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Adcock, C., Ye, C., Yin, S. et al. (1 more author) (2019) Price discovery and volatility spillover with price limits in Chinese A-shares market: a truncated GARCH approach. Journal of the Operational Research Society, 70 (10). pp. 1709-1719. ISSN 0160-5682

https://doi.org/10.1080/01605682.2018.1542973

Price discovery and volatility spillover with price limits in Chinese A-shares market: A truncated GARCH approach

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Abstract

The use of price limits by a stock exchange means that the distribution of returns is truncated. By considering a GARCH model in conjunction with a truncated distribution for the residuals, this study investigates whether price limits have an effect on price behaviour and volatility of Chinese A-shares. The analysis has been applied to A-shares traded on the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE) during the period from 2004 to 2018. The results suggest the Truncated-GARCH model outperforms a conventional model and offers substantially different insights into the effect of price limits. The delayed price discovery hypothesis is not rejected for either exchange after upper price limit hits. Limited evidence supports the volatility spillover hypothesis, as just over 5% of A-shares experience an increase of volatility after upper price limit hits on both exchanges. No evidence of reduction of volatility after price limit hits is shown in the research.

JEL Classification: C58, G19

Keywords: Price limits; Delayed price discovery; Volatility spillover; Truncated return distributions

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1. Introduction

Price limits, the levels by which stock values are allowed to rise or fall in a day, are designed to provide investors with a cooling-off period to counter noise trading and alleviate market panic (Brady Commission Report, 1988). The limits are usually stated as a percentage of the previous day's closing price. Once the stock price has increased or decreased by its daily limit, trading in that stock will be stopped. As investors are given adequate time to evaluate the market condition, this should lead to a calmer market with lower volatility. If this is true, price limits will help to prevent investors from irrational trading. However, the effectiveness of price limits is frequently debated in the literature. The presence of price limits means that the probability distribution of stock returns is doubly truncated. As described below, however, the standard method used in the literature so far to investigate the effect of price limits is to employ a GARCH model in which the effect of the limits is induced using dummy variables. In this paper, we present an extension of the GARCH model in which the effect of truncation is explicitly included in the distribution.

Theoretically, the debate about price limits is grounded in two hypotheses. The first is the delayed price discovery hypothesis, which states that prices will keep moving in the same direction in the subsequent period after price limit hits. The second is the volatility spillover hypothesis, which holds that the stock will have a higher volatility after a price limit hit. The delayed price discovery hypothesis is based on the belief that price limits only retard the speed of price adjustments to fundamental values (Fama, 1989). Phylaktis, Kavussanos and Manalis (1999) argue that the arrival and accessibility of information are the driving forces of the equilibrium price and volatility. The information, which induces a price limit hit cannot be absorbed in one day. In other words, if the equilibrium price falls outside of the pre-specified range on the day of a limit hit, the bounded price will continue to move to reflect the true price in the following period. De Bondt and Thaler (1985) find that extreme positive price movements are followed by subsequent negative price movements and vice versa. The volatility spillover hypothesis is based on similar arguments but applies to the second moment of the stock return distribution. French and

Roll (1986) assert that volatility is influenced by public and private information. In stressful circumstances, investors are more inclined to overreact to price sensitive news, which makes the market more volatile. Lehmann (1989) claims that a price limit hit creates an imbalance between a share's supply and demand. The orders that are not completed due to the imbalance will be completed in the following day. The completion of the previous orders at an existing higher or lower price implies that the pent-up volatility on the day when the limit is hit spills over to the next day. Fama (1989) also argues that volatility will spread out in the following period to reflect changes in fundamental values due to the interference in price discovery process on the day of a price limit hit. Nonetheless, the rejection of both hypotheses may not be sufficient enough to suggest the price limit is effective. An effective price limit mechanism should yield a price reversal or reduced volatility (Ma, Rao and Sears, 1989).

Since these theoretical arguments are ambiguous, it is not surprising that empirical findings on the effectiveness of the price limit reported in the literature are largely inconclusive. Price continuation has been evidenced by a positive return autocorrelation in the South Korean, Warsaw, Tokyo and Istanbul stock markets (for example, Lee and Chung, 1996; Henke and Voronkova, 2005; Bildik and Gulay, 2006). However, price reversals have also been documented by Huang (1998) for the Taiwan stock exchange and Farag (2015) for the Egyptian market. Chen, Rui and Wang (2005) also report price reversals after lower price limit hits on the two Chinese stock exchanges. For volatility spillover analysis, the majority of the studies (for example, Chung, 1991; Chen, 1993; Kim and Rhee, 1997; Kim, 2001; Henke and Voronkova, 2005; Li, Zheng and Chen, 2014; Danişoğlu and Güner, 2018) show that stocks exhibit high volatility after price limits hits. However, some exceptions have been reported for the Chinese market (Chen, Rui and Wang, 2005; Kim, Liu and Yang, 2013), South Korean market (Lee and Kim, 1995; Berkman and Lee, 2002) and Japanese market (Deb, Kalev and Marisetty, 2017).

One of the reasons for the inconclusive findings summarised above may be methodological. The main aim of this paper is to propose an extension to the existing models and thus contribute more reliable evidence to the price limit literature. Most literature (for example, Shen and Wang, 1998; Henke and Voronkova, 2005) explores price limit efficiency using models, which assume a continuous distribution for the residuals (for example, the normal or Student t distributions) and in which the effect of price limits is described by dummy variables. In the presence of price limits, however, the return distributions are doubly truncated. This is because a trading price beyond the pre-specified range will be invalid. Previous models are mis-specified theoretically if this feature is ignored and results estimated from them will be biased. In order to incorporate the truncation in the return distributions, we use a GARCH model in which the distribution of the residuals is truncated. This is referred to as the Truncated-GARCH model. It extends the GARCH in mean model, referred to simply as GARCH hereafter, used by Shen and Wang (1998) and Henke and Voronkova (2005) to explore price discovery and volatility spillover in the Chinese stock market.

This study also recognises that in China stocks are subject to trading suspension, which can last for hours, days, weeks or even months. Allison (2001) points out that some researchers tend to delete the missing values. Some companies even design software packages to perform the deletions (Von Hippel, 2004). However, Allison, Von Hippel and Little and Rubin (2002) argue that any estimation based on the deletion of missing values can be biased. In this paper, an imputation procedure is applied to estimate missing values. Last, but not least, we analyse shares separately from the Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE) to demonstrate the robustness of the model.

We utilise a dataset consisting of daily returns of 1,228 A-shares from the SSE and 1,178 A-shares from SZSE for the period January 2004 to May 2018. Our results indicate that the Truncated-GARCH model offers better statistical measures of fit than those obtained from the standard GARCH model. Based on the Truncated-GARCH model, the results indicate that the delayed price discovery hypothesis cannot be rejected: price continuation is observed for 220 out of 1,228 shares on the SSE and 218 out of 1,178 shares on the SZSE after upper price limit hits. More than 5% of the shares on both exchanges experience price reversal after price limit hits. Evidence to support the volatility spillover hypothesis is rather limited. Approximately 5% of A-shares on both exchanges undergo an increase of volatility, but this is only after upper price limit hits. Little evidence of volatility reduction after price limit hits is found in this research.

The remainder of the paper is organised as follows. Section 2 describes the data and introduces the institutional framework on price limits in China. Section 3 presents the methodology. Section 4 discusses the empirical results, and Section 5 concludes.

2. Data and Descriptive Statistics

Price limits in the Chinese stock market can be traced back to 1990 when the SSE and SZSE were established. Throughout 1990s, these two exchanges experienced distinct price limit rates ranging from 1% to 10%. The SZSE even enforced different price limits upon upward and downward price movements. After 16th December 1996, the SSE and SZSE consistently implemented a single level of price limits, which is 10%. They also introduced 5% price limits after 22nd April 1998 when the rule of ST shares was promulgated. For SSE, after 1st Jan 2016, the price limits for ST has changed back to 10%.

The daily time series data used covers the period 31st December 2003 to 18th May 2018. A-shares, which are denominated in Renminbi, were originally restricted to domestic investors only but became available to Qualified Foreign Institutional Investors (QFIIs) in November 2002. The first trading of A-shares by QFIIs was executed in July 2003. The starting point of the study period excludes this transitional phase. During the study period, 1,462 A-shares were traded on the SSE and 1,409 A-shares on the SZSE. Due to the requirements of the imputation procedure, stocks with data available for less than 85% of all trading days during the study period are excluded from the study[1]. The final dataset contains 1,228 A-shares on the SSE and 1,178 A-shares on the SZSE.

[1] Please see section 3.1 for more details of the imputation procedure.

Stock market data such as daily closing price, market value, and negotiable market value[2] are collected from the Chinese Stock Market & Accounting Research (CSMAR) database. Daily returns are calculated in the usual way using the daily closing prices. Table 1 reports summary statistics for the daily return, daily market value and daily negotiable market value of A-shares on the SSE and SZSE. A-shares on the SSE have a daily return of 0.0010, while shares on the SZSE have a daily return of 0.0026 during the sample period. The standard deviation of returns for A-shares on the SZSE also tends to be higher than that of the SSE. The Jarque-Bera tests with an average p-value of 0.001 show that very few stocks exhibit normal return distributions for both stock exchanges. Furthermore, the average p-value for the skewness component of the Jarque-Bera tests is more than 0.15, but the average p-value for partial Jarque-Bera tests for Kurtosis is 0.001. Taken together, the Jarque-Bera test results indicate that, for both stock exchanges, non-normality is dominated by excess kurtosis.

[Insert Table 1 about here]

With regard to daily market value and daily negotiable market value, A-shares on the SSE have higher values in both mean and standard deviation compared to A-shares on the SZSE.

[Insert Table 2 about here]

The procedures applied to identify price limit hits are shown in Panel A of Table 2. This study uses the daily closing price rather than the high or low price to identify price limit hits. According to Panel B of Table 2, the number of upper-limit-hits is larger than that of the lower-limit-hits. In total, there are 50,938 and 42,871 upper-limit-hits against 35,401 and 31,196 lower-limit-hits on the SSE and SZSE, respectively. The Chi-squared test in

[2] In the Chinese A-shares market, a listed company has tradable and non-tradable shares. The market value is the sum of the value of tradable and non-tradable shares. The negotiable market value is the value of tradable shares.

Panel C of Table 2 shows that the number of limit hits on the SSE is significantly (p-value 0.00004) larger than that on the SZSE.

Panel D of Table 2 summarises the number of price limit hits. First, the number of limit hits varies across different stock exchanges. For instance, the mean values of upper-limit-hits of each stock are 42 and 36 for A-shares on the SSE and SZSE, respectively. The standard deviations are 37 and 28, respectively. Similar results are found for lower-limit-hits. Panel D also reports that the mean (median) values of the number of days between consecutive price limit hits are 42 and 46 (35 and 38) for A-shares on the SSE and SZSE, respectively. This suggests that more than one price limit hit in two months is likely to occur on average.

Figures 1A and 1B show the kernel density of the returns on A-shares with humps in the densities around the price limits ($\pm 0.05, \pm 0.10$). The non-normality of stock returns in this study is attributed partially to the truncation effect of price limits. This feature motivates the consideration of truncated stock return distributions, which is discussed in the next section.

[Insert Figure 1 about here]

3. Methodology

This section first describes the method used to impute missing values. It then outlines the GARCH and Truncated-GARCH models used to investigate the effects of price limits on price discovery and volatility spillover. Finally, it contains a description of the computation of tail probabilities; that is, the probability that a price limit would be breached if it were not in place.

3.1 Imputation of Missing Values

Missing values are imputed using the following method. The model for missing values is assumed to be

$$\hat{X}_t = \hat{\mu} + \hat{\sigma} Z \,, \tag{1}$$

where $\hat{X}_t$ is stock closing price, daily negotiable turnover; $\hat{\mu}$ and $\hat{\sigma}$ are, respectively, the estimated sample mean and stand error based on X up to time $t-1$. Z is a single simulated observation from the standard normal distribution. Details of missing values of A-shares on the SSE and SZSE are available upon request. If the available data is less than 85% of all trading days from the first day of trading till 18/05/2018 or total trading time is less than one year, this stock is excluded from the sample. As a result, the final dataset contains 1,228 out of 1,462 A-shares on the SSE and 1,178 out of 1,409 A-shares on the SZSE. The two-sample Kolmogorov-Smirnov (KS) test is carried out to examine and ensure the newly generated data and original data are from the same continuous distribution (Massey, 1951). In addition, a two-sample t-test shows that mean and variance of the newly generated data are not significantly different from those of original data. As a robustness check this procedure was repeated 100 times for each stock[3].

4.2 The GARCH and Truncated-GARCH Models

Most of the empirical studies on the effect of price limits on price behaviour and volatility are based on natural experiments such as changes in the price limit rate or event studies. As shown in previous section, the number of days between consecutive price limit hits is 30-50 days on average. An event study with a 250-day estimation window for the daily stock returns (Brown and Warner, 1985) is, therefore, not suitable here. To model time varying volatility, a GARCH process, similar to the one employed in Shen and Wang (1998) and Henke and Voronkova (2005), is used. In conjunction with a standard *GARCH (1,1)* model, Shen and Wang employ dummy variables to indicate price limit hits in the mean equation. Henke and Voronkova add the price limit dummies to the variance equation. To extend this approach, the model implemented in this study also takes 90% of the price limit hits into account. This thus allows the model to differentiate the effects of price limits from the effects of extreme price movements. Following established practice in empirical studies in financial economics, the standard *GARCH (1,1)* model with normally distributed residuals is used. As Brooks (2008, p.394) states, "*GARCH (1,1) will be sufficient to capture the volatility clustering in the data, and rarely*

[3] Note that more complex models could be employed, if wished, to estimate the missing values.

is any higher order model estimated or even entertained in the academic finance literature."[4] More importantly, the first lag relationship is the focus of this research, as any effects beyond first lags may not be from price limit hits. There is a long overnight period for investors to realise that closing prices hit the limits on the previous trading day and hence, the first lag relationship could indicate how the investors will response to the limit-hits.

In the usual notation, the GARCH model employed in this study is as follows

$$R_t = \mu_t + \varepsilon_t \qquad \varepsilon_t |\ \Omega_t \sim N(0, \sigma_t^2), \tag{2}$$

with

$$\mu_t = \beta_1 + (\beta_2 + \beta_3 Tor_{t-1} + \beta_4 \sigma_{t-1} + \beta_5 Up_{t-1} + \beta_6 Lo_{t-1} + \beta_7 Up9_{t-1} + \beta_8 Lo9_{t-1}) R_{t-1} \ ,$$
$$\sigma_t^2 = \beta_9 + \beta_{10} \varepsilon_{t-1}^2 + \beta_{11} \sigma_{t-1}^2 + \beta_{12} Up_{t-1} + \beta_{13} Lo_{t-1} + \beta_{14} Up9_{t-1} + \beta_{15} Lo9_{t-1} \ .$$

The parameters, collectively denoted by θ, are estimated by maximising the log-likelihood function $(logL)$

$$\hat{\theta} = arg \max_{\theta} logL(\theta; X),$$
$$logL = -\frac{T}{2}\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T} \log(\sigma_t^2) - \frac{1}{2}\sum_{t=1}^{T} \frac{\varepsilon_t^2}{\sigma_t^2} = \sum_{t=1}^{n} \log\{\emptyset(r_t, \mu_t, \sigma_t^2)\}, \tag{3}$$

where Ω_t denotes information available at time t. R_t is the daily stock return on day t. Tor_{t-1} is the daily negotiable turnover ratio on day $t-1$, which is measured by daily negotiable turnover divided by daily negotiable market value. Up_{t-1} $(Up9_{t-1})$ and Lo_{t-1} $(Lo9_{t-1})$ are upper (90% upper) and lower (90% lower) price limit hits dummy variables taking value of one on day t if a share reaches the limit (90% of the limit) on day $t-1$ and zero otherwise. Estimated parameters are denoted with the $\wedge$ symbol and referred to collectively as $\hat{\theta} = \{\hat{\beta}_1, \hat{\beta}_2, \dots, \hat{\beta}_{15}\}$. The notation $\emptyset(x, \mu, \sigma^2)$ denotes the probability density function (pdf) of a normally distributed variable with mean μ and variance σ^2 evaluated at x.

[4] A detailed investigation by Ye (2016) indicates that other GARCH formulations do not result in significantly different results.

However, from a theoretical perspective the model at Equation (2) is mis-specified and likely to induce bias in the results. As explained above, this is because the price limits result in a set of time series data for which the observation at time t cannot deviate from its predecessor by more than ±10%. To mitigate the truncation effect, in this study a Truncated-GARCH model is built for the model at Equation (2). The difference between the GARCH and Truncated-GARCH models is the doubly truncated normal distribution, denoted TN. As above, the model for the mean is

$$R_t = \mu_t + \varepsilon_t \qquad \varepsilon_t| \ \Omega_t \sim TN(0, \sigma_t^2), \tag{4}$$

with μ_t as defined at Equation (2). The parameters are estimated by maximising the log-likelihood function ($logL$)

$$\hat{\theta} = arg\, \max_{\theta}\, logL(\theta; X).$$

$$\begin{aligned} logL = &\sum_{t'=1}^{n'} \log\{\emptyset(r_{t'}, \mu_{t'}, \sigma_{t'}^2)\} - \sum_{t'=1}^{n'} \log\{\Phi\left(\frac{U_{t'} - \mu_{t'}}{\sigma_{t'}}\right) - \Phi\left(\frac{L_{t'} - \mu_{t'}}{\sigma_{t'}}\right)\} \\ &+ \sum_{tl=1}^{nl} \log\{\Phi\left(\frac{L_{tl} - \mu_{tl}}{\sigma_{tl}}\right)\} + \sum_{tu=1}^{nu} \log\{1 - \Phi\left(\frac{U_{tu} - \mu_{tu}}{\sigma_{tu}}\right)\}, \end{aligned} \tag{5}$$

where $n' + nl + nu = T$, n' is the number of values which lie between the upper and lower limit, nl and nu are respectively the number of values which are truncated at the lower limit and upper limit. The variables in the three summations are indexed by t', tl and tu respectively. Return is denoted by r, U and L are the upper and lower limits. μ_t and σ_t^2 are the mean and conditional volatility at time t.

The model defined at Equations (2) and (4) allows the hypotheses described in the previous paragraph to be tested. In Equation (2), the estimated coefficient $\hat{\beta}_2$ measures the relationship between current return and its previous value without price-limit-hit, while $\hat{\beta}_2 + \hat{\beta}_5$ ($\hat{\beta}_2 + \hat{\beta}_6$) measures the correlation between current return and its previous value when the price hits upper (lower) limits. $\hat{\beta}_3$ and $\hat{\beta}_4$ measure how the negotiable turnover ratio and conditional standard deviation would affect stock return autocorrelations. Moreover, $\hat{\beta}_{12}$ and $\hat{\beta}_{13}$ measure the volatility after upper- and lower-limit-hits. In order to show the effects that indeed come from price limits rather than extreme price movements, it is necessary to compare the estimated coefficients between limit-hits and near-hits dummies. For example, if upper price-limit-hit induces price continuation, $\hat{\beta}_2 + \hat{\beta}_5$ needs to be significantly greater than 0 and $\hat{\beta}_5$ also needs to be significantly greater than $\hat{\beta}_7$. Detailed constructions of the hypotheses are illustrated below.

The null hypotheses for upper price limits that are tested are as follows:

Price continuation (PC): $H_0: \beta_2 + \beta_5 = 0 \; vs \; H_1: \beta_2 + \beta_5 > 0$ and $H_0: \beta_5 = \beta_7 \; vs \; H_1: \beta_5 > \beta_7$.

Price reversal (PR): $H_0: \beta_2 + \beta_5 = 0 \; vs \; H_1: \beta_2 + \beta_5 < 0$ and $H_0: \beta_5 = \beta_7 \; vs \; H_1: \beta_5 < \beta_7$.

Volatility increase (VI): $H_0: \beta_{12} = 0 \; vs \; H_1: \beta_{12} > 0$ and $H_0: \beta_{12} = \beta_{14} \; vs \; H_1: \beta_{12} > \beta_{14}$.

Volatility decrease (VD): $H_0: \beta_{12} = 0 \; vs \; H_1: \beta_{12} < 0$ and $H_0: \beta_{12} = \beta_{14} \; vs \; H_1: \beta_{12} < \beta_{14}$.

There is a similar set of hypotheses for lower price limits, which are omitted in the interests of brevity.

3.3 Tail Probabilities

An important and interesting question is what would happen without price limits? To investigate this question, it is necessary to estimate the tail probability; that is, the probability that the price would move beyond the restricted level on the days of price limit hit if there were no price limit in place. The mean and conditional variance can be estimated from Equations (2) and (4). Assuming there were no limits in place, the tail probabilities corresponding respectively to upper and lower price-limit-hits are computed as follows

$$P(x > U_t) = 1 - \int_{-\infty}^{U_t} \frac{1}{\sqrt{2\pi}\hat{\sigma}_t} exp^{\left\{-\frac{1}{2\hat{\sigma}_t^2}(x-\hat{\mu}_t)^2\right\}} dx, \tag{6}$$

and

$$P(x < L_t) = \int_{-\infty}^{L_t} \frac{1}{\sqrt{2\pi}\hat{\sigma}_t} exp^{\left\{-\frac{1}{2\hat{\sigma}_t^2}(x-\hat{\mu}_t)^2\right\}} dx, \tag{7}$$

where x denotes the return on the day of a price-limit-hit on which the upper and lower limits are U_t and L_t respectively.

For the Chinese stock market, when price limits are in operation, the maximum absolute daily return is restricted to about 10%. If the estimated tail probability shows that there is a very high chance (0.99 say) for the absolute return to exceed 10%, it may be inferred that the price would continue to move in the same direction if there was no restriction. By contrast, if the tail probability is 0.01 or less, there is a very low chance of price continuation. In Equation (6) and (7), a threshold value for the tail probability has to be chosen in order to make a judgment. The cases $P = 0.99$ and $P = 0.01$ are the extreme situations. In this study, the threshold used is $P = 0.50$. That is, if the upper (lower) tail probability is greater than 0.5, it is concluded that the price would continue to move in the same direction in the absence of price limits. As the theory suggests that price limits prevent a price from reaching its equilibrium value on the price-limit-day the true value will be reflected in the next day. In other words, the upper (lower) tail probability which is greater than 0.5 implies that the true value should be higher (lower) than the closing price and that therefore there will be a price continuation in the next day due to a price-limit-hit in the previous day.

4. Empirical Results

4.1 Comparison of the GARCH and Truncated-GARCH Models

[Insert Table 3 about here]

Table 3 shows the average goodness of fit for the GARCH and Truncated-GARCH Models. Akaike's Information Criterion (AIC)[5] is used in this study to identify a better fit. The Truncated-GARCH model shows a superior performance on both the SSE and SZSE with average smaller AICs compared to the GARCH models. The standard deviation of the AIC from the Truncated-GARCH models is also smaller, which suggests that the estimation performance is more consistent across stocks. This can also be demonstrated by a comparison of AIC of these two models for each stock. 1,109 out of 1,229 stocks

[5] The Akaike Information Criterion (AIC) is calculated as follows: $2k - 2\,\widehat{logL}$, where k is the number of variables and $\widehat{logL}$ is the estimated loglikelihood. Model selection criterion uses the smaller values of the AIC (Akaike, 1974).

from the SSE and 1,079 out of 1,178 stocks from the SZSE present smaller AICs from Truncated-GARCH models. The goodness-of-fit results imply that using the truncated distribution for the residuals should significantly improve model estimates leading to more reliable inferences.

4.2 Comparison of Price discovery and volatility spillover between two models

The analysis of price discovery and volatility spillover using the GARCH model at Equations (2) and (3), and the Truncated-GARCH model at Equation (4) and (5) are reported in Tables 4 and 5, which illustrate the analysis for A-shares on the SSE and SZSE, respectively. Results are presented at the 5%, 1% and 0.1% levels of significance, with the main commentary referring to the 5% level.

For the effect of price limits on price discovery, the two models show quite different results. For upper price limit hits, and averaging over both exchanges, under the GARCH model 14.4% [6]of stocks show price continuation (PC). Under the truncated-GARCH model the average is 18.2%. That the truncated GARCH model reveals a higher PC percentage is consistent for each of the two exchanges. For lower price limit hits, the results are very different. Averaging over the two exchanges, the GARCH model identifies PC for about 10% of shares, while the Truncated-GARCH model reports only 2.5% of shares showing price continuation. The same pattern of results is repeated at the 1% and 0.1% levels of significance.

[Insert Tables 4 and 5 about here]

Results for price reversal (PR) from the two models are also different. At the 5% significance level, the GARCH model recognises 29% of shares showing PR after upper price limit hits and 16% after lower price limit hits. The Truncated-GARCH model identifies only 4.5% of the shares with price reversal after upper limit hits and 6.7% after lower limit hits.

[6] 14.4% is calculated as follows: (170+177)/(1228+1178). Other percentages are calculated in a similar way.

The number of stocks that show a volatility increase (VI) is broadly similar for both models. Averaging on both exchanges, 6.8% [5.2%] display VI under the GARCH [Truncated-GARCH] model after upper limit hits. By contrast, the number of stocks showing VI after lower limit hits is very small, with the maximum being 0.24% for the SSE under the GARCH model. For volatility decrease (VD), the Truncated-GARCH model picks far fewer shares after upper price limit hits compared to the GARCH model. For example, at the 5% significance level 348 out of 1,228 A-shares on the SSE show a volatility decease according to the GARCH model, while the corresponding number is 18 under the Truncated-GARCH model. Similar to volatility increase, both models identify very few with a volatility decrease after lower price-limit-hits.

Results at the 1% and 0.1% significance levels report smaller numbers but consistent results, which confirm the comparisons between the two models. Results for the SSE are similar to results for the SZSE, which suggests the robustness of model comparison as investors generally operate in both markets and similar price limits rules apply to both markets. Overall, the effects of price limits on price behaviour and volatility spillover are very different from the two models. In general, the traditional GARCH model recognises significantly fewer price continuations, more price reversals and variance decreases after upper price limit hits. There is a small but similar percentage of volatility increases under both models. The GARCH model identifies significantly more price continuations and price reversals after lower price limit hits, but there is little evidence of changes in volatility.

4.3 Tail probabilities.

Table 6 reports the tail probabilities on the day of a price limit hit using both the GARCH and Truncated-GARCH models. There is a vertical panel for each model. In each panel, there are four columns. These contain results for upper and lower limit hits for A-shares on each exchange. The contents of the table are explained as follows. There are about 50,000 upper price limit hits for A-shares on the SSE, the tail probabilities are computed for each price limit hit and a histogram is constructed. Corresponding to the 60% vigintile, for the Truncated-GARCH model for upper price limits on the SSE 40% of the right hand tail probabilities are greater than 0.50. That is, given 50,000 upper price limit hits, there are about 20,000 occasions on which the price has a probability of 0.50 of exceeding the upper limit. According to the 55% vigintile, the Truncated-GARCH model panel of the table indicates that there are 45% of tail probabilities, which are larger than 0.49, 0.48, 0.49 and 0.48 for upper and lower limits for the SSE and SZSE, respectively. If the threshold value for the tail probability chosen to determine the effect of price limits on price behaviour is *P=0.50*, the 55% and 60% vigintiles indicate that the Truncated-GARCH model suggests that there will be a 40-45% chance of price continuation after a price limit hit.

The standard GARCH model shows that there are only 5-10% of tail probabilities larger than 0.50 across A-shares on both exchanges; that is, there is limited evidence of price continuation after a price limit hits. These results indicate that the volatility estimates are different for the two models, resulting in the large difference in computed tail probabilities. They are also suggestive of the bias that arises when the truncation induced by the price limits is neglected.

[Insert Table 6 about here]

4.4 Analysis of Price Discovery and Volatility Spillover for A-shares

The analysis in previous sections indicates that the Truncated-GARCH model has superior explanatory power to the GARCH model and is a better-specified model theoretically. The following discussion is therefore based on the results from the Truncated-GARCH model.

In Table 4, at the 5% significance level, 220 (31) out of 1,228 shares show price continuation after upper (lower) price-limits-hits on the SSE. On the SZSE, similar patterns are observed: 218 (27) out of 1,178 shares show price continuation after upper (lower) price limit hits. At the 1% significance level, the number of shares showing price continuation decreases to 177 (25) for the SSE and 163 (20) for the SZSE, respectively.

There are more price continuation cases after upper price limit hits compared to lower hits. The asymmetric results suggest that price limits have limited impact on price continuation after upper limit hits, but a relatively stronger impact after lower limit hits. In other words, the price limits do calm panic over selling behaviour, but they do not reduce over enthusiastic buying. Between 5% and 7% of firms experience price reversal after upper and lower price limit hits on both exchanges. There are more price reversals after lower limit hits compared to upper limit hits; for example, 81 versus 49 for the SSE in Table 4, showing that price limits are somewhat more effective on lower limit hits. Overall, the results show support for the delayed price discovery hypothesis on both exchanges after upper limit hits. Price limits work more efficiently when the lower limit is hit compared to when the upper limit is hit.

With respect to volatility, at the 5% significance level, 66 (1) A-shares experience higher volatility after upper (lower) limit hits on the SSE and 59 (0) A-shares on the SZSE. Approximately 5% of shares on both exchanges experience a volatility increase after upper price limit hits. When the significance level is set at 1%, the number of shares showing a volatility increase declines on both exchanges. Very few shares show volatility decrease on either exchange. Overall, limited evidence supports the volatility spillover hypothesis: 5% of the shares on both exchanges exhibit higher volatility after upper price limit hits. There is little evidence that price limits reduce volatility.

In Table 7, closer examination of individual model parameter estimates reveals that turnover ratio (β_3) has a negative effect on stock return autocorrelation in both stock exchanges. For example, looking at the 1% significance results, there are 137 shares on the SSE and 159 shares on the SZSE, respectively. This finding is consistent with Campbell, Grossman and Wang (1993). Some stocks show that conditional variance induces positive stock return autocorrelation (β_4). For instance, 150 and 173 shares on the SSE and SZSE. Moreover, approximately 80% of the shares show significant ARCH or GARCH effects (β_{10}, β_{11}).

[Insert Table 7 about here]

5. Conclusions

The use of price limits by a stock exchange means that the distribution of returns is truncated. By considering a GARCH model in conjunction with a truncated distribution for the residuals, this study investigates whether price limits have an effect on price behaviour and volatility of Chinese A-shares during the period 2004 to 2018. The analysis indicates that the GARCH model with truncation performs better than the standard GARCH model employed in previous studies. In addition to superior statistical properties, the truncated-GARCH model results in a number of different inferences. The truncated-GARCH model also allows the computation of tail probabilities, which provide evidence of the likelihood of price continuation if the limits were not in force.

The results based on the Truncated-GARCH model show that the delayed price discovery hypothesis is not rejected for approximately 18% of stocks on both exchanges after upper price limit hits. In addition, the volatility spillover hypothesis is also not rejected for approximately 5% of stocks on either exchange also after upper price limit hits. Overall, price limits work well to a certain extent after lower price limit hits, although it does not lead to volatility reduction. This finding suggests that price limits calm down the panic of overselling behaviour. It is plausible that, in the Chinese stock market, which is a less efficient emerging market, investors tend to overreact to information, particularly bad news. Price limits provide investors an opportunity to digest new information. The amount of price continuations and volatility increases after upper price limit hits, on the other hand, suggest that price limits have an inadequate impact on the enthusiastic over buying behaviour. Thus, there is still room for improvement of the price limit system and accompanying regulation.

Figure 1 Return Distribution

These figures display the return distribution of the A-shares on the Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE) over the period 01/2004-05/2018

Figure1A SSE A-shares

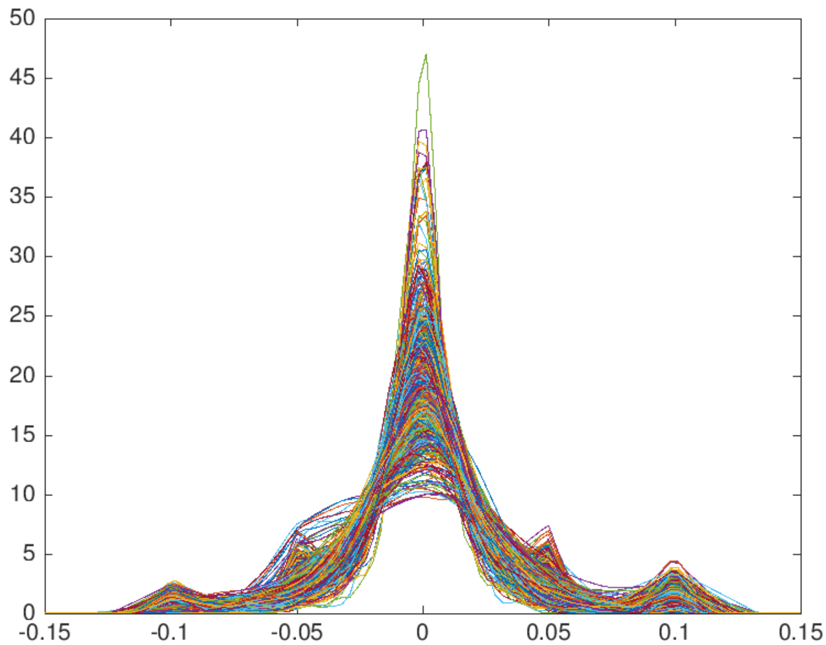

Figure1B SZSE A-shares

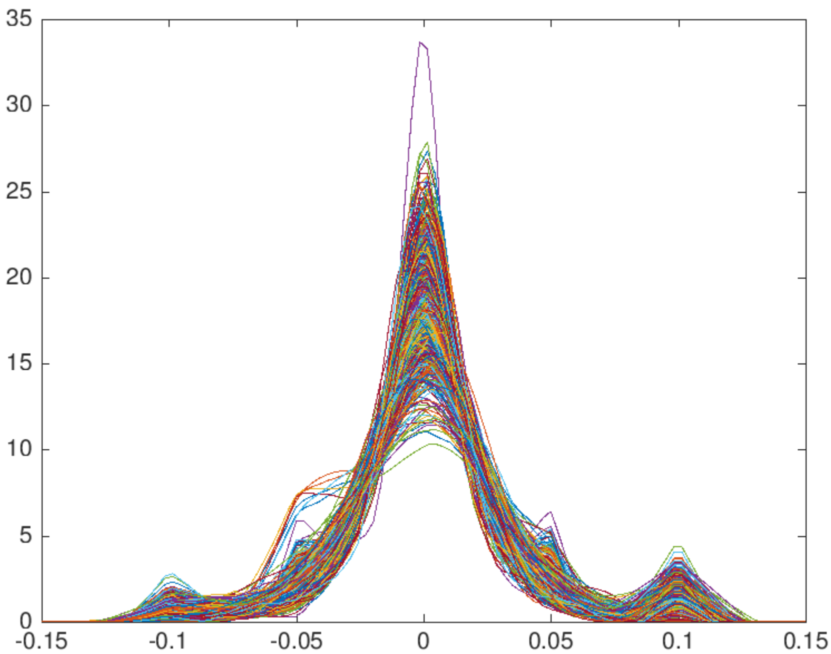

Table 1 Descriptive statistics

SSE A							
	Mean	SD	Skewness	Kurtosis	JB*	JB-S**	JB-K***
Daily Return	0.0010	0.03341	1.85	64.54	0.001	0.153	0.001
Daily Market Value (Thousand RMB)	14169447	18458367	3.30	22.05	0.001	0.001	0.001
Daily Negotiable Market Value (Thousand RMB)	19097478	9095800	0.98	4.27	0.002	0.011	0.044

SZSE A							
	Mean	SD	Skewness	Kurtosis	JB	JB-S	JB-K
Daily Return	0.0026	0.03652	2.02	50.81	0.001	0.214	0.001
Daily Market Value (Thousand RMB)	9046437	11598597	3.30	21.59	0.001	0.001	0.001
Daily Negotiable Market Value (Thousand RMB)	7797615	5106285	1.01	4.05	0.001	0.011	0.079

Note: All results are the average statistics across all stocks.

*: Reporting the p-value of overall Jarque-Bera test. Matlab restricts the p-value within the range [0.001,0.50].

**: Reporting the p-value of skewness part of the Jarque-Bera test.

***: Reporting the p-value of kurtosis part of the Jarque-Bera test.

Table 2 Price limit hits

Panel A shows the procedures to identify price limits. $P_{c,t-1}$ is closing price on day *t-1*; P_{max} and P_{min} are permissible maximum and minimum prices rounded to two decimal places. Panel B reports the total numbers of upper and lower limit hits of A-shares on both stock exchanges. Panel C shows the Chi-squared tests in comparison of the number of price limit hits between the SSE and SZSE. The Panel D summarises the average number of price limit hits across stocks.

Panel A: Procedures to Identify Price Limits Hits

Price limits hits	Step 1	Step 2	Trading Status
Upper	$P_{c,t-1}\times1.1 \approx P_{max,t}$	$P_{max,t} = P_{c,t}$	Normal[a]
	$P_{c,t-1}\times1.05 \approx P_{max,t}$	$P_{max,t} = P_{c,t}$	ST
Lower	$P_{c,t-1}\times0.9 \approx P_{min,t}$	$P_{min,t} = P_{c,t}$	Normal[a]
	$P_{c,t-1}\times0.95 \approx P_{min,t}$	$P_{min,t} = P_{c,t}$	ST

Panel B: Numbers of Price Limits Hits

	SSE (N=1228)				SZSE (N=1178)		
	Upper	Lower	Total		Upper	Lower	Total
Total	50983	35401	86384	Total	42871	31196	74067

Panel C: Chi-squared Test

	Upper	Lower	Total	Marginal Probability
SSE A	50983	35401	86384	0.5384
SZSE A	42871	31196	74067	0.4616
Total	93854	66597	160451	
Marginal Probability	0.5849	0.4150		
Expected values	Upper	Lower	Total	p-value
SSE	50529.35	35854.65	86384	0.00004
SZSE	43324.65	30742.35	74067	
Total	93854	66597	160451	
chi-squared statistics=	21.2575			

Panel D: Summary Statistics[a]

	SSE A			SZSE A		
	Upper	Lower	Days Between[b]	Upper	Lower	Days Between
Mean	42	29	42	36	26	46
SD	37	29	56	28	21	40
Min	1	0	1	2	0	1
Median	32	22	35	29	22	38
Max	264	210	1524	212	201	520

a: ST for SSE after 01/01/2016

b: It means the number of days between consecutive limit-hits.

Table 3 Goodness of Fit

This table reports the AIC for GARCH and Truncated-GARCH Models. Model is selected based on smaller AIC values.

	GARCH		Truncated-GARCH	
	SSEA	SZSEA	SSEA	SZSEA
Mean	23421.37	23129.78	12033.36	11813.28
SD	92563.29	135201.45	7652.89	5967.36
Min	30.14	30.14	30.14	30.14
Q1	4579.64	10360.70	3552.59	8324.21
Median	22029.81	17844.75	16274.07	11842.74
Q3	26960.25	25099.68	18820.16	17437.81
Max	2824419.63	4495469.54	20214.14	20185.46

Comparison of AIC between models of each stocks

	SSE (1228)	SZSE (1178)
AIC_TG<AIC_G*	1109	1079

*: AIC_TG represents AIC from Truncated-GARCH models, and AIC_G represents AIC from GARCH models.

Table 4 Models Estimation for A-shares on the SSE

This table reports the number of stocks that show price continuation (PC), price reversal (PR), volatility increase (VI) and volatility decrease (VD) after price limits. For upper price limit (PC): $\beta_2+\beta_5$ >0 and $\beta_2+\beta_5 > \beta_2+\beta_7$; (PR):$\beta_2+\beta_5$ <0 and $\beta_2+\beta_5 < \beta_2+\beta_7$; (VI): β_{12}>0 and $\beta_{12} > \beta_{14}$; (VD): β_{12}<0 and $\beta_{12} < \beta_{14}$. Same logic applies to lower price limit. The signs '>' and '<' imply significant 'larger than' and 'smaller than'.

$$R_t = \mu_t + \varepsilon_t \qquad \varepsilon_t\,|\Omega_t \sim N(0, \sigma_t^2) \text{ or } \varepsilon_t\,|\Omega_t \sim TN(0, \sigma_t^2)$$

$$\mu_t = \beta_1 + (\beta_2 + \beta_3 Tor_{t-1} + \beta_4 \sigma_{t-1} + \beta_5 Up_{t-1} + \beta_6 Lo_{t-1} + \beta_7 Up9_{t-1} + \beta_8 Lo9_{t-1}) R_{t-1}\,,$$
$$\sigma_t^2 = \beta_9 + \beta_{10}\varepsilon_{t-1}^2 + \beta_{11}\sigma_{t-1}^2 + \beta_{12} Up_{t-1} + \beta_{13} Lo_{t-1} + \beta_{14} Up9_{t-1} + \beta_{15} Lo9_{t-1}\,,$$

where R_t is the daily stock returns on day *t*. Tor_{t-1} is the daily negotiable turnover ratio on day *t-1,* which is measured by daily negotiable turnover divided by daily negotiable market value. Up_{t-1} ($Up9_{t-1}$) and Lo_{t-1} ($Lo9_{t-1}$) are upper (90% upper) and lower (90% lower) price limit hits dummy variables taking value of one on day *t* if a share hits the limit on day *t-1*.

	GARCH				Truncated-GARCH			
5% significant results								
SSE A (1228)	PC	PR	VI	VD	PC	PR	VI	VD
Upper	170	303	81	348	220	49	66	18
Lower	118	172	3	3	31	81	1	1
1% significant results								
SSE A (1228)	PC	PR	VI	VD	PC	PR	VI	VD
Upper	127	274	65	304	177	34	51	14
Lower	95	114	3	3	25	54	1	1
0.1% significant results								
SSE A (1228)	PC	PR	VI	VD	PC	PR	VI	VD
Upper	106	243	52	273	135	25	35	13
Lower	77	82	3	3	22	36	1	1

Table 5 Models Estimation for A-shares on the SZSE

This table reports the number of stocks that show price continuation (PC), price reversal (PR), volatility increase (VI) and volatility decrease (VD) after price limits. For upper price limit (PC): $\beta_2+\beta_5>0$ and $\beta_2+\beta_5>\beta_2+\beta_7$; (PR): $\beta_2+\beta_5<0$ and $\beta_2+\beta_5<\beta_2+\beta_7$; (VI): $\beta_{12}>0$ and $\beta_{12}>\beta_{14}$; (VD): $\beta_{12}<0$ and $\beta_{12}<\beta_{14}$. Same logic applies to lower price limit. The signs '>' and '<' imply significant 'larger than' and 'smaller than'.

$$R_t = \mu_t + \varepsilon_t \quad \varepsilon_t\,|\Omega_t \sim N(0,\sigma_t^2) \text{ or } \varepsilon_t\,|\Omega_t \sim TN(0,\sigma_t^2)$$

$$\mu_t = \beta_1 + (\beta_2 + \beta_3 Tor_{t-1} + \beta_4 \sigma_{t-1} + \beta_5 Up_{t-1} + \beta_6 Lo_{t-1} + \beta_7 Up9_{t-1} + \beta_8 Lo9_{t-1})R_{t-1}\,,$$
$$\sigma_t^2 = \beta_9 + \beta_{10}\varepsilon_{t-1}^2 + \beta_{11}\sigma_{t-1}^2 + \beta_{12} Up_{t-1} + \beta_{13} Lo_{t-1} + \beta_{14} Up9_{t-1} + \beta_{15} Lo9_{t-1}\,,$$

where R_t is the daily stock return on day *t*. Tor_{t-1} is the daily negotiable turnover ratio on day *t-1,* which is measured by daily negotiable turnover divided by daily negotiable market value. Up_{t-1} ($Up9_{t-1}$) and Lo_{t-1} ($Lo9_{t-1}$) are upper (90% upper) and lower (90% lower) price limit hits dummy variables taking value of one on day *t* if a share hits the limit on day *t-1*.

	GARCH				Truncated-GARCH			
5% significant results								
SZSE A (1178)	PC	PR	VI	VD	PC	PR	VI	VD
Upper	177	396	82	449	218	59	59	17
Lower	129	221	1	1	27	79	0	0
1% significant results								
SZSE A (1178)	PC	PR	VI	VD	PC	PR	VI	VD
Upper	143	353	67	402	163	44	45	13
Lower	104	156	1	1	20	56	0	0
0.1% significant results								
SZSE A (1178)	PC	PR	VI	VD	PC	PR	VI	VD
Upper	121	312	53	351	119	36	38	9
Lower	86	115	1	1	19	48	0	0

Table 6 Summary of Tail Probability

This table summarises the computed tail probabilities on the day of a upper (U) and lower (L) price limit hit. The vigintiles are reported. The explanation of the table entries is as follows. There are about 50,000 upper price limit hits for A-shares on the SSE and the tail probabilities are computed for each price limit hit. For upper price limits on the SSE, 40% of the right hand tail probabilities are greater than 0.50. That is, given 50,000 upper price limit hits, there are about 20,000 occasions on which the price has a probability of 0.50 of exceeding the restricted level (upper limit).

	GARCH				Truncated-GARCH			
	SSE		SZSE		SSE		SZSE	
Vigintiles	U	L	U	L	U	L	U	L
5%	0.01	0.01	0	0.01	0.00	0.00	0.00	0.00
10%	0.02	0.02	0.01	0.02	0.03	0.04	0.03	0.04
15%	0.03	0.03	0.03	0.03	0.10	0.12	0.11	0.13
20%	0.04	0.04	0.04	0.04	0.20	0.20	0.2	0.21
25%	0.06	0.06	0.06	0.06	0.28	0.27	0.28	0.28
30%	0.08	0.07	0.07	0.07	0.35	0.34	0.35	0.34
35%	0.10	0.09	0.10	0.09	0.40	0.38	0.40	0.39
40%	0.13	0.11	0.12	0.11	0.44	0.42	0.43	0.42
45%	0.16	0.13	0.15	0.13	0.47	0.45	0.46	0.45
50%	0.19	0.16	0.18	0.15	0.48	0.46	0.48	0.47
55%	0.23	0.18	0.22	0.18	0.49	0.48	0.49	0.48
60%	0.27	0.21	0.25	0.20	0.50	0.49	0.50	0.49
65%	0.31	0.25	0.30	0.24	0.50	0.50	0.50	0.50
70%	0.36	0.29	0.35	0.28	0.52	0.50	0.51	0.50
75%	0.41	0.33	0.40	0.32	0.54	0.51	0.53	0.52
80%	0.45	0.38	0.45	0.38	0.57	0.55	0.56	0.56
85%	0.49	0.43	0.49	0.44	0.65	0.61	0.62	0.63
90%	0.52	0.49	0.51	0.49	0.80	0.75	0.75	0.76
95%	0.63	0.52	0.61	0.52	0.93	0.89	0.91	0.90

Note: Values are shown rounded to two decimal places.

Table 7 Summary of Truncated-GARCH Model' Parameters

This table summarises the number of estimated parameters, which are significant at 0.1%, 1% and 5% from the truncated-GARCH mode. SSE (N=1,228), SZSE(N=1,178)

	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	β_{10}	β_{11}	β_{12}	β_{13}	β_{14}	β_{15}
5% significance															
SSE A Total	143	204	260	246	376	346	365	376	931	831	615	519	484	533	552
Positive	131	127	13	178	233	237	264	287	931	831	615	488	444	528	547
Negative	12	77	247	68	143	109	101	89	0	0	0	31	40	5	5
SZSE A Total	164	263	295	292	399	443	394	469	1009	859	596	557	543	560	594
Positive	156	155	13	210	250	275	242	362	1009	859	596	530	505	557	592
Negative	8	108	282	82	149	168	152	107	0	0	0	27	38	3	2
1% significance															
SSE A Total	49	139	145	207	264	253	260	271	910	795	572	364	335	371	361
Positive	46	72	8	150	160	172	191	210	910	795	572	341	300	367	358
Negative	3	67	137	57	104	81	69	61	0	0	0	23	35	4	3
SZSE A Total	59	177	167	221	293	329	272	342	985	795	528	406	397	413	426
Positive	56	86	8	173	173	194	165	265	985	795	528	386	362	410	424
Negative	3	91	159	48	120	135	107	77	0	0	0	20	35	3	2
0.1% significance															
SSE A Total	13	97	75	148	179	176	177	179	879	741	535	253	240	259	244
Positive	12	39	4	113	105	115	131	132	879	741	535	234	213	257	241
Negative	1	58	71	35	74	61	46	47	0	0	0	19	27	2	3
SZSE A Total	21	119	78	177	232	243	214	247	968	709	477	326	304	333	323
Positive	18	43	5	142	128	134	131	189	968	709	477	308	272	330	322
Negative	3	76	73	35	104	109	83	58	0	0	0	18	32	3	1

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