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Does herding effect help forecast market volatility?—Evidence from the Chinese stock market

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Abstract

This paper aims to study the predictive power of market herding effect for market volatility. We extend the widely used four types of linear HAR models by incorporating the market herding index and further introduce a nonlinear forecasting mechanism by using two machine learning algorithms—support vector regression (SVR) and random forest (RF). All the methods are applied to the Chinese stock market. We evaluate their in-sample and out-of-sample performances for various prediction step lengths. The results show that according to the RMSE and MAE, for the daily volatility prediction, the extra herding factor makes no significant contribution, and the linear model has no significant difference with the algorithms as well, whereas with the increase of step length, the herding factor shows a significant power in the weekly, monthly, and quarterly prediction, and meanwhile, the RF algorithm outperforms the other methods. However, for the QLIKE, the herding factor always significantly improves the predictions for all kinds of step lengths and methods, and the SVR algorithm with the herding factor is dominant. Overall, the herding factor helps forecast the volatility, and the extent to which the precision is improved takes on an inverted "U" shape with the increase in step length. The two algorithms are superior to the linear model, especially for the longer-term prediction, and the herding factor can help enlarge this advantage, which implies a nonlinear relationship between the herding and volatility. Besides, the extra liquidity factor plays no significant role in the volatility prediction, but the continuous variation (CV), jump variation (JV), and leverage effect are helpful in most cases.

KEYWORDS

HAR model, herding, machine learning algorithm, nonlinear prediction, volatility forecast

1 | INTRODUCTION

The volatility of financial assets is a key element in many fields of modern financial theory, such as financial risk management, asset pricing, and portfolio. Hence, modeling and predicting the volatility has always attracted the researchers' attention. There are many classic methods in the literature, such as the (G)ARCH model (Bollerslev, 1986; Engle, 1982), the SV model (Taylor, 1986), and their various extensions. Moreover, with the rapid development of information technology in the last two decades, data availability has been largely improved and the analysis of volatility based on financial high-frequency data has become an important research area. Since Andersen and Bollerslev (1998) proposed the realized volatility (RV) based on intraday high-frequency data to measure the volatility of asset return, this non-parametric measurement has been widely used in many financial areas, with the advantages of model-free and easy calculation. Corsi (2009) considered the volatility realized over different time horizons and proposed the heterogeneous autoregressive realized volatility (HAR-RV) model to explain the volatility persistence. The easy implementation with a very accurate fit of volatility has made the HAR model very popular in financial econometrics, and many extensions have been proposed. For instance, Andersen et al. (2007) decomposed the realized volatility (RV) into continuous variation (CV) and jump variation (JV) and then established the HAR-RV-J model and the HAR-RV-CJ model. They confirmed that the proposed models perform better than the traditional HAR-RV model. Corsi and Renò (2012) introduced a dummy variable to reflect the leverage effect of volatility and proposed the LHAR-RV-CJ model to explain the asymmetric impacts of positive and negative news on volatility.

However, the existing HAR model and its extensions are mainly based on the historical information of RV and its components, for example, CV and JV, barely consider the explanatory factors about investor behavior. The relationship between market volatility and investor behavior was first documented by Friedman (1953). Wang (1993) claimed that in the context of asymmetrical information, uninformed investors largely tend to follow the market trend, buying when prices rise and selling when they fall, which may drive market volatility. This behavior is often regarded as herding, which depicts the phenomenon that the market participants believe in or excessively blindly follow the public opinion atmosphere about the market, thus ignoring their own judgments on the value of the market and easily following others' investment behavior (Banerjee, 1992; Scharfstein & Stein, 1990). Lux (1995) claimed that the existence of herd behavior makes investors' views on the change in stock price converge, which may increase the risk of overvaluing or undervaluing stocks. Due to the stock price bubble, the repeated burst or filling of price depressions, herd behavior has a positive feedback mechanism on stock market volatility. Zouaoui et al. (2011) pointed out that investors' herd behavior and market irrational emotions are often accompanied, which is easy to lead to investors' overreaction to market information, thus indirectly amplifying the stock market volatility. Many empirical results have confirmed that herd behavior aggravates stock market volatility. Venezia et al. (2011) studied the impact of herd behavior on the stock market from the perspectives of institutional investors and individual investors in Israel's stock market and found that the herd behavior of individual investors is more likely to cause the aggravation of market volatility. Balcilar and Demirer (2015) found that there is a common trend between risk factors and herd behavior in Turkey's stock market, and large volatility and strong herd behavior often occur simultaneously. Litimi (2017) studied the influence of the herding effect on conditional volatility in the French stock market and found that the herding effect of most industries exacerbated the conditional variance of the industry. Blasco et al. (2012) demonstrated the linear relationship between the herding and volatility in the Spanish stock market and further examined the herding's usefulness in volatility forecasting by linearly regressing the volatility measure on the herding factor.

As an emerging market, the Chinese stock market still has some deficiencies in investors' structure and market system construction. The investors' irrational behavior may be the potential predictor of market volatility with a linear or nonlinear mechanism. Therefore, this paper is aimed to explore whether the herding behavior can improve the prediction of market volatility in the Chinese stock market and whether the nonlinear forecasting approaches are superior to the linear models. We first contribute to the existing literature by studying the prediction power of herding behavior under the framework of the HAR model. We extend the HAR model by including the herding factor to predict the volatility of the Chinese stock market. Second, we consider the nonlinear relationship between the RV and its predictors by adopting machine learning algorithms. Third, given that market liquidity, often regarded as a sentiment measure of the market, has been claimed to be an important factor that constitutes the idiosyncratic volatility of stocks (Han & Lesmond, 2011) and significantly correlates with market volatility (Engle et al., 2012; Ramos & Righi, 2020), we compare the roles of these two micro-market factors—herding and liquidity in forecasting volatility. In particular, based on the traditional HAR model and its widely used three extensions, we first establish the HAR-Herd models, HAR-Liquidity models, and HAR-Herd-Liquidity models by adding the herding and liquidity factors into the benchmark models and then apply them to the Chinese stock market. We compare their in-sample and out-of-sample performances with different prediction steps, that is, daily, weekly, monthly, and quarterly predictions. Furthermore, based on the above extended volatility's predictors, we adopt two widely used machine learning algorithms—support vector regression (SVR) and random forest (RF)—to produce a more flexible nonlinear prediction and compare their performances with the traditional linear models. The RMSE, MAE, and QLIKE are used to evaluate the prediction performance, and the final optimal methods are selected by the MCS test.

The principle findings can be summarized as follows. First, the herding factor is helpful to forecast volatility and the extent of its improvement in the precision takes on an inverted "U" shape with the increase of step length. Especially in terms of the QLIKE, the herding factor can always significantly increase the precision of predictions with all kinds of step lengths and methods, and its improvement in the precision in the weekly and monthly predictions is larger than those in the daily and quarterly predictions. Second, the two algorithms with the predictors in HAR-type models outperform the linear HAR-type models, especially for the longer-term prediction; moreover, adding the herding factor can enlarge this advantage. According to the RMSE and MAE, the RF algorithm with herding factor is superior to the other methods including the RF without considering herding itself for the weekly, monthly, and quarterly volatility. As for the QLIKE, the SVR algorithm with an additional herding factor is the dominant method for all prediction horizons considered. For instance, the reduction of QLIKE when using the SVR algorithm including the extra herding factor relative to that with the original predictors in the LHAR-RV-CJ model for monthly prediction reaches up to 51.46%. These results further imply that there is a nonlinear relationship between the market herding effect and market volatility. Third, the extra liquidity factor plays no significant role in improving the volatility prediction, but CV, JV, and leverage effect are helpful in most cases.

The rest of this paper is organized as follows. Section 2 presents the dynamic measurement of herd behavior and market liquidity and applies them to the Chinese stock market. Section 3 presents the four benchmark HAR-type models and reports the in-sample and out-of-sample performances of the extended models and two machine learning algorithms. Section 4 concludes.

2 | MEASUREMENT OF HERDING AND LIQUIDITY IN THE CHINESE STOCK MARKET

2.1 | Dynamic index of herd behavior

The classic methods for measuring herd behavior include CCK (Chang et al., 2000), LSV (Lakonishok et al., 1992), and CH (Christie & Huang, 1995) methods. Among them, the CH method is considered to have low sensitivity and poor accuracy (Bikhchandani & Sharma, 2000). The CCK method is more suitable for measuring the herd behavior of the entire market, whereas the LSV method is mainly used to measure the herd behavior of investors. Hence, we choose the CCK method to measure the herding behavior of the Chinese stock market and use it as a predictor for market volatility. In particular, we use the CCK method with a rolling window to obtain the dynamic measure of herding. First, define the cross-sectional absolute deviation (CSAD) of returns as

$$CSAD_t = \frac{1}{N}\sum\nolimits_{i=1}^{N} |r_{i,t} - r_{m,t}|, \tag{1}$$

where $r_{i,t}$ represents the return of the ith stock on day t and $r_{m,t}$ represents the market return on day t. According to Chang et al. (2000), fit the following model

$$CSAD_t = \beta_0 + \beta_1 |r_{m,t}| + \beta_2 r_{m,t}^2 + \varepsilon_t. \tag{2}$$

Chang et al. (2000) considered that when the regression coefficient β_2 in model (2) is significantly negative, it means that herd behavior exists. In order to dynamically measure the herd behavior, by selecting a certain window width, we can obtain the rolling estimate $\widehat{\beta}_{2,t}$, which can be used as a proxy to reflect herd behavior. Moreover, in order to reflect the significance of the coefficient $\beta_{2,t}$, we use the t-ratio $t_{\widehat{\beta}_{2,t}}$ of $\widehat{\beta}_{2,t}$ instead to further construct the dynamic herding index by standardizing the t-ratio as

$$H_t = \frac{\max\left(t_{\widehat{\beta}_{2,t}}\right) - t_{\widehat{\beta}_{2,t}}}{\max\left(t_{\widehat{\beta}_{2,t}}\right) - \min\left(t_{\widehat{\beta}_{2,t}}\right)}. \tag{3}$$

The larger H_t means the higher degree of herding on day t.

In the following, we use the daily closed price data of all A shares in the Shanghai Stock Exchange (SSE) and the market composite index to measure the herd behavior of the Chinese stock market. All the data are from the CSMAR database, an authoritative data service in China. The sample period is from January 4, 2013, to June 30, 2021. We use the rolling CCK method described above to calculate the dynamic herding index. We set three window widths: 126, 192, and 252 days, respectively, corresponding to half a year, three quarters, and 1 year. The results of the dynamic herding index are shown in Figure 1. It can be seen that the dynamic characteristics of the herding index under three window widths are very similar. In order to eliminate the noise of different window widths, we average the results of three kinds of window widths to obtain the final index.

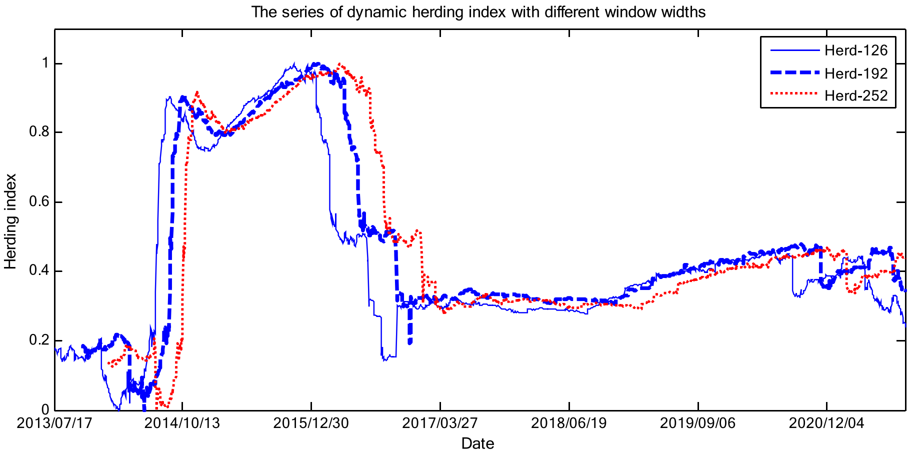

FIGURE 1 The series of the dynamic herding index with different window widths.

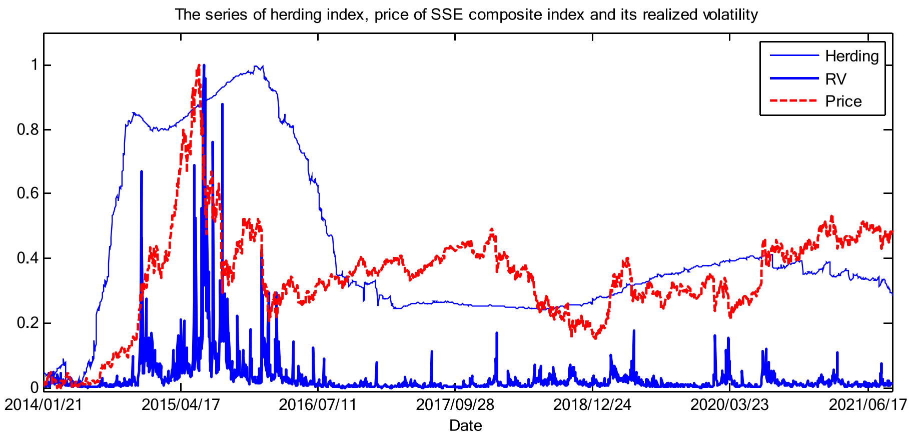

FIGURE 2 The series of the herding index, the price of the SSE composite index, and its realized volatility.

To see the herd behavior characteristics of the Shanghai stock market, the estimated herding index is compared with the daily price of the SSE Composite Index and its fluctuation (the daily RV) in the same period. The daily realized volatility of the SSE Composite Index is calculated by the intraday 5-min price data as $RV_t = \sum_{i=1}^{n} r_{m,t,i}^2$, where $r_{m,t,i}$ is the ith 5-min return of market on day t. In order to clearly compare the dynamics of each series, the herding index, price, and RV of the SSE Composite Index have been min–max standardized. The results are shown in Figure 2.

It can be seen from Figure 2 that during the abnormal fluctuation of the market (around the market crash in 2015), the market volatility is very high; meanwhile, the herding index keeps at a high level. Subsequently, as the herding index gradually eases, the market volatility tends to be stable. Hence, the herding index would be useful to predict stock market volatility.

2.2 | Dynamic measure of liquidity

We use the Amihud illiquidity measure (Amihud, 2002), which is widely used in empirical research, to measure the liquidity of the Chinese stock market. The idea of Amihud illiquidity measure is, first, defining the illiquidity measure of the ith stock on day t as

$$\text{Amihud}_{i,t} = |r_{i,t}| / VOL_{i,t}, \tag{4}$$

where $r_{i,t}$ is the daily return of ith stock and $VOL_{i,t}$ is its daily trading volume. Then, the whole market illiquidity measure for day t is defined as

$$\text{Amihud}_t = \frac{1}{N} \sum_{i=1}^{N} \text{Amihud}_{i,t}, \tag{5}$$

where N is the number of stocks in the whole market. Since the original results of Amihud_t are too small, we amplify them by 10^8 times in the following empirical study. The time span of the data is the same as before. The selected stocks are all A-shares in the Shanghai stock market. The measurement results are shown in Figure 3.

From the definition of the Amihud illiquidity measure, the large value means that the market liquidity is drying up, whereas the small value means that the market liquidity is abundant. Figure 3 shows that before the outbreak of Sino-US trade disputes (before 2018), the

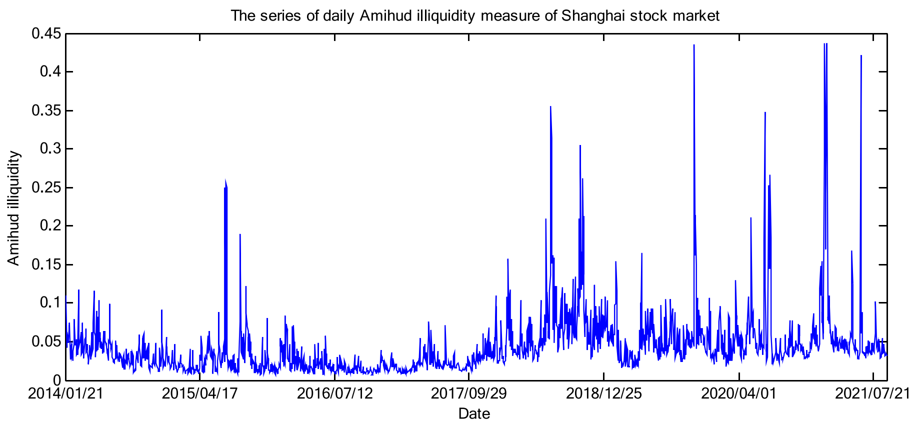

FIGURE 3 The series of daily Amihud illiquidity measures of the Shanghai stock market.

TABLE 1 Correlation of herding, liquidity, and market volatility.

		Herd	Liquidity	RV	ln (RV)
Liquidity	Pearson	0.191*** (0.000)	1		
	Spearman	0.264*** (0.000)	1		
RV	Pearson	0.435*** (0.000)	0.023 (0.334)	1	
	Spearman	0.424*** (0.000)	0.111*** (0.000)	1	
ln (RV)	Pearson	0.603*** (0.000)	0.107*** (0.000)	0.709*** (0.000)	1
	Spearman	0.424*** (0.000)	0.111*** (0.000)	1	1

Note: The results in the parenthesis are the *p* values of the significance test. ln (RV) is the logarithmic realized volatility.
***Statistical significance at the level of 1%.
**Statistical significance at the level of 5%.
*Statistical significance at the level of 10%.

liquidity crisis mainly occurred during the market crash in 2015, with a sharp loss of liquidity in the market. After the outbreak of Sino-US trade disputes (after 2018), the liquidity of the Chinese stock market is highly volatile.

2.3 | Correlation analysis

We use the (logarithmic) realized volatility of the SSE Composite Index to measure the market volatility and then study the correlation between the herding, liquidity, and market volatility. The correlation results are given in Table 1. From Table 1, the results of the Pearson correlation and Spearman correlation show that there is a significant positive correlation between the herding index and the (logarithmic) realized volatility, that is, the aggravating herd behavior and large market volatility are often associated. For the liquidity and volatility, except that the Pearson correlation between the illiquidity measure and RV is not significant, other correlation coefficients are significant at the 1% level. Hence, the market liquidity exhaustion would be accompanied by the intensification of market volatility. However, compared with the correlation between the herding index and volatility, the correlation between liquidity measure and volatility is weaker. Therefore, the herding effect may be more useful than the market liquidity in the prediction of volatility.

3 | MODELS AND FORECASTING EVALUATION

3.1 | HAR models

Since Corsi (2009) proposed the heterogeneous autoregressive realized volatility (HAR-RV) model, various extended models have been established and widely used in modeling and predicting volatility. In our study, we use the original HAR-RV model, HAR-RV-J model, and HAR-RV-CJ model proposed by Andersen et al. (2007) and the LHAR-RV-CJ model proposed by Corsi and Renò (2012), as our benchmark models. These models are given as follows:

1. HAR-RV model

$$\ln(RV_{t,t+h}) = c + \alpha_D \ln(RV_t^D) + \alpha_W \ln(RV_t^W) + \alpha_M ln(RV_t^M) + \varepsilon_{t+h}, \quad (6)$$

where $\ln(RV_{t,t+h})$ denotes the logarithmic realized volatility during the period t to $t+h$, and the prediction step h can be taken as 1, 5, 22, and 66 days, respectively, corresponding to the daily, weekly, monthly, and quarterly predictions. $\ln(RV_t^D)$ is the logarithmic realized volatility on day t, which reflects the past short-term volatility. $\ln(RV_t^W)$ is the moving average by using the 5 days' logarithmic realized volatilities up to day t, which reflects the past medium-term volatility. $\ln(RV_t^M)$ is the moving average of 22 days' logarithmic realized volatilities up to day t, which reflects the past long-term volatility.

2. HAR-RV-J model

$$\ln(RV_{t,t+h}) = c + \alpha_D \ln(RV_t^D) + \alpha_W \ln(RV_t^W) + \alpha_M ln(RV_t^M) + \alpha_J ln\,(J_t + 1) + \varepsilon_{t+h}, \quad (7)$$

where $J_t = \max(RV_t - BV_t, 0)$, and BV_t is the bi-power variation on day t, which is given as

$$BV_t = \frac{2}{\pi} \sum_{i=2}^{n} |r_{m,t,i}||r_{m,t,i-1}|. \quad (8)$$

Other variables are the same as those in model (6).

3. HAR-RV-CJ model

$$\ln(RV_{t,t+h}) = c + \alpha_D \ln(CV_t^D) + \alpha_W \ln(CV_t^W) + \alpha_M ln(CV_t^M) + \beta_D \ln(JV_t^D + 1) + \beta_W \ln(JV_t^W + 1) + \beta_M ln(JV_t^M + 1) + \varepsilon_{t+h}, \quad (9)$$

where CV_t and JV_t respectively represent the CV and JV of the price path on day t, which are given as

$$CV_t = I(z_t \le \phi_\alpha) RV_t + I(z_t > \phi_\alpha) BV_t, \quad (10)$$

$$JV_t = I(z_t > \phi_\alpha)(RV_t - BV_t), \quad (11)$$

where z_t is the test statistic to determine whether there exist jumps in asset price on day t (Huang & Tauchen, 2005). ϕ_α is the upper α quantile of standard normal distribution. If $z_t > \phi_\alpha$, there are significant jumps in asset price. $I(\cdot)$ is the indicator function. The significance level α is selected as 5%. In addition, the calculation of $\ln(CV_t^W)$, $\ln(CV_t^M)$, $\ln(JV_t^W + 1)$ and $\ln(JV_t^M + 1)$ are the same as $\ln(RV_t^W)$ and $\ln(RV_t^M)$ in the HAR-RV model.

4. LHAR-RV-CJ model

$$\ln(RV_{t,t+h}) = c + \alpha_D \ln(CV_t^D) + \alpha_W \ln(CV_t^W) + \alpha_M ln(CV_t^M) + \beta_D \ln(JV_t^D + 1) + \beta_W \ln(JV_t^W + 1) + \beta_M ln(JV_t^M + 1) + \gamma_D r_t^- + \gamma_W r_{t-5,t}^- + \gamma_M r_{t-22,t}^- + \varepsilon_{t+h} \quad (12)$$

where $r_{t-l,t}^-$ reflects the leverage effect over different periods, which is the negative average market return over l days given as

$$r_{t-l,t}^- = \frac{1}{l} \left(\sum_{i=1}^{l} r_{m,\ t+i-1} \right) I \left(\sum_{i=1}^{l} r_{m,\ t+i-1} < 0 \right). \quad (13)$$

3.2 | In-sample fitting

We extend the above four HAR-type models by adding the daily herding index and daily Amihud illiquidity factor to construct the HAR-Herd model, the HAR-Liquidity model, and the HAR-Herd-Liquidity model. Figure 4 presents the results of adj. R^2 of all the extended and benchmark HAR models with step length h ranging from 1 to 66, that is, from 1 day to one quarter. It can be seen that the fitting degrees of the models incorporating the herding factor are higher than the original models and models only incorporating the liquidity factor. Moreover, when the prediction step becomes longer, the improvement becomes more obvious. However, the liquidity factor seems to be not much helpful to the improvement of fitting, since the fitting degrees of models only adding liquidity factor are very close to that of the original HAR models, and the results of models adding both herding factor and liquidity factor are very close to that of the models only adding herding factor as well. In order to further illustrate the performances of these models, Table 2 reports the average adj. R^2 over steps from 1 to 66 of each model.

The results in Table 2 further demonstrate the conclusions obtained in Figure 4. Under each benchmark model, the average adj. R^2 of the original model is very

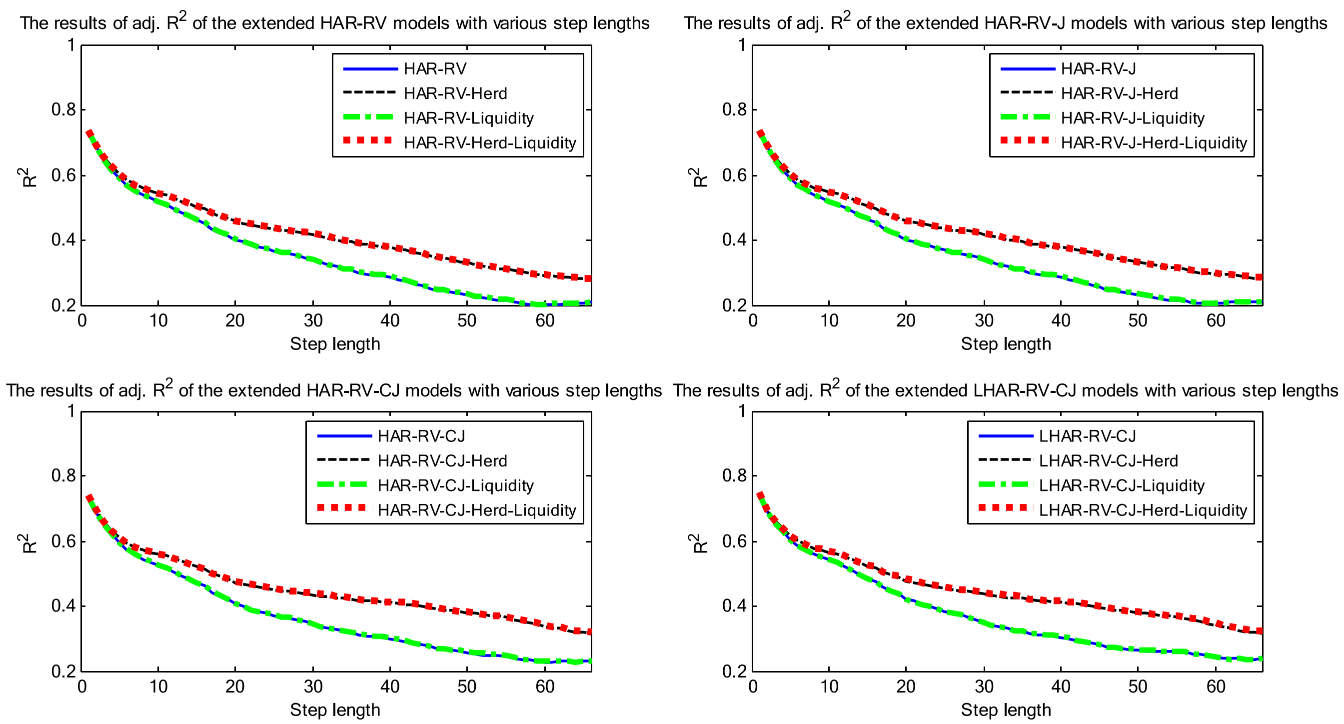

FIGURE 4 The results of adj. R^2 of the extended and benchmark HAR models with various step lengths.

TABLE 2 Average adj. R^2 for different HAR models among different steps.

	Original model	Liquidity	Herding	Herding and liquidity
HAR-RV	0.3505	0.3521	0.4190	0.4207
HAR-RV-J	0.3517	0.3534	0.4211	0.4228
HAR-RV-CJ	0.3651	0.3665	0.4476	0.4508
LHAR-RV-CJ	0.3750	0.3752	0.4503	0.4542

close to that of the model adding liquidity factor but is much less than that of the model adding herding factor. Moreover, the result of the model with herding and liquidity is also close to that of the model only with herding factor. For instance, for the benchmark HAR-RV model, the average adj. R^2 of the original model is 0.3505, which is very close to the result of the model with liquidity factor, 0.3521. The result of HAR-RV with a herding factor is 0.4190, which is larger than that of the original model and meanwhile is also very close to the result of the model with both herding and liquidity factors, 0.4207. Hence, the results suggest that herding factor is the main contributor to the improvement of model's fitting degree under each benchmark model.

3.3 | Out-of-sample prediction evaluation

In view of Chen et al. (2018), we use the data in each rolling window to estimate the models and then obtain the rolling h-step ahead predicted values of volatility. The RMSE, MAE, and QLIKE (quasi-likelihood) loss functions are used to evaluate the prediction performance, which are given as follows.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\widehat{RV}_{h,i} - RV_{h,i}\right)^2}, \tag{14}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\widehat{RV}_{h,i} - RV_{h,i}\right|, \tag{15}$$

$$QLIKE = \frac{1}{n}\sum_{i=1}^{n}\left(\ln\left(\widehat{RV}_{h,i}\right) + \frac{RV_{h,i}}{\widehat{RV}_{h,i}}\right), \tag{16}$$

where $\widehat{RV}_{h,i}$ represents the ith h-step ahead predicted value, $RV_{h,i}$ represents the true value, and n is the number of the out-of-sample volatility predictions.

Besides comparing the performances of the benchmark HAR models and their extensions, we further use two machine learning algorithms—SVR and RF method—to flexibly forecast volatility and compare their performances with the linear models as well, since in reality, there may be the nonlinear relationship between the volatility and its predictors. SVR is derived from support vector machine theory (Vapnik, 1995), which has good nonlinear prediction ability and is widely used in economic and financial forecasting problems (Kazem et al., 2013; Nazemi et al., 2018). In the following analysis, we use the SVR method based on the Gaussian radial kernel function for volatility prediction. The RF algorithm is proposed by Breiman (2001) on the basis of the traditional decision tree algorithm. It uses the bootstrap resampling method to extract multiple samples from the original sample. Each bootstrap sample is modeled by a decision tree, and then, multiple decision trees are produced. The final prediction results are obtained by voting. RF algorithm has the advantages of high prediction accuracy, good tolerance to outliers and noise, and is not prone to overfitting. We consider two cases of rolling window widths: 1 year and 2 years. The conclusions obtained in these two scenarios are consistent. Hence, in the following, we just report the results with a 2-year rolling window.

The RMSE, MAE, and QLIKE results of benchmark HAR models, HAR-Herd models, HAR-Liquidity models, HAR-Herd-Liquidity models, SVR algorithm, and RF algorithm for the daily volatility prediction are reported in Table 3 to Table 5. Every table has four blocks. Each block in these tables represents a kind of benchmark predictors, for instance, the block HAR-RV means that the predictors are $\ln\left(RV_t^D\right)$, $\ln\left(RV_t^W\right)$, and $\ln\left(RV_t^M\right)$, that is, the three predictors occurred in model (6). Every row in these tables represents the predictors used in the prediction. For instance, the row "Original predictors" means that predictors are the benchmark ones, and the row "Herd" means that the predictors include the benchmark ones and herding index. The results in bold in the tables are the smallest values in each block. They represent the optimal prediction methods among 12 combinations with four kinds of predictors and three kinds of methods under each benchmark scenario. The results in the row "Optimal in group" further show what the optimal methods are within each block. The last row "Optimal of all" gives the final optimal method with the smallest errors among all scenarios, which can be easily obtained by comparing the bold values in the table.

In Table 3, in terms of RMSE, we can see that firstly, for the daily volatility prediction, with the same prediction method, no matter the linear model, SVR or RF algorithm, the RMSE results with each kind of benchmark predictors and the extended predictors, that is, plus herding, liquidity or both, are very close. These results show that the extra micro-market factors play little role in predicting the daily volatility. Second, it's surprising to find that for the same predictors, the results of linear models are not worse than those of SVR and RF. In most cases, the results of linear models are very close to those of algorithms, and in some cases, the linear modes are even better, such as the case of HAR-RV-J, where the linear model has the smallest RMSE. These results show that the algorithms have not absolute advantages over linear HAR models for daily volatility forecasting. Third, for the same prediction method, the results in the cases of HAR-RV, HAR-RV-J, HAR-RV-CJ, and LHAR-RV-CJ also have little differences. It means that the contribution of components of price variation, such as JV and CV is not obvious.

TABLE 3 Results of RMSE of daily volatility prediction.

	HAR-RV			HAR-RV-J			HAR-RV-CJ			LHAR-RV-CJ		
	Linear	SVR	RF	Linear	SVR	RF	Linear	SVR	RF	Linear	SVR	RF
Original	0.6116	0.6131	0.6134	**0.6121**	0.6203	0.6223	0.6133	0.6293	0.6103	0.6124	0.6300	0.6025
Herd	0.6170	0.6266	0.6092	0.6177	0.6392	0.6205	0.6213	0.6367	**0.6049**	0.6187	0.6330	0.5993
Liquidity	0.6230	**0.6071**	0.6163	0.6223	0.6232	0.6245	0.6246	0.6328	0.6107	0.6221	0.6291	0.6021
Both	0.6468	0.6225	0.6111	0.6465	0.6384	0.6130	0.6606	0.6353	0.6068	0.6417	0.6337	**0.5980**
Optimal in group	HAR-RV-SVR-Liquidity			HAR-RV-J-Linear			HAR-RV-CJ-RF-Herd			LHAR-RV-CJ-RF-Both		
Optimal of all	LHAR-RV-CJ-RF-Both											

Note: The column titles HAR-RV, HAR-RV-J, HAR-RV-CJ, and LHAR-RV-CJ mean that the benchmark predictors are the same as the predictors in models (6), (7), (9), and (12) respectively. "Linear," "SVR," and "RF" respectively represent three kinds of prediction methods. The row titles "Original," "Herd," "Liquidity," and "Both" mean that the predictors are the benchmarks, the benchmarks plus herding factor, the benchmarks plus liquidity factor, and the benchmarks plus both herding and liquidity factors, respectively. The value in bold in each block is the smallest in each benchmark scenario, and the row "Optimal in group" further shows what the corresponding optimal methods are within each block. The last row "Optimal of all" gives the final optimal method with the smallest errors among all prediction methods. The meanings of row and column titles in Table 4–14 are the same as in Table 3.

In terms of MAE, the results in Table 4 confirm most of the above conclusions and suggest that the linear model is even a little better than the SVR and RF algorithms since the smallest MAEs are from the linear models in four scenarios of benchmark predictors. However, in terms of QLIKE, the results in Table 5 congruently show the obvious advantages of herding factor and SVR algorithm in forecasting. With the same predictors, the results of SVR are always much smaller than those of linear model and RF (see each row in each block), and with the same prediction method, the precisions with the additional herding factor are always higher than those with original predictors or including extra liquidity factor (see each column in each block). Compared with the original predictors, the values of QLIKE with herding factor are almost decreased by around 10%–20% under four benchmarks. The smallest QLIKEs are from the SVR algorithm with herding factor in four cases, and the values have not much difference by comparing the four bold values, which also confirms the conclusion that the roles of JV and CV are not obvious.

In sum, for the daily volatility forecasting, in the terms of RMSE and MAE, the linear HAR model is not inferior to the SVR and RF methods, and the herding

TABLE 4 Results of MAE of daily volatility prediction.

	HAR-RV			HAR-RV-J			HAR-RV-CJ			LHAR-RV-CJ		
	Linear	SVR	RF	Linear	SVR	RF	Linear	SVR	RF	Linear	SVR	RF
Original	**0.2806**	0.2815	0.2938	**0.2821**	0.2837	0.2941	**0.2776**	0.2851	0.2878	**0.2798**	0.2838	0.2831
Herd	0.2818	0.2851	0.2822	0.2832	0.2886	0.2868	0.2791	0.2858	0.2801	0.2801	0.2843	0.2772
Liquidity	0.2856	0.2821	0.2931	0.2863	0.2896	0.2928	0.2829	0.2894	0.2875	0.2855	0.2871	0.2829
Both	0.2888	0.2840	0.2819	0.2897	0.2911	0.2860	0.2868	0.2872	0.2798	0.2873	0.2873	0.2765
Optimal in group	HAR-RV-Linear			HAR-RV-J-Linear			HAR-RV-CJ-Linear			LHAR-RV-CJ-Linear		
Optimal of all	HAR-RV-CJ-Linear											

TABLE 5 Results of QLIKE of daily volatility prediction.

	HAR-RV			HAR-RV-J			HAR-RV-CJ			LHAR-RV-CJ		
	Linear	SVR	RF	Linear	SVR	RF	Linear	SVR	RF	Linear	SVR	RF
Original	0.3994	0.3016	0.4442	0.4013	0.3069	0.4409	0.4184	0.3432	0.4758	0.4138	0.3223	0.4542
Herd	0.3246	**0.2682**	0.4016	0.3283	**0.2759**	0.4037	0.3213	**0.2945**	0.4239	0.3234	**0.2772**	0.4068
Liquidity	0.4304	0.3790	0.4986	0.4327	0.3894	0.4968	0.4506	0.3995	0.5042	0.4422	0.3668	0.4855
Both	0.3730	0.3231	0.4396	0.3779	0.3366	0.4453	0.3752	0.3431	0.4458	0.3622	0.3157	0.4347
Optimal in group	HAR-RV-SVR-Herd			HAR-RV-J-SVR-Herd			HAR-RV-CJ-SVR-Herd			LHAR-RV-CJ-SVR-Herd		
Optimal of all	HAR-RV-SVR-Herd											

TABLE 6 Results of RMSE of weekly volatility prediction.

	HAR-RV			HAR-RV-J			HAR-RV-CJ			LHAR-RV-CJ		
	Linear	SVR	RF	Linear	SVR	RF	Linear	SVR	RF	Linear	SVR	RF
Original	0.6847	0.6894	0.6944	0.6823	0.6915	0.6920	0.6798	0.6866	0.6640	0.6743	0.6814	0.6547
Herd	0.6935	0.6906	0.6615	0.6915	0.6920	0.6666	0.6922	0.6841	**0.6427**	0.6872	0.6819	**0.6401**
Liquidity	0.6873	0.6872	0.6751	0.6845	0.6876	0.6779	0.6838	0.6894	0.6573	0.6994	0.6815	0.6505
Both	0.6976	0.6852	**0.6576**	0.6951	0.6868	**0.6540**	0.6972	0.6824	0.6434	0.7243	0.6817	0.6407
Optimal in group	HAR-RV-RF-Both			HAR-RV-J-RF-Both			HAR-RV-CJ-RF-Herd			LHAR-RV-CJ-RF-Herd		
Optimal of all	LHAR-RV-CJ-RF-Herd											

factor helps little. But in terms of QLIKE, the SVR method dominates the linear model and RF method; meanwhile, the herding factor always helps improve the precision.

Tables 6–8 report the results of RMSE, MAE, and QLIKE for the weekly volatility prediction. From Table 6, for the weekly volatility prediction, all the least RMSEs are from the RF method with additional factors in four scenarios, that is, HAR-RV, HAR-RV-J, HAR-RV-CJ, and LHAR-RV-CJ; see the bold values in the table. In particular, half optimals are from the RF method including herding factor and others contain both herding and liquidity factors. But by comparing the RMSEs of RF with herding, liquidity, and both factors, we find that the improvements of herding factor and both factors are very close, whereas the improvement of only adding the liquidity factor is less than that of herding factor. Hence, it's obtained that the herding factor contributes more to the weekly volatility prediction than liquidity factor. Besides, we also find that for the case of HAR-RV and HAR-RV-J with original predictors, the results of linear model, SVR, and RF method are very close. However, after considering the CV and leverage effect, the RF becomes better than the linear model and SVR (see the values in the cases of HAR-RV-CJ and LHAR-RV-CJ), and moreover, the RF method adding herding factor performs much better than the RF with benchmark predictors itself. This suggests that for the longer-term prediction, the flexible algorithm prediction is superior to the linear HAR model. Furthermore, the herding factor is a leading predictor, and its effect is nonlinear.

From Table 7, the results of MAE further confirm the above conclusions obtained in Table 6. Moreover, both the SVR and RF predictions are improved by including the herding factor, but the improvement of RF is larger than that of the SVR method. For instance, for the LHAR-RV-CJ, the MAE of the RF method with herding factor is 0.2987, which is decreased by 6.25% relative to MAE with the original predictors, 0.3186, whereas the MAE of the SVR method is decreased by 2.5%.

From Table 8, the results of QLIKE show that all the methods are improved by including the extra herding factor; moreover, the improvement of the SVR method is the largest. For the case of HAR-RV, the precision of the SVR method is increased by 44% relative to that of the original predictors, whereas the precision of the linear model and RF are increased by 36.33% and 11.34%, respectively. Under each kind of benchmark predictors, the best method with the smallest QLIKE is the SVR method with herding factor (see the bold value in each block).

TABLE 7 Results of MAE of weekly volatility prediction.

	HAR-RV			HAR-RV-J			HAR-RV-CJ			LHAR-RV-CJ		
	Linear	SVR	RF	Linear	SVR	RF	Linear	SVR	RF	Linear	SVR	RF
Original	0.3325	0.3281	0.3413	0.3306	0.3314	0.3399	0.3299	0.3333	0.3235	0.3264	0.3271	0.3186
Herd	0.3319	0.3199	0.3134	0.3297	0.3237	0.3180	0.3304	0.3201	**0.3012**	0.3276	0.3189	**0.2987**
Liquidity	0.3343	0.3293	0.3323	0.3319	0.3312	0.3342	0.3314	0.3357	0.3208	0.3319	0.3302	0.3181
Both	0.3334	0.3203	**0.3118**	0.3315	0.3245	**0.3121**	0.3320	0.3209	0.3026	0.3331	0.3219	0.3007
Optimal in group	HAR-RV-RF-Both			HAR-RV-J-RF-Both			HAR-RV-CJ-RF-Herd			LHAR-RV-CJ-RF-Herd		
Optimal of all	LHAR-RV-CJ-RF-Herd											

TABLE 8 Results of QLIKE of weekly volatility prediction.

	HAR-RV			HAR-RV-J			HAR-RV-CJ			LHAR-RV-CJ		
	Linear	SVR	RF	Linear	SVR	RF	Linear	SVR	RF	Linear	SVR	RF
Original	0.4660	0.2929	0.4798	0.4676	0.3102	0.4975	0.4993	0.3877	0.4991	0.4753	0.3610	0.5059
Herd	0.2967	**0.1637**	0.4254	0.3027	**0.1848**	0.4369	0.3109	**0.2505**	0.4251	0.3019	**0.2380**	0.4226
Liquidity	0.4532	0.3336	0.4984	0.4557	0.3409	0.5196	0.4920	0.4075	0.5077	0.4994	0.3935	0.5170
Both	0.3090	0.2032	0.4375	0.3159	0.2121	0.4428	0.3294	0.2685	0.4295	0.3438	0.2630	0.4321
Optimal in group	HAR-RV-SVR-Herd			HAR-RV-J-SVR-Herd			HAR-RV-CJ-SVR-Herd			LHAR-RV-CJ-SVR-Herd		
Optimal of all	HAR-RV-SVR-Herd											

In summary, compared with the results of daily volatility prediction, it can be seen that in the weekly volatility prediction, the algorithm prediction and herding factor gradually show their advantages, no matter in terms of RMSE, MAE, and QLIKE. In particular, for the QLIKE, the extent to that precision is improved by adding herding factor in the weekly prediction becomes larger than that in the daily prediction. Taking the case of HAR-RV for example, the QLIKE is decreased by 44% ([0.2929–0.1637]/0.2929) by adding the herding factor in the weekly prediction, whereas the QLIKE is decreased by 11.07% ([0.3016–0.2682]/0.3016) in the daily prediction.

Tables 9–11 report the results of RMSE, MAE, and QLIKE for the monthly volatility prediction. The results in Tables 9 and 10 show that for the monthly volatility prediction, in terms of RMSE and MAE, the least errors in four scenarios are from the predictions with additional predictors; moreover, most of the least values (3 in 4) come from the RF method including herding factor. The algorithm prediction is also superior to the linear model. The herding factor's role is more significant for the

TABLE 9 Results of RMSE of monthly volatility prediction.

	HAR-RV			HAR-RV-J			HAR-RV-CJ			LHAR-RV-CJ		
	Linear	SVR	RF	Linear	SVR	RF	Linear	SVR	RF	Linear	SVR	RF
Original	0.7275	0.7456	0.7646	0.7284	0.7445	0.7550	0.7282	0.7317	0.7132	0.7201	0.7168	0.6962
Herd	0.7481	0.7291	**0.6891**	0.7485	0.7353	0.7008	0.7512	0.7241	**0.6593**	0.7448	0.7133	**0.6553**
Liquidity	0.7696	0.7406	0.7483	0.7710	0.7368	0.7455	0.7930	0.7200	0.7143	1.3561	0.7061	0.6990
Both	0.7917	0.7177	0.6908	0.7921	0.7205	**0.6815**	0.7770	0.7100	0.6649	0.9868	0.7011	0.6604
Optimal in group	HAR-RV-RF-Herd			HAR-RV-J-RF-Both			HAR-RV-CJ-RF-Herd			LHAR-RV-CJ-RF-Herd		
Optimal of all	LHAR-RV-CJ-RF-Herd											

TABLE 10 Results of MAE of monthly volatility prediction.

	HAR-RV			HAR-RV-J			HAR-RV-CJ			LHAR-RV-CJ		
	Linear	SVR	RF	Linear	SVR	RF	Linear	SVR	RF	Linear	SVR	RF
Original	0.3850	0.3857	0.4037	0.3845	0.3858	0.4016	0.3896	0.3744	0.3644	0.3822	0.3671	0.3553
Herd	0.3854	0.3596	**0.3305**	0.3855	0.3653	0.3423	0.3912	0.3581	**0.3157**	0.3832	0.3516	**0.3143**
Liquidity	0.4012	0.3811	0.3901	0.4003	0.3806	0.3920	0.4045	0.3707	0.3635	0.4205	0.3604	0.3569
Both	0.4000	0.3556	0.3342	0.4000	0.3590	**0.3266**	0.3999	0.3495	0.3189	0.4029	0.3444	0.3169
Optimal in group	HAR-RV-RF-Herd			HAR-RV-J-RF-Both			HAR-RV-CJ-RF-Herd			LHAR-RV-CJ-RF-Herd		
Optimal of all	LHAR-RV-CJ-RF-Herd											

TABLE 11 Results of QLIKE of monthly volatility prediction.

	HAR-RV			HAR-RV-J			HAR-RV-CJ			LHAR-RV-CJ		
	Linear	SVR	RF	Linear	SVR	RF	Linear	SVR	RF	Linear	SVR	RF
Original	0.5942	0.3878	0.6318	0.5890	0.4081	0.6220	0.6020	0.3884	0.5597	0.5906	0.4178	0.5733
Herd	0.2586	**0.2218**	0.4285	0.2612	**0.2257**	0.4347	0.2583	**0.2045**	0.4001	0.2325	**0.2028**	0.3980
Liquidity	0.6513	0.4682	0.6454	0.6457	0.4708	0.6344	0.6645	0.4643	0.5981	0.6913	0.4923	0.6224
Both	0.3418	0.2876	0.4453	0.3438	0.2847	0.4237	0.3380	0.2583	0.4174	0.3468	0.2617	0.4192
Optimal in group	HAR-RV-SVR-Herd			HAR-RV-J-SVR-Herd			HAR-RV-CJ-SVR-Herd			LHAR-RV-CJ-SVR-Herd		
Optimal of all	LHAR-RV-CJ-SVR-Herd											

monthly volatility prediction. For instance, in the case of LHAR-RV-CJ, the herding factor decreases the RMSE and MAE respectively by 5.87% ([0.6962–0.6553]/0.6962) and 11.54% ([0.3553–0.3143]/0.3553) relative to the original predictors by adopting RF algorithm. Besides, comparing the results with the original predictors under four scenarios, it can be seen that the CV, JV, and leverage effect are helpful to improve the prediction when adopting the SVR and RF methods. In terms of QLIKE, Table 11 suggests similar results to Table 8. For the monthly volatility, all the QLIKEs of predictions including the herding factor are less than those with original predictors. The SVR algorithm is superior to the linear model and RF algorithm under four scenarios. The smallest QLIKE is from the case of LHAR-RV-CJ-SVR-Herd, where the precision is improved by 51.46% ([0.4178–0.2028]/0.4178) relative to the prediction with original predictors. The advantage of adding herding factor continues to enlarge.

Tables 12–14 report the results of RMSE, MAE, and QLIKE for the quarterly volatility prediction. From Tables 12 and 13, the best prediction is still the RF method including the herding factor according to RMSE and MAE. The RF algorithm is still better than the linear model and SVR. Herding factor is still helpful to improve the precision, but the improvement extent becomes smaller than those in the weekly and monthly predictions. In terms of QLIKE, as shown in Table 14, the optimal method is still the SVR with herding factor, but the contribution of adding herding factor becomes smaller. Taking the case of HAR-RV-CJ for example, the QLIKE is reduced by 40.16% ([0.5351–0.3202]/0.5351) relative to the precision with original predictors, which is smaller than the results of weekly and monthly predictions. These results show that the extant to that precision is improved by adding herding factor that takes on an inverted "U" pattern with the increase of prediction step length. Figure 5 shows the QLIKEs of the SVR algorithm and MAEs of the RF algorithm with original predictors (marked with stars) and original predictors plus herding factor (marked with triangles) for four kinds of step lengths in the case of LHAR-RV-CJ, which further clearly shows this inverted "U" pattern of the distance between the points marked with star and triangle with the increase of step length. Other cases follow this pattern as well.

Next, we use the model confidence set (MCS) test proposed by Hansen et al. (2011) to compare the prediction ability of the methods. We first select the best methods with the smallest errors (the smallest values on each row

TABLE 12 Results of RMSE of quarterly volatility prediction.

	HAR-RV			HAR-RV-J			HAR-RV-CJ			LHAR-RV-CJ		
	Linear	**SVR**	**RF**	**Linear**	**SVR**	**RF**	**Linear**	**SVR**	**RF**	**Linear**	**SVR**	**RF**
Original	0.7557	0.7542	0.7521	0.7543	0.7522	0.7520	0.7397	0.7016	0.6754	0.7368	0.7044	0.6781
Herd	0.7946	0.7685	**0.7329**	0.7926	0.7812	0.7418	0.7873	0.7147	**0.6647**	0.7863	0.7146	**0.6673**
Liquidity	0.8276	0.7409	0.7495	0.8194	0.7415	**0.7410**	0.8142	0.6990	0.6810	0.9119	0.7012	0.6844
Both	0.7921	0.7707	0.7395	0.7897	0.7834	0.7493	0.7818	0.7149	0.6800	0.7878	0.7114	0.6753
Optimal in group	HAR-RV-RF-Herd			HAR-RV-J-RF-Liquidity			HAR-RV-CJ-RF-Herd			LHAR-RV-CJ-RF-Herd		
Optimal of all	HAR-RV-CJ-RF-Herd											

TABLE 13 Results of MAE of quarterly volatility prediction.

	HAR-RV			HAR-RV-J			HAR-RV-CJ			LHAR-RV-CJ		
	Linear	**SVR**	**RF**	**Linear**	**SVR**	**RF**	**Linear**	**SVR**	**RF**	**Linear**	**SVR**	**RF**
Original	0.4353	0.4177	0.4077	0.4336	0.4178	0.4169	0.4244	0.3763	0.3489	0.4192	0.3758	0.3462
Herd	0.4331	0.4103	**0.3645**	0.4315	0.4207	0.3810	0.4248	0.3691	**0.3232**	0.4244	0.3679	**0.3226**
Liquidity	0.4473	0.4058	0.4021	0.4454	0.4090	0.4055	0.4353	0.3747	0.3508	0.4360	0.3723	0.3499
Both	0.4324	0.4135	0.3690	0.4305	0.4213	**0.3699**	0.4222	0.3686	0.3292	0.4217	0.3651	0.3275
Optimal in group	HAR-RV-RF-Herd			HAR-RV-J-RF-Both			HAR-RV-CJ-RF-Herd			LHAR-RV-CJ-RF-Herd		
Optimal of all	LHAR-RV-CJ-RF-Herd											

TABLE 14 Results of QLIKE of quarterly volatility prediction.

	HAR-RV			HAR-RV-J			HAR-RV-CJ			LHAR-RV-CJ		
	Linear	**SVR**	**RF**	**Linear**	**SVR**	**RF**	**Linear**	**SVR**	**RF**	**Linear**	**SVR**	**RF**
Original	0.8562	0.6447	0.7143	0.8442	0.6406	0.7667	0.7955	0.5351	0.5746	0.7523	0.5209	0.5600
Herd	0.5001	**0.4892**	0.5991	0.5158	**0.4824**	0.6483	0.4333	**0.3202**	0.4759	0.4045	**0.3423**	0.4826
Liquidity	0.9368	0.6684	0.7398	0.9243	0.6820	0.7861	0.8782	0.6058	0.6172	0.8247	0.5837	0.6020
Both	0.5683	0.5590	0.6215	0.5690	0.5616	0.6484	0.5099	0.3764	0.4931	0.4756	0.3894	0.5018
Optimal in group	HAR-RV-SVR-Herd			HAR-RV-J-SVR-Herd			HAR-RV-CJ-SVR-Herd			LHAR-RV-CJ-SVR-Herd		
Optimal of all	HAR-RV-CJ-SVR-Herd											

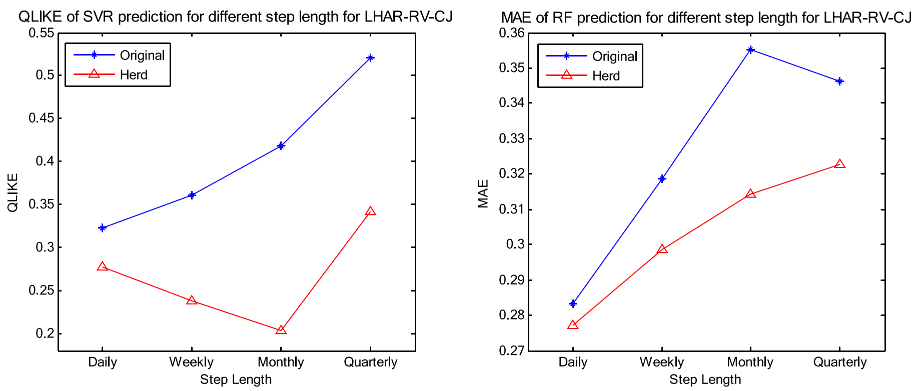

FIGURE 5 QLIKEs of the SVR algorithm (left) and MAEs of the RF algorithm (right) with different step lengths for the case LHAR-RV-CJ.

TABLE 15 Results of MCS test under different loss functions.

		Daily	Weekly	Monthly	Quarterly
MAE	Original	**HAR-RV-CJ-Original**	LHAR-RV-CJ-RF-Original	LHAR-RV-CJ-RF-Original	LHAR-RV-CJ-RF-Original
	Herd	**LHAR-RV-CJ-RF-Herd**	**LHAR-RV-CJ-RF-Herd**	**LHAR-RV-CJ-RF-Herd**	**LHAR-RV-CJ-RF-Herd**
	Liquidity	**HAR-RV-SVR-Liquidity**	LHAR-RV-CJ-RF-Liquidity	LHAR-RV-CJ-RF-Liquidity	LHAR-RV-CJ-RF-Liquidity
	Both	**LHAR-RV-CJ-RF-Both**	**LHAR-RV-CJ-RF-Both**	**LHAR-RV-CJ-RF-Both**	**LHAR-RV-CJ-RF-Both**
RMSE	Original	**LHAR-RV-CJ-RF-Original**	LHAR-RV-CJ-RF-Original	HAR-RV-CJ-RF-Original	HAR-RV-CJ-RF-Original
	Herd	**LHAR-RV-CJ-RF-Herd**	**LHAR-RV-CJ-RF-Herd**	**LHAR-RV-CJ-RF-Herd**	**HAR-RV-CJ-RF-Herd**
	Liquidity	**LHAR-RV-CJ-RF-Liquidity**	LHAR-RV-CJ-RF-Liquidity	LHAR-RV-CJ-RF-Liquidity	HAR-RV-CJ-RF-Liquidity
	Both	**LHAR-RV-CJ-RF-Both**	**LHAR-RV-J-RF-Both**	**LHAR-RV-CJ-RF-Both**	LHAR-RV-CJ-RF-Both
QLIKE	Original	HAR-RV-SVR-Original	HAR-RV-SVR-Original	HAR-RV-SVR-Original	LHAR-RV-CJ-SVR-original
	Herd	**HAR-RV-SVR-Herd**	**HAR-RV-SVR-Herd**	**LHAR-RV-CJ-SVR-Herd**	**HAR-RV-CJ-SVR-Herd**
	Liquidity	LHAR-RV-CJ-SVR-Liquidity	HAR-RV-SVR- Liquidity	HAR-RV-CJ-SVR-Liquidity	LHAR-RV-CJ-SVR-Liquidity
	Both	LHAR-RV-CJ-SVR-Both	HAR-RV-SVR-Both	HAR-RV-CJ-SVR-Both	HAR-RV-CJ-SVR-Both

Note: The four methods in every cell are the ones with the smallest values of loss function among all the prediction methods under four kinds of predictor settings for a certain prediction step length. The methods in bold are the members in the final model confidence set tested by MCS for each loss function and each step length.

in the corresponding Tables 3–14) for each setting of predictors, that is, original predictors in HAR-type models, original ones plus herding, original ones plus liquidity, and original ones plus both herding and liquidity, and then apply the MCS test to the selected methods to find out the model confidence set among those. The significance level of the test is set to 0.05. The selected four methods under each loss function for each prediction step and the selected members (in bold) in the final model confidence set by the MCS test are reported in Table 15. To illustrate, taking the first cell in the table for example, the results show that according to MAE, for the daily volatility prediction, without considering the extra micro-market factors, the best prediction with the original predictors in different kinds of HAR model settings is HAR-RV-CJ-original; the best prediction with the original predictors plus herding is LHAR-RV-CJ-RF-herd; the best prediction with the original predictors plus liquidity is HAR-RV-SVR-Liquidity; the best prediction with the original predictors plus both herding and liquidity is LHAR-RV-CJ-RF-Both. The MCS test suggests that these four methods' prediction ability has no significant difference in the daily volatility. The meanings of other cells are the same as this. Hence, it can be easily seen from the table that according to the RMSE and MAE, the extra micro-market factors make no significant contribution to the daily volatility prediction, whereas with the increase of step length, the herding factor shows a significant power in the weekly, monthly, and quarterly predictions, where the final model confidence set all contains the RF method with herding factor. Moreover, the final members in the model confidence set also show that there is no significant difference in the prediction with herding and with both herding and liquidity factors, which further suggests that the liquidity factor's contribution is not significant. However, for the QLIKE, herding factor plays a significant role in the predictions with all kinds of step lengths. All the MCS test results show that the SVR method with considering herding factor is dominant to other methods. In general, the two algorithms outperform the linear model for longer-term prediction.

Besides, the results in the table also show that the CV, JV, and leverage effect are also helpful to the prediction in most cases. The MCS test results further confirm the conclusions obtained earlier in Tables 3–14.

4 | CONCLUSIONS

In this paper, based on the linear HAR model and its usually used extensions, we aim to study the forecasting power of market herding factor in the forecasting of market volatility. We first extend the four benchmark HAR models by incorporating the additional market herding index and further introduce the nonlinear prediction by using two machine learning algorithms—SVR and RF. All the methods are applied to the Chinese stock market. We compare their in-sample and out-of-sample performance by setting different prediction steps. The MCS method is used to test the prediction abilities of all the methods considered.

The empirical results show that according to the RMSE and MAE, the extra micro-market factors make no significant contribution to the daily volatility prediction, while with the increase of step length, the herding factor shows a significant power in the weekly, monthly, and quarterly prediction. Moreover, the linear model and the two algorithms have no significant difference for the daily volatility forecasting as well, whereas for the longer-term prediction, the RF algorithm outperforms the other two methods. However, for the QLIKE, herding factor always plays a significant role in improving the precision of prediction with all kinds of step lengths and methods. Among those, the SVR algorithm with considering the herding factor is the dominant method. In general, first, the herding factor is helpful to the forecasting of volatility and the extent to which the precision is improved by adding a herding factor takes on an inverted "U" shape with the increase of step length. Second, the two algorithms are superior to the linear model for longer-term prediction, especially combined with herding factor, which suggests that there is a nonlinear relationship between the herding factor and market volatility. In addition, the results also show that the liquidity factor plays no significant role in volatility prediction. However, the CV, JV, and leverage effect are helpful in most cases.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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