binary choice model is properly specified. For all the model estimated in Table 5,  $\chi^2$  statistics form H-L test is not significant even at 10% level so we do not reject the null hypothesis. The results of H-L test provide further support that overall the models estimated in Table 5 for End of the Day analysis are significant.

The discussion on the results of Table 5 above indicates sign and significance of the estimated parameters but it does not provide information about the size of their effect on dependent variable. The coefficients of probit models are difficult to interpret because of the nonlinear nature of the model. In order to provide a better interpretation of the estimated parameter Table 5a reports marginal probability of consecutive hits associated with each of the independent variable. The marginal probabilities reported in Table 5a are evaluated at sample mean, median and mode

using estimated coefficients of Model IV of Panel A from Table 5. The marginal probabilities can be interpreted as change in probability of consecutive hit due to unit change in independent variables, though it should be noted that marginal probability calculation is not invariant to scale.

Table 5a shows that the impact of  $\Delta$ Medium,  $\Delta$ OI sign and Hit-S on the probability of consecutive price limit hit is greater than that of any other variable. One unit change in these variables individually changes probability of consecutive hit by 6% to 9% at sample mean or median. If the marginal probabilities are evaluated at most frequent values of the sample, unit change in these variables, individually, can cause 15% to 20% change in the probability of consecutive hit. For other significant variables such as NHits, HitSpan, MB, Rsd-Risk, Size and Trds absolute marginal probability values ranges from 0.4% to 6% when evaluated at sample mean, median and mode.

In comparison to Table 5a, which shows the rate of change of probability of consecutive price limit hit,  $\Pr(y = 1 | x)$  with respect to the individual variables at three different values namely at sample mean, median and mode, Figure 1a and 1b show how  $\Pr(y = 1 | x)$  changes across different values of the variables between their sample minimum and maximum. These figures plot,  $\Pr(y = 1 | x)$  from Model IV in Panel A of Table 5 against all the significant independent variables in that model. In both figures of  $\Pr(y = 1 | x)$  is plotted on vertical axis for each independent variable when other variables are fixed at their sample mode. On the horizontal axis the independent variables are plotted from their sample minimum to sample maximum. Figure 1a is plotted for the days when order imbalance changes sign after limit hit and Figure 1b is for the rest of the days.

Figure 1a and 1b shows that when all other variables are at their modal values, as firm specific risk changes from its minimum to the maximum value, the probability of consecutive hit increases by more than 70% (60%) when  $\Delta$ OI-sign is equal to 1 (0). This is the maximum change in probability of consecutive hit when the value of a single variable changes from sample minimum to sample maximum and other variables are fixed at their sample mode. Similarly, for market to book ratio the increase is about 50% (40%) in Figure 1a (1b). Probability of consecutive decreases by 50% (45%) in the days when sign of order imbalance change (do not change) as Size variable moves from its minimum to the maximum. Apart from these firm specific variables changes in  $\Delta$ Medium affects the probability of consecutive hits quite significantly. Figures 1a (1b) shows that increase in  $\Delta$ Medium from minimum to maximum value causes about 27% (24%) decrease in  $\Pr(y = 1 | x)$ . Finally in both the figures the graphs for variable Nhits and Hit Span (Hit-S and Trds) move upward (downward) quite closely. For both pair of variables difference in  $\Pr(y = 1 | x)$  is about 12% to 15% between minimum and maximum values in Figure 1a and Figure 1b. A direct comparison between Table 5a and these two figures point out that, though at sample mean, median or mode, one unit change of  $\Delta$ Medium,  $\Delta$ OI sign and Hit-S causes greater impact on probability of consecutive limit hits than any other variables, however across the sample range impact of firm specific variables such as MB, Rsd-Risk, Size is far greater than other variables.

To further investigate how change in firm specific factors and informed trading related variables jointly affect the probability of consecutive hits we plot Figure 2. We define growth firms as firms with small size, high market to book value and low firm specific risk. Firm specific factors of End of the Day analysis are

combined to construct the growth variable. Using estimates of Model IV from Panel A of Table 5, the growth variable is defined as -

$$X^* = 0.016 MB + 0.051 RsdRisk - 0.105 Size .$$

Similarly, we also define an information driven price limit hit as one with many numbers transaction hitting price limit over a long span of time, with more informed trading before first limit hit than after and with less number of hits caused by small traders. We combine those informed trading related variables in a factor as –

$$X_i = -0.351 \Delta Medium - 0.333 Hit - S + 0.057 NHits + 0.079 * Hit Span .$$

Figure 2 plots  $P(Y=1|X^*)$  against  $X^*$ , for three different values of  $X_i$ , sample minimum (i.e. low information day), sample maximum (i.e. High information day ) and sample mode (a typical trading day), when rest of the variables in the model are fixed at their sample mode. Figure 2 shows that, on a limit hit day, with low level of informed trading, even for the high growth firms, the probability of consecutive hit is about 30%. On the other hand in high information limit hit days, firms with medium level of growth have more than 50% probability of causing consecutive hits. For a limit hit day, with most frequently observed information level, highest level growth firms have about 60% chance of experiencing consecutive price limit hit. On a similar day the firms with lowest growth have less than 5% probability of experiencing consecutive hits. This figure shows that compared to the lowest growth stock, for the highest growth firm increase in probability of consecutive hit due to informed trading activity is about 200% greater.

The End of the Day analysis shows that both firm specific and trade characteristic variables are quite important in determining the probability of consecutive hit. Models estimated in Table 5 could be quite useful in creating a

flexible and improved price limit system that could successfully avoid consecutive price limit hits due to rational price movements.

#### *V.C One Hour Analysis*

As discussed in Section II, to reduce the cost improper of price limit impositions by predicting occurrence of consecutive limit hits as well as volatility spillover, One Hour Analysis can be used. Section IV provides details of the ordered models applied for the analysis. In this section we analyse the ordered probit models estimated for this purpose. Table 6 reports estimated coefficients from four different model specifications along with their standard errors and significance level. Panel A of the table reports the results estimated from the entire sample of limit hit events. Panel B and Panel C report results for upper limit hit and lower limit hit sub samples respectively.

Similar to the End of the Day analysis, all four estimated models include independent variables such as  $\Delta$ Medium1,  $\Delta$ Small1,  $\Delta$ OI-sign1, Hit-M1, Hit-S1, Nhits1, MB, Rsd-Risk, Size, Trds1 and Hit-to-Close. Dummy variables for both months of the year and days of the week are included in Model I of each panel. Model II and Model III include dummies for months of the year and dummies for days of the week respectively, along with other independent variables. Models estimated in Table 6 show if consecutive hits and volatility spillover can be predicted using various informed trading related and firm specific variables, in One Hour Analysis. Table 6 results also help to testing hypotheses described in Section III.

The results of the One Hour Analysis are quite similar to the finding of End of The Day Analysis discussed in the previous subsection. We find hypotheses *H1*, *H4*, *H5*, *H6* and *H7* are supported by the results estimated from entire sample and from the

sub sample of upper limit hit. However, other than  $H7$ , there is only weak or no support for the other hypotheses in lower limit hit sub sample.

Hypotheses  $H2$  and  $H3$  are rejected in all the models estimated for One Hour Analysis. This reflects that change in proportion of uninformed investors or proportion of informed trades hitting daily limit do not really differ between consecutive and non consecutive hits.

Hit-to-Close and Trds1 are two common control variables used in all the models estimated for One Hour Analysis. In all models estimated for entire sample and upper limit hit, coefficients of Hit-to-Close are positive and significant. This reflects limit hits on the earlier part of the trading day have greater probability of causing consecutive hits. For lower limit hit sample Hit-to-Close is not a significant variable though. Trds1 is negative and significant at 10% and 1% level for entire sample and for upper limit hit sample respectively. On the other hand, contrary to our expectations coefficients of Trds1 is significant but positive in lower limit sample for all estimated models.

For Model I, month dummies are jointly significant at 10% level in the entire sample, though they are not significant in sub samples. The day dummies are jointly significant at 5% level only for lower limit hit sample. Table 6 shows that in Model II month dummies are significant at 1% and 10% level for entire sample and for sub samples respectively. The day dummies are significant at 1% in Model III of lower limit hit sample only.

The  $\chi^2$ (Global) reported for the models suggest that the estimated coefficients are jointly significant at 1% level for all the models across the panels. Pseudo -  $R^2$  for the models estimated for the entire sample varies from 13.1% to 27.6%. For the

upper(lower) limit hit sub sample the Pseudo -  $R^2$  of the models varies from 11.7% (21.7%) to 27% (35.6%).

To compare the estimated coefficients from One Hour Analysis, Table 6a provides marginal probabilities associated with the coefficients of Model IV from Panel A of Table 6. The marginal probabilities of consecutive hit provided in Table 3a are evaluated at sample mean, median and mode using coefficients estimated in Model IV of Panel A, Table 6. Proxies for informed trading and uninformed overreaction namely  $\Delta$ Medium1 and Hit-S1 as well as the firm size are three most influential variables in terms of their marginal probability values. Table 6a reports, if evaluated at sample mode, one unit increase in  $\Delta$ Medium1 or in Hit-S1 reduces probability of consecutive hit by more than 16%. Marginal effect of Size on probability of consecutive hit is about -9% when all the variables are fixed at sample mode. The effect of unit change in firm size at sample mode is about double than its effect on probability of consecutive hits at sample mean or median.  $\Delta$ OI sign1 is another significant variable that has around -7% (-3%) marginal probability of consecutive hits when evaluated at mode (mean/median). For other significant variables such as NHits1, MB, Rsd-Risk, Hit -to-Close and Trds1 absolute marginal probability values ranges from 0.4% to 4% when evaluated at sample mean, median and mode.

Similar to Figures 1a and 1b, in Figures 2a and Figure 2b, probability of consecutive price limit hit,  $\Pr(y = 3 | x)$ , is plotted against each significant independent variables from Model IV in Panel A of Table 6 when other variables are fixed at their sample mode. Figure 2a represents days when order imbalance changes sign after limit hit while Figure 2b represents the other days.



Figure 2a (2b) shows that the probability of consecutive hit changes by about 50% to 70% (50% to 60%) as firm specific variables changes from their minimum to the maximum value. For the other variables probability of consecutive hit changes by about 10% to 20% as the variable moves from their minimum to the maximum in both the figures. These figures show that, over the entire sample range, impacts of firm specific variables on the probability of consecutive hits is greater than other variables. Though at sample mean, median or model marginal effect of informed trading or uninformed overreaction related variables are larger.

The effect of independent variables on the probability of volatility spillover is difficult to interpret from the estimated coefficients reported in Table 6 or even from the marginal probabilities associated with these coefficients [Greene (1997), page 929]. To provide a comprehensive picture of how probability of volatility spillover changes with a change in the independent variables Figure 4a and Figure 4b are plotted. Both the graphs show probability volatility spillover based on the coefficients estimated in Model IV of Panel A in Table 6. In these figures each significant independent variable takes values that varies from their sample minimum to maximum while other variables are fixed at their sample mode. Figure 4a and Figure 4b are plotted for  $\Delta OI \text{ sign}1$  equal to 1 and 0 respectively. The graphs show that probability of volatility spillover initially increases and then decreases with an increase in firm size. Variables such as market to book ratio, firm specific risk, Hit - to- close and  $NHits1$  have negative relationships with probability of volatility spillovers. On the other hand, increase in  $\Delta Medium1$ ,  $Hit-S1$  and  $Trds1$  increases probability of volatility spillovers.

To understand combine effect of informed trading related variable as well as the collective impact of firm characteristic variables, on probability of improper limit

hit impositions, similar to End of the day analysis, We also construct the informed trading factor ( $X_i$ ) and growth factor ( $X^*$ ) for One Hour Analysis. Using the estimated coefficients from Model IV of Panel A in Table 2 these factors are defined as,

$$X_i = -0.277 \Delta Medium1 - 0.275 Hit - S1 + 0.081 NHits1$$

$$X^* = 0.027 MB + 0.033 RsdRisk - 0.155 Size$$

Firms with high value in growth factors are defined as high growth firms. Limit hit day with maximum (minimum) values of informed trading factor are denoted as the high (low) information days. Figures 5a, 5b, 5c respectively describe how with increase in growth factor, the probability consecutive hit, volatility spillover and non-consecutive hits change on a low information, high information and on a most frequently observed (i.e. typical) day. Figures 5a (5c) shows that for very low (high) growth firms the probability of consecutive (non-consecutive) hits does not increase (decrease) much with the increase in informed trading. However, the probability of consecutive (non-consecutive) hits for very high (low) growth firms increases (decreases) by about 20% from a low information day to a high information day.

From Figure 5c, we find that probability of volatility spillover initially increases with growth factor and then subsequently decreases. Probability of volatility spillover is at the maximum value for relatively low growth firms on high information days compared to low information days. These figures also point out that, for relatively low (high) growth firms, the probability of volatility spillover is an increasing (decreasing) function of growth as well as informed trading activity. This result is consistent with my initial expectation that in the ordered probit model, beyond the threshold  $\delta_1$  with increase in firm growth or informed trading activity the

probability of volatility spillovers increases. On the other hand, beyond the threshold  $\delta_2$  the probability of consecutive hits increase with increase in informed trading and firm growth as a consequence the probability of volatility spillover and the probability of non-consecutive hit comes down.

Results of One Hour Analysis support most of the hypotheses proposed in Section III. The estimated ordered probit models are also found to be overall significant. Therefore, following the discussion on the One Hour Analysis, in Section IV, estimated models in Table 6 can be used for avoiding improper imposition of price limit rules.

## **VI. Summary and Conclusion**

In this study, we propose a possible improvement in effective implementation of daily price limit rules. The primary hypothesis is that, on an average, price limit hits on consecutive trading days or volatility spillover on post limit hit days are consequences of obstruction to rational price movement. We provide empirical evidence in support of this hypothesis. Through empirical analysis, we show that it is possible to predict probability of consecutive limit hits and volatility spillovers. To improve efficiency of these rules, we propose a flexible system of price limit rules based upon predicted probability of consecutive limit hit and volatility spillover.

We analyse, price limit data from Tokyo Stock Exchange (TSE) over a period of five years from January 2001 to December 2005. Binary and ordered probit models are used to analyse probability of consecutive limit hits and volatility spillovers. Results of my analysis suggest that probability of consecutive price limit hit is positively associated with informed trading. It also reflects that in non consecutive price limit hit days, limit hitting trades are primarily contributed by uninformed

traders. We also find that, in the cases of consecutive price limit hit, there is a reversal in the trend of net demand for the limit hit stock after the limit hit event. For non-consecutive limit hit events significantly less number of trades hit price limits and at the same time less number of trading hours are affected by these trades compared to the consecutive hit events. Results of my analysis also suggest that firm characteristics do affect probability of consecutive price limit hit. It shows that, market to book value and firm specific risk increase the probability of consecutive hit. Whereas size of a firm is negatively associated with the occurrence of consecutive hits. Proxies for trading activity and time of the first limit hit of the day are also found to be significant in the analyses. We also find that the estimated binary and ordered Probit models are highly significant and properly specified based upon on the results of Wald test, Pseudo -  $R^2$  square values and Hosmer-Lamesaw test .

On the basis of these evidence, we propose to make price limit rules flexible, conditional upon predicted likelihood of improper price limit impositions. We suggest that exchange officials may use End of the Day or One Hour Analysis, as described in this study, to find out the ex-ante probability of volatility spillover or consecutive hit on the subsequent trading days. Based on these predicted probabilities from One Hour Analysis (End of the Day Analysis), price limits of the limit hit (post limit hit) day may be relaxed to avoid occurrence of volatility spillover (consecutive limit hit) on the post limit hit day. Such a flexible price limit rules will help the exchange officials to avoid the cost related to the obstruction of rational price movements and will make existing price limit rules more effective and efficient.



**Table 1****Variables and A-priori Expectations**

<b>Variables</b>	<b>Non Consecutive Hit</b>	<b>Consecutive Hit</b>	<b>Explanation</b>
$\Delta \text{OI} /$ $\Delta \text{OI-Sign} /$ $\Delta \text{OI-Sign1}$	Low	High	The smaller ratio of after limit hit order imbalance over before limit hit order imbalance indicated greater change in the direction of net demand for the stock after price limit hit.
$\Delta \text{Small} /$ $\Delta \text{Small1}$	Low	High	In non-consecutive hit days greater proportion of small trades before limit hit than after price limit hit might suggest that the limit hit is caused by uninformed traders' overreaction which decreased after the hit.
$\Delta \text{Medium} /$ $\Delta \text{Medium1}$	High	Low	Greater proportion of medium size trades after price limit hit might suggest in non consecutive limit hit days informed traders are more active in the market post price limit hit as prices become more attractive due to uninformed investors' over reaction.
<b>No-of -Hits /</b> <b>NHits</b>	Low	High	We expect less number of hits with in a shorter time span for if the hits are caused by temporary investor overreaction.
<b>Hit Span</b>	Low	High	
<b>Hit-S / Hit-S1</b>	High	Low	In the case of non consecutive hits we would expect higher proportion of hits would be caused by small traders than in the case of consecutive hits.
<b>Hit-M / Hit-M1</b>	Low	High	We would expect higher proportion of hits caused by medium size trades in consecutive hit days than non consecutive hit days.
<b>MCap / Size</b>	High	Low	We expect greater uncertainty in valuation of growth firms i.e. firms with small size, high market to book ratio and high idiosyncratic risk. Therefore these firms would attract more informed trading.
<b>MB</b>	Low	High	
<b>Rsd-Risk</b>	Low	High	

<b>Table 2</b>				
<b>Trading units of listed companies in Tokyo Stock Exchange as of December 30 2003</b>				
<b>Trading Unit</b>	<b>Number of Companies</b>			
	<b>First Section</b>	<b>Second Section</b>	<b>Mothers</b>	<b>Total</b>
1 Share	39	27	65	131
10 Shares	6	1	0	7
50 Shares	5	1	0	6
100 Shares	471	152	3	626
500 Shares	39	23	0	62
1000 Shares	972	365	4	1341
3000 Shares	1	0	0	1
<b>Total</b>	1533	569	72	2174

**Table 3**

The table shows informativeness of different trade sizes. The table reports both percent of cumulative price change and percent of volume contributed by large medium and small trade sizes over a period of one month prior to the limit hit events. The trade sizes are defined on the basis of the distribution of volume associated with each trade over a period of one month prior to the limit hit events. The trades associated with volume greater than 75 percentile are classified as large trades and associated with volume less than 25 percentile are labelled as small trades, rest of the trades are identified as medium size trades.

<b>Trade size</b>	<b>Percent of Cumulative Price Change</b>	<b>Percent of Volume</b>
<b>Large</b> > 75 percentile	0.58	0.62
75 percentile >= <b>Medium</b>	0.28	0.20
> = 25 percentile		
<b>Small</b> < 25 percentile	0.14	0.18

**Table 4 - Univariate Analysis**

This Table reports descriptive statistics of independent variables and also provides results of Univariate Analyses. Mean, median and standard deviation of all the variables reported for the full sample of limit hit events and also for sub samples of consecutive and non consecutive limit hits. Independent variables used in the study for univariate analyses are  $\Delta$  OI,  $\Delta$  Small,  $\Delta$  Medium, No-of -Hits, Hit-Span, Hit-S, Hit-M, MCap, MB, Rsd-Risk, Hit-to-Close, No-of-Trds and Market Volatility. The variable  $\Delta$  OI represents change in order imbalance measured in 10Mn Yen. Variable  $\Delta$  Medium1 ( $\Delta$  Small1) is the difference between proportion of medium (small) size trades, after and before the first limit hit of the day. No-of -Hits reports number of trades hit price limit of the day. Hit-Span represents number hours of the trading day affected by price limit hits. Hit-M (Hit-S) is the proportion of the medium (small) size trades hitting price limit. MCap is market capitalisation of the stocks measured in 100 Mn Yen. MB is the market to book value ratio for a firm. Rsd-Risk is the standard deviation of market model residuals; it represents the firm specific for a security. No-of-Trds shows the number of trades in the limit hit days. Hit-to-Close is time left from first hit to the closing of the market measures in hours. Market Volatility is represented by squared daily return of the Tokyo Stock Exchange market Index (TOPIX). The results of t test for equality of mean using equal variances and unequal variances are reported as t-stat1 and t-stat 2. The results of Wilcoxon-Mann-Whitney test are reported through the Z statistics. Significance of the statistics are reported using \*\*\*, \*\* and \* for 1%, 5% and 10% significance level.

Variables	Mean			Median			Standard Deviation			Test for Equality of Mean / Median		
	Entire Sample	Non Cons	Cons	Entire Sample	Non Cons	Cons	Entire Sample	Non Cons	Cons	t stat 1	t stat 2	Z stat
$\Delta$ OI	-13.879	-17	0.071	-1.912	-2.4	-0.506	83.3	87.4	58.1	4.79***	6.2***	7.729***
$\Delta$ Small	0.078	0.076	0.086	0.061	0.06	0.07	0.224	0.221	0.234	1.09	1.05	0.979
$\Delta$ Medium	0.015	0.019	-0.002	0	0.002	0	0.184	0.182	0.191	-2.8***	-2.71***	-3.069***
No-of -Hits	16.016	15.965	16.22	8	8	8	22.676	22.914	21.708	0.32	0.33	1.628
Hit Span	1.320	1.237	1.653	0.389	0.345	0.648	1.741	1.678	1.939	6.79***	6.22***	5.049***
Hit-S	0.271	0.283	0.224	0.2	0.215	0.172	0.269	0.276	0.231	-6.19***	-6.89***	-5.496***
Hit-M	0.213	0.214	0.206	0.2	0.2	0.196	0.212	0.216	0.194	-1.16	-1.24	-0.038
MCap	646.694	719.481	352.853	127.97	143.028	94.121	3060.853	3329.091	1531.587	-3.35***	-5.07***	-10.549***
MB	4.448	3.79	7.104	2.523	2.181	3.209	8.022	6.459	12.124	11.7***	8.24***	13.402***
Rsd-Risk	5.33	4.853	7.241	4.543	3.91	6.044	3.694	3.303	4.48	18.9***	15.8***	20.93***
No-of-Trds	369.120	386.289	300.428	171	185	123.5	502.044	513.856	445.363	-4.84***	-5.28***	-6.947***
Hit-to-Close	2.957	2.943	3.011	2.383	2.365	2.465	2.019	2.01	2.053	0.96	0.94	0.558
Market Volatility	0.228	0.233	0.209	0.068	0.071	0.06	0.499	0.498	0.505	-1.37	-1.36	-1.638*



**Table 5**  
**End of The Day Analysis**

This Table reports the results of End of the Day analysis to predict probability of consecutive price limit hits. Binary probit models are used for this analysis. The dependent variable for these models takes the value 0 for non consecutive limit hits, 1 for consecutive hits. Main independent variables used in the models are  $\Delta$  Medium,  $\Delta$  Small,  $\Delta$  OI-sign, Hit-M, Hit-S, NHits, Hit-Span, MB, Rsd-Risk, Size, Hit-to-Close, Trds and Market Volatility. Variable  $\Delta$  Medium1 ( $\Delta$  Small1) is the difference between proportion of medium (small) size trades, after and before the first limit hit of the day.  $\Delta$  OI-sign is a dummy variable that takes value 1 if the sign of the order imbalance before limit hit is different from the sign of the order imbalance after price limit hit, otherwise it is 0. Hit-M (Hit-S) is the proportion of the medium (small) size trades hitting price limit. NHits is the natural logarithm of the number trades hit hitting daily price limit. Hit-Span represents number hours of the trading day affected by price limit hits. MB is the market to book value ratio for a firm. Size is the natural logarithm of market capitalisation measured in 100 Mn Yen. Rsd-Risk is the standard deviation of market model residuals, it represents the firm specific for a security. Hit-to-Close is time left from first hit to the closing of the market measures in hours. Trds is the natural logarithm of number of trades in the limit hit days. Market Volatility is represented by squared daily return of the Tokyo Stock Exchange market Index (TOPIX). Along with these variables, Model I also includes dummy variables for months of the year and days of the week to control for any seasonality or day of the week effect where as Model II and Model III uses only month dummies or only day dummies respectively. Model IV do not include month or day dummies. All the models are estimated using daily price limit data from Tokyo stock Exchange for a period of 2001 to 2005. Panel A reports estimated coefficients of the models for the entire sample of price limit hits. Panel B and Panel C provide estimated coefficients for upper limit hit and lower limit hit events respectively. The standard errors of the estimated coefficients are reported in parenthesis below the coefficients. Significance of the estimated coefficients are reported using \*\*\*, \*\* and \* for 1%, 5% and 10% significance level.

Variables	Panel A : All Limit Hits				Panel B: Upper Limit Hits				Panel C: Lower Limit Hits			
	Model I	Model II	Model III	Model IV	Model I	Model II	Model III	Model IV	Model I	Model II	Model III	Model IV
<b>Intercept</b>	-0.139 (0.270)	-0.081 (0.263)	-0.035 (0.253)	0.037 (0.245)	0.213 (0.328)	0.313 (0.32)	0.261 (0.308)	0.386 (0.299)	-0.454 (0.504)	-0.423 (0.486)	-0.135 (0.455)	-0.1513 (0.4362)
<b><math>\Delta</math> Medium</b>	-0.378*** (0.157)	-0.373*** (0.156)	-0.356** (0.156)	-0.351** (0.156)	-0.543*** (0.182)	-0.534*** (0.182)	-0.525*** (0.182)	-0.516*** (0.181)	-0.005 (0.319)	0.040 (0.3152)	0.013 (0.313)	0.0469 (0.3101)
<b><math>\Delta</math> Small</b>	0.039 (0.130)	0.019 (0.130)	0.043 (0.129)	0.022 (0.129)	0.044 (0.151)	0.0296 (0.151)	0.0178 (0.151)	0.00089 (0.15)	-0.211 (0.262)	-0.2302 (0.261)	-0.033 (0.253)	-0.0589 (0.2523)
<b><math>\Delta</math> OI sign</b>	-0.255*** (0.056)	-0.261*** (0.055)	-0.265*** (0.055)	-0.273*** (0.055)	-0.287*** (0.076)	-0.3017*** (0.075)	-0.2860*** (0.076)	-0.3021*** (0.075)	0.033 (0.128)	0.034 (0.126)	0.002 (0.124)	-0.005 (0.122)
<b>Hit-M</b>	-0.186 (0.136)	-0.174 (0.136)	-0.201 (0.135)	-0.191 (0.135)	-0.146 (0.17)	-0.112 (0.169)	-0.139 (0.169)	-0.105 (0.168)	-0.271 (0.250)	-0.333 (0.245)	-0.389* (0.241)	-0.432* (0.236)
<b>Hit-S</b>	-0.339*** (0.121)	-0.323*** (0.12)	-0.348*** (0.12)	-0.333*** (0.119)	-0.366*** (0.151)	-0.347** (0.151)	-0.373*** (0.15)	-0.356*** (0.149)	-0.426** (0.208)	-0.434** (0.207)	-0.523*** (0.202)	-0.523*** (0.201)

Table 5 continued...

Variables	Panel A : All Limit Hits				Panel B: Upper Limit Hits				Panel C: Lower Limit Hits			
	Model I	Model II	Model III	Model IV	Model I	Model II	Model III	Model IV	Model I	Model II	Model III	Model IV
<b>NHits</b>	0.0613** (0.029)	0.058** (0.029)	0.059** (0.029)	0.057** (0.028)	0.051 (0.034)	0.046 (0.034)	0.045 (0.034)	0.041 (0.033)	0.125** (0.058)	0.128** (0.057)	0.147*** (0.056)	0.148*** (0.056)
<b>Hit Span</b>	0.071*** (0.02)	0.07*** (0.02)	0.08*** (0.02)	0.079*** (0.02)	0.063*** (0.023)	0.062*** (0.023)	0.069*** (0.023)	0.069*** (0.023)	0.061 (0.044)	0.057 (0.043)	0.087*** (0.043)	0.082** (0.042)
<b>MB</b>	0.016*** (0.00294)	0.015*** (0.00293)	0.016*** (0.00293)	0.016*** (0.00293)	0.012*** (0.003)	0.012*** (0.003)	0.012*** (0.003)	0.012*** (0.003)	0.025*** (0.005)	0.023*** (0.005)	0.025*** (0.005)	0.023*** (0.005)
<b>Rsd-Risk</b>	0.053*** (0.681)	0.052*** (0.679)	0.051*** (0.679)	0.051*** (0.676)	0.052*** (0.860)	0.051*** (0.858)	0.05*** (0.856)	0.049*** (0.853)	0.051*** (1.201)	0.052*** (1.189)	0.049*** (1.184)	0.05*** (1.171)
<b>Size</b>	-0.103*** (0.021)	-0.102*** (0.02)	-0.106*** (0.02)	-0.105*** (0.02)	-0.113*** (0.025)	-0.111*** (0.025)	-0.114*** (0.024)	-0.112*** (0.024)	-0.087** (0.04)	-0.092** (0.04)	-0.1*** (0.038)	-0.103*** (0.038)
<b>Hit-to-Close</b>	-0.003 (0.016)	-0.005 (0.016)	-0.010 (0.016)	-0.012 (0.016)	0.008 (0.019)	0.005 (0.019)	0.004 (0.019)	0.002 (0.019)	-0.052 (0.034)	-0.056* (0.034)	-0.066** (0.033)	-0.066** (0.033)
<b>Trds</b>	-0.052** (0.024)	-0.05** (0.024)	-0.047** (0.024)	-0.045** (0.024)	-0.092*** (0.029)	-0.09*** (0.029)	-0.0878*** (0.029)	-0.0858*** (0.028)	-0.033* (0.02)	-0.035* (0.02)	-0.035* (0.021)	-0.036* (0.020)
<b>Market Volatility</b>	-0.015 (0.054)	-0.057 (0.052)	0.039 (0.051)	-0.006 (0.048)	-0.033 (0.125)	-0.081 (0.122)	-0.009 (0.121)	-0.059 (0.119)	-0.136* (0.072)	-0.126** (0.066)	-0.029 (0.064)	-0.026 (0.057)
<b>Month (Day) Dummy</b>	Yes (Yes)	Yes (No)	No (Yes)	No (No)	Yes (Yes)	Yes (No)	No (Yes)	No (No)	Yes (Yes)	Yes (No)	No (Yes)	No (No)
$\chi^2$ (Month)	32.526***	35.112***			20.992**	22.711***			26.863***	24.949***		
$\chi^2$ (Day)	19.554***		22.116***		17.959***		19.583***		19.528***		17.8095***	
$\chi^2$ (Global)	322.467***	307.096***	297.083***	279.121***	219.77***	204.59***	203.822***	186.722***	146.555***	133.938***	126.564***	114.077***
<b>Pseudo - R<sup>2</sup></b>	0.152	0.145	0.139	0.131	0.14	0.13	0.128	0.117	0.283	0.255	0.244	0.218
$\chi^2$ (HL)	12.523	4.917	11.316	11.359	10.714	3.938	8.71	11.003	8.479	4.677	7.422	7.865

**Table 5a****Marginal Probability of Consecutive Limit Hit from End of the Day Analysis**

This table reports marginal probability of consecutive price limit hit for the independent variables of Model IV from Panel A of the End of the Day Analysis reported in Table 2. The marginal probabilities associated with each estimated coefficient are evaluated at the sample mean, median and mode. Significance of the estimated coefficients are reported using \*\*\*, \*\* and \* for 1%, 5% and 10% significance level.

<b>Marginal Probability evaluated at the sample</b>			
<b>Variables</b>	<b>Mean</b>	<b>Median</b>	<b>Mode</b>
<b>Intercept</b>	0.0096	0.0089	0.0214
<b>Δ Medium</b>	-0.0907**	-0.0840**	-0.2030**
<b>Δ Small</b>	0.0057	0.0053	0.0127
<b>Δ OI sign</b>	-0.0707***	-0.0655***	-0.1583***
<b>Hit-M</b>	-0.0494	-0.0457	-0.1105
<b>Hit-S</b>	-0.0861***	-0.0798***	-0.1928***
<b>NHits</b>	0.0149**	0.0138**	0.0333**
<b>MB</b>	0.0042***	0.0039***	0.0093***
<b>Rsd-Risk</b>	0.0132***	0.0122***	0.0295***
<b>Size</b>	-0.0272***	-0.0252***	-0.0608***
<b>Hit Span</b>	0.0205***	0.0190***	0.0458***
<b>Hit-to-Close</b>	-0.0033	-0.0030	-0.0073
<b>Market Volatility</b>	-0.0016	-0.0014	-0.0035
<b>Trds</b>	0.0118**	0.0109**	0.0263**

Figure 1a

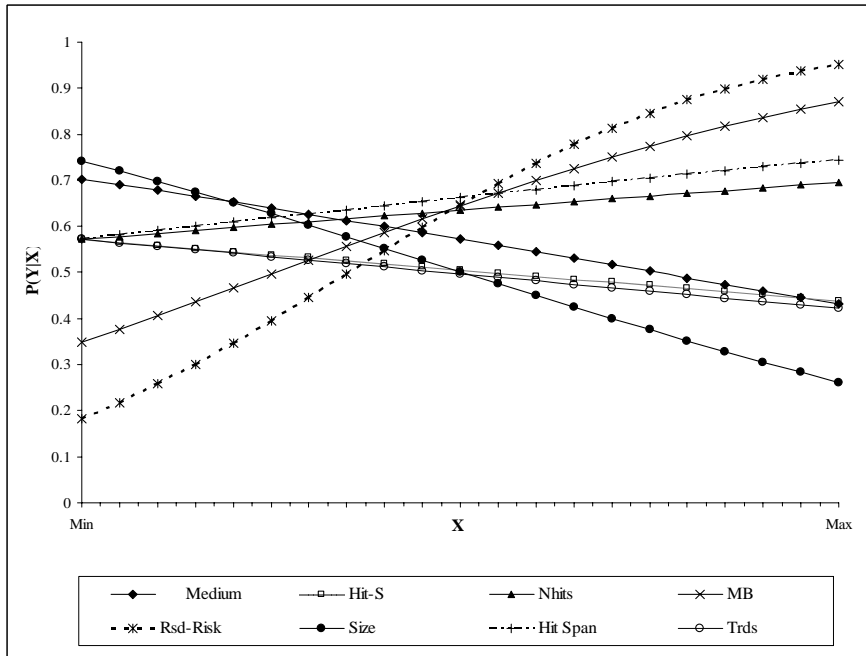


Figure 1b

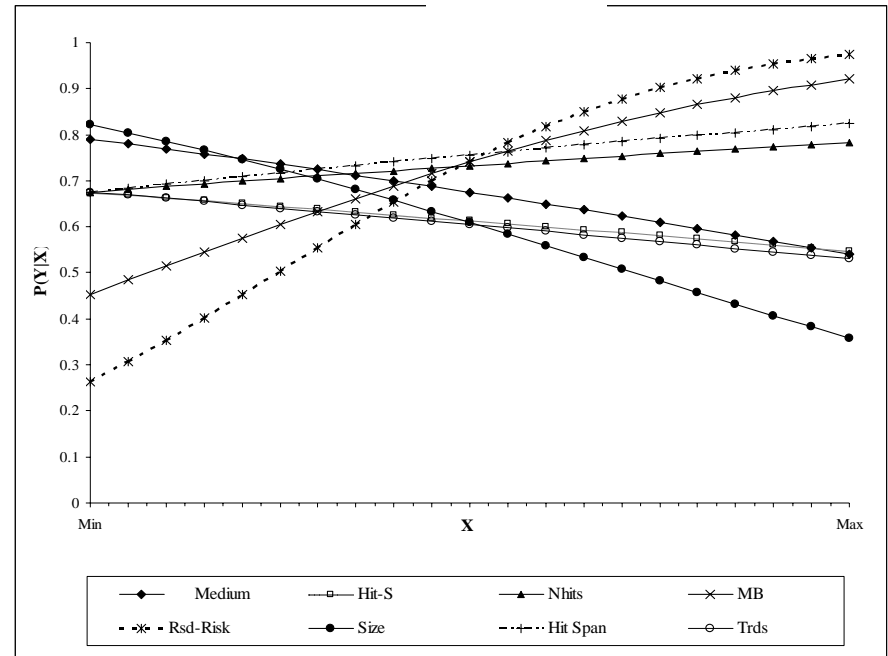
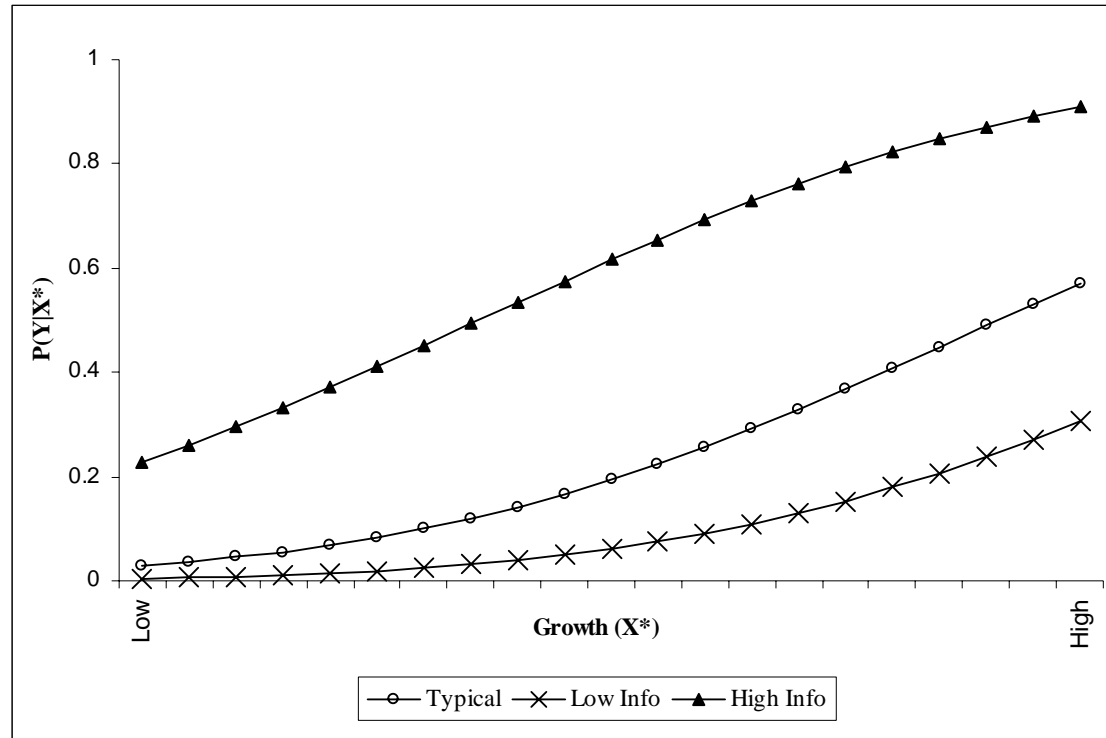


Figure 1a & 1b: These figures plot, probability of consecutive hit  $[\Pr(y = 1 | x)]$ , from Model IV in Panel A of Table 2, against all the significant independent variables in that model. In both figures on the horizontal axis the independent variables are plotted from their sample minimum to sample maximum. On the vertical axis  $\Pr(y = 1 | x)$  is plotted each independent variable while keeping other variables fixed at their sample mode. Figure 1a is plotted for the days when order imbalance changes sign after limit hit and Figure 1b is for the rest of the days.



**Figure 2:** This figure plots growth factor against probability of consecutive hit on a low information, high information and on a most frequently observed (i.e. typical) day.

**Table 6**  
**One Hour Analysis**

This Table reports the results of one Hour Analysis to predict probability of consecutive price limit hits. Ordered probit models are used for this analysis. The dependent variable for these models takes the value 1 for non consecutive limit hits, 2 for volatility spillover and 3 for consecutive hits. Main independent variables used in the models are  $\Delta$  Medium1,  $\Delta$  Small1,  $\Delta$  OI-sign1, Hit-M1, Hit-S1, NHits1, MB, Rsd-Risk, Size, Hit-to-Close, Trds1. Variables  $\Delta$  Medium1 ( $\Delta$  Small1) is the differences between proportion of medium (small) size trades, one hour after and one hour before the first limit hit of the day.  $\Delta$  OI-sign1 is a dummy variable that takes value 1 if the sign of the order imbalance of the last hour before limit hit is different from the sign of the order imbalance of the first hour after price limit hit, otherwise it is 0. Hit-M1 (Hit-S1) is the proportion of the medium (small) size trades hitting price limit with in one hour of first limit hit of the day. NHits1 is the number of limit hits with in one hour of first limit hit. MB is the market to book value ratio for a firm. Size is the natural logarithm of market capitalisation measured in 100 Mn Yen. Rsd-Risk is the standard deviation of market model residuals; it represents the firm specific for a security. Hit-to-Close is time left from first hit to the closing of the market measures in hours. Trds1 is the natural logarithm of number of trades with in one hour before first limit hit to one hour after limit hit. Along with these variables, Model I also includes dummy variables for months of the year and days of the week to control for any seasonality or day of the week effect where as Model II and Model III uses only month dummies or only day dummies respectively. Model IV do not include month or day dummies. All the models are estimated using daily price limit data from Tokyo stock Exchange for a period of 2001 to 2005. Panel A reports estimated coefficients of the models for the entire sample of price limit hits. Panel B and Panel C provide estimated coefficients for upper limit hit and lower limit hit events respectively. The standard errors of the estimated coefficients are reported in parenthesis below the coefficients. Significance of the estimated coefficients are reported using \*\*\*, \*\* and \* for 1% , 5% and 10% significance level.

Variables	Panel A : All Limit Hits				Panel B: Upper Limit Hits				Panel C: Lower Limit Hits			
	Model I	Model II	Model III	Model IV	Model I	Model II	Model III	Model IV	Model I	Model II	Model III	Model IV
<b>Intercept I</b>	0.394 (0.251)	0.594*** (0.237)	0.461** (0.238)	0.650*** (0.224)	0.621** (0.297)	0.825*** (0.280)	0.646** (0.282)	0.852*** (0.265)	0.320 (0.503)	0.453 (0.474)	0.380 (0.466)	0.464 (0.436)
<b>Intercept II</b>	1.581*** (0.252)	1.692*** (0.239)	1.642*** (0.24)	1.740*** (0.226)	1.85*** (0.299)	1.958*** (0.282)	1.867*** (0.284)	1.977*** (0.268)	1.454*** (0.505)	1.503 (0.476)	1.493*** (0.468)	1.492*** (0.438)
<b><math>\Delta</math> Medium1</b>	-0.296** (0.134)	-0.269** (0.131)	-0.301** (0.134)	-0.277** (0.13)	-0.495*** (0.16)	-0.448*** (0.155)	-0.489*** (0.16)	-0.441*** (0.154)	0.137 (0.259)	0.166 (0.255)	0.145 (0.254)	0.167 (0.25)
<b><math>\Delta</math> Small1</b>	0.072 (0.114)	0.003 (0.110)	0.052 (0.114)	-0.017 (0.110)	0.060 (0.137)	-0.037 (0.131)	0.044 (0.136)	-0.053 (0.130)	0.124 (0.219)	0.113 (0.215)	0.112 (0.214)	0.114 (0.210)
<b><math>\Delta</math> OI sign1</b>	-0.119*** (0.049)	-0.129*** (0.047)	-0.118*** (0.049)	-0.125*** (0.047)	-0.114** (0.057)	-0.117** (0.056)	-0.112** (0.057)	-0.109** (0.055)	-0.089 (0.098)	-0.097 (0.095)	-0.109 (0.097)	-0.119 (0.094)
<b>Hit-M1</b>	-0.044 (0.117)	-0.052 (0.114)	-0.056 (0.116)	-0.069 (0.113)	0.133 (0.146)	0.123 (0.142)	0.132 (0.145)	0.117 (0.142)	-0.407** (0.205)	-0.370* (0.2)	-0.467** (0.202)	-0.432** (0.197)

Table 6 continued...

Variables	Panel A : All Limit Hits				Panel B: Upper Limit Hits				Panel C: Lower Limit Hits			
	Model I	Model II	Model III	Model IV	Model I	Model II	Model III	Model IV	Model I	Model II	Model III	Model IV
<b>Hit-S1</b>	-0.305*** (0.105)	-0.281*** (0.102)	-0.294*** (0.105)	-0.275*** (0.102)	-0.402*** (0.1318)	-0.376*** (0.127)	-0.371*** (0.130)	-0.352*** (0.126)	-0.305* (0.186)	-0.205 (0.181)	-0.311* (0.183)	-0.222 (0.178)
<b>NHits1</b>	0.069*** (0.021)	0.079*** (0.021)	0.071*** (0.021)	0.081*** (0.021)	0.064*** (0.025)	0.071*** (0.025)	0.062*** (0.025)	0.070*** (0.024)	0.048 (0.046)	0.072* (0.044)	0.061 (0.045)	0.088** (0.043)
<b>MB</b>	0.0275*** (0.004)	0.026*** (0.004)	0.028*** (0.004)	0.027*** (0.004)	0.024*** (0.004)	0.023*** (0.004)	0.025*** (0.004)	0.024*** (0.004)	0.034*** (0.007)	0.034*** (0.007)	0.034*** (0.007)	0.034*** (0.007)
<b>Rsd-Risk</b>	0.031*** (0.716)	0.034*** (0.697)	0.031*** (0.715)	0.033*** (0.696)	0.024*** (0.891)	0.028*** (0.866)	0.023*** (0.882)	0.027*** (0.860)	0.041*** (1.274)	0.042*** (1.235)	0.039*** (1.261)	0.040*** (1.215)
<b>Size</b>	-0.1424*** (0.019)	-0.1567*** (0.018)	-0.1408*** (0.018)	-0.1550** (0.018)	-0.144*** (0.022)	-0.154*** (0.021)	-0.139*** (0.022)	-0.15*** (0.021)	-0.172*** (0.041)	-0.196*** (0.039)	-0.163*** (0.039)	-0.186*** (0.037)
<b>Hit-to-Close</b>	0.025** (0.012)	0.021* (0.012)	0.024** (0.012)	0.021* (0.012)	0.033** (0.014)	0.031** (0.014)	0.032** (0.014)	0.031** (0.014)	0.015 (0.025)	0.002 (0.024)	0.008 (0.025)	-0.003 (0.024)
<b>Trds 1</b>	-0.039* (0.022)	-0.04* (0.021)	-0.038* (0.022)	-0.039* (0.021)	-0.085*** (0.026)	-0.095*** (0.025)	-0.084*** (0.026)	-0.093*** (0.025)	0.09** (0.046)	0.109*** (0.044)	0.085** (0.044)	0.101* (0.042)
<b>Month (Day) Dummy</b>	Yes (Yes)	Yes (No)	No (Yes)	No (No)	Yes (Yes)	Yes (No)	No (Yes)	No (No)	Yes (Yes)	Yes (No)	No (Yes)	No (No)
$\chi^2$ (Month)	18.755*	26.031***			14.69	17.624*			15.864	18.366*		
$\chi^2$ (Day)	3.711		3.686		4.845		4.428		10.415**		10.536**	
$\chi^2$ (Global)	249.558***	286.920***	230.716***	260.620***	172.372***	195.529***	158.452***	178.666***	117.663***	127.462***	101.03***	107.536***
<b>Pseudo - <math>R^2</math></b>	0.276	0.142	0.269	0.131	0.27	0.127	0.262	0.117	0.356	0.244	0.336	0.217

**Table 6a****Marginal Probabilities from One Hour Analysis**

This table reports marginal probability of consecutive price limit hit for the independent variables of Model IV from Panel A of the One Hour Analysis reported in Table 3. The marginal probabilities for consecutive limit hit associated with each estimated coefficient are evaluated at the sample mean, median and mode. Significance of the estimated coefficients are reported using \*\*\*, \*\* and \* for 1%, 5% and 10% significance level.

<b>Variables</b>	<b>Mean</b>	<b>Median</b>	<b>Mode</b>
<b>Δ Medium1</b>	-0.0664**	-0.0615**	-0.1620**
<b>Δ Small1</b>	-0.0041	-0.0038	-0.0099
<b>Δ OI sign1</b>	-0.0301***	-0.0279***	-0.0735***
<b>Hit-M1</b>	-0.0165	-0.0153	-0.0403
<b>Hit-S1</b>	-0.0660***	-0.0612***	-0.1611***
<b>NHits1</b>	0.0196***	0.0182***	0.0478***
<b>MB</b>	0.0066***	0.0061***	0.0161***
<b>Rsd-Risk</b>	0.0081***	0.0075***	0.0197***
<b>Size</b>	-0.0371***	-0.0344***	-0.0906***
<b>Hit-to-Close</b>	0.0122*	0.0046*	0.0043*
<b>Trds 1</b>	-0.0094*	-0.0087*	-0.0229*



Figure 3a

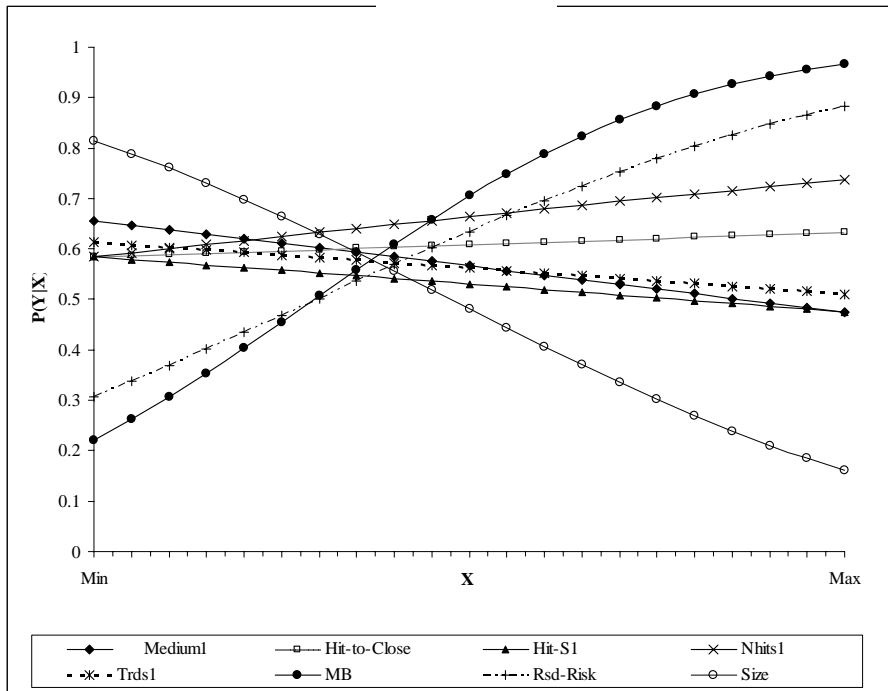
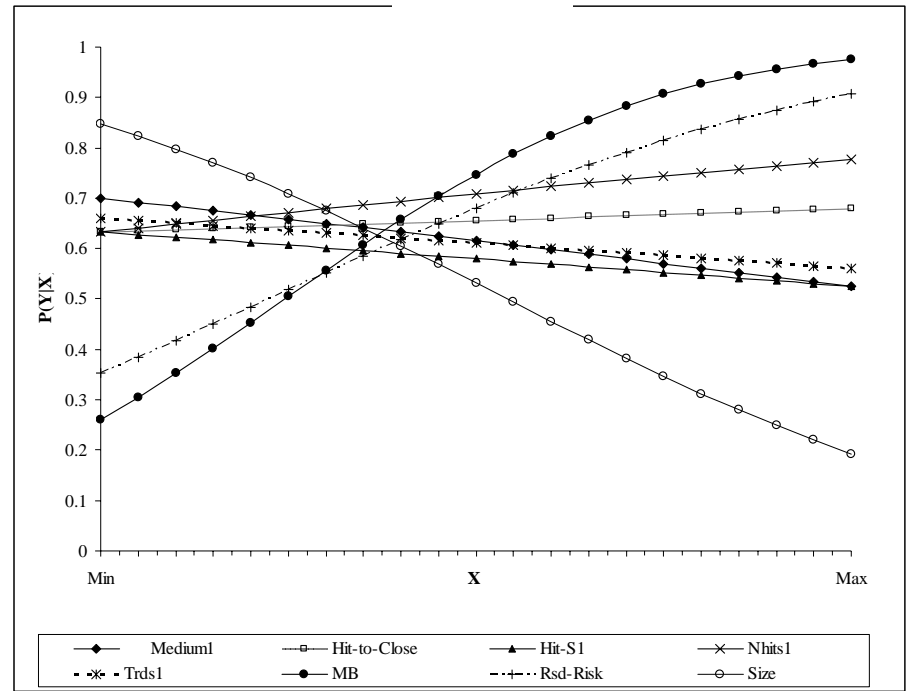


Figure 3b



**Figure 3a, 3b:** These figures plot, probability of consecutive hit [ $\Pr(y = 3 | x)$ ], from Model IV in Panel A of Table 3, against all the significant independent variables in that model. In both figures on the horizontal axis the independent variables are plotted from their sample minimum to sample maximum. On the vertical axis  $\Pr(y = 3 | x)$  is plotted each independent variable while keeping other variables fixed at their sample mode. Figure 1a is plotted for the days when order imbalance changes sign after limit hit and Figure 1b is for the rest of the days.

Figure 4a

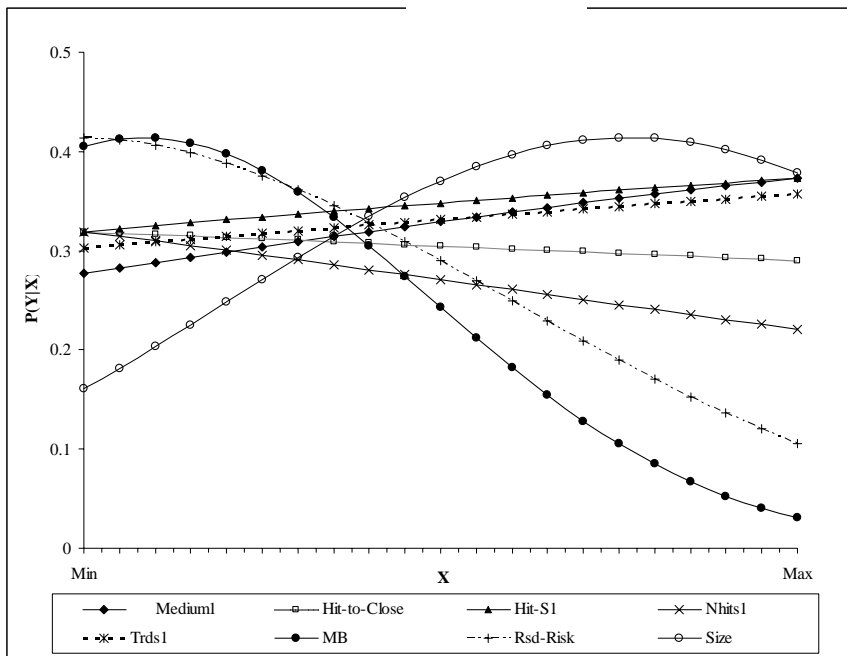
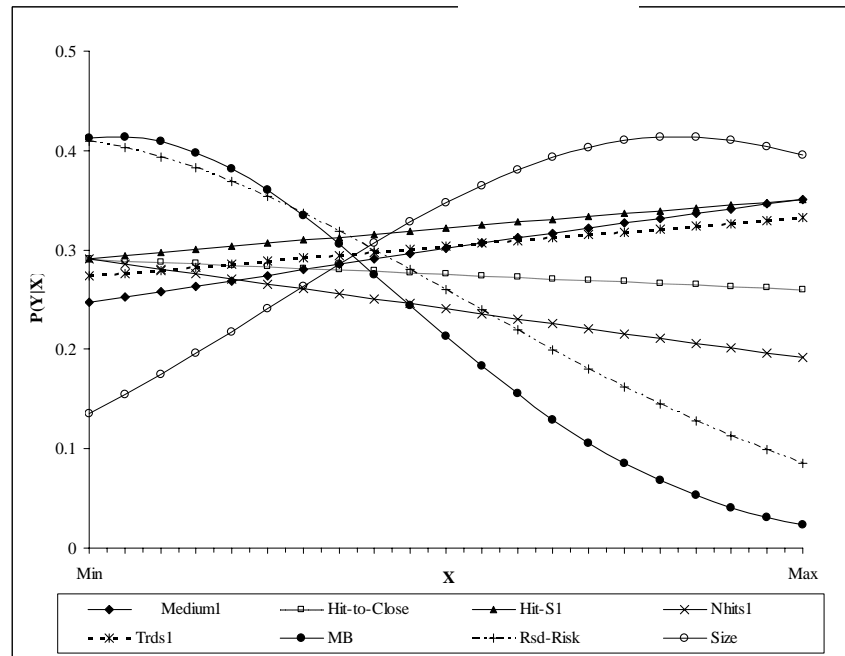
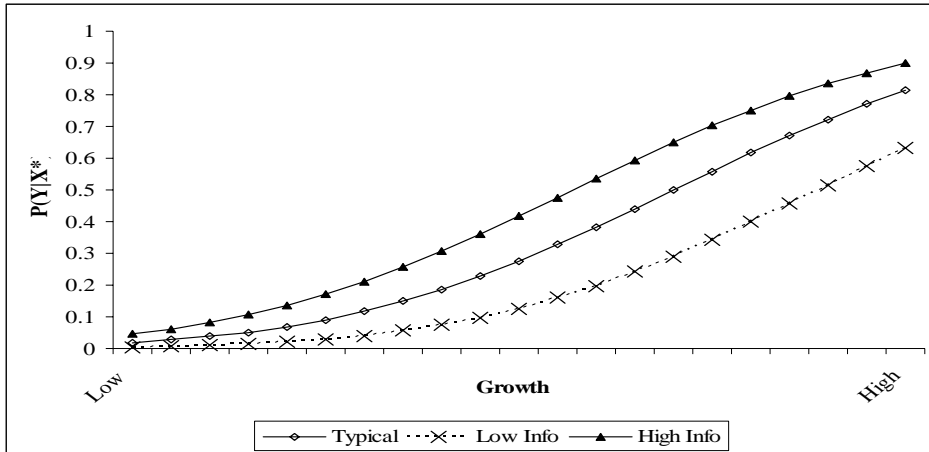


Figure 4b

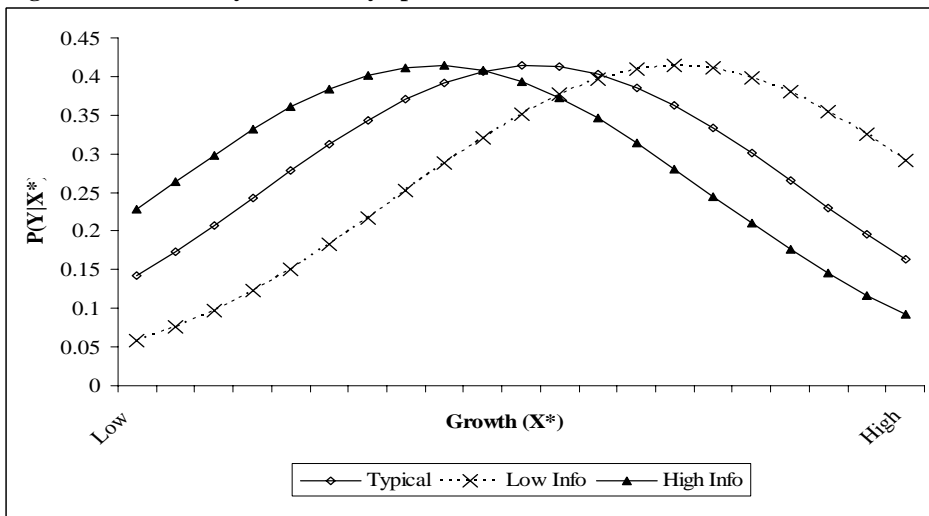


**Figure 4a, 4b:** These figures plot, probability of volatility spillover [ $\Pr(y = 2 | x)$ ], from Model IV in Panel A of Table 2, against all the significant independent variables in that model. In both figures on the horizontal axis the independent variables are plotted from their sample minimum to sample maximum. On the vertical axis  $\Pr(y = 2 | x)$  is plotted each independent variable while keeping other variables fixed at their sample mode. Figure 1a is plotted for the days when order imbalance changes sign after limit hit and Figure 1b is for the rest of the days.

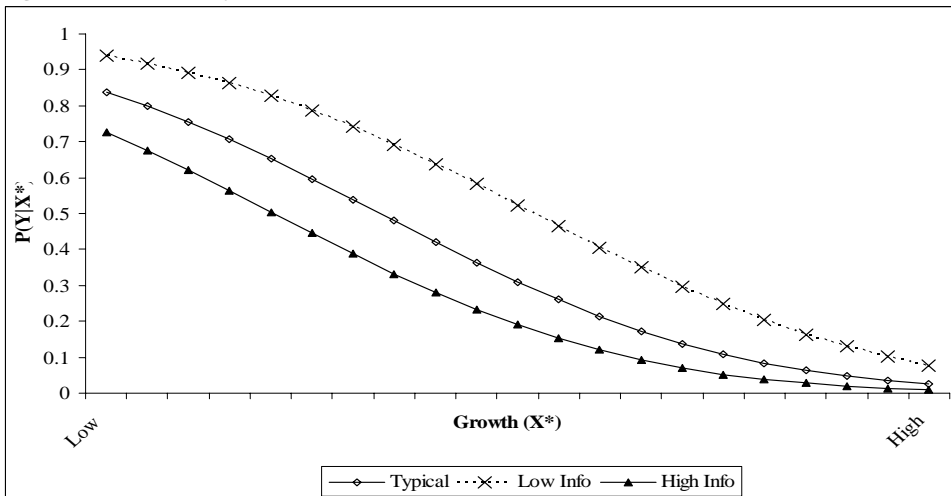
**Figure 5a : Probability of Consecutive Hit**



**Figure 5b: Probability of Volatility Spillover**



**Figure 5c: Probability of Non Consecutive Hit**



**Figure 6a, 6b, 6c:** These figures plot growth factor against probability of consecutive hit, volatility spillover and non consecutive hits respectively on a low information, high information and on a most frequently observed (i.e. typical) day.

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## **Appendix 1: Selection of Comparable Stocks to Identify Volatility Spillover**

To identify volatility spillover due to price limit rules we use a methodology which in essence similar to the methodology of Kim and Rhee (1997). We identify a comparable control stock against each limit hitting stock and compare their daily volatility, measured by squared daily return, on post limit hit day. If a limit hitting stock has higher volatility than its comparable stock on the post limit hit day then the limit hit event is classified as a limit hit causing volatility spillover.

Kim and Limpaphayom (2000) show that the profile of the stocks, which hit daily price limits frequently, is fundamentally different from the profile of rare or non limit hitters. Their findings suggest that the stocks with higher systematic and idiosyncratic risk, smaller market capital and with higher trading volume are more prone to hit daily price limits. Based on this evidence, to find out volatility spillovers, we compare limit hitting stocks against stocks that has similar propensity to hit daily price limits. To attribute the difference in volatility between the limit hitter and the comparable stock to the price limit hit event, we also need to make sure that the comparable stock has experienced a large price movement in the limit day. Therefore, we define comparable stocks as one that is closest to the limit hitter in terms of propensity of daily limit hit and also experienced a price change of at least 90% of its daily price limit but did not hit price limit on the limit hit day.

To find a control stock for every limit hitting stock such that they are comparable we use propensity score matching (PSM) methodology developed by Rosenbaum and Rubin (1983), Heckman and Robb (1986) and Heckman et al. (1997, 1998). In the academic literature of finance many recent studies use propensity score matching techniques to select control sample in a non experimental setup, studies such as Hillion and Vermaelen (2004), Drucker and Puri (2005), Cooper, Gulen and Rau (2005) and Li and Zhao (2006) are a few to

name. A detail description of the matching technique used for the sample selection of this study is described below.

Let  $D = 1$  if the stock hits price limit, and let  $D = 0$  otherwise. In principle, the  $i^{\text{th}}$  stock has an observed proxy for its  $t^{\text{th}}$  day volatility  $V_{i,t}^1$  when the  $i^{\text{th}}$  stock hits price limit on the  $t^{\text{th}}$  day and it also has another measure of its  $t^{\text{th}}$  day volatility  $V_{i,t}^0$  that would result if it were a non price limit hit day for stock  $i$ . To determine the average impact of price limit hits on daily volatility of stock returns, one would calculate the mean difference between  $V_{i,t}^1$  and  $V_{i,t}^0$  for all limit hit events. However, since  $V_{i,t}^0$  is an unobservable variable, we have a missing data problem. To resolve this issue we need to restate this problem in the population level. So we concentrate on the mean difference between of the effects of limit hit and non limit hit events on the daily volatility of the  $i^{\text{th}}$  stock of  $t^{\text{th}}$  day given the fundamental characteristics ( $X$ ) of the stock, i.e.

$$E(V_{i,t}^1 - V_{i,t}^0 | D = 1, X)$$

The expected value  $E(V_{i,t}^1 | D = 1, X)$  can be calculated from the limit hit data but we need to assume that the unobservable  $E(V_{i,t}^0 | D = 1, X)$  is approximately equal to the observable  $E(V_{i,t}^0 | D = 0, X)$  which can be calculated from the data of the stocks that do not hit price limit on  $t^{\text{th}}$  day. The selection bias due to this approximation is

$$B(X) = E(V_{i,t}^0 | D = 1, X) - E(V_{i,t}^0 | D = 0, X).$$

In this study we use an econometric method of matching that helps to reduce this bias substantially. Following Heckman and Robb (1986), we assume that all relevant differences between the stocks that hit price limit and stocks that do not, can be captured in terms of their observable fundamental characteristics  $X$ . Kim and Limpaphayom (2000) provides evidence that support this assumption, they provide a list of variables that differentiates a frequent limit

hitting stocks from an infrequent or non limit hitters. Rosenbaum and Rubin (1983) show that when

$$\begin{aligned} & (V_{i,t}^1, V_{i,t}^0) \perp D | X \\ \text{and } & 0 < P(D = 1 | X) < 1 \end{aligned} \quad (\text{PSM1})$$

then,

$$(V_{i,t}^1, V_{i,t}^0) \perp D | P(D = 1 | X)$$

where  $(\cdot \perp \cdot | X)$  operator denotes independence of left and right hand sides of the operator conditional to  $X$  and  $P(\cdot | X)$  stand for the conditional probability. The propensity score  $P(D = 1 | X)$  can be estimated using Logit or Probit models. Heckman et al. (1998) argues that condition (PSM1) is too restrictive for the estimation of  $E(V_{i,t}^1 - V_{i,t}^0 | D = 1, X)$  and proves that a weaker condition

$$E(V_{i,t}^0 | D = 1, P(D = 1 | X)) = E(V_{i,t}^0 | D = 0, P(D = 1 | X))$$

would be sufficient for the purpose.

This propensity score matching methodology is used to select comparable stocks for each limit hitting stock. We estimate the propensity to hit daily price limit for all the stocks in our sample with a Probit model. Following Kim and Limpaphyom (2000), we use various firm characteristics variable such as firm size measured by average daily market capitalization (Size), growth prospect measures by average daily market to book value ratio (MB), average daily trading volume (Vol.), systematic risk (Beta), unsystematic risk (RR) and average daily turn over ratio (TOR) in the Probit model. The Probit model used to estimate propensity scores is specified as

$$\Pr(\text{Hit} = 1 | X) = \Phi(X' \gamma)$$



where,  $X$  is a vector of firm characteristics variables and  $\gamma$  is the coefficient vector.

Details of the Probit model estimation is reported in Table A1. The p values associated with the coefficients show that all the independent variables are highly significant in the model. The McFadden  $R^2$  for the model is 24.62%. The results imply that for our sample large and highly active stocks with higher systematic risk, unsystematic risk have greater probability of hitting daily price limit. Based on the estimated coefficients we calculate propensity of daily price limit hit for each stock in our sample.

To implement the matching technique, for each limit hit event we select the nearest neighbour of the limit hitter in terms of propensity score from the sample of all the stocks that experienced a price change of at least 90% of their daily price limit on that day. A limit hit event is identified as a limit hit causing volatility spillover if daily volatility of the limit hitter is greater than the volatility of the comparable stock on the post limit hit day.

**Table A1**  
**Parameters of the Probit Model for Estimating Propensity Score**

This table reports estimated parameters and their standard errors and p values from the Probit model used for the estimation of propensity scores. The McFadden  $R^2$  value for the model also reported. The Probit model is specified as :

$$\Pr(Hit = 1|X) = \Phi(X' \gamma)$$

where,  $X$  is a vector of firm characteristics variables such as average daily market capitalization (Size), average daily market to book value ratio (MB), average daily trading volume (Vol.), systematic risk (Beta), unsystematic risk (RR) and average daily turn over ratio (TOR) and  $\gamma$  is the coefficient vector.

Variables	Parameter Estimate	Standard Error	p value
Intercept	0.1501	0.2444	0.5390
Beta	-0.6090	0.1004	<.0001
MB	-0.0774	0.0125	<.0001
Vol.	0.2516	0.0199	<.0001
Size	-0.0829	0.0243	0.0007
TOR	-0.0261	0.0098	0.0076
RR	-25.5583	2.0073	<.0001
McFadden $R^2$	0.2462		

