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# Forecasting Volatility with Price Limit Hits—Evidence from Chinese Stock Market

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**ABSTRACT:** In this article, we discuss whether price limit hits (*PLH*) contain information for volatility forecasting. Using Chinese stock market as sample, we find that *PLH* display significant forecasting power for future volatilities. Furthermore, the predictive effects on volatility are asymmetric between upper price limit hits (*UPLH*) and lower price limit hits (*LPLH*), with more pronounced effect for *LPLH*. These results are robust after controlling for jump, leverage effect, and volume in *HAR-RV* models, and they hold in crisis sub-sample and other measures of *PLH*. Finally, we provide a possible explanation for the predictive ability of *PLH* and suggest that the number of *PLH* can be used as a proxy for investor sentiment.

**KEY WORDS:** Chinese stock market, investor sentiment, price limit hits, volatility forecasting

**JEL CLASSIFICATION:** G10, G12, G15

Volatility forecasting is important for risk management and financial asset pricing. It is thus not surprising that much effort has been devoted to improving the performance of volatility forecasting (Andersen, Bollerslev, and Diebold 2007; Andersen et al. 2003; Franses and van Dijk 1996; Gokcan 2000; Hansen and Lunde 2005; Poon and Granger 2003). In this article, we use the number of price limit hits (*PLH*)—upper price limit hits (*UPLH*), lower price limit hits (*LPLH*), and their differences, the net price limit hits (*NPLH*)—to improve volatility forecasting.

We consider *PLH* for volatility forecasting for three reasons. First, there is indirect evidence that *PLH* contain useful information for volatility forecasting. Literature suggests that *PLH* are closely related to investor sentiment, and investor sentiment is useful for volatility forecasting. Ackert, Huang, and Jiang (2015) argue that an upper (lower) price limit hit is more likely to be triggered when investor sentiment is high (low, respectively). Seasholes and Wu (2007) show that the publicly observed events of stock prices hitting the price limit often attract investors' attention and thus lead to a change in investor sentiment. Brown (1999) finds that deviations from the mean level of sentiment are positively and significantly related to volatility. Lee, Jiang, and Indro (2002) find that changes in investor sentiment result in volatility adjustments. Second, daily price limits rules are widely used in stock markets, and the data on *PLH* is easily available. Daily price limits for a stock are pre-specified price boundaries based on the closing price of the previous day. According to Deb, Kalev, and Marisetty (2010), 41 out of 58 major countries have applied certain types of price limit rules in their stock markets. Third, the daily price limit mechanism serves as a circuit breaker to calm the market when it is in turmoil. However, the existing literature does not provide a clear conclusion about the relationship between *PLH* and the volatility in markets. The proponents argue that price limits are efficient in reducing price volatility as the mechanism can effectively stop the order flow after the limit hits. However, opponents argue that the price limit trading rule acts as a magnet to attract more trades, leading to higher price volatility. For example, Kim, Yagüe, and Yang (2008) show that

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volatility increases after PLH in Spanish Stock Exchange market. Hsieh, Kim, and Yang (2009) find that the probability of a price increases (decreases) significantly when the price approaches the upper (lower) price limit. Kim and Rhee (1997) and Li, Zheng, and Chen (2014) test three hypothesis (the delayed price discovery hypothesis, the volatility spillover hypothesis, and the trading interference hypothesis), and their findings suggest that volatility tends to spill over to the day following the PLH. Guo, Chang, and Hung (2017) find that such effects could even affect informationally related stocks that have a high correlation of returns, volatilities, and trading volumes with the stock experiencing PLH.

More specifically, we improve the forecasting performance of heterogeneous autoregressive realized volatility model (*HAR-RV*) by taking PLH into account. There exist numerous statistical methods for volatility forecasting. For example, the class of GARCH models and stochastic volatility models are widely used. The validity of such volatility measures, however, crucially depends on specific distributional assumptions (Andersen et al. 2001). An alternative approach is to use high-frequency intraday data to model volatility, which has been labelled as realized volatility (*RV* hereafter). Andersen et al. (2003) provide a framework to integrate high-frequency intraday data with the forecasting of daily and lower frequency return volatilities. A popular model for forecasting *RV* is the *HAR-RV* model proposed by Corsi (2009). The *HAR-RV* model has been extensively applied in the literature (Çelik and Ergin 2014; Corsi 2009; Hamid and Heiden 2015; Wang et al. 2016; Wang, Wu, and Xu 2015). Many empirical works suggest that the *HAR-RV* model has a better forecasting performance for volatility than other statistic models based on daily data (Corsi 2009; Jayawardena et al. 2016; Yun and Shin 2015). Corsi (2009) shows that the *HAR-RV* model can reproduce the main empirical features of financial returns, such as long memory, fat tails, and self-similarity.

Using a sample from 2005 to 2015 in Chinese stock market, we find, first, PLH display statistically significant in-sample forecasting power for future volatilities, and the out-of-sample forecasting power of PLH is also economically significant. Second, the effects on volatility are asymmetric between *LPLH* and *UPLH*, with more pronounced effect for *LPLH*. Third, we find that returns are temporarily higher when there are more *NPLH* (i.e., *UPLH* - *LPLH*) but return reversals occur two days thereafter, a pattern consistent with the prediction of investor sentiment theories. We, thus, provide further supporting evidence for using the number of PLH as a proxy for investor sentiment.

The rest of the article is organized as follows. The next section describes the measurement of variables and modeling. Section 3 describes our sample and gives summary statistics of the main variables. Section 4 reports empirical results. Section 5 discusses five robust tests. Section 6 provides possible explanation for the predictive ability of PLH. Conclusions are provided in the last section.

## Econometric Models

As previously described, the *HAR-RV* model has a better forecasting performance for volatility than other statistic models. It is believed that the *HAR-RV* model can better capture the characteristics of the volatility (Corsi 2009). A standard specification of *HAR-RV* can be written as follows:

$$RV_{t,t+h} = \alpha_0 + \alpha_1 RV_t + \alpha_2 RV_t^w + \alpha_3 RV_t^m + \varepsilon_{t+h}, \quad (1)$$

Where  $RV_t^w$  is the average *RV* from day  $t - 4$  to day  $t$  and denotes the weekly realized volatility.  $RV_t^m$  is the average *RV* from day  $t - 21$  to  $t$  and denotes the monthly realized volatility. We set  $h = 1, 5, 22$  to represent volatility forecasting one day, one week, and one month ahead, respectively. To estimate daily realized volatility from intraday data is a well-accepted practice (see, e.g., Bollen and Inder 2002). Following the literature (Andersen et al. 2001; Barndorff-Nielsen and Shephard 2002), the

daily realized volatility is defined by the summation of the corresponding high-frequency intraday squared returns:

$$RV_t \equiv \sum_{j=1}^n r_{tj}^2, \quad (2)$$

where  $n$  is the number of intra-day observations.

To test the predictability of PLH for realized volatilities, we add PLH to the above model (*HAR-RV-PLH* hereafter).

$$RV_{t,t+h} = \alpha_0 + \alpha_1 RV_t + \alpha_2 RV_t^w + \alpha_3 RV_t^m + \alpha_4 UPLH_t + \alpha_5 LPLH_t + \varepsilon_{t+h}, \quad (3)$$

where  $UPLH_t$  is the number of UPLH at day  $t$ , and  $LPLH_t$  is the number of LPLH at day  $t$ .

Many previous studies have shown the incorporation of jump in a volatility model could improve the forecasting performance. For example, Andersen, Bollerslev, and Diebold (2007) find a negative impact of jump on future volatility. In order to control the predictive effect of jumps on volatility, the models will be considered by combining the different types of jumps.

$$RV_{t,t+h} = \alpha_0 + \alpha_1 RV_t + \alpha_2 RV_t^w + \alpha_3 RV_t^m + \alpha_4 UPLH_t + \alpha_5 LPLH_t + \alpha_6 J_t + \varepsilon_{t+h}, \quad (4)$$

where  $J_t$  represents jumps. We extract jumps components from realized volatilities. Following the literature, we first calculate the bipower variation ( $BV$ ) developed by Barndorff-Nielsen and Shephard (2006) as:

$$BV \equiv \mu_1^{-2} \sum_{j=2}^n |r_j| |r_{j-1}|, \quad \mu_1 = \sqrt{2/\pi}. \quad (5)$$

Following Barndorff-Nielsen and Shephard (2006), we choose the following jump test statistic:

$$Z = \frac{1 - BV/RV}{\sqrt{(\frac{\pi^2}{4} + \pi m a - 5) \frac{1}{n} \max(1, TQ/BV^2)}}, \quad (6)$$

where  $TQ$  is the tripower quarticity that Barndorff-Nielsen and Shephard (2004) define as:

$$TQ = n \mu_{4/3}^{-3} \sum_{j=3}^n |r_j|^{4/3} |r_{j-1}|^{4/3} |r_{j-2}|^{4/3}, \quad (7)$$

where  $\mu_{4/3} \equiv 2^{2/3} \Gamma(7/6) \Gamma(1/2)^{-1}$ . The  $Z$  statistic defined in Equation (6) has an asymptotic normal distribution under the null hypothesis of no jump. Andersen, Bollerslev, and Diebold (2007) identify significant jumps by the realizations of  $Z$  in excess of some critical value  $\Phi_{1-\alpha}$  for a significance level  $\alpha$ . The jump component may be evaluated as:

$$J = I[Z > \Phi_{1-\alpha}] \cdot (RV - BV), \quad (8)$$

Where  $I[\cdot]$  denotes the indicator function taking the value 1 when the argument in  $[\cdot]$  is true and 0 otherwise.  $\Phi_{1-\alpha}$  is the inverse cumulative distribution function of the standard normal distribution at the confidence level  $1 - \alpha$ . In this article, we choose the significance level of  $\alpha = 0.01$ . Hence, an abnormally large value of this standardized difference between  $RV$  and  $BV$  may be interpreted as evidence in favor of a significant jump.

According to Patton and Sheppard (2015) and Pu, Chen, and Ma (2016), the incorporation of signed jumps in volatility models can significantly improve their forecasting ability; we, thus, include signed jump variation ( $SJV$ ) in  $HAR-RV$  framework as follows:

$$RV_{t,t+h} = \alpha_0 + \alpha_1 RV_t + \alpha_2 RV_t^w + \alpha_3 RV_t^m + \alpha_4 UPLH_t + \alpha_5 LPLH_t + \alpha_6 SJV_t + \varepsilon_{t+h}, \quad (9)$$

where  $SJV$  is calculated based on the realized semi-variances ( $RS$ ). Realized semi-variance is proposed by Barndorff-Nielsen, Kinnebrock, and Shephard (2010). They are defined as:

$$RS^- = \sum_{i=1}^n r_i^2 I_{[r_i > 0]}, \quad (10)$$

$$RS^+ = \sum_{i=1}^n r_i^2 I_{[r_i < 0]}. \quad (11)$$

$RS^+$  and  $RS^-$  can capture the variations due to only negative and positive returns, respectively. The limiting behavior of realized semi-variance is:

$$RS^- \xrightarrow{p} \frac{1}{2} \int_0^t \sigma_s^2 ds + \sum_{0 \leq s \leq t} \Delta p_s^2 I_{[\Delta p_s < 0]}, \quad (12)$$

$$RS^+ \xrightarrow{p} \frac{1}{2} \int_0^t \sigma_s^2 ds + \sum_{0 \leq s \leq t} \Delta p_s^2 I_{[\Delta p_s > 0]}. \quad (13)$$

Realized semi-variance includes variations due to the continuous process and jumps. We are mainly interested in the variations caused by jumps. For this purpose, we remove the variations due to the continuous process by simply subtracting one  $RS$  from the other. The remaining part is defined as the signed jump variation ( $SJV$ ):

$$SJV = RS^+ - RS^- \xrightarrow{p} \sum_{0 \leq s \leq t} \Delta p_s^2 I_{[\Delta p_s > 0]} - \sum_{0 \leq s \leq t} \Delta p_s^2 I_{[\Delta p_s < 0]}. \quad (14)$$

## Sample and Summary Statistics

This study has chosen to examine Chinese stock markets. China is the world's largest emerging and transitional economy. There are two Securities Exchanges in China: Shanghai Stock Exchange ( $SHSE$ ) and Shenzhen Stock Exchange ( $SZSE$ ), which are both pure order-driven markets. One significant difference between the two stock exchanges is the sizes of the listed companies. In general companies listed in  $SHSE$  have higher market capitalizations than those in  $SZSE$ . The Shanghai Composite Index ( $SHCI$ ) is used as the market index in this article.<sup>1</sup> In particular, we use Shanghai Composite Index 5 min high frequency to calculate realized volatility and other realized measures. The 5 min intraday data provides a balance between sampling frequency and market structure noise (Bollerslev, Tauchen, and Zhou 2009; Hansen and Lunde 2006).

There exist two kinds of daily price limits in stock markets: upper price limits ( $UPLH$ ) and lower price limits ( $LPLH$ ). The  $UPLH$  is defined as the total number of daily upper price limit hits in Chinese A-share markets. The  $LPLH$  is defined as the total number of daily lower price limit hits in Chinese A-share markets.

Beginning from 22nd April 1998, the Shanghai Stock Exchange implemented the special treatment policy (ST policy). A firm is labeled as an ST firm if there is certain abnormality in its financial status or other aspects that could lead to difficulty of investors in assessing the company's prospects. There are separate daily price limit rules for regular stocks and the ST status stocks. Regular stocks are subject to the 10% daily price limit since 1996, while the daily stock price limit for ST stock is 5% in either direction. The 10% daily PLH of ST stocks are easier to attract investors' attention than the 5% daily PLH of regular stocks. Due to the above differences of ST stocks from regular stocks, we exclude ST stocks from our analysis. Thus, only regular trading stocks are included in the calculation of *UPLH* and *LPLH*.

Our data sample covers the period of 2005–01–04 to 2015–12–31. Figure S1 depicts the *SHCI* daily closing prices (the dot line) and returns (the solid line) in the sample period. As it can be seen clearly, there is a tremendous increase and decrease of the stock index around 2008 global financial crisis and 2015 Chinese stock market crash (See Figure S1, available online). Figure S2 and Figure S3 report the number of stocks that hit the upper and lower price limit on a particular day, respectively. It varies substantially over time. We see a surge of PLH around the 2008 global financial crisis and the 2015 China stock market crash, but PLH stay relatively stable in other periods with a few mild spikes (See Figure S2 and Figure S3, available online).

Summary statistics of our sample are reported in Table S1. The maximum of daily upper *UPLH* is 1399, which took place on 13<sup>th</sup> July 2015. The maximum of daily *LPLH* is 2100, which took place on 24<sup>th</sup> August 2015 (See Table S1, available online).

## Empirical Results

We report and discuss results in three steps. We first present the in-sample analysis of the role of PLH in forecasting volatilities. With the estimated model at hand, second, we use it to perform an out-of-sample analysis. Finally, we demonstrate the economic value of improving volatility forecasting by using PLH.

### *In-Sample Analysis of Price Limit Hits and Volatilities*

In this section, we present empirical results regarding our in-sample analysis. Table 1 reports these results. To facilitate comparisons of results, we present the results without PLH and with PLH in different HAR-RV type models, separately. For each forecasting horizon, Table 1 reports the estimated slope coefficients together with *t*-statistics in parentheses. The adjusted  $R^2$ s are also reported in the last column. As one can see from Table 1, the coefficients of all three realized volatility components, *i.e.*,  $RV$ ,  $RV^w$ , and  $RV^m$ , are positive and highly significant, which is in line with previous literatures.

We focus on the relation between PLH and volatilities. Two results in Table 1 stand out. First, in general we find a significant effect of PLH on future volatilities. Looking at the adjusted  $R^2$ s of regressions in Table 1, the models with *UPLH* and *LPLH* performs better than the models without PLH. For example, the adjusted  $R^2$  of the regression of *HAR-RV-PLH* for one day (week, or month) ahead volatility forecasting is 0.538 (0.496, or 0.457), while the adjusted  $R^2$  of the regression of *HAR-RV* for one day ahead volatility forecasting is 0.452 (0.468, or 0.452). Similar effects are found in the results of regression prediction even after considering jumps. For example, controlling for jumps the adjusted  $R^2$  of *HAR-RV-J-PLH* for one day (week, or month) ahead volatility forecasting is 0.541 (0.512, or 0.469), while the adjusted  $R^2$  of *HAR-RV-J* for one day ahead volatility forecasting is 0.459 (0.489, or 0.465).

Second, there is an asymmetric effect of PLH on volatility. *LPLH* plays a more important role in volatility forecasting than *UPLH* does. For example, *LPLH* are associated with an increase in volatility at 1% level for daily, weekly, and monthly forecasting, while *UPLH* are not statistically significant. This result shows that stock market future returns become more volatile when markets are



<i>HAR-RV</i>	0.119*** (6.830)	0.105*** (4.370)	0.438*** (19.718)			9.252*** (15.243)	0.452
<i>HAR-RV-J</i>	0.210*** (10.219)	0.091*** (3.791)	0.412*** (18.566)	-0.209*** (-8.101)		8.580*** (14.173)	0.465
<i>HAR-RV-SJV</i>	0.118*** (6.771)	0.114*** (4.700)	0.429*** (19.210)		-0.053*** (-3.413)	9.240*** (15.260)	0.454
<i>HAR-RV-PLH</i>	0.091*** (5.025)	0.104*** (4.325)	0.430*** (18.752)			9.640*** (15.823)	0.457
<i>HAR-RV-J-PLH</i>	0.183*** (8.482)	0.089*** (3.723)	0.402*** (17.514)	-0.199*** (-7.690)		8.930*** (14.638)	0.469
<i>HAR-RV-SJV-PLH</i>	0.095*** (5.188)	0.108*** (4.463)	0.422*** (18.122)		-0.029* (-1.654)	9.570*** (15.666)	0.458

*Notes:*  $RV$  is the daily realized volatility.  $RV^w$  is the weekly realized volatility.  $RV^m$  is the monthly realized volatility.  $UPLH$  is the number of daily upper price limit hits, and  $LPLH$  is the number of daily lower price limit hits.  $J$  is the jump component of bipower variation.  $SJV$  is the signed jump variation.  $C$  is intercept.  $t$ -statistics are shown in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.



in general bearish (in the sense of more *LPLH*), whereas stock market future returns do not become more volatile when markets are in general more favorable (in the sense of more *UPLH*). In case of economic significance, the effects of *LPLH* on volatilities are more pronounced than those of *UPLH*. For example, in *HAR-RV-PLH* model regression results, relative to the *RV* mean ( $Mean = 2.743 \times 10^{-4}$ ), a one-standard-deviation increase (Std. Dev = 126.292) in *LPLH* today would increase *RV* by 57% the next day, while a one-standard-deviation increase (Std. Dev = 66.476) in *UPLH* today would increase *RV* by 2.42% the next day. For weekly forecasting, a one-standard-deviation increase in *LPLH* would increase 27.1% of the *RV* mean, while a one-standard-deviation increase in *UPLH* would decrease 2.45% of the *RV* mean.

These results indicate that investors in Chinese stock market react more strongly to negative news than to positive news. The positive effects of *LPLH* on volatility are not surprising. Chinese stock markets are dominated by individual investors, and they are likely to be more “emotional”. Individuals are likely to suffer from the negativity bias (Rozin and Royzman 2001). This result is consistent with standard literature which states that returns and volatility are negatively related (Aboura and Wagner 2016; Badshah et al. 2016; Bekaert and Wu 2000; Christie 1982). For example, the previous studies show this relation between returns and volatility is more prominent for negative shocks (Bekaert and Wu 2000; Giot 2005; Hibbert, Daigler, and Dupoyet 2008). Given the relation between *PLH* and investor sentiment above, one could argue that returns are temporarily lower when there is more *LPLH*. When investors suffer from lots of *LPLH*, *i.e.*, negative shocks, investors possess reason to believe recent crashes are representative of the future and will react to ongoing decline (Hibbert, Daigler, and Dupoyet 2008). Consequently, such decisions cause the level of market volatility increase. This result is also consistent with Guo, Chang, and Hung (2017), which shows that lower limit hit may signal rise in information asymmetry but upper limit hit may not. Increases in information asymmetry can cause volatility to increase (Wang 1993).

To summarize, the in-sample results suggest that the *PLH* play an important role in volatility forecasting. *PLH* have not only a transitory impact (daily forecasting) but also a relatively long-term effect (weekly and monthly forecasting) on volatility. Furthermore, the effects of *PLH* on volatility are more pronounced for *LPLH*, indicating that *LPLH* is an important forecasting driving force.

### Out-Of-Sample Analysis of Price Limit Hits and Volatilities

To explore the out-of-sample forecast performances of our models, we conduct a rolling window regression analysis. A fixed rolling estimation window is set to 1000 observations. One day ahead forecasts of  $RV_t$  are generated from our models using the interval  $[t - 1000, t - 1]$ . For the period from 20th February 2009 to 31st December 2015, we make 1670 forecasts. To quantitatively evaluate the forecasting accuracy, we follow the literature by using following four popular loss functions:

$$MSE = \frac{1}{n} \sum_{i=1}^n (\sigma_i^2 - \hat{\sigma}_i^2)^2, \quad (15)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n \leq f| \sigma_i^2 - \hat{\sigma}_i^2 |, \quad (16)$$

$$MSD = \frac{1}{n} \sum_{i=1}^n (\sigma_i - \hat{\sigma}_i)^2, \quad (17)$$

$$MAD = \frac{1}{n} \sum_{i=1}^n |\sigma_i - \hat{\sigma}_i|, \quad (18)$$

where  $\sigma_t^2$  is the actual  $RV$ ,  $\hat{\sigma}_t^2$  is the forecasts based on the  $HAR-RV$  model without or with  $PLH$ ,  $n$  is the number of forecasts.  $MSE$  and  $MAE$  are the mean squared error and mean absolute error, respectively.  $MSD$  and  $MAD$  are mean squared difference and mean absolute difference, respectively.

We also conduct the Mincer-Zarnowitz ( $MZ$ ) regression, following the analysis of Andersen and Bollerslev (1998), to evaluate the out-of-sample forecasting accuracy:

$$RV_{t+h} = \beta_0 + \beta_1 \widehat{RV}_{t+h} + \varepsilon_{t+h}, \quad (19)$$

Where  $\widehat{RV}_{t+h}$  is forecasting value from the  $HAR-RV$  model without or with  $PLH$ .

To assess the statistical significance of the difference in forecasting performance, we make pairwise model comparisons based on Diebold and Mariano (1995) test ( $DM$  test hereafter). Diebold and Mariano (1995) show that the  $DM$  test statistic follows a standard normal distribution under the null hypothesis that there is no statistically significant difference.

Table 2 compares the out-of-sample forecasting performances of different regressions. We can clearly see that  $PLH$  indeed improves the performances of the forecasting volatility. The  $HAR-RV$  models with  $PLH$  always generate lower loss functions than those of  $HAR-RV$  models without  $PLH$  except in case of  $MSE$  of monthly forecasting. In terms of the out-of-sample Mincer-Zarnowitz regression, when  $PLH$  is added to the regression equation, adjusted  $R^2$ s are larger than those of the models without  $PLH$ . These results highlight the important role of  $PLH$  in volatility forecasting regressions.

Table 3 shows the  $DM$  test statistics of the out-of-sample performance differences. A positive statistic in a cell  $(i, j)$  indicates that the model  $i$  outperforms the model  $j$ . In Table 3, all  $DM$  statistics are positive and significant at least at the 10% level. Therefore,  $DM$  tests confirm the advantages of our proposed  $HAR-RV$  models with  $PLH$  in comparison to the models without  $PLH$ .

**Table 2. The performances of the out-of-sample forecasting volatility.**

Model	<i>HAR-RV</i>	<i>HAR-RV-J</i>	<i>HAR-RV-SJV</i>	<i>HAR-RV-PLH</i>	<i>HAR-RV-J-PLH</i>	<i>HAR-RV-SJV-PLH</i>
Panel A: 1 Day						
$MSE(\times 10^{-8})$	8.671	8.964	8.276	5.688	5.731	5.808
$MAE(\times 10^{-4})$	1.218	1.197	1.212	1.109	1.081	1.105
$MSD(\times 10^{-5})$	2.644	2.585	2.564	2.303	2.222	2.297
$MAD(\times 10^{-3})$	3.578	3.446	3.549	3.449	3.307	3.418
$MZ\_R^2$	0.475	0.454	0.506	0.681	0.673	0.685
Panel B: 1 Week						
$MSE(\times 10^{-8})$	6.249	5.923	6.558	5.924	5.517	6.116
$MAE(\times 10^{-4})$	1.142	1.083	1.135	1.126	1.059	1.115
$MSD(\times 10^{-5})$	2.242	2.086	2.239	2.191	2.025	2.175
$MAD(\times 10^{-3})$	3.425	3.227	3.374	3.394	3.178	3.329
$MZ\_R^2$	0.521	0.536	0.508	0.572	0.586	0.568
Panel C: 1 Month						
$MSE(\times 10^{-8})$	5.325	5.422	5.542	5.665	5.100	5.801
$MAE(\times 10^{-4})$	1.183	1.145	1.181	1.167	1.123	1.161
$MSD(\times 10^{-5})$	2.263	2.150	2.266	2.202	2.090	2.190
$MAD(\times 10^{-3})$	3.571	3.449	3.543	3.491	3.362	3.459
$MZ\_R^2$	0.425	0.438	0.414	0.456	0.464	0.454

Notes:  $MSE$  and  $MAE$  are the mean squared error and mean absolute error respectively.  $MSD$  and  $MAD$  are mean squared difference and mean absolute difference respectively.  $MZ\_R^2$  is the  $R^2$  of Mincer-Zarnowitz regression.

**Table 3.** Diebold and Mariano (1995) test.

<i>DM</i>	HAR-RV	HAR-RV-J	HAR-RV-SJV
Panel A: 1 Day			
HAR-RV-PLH	3.608	3.703	3.559
HAR-RV-J-PLH	3.628	3.624	3.581
HAR-RV-SJV-PLH	3.488	3.422	3.495
Panel B: 1 Week			
HAR-RV-PLH	2.970	3.024	2.855
HAR-RV-J-PLH	2.939	3.098	2.792
HAR-RV-SJV-PLH	2.989	2.824	2.885
Panel C: 1 Month			
HAR-RV-PLH	1.925	2.149	1.854
HAR-RV-J-PLH	2.128	1.875	2.097
HAR-RV-SJV-PLH	2.044	2.162	1.968

*Notes:* This table shows the Diebold and Mariano (1995) test statistics *DM* of the out-of-sample performance differences. *DM* test statistic follows a standard normal distribution under the null hypothesis that there is no statistically significant difference. A positive statistic in a cell (*i*, *j*) indicates that the model *i* outperforms the model *j*.

### Economic Value

To evaluate the economic value of volatility forecasts, following Wang et al. (2016) and Neely et al. (2014), we consider a mean–variance utility investor who allocates his or her assets between stock index and risk-free asset. The utility from investing in this portfolio is:

$$U_t(r_t) = E_t(w_t r_t + r_{f,t}) - \frac{1}{2} \gamma \text{var}_t(w_t r_t + r_{f,t}), \quad (20)$$

where  $w_t$  is the weight of stock in this portfolio,  $r_t$  is the stock return in excess of risk-free rate,  $r_{f,t}$  is the risk-free rate and  $\gamma$  is the risk aversion coefficient.  $E_t(\cdot)$  and  $\text{var}_t(\cdot)$  denote conditional mean and variance given information at time  $t$ .

The investor optimally allocates the following share of the portfolio to stock market index at day  $t + 1$ :

$$w_t^* = \frac{1}{\gamma} \left( \frac{\hat{r}_{t+1}}{\hat{\sigma}_{t+1}^2} \right), \quad (21)$$

where  $\hat{r}_{t+1}$  and  $\hat{\sigma}_{t+1}^2$  are the mean and volatility forecasts of stock excess returns, respectively. We restrict the optimal weight between 0 and 1. The portfolio return at day  $t + 1$  is given by:

$$R_{t+1} = w_t^* r_{t+1} + r_{f,t+1}, \quad (22)$$

We employ two criteria, i.e., certainty equivalent return (*CER*) and Sharpe ratio (*SR*), to evaluate the performance of a portfolio constructed based on return and volatility forecasts.

The *CER* for the portfolio is:

$$CER_p = \hat{\mu}_p - \frac{1}{2} \gamma \hat{\sigma}_p^2, \quad (23)$$

where  $\hat{\mu}_p$  and  $\hat{\sigma}_p^2$  are the mean and variance of portfolio returns over the out-of-sample period, respectively.

**Table 4. Performances of portfolios formed by realized volatility forecasts.**

Models	<i>SR</i>	<i>CER</i>
HAR-RV	0.0263	2.6612
HAR-RV-J	0.0265	2.7335
HAR-RV-SJV	0.0264	2.6724
HAR-RV-PLH	0.0298	3.2583
HAR-RV-J-PLH	0.0301	3.3662
HAR-RV-SJV-PLH	0.0299	3.2656

*Notes:* This table shows the performances of portfolios formed by realized volatility forecasts. We give the Sharpe ratio (*SR*) and certainty equivalent return (*CER*) of each portfolio. All the values are annualized.

The Sharpe ratio (*SR*) is:

$$SR = \frac{\bar{\mu}_p}{\bar{\sigma}_p}, \quad (24)$$

where  $\bar{\mu}_p$  and  $\bar{\sigma}_p$  are the mean and standard deviation of portfolio excess returns, respectively.

For the risk-free rate  $r_f$ , we use the 3-month Treasury bill rate. Historical average forecasts are generally accepted as the benchmark model in forecasting stock return (see, e.g., Neely et al. 2014; Wang et al. 2016). In this study, we report results when risk aversion coefficient  $\gamma = 3$ ; the results are similar for other reasonable  $\gamma$ . In this way, the optimal weight of stock market index is only determined by the volatility forecasts.

Table 4 shows the annualized *CER* and *SR* of portfolios formed by realized volatility forecasts. We find that *HAR-RV* models with *PLH* generally result in better performances than the corresponding *HAR-RV* models without *PLH* (on average *CER* increases by 22% and *SR* increases by 13%). This indicates that the use of *PLH* in predictive regressions can improve the economic value of realized volatility forecasts.

## Robustness Tests

In this section, we examine whether or not our results are robust to different subsamples and measurements. We use (i) crisis sub-sample, (ii) net number of *PLH*, (iii) standardized *PLH* by the number of A-shares, (iv) unexpected *PLH*, (V) leverage effect and trading volume, as robustness tests.

### Crisis Sub-Sample

It may be very worthwhile to analyze the effect of *PLH* on volatility forecasting during the crisis periods. Our sample contains two important crisis periods: the 2008 global financial crisis and the 2015 Chinese stock market crash. The 2008 global financial crisis is considered by many economists to be the worst financial crisis since the Great Depression of the 1930s. During global financial crisis, stock markets dropped worldwide. The Chinese stock market peaked in October 2007 with the *SHCI* exceeding 6124 points. It then entered a pronounced decline, which accelerated markedly in 2008. By 31<sup>st</sup> October 2008, the *SHCI* had gone down to 1728 points. The 2015 Chinese stock price crash began on 12<sup>th</sup> June 2015. A third of Chinese stock market value of A-shares was lost within one month. Major aftershocks occurred around the “Black Monday” on 27<sup>th</sup> July and 24<sup>th</sup> August. From

12<sup>th</sup> June 2015 to 14<sup>th</sup> September 2015, Shanghai Composite Index fell from 5166 to 3114, implying a fall of 40% over three months.

Therefore, the crisis sub-sample we consider includes the 2008 financial crisis and the 2015 Chinese stock market crash. We follow the same regressions and forecasting procedures as before but limit the sample period to 1<sup>st</sup> July 2008 through 31<sup>st</sup> May 2010 (2008 global financial crisis sample) and 1<sup>st</sup> June 2015 through 31<sup>st</sup> December 2015 (2015 Chinese stock price crash sample). These results from crisis periods are in general consistent with the results from the full sample (See Table S2, available online).

### **Net Number of Price Limit Hits**

UPLH and LPLH may appear simultaneously on the same trading day, we thus use the net number of price limit hits (*NPLH*) instead of *UPLH* and *LPLH* as a robustness check. The *NPLH* is calculated as the number of upper price limit hits minus the number of lower price limit hits, i.e.,  $UPLH - LPLH$ . The results from *NPLH* shows the coefficients of *NPLH* are statistically significant negative at level 1% (See Table S3, available online).

### **Standardized Price Limit Hits**

In our sample, the number of A-shares is changing. Therefore, we standardize PLH with the number of A-shares. The standardized upper price limit hits (*SUPLH*) is defined as *UPLH* divided by the number of A-shares. Similarly, the standardized lower price limit hits (*SLPLH*) is defined as *LPLH* divided by the number of A-shares. The results show that *SLPLH* display statistically significant forecasting power at level 1% for future one day, one week, and one month volatilities and *SUPLH* display statistically significant forecasting power at level 5% for future one day volatilities in case of *HAR-RV-PLH* and *HAR-RV-J-PLH* (See Table S4, available online).

### **Unexpected Price Limit Hits**

In a stock market, if a stock hits its *UPLH* (*LPLH*) today, it is more likely to hit it again tomorrow. In other words, there is a serial correlation of *UPLH* (*LPLH*). To address this issue, we use unexpected price limit hits instead of *UPLH* or *LPLH* as a robustness check. The unexpected upper (lower) price limit hits *UUPHLH* (*ULPLH*) are defined as residuals in following equations:

$$UPLH_t = \alpha_0 + \alpha_1 UPLH_{t-1} + \alpha_1 UPLH_{t-1} + \cdots + \alpha_p UPLH_{t-p} + \varepsilon_t \quad (25)$$

$$LPLH_t = \alpha_0 + \alpha_1 LPLH_{t-1} + \alpha_1 LPLH_{t-1} + \cdots + \alpha_p LPLH_{t-p} + \varepsilon_t \quad (26)$$

where  $p$  is the lag length determined by AIC criteria.

Results from unexpected price limit hits show that *ULPLH* display statistically significant forecasting power at 1% level for future one day, one week, and one month volatilities, while *UUPHLH* display statistically significant forecasting power at 1% level for future one day volatilities (See Table S5, available online).

### **Leverage Effect and Trading Volume**

The leverage effect is well documented in the volatility literature. It describes the fact that volatility is likely to rise as returns fall (Wang, Keswani, and Taylor 2006). It is, therefore, possible that the relation between PLH and future realized volatilities is spurious and may merely be a consequence of the leverage effect. Additionally, there exists a relation between volatility and trading volume in asset markets. For example, Giot, Laurent, and Petitjean (2010), Chevallier and Sévi (2012), and Wang

and Huang (2012) find a positive volume-volatility relation. To control the influence of the leverage effect and the volume effect, we add both negative returns and trading volume to our forecasting equations.

$$RV_{t,t+h} = \alpha_0 + \alpha_1 RV_t + \alpha_2 RV_t^w + \alpha_3 RV_t^m + \alpha_4 NPLH_t + \alpha_5 Lev_t + \alpha_6 Vol_t + \varepsilon_{t+h}, \quad (27)$$

where  $Lev_t = \min(r_t, 0)$  represents negative daily returns and  $Vol_t$  refers to trading volume.

As a result, we find that there exist significant effects of the negative returns and trading volume on volatility. The former suggests the well-known leverage effect, and the latter is consistent with Giot, Laurent, and Petitjean (2010), Chevallier and Sévi (2012), and Wang and Huang (2012). However, the coefficients of  $NPLH$  are still statistically significant at 1% level (See Table S6, available online).

Overall, the predictive ability of PLH is robust to the alternative measurements and subsamples.

### Price Limit Hits and Investor Sentiment

Previous studies have found that change in investor sentiment results in volatility adjustments. One possible explanation for the predictive ability of PLH is that PLH can be used as a proxy for market sentiment. A central prediction in theories of investor sentiment is return reversals (Da, Engelberg, and Gao 2015). If the PLH are driven by investor sentiment, returns are expected to be temporarily higher (lower) in the days of large  $UPLH$  ( $LPLH$ ). But, because the rise in returns is due to investor sentiment instead of fundamentals, a reversal to lower (higher) returns is expected. To investigate this issue, we check return reversals by running the following regressions:

$$\begin{aligned} Returns_{t+k} &= \beta_0 + \sum_{j=1}^5 \beta_j Returns_{t+k-j} + \beta_6 Vol_t + \beta_7 RV_t + \beta_8 NPLH_t + \varepsilon_{t+k}, k \\ &= 0, 1, 2, \dots, n. \end{aligned} \quad (28)$$

In regression (28),  $Returns_{t+k}$  denote Shanghai composite index returns on day  $t+k$ . Control variables include lagged returns (up to five lags), trading volumes ( $Vol$ ), and market risks (denoted as the realized volatility  $RV$ ).  $NPLH$  is calculated as the number of  $UPLH$  minus the number of  $LPLH$ .

The results are reported in Panel A of Table 5. When  $k=0$ , the positive and significant coefficient on  $NPLH$  suggests a positive contemporaneous relationship between  $NPLH$  and returns. When there are sharp increases (declines) in  $NPLH$ , there are also sharp increases (declines) in returns. The effect is significant at 1% level. The positive effect of  $NPLH$  on returns continues in the next day. When  $k=1$ , the positive and significant coefficient on  $NPLH$  suggests that increases in  $NPLH$  predict next day higher returns (significant at 5% level). However, in two days, a price reversal occurs. When  $k=2$ , the negative and significant coefficient on  $NPLH$  is found. This result indicates that increases in  $NPLH$  predict lower returns at  $k=2$ . We have also considered longer horizons  $k=6$  and  $k=10$ . The estimated coefficients on  $NPLH$  are  $-0.622$  and  $-1.100$ , which are statistically significant at 5% or 1% level.

We also consider the effects of upper (lower) price limit hits in isolation. The regression results of  $UPLH$  and  $LPLH$  are reported in Panel B of Table 5. We find that the larger the  $UPLH$ , the higher the contemporaneous returns. However, significant returns reversals occur at  $k=2$  and  $k=10$ . A similar phenomenon is found for  $LPLH$ : The larger the  $LPLH$ , the lower the contemporaneous returns, and significant returns reversals occur at  $k=2$ ,  $k=6$ , and  $k=10$ . The last column in Table 5 provides regression results for cumulative returns from day  $t+2$  to  $t+10$ . It suggests that there is a statistically significant reversal effect from day  $t+2$  to  $t+10$ .

The trading volume of stocks hitting their price limit is often quite low. This implies that there might exist limits to arbitrage when there are PLH. We acknowledge the possibility that price limits

Table 5. Price limit hits and stock returns.

	$k = 0$	$k = 1$	$k = 2$	$k = 3$	$k = 6$	$k = 10$	$[t + 2, t + 10]$
Variables	Returns <sub><math>t</math></sub>	Returns <sub><math>t+1</math></sub>	Returns <sub><math>t+2</math></sub>	Returns <sub><math>t+3</math></sub>	Returns <sub><math>t+6</math></sub>	Returns <sub><math>t+10</math></sub>	$R_{[t+2, t+10]}$
Panel A							
Returns <sub><math>t+k-1</math></sub>	-0.038** (-2.161)	0.013 (0.606)	0.036* (1.854)	0.033* (1.704)	0.035* (1.796)	0.028 (1.441)	0.095 (1.501)
Returns <sub><math>t+k-2</math></sub>	-0.051*** (-2.940)	-0.030 (-1.507)	-0.007 (-0.319)	-0.037* (-1.927)	-0.033* (-1.704)	-0.033* (-1.707)	0.083 (1.360)
Returns <sub><math>t+k-3</math></sub>	0.015 (0.861)	0.034* (1.734)	0.037* (1.835)	0.039* (1.751)	0.030 (1.551)	0.029 (1.499)	0.081 (1.329)
Returns <sub><math>t+k-4</math></sub>	0.034* (1.953)	0.069*** (3.585)	0.068*** (3.447)	0.075*** (3.716)	0.062*** (3.202)	0.061*** (3.126)	0.054 (0.879)
Returns <sub><math>t+k-5</math></sub>	-0.037** (-2.122)	0.011 (0.578)	0.007 (0.340)	0.012 (0.584)	0.010 (0.529)	0.009 (0.477)	0.171*** (2.772)
Vol <sub><math>t</math></sub> ( $\times 10^{-3}$ )	3.723** (2.294)	-0.994 (-0.540)	-0.008 (-0.047)	-0.844 (-0.462)	0.561 (0.312)	1.200 (0.666)	0.611 (0.104)
RV <sub><math>t</math></sub>	70.775 (0.965)	267.838*** (3.223)	-15.019 (-0.181)	148.876* (1.804)	-150.349* (-1.867)	-179.976** (-2.239)	-132.895 (-0.504)
NPLH <sub><math>t</math></sub> ( $\times 10^{-3}$ )	6.017*** (27.250)	0.728** (2.568)	-0.764*** (-2.690)	-0.133 (-0.469)	-0.622** (-2.472)	-1.100*** (-4.401)	-1.790** (-2.259)
C	-0.083* (-1.880)	-0.009 (-0.193)	0.059 (1.195)	0.026 (0.515)	0.085* (1.693)	0.086* (1.722)	0.517*** (3.280)
Adj.R <sup>2</sup>	0.237	0.013	0.011	0.009	0.011	0.015	0.007
Panel B							
Returns <sub><math>t+k-1</math></sub>	-0.038** (-2.173)	0.016 (0.725)	0.035* (1.836)	0.032* (1.690)	0.035* (1.817)	0.027 (1.425)	0.095 (1.502)
Returns <sub><math>t+k-2</math></sub>	-0.047*** (-2.772)	-0.030 (-1.504)	-0.005 (-0.244)	-0.038* (-1.952)	-0.033* (-1.715)	-0.033* (-1.728)	0.081 (1.321)
Returns <sub><math>t+k-3</math></sub>	0.019 (1.124)	0.033* (1.699)	0.037* (1.836)	0.041* (1.839)	0.030 (1.568)	0.029 (1.492)	0.078 (1.272)
Returns <sub><math>t+k-4</math></sub>	0.041** (2.373)	0.068*** (3.523)	0.067*** (3.429)	0.075*** (3.722)	0.063*** (3.218)	0.061*** (3.154)	0.049 (0.790)
Returns <sub><math>t+k-5</math></sub>	-0.030* (-1.756)	0.009 (0.476)	0.006 (0.304)	0.011 (0.561)	0.011 (0.556)	0.008 (0.445)	0.167*** (2.688)
Vol <sub><math>t</math></sub> ( $\times 10^{-3}$ )	-1.522 (-0.800)	0.341 (0.158)	0.729 (0.340)	0.234 (0.109)	-0.607 (-0.288)	2.891 (1.370)	4.578 (0.664)
RV <sub><math>t</math></sub>	-93.010 (-1.171)	310.600*** (3.425)	12.166 (0.134)	185.442** (2.046)	-190.271** (-2.139)	-122.459 (-1.381)	-9.649 (-0.034)
UPLH <sub><math>t</math></sub> ( $\times 10^{-3}$ )	8.640*** (15.74)	0.031 (0.048)	-1.196* (-1.826)	-0.708 (-1.081)	-0.015 (-0.024)	-1.980*** (-3.170)	-3.770* (-1.902)
LPLH <sub><math>t</math></sub> ( $\times 10^{-3}$ )	-5.060*** (-17.72)	-0.957*** (-2.783)	0.622* (1.807)	-0.056 (-0.162)	0.840*** (2.582)	0.787** (2.426)	1.070** (2.040)
C	-0.0263 (-0.585)	-0.023 (-0.466)	0.051 (0.989)	0.014 (0.272)	0.097* (1.895)	0.067 (1.310)	0.474*** (2.923)
Adj.R <sup>2</sup>	0.245	0.013	0.011	0.010	0.011	0.016	0.008

Notes: Returns is the returns of Shanghai Composite Index. Vol is the daily trading volume. NPLH is the number of upper price limit hits minus the number of lower price limit hits, i.e.,  $UPLH - LPLH$ . RV is the daily realized volatility. C is intercept.  $t$ -statistics are shown in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% respectively.

hits might reveal limits to arbitrage (Gu, Kang, and Xu 2018), but note that limits to arbitrage mainly lead to the momentum effect in the short run, but predict no reversal in the medium or long run.

In sum, the results from Table 5 are in line with the prediction of theories of investor sentiment. In this sense, it supports the idea of using *NPLH* as a proxy for market sentiment.

## Conclusions

In this article, we discuss whether PLH contain information for volatility forecasting. First, we find that PLH play an important role in volatility forecasting. More importantly, results suggest that PLH have not only a transitory impact (for daily forecasting) but also a relatively long-term effect (for weekly and monthly forecasting) on volatility. Second, we find that the effects on volatility are asymmetric between *LPLH* and *UPLH*, with more pronounced effect for *LPLH*. Specifically, *LPLH* are significantly associated with volatility increasing. Third, we find that returns are temporarily higher (lower) during periods with more upper (lower) price limit hits, but then a return reversal follows, a result consistent with prediction of investor sentiment theories.

These findings are important for investors in Chinese stock market and emerging markets in general. A key step in risk management is volatility forecasting. Over the last decade we have seen a rise of market volatility. With Brexit, political elections in US and in Europe, and the slowdown of Chinese economy, this tendency is likely to continue. The rise in stock market volatility makes risk management more important and difficult. We suggest that price limits hits can be used to improve the prediction accuracy of volatility. These findings are also important for policy makers. Market volatility has been taken as an important monitoring indicator. Our results suggest that policy makers should use PLH to improve the forecast. More importantly, our empirical results show that the price limit rule does not reduce volatility. For example, we find that volatility of following days is higher when there are more *LPLH*. The evidence of the *LPLH* rules being ineffective in terms of reducing volatility has policy implications for countries that plan to impose similar mechanisms, especially for the emerging markets.

## Supplemental Material

Supplemental data for this article can be accessed on the [publisher's website](#).

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## Note

1. We also use Shenzhen Composite Index (*SZCI*) as the market index and conduct empirical analysis using *SZCI* realized volatility, jumps, and returns as a robustness check. The results are not reported here because they are qualitatively similar to the results using *SHCI*. The two markets are highly correlated.

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