Volatility and Daily Price Limits

Abstract:

This study provides new evidence on efficacy of daily price limit rules. In this study, we propose a methodological innovation in volatility spillover test. We modify widely used Kim and Rhee (1997) methodology by applying propensity score matching techniques. Using data from the Tokyo Stock Exchange over a period of 5 years from January 2001 to December 2005, this study shows that price limit rules work quite efficiently for lower limit hits as there is no evidence of volatility spill-over. We also find that daily price limits have differential effects on permanent and transitory components of daily volatility. Our study reports some evidence of spill-over of permanent volatility. However, we find price limit successfully curbs the transitory volatility on the post limit hit days.

Introduction

Stock Exchanges in several markets impose daily price limit rules that restrict price movement of listed stocks during trading. Such rule based price stabilising mechanisms (including circuit breakers) became popular across many stock exchanges of the world since the October ’87 market crash. The (US) “Report of the Presidential Task Force on Market Mechanism” commonly known as the *Brady Commission Report* recommended implementation of rule based price stabilising mechanisms to protect the market system. The advocates of price limit rules argue that these rules help to reduce volatility of the market during extreme market conditions. However, academic researchers are divided in their opinion about the impact of price limits on volatility. Theoretical and empirical evidence of various studies such as Fama (1989), Lehmann (1989), Subrahmanyam (1994), Kim and Rhee (1997) and Kim (2001) criticise price limit rules for being incapable of reducing volatility and also for spilling over volatility from limit hit days to post price limit hit days. On the other hand, Lee and Kim (1995) and Berkman and Lee (2002) show that daily price limits can reduce volatility in equity markets. Deb, Petko, and Marisetty (2010) provide theoretical justification for the existence of price limits in equity markets and they empirically substantiate their theory that the likelihood of imposing price limits increases with increase in the monitoring costs. Hence, price limits, as per them, are a trade off between the costs and benefits of market monitoring (by the regulator/ stock exchange).

Cognizant of this divergence of opinion on the role of price limits, we contribute to the literature by re-examining the effect of price limits on volatility. In particular, we use a new robust methodology to test the relationship between price limits and volatility and we decompose volatility into permanent and transitory components to examine the potential differential impact of price limits on the components of volatility.

One of the first studies to analyse the relationship between price limits and volatility is Kim and Rhee (1997). They found that price limits imposed in the Tokyo Stock Exchange causes volatility spill over to the following trading days and hence they conclude that price limits are not effective in reducing volatility. However, studies by Lee and Kim (1995) and Berkman and Lee (2002) on Korean market report contrary view that price limits reduce volatility. In this paper, we aim to reconcile the inconsistencies around the volatility - price limits relationship by addressing possible sample selection bias in volatility spill over test applied by Kim and Rhee (1997). As detailed in the next section, the volatility spill over test of Kim and Rhee (1997) compares average volatility of limit hitting stocks against average volatility of non-price limit hitters around limit hit events. However, such comparison may not be justified if fundamental characteristics of frequent limit hitting stocks are different from non-limit hitting group. For example, if average volatility persistence of limit hitters is significantly greater than volatility persistence in non-limit hitting group then the results of volatility spill over test in Kim and Rhee (1997) only reflects the difference in persistence of volatility between the limit hitters and non-limit hitters and do not provide evidence of volatility spill over due to price limit events.

We also contribute by decomposing the volatility into permanent and transitory components in order to understand the differential impact of price limits on both components. For price limits to be effective they should mainly target reducing the temporary component. An artificial price barrier such price limit rules should not have any significant impact on the permanent component of volatility.

Using a sample of 1048 stocks listed in the Tokyo Stock Exchange with 6176 limit hit events, during January 2001 to December 2005, we show that our modified Kim and Rhee (1997) methodology improves on Kim and Rhee (1997) by finding two important new findings in the literature. First, we find that price limits are successful in curbing transitory volatility. Second, volatility spill over holds only for upper limit hits (when stock price moves upwards) but not for lower limit hits (when stock prices move downwards). Hence, the popularity of price limits (in spite of the negative effects shown by the researchers) among the practitioners (stock exchanges) can be partially justified through our evidence.

The paper is organized in six sections. The introduction in this section is followed by a brief discussion on the related literature in Section 2. Section 3 develops and presents testable hypotheses. Section 4 describes our data and other institutional details of Tokyo Stock Exchange. As a subsection, we also present our detailed methodology for testing our proposed hypotheses. Section 5 reports the empirical results. Conclusions are presented in Section 6.

2. Related Literature

Due to the diversity of the literature streams, we divide the discussion of existing literature into two subsections namely price limits and its role on volatility and the components of daily volatility.

2.1. Price limit and Volatility

Several studies examined the relationship between price limits and volatility of the stock prices. Chung (1991) investigated the efficacy of price limit rules in the Korean stock market and found no evidence that restrictive price limits decrease the volatility of stock prices. In other words, one of the main purposes of imposing is not being served. Chen (1993) studied the effect of changes in daily price limit rules on stock price volatility in Taiwan Stock Exchange. By comparing stock price volatility of three different price limit regimes (3%, 5% and 7%) from 1985 to 1990 he also reached to the same conclusion that price limits do not reduce price volatility significantly.

Kim and Rhee (1997) examined performance of daily price limit rules imposed by the Tokyo Stock Exchange over a period of four years, from 1989 to 1992. In their research design they compared a group of stocks that have hit daily price limits against two groups of stocks that experienced large price changes (i.e. reached at least 90% and 80% of the daily price limit) but did not hit the daily price limit (however, may have the propensity to reach price limits). By comparing average daily volatility of these two groups over a window of 20 days around limit hit events they found that the average daily volatility of limit hit group is significantly higher than the 90% and 80% group in the post limit hit days. Hence they concluded that the price limit system of the Tokyo Stock Exchange is ineffective. The studies following Kim and Rhee (1997) that examined Athens Stock Exchange in Greece (Phylaktis, Kavussanos and Manalis, 1999), Taiwan Stock Exchange (Kim, 2001), and Istanbul Stock Exchange in Turkey (Bildik and Elekdag,2004) also reached similar conclusion that price limits spills over volatility to the post limit hit days (*volatility spill over hypothesis*).

In contrast to the above studies evidence, Lee and Kim (1995), by using Korean Market data, showed that price limit rules decrease stock price volatility. They compared a portfolio of stocks with high price limits against another portfolio of stocks with low price limits and found that the difference of volatility of original return is significant between these two portfolios but there is no significant difference of volatility of the residual return data after controlling for price limit rates. Therefore they attributed this difference in volatility to the difference in price limits. A similar conclusion was reached in a experimental study conducted by Westerhoff (2003): price limit can reduce volatility in the market. Also price limit rules increase with increase in the trend chasing behaviour of the traders.

2.2 Components of Volatility

Volatility is generally classified into permanent and temporary components (see, for example, Engle and Lee, 1999). However, none of the studies mentioned in Section 2.1 decompose volatility to understand the effect of price limits on the differential components of volatility. This decomposition is very important to understand the efficacy of price limit rules. Harris (1998) explains that, depending upon the cause of volatility, price limits may have different impact on volatility in the market. If volatility is caused by fundamental information then price limits would cause volatility spill over on the post price limit hit days. On the other hand, if volatility is caused by noise trading activity of uninformed traders then price limits may control such volatility.

Engle and Lee (1999) developed a component GARCH model to explain the permanent or long memory component and the rapid decaying transitory or short-term component. Andersen and Bollerslev (1997) propose that market volatility is composed of short-run memory component and long run memory component. The authors argue that the interaction among a large number of diverse information processes may contribute to the long memory characteristics of volatility, which therefore reflects inherent properties of the return generating process. Liesenfeld (2001) showed that both information arrival process and investors’ sensitivity to information affects volatility in the market. According to Muller et al. (1997) volatility of different time horizon is caused by heterogeneous traders who perceive, react to and cause different types of volatility. Shleifer (2000) showed that the presence of noise traders can be a very important factor for transitory volatility. Gallant, Hsu and Tauchen (1999), Chernov and et al. (2003), and Tauchen (2004) showed that a multi factor or at least a two-factor model performs better than a single factor model to explain the volatility persistence in stock return.

Schwert (1990), Friedman and Laibson (1989) and Maheu and McCurdy (2004) showed that the persistence property of extreme volatility is different from the ordinary volatility, which tend to be highly persistent. Extreme volatilities are short lived and decay rapidly. Engle and Mustafa (1992) also report that, in the options market, short term implied volatility reverts back to its mean at a faster rate than the long horizon implied volatility.

In this paper we follow Engle and Lee (1999) to decompose daily volatility of security returns into permanent and transitory component and use modified Kim and Rhee (1997) methodology to study the impact of price limit rules on these two components of volatility.

3. Hypotheses

This section is divided into two subsections, the first subsection focuses on developing hypothesis related to possible sample selection bias of Kim and Rhee (1997). On the basis of this hypothesis, we would propose a modification to the existing methodology of volatility spillover test. The second subsection explains hypotheses related to impacts of price limit rules on permanent and transitory component of volatility.

3.1 Sample selection bias

Kim and Rhee (1997) in their study compare volatility of the test group (stocks that hit price limits) with similar statistics of control groups (stocks that didn't hit price limits but reached at least 80% or 90% of their daily price limits) over several days around the limit hit. An implicit assumption of the research design of Kim and Rhee (1997) is that the test group stocks and the control group stocks are comparable in terms of their test statistics and that the only factor that differentiates the test group from the control group is the occurrence of the limit hit events. Kim and Rhee (1997) assume that the probability of a daily price limit hit is the same for all securities in the market. Empirical evidence suggests that this may not be the case in reality. Kim and Limpaphayom (2000) have shown that the profile of the stocks hitting price limits is fundamentally different from the profile of the non-limit hitters. Their findings suggest that the stocks with higher systematic and idiosyncratic risk, lower market capital and higher trading volume are more prone to hit daily price limits.

In Appendix 1 we show that firm characteristics do affect a stock's probability of daily price limit hit. Appendix 1 explains theoretically that probability of hitting daily price limits may not be same for all the stocks in the market if they differ in term of their fundamental characteristics such as systematic risk and idiosyncratic risk. Appendix 1 also demonstrates that the group of stocks with higher volatility persistence will hit daily price limits more frequently than the group of stocks that has lower volatility persistence.

An implication of the findings of Kim and Limpaphayom (2000) and the argument elaborated in Appendix 1 is that, probably by design, the members of the test and control groups of Kim and Rhee (1997) have a different profile in terms of their fundamentals. As a result the comparison between the two groups may not be justified. In other words, the test and control groups used in Kim and Rhee (1997) may not be comparable. Due to this probable sample selection bias, in the test for "volatility spillover" hypothesis, Kim and Rhee (1997) probably compares a group of stocks with high volatility persistence with a group of low or moderate volatility persistence. Consequently, although the differences of mean volatility between the test and control groups are statistically significant, it fails to provide any significant information about the performance of the price limit rules. Following the argument discussed above the first hypothesis to test probable sample selection bias in Kim and Rhee (1997) is:

Hypothesis 1: Frequent price limit hitters have significantly higher volatility persistence than non limit hitters.

To rectify the possible sample selection bias, in this study we use propensity score matching methodology (see Section 4.1.1 for more details) to select the members of the control group. This improvement of Kim and Rhee (1997) methodology makes the control group (group of stocks that didn't hit price limit but reached at least 80% or 90% of their daily price limit) members comparable in terms of the propensity to hit daily price limit after controlling for their fundamental characteristics. The second hypothesis tests volatility spill over after correcting possible sample selection bias using modified Kim and Rhee (1997).

Hypothesis 2: After controlling for propensity to hit daily price limits, there should not be any significant difference between daily volatility of limit hitters and non limit hitters on post price limit hit days.

3.2 Impact on permanent and transitory volatility

One major contribution of this study, as indicated earlier, is to test the impact of price limit on different components of volatility. The critiques of price limit rule argue that on the day of limit hit security prices cannot reach to their equilibrium level as a result, security prices fail to reflect the true value of the security. As traders wait to execute their orders on the day after price limit hit, volatility of post limit hit days increases. So if the volatility in the market is due to the arrival of fundamental information then instead of reducing volatility, price limit actually spills over the volatility of the limit hit day on to the post price limit hit days. However, in the literature on price limit, volatility spill over test is tested on daily volatility of the security instead of using only the component of volatility contributed by new information; in this study we test the impact of price limit on the fundamental or permanent component of the volatility. If the argument of the critiques is true then price limit should spill over the part of the daily volatility caused by fundamental information (i.e. the permanent component of volatility). Hence, the third hypothesis of this study tests the volatility spill over hypothesis for the permanent component of daily volatility.

Hypothesis 3: Price limits doe not spill over permanent component of volatility in post price limit hit days. In other words there should not be any significant difference between the permanent volatility of limit hitters and non- hitters on post price limit hit days.

Proponents of price limit rules propose that price limits give traders time to re-assess the true value of the security during a panic trading session therefore it brings down transitory volatility in the market. We test if price limit can reduce transitory component of daily volatility, using the fourth hypothesis.

Hypothesis 4: Price limit does not spill over transitory component of volatility. Therefore there is no significant difference between the transitory volatility of price limit hitters and non-hitters on post limit hit days.

4. Institutional Details, Data and Methodology

Tokyo Stock Exchange (TSE) is the second largest equity market of the world in terms of market capitalization. The exchange follows a "continuous auction" trading mechanism without any market maker or specialists. This is one of the oldest and most developed equity markets of the world with a long history of price limit rules. Price limit rules for individual stocks traded in this exchange do not allow placing bid and ask quotes beyond daily price limits but trading on a security can still continue within these limits even after a price limit hit. Details of price limit rules in Tokyo Stock Exchange are described in Table 1. As reported in Table 1, price limits in TSE are defined as absolute price changes on the basis of price levels of the securities. There are as many as 29 different price limits for stocks in various price levels starting from stocks below ¥100 to stocks with price ¥ 50,000,000 and above. The minimum absolute price limit for TSE is ¥30 where as the maximum absolute price limit is ¥10,000,000.

Insert Table 1 Here

Though Table 1 provides general price limit rules, exchange does broaden daily price limits on some special occasions. If price is stuck at daily upper or lower price limit continuously for 3 days without any trading in such a case TSE doubles the daily price limit for the stock on the 4th day. If there are trading on the 4th day then the price limit for the stock goes back to the normal level otherwise TSE continues to double daily price limit for the next trading day. In some occasions TSE even abolishes daily price limits when it assesses that the stock price would drop to the minimum price of ¥1 due to an obvious reason like bankruptcy.

Insert Table 2 Here

We use both daily and intraday price data from TSE for a period of January 2001 to December 2005. There are couple of reasons for selecting TSE for this study. First, TSE is the largest equity market with daily price limit rules. Second, as we are proposing a modification of Kim and Rhee (1997) methodology, testing this modified methodology on Japanese market will provide results comparable to Kim and Rhee (1997).

The price data is provided by SIRCA and data on firm characteristics and industry classification has been collected from DataStream International. Primarily the study uses daily open, high, low and close price data along with daily trading volume, number of shares outstanding, daily market to book value ratio and daily market capitalization data. For the purpose of robustness test we also use intraday transaction data. Starting with all the firms listed in Tokyo Stock Exchange, we filtered out stocks that are not classified under the FTSE/DJ industry classification benchmark. Initial sample for the study includes 1730 stocks.

Table 2 provides overview of the distribution of the sample stocks classified across various industries. This table also presents industry wise summary statistics of limit hit events over the sample period. The table reports a huge increase in the number of price limit hits compared to the number of price limits provided by Kim and Rhee (1997) for their sample period. In our sample, over the sample period of 5 (2001 to 2005) years 1048 stocks hit daily price limits. There are 6176 limit hit events which is, on average, more than twice the number limit hits in Kim and Rhee's sample and also more than 4 limit hits for every trading day of our sample. In terms of the absolute and relative numbers of daily price limit hits Software & Computer Service, Support Services, Media and General Financial are the industries that experience frequent price limit hits. As reported in Table 3, these are the industries that have a combination of high systematic and idiosyncratic risk, high market to book value ratio as well as a high turnover ratio (except for Media industry where turnover ratio is 1.64 only).

Insert Table 3 Here

Table 4 provides the details of year wise price limit statistics for the sample period. The table shows that the number of upper limit hits is greater than the number of lower limit hits, which is quite consistent with the findings of Kim and Rhee (1997). To keep our analysis consistent with the previous literatures, we will consider the non-consecutive limit hits only for all the following analysis. Though it should be noted as argued by Miller (1989) and also mentioned by Kim and Rhee (1997) that excluding consecutive price limit hits may induce a downward bias to estimated volatility spillover test.

Insert Table 4 Here

4.1 Methodology

This study proposes a modification of the research design of Kim and Rhee (1997) to eliminate possible sample selection bias in the original design. Following Kim and Rhee (1997) we compare the group of stocks that hit daily price limit against groups of stocks that did not hit price limit but experienced a price change of at least up to 90% and 80% of their price limit on the limit hit days. Our contribution is that we control for the propensity to hit daily price limit while constructing the control group i.e. 90% and 80% group. This modification makes the test group i.e. limit hit group and the control groups comparable in terms of their fundamental characteristics and propensity to reach daily price limits. As a result, if there is no significant difference between the volatility of these groups before limit events then any difference between these two groups post price limit hit can be attributed to the limit hit event.

Our first hypothesis argue that the evidence of volatility spill over in Kim and Rhee (1997) methodology might be a manifestation of differences in volatility persistence between the group of price limit hitters and near/non limit hitters. To test this hypothesis, we compare the average volatility persistence of both the groups using parametric and non-parametric tests. The volatility persistence for the stocks are estimated with a AR(1)-GARCH(1, 1) model

$$\left.\begin{aligned} r_t &= m + p\, r_{t-1} + e_t \\ e_t &= \sqrt{k_t}\, z_t\,, \\ e_t \,|\, \psi_{t-1} &\sim i.i.d(0, k_t), z_t \sim i.i.d(0,1) \\ k_t &= w + a\, e_{t-1}^2 + b\, k_{t-1} \end{aligned}\right\} \qquad (1)$$

where r_t is the daily return on the security, m is the expected return and k_t denotes the conditional variance of r_t given the information ψ_{t-1} available at time t-1. e_t is the error in the return process, which is identically and independently distributed with zero mean and conditional variance k_t. w, a, b are fixed parameters, for long run volatility of r_t to be covariance stationary following condition should be satisfied $a + b < 1$. $a + b$ is the measure of volatility persistence in this model.

4.1.1 Propensity Score Matching & Sample selection

To make the control group of the study comparable to the test group we use propensity score matching (PSM) methodology developed by several researchers including Rosenbaum and Rubin (1983), Heckman and Robb (1986) and Heckman, Ichimura and Todd (1997), Heckman, Ichimura and Todd (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^{th} stock has an observed proxy for its t^{th} day volatility $V_{i,t}^{1}$, when the i^{th} stock hits price limit on the t^{th} day; and it also has another measure of its t^{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^{th} stock of t^{th} day given the fundamental characteristics (*X*) of the stock, i.e.

$$E\left(V_{i,t}^{1} - V_{i,t}^{0} \middle| D = 1, X\right) \tag{2}$$

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

$$B(X) = E\left(V_{i,t}^{0} \middle| D = 1, X\right) - E\left(V_{i,t}^{0} \middle| D = 0, X\right). \tag{3}$$

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) provide evidence that support this assumption. They suggest a list of variables that differentiates a frequent limit hitting stocks from an infrequent or non limit hitters. Rosenbaum and Rubin (1983) show that if

$$\left.\begin{aligned} &\left(V_{i,t}^{1}, V_{i,t}^{0}\right) \perp D \mid X \\ &\text{and } 0 < P(D = 1 \mid X) < 1 \end{aligned}\right\} \tag{4}$$

then,

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

where $\left(. \perp . \middle| X \right)$ operator denotes independence of left and right hand sides of the operator conditional to X and $P\left(. \middle| X \right)$ stand for the conditional probability. The propensity score $P\left(D = 1 \middle| X\right)$ can be estimated using Logit or Probit models. Heckman et al. (1998) argues that conditions described in Eq.(4) is too restrictive for the estimation of Eq.(2) and proves that a weaker condition ,

$$E\left(V_{i,t}^{0} \middle| D = 1, P\left(D = 1 \middle| X\right)\right) = E\left(V_{i,t}^{0} \middle| D = 0, P\left(D = 1 \middle| X\right)\right) \qquad (4)$$

would be sufficient for the purpose.

We use this propensity score matching methodology to select our control sample of 90% and 80% group. To implement this matching technique we calculate propensity score for each stock in our sample. 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, this constitutes the 90% group. We carry out the same process with the sample of all the stocks that experienced a price change of at least 80% of their daily price limit to select the 80% group.

4.1.2 Permanent and Transitory Volatility

As discussed in previous sections, we apply Engle and Lee (1999) methodology to decompose daily volatility. Engle and Lee (1999) propose component GARCH model that allows for separation of the transitory (short run) and permanent (fundamental/long run) component of volatility. In this subsection, we provide the details of the volatility decomposition methodology used in this paper.

Following Engle and Lee (1999) let r_t denote the return on a security, μ is the expected return and the conditional variance of the return is defined as $h_t = E\left((r_t-\mu)^2 \middle| \Psi_{t-1}\right)$ where Ψ_{t-1} represents information available at time *t*-1. With this specifications the GARCH (1,1) process given by Bollerslev (1986) is defined as

$$\left.\begin{aligned} r_t &= \mu + \varepsilon_t \\ \varepsilon_t &= \sqrt{h_t}\, z_t, \\ \varepsilon_t \big| \psi_{t-1} &\sim i.i.d(0, h_t), z_t \sim i.i.d(0,1) \\ h_t &= \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \end{aligned}\right\} \tag{5}$$

Where ω, α, β are fixed parameters and ε_t is the heteroscedastic error term conditionally identically and independently distributed with zero mean and conditional variance h_t. Given the assumption that the return generating process is covariance stationary i.e., $\alpha + \beta < 1$, the unconditional variance is

$$\sigma^2 \equiv Var(r_t) = \frac{\omega}{1-\alpha-\beta}. \tag{6}$$

This allows us to rewrite the variance equation of GARCH (1, 1) model in Eq.(5) as

$$h_t = \sigma^2 + \alpha\left(\varepsilon_{t-1}^2 - \sigma^2\right) + \beta\left(h_{t-1} - \sigma^2\right) \tag{7}$$

Taking expectation on both sides of the Eq.(7) provides constant long term volatility, $E(h_t) = \sigma^2$ as the expected values of the second and third term becomes equal to zero.

In the component GARCH model, Engle and Lee modify Eq. (7) to incorporate the possibility of time varying long run volatility. According to their model the variance equation of the component GARCH (1, 1) model is defined as

$$h_t = q_t + \alpha\left(\varepsilon_{t-1}^2 - q_{t-1}\right) + \beta\left(h_{t-1} - q_{t-1}\right) \quad (8)$$

where,
$$q_t = \omega + \rho\, q_{t-1} + \phi\left(\varepsilon_{t-1}^2 - h_{t-1}\right) \quad (9)$$

the parameters in follows the condition $0 < \alpha + \beta < \rho \leq 1$. In this model q_t is the time varying long run component of volatility. The lagged forecasting error $\left(\varepsilon_{t-1}^2 - h_{t-1}\right)$ determines the time dependence of the permanent component. The transitory or the short run component of the conditional variance is defined as $(h_t - q_t)$. The conditional variance h_t is covariance stationary if permanent and transitory components are both covariance stationary or in other words if $\rho < 1$ and $\alpha + \beta < 1$. It should also be noted that the component model reduces to the GARCH (1, 1) model if either $\alpha = \beta = 0$ or $\rho = \phi = 0$.

In this study, we estimate the permanent and transitory component of daily volatility using component GARCH (1, 1) model, described above. To test hypotheses 3 and 4 described in Section 3, we apply the modified Kim and Rhee (1997) methodology, detailed in the previous subsection, on the estimated permanent and transitory volatility component.

5. Empirical Results

5.1 Sample Selection Bias

Table 5 reports the comparison of volatility persistence between the frequent limit hitter group (i.e. stocks that hit daily price limit at least 5 times over the entire sample period) and the group of stocks reaching at least 60%, 70%, 80% or 90% of daily price limit but not hitting the price limit on the days when the stocks of limit hit group hit their daily price limits. The average volatility persistence values reflect very high persistence of volatility for all the groups. Average volatility persistence for the frequent limit hitters is above 0.95 where as for the other group average persistence is around 0.86. Both the parametric two sample t tests for mean difference and non-parametric wilcoxon rank sum test for median difference shows that the average volatility persistence of the frequent limit hitter is significantly higher than that of the other groups at 1% level of significance. This result does not reject the *Hypothesis 1* described in Section 3. These results support our argument concerning possible sample selection biases in the research design of Kim and Rhee (1997).

Insert Table 5 Here

5.2 Volatility Spillover Test with Modified Kim and Rhee (1997) Methodology

Following the evidence of possible sample selection bias reported above, to reduce sample selection bias in Kim and Rhee (1997) methodology, we use propensity score matching technique to select our control sample. We estimate the propensity to hit daily price limit for all the stocks in the sample with a Probit model. Consistent with Kim and Limpaphayom (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 turnover ratio (TOR) in the Probit model. The Probit model used to estimate propensity scores is specified as

$$\Pr\left(Hit = 1 \middle| X\right) = \Phi\left(X'\gamma\right) \tag{10}$$

where, X is a vector of firm characteristics variables, γ is the coefficient vector and $\Phi(.)$ is the cumulative normal distribution function.

Insert Table 6 Here

Details of the Probit model estimation is reported in Table 6. 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 large and highly active stocks with higher systematic risk, unsystematic risk have greater probability of hitting daily price limit. For the variables such as Beta, TOR and RR our results are quite consistent with findings Kim and Limpaphayom (2000). On the other hand, the findings on impact of Size and MB on probability of daily price limit hit differ from the findings of Kim and Limpaphayom (2000).

Insert Table 7 Here

For the volatility spill over test, we identify control group sample members that are nearest neighbours to the limit-hit stocks in terms of their estimated propensity scores. Table 7 reports comparison of daily volatility of between limit-hit group and control group over a window of –10 days to +10 days of price limit hit events. Daily volatility is estimated with squared daily returns. For each day, average daily volatility between the limit hit group and 90% group / 80% group is compared using non-parametric Wilcoxon

Signed Rank test for paired samples. The table shows results of the volatility spill over test for both upper and lower limit hits. The signs “>”, “>>”, “>>>”(“<”, “<<”, “<<<“) represent that values on the right hand side being significantly smaller (greater) than the corresponding values in limit hit group at 10%, 5% and 1% level, respectively.

The volatility spill over test results presented for upper limit hits show that limit hit group experiences significantly higher volatility compared to the 90% group for first two days after limit hit and also for forth day post price limit hit. In comparison to 80% group the evidence of volatility spill over is stronger as limit hit group shows significantly higher volatility for five consecutive days post price limit hit. A close look at the results indicate that the limit hit group on an average, have significantly lower volatility than the 90% group and 80% group for two or one days before price limit hit. On limit hit days limit hit group experience significantly higher volatility than the two control groups and this high volatility persists for post limit hit days. These findings are consistent with the findings of Kim and Rhee (1997).

The results for lower limit hits that are not explored in Kim and Rhee (1997) are quite different from upper limits. The limit hit group has significantly lower volatility compared to the control groups on the days immediately before price limit hit and on the limit hit days limit hit group become significantly more volatile than the control group. However, for almost all the post limit hit days there is no significant difference of daily volatility between the limit hit group and control groups. This result for lower limit hit is quite different from earlier findings of Kim and Rhee (1997) but consistent with some of the recent findings from markets like Korea and China.

In summary, the results from Table 7 indicate asymmetric effect of price limit on volatility of limit hitting stocks. Results of this analysis indicate that price limit rules in Tokyo Stock Exchange work well for lower limit hits but for upper limit hits they spill over volatility.

Insert Table 8 Here

For robustness check we used intraday price data and used daily-realized volatility for the volatility spill over study. Our results for volatility spill over test with realized volatility using modified Kim and Rhee (1997) methodology is given in Table 8. Qualitatively the results presented in Table 8 are qualitatively similar to the results reported in Table 7. Although we don't have a plausible hypothesis for this asymmetric response the overall results indicate that there is more divergence of opinion on positive news compared to negative news. Conard et.al., (2002) show that investors reaction to bad news varies from good news and investors are more sensitive to bad news compared to good news. Their response to bad news monotonically increases with increase in the stock price. However, this response rate is quite slow for good news. Our result indirectly supports this argument: investors act quick in the right direction for bad news compared to good news.

5.3 Impact of Price limit on Permanent and Transitory Volatility

As discussed in earlier in Section 3, Permanent and Transitory components of daily volatility are estimated using the component GARCH (1,1) model proposed by Engle and Lee (1999). The summary of the estimation of the component GARCH model for all the stocks in our sample is reported in Table 9. The table shows on an average more than 80% of the ARCH coefficients and more than 65% of the GARCH coefficients are significant. All the coefficients in the permanent component specification are highly significant as ρ is significant for more than 95% times and for more than 80% stocks ω and ϕ are found to be significant.

Insert Table 9 Here

Table 10 compares the average permanent component of daily volatility between the limit hit group and 90% group / 80% group over a period of period of 21 days (–10 days to +10 days) around price limit hit events. The difference between average daily permanent volatility of limit hit group and control group is tested using Wilcoxon Signed Rank test. The significance of the difference is presented with the signs “>”, “>>”, “>>>”(“<”, “<<”, “<<<“) which represent that values on the right hand side being significantly smaller (greater) than the corresponding values in limit hit group at 10%, 5% and 1% level, respectively.

Insert Table 10 Here

Result of Wilcoxon Signed Rank test reported in Table 10 shows that there is evidence of volatility spill over for limit hit group compared to 90% group for the upper limit hits. The average permanent component of volatility for the limit hit group is significantly higher than the 90% group at 1% level of significance for six days after price limit hit though there was no significant difference between these two groups in terms of permanent volatility for almost all the days before the limit hit event. The evidence for lower limit hits compared to 90% group of lower limit hit show that there is no significant difference between the permanent volatility of limit hit group and 90% group, on the day after price limit hit. This result provides some evidence of “cooling down effect” that price limit rules do bring down permanent volatility of limit hit stocks on the day after price limit hit.

Insert Table 11 Here

The results of transitory volatility spill over test using modified methodology of Kim and Rhee (1997) is reported in Table 11. The table reports average transitory component of daily volatility estimated from component GARCH (1,1) model of Engle and Lee (1992) for all the groups over a window of –10 days to +10 days of limit hit events. It should be noted that by construction the transitory volatility measure is allowed to have negative values in the component GARCH model. Wilcoxon Signed Rank test is used to measure the significance of the difference between average transitory volatility of the limit hit group and the 90% group or 80% group. In the table the signs “>”, “>>”, “>>>”(“<”, “<<”, “<<<“) represent that values on the right hand side being significantly smaller (greater) than the corresponding values in limit hit group at 10%, 5% and 1% level respectively.

The results presented in Table 11 show that, in the case of upper limit hit events, the transitory volatility of limit hit group is not significantly higher than the transitory volatility of the control groups on post price limit hit days (except for 3rd and 6th day after price limit hit for 90% group and 3rd day after price limit hit for 80% group). The transitory volatility of the limit hit group is lower than that of the control group on limit hit days. Results for the lower limit hits are also quite similar to the results of upper limit hits. These results suggest that price limit rules brings down transitory volatility of limit hit group on price limit hit days and it does not spill over transitory volatility on post limit hit days. On the basis of the above results we do not reject our forth null hypothesis the evidence for impact of price limit on transitory volatility suggest that price limit does effectively curb short term transitory volatility and do not cause a spill over on post limit hit days. This is an important finding as this is the first study to show that price limit rules though reduces transitory volatility on limit hit days but do not spillover transitory volatility on post limit hit days.

6. Summary and Conclusion

This study investigates the impact of price limit rules on volatility of security prices in Tokyo Stock Exchange over a period of 5 years from January 2001 to December 2005. We propose a modification to widely used methodology of Kim and Rhee (1997) by applying propensity score matching technique, in order to reduce the possible sample selection bias of the existing methodology. Using the modified methodology, we provide new evidences of efficacy of price limit rules in equity markets. Results of this study show that consistent with the findings of Kim and Rhee (1997), price limit rules do spill over volatility for upper limit hits. However, results for lower limit hits are quite different from the results of Kim and Rhee (1997). We find, Price limit rules work quite efficiently for lower limit hits as there is no evidence of volatility spill over.

This study also contributes by studying the effect of price limit on both permanent and transitory component of volatility estimated through component GARCH (1,1) model of Engle and Lee (1999). The results for permanent volatility show that there is some evidence of spill over due to upper limit hits but for lower limit hits the test results are inconclusive. On the other hand, results show that for both upper and lower limit hits, price limit successfully curbs the transitory volatility and it does not spill over transitory volatility on the post limit hit days.

In summary, this study contributes to the price limit literature in terms of providing an improved methodology to test impacts of price limit rule on security prices. We also provide new evidence that shows impact of price limit rules on volatility of security return is asymmetric. This is the first study to analyse the impact of price limit on permanent component of volatility contributed by fundamental and long-term factors as well as on transitory or short-term component of volatility. Findings of this study are consistent with the arguments of the critics of price limit rules, there is some evidence that price limits spill over permanent volatility. On the other hand, we also provide evidence that supports advocates of price limits too. We find price limit rules do successfully reduce transitory volatility on limit hit days and do not spill it over the post limit hit days.

Appendix – 1

Why probability of hitting daily price limits may not be the same for all stocks?

Let us assume that daily returns r_i of security i follow normal distribution with mean μ_i and standard deviation σ_i i.e. $r_i \sim N(\mu_i, \sigma_i^2)$. Further, relative daily price limit (i.e. price limit defined in terms of percentage change in security price) is $\pm l_i$ [or $\pm L_i\% = (l_i \times 100)\%$] of p_i^b . The relative tick size $|\tau_i|$ for the security i at the beginning of any day is defined as

$$|\tau_i| = \frac{|t_i|}{p_i^b} \tag{A1}$$

where $|t_i|$ is the absolute tick size or price step and p_i^b is base price of the day or the previous day's closing price.

If the trading on a security stops for the day when the security price hits its daily price limit, then the probability (Π_i)[1] of security i not hitting the daily price limit in any trading day is equivalent to probability of r_i being in the closed range $[-(l_i - \tau_i), (l_i - \tau_i)]$, which can be symbolically represented as

$$\Pi_i = 2P\left(\frac{l_i - \tau_i}{\sigma_i}\right) \tag{A2}$$

when μ_i is assumed to be zero and $P(y) = \left(\sqrt{2\pi}\right)^{-1} \int_0^y e^{-\frac{1}{2}x^2}\, dx$.

---

[1] If trading on a security doesn't necessarily stop for the day after daily price limit is hit in such cases could be interpreted as probability of a price limit hit that sustains till the end of the day.

If $\mu_i > 0$ & $\mu_i < \left| l_i - \tau_i \right|$ then the probability of not hitting the daily price limit by security *i* on any day is

$$\Pi_i = P\left(\frac{(l_i - \tau_i) - \mu_i}{\sigma_i} \right) + P\left(\frac{(l_i - \tau_i) + \mu_i}{\sigma_i} \right) \qquad 1 - \Pi_i \qquad \text{(A3)}$$

Or,

$$\Pi_i = P\left(\frac{(l_i - \tau_i)}{\sigma_i} - \frac{1}{cv_i} \right) + P\left(\frac{(l - \tau)}{\sigma} + \frac{1}{cv_i} \right) \qquad \text{(A4)}$$

where cv_i refers to coefficient of variation for the daily returns of security i.

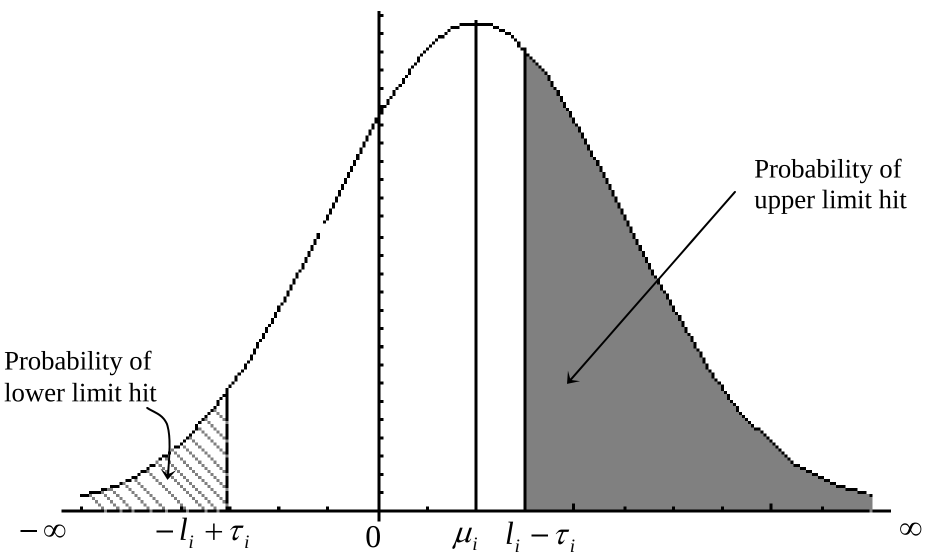

Fig. 1: Probability distribution of daily returns

From Fig.1 it is visible that,

$$\left.\begin{aligned} &\text{Probability of hitting upper price limit} = 0.5 - P\left(\frac{(l_i - \tau_i)}{\sigma_i} - \frac{1}{cv_i} \right) \\ &\text{Probability of hitting lower price limit} = 0.5 - P\left(\frac{(l_i - \tau_i)}{\sigma_i} + \frac{1}{cv_i} \right) \end{aligned}\right\} \qquad \text{(A5)}$$

As cv_i is positive, Eq.(A5) shows that the probability of a stock hitting a lower price limit is lower than its probability of hitting the upper price limit; empirical evidence of this phenomenon is reported by Kim and Rhee (1997) using Tokyo Stock Exchange data, Kim and Limpaphayom (2000) from the Stock Exchange of Thailand data and Cho et al. (2003) from Taiwan Stock exchange.

As $P(y)$ increases monotonically with an increase in y we can infer from Eq.(A2) , Eq.(A3) or Eq.(A4) that probability of a security i not hitting price limit in a day is negatively related to its daily volatility(σ^2) when all other parameters remain unchanged. This suggests that stocks with higher daily volatility are more likely to hit daily price limits when other parameters remain unchanged.

If we presume that the daily return follows the market model i.e.

$$r_i = r_f + \beta_i (r_m - r_f) + u_i \qquad \text{(A6)}$$

Where r_f and r_m stands for daily risk free return and market return, β_i is the measure of systematic risk and u_i is a random error, $u_i \sim NID(0, u_i^2)$. Then the expected return can be written as

$$\mu_i = E(r_i) = r_f + \beta_i (r_m - r_f) \qquad \text{(A7)}$$

and the total risk or return variance of security i can be represented as

$$\sigma_i^2 = \beta_i^2 \sigma_m^2 + {u_i}^2 \qquad \text{(A8)}$$

Replacing the values of μ_i and σ_i from Eq.(A7) and Eq.(A8) in Eq. (A3) we can find that the probability of a security not hitting the price limit in a day is a function of its systematic and idiosyncratic risks.

$$\Pi_i = P\left(\frac{(l_i - \tau_i) - [r_f + \beta_i (r_m - r_f)]}{\sqrt{\beta_i^2 \sigma_m^2 + u_i^{\,2}}}\right) + P\left(\frac{(l_i - \tau_i) + [r_f + \beta_i (r_m - r_f)]}{\sqrt{\beta_i^2 \sigma_m^2 + u_i^{\,2}}}\right) \tag{A9}$$

From Eq(A8) we can infer that the probability of a stock hitting price limit in a day increases with an increase of its non systematic risk ($u_i^{\,2}$) . The relationship between Π_i and β_i looks bit complicated in Eq.(A8) but with an assumption of $u_i^{\,2} = 0$, it can be shown that Π_i and β_i are negatively related. Empirically these relationships are confirmed by Kim and Limpaphayom (2000), as their findings suggests that stocks with higher systematic and residual risks tend to hit price limits more often on the Taiwan and Thailand markets.

Further if we assume that conditional daily return volatility follows GARCH (1,1) process, then we may describe the daily return and conditional volatility of security i as:

$$r_{i,t} = \mu_i + e_{i,t} \tag{A10}$$

$$e_{i,t} \big| \phi_{t-1} \sim N(0, h_{i,t}^2) \tag{A11}$$

$$E(e_{i,t}^2 \big| \phi_{t-1}) = h_{i,t}^2$$

$$h_{i,t}^2 = \omega_i + \gamma_i e_{i,t-1}^2 + \delta_i h_{i,t-1}^2 \tag{A12}$$

Where the parameters $\omega_i, \gamma_i, \delta_i$ follow the conditions $\omega_i > 0, \gamma_i > 0, \delta_i > 0$ and

$\gamma_i + \delta_i < 1$.

If Eq. (A10), (A11) and (A12) describe the dynamics of daily return and conditional volatility process, then,

$$\sigma_i^2 = E(e_{i,t}^2) = \frac{\omega_i}{1 - (\gamma_i + \delta_i)} \tag{A13}$$

And the probability Π_i can be written as

$$\Pi_i = P\left(\frac{(l_i - \tau_i) - \mu_i}{\sqrt{\dfrac{\omega_i}{1-(\gamma_i + \delta_i)}}}\right) + P\left(\frac{(l_i - \tau_i) + \mu_i}{\sqrt{\dfrac{\omega_i}{1-(\gamma_i + \delta_i)}}}\right) \qquad \text{(A14)}$$

Interpreting $(\gamma_i + \delta_i)$ as the measure of volatility persistence; Eq.(A14) suggests that if all other parameters remain unchanged securities with higher volatility persistence will carry higher chance of hitting price limits in any trading day.

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Table1

Price Limit Rules in Tokyo Stock Exchange

Previous Day's Closing Price or Special Quote		**Daily Price Limit (+/-)**
Equal or more than &	**Less than**	
	100	30
100	200	50
200	500	80
500	1,000	100
1,000	1,500	200
1,500	2,000	300
2,000	3,000	400
3,000	5,000	500
5,000	10,000	1,000
10,000	20,000	2,000
20,000	30,000	3,000
30,000	50,000	4,000
50,000	70,000	5,000
70,000	100,000	10,000
100,000	150,000	20,000
150,000	200,000	30,000
200,000	300,000	40,000
300,000	500,000	50,000
500,000	1,000,000	100,000
1,000,000	1,500,000	200,000
1,500,000	2,000,000	300,000
2,000,000	3,000,000	400,000
3,000,000	5,000,000	500,000
5,000,000	10,000,000	1,000,000
10,000,000	15,000,000	2,000,000
15,000,000	20,000,000	3,000,000
20,000,000	30,000,000	4,000,000
30,000,000	50,000,000	5,000,000
	50,000,000	10,000,000

Source: Fact Book 2005, Tokyo Stock Exchange

Table 2

Industry-wise Details of Daily Price Limit Hits

This table provides industry-wise details of daily price limit hit events in Tokyo Stock Exchange from January 2001 to December 2005. The industry classification used in this table is as per FTSE/DJ industry classification benchmark. This reports the number of firms from each industry included in the sample, industry-wise number of firms that hit daily price limit as least once in the sample period, total number of limit hit days, percentage of limit hitters in each industry and number of limit hit days per firm.

Industry	No. of Firms	No. of Limit Hitters	No. of Limit Hit Days	Percentage of Limit Hitters	No. Of Limit Hit Days Per Firm
Aerospace & Defense	6	5	23	83.33	3.83
Automobiles & Parts	107	61	139	57.01	1.30
Beverages	28	11	17	39.29	0.61
Chemicals	152	64	152	42.11	1.00
Construction & Materials	197	95	257	48.22	1.30
Electricity	1	0	0	0.00	0.00
Electronic & Electrical	165	120	526	72.73	3.19
Food & Drug Retailers	21	11	24	52.38	1.14
Food Producers	105	48	98	45.71	0.93
Forestry & Paper	25	9	14	36.00	0.56
Gas, Water & Multi-utility	7	3	20	42.86	2.86
General Financial	4	3	94	75.00	23.50
General Industrials	22	10	58	45.45	2.64
General Retailers	69	54	346	78.26	5.01
Healthcare Equipment & Services	22	18	73	81.82	3.32
Household Goods	64	34	82	53.13	1.28
Industrial Engineering	196	120	313	61.22	1.60
Industrial Metals	76	35	90	46.05	1.18
Industrial Transportation	1	0	0	0.00	0.00
Leisure Goods	38	29	136	76.32	3.58
Media	15	12	217	80.00	14.47
Mining	3	3	12	100.00	4.00
Oil & Gas Producers	16	4	9	25.00	0.56
Oil Equipment & Services	2	1	1	50.00	0.50
Personal Goods	89	57	187	64.04	2.10
Pharmaceuticals & Biotech.	46	31	117	67.39	2.54
Real Estate	7	7	26	100.00	3.71
Software & Computer Service	70	70	1855	100.00	26.50
Support Services	43	28	433	65.12	10.07
Technology Hardware & Eq.	88	71	603	80.68	6.85
Tobacco	1	0	0	0.00	0.00
Travel & Leisure	44	34	254	77.27	5.77
Total	**1730**	**1048**	**6176**	**60.58**	**3.57**

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Table 3

Industry wise Averages of Various Firm Characteristics

This table reports industry-wise average values of various firm characteristics 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 turnover ratio (TOR) for firms listed in Tokyo Stock Exchange from January 2001 to December 2005. The industry classification used in this table is as per FTSE/DJ industry classification benchmark.

	Industry Averages					
Industry	**Beta**	**MB**	**Vol.**	**Size**	**TOR**	**RR**
Aerospace & Defense	0.571	1.096	74.338	15590.167	0.844	0.028
Automobiles & Parts	0.688	1.034	579.192	254998.957	2.132	0.029
Beverages	0.429	1.210	227.786	98676.272	1.395	0.017
Chemicals	0.650	1.284	372.645	81711.011	1.729	0.028
Construction & Materials	0.716	2.688	402.373	43698.103	2.265	0.040
Electricity	0.925	1.370	857.113	61684.548	2.488	0.019
Electronic & Electrical	0.917	2.021	218.144	72513.047	6.515	0.038
Food & Drug Retailers	0.535	1.644	57.955	75693.053	1.228	0.023
Food Producers	0.425	1.324	228.270	49763.715	1.655	0.028
Forestry & Paper	0.594	1.055	408.668	79023.634	1.012	0.034
Gas, Water & Multi-utility	0.466	0.839	6.860	13506.064	0.850	0.040
General Financial	1.264	14.350	1687.852	44564.544	23.235	0.061
General Industrials	0.404	1.795	632.892	50321.092	1.303	0.035
General Retailers	0.613	3.177	162.945	31867.246	3.892	0.045
Healthcare Equipment & Services	0.784	3.307	38.576	32858.227	3.253	0.034
Household Goods	0.587	1.089	202.399	43057.279	1.560	0.040
Industrial Engineering	0.789	1.439	470.684	60892.083	2.286	0.038
Industrial Metals	0.877	1.251	1432.954	77475.533	4.036	0.034
Industrial Transportation	0.588	4.417	4170.483	2185.733	NA	0.059
Leisure Goods	0.658	3.830	590.564	312191.010	2.869	0.050
Media	0.911	4.346	46.801	86797.111	1.647	0.059
Mining	1.069	0.606	610.108	27265.837	1.573	0.134
Oil & Gas Producers	0.545	1.132	1138.640	178662.276	4.550	0.026
Oil Equipment & Services	0.807	1.816	91.886	47058.921	1.581	0.025
Personal Goods	0.733	5.819	420.549	41252.665	3.175	0.041
Pharmaceuticals & Biotech	0.473	4.231	203.346	176268.192	2.938	0.038
Real Estate	0.553	0.996	87.483	17505.389	1.351	0.031
Software & Computer Service	0.848	6.275	607.003	50504.647	12.589	0.076
Support Services	1.099	12.082	135.295	25012.158	27.503	0.059
Technology Hardware & Eq.	0.889	2.819	175.800	64762.741	3.496	0.046
Tobacco	0.331	1.134	15.725	1881968.424	1.479	0.018
Travel & Leisure	0.451	2.386	253.449	29096.999	1.602	0.064

Table 4

Year-wise Daily Price Limit Hit Details

This table provides year wise details of price limit hit events from year 2001 to 2005. It reports total number of daily price limit hits, number of upper and lower limit hits and also number of consecutive limit hit events each year.

Year	No. of Limit Hits	No. of Upper Limit hit	No. of Lower Limit hit	No. of Consecutive Limit Hits
2001	1157	764	393	328
2002	817	518	299	241
2003	1656	1231	425	570
2004	1595	1095	500	611
2005	1078	850	228	326

Table 5

Volatility Persistence Comparison

This table reports volatility persistence comparison between the group of frequent price limit hitters (i.e. stocks that hit price limit at least 5 times over the sample period) and the group of stocks reaching at least 60%, 70%, 80% or 90% of daily price limit but not hitting the price limit on the limit hit days.

Volatility persistence is estimated using AR (1) GARCH(1, 1) model

$$r_t = m + p\, r_{t-1} + e_t$$

$$e_t = \sqrt{k_t}\, z_t\,,\, e_t \big| \psi_{t-1} \sim i.i.d(0, k_t),\, z_t \sim i.i.d(0,1)$$

$$k_t = w + a\, e_{t-1}^2 + b\, k_{t-1}$$

where $a + b$ is the measure of volatility The t statistics and corresponding p (one tail) values (in the parentheses) are reported for the parametric t - test for mean difference. The z statistics and corresponding p values (one tail) (in the parentheses) are also reported from non-parametric wilcoxon rank sum test.

	Limit Hit Gr.	60% Gr.	70% Gr.	80% Gr.	90% Gr.
Average Persistence	0.957	0.8668	0.8689	0.8587	0.8615
t – statistics (equal variance)		3.54	3.31	3.46	3.11
		(0.0004)	(0.0010)	(0.0006)	(0.0019)
t – statistics (unequal variance)		2.80	2.70	2.97	2.82
		(0.0055)	(0.0073)	(0.0032)	(0.0050)
Z - statistics		2.5245	2.2103	2.4529	2.6577
		(0.0058)	(0.0135)	(0.0071)	(0.0039)

Table 6

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 turnover ratio (TOR) and γ 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		

Table 7

This table reports the comparison between average daily volatility of limit hit group and average daily volatility of 90% group or 80% group (i.e. group of stocks that reach at least 90% or 80% of their daily price limit on the days when stocks in limit hit group hit price limit) around limit days.

Daily volatility (V_t) for a stock is estimated as $V_t = r_t^2$ where r_t is the daily return for a stock.

The table shows average volatility for each group over 21 days, where day 0 is the limit hit day. Average volatility of the limit hit group is compared against that of the control groups (i.e. 90% Gr. And 80% Gr.) using Wilcoxon Signed Rank Test. The signs “>”, “>>”, “>>>”(“<”, “<<”, “<<<”) represent that values on the right hand side being significantly smaller (greater) than the corresponding values in limit hit group at 10%, 5% and 1% level respectively.

Daily Average Volatility										
	Upper Limit Hit					Lower Limit Hit				
Days	Limit Hitters		90% Group		80% Group	Limit Hitters		90% Group		80% Group
-10	0.002298		0.002808		0.002037	0.00252		0.002105	>	0.002398
-9	0.002176	<	0.002472	>>	0.000514	0.006312		0.005778	>	0.001207
-8	0.002121		0.003021		0.014971	0.00257		0.001859		0.002131
-7	0.002428		0.003607		0.00277	0.002565		0.001616	<	0.004057
-6	0.002126	<	0.002759		0.002449	0.002202		0.002427		0.00208
-5	0.003071	<<	0.0074		0.002937	0.0027	<<	0.003451	<<	0.002858
-4	0.007533		0.009098	>>	0.002664	0.006399		0.00309		0.00459
-3	0.007389		0.003527		0.003277	0.003079		0.002885		0.002072
-2	0.00361	<<	0.00606		0.006019	0.002726	<<	0.00439	<<<	0.006023
-1	0.003896	<<<	0.012566	<<<	0.011312	0.002236	<<<	0.010972	<<	0.005137
0	0.058003	>>>	0.016175	>>>	0.01376	0.349492	>>>	0.016569	>>>	0.024212
1	0.004335	>>>	0.003698	>>>	0.00335	0.016815		0.003687		0.003324
2	0.003484	>	0.003112	>>>	0.002762	0.003749		0.003439	>	0.002795
3	0.003207		0.002701	>>>	0.00258	0.005307	>>>	0.002284		0.002489
4	0.003403	>>>	0.002468	>>>	0.003082	0.01257		0.002693		0.002769
5	0.002729		0.002577	>>>	0.002169	0.005221		0.002448		0.005335
6	0.002706		0.002964		0.002682	0.005501		0.002658		0.003755
7	0.002905		0.002483		0.001975	0.003406		0.002361		0.001755
8	0.002204		0.003233		0.002497	0.001277	<<<	0.002449		0.00167
9	0.003183		0.002274		0.0023	0.002155		0.001904	<	0.002297
10	0.004495		0.001959		0.001915	0.002234		0.00212		0.001744

Table 8

This table reports the comparison between average daily realized volatility of limit hit group and average daily realized volatility of 90% group or 80% group (i.e. group of stocks that reach at least 90% or 80% of their daily price limit on the days when stocks in limit hit group hit price limit) around limit days.

Daily realized volatility (RV_t) for a stock is estimated as $RV_t = \sum_{n=1}^{m} R_n^2$ where R_n is the return for a stock over 5 a minute interval in any trading day and m is the number of 5 minute intervals in a day.

The table shows average daily realized volatility for each group over 21 days, where day 0 is the limit hit day. Average daily realized volatility of the limit hit group is compared against that of the control groups (i.e. 90% Gr. And 80% Gr.) using Wilcoxon Signed Rank Test. The signs “>”, “>>”, “>>>”(“<”, “<<”, “<<<”) represent that values on the right hand side being significantly smaller (greater) than the corresponding values in limit hit group at 10%, 5% and 1% level respectively.

Realized Volatility										
	Upper Limit Hits					Lower Limit Hits				
day	Limit Hitters		90% Group		80% Group	Limit Hitters		90% Group		80% Group
-10	0.002088		0.00198		0.001839	0.001843		0.001846	>>>	0.001616
-9	0.002278		0.001754		0.002073	0.002014		0.001624	>>>	0.001633
-8	0.002027		0.001796		0.002225	0.00191		0.001809		0.002193
-7	0.002003		0.001897	>>>	0.00211	0.001967		0.001923		0.001934
-6	0.00218	<<	0.002217	>>>	0.002147	0.00175		0.00181		0.00223
-5	0.002151		0.002005	>>>	0.002075	0.001879	<<<	0.002897		0.001893
-4	0.002145		0.00204	>>>	0.002032	0.002077		0.001745	>>>	0.001619
-3	0.002258		0.00221	>>>	0.002201	0.001882	<<	0.002091	<	0.002194
-2	0.002849		0.002748	>>>	0.002469	0.002054		0.001998		0.002086
-1	0.002514	<<	0.003269		0.002891	0.002271		0.002415		0.002226
0	0.007229		0.007257		0.006784	0.029084	>>>	0.006539	>>	0.007778
1	0.005865	>>>	0.004253	>>>	0.003364	0.034977		0.003882		0.003098
2	0.003504	>>>	0.003354	>>>	0.002725	0.039438		0.003495	>>>	0.002321
3	0.00304	>>>	0.002456	>>>	0.002409	0.031686		0.002373		0.002718
4	0.002662	>>	0.00258	>>>	0.002387	0.026114		0.002554		0.002513
5	0.002535		0.002416	>>>	0.002208	0.026006		0.002437		0.002052
6	0.002455	>>	0.00221	>>>	0.002024	0.014574		0.002335	>>	0.001709
7	0.002321		0.002452	>>>	0.001892	0.016015		0.00203		0.00177
8	0.002213		0.002263	>>>	0.001911	0.0161		0.001967	>>>	0.001702
9	0.002056		0.002209	>>>	0.001833	0.007934		0.001873		0.001631
10	0.002041		0.00199	>>>	0.001777	0.014846		0.001864	<	0.001667

Table 9

Details of Component GARCH (1, 1) Estimation

This table reports the average value of the coefficients from the component GARCH (1,1) model estimated to calculate the permanent and transitory components of daily volatility. This table presents mean and median values of the coefficients, median values t statistics of the coefficients and also reports the percentage of significant coefficients.

The component GARCH (1,1) model is specified as

$$r_t = \mu + \varepsilon_t$$

$$\varepsilon_t = \sqrt{h_t}\, z_t\,,\ \ \varepsilon_t \big| \psi_{t-1} \sim i.i.d(0, h_t),\ \ z_t \sim i.i.d(0,1)$$

$$h_t = q_t + \alpha\left(\varepsilon_{t-1}^2 - q_{t-1}\right) + \beta\left(h_{t-1} - q_{t-1}\right)$$

$$q_t = \omega + \rho\, q_{t-1} + \phi\left(\varepsilon_{t-1}^2 - h_{t-1}\right)$$

Where r_t denote daily return on a security, μ is the expected daily return and the conditional variance of daily return is defined as $h_t = E\left((r_t - \mu)^2 \big| \Psi_{t-1}\right)$ where Ψ_{t-1} represents information available at time t-1, ε_t is the heteroscedastic error term conditionally identically and independently distributed with zero mean and conditional variance h_t and $\omega, \alpha, \beta, \rho, \phi$ are fixed parameters. q_t is the time varying permanent component of the conditional variance h_t and $h_t - q_t$ is defined as the transitory component.

	μ	ω	ρ	ϕ	α	β
Coefficients (Mean)	0.000	0.034	0.921	0.109	0.081	0.182
Coefficients (Median)	0.001	0.001	0.988	0.044	0.109	0.228
t value (Median)	0.815	5.871	208.559	4.168	4.025	1.285
% of significant coefficients	24	80.9	95.2	85.2	82.8	65.9

Table 10

This table reports the comparison between average daily permanent volatility of limit hit group and average daily permanent volatility of 90% group or 80% group (i.e. group of stocks that reach at least 90% or 80% of their daily price limit on the days when stocks in limit hit group hit price limit) around limit days.

Daily permanent volatility (q_t) for a stock is estimated using component GARCH (1,1) model, specified as

$$r_t = \mu + \varepsilon_t$$

$$\varepsilon_t = \sqrt{h_t}\, z_t\,,\ \varepsilon_t \big| \psi_{t-1} \sim i.i.d(0, h_t),\ z_t \sim i.i.d(0,1)$$

$$h_t = q_t + \alpha\left(\varepsilon_{t-1}^2 - q_{t-1}\right) + \beta\left(h_{t-1} - q_{t-1}\right)$$

$$q_t = \omega + \rho\, q_{t-1} + \phi\left(\varepsilon_{t-1}^2 - h_{t-1}\right)$$

Where r_t denote daily return on a security, μ is the expected daily return and the conditional variance of daily return is defined as $h_t = E\left((r_t - \mu)^2 \big| \Psi_{t-1}\right)$ where Ψ_{t-1} represents information available at time t-1, ε_t is the heteroscedastic error term conditionally identically and independently distributed with zero mean and conditional variance h_t and $\omega, \alpha, \beta, \rho, \phi$ are fixed parameters.

The table shows average daily permanent volatility for each group over 21 days, where day 0 is the limit hit day. Average daily permanent volatility of the limit hit group is compared against that of the control groups (i.e. 90% Gr. And 80% Gr.) using Wilcoxon Signed Rank Test. The signs “>”, “>>”, “>>>”(“<”, “<<”, “<<<”) represent that values on the right hand side being significantly smaller (greater) than the corresponding values in limit hit group at 10%, 5% and 1% level respectively.

Permanent Component of Daily Volatility										
	Upper Limit Hits					Lower Limit Hits				
day	Limit Hitters		90%		80%	Limit Hitters		90%		80%
-10	0.003038		0.002711	>>>	0.002317	0.004627	>>>	0.002566	>>>	0.002423
-9	0.003181	>>	0.002826	>>>	0.002599	0.004482	>>>	0.002586	>>>	0.002365
-8	0.003077	>	0.003039	>>>	0.002474	0.004358	>>>	0.003567	>>>	0.004307
-7	0.003068		0.003082	>>>	0.002218	0.004259	>>>	0.002526	>>>	0.004111
-6	0.003024		0.003016	>>>	0.00219	0.004507	>>>	0.002556	>>>	0.004392
-5	0.003239		0.002936	>>>	0.003132	0.004479	>>>	0.002624	>>>	0.003752
-4	0.003202		0.003846	>>>	0.00299	0.004574	>>	0.003002	>>>	0.003293
-3	0.003645		0.005056	>>>	0.003089	0.00451		0.003159	>>>	0.003984
-2	0.005026		0.004859	>>>	0.002927	0.00593	>>	0.003074	>>>	0.002927
-1	0.004611		0.004773	>>>	0.00317	0.003433	>	0.002906	>>>	0.003032
0	0.003871	<	0.005434	>>>	0.003474	0.00463		0.004187	>>>	0.003871
1	0.011323	>>>	0.005739	>>>	0.003977	0.027695	>>>	0.005123	>>>	0.004586
2	0.00714	>>>	0.005123	>>>	0.003562	0.014468	>>>	0.004532	>>>	0.003583
3	0.005845	>>>	0.004574	>>>	0.003248	0.009742	>>>	0.003933	>>>	0.003308
4	0.005021	>>>	0.00415	>>>	0.003222	0.008606	>>>	0.003653	>>>	0.003066
5	0.004609	>>>	0.004012	>>>	0.003336	0.010983	>>>	0.00341	>>>	0.003054
6	0.004359	>>>	0.003727	>>>	0.00315	0.008041	>>>	0.00335	>>>	0.002913
7	0.004109		0.00413	>>>	0.003137	0.00723	>>>	0.00317	>>>	0.002849
8	0.003998		0.003464	>>>	0.002947	0.006356	>>>	0.003128	>>>	0.002735
9	0.003816		0.005113	>>>	0.002975	0.007072	>>>	0.002999	>>>	0.002638
10	0.003731		0.003396	>>>	0.003009	0.006538	>>>	0.003012	>>>	0.002641

Table 11

This table reports the comparison between average daily transitory volatility of limit hit group and average daily transitory volatility of 90% group or 80% group (i.e. group of stocks that reach at least 90% or 80% of their daily price limit on the days when stocks in limit hit group hit price limit) around limit days.

Daily transitory volatility ($h_t - q_t$) for a stock is estimated using component GARCH (1,1) model, specified as

$$r_t = \mu + \varepsilon_t$$

$$\varepsilon_t = \sqrt{h_t}\, z_t\,,\ \ \varepsilon_t \left| \psi_{t-1} \right. \sim i.i.d\,(0, h_t),\ \ z_t \sim i.i.d\,(0,1)$$

$$h_t = q_t + \alpha\left(\varepsilon_{t-1}^2 - q_{t-1}\right) + \beta\left(h_{t-1} - q_{t-1}\right)$$

$$q_t = \omega + \rho\, q_{t-1} + \phi\left(\varepsilon_{t-1}^2 - h_{t-1}\right)$$

Where r_t denote daily return on a security, μ is the expected daily return and the conditional variance of daily return is defined as $h_t = E\left((r_t - \mu)^2 \left| \Psi_{t-1} \right.\right)$ where Ψ_{t-1} represents information available at time t-1, q_t is the time varying permanent component of the conditional variance h_t , ε_t is the heteroscedastic error term conditionally identically and independently distributed with zero mean and conditional variance h_t and $\omega, \alpha, \beta, \rho, \phi$ are fixed parameters.

The table shows average daily permanent volatility for each group over 21 days, where day 0 is the limit hit day. Average daily permanent volatility of the limit hit group is compared against that of the control groups (i.e. 90% Gr. And 80% Gr.) using Wilcoxon Signed Rank Test. The signs ">", ">>", ">>>"("<", "<<", "<<<") represent that values on the right hand side being significantly smaller (greater) than the corresponding values in limit hit group at 10%, 5% and 1% level respectively.

Transitory Volatility

	Upper Limit Hits					Lower Limit Hits				
Days	Limit Hitters		90% Group		80% Group	Limit Hitters		90% Group		80% Group
-10	-0.00029	>>	-0.00028		-5.90E-05	-0.00089	<	7.14E-05	<<	1.48E-05
-9	-0.00031		-0.00022		-0.00025	-0.00077	<<	-0.00018	<<<	0.000359
-8	-0.00033		0.000398		-0.00055	-0.00041	<<<	0.000865	<<<	0.00077
-7	-0.00029	<	-0.00011		0.000771	-0.00074	<<<	-0.00028	<<<	-0.00044
-6	-0.00021	<<	0.000298		4.93E-05	-0.00083	<<<	-0.00023	<<<	3.39E-05
-5	-6.10E-05		-0.00022		-2.90E-05	-0.00083	<<<	-0.00012	<<	5.04E-05
-4	-0.00012		-0.00069		2.34E-05	-0.00078	<<	-0.00011		8.27E-05
-3	-0.00011	>>	-0.00111		6.23E-05	-0.00074	<<	-0.00029		0.000645
-2	-0.00029		-0.00041		-2.80E-05	0.000539		-0.00016		5.87E-05
-1	3.05E-05		0.000121		0.000533	-0.00046		0.000475		0.000496
0	0.000247	<<<	0.000805	<<<	0.001554	-0.00073	<<<	2.71E-06	<<<	0.000656
1	0.002142		0.002081		0.002204	0.028843		0.001829		0.001954
2	0.000557		0.00161		0.000591	0.009132		0.000439		0.000278
3	0.000435	>>>	0.000219	>>>	0.000267	0.003335		0.000411		0.000222
4	-3.30E-05		7.21E-05		0.000101	0.001473		0.000101		-5.10E-05
5	7.93E-06	>>	-9.70E-05		6.10E-05	0.006359		-0.00015		4.68E-05
6	-0.00024		4.83E-05		3.77E-05	0.00105		-0.00018		0.000296
7	-3.50E-05		-0.00043		0.000114	0.000614		4.39E-05		0.000409
8	-0.0002		-0.00016	<	-0.00012	0.000181		-0.0002		5.25E-05
9	-0.00028		-0.00147	<<	-0.00011	-0.00092	<<<	-0.0002	<<	-6.30E-05
10	-0.00016		-0.00037		-0.00025	-8.08E-05		-0.00039	<<	-7.80E-05