International Review of Financial Analysis 72 (2020) 101596

Contents lists available at ScienceDirect

International Review of Financial Analysis

journal homepage: www.elsevier.com/locate/irfa

Which popular predictor is more useful to forecast international stock markets during the coronavirus pandemic: VIX vs EPU?

Jiqian Wang [a], Xinjie Lu [a], Feng He [b,*], Feng Ma [a,*]

[a] School of Economics and Management, Southwest Jiaotong University, Chengdu, China
[b] School of finance, Tianjin University of Finance and Economics, Tianjin, China

ARTICLE INFO

Keywords:
COVID-19
International stock market
VIX
EPU
HAR framework

ABSTRACT

This study mainly investigates which predictors (VIX or EPU index) are useful to forecast future volatility for 19 equity indices based on HAR framework during coronavirus pandemic. Out-of-sample analysis shows that the HAR-RV-VIX model exhibits superior forecasting performance for 12 stock markets, while EPU index just can improve forecast accuracy for 5 equity indices, implying that VIX index is more useful for most stock markets' future volatility during coronavirus crisis. The results are robust in recursive window method, alternative realized measures and sub-sample analysis; moreover, VIX index still contains the strongest predictive ability by considering kitchen sink model and mean combination forecast. Furthermore, we further discuss the predictive effect of VIX and EPU index before the coronavirus crisis. Our article provides policy makers, researchers and investors with new insights into exploiting the predictive ability of VIX and EPU index for international stock markets during coronavirus pandemic.

1. Introduction

After the declaration of the World Health Organization that the coronavirus outbreaks a pandemic, the US stock market plummeted on March 11, 2020. More specifically, the S&P 500 decreased by 4.9% and Nasdaq decreased by 4.7% and till March 11, the Dow plunged nearly 3000 points, get its biggest drop since 1987.[1] Subsequently, several researchers pay their attention to COVID-19 pandemic's effect on the stock market (Baker et al., 2020; Gormsen & Koijen, 2020; Onali, 2020; Yilmazkuday, 2020). For example, Baker et al. (2020) argue COVID-19 pandemic leads to the unprecedented shock on US stock market compared with other infectious diseases (SARS, Ebola, Bird Flu and Swine Flu epidemics).

Closely related to risk prevention of extreme risk, tail risk, spillover etc., accurate volatility prediction can provide valuable information for market investors, policy makers, economic activities (Bollerslev, Hood, Huss, & Pedersen, 2018; Ma, Liao, Zhang, & Cao, 2019). Although it is difficult to improve forecasting accuracy, increasing studies document that popular uncertainty indexes, EPU and VIX, contain useful information for forecasting stock market volatility (Balcilar, Gupta, Kim, & Kyei, 2019; Bekaert & Hoerova, 2014; Brogaard & Detzel, 2015; Liu & Zhang, 2015). Specifically, Liang, Wei, and Zhang (2020) investigate the VIX's forecasting ability for eight international stock markets, the results indicate VIX index exhibits powerful predictive ability. Moreover, Liu and Zhang (2015) point out the EPU index is useful for forecasting S&P 500 volatility. Motivated these researches, our study verifies which popular uncertainty predictor (VIX or EPU index) is more powerful for forecasting international stock market volatility under this extreme fluctuation condition.

In our study, we employ the superior volatility measures to forecasts realized volatility (RV), which has been recorded in the numerous literature (Fang, Wang, Liu, & Song, 2018; Liu, Ma, & Zhang, 2019; Liu & Zhang, 2015; Ma, Wei, Liu, & Huang, 2018; Peng, Chen, Mei, & Diao, 2018; Pu, Chen, & Ma, 2016; Wang, Wei, Wu, & Yin, 2018; Wei, Wang, & Huang, 2010; Wen, Gong, & Cai, 2016; Wen, Zhao, Zhang, & Hu, 2019). Subsequently, we utilize the heterogeneous autoregressive (HAR) model of Corsi (2009), which has become the workhorse of forecasting models for stock volatility due to its simple linear regression techniques and consistently superior forecasting performance (Buncic & Gisler, 2016; Cubadda, Guardabascio, & Hecq, 2017; Liang et al., 2020; Liu et al., 2019; Ma et al., 2018; Pu et al., 2016; Qiu, Zhang, Xie, & Zhao, 2019; Wang, Ma, Wei, & Wu, 2016; Wen et al., 2016; Wen et al., 2019).

* Corresponding authors.
E-mail addresses: feng_ac@163.com (F. He), mafeng2016@swjtu.edu.cn (F. Ma).

[1] https://www.bbc.com/news/business-51903195

https://doi.org/10.1016/j.irfa.2020.101596
Received 11 May 2020; Received in revised form 2 July 2020; Accepted 21 July 2020
Available online 28 September 2020
1057-5219/

More specifically, Aganin (2017) compare the GARCH, ARFIMA and HAR-RV models and the results show that HAR-RV model has superior performance than GARCH and ARFIMA models; moreover, Vortelinos (2017) compares the forecasting performance of nonlinear models (Principal Components Combining, neural networks and GARCH) and HAR-RV model, the result indicate the simple HAR model is the most accurate for seven US financial markets (spot equity, spot foreign exchange rates, exchange traded funds, equity index futures, US Treasury bonds futures, energy futures, and commodities options). Furthermore, Buncic and Gisler (2017) employ the HAR-RV-type models to investigate the role of jump and leverage effect in forecasting international stock market volatility; moreover, from global international market perspective, Zhang, Ma, and Liao (2020) focus on cross-national volatility flows and also employ the HAR-RV-type models. Given the success of the HAR-RV-type models, we follow abovementioned studies and set HAR-RV model as our benchmark.

Three different sets of data including realized measures of international stock market, VIX and EPU index are employed to investigate forecasting ability of these two predictors during the coronavirus pandemic. First, following Patton and Ramadorai (2013), Buncic and Gisler (2017) and Liang et al. (2020) and among others, we utilize realized measures data from the Oxford-Man Institute's Quantitative Finance Realized Library (Realized Library),[2] that contains 19 equity indices including AEX (The Netherlands), All Ordinaries (Australia), BOVESPA (Brazil), CAC 40 (France), FTSE MIB (Italy), FTSE 100 (United Kingdom), DAX 30 (Germany), S&P TSX (Canada), Hang Seng (China Hong Kong), IBEX 35 (Spain), KOSPI (South Korea), IPC Mexico (Mexico), Nikkei 225 (Japan), S&P CNX Nifty (India), S&P 500 (United States), SSEC (China), Swiss Market Index (Switzerland), FT Straits Times (Singapore) and Euro STOXX 50 (Euro Area). Second, the VIX is an implied volatility index proposed by Chicago Board of Options Exchange and can be available from CBOE website.[3] Third, we apply US daily news-based economic policy uncertainty index (EPU) as another predictor, which can be found from the EPU website[4] and derived from thousands of newspapers and other news globally.

Our empirical design is as follows. First, we fit HAR-RV, HAR-RV-VIX and HAR-RV-EPU model to investigate the effect of VIX and EPU index for 19 considered stock markets via in-sample analysis. Second, the rolling window method is employed to forecast RV during the coronavirus crisis, and three popular evaluation approaches, Model Confidence Set (MCS), Diebold-Mariano (DM) and out-of-sample R^2 test are applied to assess out-of-sample predictive quality. Third, we apply plenty of robustness checks to reconfirm the results, including recursive window method, alternative realized measures, and sub-sample analysis. Finally, we further discuss the performance of VIX and EPU by considering other forecasting models (kitchen sink model and forecast combinations) and the periods before the coronavirus crisis.

Several remarkable findings are observed. First, via in-sample results, we find that the increase of R^2 values of HAR-RV-VIX model are larger than HAR-RV-EPU model, implying that the VIX index exhibits better interpretive ability for almost stock markets (except SSEC) than EPU. Second, we empirically find that for most international stock markets (12 equity indices in our study), VIX is more helpful to predict the stock market volatility as COVID-19 becomes a pandemic internationally. These equity indies are AEX, BOVESPA, CAC40, FTSE MIB, DAX 30, S&P TSX, IBEX 35, NIKKEI 225, S&P 500, Swiss Market Index, FT Straits Times and EUROXX 50. While for 5 international stock markets (All Ordinaries, FTSE 100, IPC Mexico, SSEC and Hang Seng), EPU can improve forecasting accuracy, especially China. However, what's interesting is that EPU and VIX are both not useful for KOSPI and S&P CNX Nifty. Third, we reconfirm our conclusions are robust by performing plenty of robustness checks including recursive window method, alternative realized measures and sub-sample analysis. Finally, we further discuss the forecasting ability of VIX and EPU index by considering the kitchen sink model and forecast combinations, the results indicate that VIX still contains more useful content for future volatility. Furthermore, considering the periods before the coronavirus crisis, we get similar conclusion that VIX index is the most predictive for most of the stock markets.

Our article contributes to the existing literature from following aspects. First, to our best of knowledge, this is the first paper that identifies either EPU or VIX is more helpful to predict stock market volatility during coronavirus crisis. Second, we find that existing literatures mostly study EPU's or VIX's individual effects on a single stock market, if any, almost be G7 stock market, and rare literature focus on the multiple stock markets. Thus, we expand the existing researches to focus on up to 19 international stock markets. Our article tries to provide policy makers, researchers and investors with new valuable information to exploit the predictive ability of VIX and EPU index for international stock markets during coronavirus pandemic.

The remainder of the paper is structured as follows. Section 2 shows the realized variance, forecasting models and forecast evaluation approaches. Section 3 describes the descriptive information of data. The main results of in-sample, out-of-sample estimation analysis and robustness checks are in Section 4. Further analysis is provided in Section 5. Section 6 concludes.

2. Methodology

Following Andersen and Bollerslev (1998), we sum the squared intraday high-frequency returns to construct the RV, for a specific trading day t, which is written as:

$$RV_t = \sum_{j=1}^{M} r_{t,j}^2, \tag{1}$$

where $M = 1/\Delta$ and Δ is the sampling rate, $r_{t,j}$ represents the j^{th} intraday returns of day t. Subsequently, when $\Delta \to 0$, RV can be expressed as:

$$RV_t \to \int_0^t \sigma^2(s)ds + \sum_{0<s\leq t} k^2(s), \tag{2}$$

where $\int_0^t \sigma^2(s)ds$ is the integrated variance (IV) and $\sum_{0<s\leq t} k^2(s)$ indicates the discontinuous parts of jump in the quadratic variation process. According to Barndorff-Nielsen and Shepherd (2004), IV can be calculated by bi-power variation (BPV) as follow:

$$BPV_t = \mu_1^{-2} \sum_{j=2}^{1/\Delta} |r_{t,j}||r_{t,j-1}|, \tag{3}$$

where $\mu_1 = \sqrt{2/\pi} \approx 0.7979$.

2.1. Forecasting models

In our study, we set the popular HAR-RV model as our benchmark model, which incorporates daily, weekly and monthly realized variance components and is written as:

Model 1: HAR-RV.

$$RV_{t+1} = \beta_0 + \beta_d RV_t + \beta_w RVW_t + \beta_m RVM_t + \varepsilon_{t+1}, \tag{4}$$

where RV_t, RVW_t and RVM_t represent daily, weekly and monthly RV, respectively. Moreover, $RVW_t = \frac{1}{5}\sum_{i=1}^{5} RV_i$, $RVM_t = \frac{1}{22}\sum_{i=1}^{22} RV_i$ and ε_{t+1} is the disturbance term.

Subsequently, we add the VIX and EPU information on trading day t to construct the HAR-RV-VIX and HAR-RV-EPU model for each stock market. These two HAR specifications are:

[2] https://realized.oxford-man.ox.ac.uk/.

[3] http://www.cboe.com/vix.

[4] http://www.policyuncertainty.com/us_monthly.html.

Model 2: HAR-RV-VIX.

$$RV_{t+1} = \beta_0 + \beta_d RV_t + \beta_w RVW_t + \beta_m RVM_t + \beta_{VIX} VIX_t + \varepsilon_{t+1}, \tag{5}$$

Model 3: HAR-RV-EPU.

$$RV_{t+1} = \beta_0 + \beta_d RV_t + \beta_w RVW_t + \beta_m RVM_t + \beta_{EPU} EPU_t + \varepsilon_{t+1}, \tag{6}$$

2.2. Forecast evaluation approaches

2.2.1. Model confidence set test

The model confidence set (MCS) test of Hansen, Lunde, and Nason (2011) is popularly applied to evaluate the out-of-sample predictive accuracy (Kim & Won, 2018; Liang et al., 2020; Liu et al., 2019; Ma et al., 2018; Ma, Liao, et al., 2019; Pu et al., 2016; Wei et al., 2010; Wen et al., 2016; Wen et al., 2019). Following Ma, Zhang, Wahab, and Lai (2019) and Mei, Ma, Liao, and Wang (2020), we consider confidence level α at 0.25 to ascertain the best model set, moreover, stationary bootstrap approach[5] is used to evaluate the interpretation of the MCS tests' *p*-value. In other words, it implies that the predictive models have a better out-of-sample prediction performance when their MCS *p*-values are over 0.25. Additionally, the QLIKE and MSE loss functions are popularly employed to evaluate predictive performance (Bekierman & Manner, 2018) and have been proven they are robust in forecasting volatility present noise (Patton, 2011). These two evaluation criteria can be evaluated as follow:

$$QLIKE = L^{-1} \sum_{a=1}^{L} \left(ln\left(\widehat{RV_f}\right) + \left(\frac{RV_a}{\widehat{RV_f}}\right) \right), \tag{7}$$

$$MSE = L^{-1} \sum_{a=H+1}^{L} \left(RV_a - \widehat{RV_f}\right)^2, \tag{8}$$

where $\widehat{RV_f}$ indicates forecasts from forecasting models, while RV_a represents actual volatility and L is the length of out-of-sample evaluation period.

2.2.2. Diebold-Mariano (DM) test

In addition to the MCS test, we introduce another popular forecast evaluation approach, DM test, which is widely used and recommended by many prediction literature (Gong & Lin, 2018; Liang et al., 2020). DM statistics can assess paired difference of forecasting models; therefore, we perform this test to investigate the different forecasting ability among HAR-RV-VIX, HAR-RV-EPU model and our benchmark HAR-RV model for every equity index. DM statistic is calculated as:

$$DM\ statistic = \frac{\overline{d}}{\sqrt{Var(d)}}, \tag{9}$$

where $\overline{d} = \frac{1}{q}\sum_{t=m+1}^{m+q} d_t$, d_t denotes the differential of QLIKE and MSE loss functions, $Var(d)$ is the variance of d_t. The positive (negative) DM statistic denote forecasting model outperforms (underperforms) the benchmark.

2.2.3. Out-of-sample R^2 test

The last method is out-of-sample R^2 test, using this method, we can assess the significance of differences across different models. The R^2_{OOS} measure is defined as:

$$R^2_{oos} = 1 - \frac{\sum_{j=1}^{N}\left(\mathrm{RV}_a - RV^2_{j,n}\right)^2}{\sum_{t=1}^{N}\left(\mathrm{RV}_a - RV^2_{0,n}\right)^2}, \tag{10}$$

[5] Regarding evaluating the MCS *p*-value, more technical details can be found in Hansen et al. (2011).

Table 1
Descriptive statistics of RVs, VIX and EPU.

Equity index	Full sample period	Observations	Mean	Std.dev	Skewness	Kurtosis	Jarque-Bera	Q (5)	Q (22)	ADF
AEX	2000.01.03–2020.03.25	5021	14.533	9.278	2.833	13.214	43,160.086***	15,167.968***	42,711.916***	−20.319***
All Ordinaries	2000.01.04–2020.03.25	4975	9.467	6.237	4.774	45	437,784.291***	9750.320***	23,326.555***	−28.947***
BOVESPA	2000.01.03–2020.03.25	4853	17.615	9.386	3.536	20.811	97,492.028***	11,212.170***	28,920.837***	−25.457***
CAC 40	2000.01.03–2020.03.25	5022	15.923	9.416	2.821	14.929	53,192.352***	14,321.986***	39,733.458***	−21.725***
FTSE MIB	2009.06.01–2020.03.25	2675	15.441	8.061	2.48	10.611	15,237.077***	5856.741***	13,451.371***	−18.963***
FTSE 100	2000.01.04–2020.03.25	4998	14.54	9.668	3.98	31.008	212,567.376***	11,358.662***	30,920.674***	−27.692***
DAX 30	2000.01.03–2020.03.25	4998	17.284	10.817	2.513	10.59	28,559.141***	14,786.448***	45,115.045***	−21.299***
S&P TSX	2002.05.02–2020.03.25	4392	11.133	9.835	7.551	132.846	3,263,897.818***	9798.737***	28,416.573***	−25.895***
Hang Seng	2000.01.03–2020.03.25	4829	13.802	7.445	3.254	19.97	88,578.101***	11,761.502***	36,277.178***	−26.118***
IBEX 35	2000.01.03–2020.02.18	4913	16.686	8.683	2.287	12.297	35,167.053***	12,200.090***	34,978.568***	−24.449***
KOSPI	2000.01.04–2020.03.25	4822	14.765	9.275	2.585	12.453	36,452.147***	15,144.979***	46,312.570***	−19.535***
IPC Mexico	2000.01.03–2020.03.25	4938	12.415	7.53	3.627	24.751	136,595.431***	7224.201***	19,919.771***	−34.916***
Nikkei 225	2000.02.02–2020.03.25	4754	14.136	7.857	2.928	16.627	61,429.879***	10,157.403***	26,958.002***	−25.730***
S&P CNX Nifty	2000.01.03–2020.03.25	4841	14.802	10.444	5.176	59.87	743,071.160***	9686.267***	25,581.028***	−28.050***
S&P 500	2000.01.03–2020.03.25	5063	13.344	9.466	3.215	18.82	83,275.708***	13,856.935***	40,767.137***	−22.617***
SSEC	2000.01.04–2020.03.25	4719	17.236	10.841	2.232	7.899	16,154.436***	11,499.605***	33,251.069***	−24.043***
Swiss Market Index	2000.01.04–2020.03.25	4941	12.542	8.065	4.083	28.374	179,122.411***	14,218.668***	36,899.484***	−21.217***
FT Straits Times	2015.09.21–2020.03.25	1102	8.741	3.616	5.331	45.436	99,118.318***	2042.441***	3042.315***	−12.599***
Euro STOXX 50	2000.01.03–2020.03.25	5026	16.986	10.757	3.234	20.326	95,094.324***	12,777.774***	34,578.186***	−24.629***
VIX	2000.01.03–2020.03.25	5089	19.6	8.79	2.315	8.368	19,357.983***	22,766.131***	74,766.205***	−6.410***
EPU	2000.01.01–2020.03.26	7392	104.244	70.102	2.156	8.703	29,015.913***	10,782.693***	29,958.905***	−40.840***

Notes: This table reports the descriptive statistics of RVs, VIX and EPU. Columns one to three show equity index, full sample period and observations, columns 4–11 display the descriptive statistics including mean, standard deviation (Std.dev), skewness, kurtosis, Jarque-Bera test (Jarque-Bera), Ljung-Box test (Q (5), Q (22)) and Augmented Dickey-Fuller test (ADF). The name of each equity index is used to indicate the RV respectively. Asterisk ***, ** and * denote rejections of null hypothesis at 1%, 5% and 10% level.

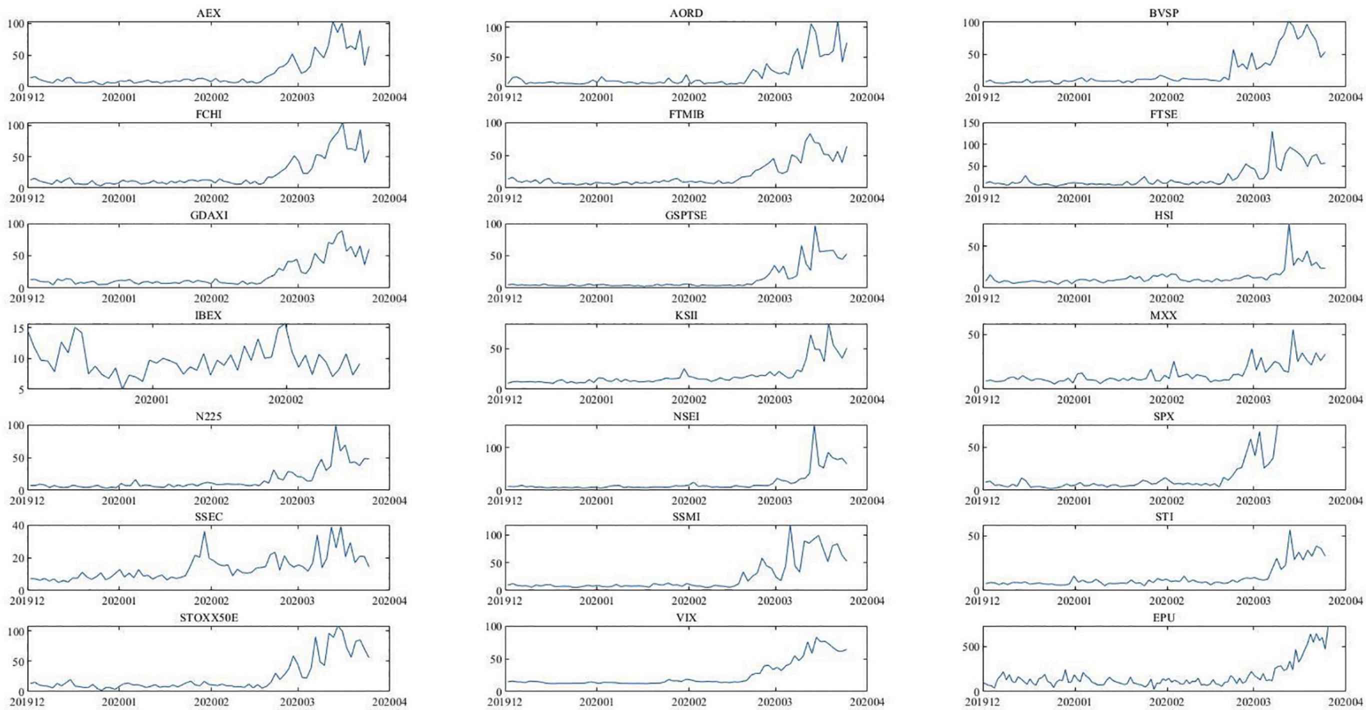

Fig. 1. RVs, VIX and EPU.

where $RV^2_{0,\ n}$ and $RV^2_{j,\ n}$ represent the volatility obtained from the benchmark model and model j, respectively. Furthermore, we introduce the MSPE-adjusted statistic, following Clark and West (2007), to identify whether the extended models and benchmark model can exhibit heterogeneous performance in forecasting stock future RV. A positive (negative) R^2_{OOS} indicates the forecasts from extended models have lower (larger) MSPE than the benchmark model, implying competing models outperform(underperform) the benchmark model.

3. Data

The study purposely explores the forecasting ability of VIX and EPU index during the coronavirus pandemic period in global stock market. Therefore, we use three different sets of data including RV of each equity index, VIX and EPU index.

First, we apply daily RV available from the Realized Library. In our study, we select 19 equity indices including AEX (The Netherlands), All Ordinaries (Australia), BOVESPA (Brazil), CAC 40 (France), FTSE MIB (Italy), FTSE 100 (United Kingdom), DAX 30 (Germany), S&P TSX (Canada), Hang Seng (China Hong Kong), IBEX 35 (Spain), KOSPI (South Korea), IPC Mexico (Mexico), Nikkei 225 (Japan), S&P CNX Nifty (India), S&P 500 (United States), SSEC (China), Swiss Market Index (Switzerland), FT Straits Times (Singapore) and Euro STOXX 50 (Euro Area). All the realized measures of each equity index that we utilize are evaluated by sum the squared 5-min high-frequency price returns. Note that, 5-min sampling data as a rule of thumb can offer a balance between market microstructure noise and predictive improvement (Liu, Patton, & Sheppard, 2015). The whole sample of each equity index are shown in Table 1, and we transform all variance measures to annualized volatilities.

Second, the VIX is an implied volatility index proposed by CBOE and is computed from put and call options of S&P 500 index, holding maturities of nearly 22 trading days. In our study, we collect the VIX data from CBOE website.

Third, as the proxy of uncertainty, we apply the US daily news index to investigate whether the EPU contains useful forecasting information during coronavirus pandemic, which is derived from archives of thousands of newspapers and other news source globally. The EPU index is available from the EPU website and more information can be included in Baker et al. (2016). Subsequently, we clean the VIX and EPU data by matching the same trading day from each equity index.

Table 1 reports the descriptive features for each stock market RVs, VIX and EPU index.[6] We observe that all the realized measures of each equity index, VIX and EPU index show significantly right-skewed and leptokurtic. The Jarque-Bera statistic test demonstrates all the variables do not have normally distribution at the 1% significance level, while they have auto-correlations at the 1% significance level from Ljung-Box test. Finally, we employ ADF test to examine the exist of a unit root, the results indicate all the measures are stationary. Fig. 1 illustrates the graphical representations of each equity index, VIX and EPU index during evaluation period. It can be observed that RV of each equity index, VIX and EPU increase sharply when coronavirus crisis breaks out.

4. Empirical results

4.1. In-sample estimation results

We fit three regression models for 19 considered stock markets to estimate the coefficient and investigate the effect of VIX and EPU index via in-sample analysis over the whole period. Tables 2-4 report the estimation result, obviously, we have several remarkable findings that are interesting to highlight here.

First, from the estimated results of HAR-RV shown in Table 2, the coefficient estimates of different RV lags (β_d, β_w and β_m) for 19 stock markets are significantly positive at the 1% level, implying that RV exhibits high persistence. The adjusted R^2 values are between 0.426 for the FT Straits Times (Singapore) and 0.798 for KOSPI (South Korea), with an average value of 0.671, suggesting our benchmark model has the better interpretive ability.

Second, the HAR-RV-VIX model's results of each equity index shown

[6] RVs represent the time series of RV for each equity index, and the name of each equity index is used to indicate the RV.

Table 2
HAR-RV model parameter estimates.

Index	Observations	β_0	β_d	β_w	β_m	Adjusted R^2
AEX	5021	0.103	0.453	0.374	0.127	0.756
The Netherlands		[0.000]	[0.000]	[0.000]	[0.000]	
All Ordinaries	4975	0.145	0.250	0.422	0.247	0.557
Australia		[0.000]	[0.000]	[0.000]	[0.000]	
BOVESPA	4853	0.229	0.443	0.312	0.158	0.593
Brazil		[0.000]	[0.000]	[0.000]	[0.000]	
CAC 40	5022	0.108	0.437	0.371	0.146	0.741
France		[0.000]	[0.000]	[0.000]	[0.000]	
FTSE MIB	2675	0.189	0.448	0.329	0.145	0.626
Italy		[0.000]	[0.000]	[0.000]	[0.000]	
FTSE 100	4998	0.134	0.353	0.390	0.196	0.662
United Kingdom		[0.000]	[0.000]	[0.000]	[0.000]	
DAX 30	4998	0.099	0.419	0.372	0.167	0.750
Germany		[0.000]	[0.000]	[0.000]	[0.000]	
S&P TSX	4392	0.106	0.352	0.347	0.244	0.683
Canada		[0.000]	[0.000]	[0.000]	[0.000]	
Hang Seng	4829	0.114	0.301	0.368	0.280	0.663
China Hong Kong		[0.000]	[0.000]	[0.000]	[0.000]	
IBEX 35	4913	0.112	0.448	0.335	0.171	0.742
Spain		[0.000]	[0.000]	[0.000]	[0.000]	
KOSPI	4822	0.076	0.433	0.332	0.201	0.798
South Korea		[0.000]	[0.000]	[0.000]	[0.000]	
IPC Mexico	4938	0.198	0.335	0.315	0.258	0.547
Mexico		[0.000]	[0.000]	[0.000]	[0.000]	
Nikkei 225	4754	0.146	0.465	0.283	0.188	0.668
Japan		[0.000]	[0.000]	[0.000]	[0.000]	
S&P CNX Nifty	4841	0.116	0.411	0.327	0.209	0.695
India		[0.000]	[0.000]	[0.000]	[0.000]	
S&P 500	5063	0.107	0.474	0.316	0.158	0.722
United States		[0.000]	[0.000]	[0.000]	[0.000]	
SSEC	4719	0.125	0.502	0.247	0.198	0.724
China		[0.000]	[0.000]	[0.000]	[0.000]	
Swiss Market Index	4941	0.111	0.467	0.367	0.116	0.767
Switzerland		[0.000]	[0.000]	[0.000]	[0.000]	
FT Straits Times	1102	0.230	0.306	0.252	0.327	0.426
Singapore		[0.000]	[0.000]	[0.000]	[0.000]	
Euro STOXX 50	5026	0.144	0.337	0.428	0.174	0.632
Euro Area		[0.000]	[0.000]	[0.000]	[0.000]	

Notes: This table reports parameter estimates from OLS regression for 19 stock markets over the full sample period. Columns 1–2 report equity index and observations, columns 3–7 display the parameter estimation, *p*-values (below the estimates), and Adjusted R^2.

Table 3
HAR-RV-VIX model parameter estimates.

Index	Observations	β_0	β_d	β_w	β_m	β_{VIX}	Adjusted R^2	ΔR^2
AEX	5021	−0.217	0.385	0.319	0.025	0.309	0.768	1.564
The Netherlands		[0.000]	[0.000]	[0.000]	[0.227]	[0.000]		
All Ordinaries	4975	−0.069	0.234	0.394	0.205	0.138	0.564	1.301
Australia		[0.051]	[0.000]	[0.000]	[0.000]	[0.000]		
BOVESPA	4853	0.151	0.428	0.301	0.119	0.089	0.597	0.674
Brazil		[0.000]	[0.000]	[0.000]	[0.000]	[0.000]		
CAC 40	5022	−0.159	0.369	0.316	0.026	0.315	0.754	1.704
France		[0.000]	[0.000]	[0.000]	[0.232]	[0.000]		
FTSE MIB	2675	−0.029	0.418	0.306	0.103	0.169	0.634	1.17
Italy		[0.559]	[0.000]	[0.000]	[0.001]	[0.000]		
FTSE 100	4998	−0.262	0.265	0.305	0.016	0.449	0.685	3.562
United Kingdom		[0.000]	[0.000]	[0.000]	[0.507]	[0.000]		
DAX 30	4998	−0.152	0.370	0.326	0.089	0.249	0.758	1.137
Germany		[0.000]	[0.000]	[0.000]	[0.000]	[0.000]		
S&P TSX	4392	−0.153	0.323	0.318	0.186	0.180	0.688	0.795
Canada		[0.000]	[0.000]	[0.000]	[0.000]	[0.000]		
Hang Seng	4829	−0.009	0.280	0.345	0.219	0.134	0.669	0.902
China Hong Kong		[0.744]	[0.000]	[0.000]	[0.000]	[0.000]		
IBEX 35	4913	−0.030	0.422	0.316	0.130	0.130	0.746	0.626
Spain		[0.271]	[0.000]	[0.000]	[0.000]	[0.000]		
KOSPI	4822	−0.047	0.422	0.324	0.176	0.080	0.800	0.219
South Korea		[0.076]	[0.000]	[0.000]	[0.000]	[0.000]		
IPC Mexico	4938	0.075	0.325	0.306	0.225	0.086	0.551	0.551
Mexico		[0.043]	[0.000]	[0.000]	[0.000]	[0.000]		
Nikkei 225	4754	−0.059	0.435	0.258	0.139	0.164	0.677	1.334
Japan		[0.064]	[0.000]	[0.000]	[0.000]	[0.000]		
S&P CNX Nifty	4841	0.028	0.408	0.323	0.206	0.040	0.695	0.09
India		[0.436]	[0.000]	[0.000]	[0.000]	0.001		
S&P 500	5063	−0.673	0.336	0.216	−0.071	0.665	0.746	3.261
United States		[0.000]	[0.000]	[0.000]	0.001	[0.000]		
SSEC	4719	0.106	0.502	0.248	0.196	0.008	0.724	−0.004
China		[0.004]	[0.000]	[0.000]	[0.000]	[0.480]		
Swiss Market Index	4941	−0.087	0.416	0.332	0.045	0.199	0.775	1.057
Switzerland		[0.000]	[0.000]	[0.000]	[0.025]	[0.000]		
FT Straits Times	1102	0.031	0.258	0.167	0.322	0.184	0.449	5.38
Singapore		[0.681]	[0.000]	[0.002]	[0.000]	[0.000]		
Euro STOXX 50	5026	−0.158	0.282	0.361	0.042	0.343	0.648	2.56
Euro Area		[0.000]	[0.000]	[0.000]	[0.103]	[0.000]		

Notes: Columns 1–2 report equity index and observations, columns 3–9 display the parameter estimation, *p*-values (below the estimates), Adjusted R^2, and the percent increase of R^2 (ΔR^2), respectively.

Table 4
HAR-RV-EPU model parameter estimates.

Index	Observations	β_0	β_d	β_w	β_m	β_{EPU}	Adjusted R^2	ΔR^2
AEX	5021	0.080	0.452	0.373	0.126	0.007	0.756	0.003
The Netherlands		[0.004]	[0.000]	[0.000]	[0.000]	[0.229]		
All Ordinaries	4975	0.079	0.248	0.421	0.241	0.019	0.557	0.102
Australia		[0.029]	[0.000]	[0.000]	[0.000]	[0.007]		
BOVESPA	4853	0.168	0.442	0.310	0.155	0.017	0.594	0.106
Brazil		[0.000]	[0.000]	[0.000]	[0.000]	[0.004]		
CAC 40	5022	0.094	0.437	0.371	0.144	0.005	0.741	−0.002
France		[0.001]	[0.000]	[0.000]	[0.000]	[0.417]		
FTSE MIB	2675	0.166	0.448	0.328	0.144	0.006	0.626	−0.013
Italy		[0.002]	[0.000]	[0.000]	[0.000]	[0.510]		
FTSE 100	4998	0.102	0.352	0.389	0.193	0.011	0.662	0.014
United Kingdom		[0.002]	[0.000]	[0.000]	[0.000]	[0.123]		
DAX 30	4998	0.081	0.419	0.371	0.166	0.005	0.750	−0.001
Germany		[0.007]	[0.000]	[0.000]	[0.000]	[0.370]		
S&P TSX	4392	0.068	0.351	0.346	0.241	0.011	0.683	0.01
Canada		[0.060]	[0.000]	[0.000]	[0.000]	[0.162]		
Hang Seng	4829	0.081	0.300	0.367	0.279	0.009	0.663	0.016
China Hong Kong		[0.015]	[0.000]	[0.000]	[0.000]	[0.111]		
IBEX 35	4913	0.101	0.448	0.334	0.169	0.004	0.742	−0.004
Spain		[0.000]	[0.000]	[0.000]	[0.000]	[0.484]		
KOSPI	4822	0.092	0.433	0.332	0.201	−0.004	0.798	−0.002
South Korea		[0.001]	[0.000]	[0.000]	[0.000]	[0.441]		
IPC Mexico	4938	0.171	0.335	0.314	0.256	0.008	0.548	0.002
Mexico		[0.000]	[0.000]	[0.000]	[0.000]	[0.288]		
Nikkei 225	4754	0.132	0.465	0.283	0.188	0.004	0.668	−0.007
Japan		[0.000]	[0.000]	[0.000]	[0.000]	[0.538]		
S&P CNX Nifty	4841	0.118	0.411	0.327	0.209	0.000	0.695	−0.009
India		[0.002]	[0.000]	[0.000]	[0.000]	[0.943]		
S&P 500	5063	0.041	0.473	0.314	0.153	0.020	0.723	0.052
United States		[0.206]	[0.000]	[0.000]	[0.000]	[0.005]		
SSEC	4719	0.089	0.502	0.247	0.199	0.008	0.724	0.004
China		[0.021]	[0.000]	[0.000]	[0.000]	[0.229]		
Swiss Market Index	4941	0.092	0.467	0.366	0.115	0.006	0.767	0.003
Switzerland		[0.000]	[0.000]	[0.000]	[0.000]	[0.235]		
FT Straits Times	1102	0.283	0.307	0.254	0.319	−0.009	0.426	−0.05
Singapore		[0.004]	[0.000]	[0.000]	[0.000]	[0.434]		
Euro STOXX 50	5026	0.113	0.336	0.427	0.170	0.011	0.632	0.012
Euro Area		[0.002]	[0.000]	[0.000]	[0.000]	[0.159]		

Notes: Columns 1–2 report equity index and observations, columns 3–9 display the parameter estimation, *p*-values (below the estimates), Adjusted R^2, and the percent increase of R^2 (ΔR^2), respectively.

Table 5
Results of the MCS test.

Forecasting models	QLIKE		MSE	
	Range	SeimQ	Range	SeimQ
Panel A: AEX				
HAR-RV	0.0230	0.0111	0.0210	0.0099
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0230	0.0125	0.0210	0.0127
Panel B: All Ordinaries				
HAR-RV	0.1548	0.1548	0.1208	0.1208
HAR-RV-VIX	0.0174	0.0149	0.0290	0.0256
HAR-RV-EPU	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Panel C: BOVESPA				
HAR-RV	0.0058	0.0065	0.0134	0.0095
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0336	0.0336	0.0359	0.0359
Panel D: CAC 40				
HAR-RV	0.0122	0.0081	0.0088	0.0044
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0122	0.0081	0.0088	0.0044
Panel E: FTSE MIB				
HAR-RV	0.0088	0.0053	0.0077	0.0069
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0088	0.0053	0.0077	0.0069
Panel F: FTSE 100				
HAR-RV	0.1266	0.1266	0.2775	0.2775
HAR-RV-VIX	0.0189	0.0121	0.0221	0.0167
HAR-RV-EPU	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Panel G: DAX 30				
HAR-RV	0.0075	0.0050	0.0053	0.0053
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0075	0.0050	0.0053	0.0053
Panel H: S&P TSX				
HAR-RV	0.0152	0.0161	0.0107	0.0122
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0152	0.0161	0.0107	0.0122
Panel I: Hang Seng				
HAR-RV	0.0146	0.0416	0.0434	0.0731
HAR-RV-VIX	0.0146	0.0416	0.0434	0.0731
HAR-RV-EPU	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Panel J: IBEX 35				
HAR-RV	0.0593	0.0720	0.0770	0.0770
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0532	0.0720	0.0518	0.0421
Panel K: KOSPI				
HAR-RV	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-VIX	0.0206	0.0116	0.0278	0.0169
HAR-RV-EPU	0.0993	0.0993	0.1550	0.1550
Panel L: IPC Mexico				
HAR-RV	**0.3653**	**0.3653**	**0.2867**	**0.2867**
HAR-RV-VIX	0.0066	0.0054	0.0197	0.0167
HAR-RV-EPU	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Panel M: Nikkei 225				
HAR-RV	0.0026	0.0007	0.0109	0.0073
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0026	0.0013	0.0109	0.0073
Panel N: S&P CNX Nifty				
HAR-RV	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-VIX	0.1527	0.1268	0.2219	0.2060
HAR-RV-EPU	**0.5176**	**0.5176**	**0.8366**	**0.8366**
Panel O: S&P 500				
HAR-RV	0.0272	0.0157	0.0716	0.0460
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0272	0.0171	0.0716	0.0460
Panel P: SSEC				
HAR-RV	0.0849	0.0849	0.1336	0.1336
HAR-RV-VIX	0.0063	0.0083	0.0045	0.0060
HAR-RV-EPU	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Panel Q: Swiss Market Index				
HAR-RV	0.0845	0.0382	0.0919	0.0423
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0845	0.0727	0.0919	0.0827
Panel R: FT Straits Times				
HAR-RV	0.2239	0.1289	**0.2709**	0.2124
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.2239	0.1015	**0.2709**	0.1698
Panel S: Euro STOXX 50				
HAR-RV	0.0038	0.0024	0.0072	0.0060
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0038	0.0024	0.0072	0.0060

Notes: This table shows MCS results, and the p-value is calculated according to the range and semi-quadratic (SeimQ) statistics. The p-value >0. 25 are indicated in bold and p-value = 1 are indicated in bold and are underlined. For each equity index, forecasts range from December 1, 2019 to March 25, 2020. Panel A-S show 19 stock markets respectively.

in Table 3. Interestingly, we observe that the β_{VIX} of S&P 500 (United States) is 0.665 and β_{VIX} of SSEC (China) is 0.008. Furthermore, the results of p-values show VIX exhibits significantly influence for each equity index except SSEC. Comparing the magnitude of the R^2 values of our benchmark model, FT Straits Times obtains the largest improvement, with the increase of R^2 (ΔR^2) value about 5.38%, the ΔR^2 values of FTSE 100 and S&P 500 extends 3.26%. For remaining stock markets, 8 stock markets yield ΔR^2larger than 1% (AEX, All Ordinaries, CAC 40, DAX 30, FTSE MIB, Nikkei 225, Swiss Market Index and Euro STOXX 50), 6 of them improve by larger than 0.2% (Hang Seng, S&P TSX, BOVESPA, IBEX 35, IPC Mexico and KOSPI), the ΔR^2 value of S&P CNX Nifty is less than 0.1%, with the improvement of SSEC is negative. In short, these results indicate that the VIX can improve in-sample fit performance for major stock markets that we consider.

Third, Table 4 shows estimate results of HAR-RV-EPU, we find that the magnitude of β_{EPU} is between 0.2 for S&P 500 and − 0.009 for FT Straits Times, moreover, the coefficient estimates of β_{EPU} are positive and significant for only 4 stock markets (All Ordinaries, BOVESPA, CAC 40 and S&P 500), with the β_{EPU} of 15 remaining indices are not significant. For considering ΔR^2, we observe that the ΔR^2 values of 8 stock markets are negative (CAC 40, FTSE MIB, DAX 30, IBEX 35, KOSPI, Nikkei 225, S&P CNX Nifty and FT Straits Times), while the improvement of remaining 11 equity indices is positive, of which 9 of them showing improvements of lower than 0.1%.

Finally, comparing the in-sample results of regression models, we observe that the ΔR^2 value of HAR-RV-VIX is larger than HAR-RV-EPU model, implying that the VIX exhibits better interpretive ability for almost all stock markets (except SSEC) than EPU. Moreover, via in-sample analysis, the p-values of estimates indicate the β_{VIX} and β_{EPU} are significant for 18 and 4 equity indices respectively, indicating the VIX is more important than EPU for future RV.

4.2. Out-of-sample results

In this section, we employ three popular forecast evaluation approaches to assess the predictive ability of VIX and EPU for each stock market, moreover forecasts are obtained by rolling window method and ranges from December 1, 2019 to March 25, 2020.

4.2.1. MCS test results

Table 5 reports the MCS p-values of forecasting models for 19 stock markets that we consider, which are evaluated based on the range and semi-quadratic statistics. As described in Section 2.3.1, the larger MCS p-value, the more superior forecasting performance the model owns. There are several remarkable findings. First, the HAR-RV-VIX model

Table 6
Results of the out-of-sample R^2.

Equity index	Country/Region	Observations	R^2_{OOS}(%)	MSPE-Adj.	*p*-value
Panel A: HAR-RV-VIX model					
AEX	The Netherlands	5021	0.6493	3.2810	0.0005
All Ordinaries	Australia	4975	−0.4939	−3.4629	0.9997
BOVESPA	Brazil	4853	0.3861	4.3145	0.0000
CAC 40	France	5022	1.3234	4.2464	0.0000
FTSE MIB	Italy	2675	1.3608	4.6644	0.0000
FTSE 100	United Kingdom	4998	−2.0717	−3.5346	0.9998
DAX 30	Germany	4998	1.9008	4.6974	0.0000
S&P TSX	Canada	4392	1.2425	4.1212	0.0000
Hang Seng	China Hong Kong	4829	−0.5093	−1.2285	0.8904
IBEX 35	Spain	4913	3.0327	2.2614	0.0119
KOSPI	South Korea	4822	−1.0758	−3.6138	0.9998
IPC Mexico	Mexico	4938	−1.4267	−3.6588	0.9999
Nikkei 225	Japan	4754	0.6619	4.0165	0.0000
S&P CNX Nifty	India	4841	−0.0818	−1.9825	0.9763
S&P 500	United States	5063	5.7365	3.0442	0.0012
SSEC	China	4719	−0.2456	−4.3178	1.0000
Swiss Market Index	Switzerland	4941	0.2175	2.2232	0.0131
FT Straits Times	Singapore	1102	0.4771	1.5678	0.0585
Euro STOXX 50	Euro Area	5026	1.4361	4.1946	0.0000
Panel B: HAR-RV-EPU model					
AEX	The Netherlands	5021	0.0595	2.5006	0.0062
All Ordinaries	Australia	4975	0.0802	1.7709	0.0383
BOVESPA	Brazil	4853	0.1569	2.1467	0.0159
CAC 40	France	5022	0.0624	2.8823	0.0020
FTSE MIB	Italy	2675	0.0707	2.6608	0.0039
FTSE 100	United Kingdom	4998	0.0666	1.2367	0.1081
DAX 30	Germany	4998	0.0699	2.5268	0.0058
S&P TSX	Canada	4392	0.0736	2.2895	0.0110
Hang Seng	China Hong Kong	4829	0.2159	2.6505	0.0040
IBEX 35	Spain	4913	−0.6678	−1.6422	0.9497
KOSPI	South Korea	4822	−0.0253	−1.5701	0.9418
IPC Mexico	Mexico	4938	0.1349	1.2222	0.1108
Nikkei 225	Japan	4754	0.0462	2.6690	0.0038
S&P CNX Nifty	India	4841	−0.0001	−0.2359	0.5933
S&P 500	United States	5063	0.1620	0.9542	0.1700
SSEC	China	4719	0.1086	1.6075	0.0540
Swiss Market Index	Switzerland	4941	0.0387	2.0744	0.0190
FT Straits Times	Singapore	1102	−0.0278	−1.5101	0.9345
Euro STOXX 50	Euro Area	5026	0.1174	2.3850	0.0085

Notes: Columns 1–3 report equity index, country or region and observations, columns 4–6 display the R^2_{OOS}, MSPE-adjusted statistic and *p*-value, respectively. If the R^2_{oos} is larger than zero, implying that corresponding model outperform the benchmark model. For each equity index, forecasts range from December 1, 2019 to March 25, 2020.

Table 7
Results of the DM test.

Equity index	Country/Region	Observations	DM1	*p*-value1	DM2	*p*-value2
Panel A: HAR-RV-VIX model						
AEX	The Netherlands	5021	3.1655	0.0008	3.2469	0.0006
All Ordinaries	Australia	4975	−3.9315	1.0000	−3.5296	0.9998
BOVESPA	Brazil	4853	4.5637	0.0000	4.3000	0.0000
CAC 40	France	5022	3.8526	0.0001	4.2087	0.0000
FTSE MIB	Italy	2675	4.7750	0.0000	4.6374	0.0000
FTSE 100	United Kingdom	4998	−3.9643	1.0000	−3.6529	0.9999
DAX 30	Germany	4998	4.5354	0.0000	4.6727	0.0000
S&P TSX	Canada	4392	3.9869	0.0000	4.0897	0.0000
Hang Seng	China Hong Kong	4829	−1.0181	0.8457	−1.3000	0.9032
IBEX 35	Spain	4913	2.3210	0.0101	2.1103	0.0174
KOSPI	South Korea	4822	−3.8787	0.9999	−3.6521	0.9999
IPC Mexico	Mexico	4938	−4.1165	1.0000	−3.7064	0.9999
Nikkei 225	Japan	4754	4.7668	0.0000	3.9895	0.0000
S&P CNX Nifty	India	4841	−2.3639	0.9910	−2.0015	0.9773
S&P 500	United States	5063	3.5836	0.0002	2.9201	0.0017
SSEC	China	4719	−4.2628	1.0000	−4.3269	1.0000
Swiss Market Index	Switzerland	4941	2.2585	0.0120	2.2000	0.0139
FT Straits Times	Singapore	1102	1.8208	0.0343	1.5061	0.0660
Euro STOXX 50	Euro Area	5026	4.5543	0.0000	4.1510	0.0000
Panel B: HAR-RV-EPU model						
AEX	The Netherlands	5021	2.4072	0.0080	2.4928	0.0063
All Ordinaries	Australia	4975	1.5257	0.0635	1.7585	0.0393
BOVESPA	Brazil	4853	2.0307	0.0211	2.1294	0.0166
CAC 40	France	5022	2.7520	0.0030	2.8749	0.0020
FTSE MIB	Italy	2675	2.6144	0.0045	2.6518	0.0040
FTSE 100	United Kingdom	4998	1.7646	0.0388	1.2257	0.1101
DAX 30	Germany	4998	2.5565	0.0053	2.5194	0.0059
S&P TSX	Canada	4392	2.3220	0.0101	2.2822	0.0112
Hang Seng	China Hong Kong	4829	3.2163	0.0006	2.6289	0.0043
IBEX 35	Spain	4913	−0.2378	0.5940	−1.6782	0.9533
KOSPI	South Korea	4822	−1.7944	0.9636	−1.5757	0.9425
IPC Mexico	Mexico	4938	1.0195	0.1540	1.2065	0.1138
Nikkei 225	Japan	4754	2.8600	0.0021	2.6632	0.0039
S&P CNX Nifty	India	4841	−0.7277	0.7666	−0.2375	0.5939
S&P 500	United States	5063	1.4744	0.0702	0.9379	0.1742
SSEC	China	4719	1.7606	0.0391	1.5871	0.0562
Swiss Market Index	Switzerland	4941	2.1479	0.0159	2.0700	0.0192
FT Straits Times	Singapore	1102	−1.5911	0.9442	−1.5537	0.9399
Euro STOXX 50	Euro Area	5026	2.7958	0.0026	2.3745	0.0088

Notes: This table shows the DM test results, columns 1–3 report equity index, country or region and observations, columns 4–6 display the DM 1, *p*-value1, DM 2 and *p*-value2, respectively. DM 1(2) represents the DM statistics based on QLIKE (MSE) loss function. Positive (negative) values of the DM statistics indicate that the forecasting model outperforms (underperforms) the benchmark. For each equity index, forecasts range from December 1, 2019 to March 25, 2020.

Table 8
Results of the MCS test based on recursive window.

Forecasting models	QLIKE		MSE	
	Range	SeimQ	Range	SeimQ
Panel A: AEX				
HAR-RV	0.0236	0.0116	0.0225	0.0101
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0236	0.0134	0.0225	0.0125
Panel B: All Ordinaries				
HAR-RV	0.1454	0.1454	0.1202	0.1202
HAR-RV-VIX	0.0201	0.0181	0.0327	0.0279
HAR-RV-EPU	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Panel C: BOVESPA				
HAR-RV	0.0054	0.0056	0.0147	0.0108
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0256	0.0256	0.0237	0.0237
Panel D: CAC 40				
HAR-RV	0.0131	0.0083	0.0068	0.0044
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0131	0.0083	0.0068	0.0044
Panel E: FTSE MIB				
HAR-RV	0.0055	0.0044	0.0061	0.0050
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0055	0.0044	0.0061	0.0050
Panel F: FTSE 100				
HAR-RV	0.1154	0.1154	0.2506	0.2506
HAR-RV-VIX	0.0181	0.0116	0.0234	0.0175
HAR-RV-EPU	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Panel G: DAX 30				
HAR-RV	0.0072	0.0061	0.0063	0.0053
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0072	0.0061	0.0063	0.0053
Panel H: S&P TSX				
HAR-RV	0.0141	0.0142	0.0105	0.0112
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0141	0.0142	0.0105	0.0112
Panel I: Hang Seng				
HAR-RV	0.0148	0.0401	0.0413	0.0754
HAR-RV-VIX	0.0148	0.0401	0.0413	0.0754
HAR-RV-EPU	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Panel J: IBEX 35				
HAR-RV	0.0667	0.0784	0.0766	0.0766
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0600	0.0784	0.0524	0.0441
Panel K: KOSPI				
HAR-RV	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-VIX	0.0226	0.0115	0.0358	0.0220
HAR-RV-EPU	0.0942	0.0942	0.1364	0.1364
Panel L: IPC Mexico				
HAR-RV	0.3014	0.3014	0.2563	0.2563
HAR-RV-VIX	0.0061	0.0051	0.0182	0.0176
HAR-RV-EPU	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Panel M: Nikkei 225				
HAR-RV	0.0024	0.0014	0.0137	0.0082
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0024	0.0015	0.0137	0.0082
Panel N: S&P CNX Nifty				
HAR-RV	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-VIX	0.1420	0.0847	0.1981	0.1055
HAR-RV-EPU	0.2123	0.2123	0.1981	0.1858
Panel O: S&P 500				
HAR-RV	0.0285	0.0150	0.0671	0.0441
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0285	0.0161	0.0671	0.0441
Panel P: SSEC				
HAR-RV	0.0798	0.0798	0.1332	0.1332
HAR-RV-VIX	0.0069	0.0085	0.0046	0.0064
HAR-RV-EPU	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Panel Q: Swiss Market Index				
HAR-RV	0.1010	0.0413	0.1133	0.0497
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.1010	0.0860	0.1133	0.1021
Panel R: FT Straits Times				
HAR-RV	0.3032	0.1995	0.3347	0.3347
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.3032	0.1668	0.3314	0.2610
Panel S: Euro STOXX 50				
HAR-RV	0.0045	0.0031	0.0066	0.0048
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0045	0.0031	0.0066	0.0048

Notes: For each equity index, out-of-sample evaluation period ranges from December 1, 2019 to March 25, 2020.

yield the largest MCS *p*-values for 12 of 19 equity indices (AEX, BOVESPA, CAC 40, DAX 30, FTSE MIB, S&P TSX, IBEX 35, Nikkei 225, S&P 500, Swiss Market Index, FT Straits Times and Euro STOXX 50) under QLIKE and MSE loss functions, implying the VIX exhibits superior forecasting quality for these markets during coronavirus crisis period. Second, we notice that EPU can improve the forecasting accuracy for 5 stock markets, showing that EPU index can improve predictive accuracy for All Ordinaries, FTSE 100, Hang Seng, IPC Mexico and SSEC. Finally, the HAR-RV model ranks at the top of the MCS for 2 remaining stock markets, indicating VIX and EPU index have no effect for predicting future RV for S&P CNX Nifty and KOSPI index.

4.2.2. Out-of-sample R^2 results

The results are shown in Table 6. A positive (negative) R^2_{OOS} indicates the forecasts from extended models outperform (underperform) the benchmark model. We find several noteworthy results. First, in fact, the R^2_{OOS} values of HAR-RV-VIX are positive and significant for 12 of 19 stock markets, implying the VIX index can improve the forecasting accuracy. These equity indices are AEX, BOVESPA, CAC 40, DAX 30, FTSE MIB, S&P TSX, IBEX 35, Nikkei 225, S&P 500, Swiss Market Index, FT Straits Times and Euro STOXX 50. Second, we observe that the in All Ordinaries, FTSE 100, Hang Seng, IPC Mexico and SSEC, the R^2_{OOS} values of HAR-RV-EPU model are positive while HAR-RV-VIX model's values are negative, suggesting EPU exhibits forecasting ability for these 5 stock markets. Third, the R^2_{OOS} values of HAR-RV-VIX and HAR-RV-EPU model are negative for S&P CNX Nifty and KOSPI, indicating that VIX and EPU index lead to a worsening forecast performance. In short, the out-of-sample R^2 results are consistent with MCS test.

4.2.3. DM test results

Table 7 denotes the results of DM test, as described in Section 2.3.2, the positive (negative) DM statistic indicates forecasting model exhibits superior (worsen) forecasting performance than benchmark model. The empirical results show VIX index contains superior predictive ability consistently for 12 of 19 stock markets, including AEX, BOVESPA, CAC 40, DAX 30, FTSE MIB, S&P TSX, IBEX 35, Nikkei 225, S&P 500, Swiss Market Index, FT Straits Times and Euro STOXX 50. Moreover, HAR-RV-EPU model still outperforms other competing models for All Ordinaries, FTSE 100, Hang Seng, IPC Mexico and SSEC stock markets over the out-of-sample period. Similarly, VIX and EPU index exhibit weak forecasting performance for S&P CNX Nifty and KOSPI. The DM result is consistent with MCS and out-of-sample R^2 test.

4.3. Robustness checks

4.3.1. Recursive window method

In previous study we employ rolling window method to obtain

Table 9
Results of the MCS test based on RK.

Forecasting models	QLIKE		MSE	
	Range	SeimQ	Range	SeimQ
Panel A: AEX				
HAR-RV	0.0116	0.0067	0.0137	0.0068
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0116	0.0067	0.0137	0.0078
Panel B: All Ordinaries				
HAR-RV	0.1258	0.1258	0.1120	0.1120
HAR-RV-VIX	0.0252	0.0195	0.0370	0.0297
HAR-RV-EPU	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Panel C: BOVESPA				
HAR-RV	0.0119	0.0183	0.0279	0.0394
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	**0.3131**	**0.3131**	**0.4735**	**0.4735**
Panel D: CAC 40				
HAR-RV	0.0078	0.0053	0.0072	0.0046
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0078	0.0053	0.0072	0.0046
Panel E: FTSE MIB				
HAR-RV	0.0063	0.0044	0.0052	0.0040
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0063	0.0044	0.0052	0.0040
Panel F: FTSE 100				
HAR-RV	0.1401	0.3183	**0.2644**	**0.4602**
HAR-RV-VIX	0.1401	0.3183	**1.0000**	**1.0000**
HAR-RV-EPU	**1.0000**	**1.0000**	**0.9836**	**0.9836**
Panel G: DAX 30				
HAR-RV	0.0080	0.0053	0.0048	0.0036
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0080	0.0053	0.0048	0.0036
Panel H: S&P TSX				
HAR-RV	0.0218	0.0192	0.0354	0.0311
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0218	0.0192	0.0354	0.0311
Panel I: Hang Seng				
HAR-RV	0.0170	0.0693	0.0339	0.1140
HAR-RV-VIX	**0.7207**	**0.7207**	0.0339	0.1140
HAR-RV-EPU	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Panel J: IBEX 35				
HAR-RV	**0.5157**	**0.4569**	**0.9630**	**0.9630**
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	**0.5157**	**0.4569**	0.1342	**0.2939**
Panel K: KOSPI				
HAR-RV	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-VIX	0.0191	0.0093	0.0283	0.0162
HAR-RV-EPU	0.0674	0.0674	0.1391	0.1391
Panel L: IPC Mexico				
HAR-RV	**0.6227**	**0.6227**	**0.5148**	**0.5148**
HAR-RV-VIX	0.0014	0.0015	0.0047	0.0043
HAR-RV-EPU	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Panel M: Nikkei 225				
HAR-RV	0.0060	0.0024	0.0107	0.0073
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0060	0.0030	0.0107	0.0073
Panel N: S&P CNX Nifty				
HAR-RV	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-VIX	0.0962	0.0529	0.1569	0.0815
HAR-RV-EPU	0.1751	0.1751	0.1804	0.1804
Panel O: S&P 500				
HAR-RV	0.0127	0.0063	0.0585	0.0414
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0127	0.0077	0.0585	0.0414
Panel P: SSEC				
HAR-RV	0.0316	0.0316	0.0590	0.0590
HAR-RV-VIX	0.0054	0.0036	0.0043	0.0024
HAR-RV-EPU	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Panel Q: Swiss Market Index				
HAR-RV	0.0141	0.0090	0.0117	0.0074
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0141	0.0090	0.0117	0.0074
Panel R: FT Straits Times				
HAR-RV	0.0080	0.0057	0.0102	0.0065
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0080	0.0031	0.0102	0.0041
Panel S: Euro STOXX 50				
HAR-RV	0.0017	0.0013	0.0072	0.0045
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0017	0.0013	0.0072	0.0045

Notes: For each equity index, forecasts range from December 1, 2019 to March 25, 2020.

forecasts for each stock markets, for convincing our results we use another forecasting window method, recursive window, to re-do the empirical analysis (Byun, Frijns, & Roh, 2018; Ma et al., 2018; Neely, Rapach, Tu, & Zhou, 2014). Table 8 reveals that the HAR-RV-VIX model yield the largest *p*-value of 1 for 12 stock markets including AEX, BOVESPA, CAC 40, DAX 30, FTSE MIB, S&P TSX, IBEX 35, Nikkei 225, S&P 500, Swiss Market Index, FT Straits Times and Euro STOXX 50, moreover HAR-RV-EPU model has a higher forecast accuracy for All Ordinaries, FTSE 100, Hang Seng, IPC Mexico and SSEC equity index while HAR-RV model exhibits powerful predictive ability than other competing models for S&P CNX Nifty and KOSPI index under QLIKE and MSE criteria. Therefore, our conclusions are robust to recursive window.[7]

4.3.2. Alternative realized measures

In this subsection, we employ alternative realized measures, the realized kernel (RK), to re-examine the forecasting ability of VIX and EPU index for 19 stock markets that we consider during the coronavirus crisis period. Barndorff-Nielsen, Hansen, Lunde, and Shephard (2008) propose RK and argue this realized measures are robust to microstructure noise, which is widely used for forecasting volatility (Liang et al., 2020; Ma et al., 2018; Ma, Zhang, et al., 2019). The RK is also collected from Realized Library and can be evaluate as follow:

$$RK_t = \sum_{j=-h}^{H} k\left(\frac{j}{j+1}\right)\gamma_j, \tag{11}$$

$$\gamma_j = \sum_{i=|j|+1}^{n} r_{t,i} r_{t,i-|j|}, \tag{12}$$

where $k(x)$ represents the Parzen kernel function, and H is a bandwidth parameter (Barndorff-Nielsen, Hansen, Lunde, & Shephard, 2009).

The MCS results for the 19 equity indices using RK are shown in Table 9. The results donate the HAR-RV-VIX model outperforms competing models for 12 of 19 stock markets including AEX, BOVESPA, CAC 40, DAX 30, FTSE MIB, S&P TSX, IBEX 35, Nikkei 225, S&P 500, Swiss Market Index, FT Straits Times and Euro STOXX 50, while the HAR-RV-EPU model exhibits superior predictive quality for 5 equity indices including All Ordinaries, FTSE 100, Hang Seng and IPC Mexico, moreover HAR-RV model shows the best prediction performance for S&P CNX Nifty and KOSPI index. Thus, these findings are extremely consistent with previous results.

[7] Note that our our-of-sample R^2 and DM test are consistent with MCS test. For brevity we do not report these results in robustness checks and further discussion, but they can be available in online appendix.

Table 10
Sub-sample results of the MCS test.

Forecasting models	QLIKE		MSE	
	Range	SeimQ	Range	SeimQ
Panel A: AEX				
HAR-RV	0.0227	0.0188	0.0189	0.0154
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0227	0.0188	0.0189	0.0154
Panel B: All Ordinaries				
HAR-RV	**0.9633**	**0.9647**	**0.8090**	**0.8573**
HAR-RV-VIX	**1.0000**	**1.0000**	**0.8090**	**0.8573**
HAR-RV-EPU	**0.9633**	**0.9647**	**1.0000**	**1.0000**
Panel C: BOVESPA				
HAR-RV	0.0106	0.0095	0.0183	0.0146
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0106	0.0095	0.0183	0.0146
Panel D: CAC 40				
HAR-RV	0.0138	0.0122	0.0071	0.0062
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0138	0.0122	0.0071	0.0062
Panel E: FTSE MIB				
HAR-RV	0.0067	0.0073	0.0076	0.0078
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0067	0.0073	0.0076	0.0078
Panel F: FTSE 100				
HAR-RV	**0.8695**	**0.8695**	**1.0000**	**1.0000**
HAR-RV-VIX	0.0255	0.0203	0.0347	0.0272
HAR-RV-EPU	**1.0000**	**1.0000**	**0.9615**	**0.9615**
Panel G: DAX 30				
HAR-RV	0.0078	0.0079	0.0049	0.0052
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0078	0.0079	0.0049	0.0052
Panel H: S&P TSX				
HAR-RV	0.0163	0.0190	0.0144	0.0161
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0163	0.0190	0.0144	0.0161
Panel I: Hang Seng				
HAR-RV	**0.2537**	**0.3034**	**0.2949**	**0.2590**
HAR-RV-VIX	**0.2537**	**0.3034**	**0.2949**	**0.2590**
HAR-RV-EPU	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Panel J: IBEX 35				
HAR-RV	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-VIX	**0.8369**	**0.8969**	**0.3380**	0.2159
HAR-RV-EPU	**0.8369**	**0.8969**	**0.3380**	**0.2532**
Panel K: KOSPI				
HAR-RV	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-VIX	0.0106	0.0115	0.0171	0.0169
HAR-RV-EPU	0.1735	0.1735	0.1421	0.1421
Panel L: IPC Mexico				
HAR-RV	**1.0000**	**1.0000**	**0.7776**	**0.7776**
HAR-RV-VIX	0.2495	0.2128	0.2064	0.1824
HAR-RV-EPU	**0.9790**	**0.9790**	**1.0000**	**1.0000**
Panel M: Nikkei 225				
HAR-RV	**0.8008**	**0.7759**	**0.7232**	**0.6820**
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	**0.8008**	**0.7759**	**0.7232**	**0.6820**
Panel N: S&P CNX Nifty				
HAR-RV	0.0097	0.0080	0.0046	0.0040
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0097	0.0080	0.0046	0.0040
Panel O: S&P 500				
HAR-RV	0.0242	0.0251	0.0710	0.0643
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0242	0.0251	0.0710	0.0643
Panel P: SSEC				
HAR-RV	**0.8805**	**0.8805**	**1.0000**	**1.0000**
HAR-RV-VIX	0.0140	0.0127	0.0101	0.0082
HAR-RV-EPU	**1.0000**	**1.0000**	**0.9445**	**0.9445**
Panel Q: Swiss Market Index				
HAR-RV	0.0362	0.0281	0.0332	0.0243
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0362	0.0281	0.0332	0.0243
Panel R: FT Straits Times				
HAR-RV	**0.7300**	**0.7300**	**0.6404**	**0.6404**
HAR-RV-VIX	**0.6626**	**0.6093**	**0.5197**	**0.4527**
HAR-RV-EPU	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Panel S: Euro STOXX 50				
HAR-RV	0.0061	0.0042	0.0068	0.0061
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0061	0.0042	0.0068	0.0061

Notes: For each equity index, out-of-sample evaluation period ranges from December 1, 2019 to March 25, 2020.

4.3.3. *Sub-sample analysis*

In this subsection, we employ sub-sample to re-do out-of-sample results. Our full sample contains between 1102 (FT Straits Times) and 5063 (S&P 500) trading days, we set sub-sample length as half of full sample for 19 stock markets, the MCS results are shown in Table 10. We find that VIX index contains more useful predictive content from HAR-RV-VIX model to 11 stock markets including AEX, BOVESPA, CAC 40, DAX 30, FTSE MIB, S&P TSX, Nikkei 225, S&P CNX Nifty, S&P 500, Swiss Market Index and Euro STOXX 50 during coronavirus crisis period, moreover EPU index is useful for forecasting future volatility on All Ordinaries, FTSE 100, Hang Seng, IPC Mexico, SSEC and FT Straits Times, while VIX and EPU index don't work for forecasting future volatility in terms of IBEX 35 and KOSPI index. These results using sub-sample analysis are also consistent with our conclusions.

5. Further discussions

5.1. *Kitchen sink and combination forecast*

From our empirical results, we find the VIX contains more useful predictive content than EPU index for most of equity indices that we consider. We further discuss the forecasting performance of VIX and EPU index when we consider kitchen sink model (KS) and combination forecast due to several reasons. First, considering the information flows and financial globalization, we introduce KS model that incorporate the VIX and EPU in the benchmark model (Peng et al., 2018). Second, many studies improve forecasting accuracy based on forecast combinations (Baumeister & Kilian, 2015; Liang et al., 2020; Zhang, Ma, Shi, & Huang, 2018). In our study, we just consider mean combination forecast that is equal-weighted average of the forecasts from HAR-RV, HAR-RV-VIX and HAR-RV-EPU model. And the KS model can be written as:

$$RV_{t+1} = \beta_0 + \beta_d RV_t + \beta_w RVW_t + \beta_m RVM_t + \beta_{VIX} VIX_t + \beta_{EPU} EPU_t + \varepsilon_{t+1}, \tag{13}$$

From MCS test shown in Table 11, we have several remarkably findings. First, HAR-RV-VIX model yield largest p-value of 1 for 9 stock markets including AEX, CAC 40, DAX 30, FTSE MIB, IBEX 35, Nikkei 225, Swiss Market Index, FT Straits Times and Euro STOXX 50, while HAR-RV-EPU model ranks the top of MCS for 5 equity indices including All Ordinaries, FTSE 100, Hang Seng, IPC Mexico and SSEC, moreover HAR-RV outperforms competing models for KOSPI and S&P CNX Nifty index over out-of-sample period during coronavirus crisis. Second, in BOVESPA, S&P TSX and S&P 500 market, KS model owns the superior predictive ability. Finally, the mean combination forecast is not useful for forecasting future volatility for each stock.

Table 11
Results of the MCS test considering other forecasting models.

Forecasting models	QLIKE		MSE	
	Range	SeimQ	Range	SeimQ
Panel A: AEX				
HAR-RV	0.0238	0.0129	0.0198	0.0115
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0299	0.0166	0.0273	0.0169
KS	0.0874	0.0874	0.0899	0.0899
Mean	0.0299	0.0179	0.0273	0.0181
Panel B: All Ordinaries				
HAR-RV	0.1591	0.1591	0.1298	0.1298
HAR-RV-VIX	0.0195	0.0109	0.0355	0.0221
HAR-RV-EPU	**1.0000**	**1.0000**	**1.0000**	**1.0000**
KS	0.0195	0.0109	0.0355	0.0227
Mean	0.0254	0.0151	0.0375	0.0276
Panel C: BOVESPA				
HAR-RV	0.0083	0.0071	0.0129	0.0088
HAR-RV-VIX	**0.3873**	**0.3873**	**0.3401**	**0.3401**
HAR-RV-EPU	0.0469	0.0459	0.0550	0.0475
KS	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Mean	0.0103	0.0215	0.0141	0.0220
Panel D: CAC 40				
HAR-RV	0.0206	0.0144	0.0192	0.0100
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0206	0.0144	0.0203	0.0100
KS	0.0628	0.0628	0.0843	0.0843
Mean	0.0220	0.0165	0.0204	0.0134
Panel E: FTSE MIB				
HAR-RV	0.0084	0.0035	0.0090	0.0066
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0084	0.0035	0.0090	0.0041
KS	**0.2597**	**0.2597**	0.1763	0.1763
Mean	0.0084	0.0053	0.0090	0.0041
Panel F: FTSE 100				
HAR-RV	0.1299	0.1299	0.2724	0.2724
HAR-RV-VIX	0.0173	0.0096	0.0230	0.0125
HAR-RV-EPU	**1.0000**	**1.0000**	**1.0000**	**1.0000**
KS	0.0169	0.0085	0.0230	0.0127
Mean	0.0196	0.0123	0.0259	0.0185
Panel G: DAX 30				
HAR-RV	0.0085	0.0045	0.0069	0.0046
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0085	0.0045	0.0069	0.0028
KS	**0.3998**	**0.3998**	**0.4251**	**0.4251**
Mean	0.0086	0.0062	0.0069	0.0028
Panel H: S&P TSX				
HAR-RV	0.0166	0.0146	0.0147	0.0115
HAR-RV-VIX	**0.9118**	**0.9118**	**0.8012**	**0.8012**
HAR-RV-EPU	0.0166	0.0101	0.0147	0.0087
KS	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Mean	0.0166	0.0101	0.0147	0.0090
Panel I: Hang Seng				
HAR-RV	0.0205	0.1159	0.0428	0.1350
HAR-RV-VIX	0.0205	0.1159	0.0428	0.1350
HAR-RV-EPU	**1.0000**	**1.0000**	**1.0000**	**1.0000**
KS	0.0205	0.0729	0.0428	0.0952
Mean	0.1306	0.1306	0.0428	0.1350
Panel J: IBEX 35				
HAR-RV	0.0754	0.0832	0.0804	0.0640
HAR-RV-VIX	**1.0000**	**1.0000**	**0.2999**	**0.2999**
HAR-RV-EPU	0.0301	0.0403	0.0249	0.0259
KS	**0.8965**	**0.8965**	**1.0000**	**1.0000**
Mean	0.0568	0.0575	0.0481	0.0514
Panel K: KOSPI				
HAR-RV	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-VIX	0.0185	0.0109	0.0316	0.0175
HAR-RV-EPU	0.1028	0.1028	0.1518	0.1518
KS	0.0103	0.0062	0.0241	0.0127
Mean	0.0185	0.0112	0.0316	0.0206
Panel L: IPC Mexico				
HAR-RV	**0.3671**	**0.3671**	**0.2975**	**0.2975**
HAR-RV-VIX	0.0079	0.0036	0.0225	0.0143
HAR-RV-EPU	**1.0000**	**1.0000**	**1.0000**	**1.0000**
KS	0.0076	0.0034	0.0225	0.0147
Mean	0.0100	0.0073	0.0236	0.0186
Panel M: Nikkei 225				
HAR-RV	0.0033	0.0030	0.0170	0.0091
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0052	0.0056	0.0175	0.0111
KS	0.1714	0.1714	0.1486	0.1486
Mean	0.0052	0.0091	0.0175	0.0185
Panel N: S&P CNX Nifty				
HAR-RV	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-VIX	0.1863	0.1021	0.2295	0.1580
HAR-RV-EPU	**0.5217**	**0.5217**	**0.8343**	**0.8343**
KS	0.1863	0.0911	0.2137	0.1248
Mean	0.1863	0.1322	0.2302	0.2114
Panel O: S&P 500				
HAR-RV	0.0210	0.0159	0.0660	0.0413
HAR-RV-VIX	**0.9000**	**0.9000**	**0.6681**	**0.6681**
HAR-RV-EPU	0.0269	0.0198	0.0663	0.0447
KS	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Mean	0.0272	0.0299	0.0663	0.0638
Panel P: SSEC				
HAR-RV	0.0849	0.0849	0.1276	0.1276
HAR-RV-VIX	0.0097	0.0117	0.0035	0.0057
HAR-RV-EPU	**1.0000**	**1.0000**	**1.0000**	**1.0000**
KS	0.0097	0.0341	0.0035	0.0275
Mean	0.0097	0.0341	0.0035	0.0275
Panel Q: Swiss Market Index				
HAR-RV	0.0679	0.0677	0.0762	0.0880
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.1275	0.1099	0.1903	0.1431
KS	0.1275	0.1099	0.1903	0.1431
Mean	0.1275	0.1099	0.1482	0.1431
Panel R: FT Straits Times				
HAR-RV	**0.2570**	0.1591	**0.3969**	**0.2680**
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.2201	0.1309	**0.3335**	0.2247
KS	**0.2993**	**0.2993**	**0.3969**	**0.2973**
Mean	**0.2570**	0.1941	**0.3969**	**0.2973**
Panel S: Euro STOXX 50				
HAR-RV	**0.2570**	**0.1591**	**0.3969**	**0.2680**
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.2201	0.1309	**0.3335**	0.2247
KS	**0.2993**	**0.2993**	**0.3969**	**0.2973**
Mean	**0.2570**	0.1941	**0.3969**	**0.2973**

Notes: For each equity index, out-of-sample evaluation period ranges from December 1, 2019 to March 25, 2020.

5.2. *Before coronavirus crisis*

The previous forecasts of each index are obtained from rolling window method and range from December 1, 2019 to March 25, 2020. In this subsection, we further investigate the forecasting ability of VIX and EPU index before coronavirus crisis. For comparing the effect of VIX and EPU index, we set the same forecast window as the period of coronavirus crisis for each equity index.

Table 12 displays the results of MCS test, we have some interesting findings. First, we obviously find that HAR-RV-VIX model can rank the top of MCS *p*-values for 14 of 19 equity indices including AEX, All Ordinaries, BOVESPA, CAC 40, FTSE 100, DAX 30, Hang Seng, IBEX 35, KOSPI, IPC Mexico, S&P CNX Nifty, S&P 500, Swiss Market Index, Euro STOXX 50, moreover EPU index can improve the accuracy of volatility forecasting for 2 of 19 indices including SSEC and FT Straits Times, while the VIX and EPU index don not contain predictive information for

Table 12
Results of the MCS test before coronavirus.

Forecasting models	QLIKE		MSE	
	Range	SeimQ	Range	SeimQ
Panel A: AEX				
HAR-RV	0.0241	0.0207	0.0416	0.0291
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0241	0.0207	0.0416	0.0291
Panel B: All Ordinaries				
HAR-RV	0.0015	0.0011	0.0011	0.0007
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0015	0.0011	0.0011	0.0003
Panel C: BOVESPA				
HAR-RV	**0.6928**	**0.6579**	**0.9672**	**0.9586**
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	**0.7676**	**0.7676**	**0.9672**	**0.9586**
Panel D: CAC 40				
HAR-RV	0.0532	0.0462	0.0935	0.0799
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0532	0.0462	0.0935	0.0799
Panel E: FTSE MIB				
HAR-RV	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-VIX	**0.8247**	**0.8051**	**0.5331**	**0.4095**
HAR-RV-EPU	**0.9783**	**0.9783**	**0.5331**	**0.4211**
Panel F: FTSE 100				
HAR-RV	0.0175	0.0150	0.0171	0.0151
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0175	0.0150	0.0171	0.0151
Panel G: DAX 30				
HAR-RV	**0.4159**	**0.3459**	**0.4681**	**0.3611**
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	**0.4159**	**0.3459**	**0.4681**	**0.3303**
Panel H: S&P TSX				
HAR-RV	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-VIX	0.0102	0.0088	0.0172	0.0168
HAR-RV-EPU	0.1487	0.1487	0.1432	0.1432
Panel I: Hang Seng				
HAR-RV	0.0939	0.0797	0.0477	0.0415
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0939	0.0797	0.0477	0.0415
Panel J: IBEX 35				
HAR-RV	0.1697	0.1463	0.2437	0.2165
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.1697	0.1463	0.2437	0.2165
Panel K: KOSPI				
HAR-RV	**0.4555**	**0.4352**	**0.3997**	**0.3589**
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	**0.4555**	**0.4352**	**0.3997**	**0.3589**
Panel L: IPC Mexico				
HAR-RV	0.0054	0.0038	0.0083	0.0050
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0054	0.0038	0.0083	0.0050
Panel M: Nikkei 225				
HAR-RV	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-VIX	0.1077	0.2553	0.0193	0.0581
HAR-RV-EPU	0.1077	0.2553	0.0193	0.0581
Panel N: S&P CNX Nifty				
HAR-RV	0.1635	0.1635	0.1187	0.1187
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.1206	0.1344	0.0953	0.1111
Panel O: S&P 500				
HAR-RV	**0.8411**	**0.7990**	**0.3665**	**0.3451**
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	**0.8411**	**0.7990**	**0.3665**	**0.3451**
Panel P: SSEC				
HAR-RV	**0.4311**	**0.2972**	**0.3021**	**0.3109**
HAR-RV-VIX	**0.4311**	**0.3873**	**0.5627**	**0.5627**
HAR-RV-EPU	**1.0000**	**1.0000**	**1.0000**	**1.0000**

Table 12 (*continued*)

Forecasting models	QLIKE		MSE	
	Range	SeimQ	Range	SeimQ
Panel Q: Swiss Market Index				
HAR-RV	0.0023	0.0016	0.0042	0.0034
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	0.0023	0.0016	0.0042	0.0027
Panel R: FT Straits Times				
HAR-RV	**0.5591**	**0.5446**	**0.5267**	**0.4852**
HAR-RV-VIX	**0.5591**	**0.5446**	**0.5267**	**0.4852**
HAR-RV-EPU	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Panel S: Euro STOXX 50				
HAR-RV	**0.3299**	**0.2609**	0.1629	0.1340
HAR-RV-VIX	**1.0000**	**1.0000**	**1.0000**	**1.0000**
HAR-RV-EPU	**0.3299**	0.2301	0.1629	0.1103

Notes: In this table, we set the same forecast window as the period of coronavirus crisis for each equity index.

3 equity indices including FTSE MIB, S&P TSX and Nikkei 225. Second, for 9 equity indices including AEX, BOVESPA, CAC 40, DAX 30, IBEX 35, S&P 500, SSEC, Swiss Market Index and Euro STOXX 50, we find that the forecasting ability of VIX and EPU index is identical whether coronavirus crisis breaks out or not. Third, what's interesting is that the forecasting ability of EPU and VIX index has changed for 10 of 19 stock markets. More specifically, the predictive effect of VIX index is lost during the coronavirus pandemic for 7 of 19 equity indices including AORD, FTSE 100, Hang Seng, KOSPI, IPC Mexico and Nikkei 225. Moreover, for FTSE MIB, S&P TSX and Nikkei 225 index, the VIX and EPU index can not help to forecast before the coronavirus crisis, while the HAR-RV-VIX model outperforms the competing model during the coronavirus crisis.

6. Conclusion

The main purpose of our paper is to explore which predictors (VIX or EPU index) are useful to forecast volatility for 19 equity indices during coronavirus pandemic. We collect the data of realized measures from Realized Library and construct three forecasting models to forecast volatility during coronavirus crisis. There are serval crucial results that are interesting to highlight here. First, the in-sample results reveal ΔR^2 values of HAR-RV-VIX model are larger than HAR-RV-EPU model, implying that the VIX index exhibits strong explanatory ability for almost all stock markets (except SSEC) than EPU. Second, based on three popular forecast evaluation approaches, MCS test, out-of-sample R^2 and DM test, we find HAR-RV-VIX model exhibits superior forecasting performance for 12 stock markets while EPU index just can improve forecast accuracy for 5 indices, implying that VIX index is more useful for future volatility during coronavirus crisis. Third, recursive window method, alternative realized measures and sub-sample analysis are used to confirm our conclusions. Finally, VIX index still contains the strongest predictive ability by considering kitchen sink model and mean combination forecast. Even before the coronavirus crisis, we get similar conclusion that VIX index is the most predictive for most of the stock market. Possible reason can be that, as is known to all, VIX is also regarded as the "panic index", and it tends to rise before news is released (Shaikh, 2019), while the EPU is constructed from daily news, which makes VIX may contains more predictive information than EPU index. Therefore, it is maybe the potent characteristics within these two uncertainty indexes that make VIX and EPU have different forecasting performances.

And for investors and authorities of 8 equity indices (AEX, BOVESPA, CAC 40, DAX 30, IBEX 35, S&P 500, Swiss Market Index and Euro STOXX 50), VIX index is always more important, while VIX index is valuable for 4 stock markets during pandemic crisis or high volatility level, including FTSEMIB, S&P TSX, NIKKEI 225, FT Straits Times);

moreover, EPU index is consistently efficient for investors in China (SSEC) and can help to improve the accuracy for 4 stock markets including AORD, FTSE 100, Hang Seng and IPC Mexico during period of high fluctuation. Overall, our study can offer new insights into exploiting the predictive ability of VIX and EPU index for international stock market during coronavirus pandemic.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors are grateful to the editor and anonymous referees for insightful comments that significantly improved the paper. This work is supported by the Natural Science Foundation of China [71701106, 71701170, 72071162], the Humanities and Social Science Fund of the Ministry of Education [17YJC790105, 17XJCZH002].

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.irfa.2020.101596.

References

Aganin, A. (2017). Forecast comparison of volatility models on Russian stock market. *Applied Econometrics, 48*, 63–84.
Andersen, T. G., & Bollerslev, T. (1998). Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. *International Economic Review, 39*(4), 885–905.
Baker, S., Bloom, N., Davis, S. J., Kost, K., Sammon, M., & Viratyosin, T. (2020). The unprecedented stock market reaction to COVID-19. *Covid Economics: Vetted and Real-Time Papers, 1*(3).
Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics, 131*(4), 1593–1636.
Balcilar, M., Gupta, R., Kim, W. J., & Kyei, C. (2019). The role of economic policy uncertainties in predicting stock returns and their volatility for Hong Kong, Malaysia and South Korea. *International Review of Economics and Finance, 59*, 150–163.
Barndorff-Nielsen, O. E., Hansen, P. R., Lunde, A., & Shephard, N. (2008). Designing realized kernels to measure the ex-post variation of equity prices in the presence of noise. *Econometrica, 76*, 1481–1536.
Barndorff-Nielsen, O. E., Hansen, P. R., Lunde, A., & Shephard, N. (2009). Realized kernels in practice: Trades and quotes. *The Econometrics Journal, 12*, 1–32.
Barndorff-Nielsen, O. E., & Shephard, N. (2004). Power and bipower variation with stochastic volatility and jumps. *Journal of Financial Econometrics, 2*, 1–37.
Baumeister, C., & Kilian, L. (2015). Forecasting the real price of oil in a changing world: A forecast combination approach. *Journal of Business & Economic Statistics, 33*(3), 338–351.
Bekaert, G., & Hoerova, M. (2014). The VIX, the variance premium and stock market volatility. *Journal of Econometrics, 183*(2), 181–192.
Bekierman, J., & Manner, H. (2018). Forecasting realized variance measures using time-varying coefficient models. *International Journal of Forecasting, 34*(2), 276–287.
Bollerslev, T., Hood, B., Huss, J., & Pedersen, L. H. (2018). Risk everywhere: Modeling and managing volatility. *The Review of Financial Studies, 31*(7), 2729–2773.
Brogaard, J., & Detzel, A. (2015). The asset-pricing implications of government economic policy uncertainty. *Management Science, 61*(1), 3–18.
Buncic, D., & Gisler, K. I. (2016). Global equity market volatility spillovers: A broader role for the United States. *International Journal of Forecasting, 32*(4), 1317–1339.
Buncic, D., & Gisler, K. I. (2017). The role of jumps and leverage in forecasting volatility in international equity markets. *Journal of International Money and Finance, 79*, 1–19.
Byun, S. J., Frijns, B., & Roh, T. Y. (2018). A comprehensive look at the return predictability of variance risk premia. *Journal of Futures Markets, 38*(4), 425–445.
Clark, T. E., & West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics, 138*, 291–311.
Corsi, F. (2009). A simple approximate long-memory model of realized volatility. *Journal of Financial Econometrics, 7*(2), 174–196.
Cubadda, G., Guardabascio, B., & Hecq, A. (2017). A vector heterogeneous autoregressive index model for realized volatility measures. *International Journal of Forecasting, 33*(2), 337–344.
Fang, X., Wang, B., Liu, L., & Song, Y. (2018). Heterogeneous traders, the leverage effect and volatility of the Chinese P2P market. *Journal of Management Science and Engineering, 3*(1), 39–57.
Gong, X., & Lin, B. (2018). Structural breaks and volatility forecasting in the copper futures market. *Journal of Futures Markets, 38*, 290–339.
Gormsen, N. J., & Koijen, R. S. (2020). *Coronavirus: Impact on stock prices and growth expectations*. University of Chicago, Becker Friedman Institute for Economics (Working Paper, (2020−22)).
Hansen, P. R., Lunde, A., & Nason, J. M. (2011). The model confidence set. *Econometrica, 79*, 453–497.
Kim, H. Y., & Won, C. H. (2018). Forecasting the volatility of stock price index: A hybrid model integrating LSTM with multiple GARCH-type models. *Expert Systems with Applications, 103*, 25–37.
Liang, C., Wei, Y., & Zhang, Y. (2020). Is implied volatility more informative for forecasting realized volatility: An international perspective. *Journal of Forecasting*. https://doi.org/10.1002/for.2686 (Forthcoming).
Liu, J., Ma, F., & Zhang, Y. (2019). Forecasting the Chinese stock volatility across global stock markets. *Physica A: Statistical Mechanics and its Applications, 525*, 466–477.
Liu, L., & Zhang, T. (2015). Economic policy uncertainty and stock market volatility. *Finance Research Letters, 15*, 99–105.
Liu, L. Y., Patton, A. J., & Sheppard, K. (2015). Does anything beat 5-minute RV? A comparison of realized measures across multiple asset classes. *Journal of Econometrics, 187*, 293–311.
Ma, F., Liao, Y., Zhang, Y., & Cao, Y. (2019). Harnessing jump component for crude oil volatility forecasting in the presence of extreme shocks. *Journal of Empirical Finance, 52*, 40–55.
Ma, F., Wei, Y., Liu, L., & Huang, D. (2018). Forecasting realized volatility of oil futures market: A new insight. *Journal of Forecasting, 37*(4), 419–436.
Ma, F., Zhang, Y., Wahab, M. I. M., & Lai, X. (2019). The role of jumps in the agricultural futures market on forecasting stock market volatility: New evidence. *Journal of Forecasting, 38*(5), 400–414.
Mei, D., Ma, F., Liao, Y., & Wang, L. (2020). Geopolitical risk uncertainty and oil future volatility: Evidence from MIDAS models. *Energy Economics, 86*, 104624.
Neely, C. J., Rapach, D. E., Tu, J., & Zhou, G. (2014). Forecasting the equity risk premium: The role of technical indicators. *Management Science, 60*(7), 1772–1791.
Onali, E. (2020). COVID-19 and Stock Market Volatility. *Available at SSRN, 3571453*.
Patton, A. J. (2011). Volatility forecast comparison using imperfect volatility proxies. *Journal of Econometrics, 160*, 246–256.
Patton, A. J., & Ramadorai, T. (2013). On the high-frequency dynamics of hedge fund risk exposures. *The Journal of Finance, 68*(2), 597–635.
Peng, H., Chen, R., Mei, D., & Diao, X. (2018). Forecasting the realized volatility of the Chinese stock market: Do the G7 stock markets help? *Physica A: Statistical Mechanics and its Applications, 501*, 78–85.
Pu, W., Chen, Y., & Ma, F. (2016). Forecasting the realized volatility in the Chinese stock market: Further evidence. *Applied Economics, 48*(33), 3116–3130.
Qiu, Y., Zhang, X., Xie, T., & Zhao, S. (2019). Versatile HAR model for realized volatility: A least square model averaging perspective. *Journal of Management Science and Engineering, 4*(1), 55–73.
Shaikh, I. (2019). On the relationship between economic policy uncertainty and the implied volatility index. *Sustainability, 11*(6), 1628.
Vortelinos, D. I. (2017). Forecasting realized volatility: HAR against principal components combining, neural networks and GARCH. *Research in International Business and Finance, 39*, 824–839.
Wang, Y., Ma, F., Wei, Y., & Wu, C. (2016). Forecasting realized volatility in a changing world: A dynamic model averaging approach. *Journal of Banking & Finance, 64*, 136–149.
Wang, Y., Wei, Y., Wu, C., & Yin, L. (2018). Oil and the short-term predictability of stock return volatility. *Journal of Empirical Finance, 47*, 90–104.
Wei, Y., Wang, Y., & Huang, D. (2010). Forecasting crude oil market volatility: Further evidence using GARCH-class models. *Energy Economics, 32*(6), 1477–1484.
Wen, F., Gong, X., & Cai, S. (2016). Forecasting the volatility of crude oil futures using HAR-type models with structural breaks. *Energy Economics, 59*, 400–413.
Wen, F., Zhao, Y., Zhang, M., & Hu, C. (2019). Forecasting realized volatility of crude oil futures with equity market uncertainty. *Applied Economics, 51*(59), 6411–6427.
Yilmazkuday, H. (2020). Covid-19 effects on the S&P 500 index. *Available at SSRN, 3555433*.
Zhang, Y., Ma, F., & Liao, Y. (2020). *Forecasting global equity market volatilities*. Forthcoming: International Journal of Forecasting.
Zhang, Y., Ma, F., Shi, B., & Huang, D. (2018). Forecasting the prices of crude oil: An iterated combination approach. *Energy Economics, 70*, 472–483.