The Effect of Price Limits on Price Discovery in China's Stock Market *

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Abstract

This paper studies the effect of price limits on price discovery process in China's stock market by examining whether the price limit strengthens the daily return autocorrelation. Using two conventional methods, OLS and GARCH, we find that when the price hits the upper limit, the autocorrelation is strengthened. However, when the price hits the lower limit, the effect on autocorrelation is inconclusive. Since daily price limit may bias the conventional econometric methods, we also use GMM consistent estimators to estimate the models. Overall, the price limits effects obtained by the GMM method are stronger than those of the OLS and GARCH methods. Specifically, both upper limit hitting and lower limit hitting strengthen the autocorrelation significantly. We thus conclude that price limits do delay the price discovery process in China's stock market.

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1 Introduction

China's stock market includes two stock exchanges – Shanghai Stock Exchange and Shenzhen Stock Exchange. Both stock exchanges imposes a 10% price limit on common stocks.[1] Price limits were introduced in July, 1990 with the birth of the Chinese stock market. Initially, trading on the stock market was very thin. In order to stimulate trading, the price limit was abandoned on May 12, 1992. From 1992 to 1995, the market gradually became heated. To maintain the stability of China's stock market, the price limit was restored on December 16, 1996 to prevent excessive speculation. The policy remains effective to date.

In China's stock market it is quite common to see consecutive price limit hitting. For example, stock No. 600477 in Shanghai Stock Exchange kept hitting the upper limit for 4 consecutive trading days since August 29, 2008. The record for Shanghai Stock Exchange is 42 consecutive trading days, established by stock No. 600385 beginning from February 28, 2007.[2]

Price limits have been a topic for debates for many years. Those who oppose to the policy argue that it may hurt market efficiency. For example, Fama (1989) proposed the delayed price discovery hypothesis. According to the hypothesis, if the true equilibrium price falls outside the daily price limits, the price will continue to move in a direction towards equilibrium even in the presence of price limits. Price limits only prolong the number of trading days it will take for the market to adapt to a disturbance towards the new equilibrium. Following the hypothesis, we will observe price continuation after the price hits the limits. However, price limits are prevalent in many stock markets in the world, including China, Austria, Belgium, France, Italy, Japan, Korea, Malaysia, Mexico, the Netherlands, Spain, Switzerland, Taiwan and Thailand. The support for price limits is based on the overreaction hypothesis, which maintains that stock prices may often reach the limits due to investors' overreaction to new information. Imposing price limits gives market participants extra time to evaluate the information and reposition their investment. Price limits are helpful to prevent excessive volatility and to protect investors by limiting potential daily losses to a maximum. If this is the case, we may observe return reversals after the price hits the limits.

Empirical studies have offered mixed evidence about the two hypotheses. Ma, Rao and Sears (1989) find both price continuation and reversal in the American futures markets. Kim and Rhee (1997) compare the behavior of the stocks that reach a price limit to that of stocks that come close to the limit, and find evidence of price continuation in the Tokyo stock exchange. George et.al (2005) and Phylaktis et. al (1999) find price continuation in the Athen stock market. The overreaction hypothesis is supported by Huang et al. (2001) and Al-Khouri and Ajlouni (2007).

In this paper, we explore whether price limits harm the price discovery process in the Chinese stock market. Wu and Xu (2002), Chen (2005), and Qu (2007) have done extensive

[1]For special stocks whose codes begin with ST, the price limit is $\pm 5\%$. Since January 8th, 2007, the same rule also applies to the stocks that have not completed the non-tradable share reform. There are no price limits on the first listing day.

[2]Actually, many market participants view the price limit hitting as a sigal to buy (if it is a up limit hit) or sell (if it is a down limit hit).

studies on the Chinese stock market. All three articles use the method similar to Kim and Rhee (1997) and find evidence of price continuation in China's stock market. We will explore this issue from a different perspective. The basic idea is to study the effect of price limit on return predictability. If the delayed price discovery hypothesis holds, we expect the price limit to strengthen the return autocorrelation. On the other hand, if the overreaction hypothesis holds, the return autocorrelation will be weakened by the price limit. This approach was initially used by Shen and Wang (1998) to study the impact of price limit on the return predictability in the Taiwan stock market.

It is well documented that both lagged return and turnover ratio are significant predictors of daily returns so we include them as two control variables. [3] Dummy variables are used to capture the effect of a price limit hit. We first adopt the traditional OLS and GARCH methods to estimate the effects of price limit hitting on the price discovery process. Using traditional methods, we find that the upper limit hitting strengthens the return autocorrelation, but not for the lower limit hitting. Since the observed prices are truncated by the limits, we adopt the GMM approach proposed by Shen and Wang (1998) to treat the price limit data. Estimation results by GMM report that both the upper limit hitting and the lower limit hitting have a significant effect on strengthening the return autocorrelation. Thus, our empirical studies show that price limits may delay the price discovery process in China's stock market.

2 Data Description

To study the effect of price limits, we pick 33 sample stocks of HuShen 300 index, which is considered to be a good representative for the whole Chinese stock market. We use the same industry structure as the Hushen 300 Index to construct the sample. The sample period covers from December 16, 1996 to June 10, 2009.[4] The data are from the Resset Database. Stock returns have been adjusted for dividend payments. For stock 000100, the name was changed from TCL to STTCL from May 28, 2007 to March 27, 2008 and the price limit of 5% applies. [5] Otherwise, the 10% price limit applies.

Table 1 presents the descriptive statistics of stock returns. From table 1, we can see that most series of stock returns have a positive mean and a large standard deviation. Sample means are insignificantly different from zero, which is a common feature of stock returns across the world. In general, stock returns exhibit skewness to the right and large kurtosis. For all 33 stocks, the number of up price limit hitting is larger than that of down price limit hit. The percentage of hit days ranges from 0.598% to 5.705%. Therefore, price limit hitting is quite frequent for these stocks and is non-trivial. The imposition of price limits is expected to affect the behavior of stock returns.

[Table 1]

[3]Poterba and Summers (1988), Conrad et al. (1991) and Lehmann (1990) show significant positive autocorrelation in daily returns. Campbell et al. (1993) show that trading volume can forcast future returns.

[4]Both Shenzhen Stock Exchange and Shanghai Stock Exchange resumed price limits on December 16, 1996.

[5]ST is a short for "special treatment". It indicats that the company has suffered operating losses for 2 years in a row.

3 Model Specifications

Following Shen and Wang (1998), we employ the following models to investigate the effects of price limits on the price discovery process:

$$
\begin{aligned}
r_t^* &= \beta_0 + \beta_1 r_{t-1}^* + \varepsilon_t, & (1)\\
r_t^* &= \beta_0 + (\beta_2 + \beta_3 TO_{t-1}) r_{t-1}^* + \varepsilon_t, & (2)\\
r_t^* &= \beta_0 + (\beta_4 + \beta_5 PLU_{t-1} + \beta_6 PLL_{t-1}) r_{t-1}^* + \varepsilon_t, & (3)\\
r_t^* &= \beta_0 + (\beta_7 + \beta_8 TO_{t-1} + \beta_9 PLU_{t-1} + \beta_{10} PLL_{t-1} +) r_{t-1}^* + \varepsilon_t, & (4)
\end{aligned}
$$

where r_t^* is the equilibrium stock return that clears the market, TO_t is the turnover at time t, and PLU_t and PLL_t are the price limit dummy variables for the upper and lower price limit hitting, respectively. The dummy variables are equal to 1 if the observed price hits the price limit and 0 otherwise. Since it is well documented that the stock returns are characterized by positive autocorrelation over a short interval (Poterba and Summers, 1988; Boudoukh et al., 1994), the autocorrelation coefficients β_1, β_2, β_4, and β_7 are expected to be positive. Previous theoretical studies and empirical evidence suggest that the volume effect is negative (Campbell et al., 1993; Blume et al., 1994; Boudoukh et al., 1994), so we expect autocorrelation is lower on high-volume days than on low-volume days. Specifically, we expect β_3 to be negative. If this is true, the daily first autocorrelation of stock returns decreases when the volume increases, and may even become negative when the trading volume is sufficiently large (see equation 2).

Autocorrelation can catch the trend of daily return in the short term. Here we want to investigate whether limit hits intensify the autocorrelation. When the price hits the limit, there are two possibilities. First, if the movement is caused by big news, and the new equilibrium value of the stock is outside the daily price limit range, the stock price will be pushed to the daily price limit. In this case, on the next day, the stock price may continue to move in the same direction, and as a result, the return autocorrelation will be enhanced. On the other hand, the price limit hit may be caused by investors' overreaction. For example, suppose that the fair price of the stock should increase by 5%. However, investors overreact to the news and push the stock price to hit the 10% upper limit. In this case, on the next day, the stock price may reverse and move in the opposite direction. As a result, the return autocorrelation is weakened. If the delayed price discovery hypothesis holds, β_5, β_6, β_9, and β_{10} are expected to be positive. If the overreaction hypothesis holds, these coefficients are expected to be negative.

4 Estimation Results

In models (1) to (4), the equilibrium returns are required. Note that equilibrium returns cannot be observed during the price limit hitting days because price limits restrict the range of the price movement. We will first present the estimation results of OLS and GARCH where the observed prices are treated as if they were the equilibrium prices.[6] However, as pointed out by Chiang and Wei (1995) and Chou (1997), this treatment of data may produce spurious results because the true relationship among stock returns is distorted. To correct for this problem, we also present estimation results based on the GMM approach proposed by Wei and Chiang (2004) and Shen and Wang (1998). The GMM approach is designed specifically to deal with data that are censored by the price limit. It will yield consistent estimates of the true parameters under the assumption that the generating process of stock returns are invariant with price limits. Although the estimations by OLS and GARCH may be biased, they still have some merits and can be complementary to the GMM estimations. OLS can serve as a benchmark, while GARCH considers conditional heteroscedasticity.

4.1 Results of OLS Estimation

Table 2 reports the OLS estimation results of models (1) and (2). The estimated coefficients in model (1) are positive for 27 out of the 33 stocks, in which 12 are significant at the 5% level. When the interaction term $TO_{t-1}r^*_{t-1}$ is added, 25 autocorrelation coefficients are positive, in which 8 are significant at the 5% level. The autocorrelation coefficients thus have the expected sign. Furthermore, among the 33 stocks, 21 have negative coefficients on the interaction term, $TO_{t-1}r^*_{t-1}$, which suggests that the autocorrelation coefficient declines when the turnover increases; this is consistent with the negative volume effect reported by previous literature.

Table 3 reports the OLS estimation results of model (3), which only considers the price limits hitting and its effects on the autocorrelation. The coefficients for the autocorrelation, β_4, is only positive for 15 stocks. However, the upper limit hitting-interaction term, β_4, is positive 32 out of the 33 stocks, and is significant for 24 stocks; this means that when the price hits the upper limit, the autocorrelation coefficient tends to increase. On the other hand, the coefficient for the lower limit hitting-interacting term is negative for 17 stocks (and significantly negative for 2 stocks), and positive for 16 stocks (and significantly positive for 6 stocks). The OLS estimation results of model (3) suggest that the effect of the lower limit hitting on the autocorrelation is somewhat inconclusive.

Table 4 reports the OLS estimation results of model (4). The estimated coefficients, β_7, is positive for 25 out of the 33 stocks. The turnover reduces the autocorrelation for most stocks since β_8 is negative for 29 stocks, and significantly negative for 14 stocks. Moreover, the coefficient for PLU_{t-1} is positive except for 1 stock, and significantly positive for 24 stocks. The coefficient of PLL_{t-1} is positive for 20 stocks (and significantly positive for 6 stocks) and negative for 13 stocks (and significantly negative for 2 stocks). Hence, when the price hits the upper limit, the autocorrelation tends to increase, while when the price hits the lower limit, the relationship becomes somewhat ambiguous.

Overall, OLS estimation results are consistent with the positive autocorrelation phenomenon for short horizons and the commonly testified negative volume effect. For the price limits effect, when price hits the upper limit, the autocorrelation tends to increase; when lower limit hitting happens, the effect is somewhat ambiguous.

[Table 2]

[6] This is the most common approach in the empirical study of stock markets.

[Table 3]
[Table 4]

4.2 Results of GARCH Estimation

Since asset price typically displays heteroscedasticity, OLS may be inefficient in estimating the autocorrelation coefficient. This section uses the GARCH (1, 1) model to estimate. Thus the errors are assumed to follow a GARCH (1, 1) process as

$$\begin{aligned} \varepsilon_t|\Omega_{t-1} &\sim N(0, h_t); \\ h_t &= \theta_0 + \theta_1 h_{t-1} + \theta_2 \varepsilon_{t-1}^2. \end{aligned}$$

where Ω_{t-1} is the information set up to time $t-1$, h_t is the conditional variance, and θ_i $(i = 0, 1, 2)$ are unknown positive coefficients.

Since the results of GARCH (1,1) estimation in general agree with the OLS estimation, we only report the estimation results of model (4), which are shown in table 5. The 20 out of 33 estimated coefficients, β_7, are positive. 26 out of 33 coefficients β_8 are negative, however only 5 of them are significant. All coefficients on PLU_{t-1}, β_9, are positive and 12 of them are significant. Among 33 coefficients for PLL_{t-1}, 17 are positive and 16 are negative. Among those, 3 positive ones are significant and no negative ones are significant.

Therefore, compared to the OLS estimation results, conclusions do not change much except that $GARCH(1, 1)$ estimation results are less significant on average.

[table 5]

4.3 Results of GMM Estimation

In this section, we present the results from GMM estimation.

4.3.1 Methodology

The OLS and GARCH estimation assumes that the equilibrium returns are equal to the observed returns; this may not be true, especially when the stock price hits the limits. Wei and Chiang (2004) and Shen and Wang (1998) propose the following GMM approach to deal with this problem..

Assume that the price limits do not affect the true price generating process of the asset. Denote the equilibrium price as $P_{i,t}^*$, and the observed price as $P_{i,t}$ for stock i at time t. The generating function of the observed return, $r_{i,t}$, is as follows:

$$r_{i,t} = \begin{cases} l_u & \text{if } \log P_{i,t}^*/P_{i,t} \geqslant l_u, \\ \log P_{i,t}^*/P_{i,t} & \text{if } l_d < \log P_{i,t}^*/P_{i,t} < l_u, \\ l_d & \text{if } \log P_{i,t}^*/P_{i,t} \leq l_d, \end{cases}$$

where l_u and l_d are the upper and lower price limits, respectively. Obviously, whether the price hits limit depends on whether the equilibrium return $r_{i,t}^*$ lies within the limit range or not, but not on the magnitude of $r^*_{i,t}$. If $r^*_{i,t}$ lies outside the limit range, it is truncated at l_u or l_d. This truncated data problem can be eliminated by converting the original time series (sampled daily) into an irregularly observed or unequally spaced time series. Specifically, for those days when the price limit is hit, we can aggregate returns across consecutive days and treat the multi-day return as a single unit, instead of using the "price-limited" returns on individual days. In the following, we will suppress the subscript i to simplify the notations. Assuming that the stock price hits the price limit at time t, but it does not for time $t-1$ and $t+1$, namely, $P^*_t \neq P_t$, $P^*_{t-1} = P_{t-1}$, $P^*_{t+1} = P_{t+1}$, thus

$$r_{t+1} + r_t = \log P^*_{t+1}/P_t + \log P_t/P^*_{t-1} = \log P^*_{t+1}/P^*_{t-1} = r^*_{t+1} + r^*_t \equiv z_{t,2}.$$

The two-day true returns, $z_{t,2}$, can be evaluated even when the daily true returns r^*_{t+1} and r^*_t are not observed. The subscript 2 in $z_{t,2}$ means that $z_{t,2}$ is a sum of two terms. The expected value of $z_{t,2}$ is 2μ, which is the mean of r^*_t. Similarly, for the case where the prices reach the limits in two consecutive days, t and $t+1$, we have

$$r_{t+2} + r_{t+1} + r_t = r^*_{t+2} + r^*_{t+1} + r^*_t \equiv z_{t,3}.$$

The expected value of $z_{t,3}$ is 3μ. The analysis is easily extended to the n limits case. Based on this feature of price limit hitting, Shen and Wang (1998) derived the following four GMM estimators:

Theorem 1 *Assuming that r^*_t is subject to the price limit, and $r^*_t \sim iid\ N(\mu, \sigma^2)$, then the GMM estimators of μ and σ^2 are given by:*

$$\begin{aligned}
\widehat{\mu} &= \frac{\sum_{t\in S_1} z^r_{t,1} + \sum_{t\in S_2} z^r_{t,2} + \cdots + \sum_{t\in S_{n+1}} z^r_{t,n+1}}{N_1 + 2N_2 + \cdots + (n+1)N_{n+1}} \\
&= \frac{\sum_{t\in S_1} z^r_{t,1} + \sum_{t\in S_2} z^r_{t,2} + \cdots + \sum_{t\in S_{n+1}} z^r_{t,n+1}}{T}, \\
\widehat{\sigma}^2 &= \frac{\sum_{t\in S_1}(z^r_{t,1} - \widehat{\mu})^2 + \sum_{t\in S_2}(z^r_{t,2} - 2\widehat{\mu})^2 + \cdots + \sum_{t\in S_{n+1}}(z^r_{t,n+1} - (n+1)\widehat{\mu})^2}{T},
\end{aligned}$$

where $z^r_{t+n} = \sum_{k=1}^{n} r_{t+k-1}$, $S_{k+1}(k = 1, 2, \cdots, n)$ is the set of first days of k consecutive hitting sequences, n is the maximum number of consecutive price limit hitting in the sample, S is the set of all non-limit days, S' is the set of days such that each day of this set is exactly the following day (which is a non-limit day) of a k-day limit, $S_1 = S/S'$, and T is the total number of observations. Note that $T = N_1 + 2N_2 + \cdots + (n+1)N_{n+1}$, where N_k is the number of observations in the set S_k.

Theorem 2 *Assuming that r^*_t is subject to the price limit but x_t is not, then the GMM* *estimator of covariance of r_t^* and x_t is*

$$
\begin{aligned}
\widehat{cov}(r_t^*, x_t) &= \frac{1}{T}\sum_{t\in S_1}(z_{t,1}^r - \widehat{\mu})(z_{t,1}^x - \widehat{\mu}_x) \\
&+\frac{1}{T}\sum_{t\in S_2}(z_{t,2}^r - 2\widehat{\mu})(z_{t,2}^x - 2\widehat{\mu}_x) \\
&+\cdots \\
&+\frac{1}{T}\sum_{t\in S_{n+1}}(z_{t,n+1}^r - (n+1)\widehat{\mu})(z_{t,n+1}^x - (n+1)\widehat{\mu}_x)
\end{aligned}
$$

where $z_{t+n}^x = \sum_{k=1}^n x_{t+k-1}$ and $\widehat{\mu}_x$ is the estimated mean of x_t.

Theorem 3 *Assuming that both r_t^* and x_t^* are subject to the price limits, then the GMM-based estimator of covariance is*

$$
\begin{aligned}
\widehat{cov}(r_t^*, x_t^*) &= \frac{1}{T}\sum_{t\in(S_1\cup S_1^x)}(z_{t,1}^r - \widehat{\mu})(z_{t,1}^x - \widehat{\mu}_x) \\
&+\frac{1}{T}\sum_{t\in(S_2\cup S_2^x)}(z_{t,2}^r - 2\widehat{\mu})(z_{t,2}^x - 2\widehat{\mu}_x) \\
&+\frac{1}{T}\sum_{t\in S_3 \text{ or } t\in S_3^x,\text{ or, } t\in S_2 \text{ and } t+1\in S_2^x,\text{ or, } t+1\in S_2 \text{ and } t\in S_2^x}(z_{t,3}^r - 3\widehat{\mu})(z_{t,3}^x - 3\widehat{\mu}_x) + \cdots]
\end{aligned}
$$

Theorem 4 *If r_t^* is first-order autocorrelated, then the GMM estimator of variance and ρ are*

$$
\begin{aligned}
\widehat{\sigma}^2 &= \frac{\sum_{t\in S_1}(z_{t,1}^r - \widehat{\mu})^2 + \sum_{t\in S_2}(z_{t,2}^r - 2\widehat{\mu})^2 + \cdots + \sum_{t\in S_{n+1}}(z_{t,n+1}^r - (n+1)\widehat{\mu})^2}{N_1 + (2+2\widehat{\rho})N_2 + (3+4\widehat{\rho})N_2 \cdots + (n+1+2n\widehat{\rho})N_{n+1}}, \\
\widehat{\rho} &= \widehat{cov}(r_t^*, r_{t+1}^*)/\widehat{\sigma}^2.
\end{aligned}
$$

Based on these four GMM estimators, we use model (2) to illustrate the GMM approach. The demeaned equation of model (2) can be written as:

$$r_t^* - \mu = \beta_2(r_{t-1}^* - \mu) + \beta_3(rto_{t-1}^* - \mu_{rto}) + \varepsilon_t,$$

where $rto_{t-1}^* = TO_{t-1} \times r_{t-1}^*$, or in matrix form

$$\widetilde{r_t^*} = \widetilde{x}_t{}'\beta + \varepsilon_t,$$

where $\widetilde{r_t^*} = r_t^* - \mu$, $\widetilde{x}_t = (r_{t-1}^* - \mu, rto_{t-1}^* - \mu_{rto})'$ and $\beta = (\beta_2, \beta_3)'$. Then

$$
\begin{aligned}
\widehat{\beta} &= (\widetilde{x}_t\widetilde{x}_t')^{-1}(\widetilde{x}_t\widetilde{r}_t^*), \\
var(\widehat{\beta}) &= \widehat{\sigma}^2((\widetilde{x}_t\widetilde{x}_t')^{-1}.
\end{aligned}
$$

These formulae are the same as the OLS estimators. However, when $\widetilde{x}_t$ and $\widetilde{r_t^*}$ are subject to the price limit, the conventional OLS estimators are biased. We can write $\widetilde{x}_t\widetilde{x}_t'$

and $\widetilde{x}_t\widetilde{r}_t^*$ in the form of variance and covariance:

$$\begin{aligned}
\widetilde{x}_t\widetilde{x}_t' &= T\begin{bmatrix} var(\widetilde{r_t^*}) & cov(\widetilde{r_t^*}, \widetilde{rto}_{t-1}^*) \\ cov(\widetilde{r_t^*}, \widetilde{rto}_{t-1}^*) & var(\widetilde{rto}_{t-1}^*) \end{bmatrix} \\
\widetilde{x}_t\widetilde{r}_t^* &= T\begin{bmatrix} cov(\widetilde{r_t^*}, \widetilde{r}_{t-1}^*) \\ cov(\widetilde{r_t^*}, \widetilde{rto}_{t-1}^*) \end{bmatrix}.
\end{aligned}$$

These variances and covariances can be calculated based on the previous four theorems. Once the variance and covariance terms are determined, we can obtain consistent estimates $\widehat{\beta}$ following $\widehat{\beta} = (\widetilde{x}_t\widetilde{x}_t')^{-1}(\widetilde{x}_t\widetilde{r}_t^*)$.

4.3.2 GMM estimation results

Table 6 reports the GMM estimation results of model (1) and (2). All stocks show positive autocorrelation (i.e., $\beta_1 > 0$), and β_1 is significant for all but one stock. For all 33 stocks, β_1 is larger than those obtained from OLS or GARCH estimation. Therefore, OLS or GARCH estimation underestimates β_1. When the turnover-interacted variables are considered, the autocorrelation coefficient, β_2, remains positive for 25 stocks (and significant for 20 stocks). Among the 7 cases with a negative β_2, only one is significant. The coefficients of turnover-interacted variables, β_3, are positive for 28 stocks, and significant for 22 stocks. The coefficient β_3 is negative for 5 stocks and is significant at the 10% level for one stock. These results are inconsistent with the OLS and GARCH estimation which suggests negative volume effect. As shown later, this inconsistence is significantly weakened if model (4) is used.

Table 7 reports the results for model (3) where only the price limit hitting dummies are considered. The coefficient of the upper price limit hitting, β_5, is positive and significant at the 1% level for all stocks. The coefficient of the lower price limit hitting, β_6, are positive and significant at the 1% level for 30 stocks (the coefficient is insignificant for the remaining 3 stocks and negative for 1 stock).

The estimation results for model (4) ares shown in table 8. When we consider both the turnover-interacted variable and price limit hitting. The coefficient of the turnover-interacted term, β_6, becomes negative for 17 stocks and significant for 4 stocks. For 16 stocks, β_6 remains positive, but is only significant for 2 stocks. Therefore, the volume effect is not very strong in China's stock markets. Similar to the findings for model (3), the coefficient of the upper price limit hitting, β_9, is positive and significant at 1% level for all stocks. The coefficient for lower price limit hitting, β_{10}, is positive and significant at the 1% level for 30 stocks. For 3 stocks, β_{10} is insignificant and negative for one stock.

[table 6]
[table 7]
[table 8]

5 Conclusion

This paper studies the effect of price limits on price discovery process in China's stock market by examining whether the price limit strengthens the daily return autocorrelation or not. Using two conventional methods, OLS and GARCH, we find the positive autocorrelation in the short horizon and the negative volume effect as in previous literature. When the price hits the upper limit, the autocorrelation is strengthened. When the price hits the lower limit, the effect on autocorrelation is inconclusive. The result seems to suggest that the delayed price discovery hypothesis holds for the upper price limit, however, both the overreaction hypothesis and the delayed price discovery hypothesis are reasonable for the lower price limit.

Since daily price limits may bias the conventional econometric methods, we also use the GMM consistent estimators to estimate the model. Overall, the price limits effects obtained by the GMM method are stronger than those of the OLS and GARCH methods. Specifically, both upper limit hitting and lower limit hitting strengthen the autocorrelation significantly. Thus, price limits do delay the price discovery process. The results obtained based on GMM also show that the volume effect is not so strong in China's stock market.

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Table 1: Descriptive statistics of stocks returns

Code	Mean	Std. dev	Excess skewness	Excess kurtosis	UH	LH	HS
000002	0.001	0.029	0.232	2.262	29	19	1.618
000100	0.000	0.032	-0.003	1.378	38	30	5.705
000402	0.002	0.031	0.625	6.332	26	15	1.387
000629	0.001	0.027	-0.135	6.721	30	18	1.709
000709	0.001	0.026	0.297	3.520	19	12	1.101
000825	0.001	0.026	0.249	2.904	16	5	0.833
000858	0.001	0.025	0.455	3.004	13	4	0.645
000897	0.001	0.031	0.144	1.919	32	16	2.024
000898	0.001	0.027	0.403	2.379	17	7	0.883
000917	0.001	0.032	-0.005	1.826	30	26	2.340
002024	0.003	0.033	0.425	1.242	14	5	1.641
600001	0.000	0.023	0.425	4.139	15	3	0.681
600005	0.001	0.028	0.250	2.364	19	6	1.068
600010	0.001	0.025	0.279	3.531	16	3	0.965
600016	0.001	0.025	0.326	2.375	10	2	0.598
600018	0.001	0.035	0.249	1.046	12	5	2.660
600019	0.001	0.024	0.235	3.588	11	4	0.747
600028	0.001	0.026	0.386	3.052	15	4	1.028
600037	0.001	0.028	-0.007	2.155	12	9	1.054
600050	0.001	0.026	0.414	3.466	12	5	1.068
600104	0.001	0.027	0.339	2.695	26	8	1.234
600320	0.001	0.028	0.474	4.700	12	2	0.702
600500	0.001	0.03	0.134	2.667	19	10	1.315
600598	0.001	0.03	0.075	2.228	23	13	2.100
600808	0.001	0.028	0.369	2.821	34	13	1.586
600832	0.001	0.029	0.471	3.738	46	14	2.009
600900	0.001	0.023	0.401	3.861	2	4	0.560
601006	0.002	0.034	0.053	0.840	7	7	1.991
601333	0.000	0.03	-0.106	1.388	3	2	0.824
601390	0.000	0.031	0.278	1.866	5	3	2.100
601398	0.001	0.027	0.265	2.256	4	3	1.085
601600	0.000	0.042	0.082	0.234	15	8	4.554
601991	0.001	0.041	0.070	0.472	17	9	4.333

Notes:

UH: number of upper limit hits; LH: number of lower limit hits; HS: % of hit days.

Table 2: OLS estimation results of model (1) and (2)

Code	β_1	t-value	β_1	t-value	β_1	t-value
000002	0.011	0.623	0.011	0.394	0.000	0.014
000100	0.050*	1.712	0.144***	3.203	-0.038***	-2.742
000402	0.056***	3.055	0.060**	2.249	-0.002	-0.179
000629	0.040**	2.124	0.038	1.374	0.001	0.086
000709	0.067***	3.540	0.073***	2.927	-0.005	-0.385
000825	0.073***	3.676	0.109***	3.832	-0.034*	-1.761
000858	0.051***	2.642	0.051	1.629	0.001	0.038
000897	0.041**	1.975	0.029	0.938	0.006	0.495
000898	0.048**	2.525	0.071***	2.736	-0.026	-1.290
000917	0.012	0.584	-0.046	-1.427	0.025**	2.331
002024	0.077***	2.612	0.155***	3.288	-0.108**	-2.119
600001	0.027	1.376	0.023	0.784	0.002	0.187
600005	0.064***	3.081	0.072**	2.310	-0.008	-0.363
600010	0.040*	1.755	-0.005	-0.152	0.019**	2.252
600016	-0.022	-0.971	-0.013	-0.366	-0.008	-0.298
600018	0.011	0.280	-0.060	-1.065	0.156*	1.779
600019	0.058***	2.609	0.071*	1.818	-0.019	-0.392
600028	0.008	0.325	0.003	0.075	0.028	0.127
600037	0.032	1.405	0.056	1.602	-0.020	-0.910
600050	-0.031	-1.241	0.004	0.098	-0.023	-1.106
600104	0.004	0.228	0.065**	2.510	-0.078***	-3.462
600320	0.025	1.102	0.021	0.658	0.002	0.188
600500	0.027	1.258	-0.002	-0.066	0.019	1.067
600598	0.004	0.164	0.071*	1.671	-0.039*	-1.920
600808	0.008	0.417	0.037	1.363	-0.036	-1.461
600832	-0.005	-0.286	-0.001	-0.032	-0.005	-0.267
600900	-0.019	-0.618	0.091*	1.731	-0.118**	-2.569
601006	0.000	0.000	0.069	1.097	-0.162	-1.376
601333	-0.085**	-2.100	-0.062	-0.956	-0.017	-0.474
601390	-0.005	-0.103	0.034	0.401	-0.037	-0.590
601398	0.063	1.586	0.093	1.443	-0.211	-0.598
601600	0.088**	1.963	0.092	1.224	-0.007	-0.069
601991	0.050**	1.217	-0.005	-0.081	0.154	1.340

Notes:

***, **, *: significant at the 1%, 5% and 10%, respectively.

Table 3: OLS estimation results of model (3)

Code	β_4	t-value	β_4	t-value	β_4	t-value
000002	-0.022	-1.085	0.264***	4.655	0.028	0.405
000100	0.016	0.453	0.101	1.229	0.144	1.623
000402	0.033*	1.671	0.180***	2.827	0.123	1.494
000629	-0.011	-0.522	0.221***	4.106	0.220***	3.265
000709	0.072***	3.505	0.021	0.333	-0.118	-1.498
000825	0.078***	3.660	0.036	0.535	-0.267**	-2.295
000858	0.026	1.262	0.394***	5.415	-0.179	-1.403
000897	0.015	0.646	0.167***	2.785	0.037	0.454
000898	0.033	1.612	0.226***	3.275	-0.095	-0.909
000917	-0.008	-0.325	0.034	0.537	0.143**	2.131
002024	0.046	1.438	0.178*	1.890	0.306**	2.021
600001	0.012	0.557	0.133***	2.124	0.034	0.254
600005	0.060***	2.678	0.020	0.302	0.055	0.482
600010	0.025	1.012	0.150***	2.225	-0.178	-1.215
600016	-0.044*	-1.882	0.253***	3.040	0.179	0.990
600018	-0.055	-1.247	0.498***	4.540	-0.136	-0.847
600019	0.053**	2.218	0.070	0.931	-0.048	-0.395
600028	-0.001	-0.049	0.151**	2.129	-0.289**	-2.216
600037	0.002	0.091	0.180**	2.119	0.278***	2.855
600050	-0.066**	-2.429	0.362***	4.591	-0.115	-0.972
600104	-0.018	-0.872	0.207***	3.593	-0.086	-0.868
600320	0.009	0.405	0.181**	2.110	0.159	0.781
600500	-0.005	-0.223	0.315***	4.376	0.028	0.295
600598	-0.028	-1.031	0.239***	3.489	-0.030	-0.341
600808	-0.011	-0.515	0.091*	1.749	0.081	1.021
600832	-0.043**	-2.039	0.092*	1.911	0.377***	4.661
600900	-0.017	-0.520	-0.027	-0.166	-0.015	-0.127
601006	-0.010	-0.249	0.100	0.739	0.020	0.151
601333	-0.075*	-1.756	0.032	0.181	-0.343	-1.612
601390	-0.074	-1.277	0.511***	3.391	-0.023	-0.121
601398	0.000	-0.002	0.525***	3.783	0.289*	1.825
601600	0.035	0.679	0.356***	2.923	-0.084	-0.534
601991	0.001	0.015	0.382***	3.477	-0.169	-1.179

Notes:

***, **, *: significant at the 1%, 5% and 10%, respectively.

Table 4: OLS estimation results of model (4)

Code	β_7	t-value	β_8	t-value	β_9	t-value	β_{10}	t-value
000002	0.011	0.391	-0.017*	-1.664	0.298***	4.945	0.034	0.497
000100	0.118*	2.509	-0.046***	-3.170	0.182**	2.128	0.136	1.543
000402	0.044	1.613	-0.006	-0.575	0.186***	2.882	0.121	1.469
000629	0.002	0.074	-0.009	-0.678	0.230***	4.145	0.217***	3.206
000709	0.077***	3.031	-0.005	-0.335	0.026	0.394	-0.115	-1.457
000825	0.114***	3.938	-0.036*	-1.837	0.052	0.769	-0.264**	-2.275
000858	0.065**	2.112	-0.044*	-1.702	0.435***	5.677	-0.169	-1.321
000897	0.026	0.819	-0.007	-0.507	0.178***	2.788	0.041	0.504
000898	0.060**	2.284	-0.033	-1.637	0.239***	3.446	-0.085	-0.814
000917	-0.056	-1.713	0.024**	2.117	-0.012	-0.185	0.126*	1.857
002024	0.126***	2.620	-0.113**	-2.220	0.188**	1.994	0.308**	2.037
600001	0.019	0.669	-0.005	-0.386	0.140**	2.151	0.039	0.288
600005	0.069**	2.195	-0.010	-0.434	0.027	0.388	0.056	0.485
600010	-0.004	-0.143	0.015*	1.665	0.109	1.528	-0.195	-1.333
600016	-0.015	-0.402	-0.030	-1.072	0.275***	3.208	0.185	1.024
600018	-0.071	-1.264	0.043	0.455	0.479***	4.086	-0.151	-0.919
600019	0.073*	1.879	-0.034	-0.657	0.084	1.073	-0.045	-0.371
600028	0.007	0.164	-0.055	-0.243	0.155**	2.123	-0.287**	-2.186
600037	0.028	0.784	-0.022	-0.979	0.184**	2.165	0.277***	2.844
600050	0.017	0.420	-0.060***	-2.749	0.435***	5.237	-0.113	-0.956
600104	0.053**	2.015	-0.099***	-4.337	0.258***	4.389	-0.104	-1.048
600320	0.015	0.490	-0.004	-0.282	0.186**	2.121	0.160	0.786
600500	0.016	0.451	-0.016	-0.792	0.340***	4.316	0.032	0.333
600598	0.079*	1.851	-0.070***	-3.269	0.317***	4.378	-0.022	-0.244
600808	0.027	0.975	-0.052**	-2.034	0.116**	2.180	0.103	1.286
600832	-0.037	-1.415	-0.007	-0.339	0.094**	1.935	0.376***	4.654
600900	0.091*	1.723	-0.123***	-2.590	0.046	0.271	0.039	0.321
601006	0.059	0.900	-0.162	-1.371	0.100	0.738	0.012	0.089
601333	-0.052	-0.809	-0.017	-0.458	0.053	0.294	-0.337	-1.579
601390	-0.018	-0.211	-0.054	-0.864	0.521***	3.443	-0.028	-0.148
601398	0.043	0.658	-0.303	-0.867	0.530***	3.812	0.300**	1.886
601600	0.065	0.828	-0.054	-0.509	0.363***	2.959	-0.094	-0.591
601991	-0.011	-0.183	0.038	0.319	0.372***	3.232	-0.170	-1.182

Notes:

***, **, *: significant at the 1%, 5% and 10%, respectively.

Table 5: GARCH (1,1) estimation results of model (4)

Code	β_7	t-value	β_8	t-value	β_9	t-value	β_{10}	t-value
000002	-0.002	-0.057	-0.011	-0.785	0.292***	3.606	0.016	0.125
000100	0.093**	2.107	-0.040***	-2.643	0.149	1.262	0.207*	1.986
000402	0.033	1.131	-0.003	-0.161	0.146*	1.784	0.005	0.033
000629	0.009	0.338	-0.009	-0.586	0.155*	1.871	0.072	0.716
000709	0.026	1.055	0.012	0.613	0.050	0.457	-0.116	-0.821
000825	0.028	1.150	-0.013	-1.059	0.085	0.846	-0.197	-1.185
000858	0.039	1.367	-0.034	-1.054	0.398***	2.821	-0.172	-0.425
000897	-0.004	-0.132	0.001	0.051	0.182**	2.135	0.050	0.378
000898	0.033	1.200	-0.026	-0.934	0.169	1.455	-0.064	-0.285
000917	-0.054*	-1.757	0.019	1.492	0.023	0.276	0.117	1.488
002024	0.131***	2.647	-0.090	-1.480	0.092	0.845	0.290	1.433
600001	-0.013	-0.505	0.002	0.156	0.094	0.691	0.008	0.016
600005	0.046	1.444	0.009	0.285	0.042	0.249	0.052	0.096
600010	-0.016	-0.545	0.018	1.532	0.074	0.614	-0.188	-1.160
600016	-0.040	-1.131	-0.004	-0.110	0.254	1.581	0.174	0.338
600018	-0.014	-0.232	-0.066	-0.549	0.592***	3.650	-0.049	-0.175
600019	0.032	0.832	-0.004	-0.064	0.087	0.395	-0.036	-0.164
600028	0.004	0.103	0.061	0.255	0.121	0.992	-0.318	-0.595
600037	0.061*	1.745	-0.051**	-1.982	0.244*	1.975	0.251	1.333
600050	0.004	0.084	-0.047	-1.377	0.489***	3.58	-0.146	-0.585
600104	0.055**	1.972	-0.082***	-2.627	0.162*	1.876	-0.092	-0.650
600320	0.039	1.193	-0.004	-0.165	0.232	0.821	0.172	0.503
600500	0.015	0.433	-0.008	-0.368	0.309**	2.241	-0.011	-0.058
600598	0.018	0.471	-0.045*	-1.765	0.264	1.503	-0.071	-0.598
600808	-0.004	-0.148	-0.015	-0.511	0.105	1.388	0.117	0.833
600832	-0.006	-0.217	-0.028	-0.857	0.003	0.044	0.246**	2.036
600900	0.071	1.239	-0.109*	-1.769	0.073	0.066	0.058	0.216
601006	0.050	0.687	-0.145	-1.228	0.104	0.241	0.052	0.284
601333	-0.034	-0.491	-0.025	-0.611	0.036	0.182	-0.341	-0.014
601390	-0.014	-0.164	-0.027	-0.409	0.455**	2.457	-0.071	-0.626
601398	0.020	0.267	-0.161	-0.364	0.491*	1.953	0.324**	2.022
601600	0.107	1.294	-0.091	-0.782	0.358**	2.059	-0.137	-0.612
601991	-0.003	-0.051	-0.103	-0.761	0.456***	2.907	-0.219	-0.839

Notes:

***, **, *: significant at the 1%, 5% and 10%, respectively.

Table 6: GMM-Price limit estimation results of model (1) and (2)

Code	β_1	t-value	β_1	t-value	β_1	t-value
000002	0.248***	13.507	0.080***	2.803	0.075***	7.793
000100	0.340***	11.706	0.317***	6.898	0.009	0.629
000402	0.249***	13.505	0.249***	9.391	0.000	0.000
000629	0.381***	20.127	0.386***	13.176	-0.004	-0.240
000709	0.229***	12.108	0.143***	5.621	0.071***	5.008
000825	0.202***	10.143	0.219***	7.736	-0.016	-0.818
000858	0.186***	9.560	-0.020	-0.626	0.213***	8.366
000897	0.296***	14.370	0.072**	2.280	0.113***	9.325
000898	0.187***	9.733	0.143***	5.429	0.049**	2.443
000917	0.320***	15.675	0.044	1.385	0.117***	11.169
002024	0.257***	8.685	0.329***	6.723	-0.099*	-1.850
600001	0.210***	10.766	0.080***	2.719	0.068***	5.866
600005	0.228***	11.009	0.126***	3.810	0.098***	3.995
600010	0.215***	9.504	0.041	1.385	0.072***	8.864
600016	0.077***	3.452	-0.034	-0.936	0.104***	3.872
600018	0.275***	6.916	-0.031	-0.515	0.596***	6.890
600019	0.207***	9.257	0.064	1.607	0.223***	4.348
600028	0.198***	8.485	-0.047	-1.114	1.527***	6.993
600037	0.217***	9.682	0.210***	5.946	0.006	0.254
600050	0.143***	5.685	0.014	0.342	0.081***	3.882
600104	0.218***	11.418	0.212***	8.097	0.007	0.323
600320	0.140***	6.241	0.081***	2.606	0.034***	2.749
600500	0.214***	10.036	-0.010	-0.293	0.137***	8.247
600598	0.256***	10.553	0.031	0.717	0.129***	6.213
600808	0.277***	15.086	0.146***	5.214	0.163***	6.197
600832	0.327***	17.868	0.254***	10.130	0.084***	4.250
600900	0.102***	3.325	0.119**	2.275	-0.019	-0.402
601006	0.199***	5.250	0.267***	4.290	-0.166	-1.387
601333	0.019	0.472	-0.110**	-1.724	0.095***	2.648
601390	0.242***	4.701	0.187**	2.141	0.049	0.785
601398	0.079**	1.988	-0.097	-1.404	1.234***	3.104
601600	0.362***	8.109	0.295***	3.895	0.114	1.085
601991	0.236***	5.730	0.018	0.286	0.498***	4.443

Notes:

The true returns are estimated by aggregation.

***, **, *: significant at the 1%, 5% and 10%, respectively.

Table 7: GMM-Price limit estimation results of model (3)

Code	β_1	t-value	β_1	t-value	β_1	t-value
000002	0.000	-0.018	1.110***	19.385	1.048***	16.138
000100	0.106***	3.095	0.690***	8.135	1.112***	12.007
000402	0.052**	2.519	0.916***	15.501	1.122***	17.861
000629	0.019	0.827	0.933***	19.225	1.308***	23.576
000709	0.089***	4.292	0.855***	13.798	0.723***	9.859
000825	0.108***	5.050	0.732***	11.350	0.618***	5.309
000858	0.021	1.002	1.956***	22.716	0.652***	5.027
000897	0.046*	1.916	1.046***	17.095	1.116***	13.976
000898	0.051**	2.428	1.053***	14.474	0.920***	8.597
000917	0.022	0.945	1.066***	17.250	1.807***	25.996
002024	0.091***	2.734	1.188***	12.416	0.218	1.348
600001	0.045**	2.112	1.134***	17.369	1.312***	9.594
600005	0.066***	2.905	0.933***	13.416	1.603***	13.675
600010	0.048*	1.938	1.036***	15.663	0.396***	3.479
600016	-0.031	-1.325	0.927***	11.801	1.269***	6.900
600018	-0.029	-0.605	1.146***	11.309	0.788***	4.468
600019	0.085***	3.481	0.874***	11.168	0.880***	7.144
600028	0.020	0.794	1.169***	15.862	0.697***	5.315
600037	0.046*	1.864	1.105***	12.351	1.138***	11.090
600050	-0.025	-0.874	0.941***	11.964	0.766***	6.299
600104	0.024	1.106	1.071***	19.306	0.696***	6.849
600320	0.023	0.957	1.137***	12.790	1.511***	7.297
600500	0.005	0.222	1.145***	16.248	1.195***	11.878
600598	0.001	0.034	1.301***	17.645	0.792***	9.248
600808	0.022	1.048	1.008***	20.900	1.292***	17.153
600832	-0.008	-0.387	1.214***	28.297	1.214***	17.760
600900	-0.007	-0.231	0.680***	4.108	1.221***	10.208
601006	-0.004	-0.094	1.433***	10.357	0.808***	5.846
601333	-0.067	-1.585	1.275***	7.324	0.742***	3.545
601390	-0.067	-1.098	1.578***	8.995	1.307***	6.436
601398	-0.010	-0.217	0.661***	5.022	-0.032	-0.234
601600	0.092*	1.661	0.920***	7.222	0.847***	4.970
601991	0.012	0.229	0.825***	7.393	0.264*	1.850

Notes:

The true returns are estimated by aggregation.

***, **, *: significant at the 1%, 5% and 10%, respectively.

Table 8: GMM-Price limit estimation results of model (4)

Code	β_7	t-value	β_8	t-value	β_9	t-value	β_{10}	t-value
000002	-0.002	-0.052	0.001	0.057	1.109***	17.514	1.048***	16.136
000100	0.142***	2.952	-0.017	-1.067	0.719***	8.077	1.109***	11.973
000402	0.056**	2.007	-0.003	-0.240	0.919***	15.342	1.120***	17.711
000629	0.037	1.159	-0.013	-0.813	0.941***	18.990	1.302***	23.293
000709	0.084***	3.260	0.005	0.325	0.850***	13.260	0.719***	9.684
000825	0.166***	5.814	-0.060***	-3.073	0.772***	11.733	0.617***	5.300
000858	0.016	0.510	0.005	0.199	1.949***	21.136	0.651***	5.021
000897	0.006	0.179	0.025*	1.894	0.993***	14.756	1.099***	13.681
000898	0.069**	2.569	-0.022	-1.075	1.070***	14.367	0.928***	8.646
000917	-0.070**	-2.165	0.046***	4.042	0.967***	14.555	1.776***	25.384
002024	0.195***	3.865	-0.147***	-2.743	1.207***	12.579	0.231	1.427
600001	0.046	1.540	0.000	-0.027	1.134***	16.613	1.312***	9.534
600005	0.048	1.451	0.018	0.709	0.921***	12.853	1.601***	13.657
600010	0.004	0.140	0.023***	2.617	0.958***	13.201	0.387***	3.399
600016	-0.044	-1.209	0.013	0.457	0.916***	11.166	1.267***	6.893
600018	-0.064	-1.064	0.098	0.965	1.085***	9.111	0.755***	4.206
600019	0.063	1.571	0.037	0.680	0.856***	10.360	0.877***	7.113
600028	-0.035	-0.837	0.387*	1.665	1.124***	14.357	0.691***	5.269
600037	0.068*	1.856	-0.018	-0.801	1.112***	12.370	1.137***	11.083
600050	0.010	0.246	-0.026	-1.121	0.983***	11.311	0.765***	6.295
600104	0.087***	3.216	-0.089***	-3.829	1.120***	19.672	0.681***	6.697
600320	0.028	0.889	-0.003	-0.247	1.142***	12.467	1.511***	7.295
600500	0.033	0.919	-0.021	-1.042	1.194***	14.141	1.203***	11.923
600598	0.034	0.762	-0.022	-0.955	1.333***	16.401	0.795***	9.281
600808	0.024	0.853	-0.003	-0.123	1.010***	20.413	1.293***	17.010
600832	-0.026	-0.959	0.021	1.072	1.207***	27.885	1.216***	17.783
600900	0.101*	1.931	-0.125***	-2.638	0.755***	4.494	1.271***	10.494
601006	0.051	0.777	-0.131	-1.091	1.433***	10.358	0.799***	5.768
601333	-0.096	-1.508	0.023	0.610	1.248***	6.948	0.731***	3.479
601390	-0.005	-0.051	-0.060	-0.945	1.609***	9.018	1.325***	6.496
601398	-0.155***	-2.162	1.056***	2.643	0.627***	4.741	-0.043	-0.314
601600	0.066	0.811	0.047	0.437	0.911***	7.049	0.855***	4.988
601991	-0.020	-0.305	0.105	0.810	0.773***	5.971	0.248	1.724

Notes:

The true returns are estimated by aggregation.

***, **, *: significant at the 1%, 5% and 10%, respectively.