Do Price Limits Hurt the Market?

Chia-Hsuan Yeh [a,*], Chun-Yi Yang [b]

[a] *Department of Information Management, Yuan Ze University, Chungli, Taoyuan 320, Taiwan*
[b] *Department of Information Management, Yuan Ze University, Chungli, Taoyuan 320, Taiwan*

Abstract

Under an artificial stock market composed of bounded-rational and heterogeneous traders, this paper examines whether or not price limits generate the negative effects on the market. Through testing the volatility spillover hypothesis, the delayed price discovery hypothesis, and the trading interference hypothesis, we find that no evidence of volatility spillover is observed. However, the phenomena of delayed price discovery and trading interference indeed exist, and their significance depends on the level of the price limits.

Key words: Price Limits, Artificial Stock Market, Agent-Based Modeling, Genetic Programming

JEL classification: D83, D84, G11, G12

* Corresponding author. Tel: +886 3 4638800 ext. 2616, Fax: +886 3 4352077
Email addresses: imcyeh@saturn.yzu.edu.tw (Chia-Hsuan Yeh), ckhyde.yang@gmail.com (Chun-Yi Yang).
URL: http://comp-int.mis.yzu.edu.tw/faculty/yeh/ (Chia-Hsuan Yeh).

1. Introduction

Price limit rules have been applied in financial markets for a long time. However, a consensus in terms of opinion has not so far been reached. Basically, the main reason why there are debates between the pros and cons is that they rest on different assumptions regarding the traders' rationality. The proponents believe that traders are irrational and tend to overreact to market information. In fact, the empirical evidence found in Tversky and Kahneman (1974) upholds this argument. In this situation, asset prices exhibit large fluctuations, so that they deviate from their fundamental values. Appropriate financial regulations such as price limits can provide a cooling-off period for traders to reassess the intrinsic values of the asset, and help to curb traders' irrational behavior. Such a reasoning is referred to as the overreaction hypothesis. If the imposition of price limits does succeed in inhibiting traders' overreaction behavior, it is to be expected that price reversals will be observed in the following trading days after the limit moves, and price limits will thus help to improve the price discovery. Studies such as that by Ma et al. (1989) support the overreaction hypothesis.

On the other hand, the opponents believe that traders are sufficiently rational and can process information efficiently, so that they are able to figure out the intrinsic values of the asset. In this case, the imposition of price limits will generate several negative effects. These effects are claimed by the information hypothesis (or the delayed price discovery hypothesis), the volatility spillover hypothesis, and the trading interference hypothesis. The information hypothesis claims that the main effect of price limits is to delay the process of price discovery. If the limit moves are present and the intrinsic value of the asset price falls outside the current permitted price variation range, all trading will be suspended and will not resume until the intrinsic value lies within the new price variation range. Delayed price discovery is supported by Fama (1989) and Chen (1998). The volatility spillover hypothesis states that volatility increases on the subsequent trading days after the limit moves due to the imbalance orders caused by price limits. Another cost induced by the limit rules is proposed by the trading interference hypothesis, which claims that the trading activity will be interfered with once asset prices hit the limits. As a result, the trading activity on the subsequent trading days will increase. In fact, Kim and Rhee (1997) provide a more in-depth investigation regarding the effects of price limits on the Tokyo Stock Exchange. In their study, the stocks were classified into two categories: one that experienced the limit hits, and the other for which the prices did not but got close to the hitting levels. Their findings support each of the three hypotheses regarding the negative effects of price limits.

The contention that traders are generally irrational overlooks the fact that traders may adapt to and learn how to react to the market environment. They may end up behaving rationally. The argument that traders could always behave rationally is also unrealistic because it is not supported by the relevant psychological experiments. In reality, traders are neither always irrational nor completely rational; instead, they are characterized by bounded rationality and rely heavily on the adaptive learning method to figure out how to manage their portfolio under uncertainty. Uncertainty comes from not only incomplete and/or imperfect information, but also how traders interact with each other as well as market regulations. In addition, the rationality of the market is not necessarily consistent with that at the individual's level. Gode and Sunder (1993) show that the market's rationality could result from the individuals' irrationality. Therefore, it is necessary and valuable to understand whether or not such negative effects argued by the opponents still exist in a situation where traders are characterized by bounded rationality, and if there are any, when and how they emerge. However, these issues are difficult to clarify based on empirical investigation. The reasons are as follows. First, the market environment usually changes over time. Even though there exists strong evidence exhibiting the negative impacts of price limits, we are still unable to understand whether such phenomena result from the essential properties of price limits or from the market uncertainty by which the positive side of the price limits is overwhelmed. Second, it is quite difficult to empirically discriminate between the information hypothesis and the overreaction hypothesis, if we have no idea regarding what had been on the traders' minds and how to predict what would have happened had the price limits not been imposed.

Based on the difficulties described above, it seems that a simulated financial market composed of many heterogeneous traders whose learning behavior is appropriately represented is a promising and convincing way. In such an environment, traders coevolve. Each trader's decisions may give rise to significant impacts on others. Studies such as Day and Huang (1990), Kirman (1991), Chiarella (1992), Lux (1995, 1997, 1998), Arthur et al. (1997), Brock and Hommes (1998), LeBaron et al. (1999), LeBaron (2000, 2001), Hommes (2001), Chiarella and He (2001, 2002, 2003), and Chiarella et al. (2002, 2006) have been conducted under heterogeneous agent frameworks, and they successfully replicate and explain the stylized facts observed in financial markets.

In Westerhoff (2003), a heterogeneous chartist-fundamentalist framework is proposed to examine the effectiveness of price limits. The imposition of price limits is found to reduce volatility and make prices less distorted. These positive effects are more significant if more traders engage in trend-extrapolating behavior. Similar results are also obtained in Westerhoff (2006, 2008). However, two assumptions employed in these papers seem to be inappropriate in a general environment. First, pre-specifying functional forms used by fundamentalists or chartists may highly restrict their ability to process information and further narrow the possibly emergent phenomena which is the main purpose of the heterogeneous-agent approach. The importance of these characteristics is also mentioned in Kirman (2006) and LeBaron (2006). In Kirman (2006):

> To conclude this section it is worth remarking that almost all of the formal evolutionary models in economics consider individuals choosing from a fixed set of alternatives. This is not compatible with a biological view because no new possibilities emerge in such models. The variations produced by mutations are absent so the result of the individual choices must be either convergence to a point or some complicated dynamics within the set. If we were to pursue the evolutionary analogy we would allow for the arrival of new strategies. (p. 101)

Also, in LeBaron (2006):

> However, a key reason for doing computer modeling is that the use of more sophisticated trading strategies in many-type models needs to be understood as well. There are two basic reasons for this. First, many-type models take emergence very seriously in that they do not bias toward any particular strategy load ex ante by the researcher. The strategies that end up being used are those that appear and persist inside a learning structure. They therefore partially answer a criticism of the few-type models that their specification of trading strategies is ad hoc. Second, they use the computer and the learning algorithms to continuously search the time series record to smoke out new trading opportunities. This is something that is not present in the few-type models. (pp. 1225-1226)

Second, the assumption that traders are aware of the fundamental values of the assets is mainly employed to distinguish the fundamentalists from the chartists, while it is not easy to justify why traders have this information and they would respond accordingly.

In this paper, we propose the adoption of an artificial stock market composed of bounded-rational and heterogeneous traders. In this simulated market environment, we follow the methods proposed in Kim and Rhee (1997) to examine whether or not there is any evidence of the appearance of volatility spillovers, delayed price discovery, or trading interference in the markets with the different ranges of price limits, compared with the benchmark market where there is no price limit. The advantages of this approach are twofold. First, it provides a channel to visualize the negative effects as well as their duration resulting from the different price limit levels, if there are any. Second, if the existence of price limits generates both positive and negative effects, we are able to understand when such a property emerges.

Our market environment is closely related to that of Brock and Hommes (1998) and the Santa Fe Artificial Stock Market (SF-ASM) of Arthur et al. (1997) and LeBaron et al. (1999). However, traders' expectations as well as their learning behavior are modeled by the genetic programming (GP) algorithm. The advantage of GP is that it can dynamically represent hierarchical strategies of different sizes and shapes. In the framework of GP, traders are freely allowed to form various types of forecasting functions which may be characterized as fundamental-like or technical-like rules during different time periods. This property meets the requirements mentioned in Kirman (2006) and LeBaron (2006). In addition, the double auction (DA) which is the principal trading mechanism for many financial markets is used as our trading system. Therefore, we are able to analyze high-frequency data such as intra-day trading behavior under this framework.

The remainder of this paper is organized as follows. Section 2 describes the basic framework of the artificial stock market and the traders' characteristics. The model calibration and the simulation design are presented in Section 3. Section 4 presents the results of testing the three hypotheses. Section 5 concludes.

2. The model

The basic framework considered in this paper is the same as that used in Yeh (2008). For the purpose of calibrating the model to fit different frequencies of real financial data, we adopt the same design used in He and Li (2007) which slightly modifies the model of Brock and Hommes (1998) and the SF-ASM.

There are two types of assets for traders to invest in. The risk-free asset, money, is perfectly elastically supplied. Its gross return is $R = 1 + r/K$, where r is a constant interest rate per annum and K means the frequency measured in one year. [1] The other one which is risky, stock, has a stochastic dividend process (D_t) not known to traders. Assume that all traders have the same constant absolute risk aversion (CARA) utility function, i.e. $U(W_{i,t}) = -exp(-\lambda W_{i,t})$, where λ is the degree of absolute risk aversion. The trader i's wealth at $t+1$, $W_{i,t+1}$, is determined by

$$W_{i,t+1} = RW_{i,t} + (P_{t+1} + D_{t+1} - RP_t)h_{i,t}, \tag{1}$$

where P_t is the price per share of the stock and $h_{i,t}$ refers to the shares of the stock held by trader i at time t. Given the information up to t, each trader's forecasts of the conditional expectation and variance at $t+1$ are denoted by $E_{i,t}(\cdot)$ and $V_{i,t}(\cdot)$, respectively. The excess return at $t+1$, R_{t+1}, is given by $P_{t+1} + D_{t+1} - RP_t$. Then we have

$$\begin{aligned} E_{i,t}(W_{t+1}) &= RW_{i,t} + E_{i,t}(P_{t+1} + D_{t+1} - RP_t)h_{i,t} \qquad (2) \\ &= RW_{i,t} + E_{i,t}(R_{t+1})h_{i,t}, \\ V_{i,t}(W_{t+1}) &= h_{i,t}^2 V_{i,t}(P_{t+1} + D_{t+1} - RP_t) = h_{i,t}^2 V_{i,t}(R_{t+1}). \qquad (3) \end{aligned}$$

Each trader maximizes the one-period expected utility function subject to Eq. (1). The optimal share of stock holding for each trader, $h^*_{i,t}$, is given by

$$h^*_{i,t} = \frac{E_{i,t}(R_{t+1})}{\lambda V_{i,t}(R_{t+1})}. \tag{4}$$

Each trader's reservation price can be derived by simply assuming the current stock holding is at the optimal level. That is, $h^*_{i,t} = h_{i,t}$, and then we have

$$P_i^R = \frac{E_{i,t}(P_{t+1} + D_{t+1}) - \lambda h_{i,t} V_{i,t}(R_{t+1})}{R}. \tag{5}$$

2.1. *Traders*

According to Eq. (5), it is clear that P_i^R is mainly determined by the conditional expectation and variance. In this paper, each trader's conditional expectation is modeled by the following function:

$$E_{i,t}(P_{t+1} + D_{t+1}) = \begin{cases} (P_t + D_t)[1 + \theta_0 \tanh(\dfrac{\ln(1 + f_{i,t})}{\omega})] & \text{if } \ f_{i,t} \geq 0.0, \\ (P_t + D_t)[1 - \theta_0 \tanh(\dfrac{\ln(|-1 + f_{i,t}|)}{\omega})] & \text{if } \ f_{i,t} < 0.0, \end{cases} \tag{6}$$

where $f_{i,t}$ is the function evolved using GP based on currently available information. The information consists of the price and dividend histories up to the last few periods. Let $\sigma^2_{i,t}$ denote $V_{i,t}(R_{t+1})$. Each trader's conditional variance is modeled by

$$\sigma^2_{i,t} = (1 - \theta_1 - \theta_2)\sigma^2_{i,t-1} + \theta_1(P_t + D_t - u_{t-1})^2 + \theta_2[(P_t + D_t) - E_{i,t-1}(P_t + D_t)]^2, \tag{7}$$

[1] The value of K can be set as 1, 12, 52, and 250 when the trading periods are a year, month, week, and day, respectively.

where

$$u_t = (1 - \theta_1)u_{t-1} + \theta_1(P_t + D_t). \tag{8}$$

This functional form of the conditional variances is proposed on the basis of those forms used in LeBaron et al. (1999) and He and Li (2007). At the end of each period, each trader updates his estimated conditional variance of the active model. The performance of each model is defined by the value of strength:

$$s_{i,j,t} = -\sigma^2_{i,j,t}, \tag{9}$$

where $s_{i,j,t}$ is the strength of the jth model for trader i in period t. The traders' learning takes place every N_{EC} periods (evolutionary cycle) asynchronously. At the beginning of each evolutionary cycle, each trader randomly chooses N_T out of N_I models. The one with the highest strength value is chosen as the model used in the periods of the same evolutionary cycle. At the end of each evolutionary cycle, the worst model is eliminated and a new model is generated through an evolutionary process devised in GP by means of crossover, mutation, or immigration operators.

2.2. *Market mechanism*

It is clear that the price behavior heavily relies on the mechanism of price determination. In the literature, most models fall into one of the following three approaches. One is to consider a simple price adjustment mechanism. In this case, price is purely determined by the excess demand and the coefficient of adjustment speed. The major drawback of this method is that the value of the coefficient of adjustment speed is exogenously given and can not be chosen objectively. The second method adopts either a computational procedure or an analytical way to clear the market. However, this approach is unable to capture the continuous trading phenomenon observed in actual markets as well as the intraday trading behavior. The third method is the DA mechanism of which the advantages are not only its being widely employed in financial markets but also that it provides room for simulating the intraday trading process.

This paper considers a simplified continuous DA process which is a modified version of Yang (2002) and is also used in Yeh (2008). To mimic the intraday trading process, each trading period (day) is decomposed into N_R rounds. At the beginning of each round, the traders take turns in participating in the trading and the order is determined by a random permutation. Once the last trader has completed his action, the current round ends and the next starts off with a new random permutation. Each trader can post his order of bid or ask when he enters the market. The rules for posting a bid or an ask are very intuitive. First, only the highest price for buying (the best bid, B_b) and the lowest price for selling (the best ask, B_a) are observable to the traders. Second, any subsequent bid (ask) must be higher (lower) than the current one if a bid (an ask) exists on the billboard. Finally, each trader, based on his reservation price and the existing best ask or best bid, decides whether he should post (or accept) a bid or an ask order. It works as follows:

- If B_b and B_a exist ($B_a > B_b$),
  - If $P_i^R > B_a$, he will post a market order, and buy at B_a.
  - If $P_i^R < B_b$, he will post a market order, and sell at B_b.
  - If $B_b \leq P_i^R \leq B_a$ and $P_i^R < (B_a + B_b)/2$, he will post a sell order at a price uniformly distributed in $(P_i^R,\, P_i^R + S_i)$. $S_i = (\frac{\lambda\sigma^2_{i,t}}{1+r})\Delta h$. S_i is the maximum spread from the reservation price.
  - If $B_b \leq P_i^R \leq B_a$ and $P_i^R \geq (B_a + B_b)/2$, he will post a buy order at a price uniformly distributed in $(P_i^R - S_i,\, P_i^R)$.
- If only B_a exists,
  - If $P_i^R > B_a$, he will post a market order, and buy at B_a.
  - If $P_i^R \leq B_a$, he will post a buy order at a price uniformly distributed in $(P_i^R - S_i,\, P_i^R)$.
- If only B_b exists,
  - If $P_i^R < B_b$, he will post a market order, and sell at B_b.

- If $P_i^R \geq B_b$, he will post a sell order at a price uniformly distributed in $(P_i^R,\ P_i^R + S_i)$.

– If no bid and ask exist,

- he will have an equal chance to post a buy or a sell order at a price uniformly distributed in $(P_i^R - S_i,\ P_i^R)$ or $(P_i^R,\ P_i^R + S_i)$, respectively.

A transaction occurs when the existing bid or ask is accepted, or the bid and ask cross. For the sake of simplicity, we assume that only a fixed amount of stock (Δh) is traded in each transaction and traders are not allowed to sell short or buy on margin. Any unfulfilled order of each trader in a round is canceled when he makes a new decision in the subsequent rounds, and all unfulfilled orders in the order book are deleted when a period is closed. The last transaction price in each period represents the price of this period.

3. Simulation design

Before conducting our simulations, the parameters of traders' characteristics regarding learning behavior and those of the GP algorithm are calibrated to generate time series, which mimic several stylized facts of the daily data in actual financial markets. Table 1 summarizes the control parameters of our simulations. At the beginning of each simulation, each trader has one share of the stock and \$100 dollars in cash. No one trader is allowed to hold more than 10 shares of the stock. The public information which includes the stock price and dividend histories up to the last 5 periods is available for traders to form their expectations. Each simulation run has 20,000 periods and 50 rounds per period.

Table 2 reports the statistical properties of the time series data generated by our calibrated model. The second and third columns are the minimum and maximum returns in percentage terms, respectively. These range from -45.11% to 32.10%. The fourth column shows the market volatility which is measured by the average of the absolute returns, and its value lies between 0.31% and 0.83%. Both the kurtosis (K) and the tail index α of the raw returns are the statistics which indicate the existence of fat tails. Following the procedure proposed in Hill (1975), the α value is obtained based on 5 percent of the largest observations. The phenomenon of a fat tail is more significant when the α value is smaller. It is obvious that the kurtosis of the time series data generated by our model is far greater than 3, and the α value ranges from 1.97 to 4.97.[2] The Hurst exponents of the raw and the absolute returns are summarized in the seventh and the last columns, respectively. It is well-known that the Hurst exponent is employed to describe the memory of a time series. Its value lies between 0 and 1. A time series with a random walk has the value of 0.5, while $0.5 < H < 1$ ($0 < H < 0.5$) indicates a persistent (an anti-persistent) time series. It is observed that the values of the Hurst exponent for the raw return series are close to 0.5, and that those of the absolute returns are about 0.9, which shows the existence of volatility clustering.[3]

Figure 1 displays the results of the time series data for a typical run generated by our model. The top panel shows the time series of 20,000 periods. The second panel denotes the respective return series. To see more structures of the return series, we also plot the distribution of the returns together with the normal distribution (presented in the black line) of which the variance is the same as that of the former. Compared with the normal distribution, our model generates the return distributions with higher probabilities around the mean and the tails. In addition, as with the phenomena usually observed in real financial markets, the autocorrelation feature of the raw returns is insignificant at the 5% significance level for most of the lag periods, while it is significant for the absolute returns. Therefore, the results of Table 2 and Figure 1 have indicated that our model provides an acceptable fit based on the empirical features.

On the basis of this calibrated model, we examine whether the imposition of price limits generates any negative effect on the market through testing the three hypotheses. We consider six markets with different price limits together with a market without the price limit rules. From Market A to Market F, the maximum allowed percentages in terms of the price change in each period are set to be 0.5%, 1%,

[2] During the 1972-2008 period, the α values of the Dow Jones Industrial Average Index (DJIA), Nasdaq Composite Index, and the S&P 500 are 3.74, 3.71, and 4.02, respectively.

[3] During the 1972-2008 period, the Hurst exponents of the raw returns (absolute returns) of the DJIA, Nasdaq, and the S&P 500 are 0.53, 0.56, and 0.53 (0.96, 0.97, and 0.96), respectively.

Table 1
Parameters for simulations

The stock market	
Shares of the stock (h) for each trader	1
Initial money supply (M_0) for each trader	\$100
Interest rate (r, r_d)	(0.05, 0.0002)
Stochastic process (D_t)	N($\overline{D}$, σ_D^2)=N(0.02, 0.004)
Amount for each trade (Δh)	1
Maximum shares of stock holding ($\overline{h}$)	10
Number of rounds for each period (N_R)	50
Number of periods (N_P)	20,000
Traders	
Number of traders (N)	100
Number of strategies for each trader (N_I)	20
Tournament size (N_T)	5
Evolutionary cycle (N_{EC})	5
λ	0.5
θ_0	0.5
ω	15
θ_1	0.01
θ_2	0.001
Parameters of genetic programming	
Function set	{if-then-else;and,or,not;$\geq$,$\leq$,= +,-,$\times$,%,sin,cos,abs,sqrt}
Terminal set	{P_{t-1}, ..., P_{t-5}, D_{t-1}, ..., D_{t-5}, R}
Selection scheme	Tournament selection
Tournament size	2
Probability of creating a tree by immigration (P_I)	0.1
Probability of creating a tree by crossover (P_C)	0.7
Probability of creating a tree by mutation (P_M)	0.2

R denotes the ephemeral random constant.

Table 2
Stylized facts of the calibrated model

	$r_{\min}$	$r_{\max}$	$\lvert r\rvert$	K	α	H_r	$H_{\lvert r\rvert}$
Minimum	-45.11	11.80	0.31	13.19	1.91	0.46	0.90
Median	-20.98	17.32	0.49	49.16	3.41	0.52	0.91
Average	-23.48	20.49	0.51	44.74	3.39	0.52	0.91
Maximum	-13.85	32.10	0.83	81.38	4.97	0.57	0.94

The values of minimum, median, average, and maximum are obtained based on 20 simulation runs.

3%, 5%, 7%, and 10%, respectively, while there exist no price limits in Market G. Such a design may help us to better understand whether or not different levels of price limits result in different effects. We perform 30 runs for each market, and each run starts with a different random seed.

4. Results

In Kim and Rhee (1997), the tests are conducted based on an event study where the event day represents the day on which the stock prices experience the price limit hits. However, for the days with the limit moves but without closing at the limits, it is very possible that the return volatility will not spill over and/or the price trend will not continue on the following day. In addition, the trading may

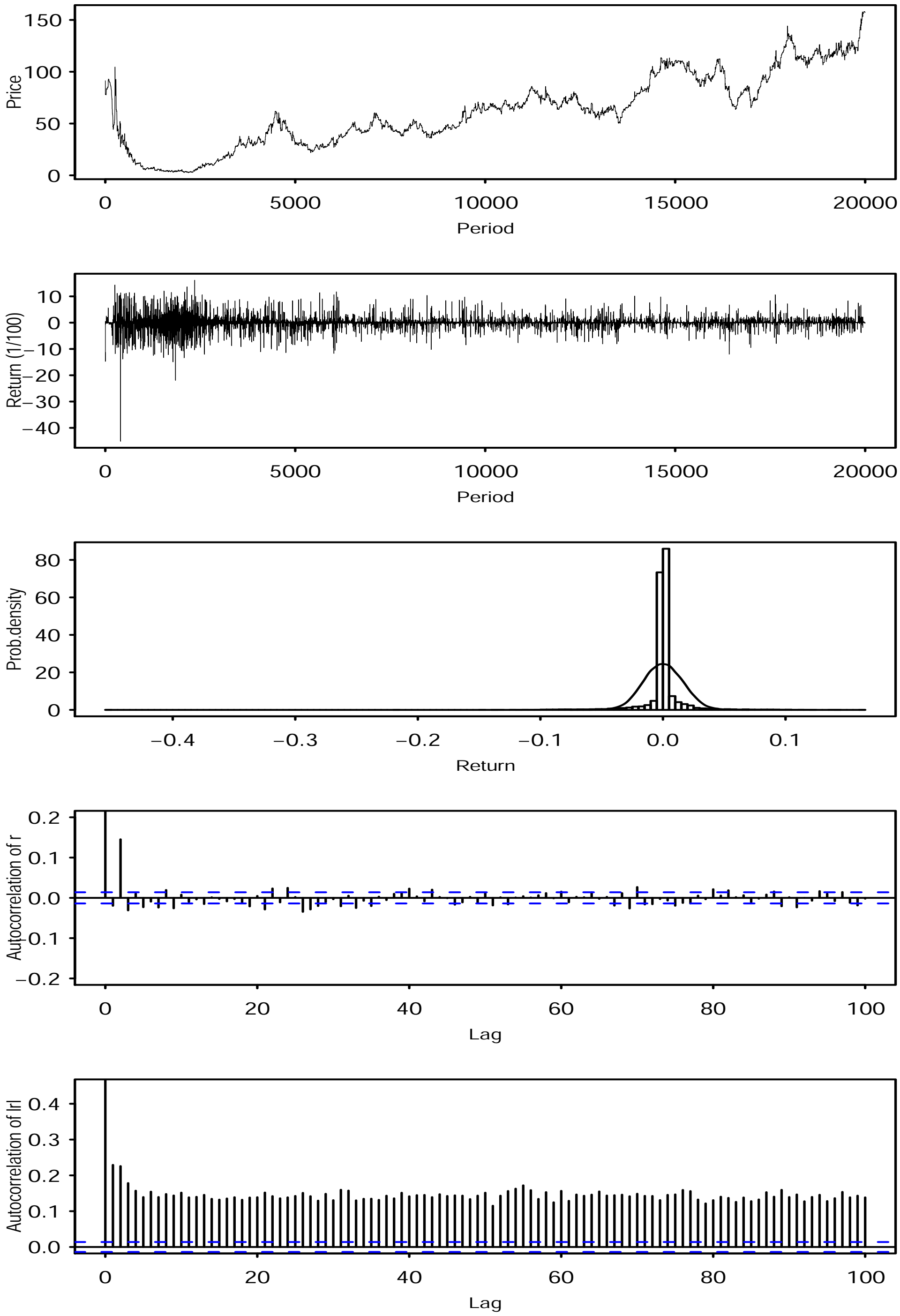

Fig. 1. Time series properties of the calibrated model

not be interfered with on the limit days because the overreaction behavior has been corrected, and/or one-sided shocks have been absorbed, so that trading is not delayed. Therefore, from the perspective of investigating the existence of the negative effects of price limits, we can just focus on the locked limit days, i.e. the days with daily closing prices reaching the price limits, on which the negative effects will emerge, if there are any.

To understand how the market would behave if the current rules of price limits were absent, we also present the corresponding results observed in Market G, the market where no price limits are imposed, when the respective price limits are set as the limit criteria. In other words, an objective benchmark is provided in this situation. Such an advantage is not obtainable if empirical examination is adopted instead.

4.1. *The volatility spillover hypothesis*

Following the procedure used in Kim and Rhee (1997), we perform an event study to examine the existence of volatility spillovers. The event, Day_{Hit}, is defined as the locked limit days. Similarly, $\text{Day}_{0.9}$ represents the event in which the daily closing prices reach at least 90% but less than 100% of the limits. Consider an 11-day event window: Day -5 to +5. Day 0 indicates the event day, and Day -i and Day +i (i=1, 2,..., 5) are the ith day before and after the event day, respectively.

The volatility is measured by the absolute return. The existence of volatility spillovers could be supported by the phenomenon that the volatility during the post-event periods (Day 1 to Day 5) for the event Day_{Hit} would be higher than that for $\text{Day}_{0.9}$. The median of the absolute returns over the 11-day window across 30 runs for all events are reported in Table 3. The values presented in the parentheses are the corresponding results observed in Market G when the respective price limits are set as the limit criteria.

It is shown that the volatility on Day 1 is rather small compared with that on Day 0 under Day_{Hit}. This phenomenon is usually employed as the evidence in support of the effectiveness of price limits in reducing volatility. However, as mentioned in Lehmann (1989) and Miller (1989), volatility tends to decline after the day characterized by large volatility. Such a phenomenon is also observed in the event $\text{Day}_{0.9}$, and the corresponding results in Market G. Therefore, the conclusion that is purely based on this result is too premature.

When focusing on the volatility during the post-event periods for Day_{Hit} in comparison with that for $\text{Day}_{0.9}$, we find two interesting pictures. First, from Market A to Market F, most of the post-event periods exhibit lower volatility for Day_{Hit} than that for $\text{Day}_{0.9}$. This result is contrary to the volatility spillover hypothesis and reveals the effectiveness of price limits in reducing volatility. Second, the usefulness of price limits can be further confirmed by the corresponding results in Market G. Because there are no price limits imposed on Market G, it is to be expected that no significant difference in the magnitude of volatility between Day_{Hit} and $\text{Day}_{0.9}$ during the post-event periods would be observed if the traders were able to process information efficiently, while we observe the opposite result. In Market G, when the limit criterion is made higher than 1%, it is shown that Day_{Hit} possesses higher volatility than $\text{Day}_{0.9}$ during the post-event periods. This indicates an important phenomenon: under no price limits, the traders' overreaction persists for several periods so as to generate large volatility in the subsequent periods. However, this result does not hold any more if the limit criterion is very stringent, such as 0.5% or 1%. Basically, our results do not support the volatility spillover hypothesis. On the contrary, the imposition of price limits helps to reduce volatility. Such a positive effect results from the function of the price limits by which traders' overreaction behavior is curbed. This function can be evidenced by the results from the benchmark market where no price limits are imposed.

4.2. *The delayed price discovery hypothesis*

The delayed price discovery hypothesis claims that positive (negative) overnight returns may come after the occurrence of upper-limit hits (lower-limit hits). In Kim and Rhee (1997), two return series are provided to examine whether or not price limits delay the price discovery: open-to-close returns ($R_{t,OC}$) and close-to-open returns ($R_{t+1,CO}$) on the event day, where 'O' and 'C' represent the opening and closing prices, respectively. However, the opening price is quite noisy because it crucially depends on the order of traders' bids and asks. Therefore, in this paper, while we adopt an event-day research method similar to that in Kim and Rhee (1997), the opening price is replaced by the daily average price (A) which is

Table 3
Volatility spillover test

Day	Market A Day$_{\text{Hit}}$		Market A Day$_{0.9}$	Market B Day$_{\text{Hit}}$		Market B Day$_{0.9}$
-5	0.389 (1.884)	≪ (≪)	0.447 (2.087)	0.513 (1.776)	≪ (<)	0.560 (1.884)
-4	0.401 (1.979)	≪	0.507 (2.068)	0.523 (1.875)	≪	0.621 (2.046)
-3	0.414 (1.932)	≪	0.500 (2.046)	0.539 (1.820)	≪ (≪)	0.667 (2.063)
-2	0.465 (2.303)	(≫)	0.536 (2.171)	0.601 (2.312)	(≫)	0.646 (2.218)
-1	0.490 (2.057)		0.543 (2.227)	0.625 (1.970)	<	0.689 (2.100)
0	4.997 (13.929)	≫ (≫)	4.740 (4.695)	9.996 (20.692)	≫ (≫)	9.508 (9.439)
1	0.491 (2.072)		0.515 (2.176)	0.628 (1.981)	≪	0.723 (2.061)
2	0.463 (2.275)	(≫)	0.523 (2.233)	0.605 (2.266)	(≫)	0.679 (2.223)
3	0.413 (1.911)	< (≪)	0.482 (2.127)	0.544 (1.807)	≪	0.640 (1.998)
4	0.398 (1.960)	≪ (<)	0.506 (2.199)	0.518 (1.862)	≪	0.577 (1.998)
5	0.390 (1.879)	≪ (<)	0.468 (2.076)	0.510 (1.768)	≪	0.622 (1.904)

Day	Market C Day$_{\text{Hit}}$		Market C Day$_{0.9}$	Market D Day$_{\text{Hit}}$		Market D Day$_{0.9}$
-5	0.975 (2.234)	≪ (≫)	1.076 (1.796)	1.179 (2.790)	(≫)	1.183 (2.013)
-4	0.978 (2.469)	≪ (≫)	1.076 (1.886)	1.177 (3.244)	< (≫)	1.251 (2.214)
-3	1.012 (2.312)	(≫)	1.058 (1.924)	1.235 (2.806)	(≫)	1.226 (2.270)
-2	1.121 (3.551)	(≫)	1.254 (2.271)	1.384 (5.423)	(≫)	1.445 (3.058)
-1	1.133 (2.550)	(≫)	1.136 (2.170)	1.415 (3.046)	(≫)	1.337 (2.436)
0	29.992 (48.399)	≫ (≫)	28.460 (28.375)	49.991 (69.000)	≫ (≫)	47.609 (47.249)
1	1.164 (2.560)	(≫)	1.173 (2.024)	1.398 (3.101)	(≫)	1.342 (2.398)
2	1.105 (3.391)	≪ (≫)	1.220 (2.210)	1.366 (5.034)	(≫)	1.406 (2.708)
3	1.049 (2.352)	(≫)	1.078 (1.777)	1.255 (2.880)	(≫)	1.251 (2.070)
4	0.996 (2.481)	(≫)	1.033 (1.796)	1.223 (3.178)	(≫)	1.246 (2.133)
5	0.993 (2.240)	(≫)	1.013 (1.820)	1.187 (2.777)	(≫)	1.208 (1.917)

Day	Market E Day$_{\text{Hit}}$		Market E Day$_{0.9}$	Market F Day$_{\text{Hit}}$		Market F Day$_{0.9}$
-5	1.349 (3.166)	≪ (≫)	1.504 (2.902)	1.592 (3.164)	< (≪)	1.720 (3.812)
-4	1.378 (3.689)	≪ (>)	1.574 (3.504)	1.497 (3.992)	<	1.751 (3.962)
-3	1.384 (3.236)	(≫)	1.467 (2.587)	1.626 (3.628)	<	1.834 (3.427)
-2	1.626 (7.103)	≪ (≫)	1.923 (5.414)	1.748 (7.082)	≪	2.502 (8.031)
-1	1.696 (3.461)	(≫)	1.586 (2.864)	2.108 (3.653)		2.002 (3.516)
0	69.990 (85.647)	≫ (≫)	66.337 (66.370)	99.990 (110.654)	≫ (≫)	94.543 (94.451)
1	1.598 (3.344)		1.678 (3.082)	1.998 (3.542)		1.921 (3.184)
2	1.542 (6.015)	≪ (≫)	1.739 (5.088)	1.656 (6.867)	≪	2.640 (6.515)
3	1.466 (3.037)		1.508 (3.016)	1.685 (3.147)	≪	1.893 (3.267)
4	1.387 (3.654)	≪ (≫)	1.432 (3.163)	1.622 (4.173)		1.667 (3.525)
5	1.392 (2.997)		1.388 (2.918)	1.585 (3.457)	(>)	1.673 (3.073)

The values shown in this table are multiplied by 10^3. $>$ and $\gg$ (or $<$ and $\ll$) mean that, based on the Wilcoxon signed-rank test, the medians on the left are significantly greater (smaller) than those on the right at the 5% and 1% significance levels, respectively.

defined as the average of daily opening, closing, high, and low prices. Such a design is also employed in Chen (1998).

The symbols '+', '0', and '-' mean that the return is greater than, equal to, and less than zero, respectively. Three types of price movement (price continuation, price reversal, and no change) are classified based on the following rules:

– Price continuation:
  · For upper locked limit days: $[R_{t,AC}, R_{t+1,CA}]$ = [+, +], or [0, +].
  · For lower locked limit days: $[R_{t,AC}, R_{t+1,CA}]$ = [-, -], or [0, -].
– Price reversal:
  · For upper locked limit days: $[R_{t,AC}, R_{t+1,CA}]$ = [+, -], or [0, -].
  · For lower locked limit days: $[R_{t,AC}, R_{t+1,CA}]$ = [-, +], or [0, +].
– No change:
  · For upper locked limit days: $[R_{t,AC}, R_{t+1,CA}]$ = [+, 0], or [0, 0].
  · For lower locked limit days: $[R_{t,AC}, R_{t+1,CA}]$ = [-, 0], or [0, 0].

Table 4 gives the frequency of price continuations, price reversals, and no changes for all events. To be in line with the phenomenon of delayed price discovery, we expect to observe that price continuation occurs more often for Day_{Hit} than for $\text{Day}_{0.9}$. In Table 4, it is clear that the frequency of price continuation (P_c) for Day_{Hit} is indeed higher than that for $\text{Day}_{0.9}$. Therefore, we do observe the evidence of delayed price discovery. Besides this result, when we focus on the market without price limits, regardless of which limit criterion is considered, the value of P_c or P_r (the frequency of price reversals) is rather stationary, except the frequency of price reversals observed in the case when 5% is set as the limit criterion, and P_c is far smaller than P_r for Day_{Hit}. By contrast, when price limits are imposed, the value of P_c (P_r) largely increases (decreases). This part further reveals the existence of delayed price discovery. Interestingly, in the events of $\text{Day}_{0.9}$, prices do not reach the limits. Therefore, it is supposed that the frequency of price continuations or price reversals would exhibit no significant difference between the markets with and without the price limits. However, we find that the result is the same as that for Day_{Hit}. The imposition of price limits results in a higher (lower) frequency of price continuation (price reversal). Actually, our findings confirm the results described in Isaac and Plott (1981) where price limits will generate substantial effects on the market, even though they are not binding.

> The observation that the price controls are not binding (in the sense used in partial-equilibrium analysis) is not sufficient to conclude that the controls are neutral either as to the conduct of prices or to market efficiency. Conversely, the fact that market transactions are occurring below a price ceiling or above a price floor will not be sufficient to conclude that removing controls will leave prices and quantities unchanged. (p. 459)

On the other hand, from Market A to Market F, P_c (P_r) is larger (smaller) when the price limit level is higher than or equal to 1.5% (Market B to Market F), compared with that in Market A. This outcome presents the positive side for the imposition of stringent price limits in light of the fact that price continuation (price reversal) appears less (more) often. In sum, solely from the perspective of testing the delayed price discovery hypothesis, we find that price limits have both positive and negative effects. In comparison with the market without price limits, the imposition of price limits does result in delayed price discovery. However, in the presence of price limits, we may prefer stringent price limits that will effectively help to curb traders' overreaction behavior, so that the frequency of price reversals becomes higher.

4.3. *The trading interference hypothesis*

As a confirmation of the validity of the trading interference hypothesis, we expect that the rational trading on the locked limit days will be restricted. Therefore, the trading volume will increase on the day after the locked limit day (Day 1). However, such a phenomenon will not be observed in the case of event $\text{Day}_{0.9}$ or in the market without price limits. To examine the existence of trading interference, we simply focus on the percentage change in trading volume. Table 5 reports the median of percentage changes in trading volume over the 11-day window across 30 runs for all events.

In Table 5, when the price limits are absent, on average, the absolute values of the percentage changes are larger from Day -2 to Day 2, when the limit criterion is made higher, except for those on $\text{Day}_{0.9}$ for Market B. This result indicates that the larger variations in volume will persist for several periods. It is also shown that the trading volume increases on Day 0 and decreases on Day 1 for both Day_{Hit} and $\text{Day}_{0.9}$. In addition, on Day -1, the percentage change is negative and its absolute value is usually

Table 4
Delayed price discovery test

Price Behavior	Day_{Hit}	$\text{Day}_{0.9}$	$z_{\text{H},0.9}$
Market A			
Continuation	0.4755 (0.1416)	0.1679 (0.1220)	** (**)
Reversal	0.5244 (0.8558)	0.8313 (0.8757)	** (**)
No change	0.0001 (0.0026)	0.0007 (0.0023)	**
Market B			
Continuation	0.5403 (0.1495)	0.2061 (0.1292)	** (**)
Reversal	0.4597 (0.8483)	0.7939 (0.8665)	** (**)
No change	0.0000 (0.0022)	0.0000 (0.0044)	NA (**)
Market C			
Continuation	0.6935 (0.1707)	0.2163 (0.1566)	**
Reversal	0.3065 (0.8270)	0.7837 (0.8417)	** (*)
No change	0.0000 (0.0023)	0.0000 (0.0017)	NA
Market D			
Continuation	0.6748 (0.1759)	0.2814 (0.1627)	**
Reversal	0.3252 (0.7186)	0.8211 (0.8348)	**
No change	0.0000 (0.0030)	0.0000 (0.0025)	NA
Market E			
Continuation	0.6681 (0.1742)	0.2086 (0.1826)	**
Reversal	0.3317 (0.8209)	0.7914 (0.8155)	**
No change	0.0001 (0.0048)	0.0000 (0.0019)	
Market F			
Continuation	0.7406 (0.1691)	0.2588 (0.1647)	**
Reversal	0.2594 (0.8237)	0.7412 (0.8318)	**
No change	0.0000 (0.0072)	0.0000 (0.0036)	NA

The last column shows, based on the z test, the significance regarding the difference in frequency between the event Day_{Hit} and $\text{Day}_{0.9}$, i.e. $P_{i,Hit}$-$P_{i,0.9}$, where i=c or r. * and ** mean that the difference is significantly different from zero at the 5% and 1% significance levels, respectively.

higher than those from Day -5 to Day -2, and the percentage change is positive on Day 0. These results imply that the volume and the price may increase with higher percentages on the next day (Day 0) if the volume decreases by a higher percentage compared with the absolute value of the percentage change on the previous days.

On the other hand, when the price limits are imposed, we observe several interesting phenomena. First, the volume behavior on Day -1 for Day_{Hit} is quite different from that in Market G. The picture that, as the price limit level increases, the higher percentage reductions in volume on Day -1 may result in the higher percentage increases on Day 0 is not observed. The higher percentage reductions on Day -1 are found when the price limits are more stringent, while their values range from -1.21% in Market D to -1.89% in Market F, together with a positive exception in Market C (1.07%). Second, from Market A to Market D, the trading volume for Day_{Hit} increases and decreases on Day 0 and Day 1, respectively, of which the values range from 9.97% to 53.03% and from -30.91% to -8.95%. The more stringent the price limits are, the larger the absolute values of the percentage changes are on both Day 0 and Day 1. These results are inconsistent with the trading interference hypothesis. In other words, the price limits do not interfere with the trading activity but improve the trading opportunity. Third, from Market E

Table 5
Trading interference test

Day	Market A Day_{Hit}		Market A $Day_{0.9}$	Market B Day_{Hit}		Market B $Day_{0.9}$
-5	-2.09% (-0.55%)	$>$	-2.78% (0.00%)	-2.17% (-0.58%)		-0.81% (-0.57%)
-4	-1.03% (0.60%)	$<$	0.83% (0.00%)	-1.68% (0.64%)		-1.97% (0.58%)
-3	-2.52% (-0.61%)		-2.54% (-0.54%)	-1.90% (-0.65%)		-1.69% (-0.58%)
-2	0.79% (1.18%)	$(\gg)$	0.62% (0.52%)	-0.84% (1.30%)	$(>)$	0.00% (0.68%)
-1	-4.79% (-1.18%)	$(\ll)$	-4.11% (-0.61%)	-3.53% (-1.32%)		-5.26% (-1.18%)
0	53.03% (2.29%)	$\gg (\gg)$	1.56% (0.57%)	52.59% (2.82%)	$\gg (\gg)$	2.46% (1.85%)
1	-30.91% (-2.03%)	$\ll (\ll)$	-9.90% (-0.58%)	-30.19% (-2.58%)	$\ll (\ll)$	-10.74% (-1.65%)
2	-7.76% (1.23%)	$\ll (\gg)$	2.80% (0.59%)	-11.60% (1.32%)	$\ll$	2.73% (1.21%)
3	-5.41% (-1.11%)	$\ll (\ll)$	-3.08% (-0.58%)	-5.52% (-1.17%)	$<$	-4.59% (-1.14%)
4	-1.84% (0.61%)	$(>)$	-2.74% (0.55%)	-3.16% (0.63%)	$<$	-2.19% (0.64%)
5	-2.26% (-0.57%)		-1.59% (-0.54%)	-1.69% (-0.58%)		-2.11% (-0.66%)

Day	Market C Day_{Hit}		Market C $Day_{0.9}$	Market D Day_{Hit}		Market D $Day_{0.9}$
-5	-1.38% (-0.61%)	$(<)$	-2.07% (0.00%)	-1.37% (-0.81%)		-1.23% (-0.55%)
-4	-3.13% (1.21%)	$\ll (\gg)$	0.00% (0.00%)	-2.92% (1.81%)	$(\gg)$	-1.61% (0.88%)
-3	0.00% (-1.12%)	$\gg (\ll)$	-3.92% (-0.54%)	-0.55% (-1.69%)	$\gg (\ll)$	-3.25% (-0.62%)
-2	-4.79% (1.80%)	$\ll (\gg)$	0.77% (0.55%)	-3.15% (2.68%)	$\ll (\gg)$	1.36% (0.75%)
-1	1.07% (-1.76%)	$\gg (\ll)$	-5.34% (-0.52%)	-1.21% (-2.94%)	$\gg (\ll)$	-5.41% (-0.56%)
0	16.33% (2.96%)	$\gg (\gg)$	8.09% (1.38%)	9.97% (4.62%)	$\gg (\gg)$	3.91% (1.25%)
1	-11.66% (-2.52%)	$\gg (\ll)$	-18.21% (-0.65%)	-8.95% (-4.16%)	$\gg (\ll)$	-18.34% (-0.67%)
2	-19.66% (1.19%)	$\ll (\gg)$	5.00% (0.00%)	-18.78% (2.46%)	$\ll (\gg)$	2.90% (-0.57%)
3	-4.13% (-0.63%)	$> (\ll)$	-5.17% (0.00%)	-5.63% (-1.82%)	$(\ll)$	-3.10% (0.64%)
4	-3.60% (0.00%)	$\ll (\gg)$	-0.71% (-0.57%)	-2.72% (1.12%)	$\ll (\gg)$	-1.86% (-1.03%)
5	-1.99% (0.00%)	$(<)$	-2.45% (0.00%)	-2.07% (-0.65%)	$(\ll)$	-1.94% (1.21%)

Day	Market E Day_{Hit}		Market E $Day_{0.9}$	Market F Day_{Hit}		Market F $Day_{0.9}$
-5	-1.38% (-1.23%)		-2.43% (-1.26%)	1.23% (-1.69%)	$>$	-2.61% (-1.27%)
-4	-3.36% (2.00%)	$<$	0.00% (1.89%)	-4.93% (2.61%)	$<$	-1.34% (1.94%)
-3	0.76% (-2.24%)	$\gg$	-4.23% (-1.37%)	0.48% (-2.56%)		-2.09% (-3.11%)
-2	-4.17% (3.47%)	$\ll$	1.41% (2.91%)	-4.55% (4.05%)	$<$	-1.96% (4.00%)
-1	-1.59% (-3.91%)	$\gg (\ll)$	-7.31% (-2.33%)	-1.89% (-5.08%)	$\gg$	-8.70% (-4.68%)
0	-2.29% (6.21%)	$\ll (\gg)$	8.21% (3.79%)	-10.45% (6.42%)	$\ll (<)$	8.39% (7.12%)
1	14.71% (-5.83%)	$\gg (\ll)$	-21.73% (-3.37%)	55.56% (-5.99%)	$\gg (>)$	-23.49% (-7.55%)
2	-19.35% (3.68%)	$\ll (\gg)$	3.98% (1.28%)	-19.92% (4.43%)	$\ll$	0.93% (5.26%)
3	-4.27% (-3.05%)	$\gg (\ll)$	-8.25% (-1.08%)	-5.26% (-3.95%)		-3.27% (-3.55%)
4	-2.34% (1.89%)	$\ll (\gg)$	-1.44% (0.70%)	-3.24% (3.18%)		-3.39% (1.92%)
5	-1.64% (-1.70%)	$(\ll)$	-2.39% (0.00%)	1.71% (-2.11%)	$\gg$	-2.78% (-1.64%)

$>$ and $\gg$ (or $<$ and $\ll$) mean that, based on the Wilcoxon signed-rank test, the medians on the left are significantly greater (smaller) than those on the right at the 5% and 1% significance levels, respectively.

to Market F, the results are reversed. The trading volume decreases on Day 0 and increases on Day 1 for Day_{Hit}, which is more apparent when the price limit level is higher. This part supports the trading interference hypothesis. Fourth, for the event of $Day_{0.9}$, because the prices do not close at the limits, we would expect that the trading will not be affected, compared with that in the market without the price limits. From Market A to Market F, it is clear that the trading volume increases on Day 0 and decreases on Day 1, and is qualitatively the same as that observed in Market G. However, the absolute values of the percentage changes are larger when the price limits are imposed. Such a phenomenon further confirms the claim made in Isaac and Plott (1981).

Basically, our results of the test of the trading interference hypothesis possess some features similar to those obtained in that of the delayed price discovery hypothesis. The imposition of price limits generates both positive and negative effects. The final outcome crucially depends on the level of price limits. Our findings indicate that, below the 7% price limit (Market A to Market D), there is no evidence of trading interference. The price limits result in an increase rather than a decrease in the trading activity. However, when the price limit level is higher (Market E to Market F), the phenomenon of trading interference emerges. The higher the price limit level is, the more apparent this phenomenon is.

4.4. *Further analysis*

Relaxing the assumption of full rationality and assuming that traders are unaware of the fundamental value of the asset, we are not surprised with the finding that both the positive and the negative effects of the imposition of price limits may coexist. The aggregate market properties then depend on which side dominates the other. Basically, the rationale behind these results can be found in the argument referred to in Tversky and Kahneman (1974):

> In many situations, people make estimates by starting from an initial value that is adjusted to yield the final answer. ... That is, different starting points yield different estimates, which are biased toward the initial values. We call this phenomenon anchoring. (p. 1128)

It is the anchoring effect that affects the traders' expectations, so that the existence of price limits will come into play. Therefore, the aggregate impacts of price limits are the outcome resulting from the interaction between the price limit rules and those bounded-rational traders without the information regarding the fundamental value of the stock.

The price limits serve as an external strength in "adjusting" the traders' expectations regarding the future and keeping them in a narrower range, so that the price volatility is stabilized. However, such an adjustment takes place by way of distorting the price dynamics so as to modify the traders' expectations. This effect happens because the traders are unaware of the intrinsic value of the stock, and their bounded rationality and adaptive learning behavior drive them to search for the intrinsic value of the stock from a starting point which is estimated on the basis of the incomplete information currently available to them. Therefore, their estimates of the intrinsic value are biased toward such a staring point. As a consequence, the anchoring effect may lead to insufficient expectation adjustment. The presence of price limit hits as additional information, together with the altered price dynamics, reshapes the situations that the traders encounter as well as the corresponding starting point, and thus the traders' estimates would be different from those they made under the situation in which the price limits are not imposed. The more restrictive the price limits are, the more insufficient the expectation adjustment is. Such insufficiency would be helpful in curbing traders' overreaction behavior. Price limits are more effective in reducing volatility if the price limit level is more stringent. However, as the price limit level increases, the positive effect of price limits resulting from adjusting the traders' expectations, i.e. the force that curbs the traders' overreaction, is weaker, and the negative impacts becomes more apparent.

Although we observe the evidence of delayed price discovery in Table 4, the test employed in Kim and Rhee (1997), however, gives rise to a serious problem. Unlike the tests regarding volatility spillover and trading interference, this test is performed simply based on two return series, open-to-close returns ($R_{t,OC}$) and close-to-open returns ($R_{t+1,CO}$), on the event day. It does not take the price trend in the days after the event day into account. Therefore, this test may misevaluate the effects of delayed price discovery. The phenomenon of delayed price discovery can be also visualized based on larger time scales. In Figure 2, we present a typical run for the price dynamics under 0.5%, 1%, 5%, and 10% price limits. The dash line is the dynamics of the fundamental value of the stock. It is clear that, under the stringent price limits such as the 0.5% and the 1% levels, the price dynamics exhibits an increasing trend which is a sign of delayed price discovery, while it fluctuates over a range instead when the price limits are large enough, e.g. the 5% and the 10% price limits. These properties further indicate that the phenomenon of delayed price discovery is more serious if the price limits are more restrictive.

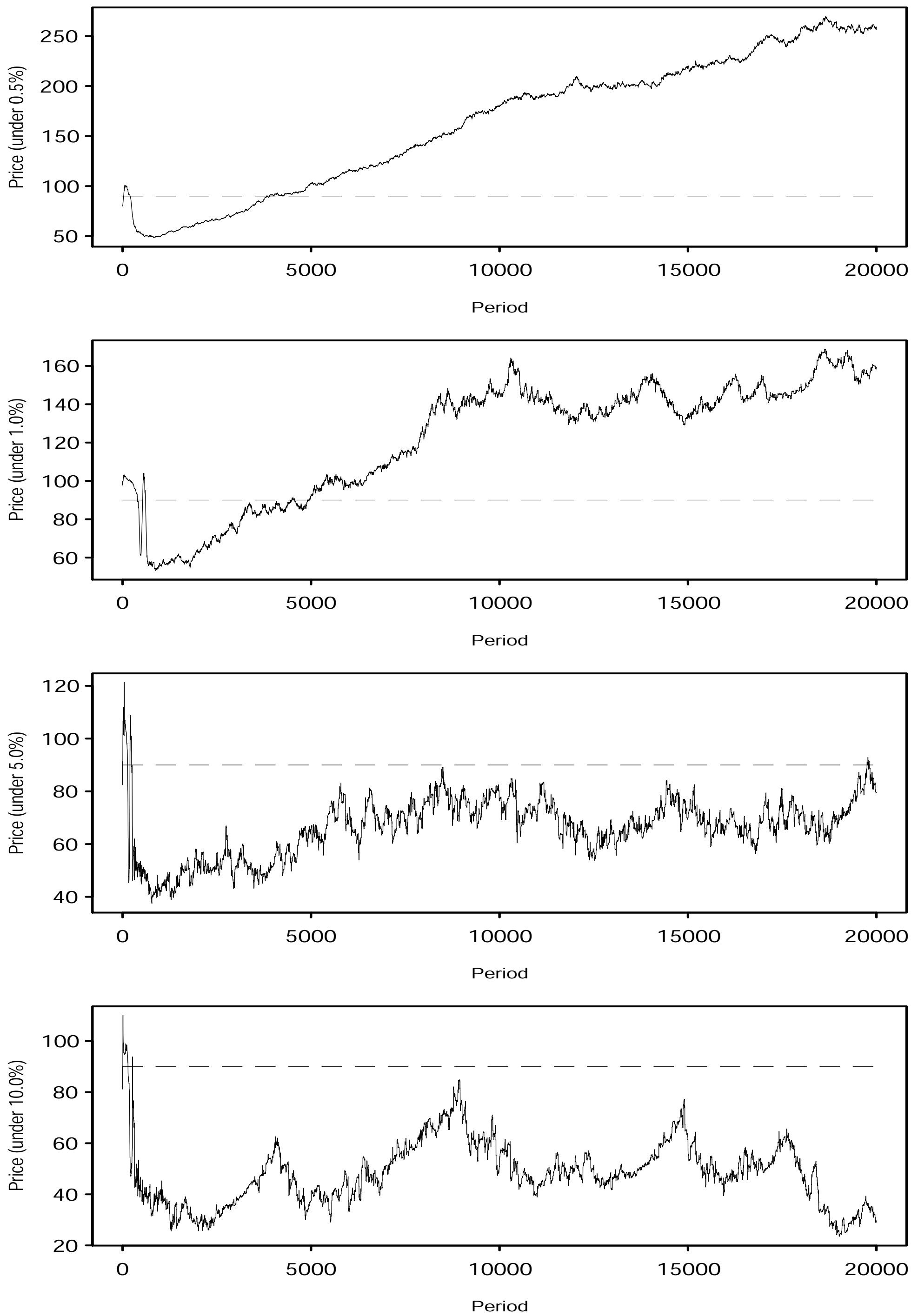

Fig. 2. Price series under 0.5%, 1%, 5%, and 10% price limits

The influence of price limits on trading activity is not so straightforward because price limits will affect the heterogeneity and the distribution of traders' reservation prices as well as the trading opportunity between the buyers and the sellers. To have a better understanding regarding its impacts on trading activity, we focus on the relationship between the range of traders' reservation prices and the range

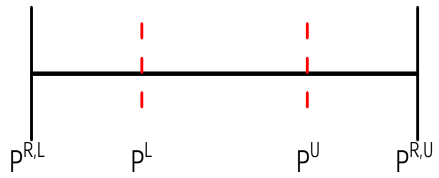

Fig. 3. Price ranges

of price variation imposed by price limits. In Figure 3, $P^{R,U}$ and $P^{R,L}$ denote the maximum and the minimum of traders' reservation prices in a period, respectively, and P^U and P^L are the upper and the lower price limits in a period, respectively. Consider the situation where the range of traders' reservation prices covers that of price variation imposed by price limits, i.e. $[P^L, P^U] \subset [P^{R,L}, P^{R,U}]$,[4] The locked limits happen when the strength resulting from the buyers (or the sellers) overwhelms the other side under the current price limit level. Different price limit levels will result in different distributions of trading opportunities among traders. Take as an example a case in which an upper locked limit happens and the strength resulting from the buyers still maintains its dominance over the sellers. The traders whose reservation prices are higher than P^U are the buyers, while the traders are the sellers if their reservation prices are lower than P^U. Therefore, the trading opportunity will be exploited under the mating between the buyers and the sellers.

The presence of price limits may generate two different situations for the one-sided shocks when the locked limits happen at the outset: the trading opportunity has or has not been fully exploited. The situation where the trading opportunity has not been fully exploited more probably appears when the price limit level is lower, while the other usually happens when the price limit level is higher. In the former case, the existence of price limits helps to increase the trading volume because the prices are prohibited from reaching beyond the authorized range of variations, so that the difference between the number of buyers and the number of sellers remains unchanged. This provides the time for the buyers and the sellers to exploit the trading opportunity. However, in the latter case, due to the fact that the price limit level is high enough, the price will quickly reach the limits. For the events of upper (lower) locked limits, it is very possible that a buyer (seller) has switched to be a seller (buyer) before he would successfully purchase (sell) the stock because the price has gone above (below) his reservation price. The number of buyers (sellers) will soon be much smaller than that of sellers (buyers), so that the trading volume is lower. Therefore, the imposition of price limits results in two different forces which drive the trading volume toward the opposite directions. These explain why the volume largely increases on the locked limit days when the price limits are stringent, while it decreases when the price limit level is high enough.

5. Conclusion

In this paper, we examine whether or not the imposition of price limits generates negative impacts on the market. We find that price limits help to reduce volatility. The main reason for the rejection of the volatility spillover hypothesis is that, in the market populated by bounded-rational traders who have no information regarding the fundamental value of the asset, what the traders can do is to make the forecasts on the basis of the current situation. Therefore, it is the anchoring effect that results in lower volatility by which traders' overreaction behavior is curbed. However, this positive effect is at the expense of distorting traders' expectations and inhibiting traders' abilities from inferring the fundamental value of the asset. Therefore, the phenomenon of delayed price discovery is more apparent when the price limits are more restrictive. The impact of the imposition of price limits on trading volume crucially depends on the level of price limits because the price limits have both opposite effects on trading activity. Therefore,

[4] Of course, there are other patterns for the relationship between $[P^{R,L}, P^{R,U}]$ and $[P^L, P^U]$. However, we find that the case of $[P^L, P^U] \subset [P^{R,L}, P^{R,U}]$ is the most possible one. Approximately 99% of all locked limit days belong to this type.

whether we should impose price limits or not and what the appropriate range of the price limits should be crucially hinge on the goals of the policy-makers that take into consideration how to maintain a balance between the positive and the negative impacts.

Acknowledgement

Research support from NSC Grant no. 97-2410-H-155-010 is gratefully acknowledged.

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