Available online at www.sciencedirect.com
SCIENCE DIRECT®
Journal of Empirical Finance 12 (2005) 269–290
Journal of EMPIRICAL FINANCE
www.elsevier.com/locate/econbase

Price limit performance: evidence from transactions data and the limit order book

Soon Huat Chan[a], Kenneth A. Kim[b], S. Ghon Rhee[c,*]

[a]Block 160, Bishan Street, 13, #03-142, 570160, Singapore
[b]State University of New York at Buffalo, School of Management, 344 Jacobs Hall, Buffalo, NY 14260, USA
[c]University of Hawai'i, College of Business Administration, 2404 Maile Way, Honolulu, HI 96822-2282, USA

Accepted 8 January 2004

Abstract

In recent years, organized stock exchanges with daily price limits adopted wider limits as narrower limits were criticized for jeopardizing market efficiency. This study examines the impact of a wide price limit on price discovery processes, using data from the Kuala Lumpur Stock Exchange. Specifically, examined is the impact of daily price limits on (i) information asymmetry; (ii) arrival rates of informed traders; and (iii) order imbalance. Using both trade-to-trade transaction data and the limit order book, we compile evidence that price limits do not improve information asymmetry, delays the arrival of informed traders, and exacerbates order imbalance. These results suggest that price limits on individual securities do not improve price discovery processes but impose serious costs even when the limit band is as wide as 30%.

JEL classifications: G10; G14
Keywords: Price limit; Information asymmetry; Informed traders; Order imbalance; Kuala Lumpur Stock Exchange

* Corresponding author.
E-mail addresses: shchan8318@mail.com (S.H. Chan), kk52@buffalo.edu (K.A. Kim), rheesg@hawaii.edu (S.G. Rhee).

0927-5398/$ - see front matter © 2004 Elsevier B.V. All rights reserved.
doi:10.1016/j.jempfin.2004.01.001

1. Introduction

In the securities markets, daily price limits represent literal boundaries on where individual security prices are allowed to move, often both upward and downward, and they are typically prespecified by a percentage based on a previous trading session's closing price. Such price limit mechanisms are employed in the U.S. futures markets, but they are also used in many stock exchanges around the world, including Austria, Belgium, France, Italy, Japan, Korea, Malaysia, Mexico, Netherlands, Spain, Switzerland, Taiwan, and Thailand (Roll, 1989; Rhee and Chang, 1993; Rhee, 2000). Despite their significant presence, however, Harris (1998) contends that we still do not know enough about these market mechanisms to make informed decisions regarding market regulation. Harris (1998) states that appropriate study samples using U.S. data are difficult to obtain. For example, most price limit studies using U.S. futures market data are only able to employ a few contracts (e.g., Chen, 1998; Ma et al., 1989), which hinders cross-sectional analyses. Consequently, France et al. (1994) state that there are many unanswered questions regarding price limit mechanisms. In our paper, we attempt to provide some much-needed insight into the effects of price limits by investigating transactions data and the limit order book of a stock market that imposes a daily price limit on its individual securities.[1] Specifically, we study the price limit system of the Kuala Lumpur Stock Exchange (KLSE) of Malaysia.

The primary impetus for studying the KLSE is that we wish to study a market with a wide price limit. The KLSE uses a 30% price limit per trading session. This limit band is much wider than most other exchanges. Recently, several papers have examined the impacts of narrow price limits and have found them to be overly restrictive. For example, Chen (1997) examines Taiwan's previous 7% price limit, Chen (1998) and Park (2000) study the relatively narrow price limits of the U.S. futures markets, Kim and Rhee (1997) investigate the narrow limits of the Tokyo Stock Exchange, and Phylaktis et al. (1999) examine the 4–8% price limit of the Athens Stock Exchange. All of these researchers find potential problems with price limits. However, based on their research, we do not really know whether *narrow* price limits are bad, or if price limits per se are bad. A policy question that is often raised is "if price limits are to be adopted, then what is the appropriate level?" In fact, conventional wisdom even suggests that wide price limits may be harmless. For example, the Stock Exchange of Thailand recently increased their price limit from 10% to 30%, and the Korea Stock Exchange recently increased their price limit from 6% to 15%. Thus, the impact of wide price limits remains an important policy issue, and a study of wide price limits brings out practical merits for market regulators and for academicians with regulatory policy

[1] Recently, papers have begun studying the impacts of trading halts on individual stocks. For example, Christie et al. (2002) and Lee et al. (1994) study NASDAQ and NYSE imposed trading halts, respectively, and they both find that trading volume and volatility are higher after the halt. Corwin and Lipson (2000) argue that the lack of liquidity surrounding the halt causes the abnormal volatility. However, while the literature on trading halts can provide some hints into price limit effects, it is important to realize that halts differ from price limits in at least two significant ways. As pointed out by Kim and Sweeney (2002), (i) prices before a halt are not capped as they are with price limits and (ii) trading halts are not mechanically or predictably imposed but are subjectively imposed under certain circumstances (e.g., due to impending news or an order-imbalance).

research interests. The 30% price limit per trading session of the KLSE, therefore, should provide an important first step toward investigating this issue.[2]

Practical considerations also led us to study the KLSE. Among the few stock markets that we wished to investigate, the KLSE was the only one whose transaction data and limit order book data were available to us. Transactions data and/or limit order books from non-U.S. exchanges are difficult to obtain (and decipher), as reflected by the lack of non-U.S. market microstructure studies.[3] Therefore, while this paper contributes to the important expanding market microstructure literature, we also view the fact that our data allow us to study price limit effects at the microstructure level as extremely fortuitous. For example, rather than making inferences on market behavior using only daily data, we will be able to actually observe what happens just prior to, and immediately after, a price-limit-hit. As noted by Lehmann (1989) and Ma et al. (1989), it is difficult to assess price limit effects when relying on only daily data. Finally, as pointed out by Harris (1998), the main reason why price limit studies are "quite scant" is primarily due to the lack of meaningful data.

Aside from examining the transactions data and limit order book of a market that employs a wide price limit, our research makes several other very important contributions. First, we examine the impact of price limits on information asymmetry. A popular justification for price limit mechanisms is that they moderate the effects of uncertainty and/or irrationality in the markets by imposing price boundaries. When an "irrational" price reaches its limit, it supposedly provides all traders with time to assess and to recognize the 'true' or equilibrium price (for example, the Tokyo Stock Exchange states that their price limits represent "time-out" opportunities). In this context, price limits are supposed to mitigate information asymmetry. However, Amihud and Mendelson (1987, 1991) and Gerety and Mulherin (1992) argue that rational equilibrium prices can only be realized through continuous trading. In addition, informed traders with private information may be unable or unwilling to reveal their information when price limits are hit simply because prices are not allowed to move beyond their limits (Kim and Rhee, 1997; Kim and Sweeney, 2002). Hence, price limits may not mitigate information asymmetry, but instead, price limits may actually increase information asymmetry. We investigate this issue by examining the degree of information asymmetry before and after a price-limit-hit. If limit-hits do provide time for information dissemination and revelation, then the degree of information asymmetry should be reduced after the limit-hit. Our results, however, indicate that price-limit-hits do *not* reduce information asymmetry.

Our investigation of information asymmetry naturally leads to another, but related, empirical investigation. When the degree of information asymmetry is high, then there is more noise (uninformed) trading (French and Roll, 1986). Uninformed trading leads to price volatility that is unrelated to fundamental value and thus undesirable. Miller (1991) refers to this harmful volatility as episodic volatility, and Harris (1998) refers to it as transitory volatility. During times of uncertainty, if noise trading intensifies, then it may be useful to curb trading. However, the existence of price limits may just as likely exacerbate the noise-

[2] A secondary reason for studying the KLSE is that we can examine price limit performance within a periodic call market. See Henke and Voronkova (2003) for an extreme example of this setting.

[3] A few exceptions include studies of the Tokyo Stock Exchange (Lehmann and Modest, 1994; Hamao and Hasbrouck, 1995; Ahn et al., 2002a,b), the Taiwan Stock Exchange (Chang et al., 1999), the Paris Bourse (Biais et al., 1995), and recently the Hong Kong Stock Exchange (e.g., Ahn et al., 2001).

trading problem. Kim and Rhee (1997) and Kim and Sweeney (2002) conjecture that information-based trading does not take place during trading sessions when limit-hits occur because rational expectation prices cannot be realized. Instead, informed traders must wait for subsequent trading sessions when price limits have been revised, which mean that information revelation and price discovery is delayed. In the Kim and Rhee (1997) study, they examine price continuation and reversal behavior to see if price limits delay information-based trading. In our investigation, we conduct a much more direct investigation by comparing arrival rates of informed traders before and after a limit-hit. Overall, we find that arrival rates increase after a limit-hit, revealing a delay in information revelation.

A third empirical investigation focuses on order imbalance. On one hand, price-limit-hits can be induced by order imbalances, as one-sided supply or demand will drive prices to the limit (Lehmann, 1989). In other words, order imbalances lead to limit-hits. However, it is also possible that the existence of price limits may actually create or exacerbate order imbalances, which, in turn, lead to limit-hits. For example, traders may suboptimally advance their trades in anticipation of a price-limit-hit, which then accelerates the price movement to the limit-hits.[4] If traders suspect that trading will cease when prices reach the upper (lower) limit, they will then buy (sell) frantically before the price-limit-hit occurs. This behavior suggests that volume will be one-sided prior to the limit-hit. In other words, the price limits themselves could cause order imbalances.

To investigate the impact of price limits on order imbalances, we examine the KLSE order file just prior to and immediately after a limit-hit. We find order imbalances prior to the limit-hit, which is consistent with the view that the impending limit-hit causes order imbalances. For example, for a control group that also experienced a large price change, but without a limit-hit, we do not find a similar order imbalance just prior to its large price change. Further, when we look to the period immediately after limit-hits, we find order imbalance reversals (i.e., an order imbalance exists, but in the other direction). This reversal activity further suggests that traders are attempting to correct for (reverse) their earlier suboptimal trades. If the prehit trades had been not suboptimally executed in anticipation of an impending limit-hit, then an order imbalance during the *post*limit-hit period would not have been observed. Overall, this evidence suggests that limit-hits disrupt the liquidity of the markets and cause order imbalances.

Finally, we should mention that the past empirical work on price limits has focused primarily on volatility. The recent literature is beginning to converge toward the opinion that price limits do not moderate volatility (for example, see Chen's, 1998 and Park's, 2000 studies on U.S. futures markets, Kim's, 2001 study of the Taiwan Stock Exchange, Kim and Rhee's, 1997 study of the Japanese market, and Phylaktis et al.'s, 1999 study of the Greek market). However, if excessive volatility is an outcome of irrational behavior and if price limits exacerbates this, as the literature suggests, then it may be just as important, if not more important, to focus on exactly why price limits cannot reduce harmful volatility. Prior papers do not explicitly investigate this issue, leaving the relationship between price limits and volatility as somewhat ambiguous. In our paper, we provide some important empirical evidence on the link between price limits and excessive

[4] This possibility is analogous to Subrahmanyam's (1994, 1995) gravitational effect hypothesis with respect to trading halts.

volatility. If price limits do not reduce information asymmetry, but instead delays information trading and contributes to the order imbalance, then this reveals how and why price limits are ineffective in reducing transitory volatility. Therefore, what further differentiates our paper from others is that we address important questions that have been raised regarding price limits but not yet been investigated.

The rest of this study is organized as follows. Section 2 discusses the institutional background of the KLSE. Section 3 describes our data and presents summary statistics. Section 4 outlines our empirical design and findings. The last section summarizes the results and presents concluding remarks.

2. Institutional background of the KLSE

Trading takes place 5 days a week (Monday–Friday), except on public holidays and other market holidays (when the Exchange is declared closed by the KLSE Committee). During the study period of 1995–1996, there are two trading sessions per market day: a morning session (9:30 a.m.–12:30 p.m.) and an afternoon session (2:30 p.m.–5:00 p.m.).[5] Orders are entered 30 min prior to the market open both in the morning and afternoon.

Like all other stock exchanges in Asia, the KLSE is a purely order-driven market with no designated market makers or specialists. Trading on the KLSE was fully computerized in 1992, with the full implementation of the System on Computerized Order Routing and Execution (SCORE). SCORE has eliminated the need for a trading floor at the Exchange. Trading is facilitated through the Exchange's 62 member brokerage firms located all over the country. Brokerage companies are equipped with the KLSE's enhanced broker front–end system, WinSCORE, whereby each dealer operates from an integrated terminal providing real-time market information dissemination as well as order and trade routing and confirmation.

The KLSE uses the call market system to determine the matching price. The trading rules are as follows: (i) the match price is where the most number of shares can be transacted; (ii) when there is more than one price at which the most number of shares can be transacted, the price closest to the last traded price shall be the matching price; (iii) all buy orders quoted above the matching price and sell orders quoted below the matching price are executed at the matching price. Unexecuted or partially filled orders at the market's opening are left on the order book for subsequent call market trading. After the opening price is determined, subsequent orders are batched over various time intervals ranging from 1 to 90 s, depending on a security's trading activity.[6] Throughout the trading session, the same call market matching principle is used.

Companies are listed on either the 'main' board or the 'second' board. At the end of 1996, a total of 621 companies (including three property trust funds) were listed on the KLSE. These include 413 companies on the main board and the remaining 208 companies

[5] Effective December 15, 1997, the morning trading session begins at 9:00 a.m. instead of 9:30 a.m.

[6] KLSE's trading staff indicates that the average time interval for the majority of listed stocks is even shorter, ranging from 3 to 10 seconds.

on the second board.[7] Second board companies are generally younger and smaller in capitalization, with the average firm size being about one-sixth of main board companies.[8] At the end of 1996, the KLSE ranked 11th in the world in terms of market capitalization ($307 billion) and 15th in terms of annual turnover (66%).[9]

A daily price limit is a key institutional feature of the KLSE. The price limit is fixed at 30% per trading session: the upper [lower] limit price for the current trading session is equivalent to 130% [70%] of the closing price of the last trading session. Therefore, if a stock consecutively hits the upper limit price in the morning and the afternoon sessions, the price could jump up [down] by as much as 69% [51%] in a day. As mentioned previously, this price limit band is extremely wide as compared to other stock exchanges: for example, Austria (5%), China (10%), France (7%), Greece (4–8%), Korea (15%), and Taiwan (7%).

3. Data and summary statistics

In this study, we use real-time transaction data (posttrade files) and the order flow data (pretrade files) of the KLSE during a 2-year period from January 3, 1995 to December 31, 1996. Due to the wide price limit band of $\pm 30\%$, price limit-hits are not a frequent affair. In total, we identify 170 cases of limit-hits during our study period.[10] A total of 110 limit-hits occurred during the morning trading session, and the remaining cases were recorded in the afternoon trading session.

To conduct our study, we form two stock groups. The first stock group includes those stocks that actually hit the 30% limit, and they are denoted as LHG (Limit-hit Group). For our second stock category, we identify those stocks that also experienced a dramatic price change (by at least 15%) from the previous session's closing price, but they do *not* hit a price limit. This latter stock group is denoted NHG (No-hit Group), and it represents a very important control sample as we only identify these stocks during sessions when a limit-hit occurs. Furthermore, as Kim and Rhee (1997) point out, effects associated with limit-hits can be associated with either (1) the price limit or (2) the large price change.[11] For example, if we observe delays in the arrival of informed trading for LHG stocks, we cannot be sure if this delay is due to the limit-hit or if it is due to the large price change. Therefore, by identifying both LHG and NHG stocks, we have created study samples where all stocks experienced a large price change, but only some of the stocks actually hit their price limits. Any notable differences between LHG stocks and NHG

[7] It should be noted that once foreign ownership of a company reaches 30%, the firm's shares are then traded on a Foreign Board. However, there are only a few such companies, e.g., Public Bank and Malaysian International Shipping Corporation (Kim, 1996).

[8] In addition, more than 100 securities of Malaysian companies were traded on Singapore's over-the-counter market, Clob International, during the study period, but their volume was not significant (Kim, 1996).

[9] See *Emerging Stocks Factbook 1997* of the International Finance Corporation.

[10] Of the 170 cases, only six of them hit the lower limits while the rest hit the upper limit. This is not surprising considering that KLSE enjoyed a bull market trend during the study period, especially in 1996.

[11] Lehmann (1989) and Miller (1989) make a similar point.

Table 1
Sample sizes

Sample	Limit-hit Group (LHG)								No-hit Group (NHG)							
Board	Main Board				Second Board				Main Board				Second Board			
Year	1995		1996		1995		1996		1995		1996		1995		1996	
Session	M	A	M	A	M	A	M	A	M	A	M	A	M	A	M	A
Number of cases	2	3	21	5	2	2	44	19	1	0	41	12	4	4	86	27
Subtotal	98								175							

Two sets of stocks have been identified. Limit-hit group (LHG) contains 98 stocks that hit the 30%—limit during a particular trading session, whereas no-hit group (NHG) contains 175 stocks that experience a price change of at least 15% but less than 30% of the previous session closing price. This table presents the number of cases in each of the two sample groups during the study period, 1995–1996, tabulated by board, year, and trading session. Main Board stocks are more established firms, including blue chip firms, while Second Board stocks are younger and smaller in market capitalization. Sessions M and A stand for morning (9:30 a.m.–12:30 p.m.) and afternoon (2:30 p.m.–5:00 p.m.) trading sessions, respectively.

stocks can then be associated with the price limit effect rather than a large-price-change effect.[12]

In selecting the final study samples of both stock groups, a number of factors were considered. First, to conduct meaningful analyses, we require each stock to have at least 100 trades within each trading session.[13] We also excluded stocks with limit-hits over consecutive sessions.[14] These screens reduced the LHG sample to 101 cases, out of which 98 cases were upper limit-hits. For our NHG sample, we identify 175 cases, out of which there were zero cases of price declines. Therefore, our final LHG sample only consists of upper limit-hit stocks (n=98), and our final NHG sample only consists of price increases (n=175). Although some earlier published work suggests that upper and lower limit-hits affect stocks in similar ways, we importantly acknowledge that samples that only include price *increases* represent a weakness to our study.[15]

The sample sizes of the two stock categories are presented in Table 1 and broken down according to board (main board vs. second board), year (1995 vs. 1996), and trading session (morning vs. afternoon). From this table, we observe that: (i) a majority of the limit-hits occur during 1996 (89 out of the 98 cases), (ii) the second board constitutes about two-thirds of the LHG sample, and (iii) 70% of the limit-hits occur in the morning

[12] For the NHG category, we considered tighter selection criterions such as 20% and 25% price changes, but these alternative screens yielded insufficient (for statistical testing) sample sizes. However, results using an 18% cutoff for NHG stocks yield the same findings as our reported findings, suggesting that tighter selection criterions may not produce different results. We interpret the robustness of our findings to suggest that the difference between a 15% and a 30% price change is less significant than the difference between, say, a 1% and a 16% price change. Results using an 18% cutoff for NHG stocks are available from the authors upon request.

[13] The number of trades during each limit-hit session varies from a single trade to a maximum of 7314 trades.

[14] Without this screen, the results are qualitatively similar to those reported. However, because we will conduct an event-type study, we restrict our sample to where the event takes place in a single session to provide unambiguous results and to make comparisons to our control group meaningful.

[15] For example, Kim and Rhee (1997) find qualitatively similar results when comparing up-hit and down-hit events on the Tokyo Stock Exchange. However, given that an important regulatory aspect with regard to price limits is the issue of market quality when the market is crashing, specifically and carefully studying down-hit effects represent a fruitful future research endeavor.

Table 2
Descriptive statistics

	Mean	Standard deviation	Max	Median	Min
Panel A: limit-hit group (LHG; n=98 stocks)					
Trading volume (in 1000 shares)	3502	5707	33,004	1565	57
Trading value (in RM million)	32.62	44.85	257.72	17.17	0.56
Trade frequency (in number of trades)	1302	1386	7314	892	56
Trading volume per trade (in shares)	2177	1271	9636	1818	517
Trading value per trade (in RM)	25,963	24,505	192,845	19,306	3008
Turnover ratio	0.0832	0.0855	0.4283	0.0590	0.0014
Capitalization (in RM million)	525	628	3532	271	74
Return volatility	0.0505	0.0228	0.1472	0.0439	0.0210
Panel B: no-hit group (NHG; n=175 stocks)					
Trading volume (in 1000 shares)	1509	1854	13,643	957	51
Trading value (in RM 1 million)	14.40	16.72	111.60	8.48	0.86
Trade frequency (in number of trades)	684	558	3700	514	102
Trading volume per trade (in shares)	1979	948	8977	1790	418
Trading value per trade (in RM)	20,474	15,993	109,928	15,444	5373
Turnover ratio	0.0517	0.0528	0.3275	0.0336	0.0007
Capitalization (in RM million)	426	511	3582	268	81
Return volatility	0.0439	0.0155	0.1472	0.0431	0.0164

This table provide summary statistics on session trading volume, trading value, trade frequency, trading volume and value per trade, the session turnover ratio, and market capitalization for two groups: limit-hit group (LHG) and non-hit group (NHG). The session turnover ratio is computed by using the trading volume (in shares) during Session S_0 (the event session) divided by the total number of shares outstanding for the stock. Market capitalization is the product of the number of shares outstanding and the year-end share price. Return volatility is the standard deviation of daily stock returns, excluding observations when daily return is greater than 15%.

trading session.[16] Because the observations are not evenly distributed across boards, years, and trading sessions, we will incorporate dummy variables when we conduct our analyses to capture the possibility of an inherent effect associated with trading location (board), period (year), and time of day (session).

Table 2 reports descriptive statistics for our two stock groups. During the session of the large price change, LHG stocks have greater trading activities than NHG stocks. Specifically, LHG stocks record, on average, higher trading volume and value, a larger number of trades, and higher turnover ratios than NHG stocks. LHG stocks are also larger than NHG stocks with regard to market capitalization, and they experience greater return volatility.[17] Therefore, to incorporate the possibility that differences in trading activity, firm size, and volatility may explain differences between LHG and NHG stocks rather than the limit-hits themselves, we include a trading activity variable, a firm size variable, and a

[16] During the 2-year study period, 1995–1996, the Malaysian stock market experienced an unusual bull market trend. Main board stocks yielded an annual return of 2% in 1995 and 36% in 1996, whereas second board stocks produced an annual return of 43% in 1995 and 93% in 1996.

[17] Our return volatility measure is the standard deviation of daily returns. In calculating these standard deviations, we exclude observations where the return is greater than 15% so that our volatility measure captures “normal” volatility.

Table 3
Duration of limit-halt

	Sample size	Mean (min)	Standard deviation (min)	Minimum (min)	Median (min)	Maximum (min)
Total sample	98	63.16	60.30	0.20	40.09	178.88
Morning session	69	70.99	62.21	0.33	54.75	178.88
Afternoon session	29	44.53	51.82	0.20	14.65	146.48

Summarized in this table is the duration of the limit-halt as measured from the first limit-hit occurrence until the last moment when the price still remains at the limit (i.e., prior to the emergence of a new price) for the 98 limit-hit (LHG) stocks. The summary statistics are reported by trading sessions.

volatility variable as controls when we conduct our comparative analyses between the two stock groups.[18]

Once stock prices hit the limit, they are not allowed to move beyond the limits. However, trades may still be executed if there are matching buy and sell prices during each call market batch-matching. Table 3 reports on the duration of the limit-hit for LHG stocks. Within the same trading session when limit-hit occurs, duration is measured from the time when the stock first hits its limit to the last moment the price stays at the limit, i.e., prior to the emergence of a new price or until the close of the trading session. There are also instances of multiple limit-hits within a session. For these instances, we consider the limit-hit to be in effect from the first limit-hit until the last moment the price stays at the last limit-hit or until the close of the trading session, although there were price bounces.[19]

As summarized in Table 3, the duration of limit-hits ranges from 0.20 to 179 min with an average of 63 min. Limit-hits occurring in the morning trading session tend to last longer than those that occur in the afternoon session (71 vs. 45 min). This may be due to the morning trading session being 30 min longer than the afternoon session. Also, limit-hits that occur in the earlier part of the trading session tend to have longer limit-hits.[20] Due to the large variation in duration, we cannot neglect the possibility that it may be an important variable when we conduct our analyses. Hence, a duration variable is also included when we conduct our analyses on limit-hits.

4. Empirical test design and findings

4.1. Test design

To conduct our empirical investigations, we use an event-study type approach. The event session when a limit-hit occurs is defined as S_0, whereas the session prior to S_0 is signified by S_{-1}, and the session immediately after the limit-hit by S_{+1}. Therefore, we can

[18] Kim and Limpaphayom (2000) find that stocks that frequently hit price limits are those stocks that have more volatility and trading activity but have smaller market capitalizations.

[19] The bounces in prices within the limit-hit are considered to be due to bid-ask bounce or transitory prices moving towards equilibrium.

[20] The correlation between the time-length from the session opening to the first limit-hit and the duration of limit-hit is significantly negative at -0.65.

conveniently form three subperiods surrounding each limit-hit: (1) the prehit period, which is defined from the beginning of S_{-1} to the first limit-hit in S_0; (2) the limit-hit period, which takes place in S_0; and (3) the posthit period, which is defined from the end of the limit-hit period in S_0 to the end of S_{+1}. For NHG, S_0 is the session of the large price change, which is defined by a change of at least 15% but less than 30%. In addition, for NHG, S_0 is also the same session where another stock experienced a limit-hit. Therefore, the identification and length of the preperiods and postperiods for NHG stocks are also determined by when limit-hits take place.

We wish to examine if price limits affect (i) the degree of information asymmetry; (ii) the arrival rate of informed traders; and (iii) the extent of order imbalances. In order to conduct these investigations, therefore, we will compare each of these characteristics from the prehit period to the posthit period to see how limit-hits affect each one of them. Furthermore, to determine whether or not the change is significant, we will use pre-to-postchanges of NHG stocks as a benchmark. Just like with LHG stocks, NHG stocks also experience a large price change during the same session, but NHG stocks do not experience a limit-hit. Thus, if we observe an effect in LHG stocks that is absent in NHG stocks, then the effect can be associated to the limit-hit.

However, we are fully aware that simply comparing these pre-to-posthit changes between LHG and NHG will lead to premature conclusions because, as we have seen from the summary statistics, there are many differences between LHG and NHG stocks. For example, we may observe declines in information asymmetry for LHG that is larger than declines in information asymmetry for NHG. At first blush, this may imply that limit-hits improved information asymmetry; however, because LHG stocks trade more frequently, because LHG stocks are bigger, etc., we cannot simply associate the improvements in information asymmetry to the limit-hit. Therefore, to ensure that the change in information asymmetry, arrival rates of informed traders, and order imbalance level is associated with the limit-hit itself, we model these changes as dependent variables in a regression setting with control variables. By doing this, we conduct a more meaningful mean-difference test between the pre- and posthit periods. Specifically, the following regression model is used:

$$\Delta_j = \alpha_0 + \alpha_1\,\mathrm{LHG}_j + \alpha_2\,\mathrm{BOARD}_j + \alpha_3\,\mathrm{YEAR}_j + \alpha_4\,\mathrm{SESSION}_j + \alpha_5\,\mathrm{TURNOVER}_j + \alpha_6\,\mathrm{SIZE}_j + \alpha_7\,\mathrm{DURATION}_j + \alpha_8\,\mathrm{VOLATILITY} + \eta_j, \tag{1}$$

where Δ_j denotes the vector of the changes in one of the following dependent variables: information asymmetry, arrival rates of informed traders, and order imbalance from the pre- to posthit periods for stock j. LHG, BOARD, YEAR, and SESSION are dummy variables equal to 1 if stock j belongs to the limit-hit group (LHG), if stock j belongs to the second board, if the year is 1996, and if the trading session is the afternoon session, respectively, and 0 otherwise. TURNOVER is defined as the combined trading volume (in number of shares) in the pre- and posthit periods divided by the total shares outstanding. SIZE captures a potential firm size effect and is defined as the natural logarithm of market capitalization. DURATION is the natural logarithm of the duration of the limit-hit, in minutes, from the first limit-hit occurrence until the last moment when the price stays at the limit. For NHG stocks, DURATION is equal to zero.

VOLATILITY is the standard deviation of daily stock returns, excluding observations when daily returns are greater than 15%. In the context of control variables, therefore, any time the LHG dummy variable is significant, we can then attribute significant pre-to-posthit changes with the limit-hit. A more detailed discussion focusing on each of our three investigations follows.

4.2. Information asymmetry

Price limit proponents suggest that limit-hits provide time for information resolution and transmission. Hence, limit-hits are posited to reduce information asymmetry and uncertainty in the markets. If price limits are effective in this regard, then the degree of information asymmetry should improve (i.e., decrease) after limit-hits. Thus, the following null hypothesis can be tested:

H1. Price-limit-hits do not improve information asymmetry.

In measuring information asymmetry, we start with the Bayesian model of intraday price formation. This model was designed and empirically tested by Madhavan and Smidt (1991) and later applied by Choi and Subrahmanyam (1994).[21] In their model, the expected value of a stock is expressed as a combination of the prior mean, which reflects public information, and a noisy signal regarding private information contained in the current order flow. Formally, a revision in transaction price for stock j is given by:

$$\Delta\text{PRICE}_{jt} = \beta_{0+}\beta_{1j}q_{jt} + \beta_{2j}D_{jt} + \beta_{3j}D_{jt-1} + \varepsilon_{jt} - \rho_j\varepsilon_{jt-1}, \tag{2}$$

where ΔPRICE_{jt} represents the change in two consecutive transaction prices from time $t-1$ to t; q_{jt} is the signed transaction size, and D_{jt} is an indicator variable equal to+1 or -1 if the current price change was an increase or decrease, respectively. The ε's are white noise error terms, and ρ_j, which denotes the first-order error autoregressive correlation, is treated as a parameter for estimation.

Two caveats in utilizing Eq. (2) for the Malaysian market deserve to be mentioned.[22] First, Madhavan and Smidt's (1991) Bayesian model assumes that New York Stock Exchange's specialists provide liquidity, whereas no market makers exist in the Malaysian market. A critical question then is who provides liquidity in an order-driven market in the absence of market markers. Based on Taiwan Stock Exchange's call market-based transaction data, Lee et al. (2004) report that all trader types are successful de facto market makers, with large domestic investors conducting the most informed trades and large individuals serving as noise or liquidity traders. Additionally, implicit in many papers on

[21] Hasbrouck (1991) provides another useful measure of information asymmetry that relies on bid and ask quotes. However, we are unable to use his approach because KLSE's bid and prices are not available to us. Under its call auction trading system, the KLSE tracks the best bid and ask prices of the unexecuted orders after each trade is executed. These arrangements are typical of any order-driven markets where no market makers exist regardless of whether stock exchanges employ the call auction method of the continuous auction method. As discussed in the latter part of the empirical section, the only bid and ask data available to us are the best bid and ask prices of unexecuted orders after the last trade of the day is executed.

[22] We are grateful to a referee for raising these issues. The two caveats are also applicable to the application of Easley et al. (1996) in the following section.

spread components is that limit order traders are assumed to provide liquidity, and the Kuala Lumpur Stock Exchange is no exception to this reality in applying the Madhavan and Smidt model to the Malaysian market data.[23]

Second, the usual buy/sell classification scheme by Lee and Ready (1991) is not readily applicable to the call market method since all orders are batched for execution at a single price. As a result, there are multilateral trades at one price (Pagano and Schwartz, 2003). Ideally speaking, we would like to have sequentially ordered buys and sells as in the continuous auction method. In the call market environment, however, we have opted to examine whether the price change is an increase or a decrease from the immediately preceding executed price rather than sorting executed trades into buyer- or seller-initiated trades. One mitigating factor that minimizes potential errors in our approach is the extremely short batching period at the KLSE, which usually ranges from 3 to 10 s, before a new matching price is determined.[24] The data on buy and sell orders available from the KLSE limit order book were a valuable in our effort in assessing the direction of a security's price movement.

From the Madhavan and Smidt (1991) model, we can extract an information asymmetry measure by calculating $\text{SYMM}_j=(|\beta_{3j}|/\beta_{2j})$. Because β_3 is the parameter coefficient for D_{jt-1}, which reflects prior beliefs, SYMM measures the weight placed by liquidity traders on the information content of the order flow. If order flow is uninformative (because the ratio of private to public information is small), then the weight is near unity. Conversely, with severe information asymmetries, the liquidity providers' beliefs are very sensitive to order flow, and the weight is negligible. Since no market markers exist on the KLSE, traders that place public limit orders are the ones providing liquidity on the KLSE. In other words, the larger the value of SYMM, the lower the information asymmetry.

We execute Eq. (2) separately for the pre- and posthit periods for both LHG and NHG stocks.[25] If the price limit rule is effective in improving information asymmetry, then we will expect the values of SYMM to be higher (which implies lesser information asymmetry) in the post-limit-hit period for the LHG stocks. Summarized below are our estimates of information asymmetry for both LHG and NHG stocks. From these estimates,

Period		LHG Stocks	NHG Stocks
Prehit period	Mean	0.7078	0.7426
	Median	0.7285	0.7450
Posthit period	Mean	0.7519	0.7747
	Median	0.7717	0.7877

we see that information asymmetry in the KLSE is significant, as the SYMM ratio is significantly less than one. With regard to our study's particular focus, we note that

[23] A most comprehensive review is found from Huang and Stoll (1997), and a recent application of bid-ask spread decomposition in an order-driven market is found in Ahn et al. (2002a,b).

[24] In a study relevant to this issue, Lang and Lee (1999) compile empirical evidence from the Taiwan Stock Exchange data that the call market method converges to the continuous auction method as trading frequency increases.

[25] We require at least 30 prices for model estimation; otherwise SYMM is treated as a missing value.

SYMM increases during the posthit period (i.e., information asymmetry decreases), and it appears that the increase in SYMM is slightly larger for LHG stocks.

However, to determine whether or not increases in SYMM for the LHG stocks are specifically associated with the limit-hit, we use regression analysis. To identify the changes in the degree of information asymmetry from the pre- to posthit period, we measure $\Delta\text{SYMM}_j = \log(\text{SYMM}_{j,\text{post}}/\text{SYMM}_{j,\text{pre}})$. These calculations are reported in Table 4.

As summarized in Panel A of Table 4, both LHG and NHG stocks report mean [median] increases in SYMM of 7.03% [4.91%] and 5.69% [2.86%], respectively. Because both groups of stocks record increases, the reduction in information asymmetry cannot be attributed to price limits alone. In addition, we cannot say with confidence that the larger improvement in information asymmetry for LHG stocks is due to the limit-hit because

Table 4
Information asymmetry: regression results

A. Summary statistics of ΔSYMM

	Mean	Median
LHG Stocks	0.0703	0.0491
NHG Stocks	0.0569	0.0286

B. Regression results

	Coefficients	t-statistics
Intercept	−1.1853	−1.507
LHG	0.0247	0.663
BOARD	0.0852	1.562
YEAR	−0.0102	−0.141
SESSION	−0.0698	−2.133**
TURNOVER	−0.2689	−1.229
SIZE	0.0651	1.640
DURATION	−0.0009	−0.100
VOLATILITY	−1.0411	−0.933
R^2	0.0356	
F-statistic	1.10	
N	248	

Summarized in this table are the results of the following regression:

$$\Delta\text{SYMM}_j = \alpha_0 + \alpha_1\ \text{LHG}_j + \alpha_2\ \text{BOARD}_j + \alpha_3\ \text{YEAR}_j + \alpha_4\ \text{SESSION}_j + \alpha_5\ \text{TURNOVER}_j + \alpha_6\ \text{SIZE}_j + \alpha_7\ \text{DURATION}_j + \alpha_8\ \text{VOLATILITY}_j + \eta_j,$$

where ΔSYMM_j denotes the change in the degree of information asymmetry from the pre- to posthalt-period, LHG, BOARD, YEAR, and SESSION are indicator variables which take the value of 1 if the stock belongs to the limit-hit group, if the stock belongs to the second board, if the year is 1996, and if the trading session is the afternoon session, and 0 otherwise. TURNOVER is defined as the combined trading volume (in number of shares) in the pre- and posthalt-periods divided by the total shares outstanding. SIZE represents firm size and is defined as the natural logarithm of year-end market capitalization. DURATION is the natural logarithm of the duration of limit-halt in minutes from the first limit-hit occurrence until the last moment when the price still stays at the limit. VOLATILITY is the standard deviation of daily stock returns, excluding observations when daily returns are greater than 15%. Parameter coefficient estimates and heteroscedastic-consistent t-statistics are reported. Statistical significance at the 5% level is denoted by **.

there are several other differences between LHG and NHG stocks. Therefore, to conduct a meaningful mean difference test, we rely on the multiple regression as defined by Eq. (1), and we use $\Delta SYMM_j$ as the dependent variable.[26] If the reduction in the degree of information asymmetry for LHG stocks is indeed caused by price limits, then the coefficient for the LHG dummy variable should be positively significant. The regression results are reported in Panel B of Table 4. The estimated coefficient of LHG is positive (0.0247) but not significant. Thus, the result does not support the view that price limits reduce information asymmetry. The estimated coefficient of SESSION is negative, signifying that limit-hits in the afternoon trading session do not necessarily reduce information asymmetry. The turnover ratio, board listing, size, volatility, and year do not show any significant impact on the change in information asymmetry. Overall, based on these results, we cannot reject the null hypothesis, H1. While we do observe reductions in information asymmetry, we cannot associate it with the limit-hit.

Before leaving this section, we provide results from an alternative test on information asymmetry. Although KLSE-released bid and ask prices after each trade are not available to us, we have access to data on the best *unexecuted* bid and ask prices at each trading day's close. Using these data, we calculate percent "spread" measures before and after limit-hit days. Overall, on the day before the limit-hit day, on the limit-hit day, and on the day after the limit-hit day, the spreads are 1.07%, 1.03%, and 1.09%, respectively. There are no statistically significant differences among these spreads. These results further suggest that price limits do not improve information asymmetry, and that they do not enhance market quality from a transaction cost perspective.[27]

4.3. Informed trades

An impending limit-hit may keep informed traders away due to the price constraints that exist during the prehit period. Here, price limits would delay information revelation and price discovery because informed traders enter the market *after* a limit-hit has taken place. Thus, the following null hypothesis can be tested:

[26] Note that SYMM is a ratio of coefficients from Eq. (2). Therefore, if there is a measurement error problem with the explanatory variables in Eq. (2), then it is possible that the SYMM variable for any particular security is misspecified. However, even if we use SYMM as a dependent variable in a separate regression, we will still obtain estimated coefficients that are asymptotically consistent. Assume that the observed dependent variable Y (which is estimated as $\log(SYMM_{j,post}/SYMM_{j,pre})$ in our regression) equals the true Y^* plus error v. Then, we can rewrite this equation as $Y=Z\gamma+\varepsilon+v$ since the true equation is $Y^*=Z\gamma+\varepsilon$. Then, $Y=Z\gamma+\mu$, where $\mu=\varepsilon+v$, and $\mathrm{cov}(Z, \mu)=\mathrm{cov}(Z, \varepsilon+v)=0$. Thus, the assumption of OLS is not violated. Furthermore, because our study period is pre-selected to be one where the price is approaching the limit, there is a chance that OLS assumptions are violated for this particular reason (e.g., the residual could have a non-zero mean). We conducted various diagnostic checks on Eq. (2), but we find no violations of OLS assumptions. We believe the reason for this is that Eq. (2) can be viewed as an "improvement" over straight-forward OLS, which is a contention also made by Madhaven and Smidt. For example, following Madhavan and Smidt (1991), Eq. (2) incorporates a first-order error auto-regressive term. Without this term, for example, Durbin–Watson statistics reveal significant auto-correlation. However, by including the auto-regressive factor, our error terms are white noises with zero mean residuals. The residuals' means are mostly around zero and their t-statistics are not significant, indicating that we cannot reject the null hypothesis of zero means. Residual plots confirm the same. The data and the computer programs are available from the authors upon request.

[27] We would like to thank a referee for her (his) suggestion that a measure of transaction costs be examined.

H2. The arrival rate of informed traders remains unchanged after limit-hits.

The arrival rate of informed traders is one of four parameters in a model developed and tested by Easley et al. (1996). Specifically, in the Easley et al. (1996) model, the probability of information-based trading in a stock is a function of four parameters: α=the probability of an information event; δ=the probability that the new information is bad news; μ=the arrival rate of informed traders; and ε=the arrival rate of uninformed traders. Using the total number of buy and sell orders, each of these parameters can be estimated from a likelihood function. Thus, their model provides a convenient and readily applicable estimation method for the arrival rate of informed traders. The data used for our investigation are obtained from the KLSE order (pretrade) file that consists of the entire public limit order book of buy and sell orders during the 2-year study period. In the absence of market makers or dealers, liquidity on the KLSE is provided solely by public limit orders.

Trade arises from both informed traders (those who have seen any signal) and uninformed traders. On any day, arrivals of uninformed buyers and uninformed sellers are determined by independent Poisson processes. Uninformed buyers and uninformed sellers each arrive at rate $\boldsymbol{\epsilon}$ where this rate is defined as per minute of the trading day. On days for which information events have occurred, informed traders also arrive. In their model, Easley et al. (1996) assume that all informed traders are risk neutral and competitive. If a trader observes a good signal, then the profit maximizing trade is to buy the stock; conversely, he will sell if he observes a bad signal. It is assumed that the arrival of news to one trader at a time, and his subsequent arrival at the market, also follows a Poisson process. The arrival rate for this process is μ. All of these arrival processes are assumed to be independent. Therefore, on any day, Easley et al. determine that the arrivals of both informed and uninformed traders follows independent Poisson processes. While the Easley et al. measure is estimated over a number of days, we adapt their measure to a few hours by tallying the number of buy and sell orders during each 2-min interval. During any interval or part of the day, the arrival of both informed and uninformed traders will be determined by independent Poisson processes as well.

Using the Easley et al. (1996) model specification, the parameters of the trade process for each stock in our sample are then estimated by maximizing the following likelihood function which is conditional on the stock's order flow data:

$$L(M|\boldsymbol{\theta}) = \Pi_{i=1 \text{ to } I} L(\theta|B_i,\ S_i), \tag{3}$$

where M is the data set, $\boldsymbol{\theta}$ is the vector of the four parameters estimated in the Easley et al. model, and B and S are the number of buys and sells in each i 2-min intervals over I days, respectively.[28] From this procedure, we extract the parameter estimate, μ, that measures the arrival rate of informed traders.

[28] The likelihood is defined as:

$$L((B,S)|\theta) = \left[(1-\alpha)^* e^{-\varepsilon\ T}(\varepsilon T)^B/B!\right] e^{-\varepsilon T}(\varepsilon T)^S/S! + \left[\alpha\delta^* e^{-\varepsilon T}(\varepsilon T)^B/B!\right] e^{-(\mu+\varepsilon)T}[(\mu+\varepsilon)T]^S/S!$$
$$+ \left[\alpha(1-\delta)^* e^{-(\mu+\varepsilon)T}[(\mu+\varepsilon)T]^B/B!\right] e^{-\varepsilon T}[\varepsilon T]^S/S!$$

In estimating the parameters of the above equation, we use the NLP procedure in SAS to maximize the likelihood function. The SAS/ETS User's Guide (SAS Institute, 1993) provides additional information on this procedure.

Summary statistics on the arrival rate of informed traders, μ, is presented below for both LHG and NHG stocks. From these statistics, it appears that price limits postpone the arrival of informed traders, as their arrival rate increases for LHG stocks during the posthit period. For NHG stocks, the arrival rates remain relatively constant from one period to the next (in fact, there even appears to be some decrease in arrival rates for NHG stocks).

Period		LHG Stocks	NHG Stocks
Prehit period	Mean	9.4691	4.7958
	Median	7.3493	4.1591
Posthit period	Mean	10.6179	4.3160
	Median	9.0130	3.1268

To ensure that it is the limit-hit itself that is causing the delay in the arrival of informed trading for LHG stocks, we first compute the change in the arrival rate of informed traders from the pre- to posthit periods for each stock. This change, denoted by $\Delta \text{ARIV}_j = \log(\mu_{j,\text{post}}/\mu_{j,\text{pre}})$, is then used as a dependent variable in Eq. (1) to conduct a mean difference test between LHG and NHG stocks. The regression result is presented in Table 5.

As summarized in Panel A of Table 5, LHG stocks show a mean [median] increase of 16.04% [23.4%] in the arrival rates of informed traders, while the NHG stocks show a 6.70% [22.48%] decline. Regression results are presented in Panel B. From the regression results, we observe that the estimated coefficient of LHG is positive and significant. Thus, we reject the null hypothesis H2 because (i) we do observe an increase in the arrival rate of informed traders after limit-hits and (ii) the significant LHG coefficient from the regression results reveals that this increase is specifically associated with the limit-hit. Some informed traders have to wait for the resumption of trading to incorporate their private information into stock prices. Thus, it is during the posthit period, when new limits are allowed, that the informed traders enter the markets and trade on their private information. This finding indicates that price limits do not serve its main purposes of facilitating information resolution and reducing information asymmetry. Instead, price limits appear to delay the arrival of information, which delays the price discovery process.

4.4. Order imbalance

Price limit advocates argue that limit-hits provide time to allow the market to absorb massive one-sided volume (i.e., to correct order imbalances). However, a potentially ironic outcome of price limits is that they could just as easily be the cause of the order imbalance. If traders know that trading will be stopped when prices reach the upper [lower] limit, they will then buy [sell] frantically before the circuit breaker is triggered, this suggests that volume will be one-sided, which, in turn, will actually accelerate the price movement to the limit, exhibiting the magnet effect. During the posthit period, when limit-prices are revised, traders must now submit buy and sell orders based on equilibrium price beliefs, which results in an equal number of buys and sells, and no order imbalance should be observed. In reality, however, this may not happen. Thus, any order imbalance reversals subsequent to limit-hits again reveal the existence of suboptimal orders during the prehit

Table 5
Arrival rate informed traders: regression results

A. Summary statistics of ΔARIV

	Mean	Median
LHG Stocks	0.1604	0.2340
NHG Stocks	−0.0670	−0.2248

B. Regression results

	Coefficients	*t*-statistics
Intercept	0.8303	0.346
LHG	0.2612	2.100**
BOARD	−0.2039	−1.166
YEAR	−0.1551	−0.633
SESSION	0.0534	0.361
TURNOVER	−0.5925	−0.566
SIZE	−0.0306	−0.245
DURATION	0.0356	1.000
VOLATILITY	−2.3431	−0.800
R^2	0.0312	
F-statistic	0.92	
N	237	

Summarized in this table are the results of the following regression:

$$\Delta \text{ARIV}_j = \alpha_0 + \alpha_1 \text{ LHG}_j + \alpha_2 \text{ BOARD}_j + \alpha_3 \text{ YEAR}_j + \alpha_4 \text{ SESSION}_j + \alpha_5 \text{ TURNOVER}_j + \alpha_6 \text{ SIZE}_j + \alpha_7 \text{ DURATION}_j + \alpha_8 \text{ VOLATILITY}_j + \eta_j,$$

where ΔARIV_j denotes the change in the arrival rate of informed traders from the pre- to posthalt-period, LHG, BOARD, YEAR, and SESSION are indicator variables which take the value of 1 if the stock belongs to the limit-hit group, if the stock belongs to the second board, if the year is 1996, and if the trading session is the afternoon session, and 0 otherwise. TURNOVER is defined as the combined trading volume (in number of shares) in the pre- and posthalt-periods divided by the total shares outstanding. SIZE represents firm size and is defined as the natural logarithm of year-end market capitalization. DURATION is the natural logarithm of the duration of limit-halt in minutes from the first limit-hit occurrence until the last moment when the price still stays at the limit. VOLATILITY is the standard deviation of daily stock returns, excluding observations when daily returns are greater than 15%. Sample sizes vary due to missing observations. Parameter coefficient estimates and heteroscedastic-consistent t-statistics are reported. Statistical significance at the 5% level is denoted by **.

period, which, in turn, caused a magnet effect. To examine this possibility, we will test the following null hypothesis:

H3. The order imbalance remains unchanged after limit-hits.

We measure order imbalance, IMBAL, as the ratio of buy orders to total orders, with regard to the number of shares. If this ratio is 0.5, then demand equals supply. A ratio greater than 0.5 implies that there are more buys than sells, creating an upward price pressure. During the prehit period, if price limits induced order imbalances, then we expect LHG stocks to have an IMBAL ratio greater than 0.5.[29] During the posthit period,

[29] We find a significant correlation between the prehit order imbalance and LHG dummy variables, which is direct evidence that the prehit order imbalance is a result of the price limit imposed.

however, LHG stocks are expected to experience a significant order imbalance in the other direction (more sells than buys) as traders will try to reverse their earlier suboptimal trades. For NHG stocks, in the absence of an impending limit-hit, there should be no order imbalance during the prehit period and no subsequent order imbalance reversal.

Summarized below are the estimates of order imbalance for both LHG and NHG stocks. As expected, LHG stocks have a mean IMBAL ratio of 0.5386 in the prehit period, and this ratio declines to 0.4515 in the posthit period. The order imbalance *prior to* the limit-hit suggests a "magnet" effect (i.e., where suboptimal trades are being made in anticipation of a limit-hit), and the subsequent order imbalance reversal *after* the limit-hit lends further support that a magnet effect did take place during the prehit period.[30] Interestingly, NHG stocks show IMBAL ratios less than 0.5 during both the pre- and posthit periods, but there is no order imbalance reversal from the prehit to the posthit period, consistent with our expectations.[31]

Period		LHG Stocks	NHG Stocks
Prehit period	Mean	0.5386	0.4622
	Median	0.5111	0.4567
Posthit period	Mean	0.4515	0.4228
	Median	0.4356	0.4216

To verify that the LHG's order imbalance reversal is specifically associated with the limit-hit, we first estimate a new variable, $\Delta\text{IMBAL}_j=\log(\text{IMBAL}_{j,\text{post}}/\text{IMBAL}_{j,\text{pre}})$, where ΔIMBAL_j represents the change in order imbalance from the prehit period to the posthit period, and it is used as the dependent variable in model (1). If the limit-hit did cause the order imbalance reversal, which would support a magnet effect, then the estimated coefficient for the LHG dummy variable should be negative and significant. The regression result is presented in Table 6.

As summarized in Panel A of Table 6, the cross-sectional mean [median] of ΔIMBAL_j is −16.22% and −8.36% for the LHG and NHG stocks, respectively. Because both groups show a decline in the degree of order imbalance, the critical question is whether the LHG variable in the multiple regression will have a significant negative coefficient. As reported in Panel B, the limit-hit is responsible for the order imbalances experienced by LHG stocks during the pre- and posthit periods. Thus, we may infer that price limits do not achieve the objective of cooling off the market. Rather, a magnet effect exacerbates the degree of order imbalance. The estimated coefficients of both SESSION and TURNOVER are positive and significant, indicating that limit-hits in the afternoon trading session and stocks with higher turnover experience a significant increase in buying pressure during the posthit periods. The positive coefficient on the SESSION variable is interesting, which may be explained from two different angles: first, a desire to be "long" in an appreciating stock during which the overnight nontrading period moderates an investor's desire to reverse their suboptimal buy orders even if the stock price appreciation is irrational; and second,

[30] Cho et al. (2003) report a significant magnet effect when the prices reach the upper limits but not the lower limits.

[31] All reported means are significantly different from 0.5 at the 1% level.

Table 6
Order imbalance: regression results

A. Summary statistics of ΔIMBAL

	Mean	Median
LHG stocks	−0.1622	−0.1622
NHG stocks	−0.0836	−0.1140

B. Regression results

	Coefficients	*t*-statistics
Intercept	−0.2256	−0.387
LHG	−0.1015	−3.619***
BOARD	0.0329	0.707
YEAR	0.0021	0.008
SESSION	0.1670	5.211***
TURNOVER	0.8242	4.231***
SIZE	0.0050	0.173
DURATION	−0.0141	−1.530
VOLATILITY	−0.4437	−0.648
R^2	0.1712	
F-statistic	6.64***	
N	266	

Summarized in this table are the results of the following regression:

$$\Delta\mathrm{IMBAL}_j = \alpha_0 + \alpha_1\ \mathrm{LHG}_j + \alpha_2\ \mathrm{BOARD}_j + \alpha_3\ \mathrm{YEAR}_j + \alpha_4\ \mathrm{SESSION}_j + \alpha_5\ \mathrm{TURNOVER}_j + \alpha_6\ \mathrm{SIZE}_j + \alpha_7\ \mathrm{DURATION}_j + \alpha_8\ \mathrm{VOLATILITY}_j + \eta_j,$$

where $\Delta\mathrm{IMBAL}_j$ denotes the change in order imbalance from the pre- to posthalt-period, LHG, BOARD, YEAR, and SESSION are indicator variables which take the value of 1 if the stock belongs to the limit-hit group, if the stock belongs to the second board, if the year is 1996, and if the trading session is the afternoon session, and 0 otherwise. TURNOVER is defined as the combined trading volume (in number of shares) in the pre- and posthalt-periods divided by the total shares outstanding. SIZE represents firm size and is defined as the natural logarithm of year-end market capitalization. DURATION is the natural logarithm of the duration of limit-halt in minutes from the first limit-hit occurrence until the last moment when the price still stays at the limit. VOLATILITY is the standard deviation of daily stock returns, excluding observations when daily returns are greater than 15%. Sample sizes vary due to missing observations. Parameter coefficient estimates and heteroscedastic-consistent *t*-statistics are reported. Statistical significance at the 1% level is denoted by ***.

the influx of news commentary regarding limit-hits in the afternoon session may stimulate buyers to jump onto the bandwagon, causing a sustained buying pressure during the posthit period which may include the morning session on the following day.

5. Conclusions

This paper studies the Kuala Lumpur Stock Exchange's 30% price limit system. Prior papers have criticized narrow price limits, and, consequently, these studies can only suggest that narrow price limits, not price limits per se, are bad (which is a rather unsurprising finding). An 'optimal' price limit range, if it exists, could occur at wider price limits. By examining the KLSE's wide price limit band, we take an important first step towards addressing this issue. In addition, the KLSE is a useful market to study because its market characteristics (e.g., volatility and turnover activity) are similar to other markets, making our findings potentially applicable to other markets. At the same time, the KLSE employs a call auction trading system, giving us an opportunity to see price limits effects under a somewhat unique market structure. Finally, our study makes use of transactions data and the limit order book. Thus, we are able to contribute to the expanding market microstructure literature, while adding to the price limit literature with more meaningful data.

In this paper, we address new research questions regarding price limits. Specifically, we examine the impacts of price limits on information asymmetry, arrival rates of informed traders, and order imbalance. In conducting our study, we first identify a study sample of stocks that actually hit their price limit. By comparing the pre- and posthit periods, we can then identify the impact of the limit-hit. However, we are well aware that any observed differences between the pre- and posthit periods could be associated to (i) the price-limit-hit or (ii) the large price change. Therefore, we create a control sample of stocks that also experience a large price change but did not hit their limit. By looking at pre- to posthit period changes within each stock group and by comparing these changes across the two stock groups, we can better identify the impacts of price limits. Specifically, we find that price limits (1) do not improve information asymmetry, (2) delay the arrival of information, and (3) cause order imbalances prior to and after a limit-hit.

In conclusion, our results reveal that even in a market with a wide price limit band, price limits do not improve market efficiency but impose serious costs. Recently, the Stock Exchange of Thailand expanded their price limits from 10% to 30%, but the Taiwan Stock Exchange narrowed their price limits from 7% to 3.5%. However, based on prior research and our own empirical study, trying to identify the optimal price limit level may be a futile task. Instead, policy makers may wish to consider eliminating these price limit mechanisms.

Acknowledgements

We are grateful to two anonymous referees, Stephen Brown, Rosita P. Chang, David Cho, David Ding, Daphne Du, Jeff Harris, Victor Huang, Sang-Hyop Lee, Greg Stone, Tony Tang, Qinghai Wang, seminar participants at the 1998 PACAP/FMA Finance Conference in Kuala Lumpur (Malaysia), the 1999 FMA meetings in Orlando, and University of Hawaii Finance Seminar for their comments on earlier versions of this paper. The usual disclaimer applies.

References

Ahn, H.-J., Bae, K.-H., Chan, K., 2001. Limit orders, depth, volatility: evidence from the stock exchange of Hong Kong. Journal of Finance 56, 767–788.

Ahn, H.-J., Cai, J., Hamao, Y., 2002a. Changes in tick size and liquidity provision on the Tokyo Stock Exchange. City University of Hong Kong Working Paper.

Ahn, H.-J., Cai, J., Hamao, Y., Ho, R.Y.K., 2002b. The components of the bid-ask spreads in a limit-order market: evidence from the Tokyo Stock Exchange. Journal of Empirical Finance 9, 399–430.

Amihud, Y., Mendelson, H., 1987. Trading mechanisms and stock returns: an empirical investigation. Journal of Finance 42, 533–553.

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

Biais, B., Hillion, P., Spatt, C., 1995. An empirical analysis of the limit order book and the order flow in the Paris Bourse. Journal of Finance 50, 1655–1689.

Chang, R.P., Huang, N.K., Ghon Rhee, S., Shu, S.Z., 1999. The effects of trading methods on volatility and liquidity: evidence from the Taiwan Stock Exchange. Journal of Business Finance and Accounting 26, 137–170 (January/March).

Chen, Y.-M., 1997. Price limits and liquidity: a five-minute data analysis. Journal of Financial Studies 4, 45–65.

Chen, H., 1998. Price limits, overreaction, and price resolution in futures markets. Journal of Futures Markets 18, 243–263.

Choi, H., Subrahmanyam, A., 1994. Using intraday data to test the effects of index futures on the underlying stock markets. Journal of Futures Markets 14, 293–322.

Cho, D.D., Russell, J., Tiao, G.C., Tsay, R., 2003. The magnet effect of price limits: evidence from high-frequency data on Taiwan Stock Exchange. Journal of Empirical Finance 10, 133–168.

Christie, W.G., Corwin, S.A., Harris, J.H., 2002. Nasdaq trading halts: the impact of market mechanisms on prices, trading activity, and execution costs. Journal of Finance 57, 1443–1478.

Corwin, S.A., Lipson, M.L., 2000. Order flow and liquidity around NYSE trading halts. Journal of Finance 55, 1771–1801.

Easley, D., Kiefer, N.M., O'Hara, M., Paperman, J.B., 1996. Liquidity, information, and infrequently traded stocks. Journal of Finance, 1405–1436.

France, V.G., Kodres, L.E., Moser, J.T., 1994. A review of regulatory mechanisms to control the volatility of prices, federal reserve bank of Chicago. Economic Perspectives 18, 15–26.

French, K., Roll, R., 1986. Stock return variances: the arrival of information and the reaction of traders. Journal of Financial Economics 7, 5–26.

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

Hamao, Y., Hasbrouck, J., 1995. Securities trading in the absence of dealers: trades and quotes in the Tokyo Stock Exchange. Review of Financial Studies 8, 849–878.

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

Hasbrouck, J., 1991. The summary informativeness of stock trades: an econometric analysis. Review of Financial Studies 4, 571–595.

Henke, H., Voronkova, S., 2003. Price limits on a call auction market: evidence from the Warsaw Stock Exchange. European University Viadrina Working paper.

Huang, R.D., Stoll, H.R., 1997. The components of the bid-ask spreads: a generalized approach. Review of Financial Studies 10, 995–1034.

Kim, H., 1996. Fundamental Analysis Worldwide, Special Edition: Malaysia. Pacific Investment Research, New Jersey, USA.

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

Kim, K.A., Limpaphayom, P., 2000. Characteristics of stocks that frequently hit price limits: empirical evidence from Taiwan and Thailand. Journal of Financial Markets 3, 315–332.

Kim, K.A., Ghon Rhee, S., 1997. Price limit performance: evidence from the Tokyo Stock Exchange. Journal of Finance 52, 885–901.

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

Lang, L.H.P., Lee, Y.T., 1999. The performance of various transaction frequencies under call markets. Pacific-Basin Finance Journal 7, 23–40.

Lee, C.M.C., Ready, M.J., 1991. Inferring trade direction from intraday data. Journal of Finance 46, 733–746.

Lee, C.M.C., Ready, M.J., Seguin, P.J., 1994. Volume, volatility, and New York Stock Exchange trading halts. Journal of Finance 49, 183–214.

Lee, Y.-t., Liu, Y.-J., Roll, R., Subramanyam, A., 2004. Order imbalances and market efficiency: evidence from the Taiwan Stock Exchange. Journal of Financial and Quantitative Analysis 39, 327–341.

Lehmann, B.N., Modest, D.M., 1994. Liquidity on the Tokyo Stock Exchange: a bird's eye view. Journal of Finance 49, 183–214.

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

Ma, C.K., Rao, R.P., Stephen Sears, R., 1989. Volatility, price resolution, and the effectiveness of price limits. Journal of Financial Services Research 3, 165–199.

Madhavan, A., Seymour, S., 1991. A Bayesian model of intraday specialist pricing. Journal of Financial Economics 30, 99–134.

Miller, M.H., 1989. Commentary: volatility, price resolution, and the effectiveness of price limits. Journal of Financial Services Research 3, 201–203.

Miller, M.H., 1991. Volatility, episodic volatility, and coordinated circuit breakers. In: Rhee, S.G., Chang, R.P. (Eds.), Pacific-Basin Capital Markets Research. North Holland, Amsterdam, Netherlands.

Pagano, M.S., Schwartz, R.A., 2003. A closing call's impact on market quality at Euronext Paris. Journal of Financial Economics 68, 439–484.

Park, C.W., 2000. Examining futures price changes and volatility on the trading day after a limit-lock day. Journal of Futures Markets 20, 445–466.

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

Rhee, S.G., 2000. Rising to Asia's challenge: enhanced role of capital markets. Rising to the Challenge in Asia: A Study of Financial Markets. Asian Development Bank, Manila, Philippines, pp. 107–174.

Rhee, S.G., Chang, R.P., 1993. The microstructure of Asian equity markets. Journal of Financial Services Research 6, 437–454.

Roll, R., 1989. Price volatility, international market links, and their implications for regulatory policies. Journal of Financial Services Research 3, 211–246.

SAS Institute, 1993. SAS/ETS® User's Guide, Version 6, Second Edition. SAS Institute, Cary, NC.

Subrahmanyam, A., 1994. Circuit breakers and market volatility: a theoretical perspective. Journal of Finance 49, 237–254.

Subrahmanyam, A., 1995. On rules versus discretion in procedures to halt trade. Journal of Economics and Business 47, 1–16.