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The role of the IDEMV in predicting European stock market volatility during the COVID-19 pandemic

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ABSTRACT

The main purpose of this paper is to investigate whether the Infectious Disease EMV tracker (IDEMV) proposed by Baker et al. (2020) has additional predictive ability for European stock market volatility during the COVID-19 pandemic. The three European stock markets we consider are France, UK and Germany. Our investigation is based on the HAR and its augmented models. We find that the IDEMV has stronger predictive power for the France and UK stock markets volatilities during the global pandemic, and the VIX has also superior predictive ability for the three European stock markets during this period.

1. Introduction

The World Health Organization (WHO) officially announced the outbreak of coronavirus (COVID-19) as a global pandemic on March 11, 2020. Its outstanding characteristics are manifested as unknown etiology, no targeted drugs, and lack of sufficient experience reserves for treatment methods. All countries are responding to this epidemic in groping. It has caused considerable losses to the global economy. Therefore, how to deal with the impact of the epidemic on the global economy is a hot topic that has been concerned recently (see, e.g., Ashraf, 2020; Corbet et al., 2020; Goodell, 2020; Sharif et al., 2020; Wagner, 2020; Zhang et al., 2020a).

The modeling and forecasting of stock market volatility has always been a hotspot and difficulty in academic research (see, e.g., Wei et al., 2010; Wen et al., 2016; Hong and Lee, 2017; Ma et al., 2019; Liang et al., 2020a, 2020b; Zhang et al., 2020b). At the same time, it is very important for risk management and option pricing in practical applications. Baker et al. (2020) design the Infectious Disease EMV tracker to study the US stock market volatility during the global pandemic.[1] In addition, an influential study of Buncic and Gisler (2016) shows that US stock market information has a superior predictive ability for the volatility of international stock markets. Our motivation comes from this. The main purpose of this paper is to explore whether the IDEMV has additional predictive ability for European stock market realized volatility (RV) during the global pandemic. The three European stock indices we consider are the CAC 40 (FCHI), the FTSE 100 (FTSE), the DAX (GDAXI).

We use the HAR model as the baseline model, which is consistent with Buncic and Gisler (2016). In addition to the HAR extension models used by Buncic and Gisler (2016), we also consider two competitive models (i.e., HAR-USRV-IDEMV and HAR-ALL) to examine the predictive ability of IDEMV for the three European stock markets. The out-of-sample results suggest that the IDEMV

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[1] For more detailed introduction, please refer to Baker et al. (2020).

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contains useful information in predicting the RVs of the FCHI and FTSE indices during the global pandemic, while ineffective for German stock market. Furthermore, as supposed to the whole out-of-sample periods, the VIX has stronger predictive ability for the three European stock indices during the COVID-19, implying that the information in the US stock market still has a leading position during this period. Finally, we check the model's predicted performance each month during the global pandemic, and find that the results are robust.

This research is closely related to Buncic and Gisler (2016) and Baker et al. (2020). Our contribution and the biggest difference are as follows. First, we examine the impact of U.S. stock market information on European stock market volatility during the global pandemic (COVID-19). Second, we use the IDEMV to predict the RVs of the European stock markets and observe that the IDEMV has superior predictive power for the FCHI and FTST indices during the global pandemic. Third, the VIX is more predictive for the three European stock indices during the global pandemic. Thus, our study complements the research on European stock market volatility during the global pandemic, and is of some help to market participants and policy makers.

The remainder of the paper is organized as follows. Section 2 provides econometric models and data. We present the out-of-sample assessment results in Section 3. Finally, Section 4 concludes.

2. Methodology and data

2.1. Econometric models

The focus of this study is European stock markets realized volatility predictions. The related theory of the realized variance (volatility) can be found in the original studies of Andersen and Bollerslev (1998) and Andersen et al. (2003). The definition of RV is the summation of the intraday squared returns, which is given by

$$RV_t = \sum_{k=1}^{F} r_{t,k}^2,\ r_{t,k} = \ln(p_{t,k}) - \ln(p_{t,k-1}), \tag{1}$$

where $p_{t,k}$ denotes the kth intraday price, $r_{t,k}$ denotes the kth intraday return, and F is the total number of fixed frequencies during the trading day.

We employ the standard HAR-RV model of Corsi (2009) as our benchmark model, the most important features of the HAR-RV model are that it effectively captures the characteristics of volatility and it is easy to implement and can be estimated with OLS. The HAR-RV model can be written as

$$\mathrm{RV}_{t+1} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \omega_{t+1}, \tag{2}$$

$$RV_{w,t} = \frac{1}{5}(RV_t + RV_{t-1} + \ldots + RV_{t-4}), \tag{3}$$

$$RV_{m,t} = \frac{1}{22}(RV_t + RV_{t-1} + \ldots + RV_{t-21}). \tag{4}$$

where RV_t, $RV_{w,t}$, and $RV_{m,t}$, represent daily, weekly, and monthly RV, respectively.

Following Buncic and Gisler (2016), we add the US stock market information to the baseline model, that is, HAR-USRV-VIX model, which is given by

$$\begin{aligned}\mathrm{RV}_{t+1} &= \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \beta_d^{US} RV_t^{US} + \beta_w^{US} RV_{w,t}^{US}\\ &+ \beta_m^{US} RV_{m,t}^{US} + \beta_d^{VIX} VIX_t + \beta_w^{VIX} VIX_{w,t} + \beta_m^{VIX} VIX_{m,t} + \omega_{t+1},\end{aligned} \tag{5}$$

where RV_t^{US}, $RV_{w,t}^{US}$, and $RV_{m,t}^{US}$ indicate daily, weekly, and monthly US stock RV, respectively. And $VIX_{w,t}$ and $VIX_{m,t}$ represent weekly and monthly VIX.

To investigate the role of the IDEMV, we replace the HAR components of VIX in the HAR-USRV-VIX model with the HAR components of IDEMV. Thus, we obtain HAR-USRV-IDEMV model, which is expressed as

$$\begin{aligned}\mathrm{RV}_{t+1} &= \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \beta_d^{US} RV_t^{US} + \beta_w^{US} RV_{w,t}^{US}\\ &+ \beta_m^{US} RV_{m,t}^{US} + \beta_d^{VIX} IDEMV_t + \beta_w^{VIX} IDEMV_{w,t} + \beta_m^{VIX} IDEMV_{m,t} + \omega_{t+1},\end{aligned} \tag{6}$$

where $IDEMV_{w,t}$ and $IDEMV_{m,t}$ represent weekly and monthly IDEMV. In addition, we consider both VIX and IDEMV, namely, HAR-ALL model, which is written as,

$$\begin{aligned}\mathrm{RV}_{t+1} &= \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \beta_d^{US} RV_t^{US} + \beta_w^{US} RV_{w,t}^{US}\\ &+ \beta_m^{US} RV_{m,t}^{US} + \beta_d^{VIX} VIX_t + \beta_w^{VIX} VIX_{w,t} + \beta_m^{VIX} VIX_{m,t} + \beta_d^{VIX} IDEMV_t\\ &+ \beta_w^{VIX} IDEMV_{w,t} + \beta_m^{VIX} IDEMV_{m,t} + \omega_{t+1}.\end{aligned} \tag{7}$$

2.2. Data

In this study, we employ daily realized variance to measure European stock markets volatilities. We use the 5-minute sampling frequency to compute the RV, because the 5-minute sampling frequency is widely used in volatility-related research and is superior to other sampling frequencies (Gong and Lin, 2017, 2018; Mei et al., 2018). The realized variances of the European stock indices (i.e., FCHI, FTSE, GDAXI) are collected from the Oxford-Man Institute's Realized Library.[2] The data of the IDEMV can be downloaded from: http://www.policyuncertainty.com/infectious_EMV.html. We obtain the daily VIX data from: https://finance.yahoo.com/. The full sample goes from February 2, 2000, to April 15, 2020. We turn all international realized variances into annualised realized volatilities.

3. Empirical results

In this section, we only report the out-of-sample predicted performance, because investors and policy makers are most concerned about the out-of-sample results.[3] We use the rolling window method to generate the out-of-sample predictions, and the rolling window length is 500.

First, to quantitatively evaluate the forecasting accuracy, we employ two robust loss functions of QLIKE and MSE, which are widely used in various volatility prediction studies. The definition of the two loss criteria are

$$QLIKE = \frac{1}{q}\sum_{t=m+1}^{m+q}\left(\ln(\hat{RV}_t) + \frac{RV_t}{\hat{RV}_t}\right), \tag{8}$$

$$MSE = \frac{1}{q}\sum_{t=m+1}^{m+q}(RV_t - \hat{RV}_t)^2, \tag{9}$$

where RV_t is actual RV on trading day t, $\hat{RV}_t$ represents the RV forecasts generated by prediction models, m and q denote the length of in-sample estimation period and out-of-sample evaluation period, respectively. Second, we utilize the Model confidence Set (MCS) test proposed by Hansen et al. (2011) to assess the out-of-sample results and determine whether the prediction models used have statistically significant differences in out-of-sample forecasting performance.[4] A MCS is a subset of models that contains the best model with a given level of confidence. The significance level of MCS we choose is 10%. Evidently, the larger the MCS p-value, the better the prediction ability of the corresponding model. In addition to the MCS test, we also employ out-of-sample R^2 (R^2_{OOS}) to assess prediction quality, which is defined as

$$R^2_{OOS} = 1 - \frac{\sum_{k=1}^{q}(RV_{m+k} - \hat{RV}_{m+k})^2}{\sum_{k=1}^{q}(RV_{m+k} - \hat{RV}_{m+k,bench})^2}, \tag{10}$$

where RV_{m+k}, $\hat{RV}_{m+k}$ and $\hat{RV}_{m+k,bench}$ are, respectively, the actual RV, forecast RV, and benchmark RV on day $m + k$, and m and q represent the lengths of the initial in-sample period and out-of-sample period, respectively. Obviously, if the value of R^2_{OOS} is greater than 0, the forecast from the model of interest is better than the benchmark model.

Table 1 reports the out-of-sample forecasting quality during whole out-of-sample periods and global pandemic. From the Panel A of Table 1, we find that during whole out-of-sample periods, the HAR-USRV-VIX model can generate the largest MCS p-values of 1 under QLIKE and MSE and produce the significantly positive R^2_{OOS} value of 12.289%. However, during the global pandemic (COVID-19), we observe that the HAR-USRV-VIX model can successfully enter the MCS under two loss criteria and produce a significantly positive R^2_{OOS} value of 25.714%, the HAR-USRV-IDEMV model has a significantly positive R^2_{OOS} value of 3.466%, and the HAR-ALL model can pass the MCS test under MSE and produce the largest R^2_{OOS} value of 35.312%. These evidences show that the IDEMV has a certain predictive ability and the HAR-ALL model has the best predictive power during the global pandemic. In term of the FTSE, we find that the HAR-USRV-VIX model is still the best prediction models during whole out-of-sample periods, however, during the COVID-19 pandemic, the HAR-USRV-IDEMV model can survive in the MCS and yield a significantly positive R^2_{OOS} value of 14.414%, and the HAR-ALL model has the largest MCS p-values and the largest positive R^2_{OOS} value, indicating that the IDEMV contains useful information for the FTSE during the COVID-19 pandemic. For the GDAXI, we can see that the HAR-USRV-VIX model yields the best prediction during whole out-of-sample periods and global pandemic, but the predictive power is stronger during the COVID-19 pandemic.

Table 2 shows the predicted performance for the FCHI in January, February and March 2020. Obviously, the HAR-USRV-IDEMV model can produce significantly positive R^2_{OOS} values in January, February and March 2020, which are 10.600%, 48.987%, and 38.681%. In addition, we find that the HAR-ALL model has the best predictive ability during COVID-19 pandemic. Especially in March 2020, the HAR-ALL model can significantly beat other competing models. Table 3 presents the predicted performance for the FTSE in January, February and March 2020. It is evident that during the COVID-19 the IDEMV contains useful information and the HAR-ALL model has the best predictive ability. From the results of Table 4, we observe that the HAR-USRV-IDEMV model can pass

[2] It must be emphasized that RV calculated using high frequency data does not include overnight information.

[3] The in-sample estimation results are available upon request.

[4] For more detailed introduction about MCS technology, please refer to Hansen et al. (2011).

Table 1
Out-of-sample forecasting performance during whole out-of-sample periods and global pandemic.

	During whole out-of-sample periods				During the global pandemic (COVID-19)			
	QLIKE	MSE	R^2_{OOS} (%)	MSFE-adjusted	QLIKE	MSE	R^2_{OOS} (%)	MSFE-adjusted
Panel A: FCHI								
HAR-RV	0.001	0.001			**0.168**	**0.120**		
HAR-USRV-VIX	**1.000**	**1.000**	12.289 ***	8.841	**1.000**	**0.586**	25.714 ***	2.310
HAR-USRV-IDEMV	0.001	0.001	−4.183 ***	4.500	**0.116**	0.004	3.466 ***	2.450
HAR-ALL	0.001	0.106	7.947 ***	8.083	**0.168**	**1.000**	35.312 ***	2.847
Panel B: FTSE								
HAR-RV	0.000	0.036			0.077	**0.114**		
HAR-USRV-VIX	**1.000**	**1.000**	9.227 ***	7.484	**0.451**	**0.132**	11.563 **	2.191
HAR-USRV-IDEMV	0.006	0.036	−0.536 ***	6.201	**0.735**	**0.289**	14.414 ***	2.650
HAR-ALL	0.000	0.036	5.232 ***	8.437	**1.000**	**1.000**	16.466 ***	2.680
Panel C: GDAXI								
HAR-RV	0.001	0.011			0.057	0.062		
HAR-USRV-VIX	**1.000**	**1.000**	8.000 ***	9.205	**1.000**	**1.000**	39.006 ***	2.574
HAR-USRV-IDEMV	0.001	0.011	−12.090	0.951	0.057	0.062	−230.372	−2.460
HAR-ALL	0.001	0.011	−8.392 ***	5.228	0.057	0.062	−253.900	−2.357

Notes: The significance level of MCS we choose is 10%. *, **, and *** indicate significant at the 10%, 5%, and 1% levels, respectively. The following table is also consistent.

Table 2
Predicted performance for the FCHI in January, February and March 2020.

	QLIKE	MSE	R^2_{OOS} (%)	MSFE-adjusted
Panel A: January 2020				
HAR-RV	**0.798**	**0.509**		
HAR-USRV-VIX	**0.954**	**0.873**	11.999 **	1.870
HAR-USRV-IDEMV	**0.954**	**0.873**	10.600 *	1.614
HAR-ALL	**1.000**	**1.000**	15.082 **	2.143
Panel B: February 2020				
HAR-RV	**0.174**	**0.237**		
HAR-USRV-VIX	**0.924**	**0.308**	52.841 **	1.773
HAR-USRV-IDEMV	**0.572**	**0.265**	48.987 *	1.615
HAR-ALL	**1.000**	**1.000**	65.990 **	1.702
Panel C: March 2020				
HAR-RV	0.004	0.009		
HAR-USRV-VIX	0.004	0.009	28.273 **	2.169
HAR-USRV-IDEMV	0.004	0.009	38.681 ***	2.943
HAR-ALL	**1.000**	**1.000**	57.880 ***	3.094

Table 3
Predicted performance for the FTSE in January, February and March 2020.

	QLIKE	MSE	R^2_{OOS} (%)	MSFE-adjusted
Panel A: January 2020				
HAR-RV	**0.174**	**0.237**		
HAR-USRV-VIX	**0.924**	**0.308**	52.841 **	1.773
HAR-USRV-IDEMV	**0.572**	**0.265**	48.987 *	1.615
HAR-ALL	**1.000**	**1.000**	65.990 **	1.702
Panel B: February 2020				
HAR-RV	**0.163**	**0.292**		
HAR-USRV-VIX	**0.804**	**0.556**	30.145 *	1.629
HAR-USRV-IDEMV	**0.804**	**0.556**	28.802 **	1.750
HAR-ALL	**1.000**	**1.000**	31.694 **	1.659
Panel C: March 2020				
HAR-RV	0.084	0.030		
HAR-USRV-VIX	0.084	0.030	11.130 **	1.749
HAR-USRV-IDEMV	**0.473**	**0.347**	14.690 ***	2.362
HAR-ALL	**1.000**	**1.000**	16.769 ***	2.318

Table 4
Predicted performance for the GDAXI in January, February and March 2020.

	QLIKE	MSE	R^2_{OOS} (%)	MSFE-adjusted
Panel A: January 2020				
HAR-RV	**0.634**	**0.501**		
HAR-USRV-VIX	**1.000**	**1.000**	15.513 **	1.958
HAR-USRV-IDEMV	**0.830**	**0.776**	7.319 *	1.369
HAR-ALL	**0.830**	**0.809**	11.949 *	1.585
Panel B: February 2020				
HAR-RV	0.079	**0.101**		
HAR-USRV-VIX	**1.000**	**1.000**	47.289 **	1.663
HAR-USRV-IDEMV	0.069	0.096	−102.627	−1.900
HAR-ALL	0.047	0.096	−76.341	−1.763
Panel C: March 2020				
HAR-RV	0.026	0.022		
HAR-USRV-VIX	**1.000**	**1.000**	37.420 **	2.297
HAR-USRV-IDEMV	0.026	0.001	−274.850	−2.702
HAR-ALL	0.005	0.000	−313.536	−2.693

the MCS test and produce a significantly positive R^2_{OOS} value of 7.319% only in January 2020, however, the HAR-USRV-VIX model is always the best prediction model. Thus, our results are robust.

Furthermore, we also calculate the cumulative difference between the squared forecast errors of the two prediction models in the out-of-sample period as a robustness check. This cumulative difference (named CumSFE) is a tool commonly used in prediction study to highlight the predictive performance over time of the two prediction models. The CumSFE can be expressed as

$$\text{CumSFE}=\sum_{t=m+1}^{m+q}\left((\hat{RV}_t^{Model}-RV_t)^2-\left(\hat{RV}_t^{bench}-RV_t\right)^2\right). \tag{11}$$

Obviously, if the value of CumSFE is less than 0, implying that the benchmark model performs poor predictive ability. Figs. 1–3 show the CumSFE for the FCHI, FTSE, and GDAXI, respectively. We find the CumSFE values are negative for the FCHI and FTSE indices. However, for the GDAXI, we observe that the CumSFE value is negative only between HAR-USRV-VIX and HAR-RV. Therefore, our results are robust to the CumSFE.

4. Conclusion

In this paper, we investigate whether the IDEMV has additional predictive ability for European stock market volatility during the COVID-19 pandemic. The three European stock markets we consider are France, UK and Germany. Our investigation is based on the HAR and its augmented models. According to the results of the MCS and R^2_{OOS} tests, we find that the IDEMV has stronger predictive power for the France and UK stock markets volatilities during the COVID-19 pandemic, and the VIX has also superior predictive ability for the three European stock markets during this period.

Therefore, this study complements the research on European stock market volatility during the global pandemic, and is of some help to market participants and policy makers in risk management and portfolios. The limitations of this study are as follows. This study only focuses on the three important indices of European stock markets, and does not explore IDEMV's ability to predict volatilities in other international stock markets. Moreover, limited data during the COVID pandemic may lead to certain inaccurate results. These limitations provide a good direction for further research.

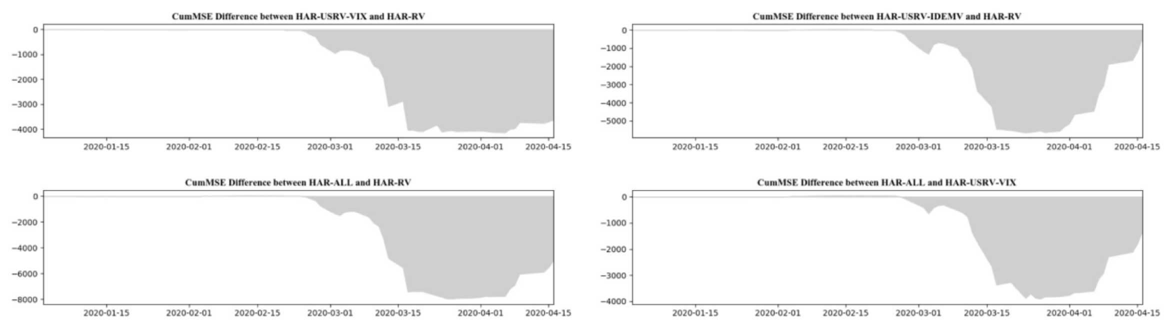

Fig. 1. The CumSFE for the FCHI.

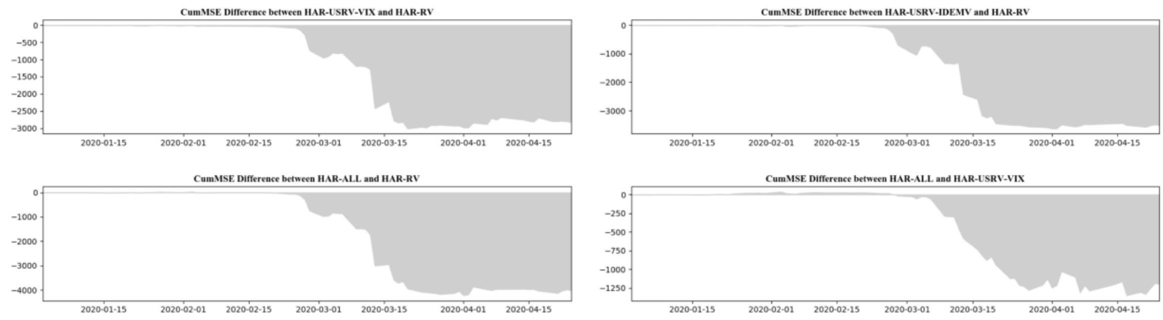

Fig. 2. The CumSFE for the FTSE.

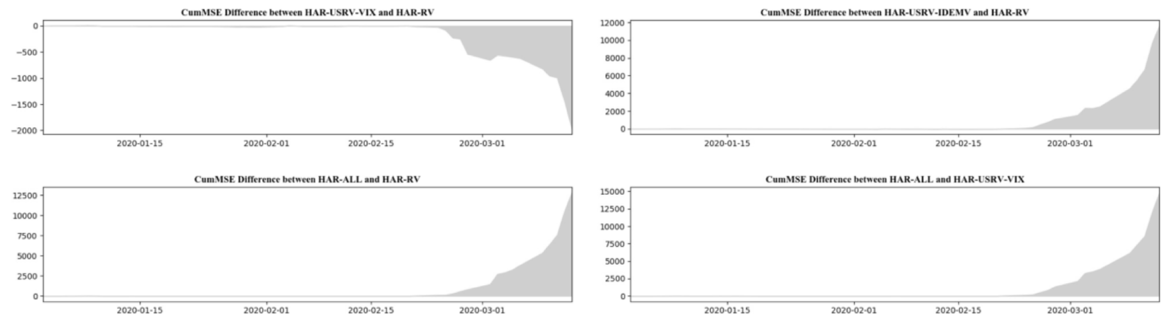

Fig. 3. The CumSFE for the GDAXI.

Declaration of Competing Interest

We declare that there is not conflict of interest.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2020.101749.

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