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Global financial stress index and long-term volatility forecast for international stock markets

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ABSTRACT

In this study, we examine the long-term predictive role of the global financial stress index (GFSI) on equity market volatility and provide a comprehensive analysis using GFSI for the realized volatilities of 21 international stock indices. By focusing on the out-of-sample analysis, we show that GFSI has strong predictive information in forecasting the long-term realized volatilities for most of these equity indices, and it performs better than the Chicago Board Options Exchange volatility index (VIX), the United States economic policy uncertainty (USEPU), global economic policy uncertainty (GEPU), and geopolitical risk (GPR). In terms of the predictive performance during the COVID-19 pandemic, we further show the significantly effective role of GFSI for the long-term realized volatilities of equity markets. In dealing with the high-level global financial stress, our study helps policymakers from many countries to prevent large market fluctuations and decrease economic damage, and facilitate market participants to form better risk-aversion investment strategies.

1. Introduction

Bauwens et al. (2012) report that stock volatility, as a representative of risk, is closely related to risk management and asset pricing. Accurately estimating and predicting volatility remains an arduous task for researchers, investors, and policy makers. Most studies measure volatility by Realized Volatility (RV) and use Heterogeneous Autoregressive-Realized Volatility (HAR-RV) types of models to predict stock market volatility (Corsi, 2009; Paye, 2012; Engle et al., 2013; Wang et al., 2018). Incorporating economic fundamentals and macroeconomic variables facilitates volatility forecasting (Paye 2012; Engle et al. 2013). The extant literature has used HAR-RV models to validate the predictive power of a large number of predictor variables, such as sentiment indices (e.g., Audrino et al., 2020), economic policy uncertainty indices (e.g., Wang et al., 2020), and the volatility index (e.g., Fernandes et al., 2014). The process of economic globalization is particularly complex, and cross-investment behavior between different countries has become a common phenomenon. Improving the prediction accuracy of volatility is still challenging for scholars.

In this study, we focus on the comprehensive role of GFSI as a predictor in forecasting equity RV for global equity markets. Financial stress is rapidly contagious through hedging transactions across markets, and it is also transmitted among submarkets in a financial

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system (Louzis & Vouldis 2012; Park & Mercado 2014). GFSI is an important international economic and financial fundamental indicator, which is designed to reflect vulnerabilities in global financial intermediation and risks in the financial system and facilitate to monitor financial market conditions. Specifically, GFSI is constructed from 23 stress indicators and covers the stress information from 5 asset classes (stocks, interest rates, credit, foreign exchange, and commodity markets) and 3 financial market pressures in different regions (risk, hedging demand, and investor risk appetite). Compared with the volatility index (e.g., VIX), the breadth and depth of the GFSI allow it to measure global pressure more accurately. In terms of modeling and forecasting asset volatility, different from some studies focusing on the oil markets and regional economies (Gkillas et al. 2020; Das et al. 2022; Pang et al. 2023),[1] we aim to provide a comprehensive analysis for using GFSI to predict international equity market volatilities (21 equity market indices). Identifying the effective prediction role of GFSI in international equity markets may help policymakers from many countries and global economic organizations in formulating their policy responses to decrease the corresponding economic damage, and help with more favorable investment decisions for market participants, especially cross-market international investors and institutions.

Besides considering GFSI to improve prediction accuracy for RVs of international equity markets, we also introduce several important global economic/financial variables that are related to asset volatility, to compare their forecasting performance with that of GFSI, including the Chicago Board Options Exchange volatility index (VIX), the United States economic policy uncertainty (USEPU), global economic policy uncertainty (GEPU), and geopolitical risk (GPR) (Bekaert & Hoerova, 2014; Brogaard & Detzel, 2015; Liu & Zhang, 2015; Chen et al., 2017; Balcilar, et al., 2019; Liang et al., 2020; Wang et al., 2020). In this study, we incorporate GFSI and these global financial-related variables into the basic HAR-RV model that contains three endogenous RV components, and conduct the predictive models of HAR-GFSI, HAR-VIX, HAR-USEPU, HAR-GEPU, and HAR-GPR, respectively. Then we forecast the long-term RV for each one among the 21 international equity market indices. We show that GFSI can accurately predict the long-term volatility of most international stock markets, and perform best among the predictors we considered.[2] Our findings also hold true during the COVID-19 pandemic.

This study contributes to the existing research in the following aspects. Since the global financial crisis in 2008, avoiding systemic risk has become a major concern for investors worldwide. Many studies have detected the role of the individual and regional financial stress indices for the financial market (Evgenidis & Tsagkanos 2017; Ronald et al. 2018; Gupta et al. 2019; Gkillas et al. 2020). In contrast to the country- or region-side financial stress indices, the GFSI reflects systemic risk and potential uncertainties across global financial markets. This study provides extensive evidence of the long-term predictive power of the GFSI for the volatility of international stock markets, rather than focusing on only the Bitcoin or oil markets (Bouri et al., 2018; Gkillas et al., 2020). Our finding enables investors to better perceive global systemic risks and make investment plans to avoid future investment risks. Moreover, for cases with high financial stress, various countries' financial supervision departments can quickly formulate risk prevention mechanisms in response to such global systemic risks. We also explore the predictive impacts of these predictors during the COVID-19 pandemic, and further show the robust forecasting performance of GFSI in international equity markets.

Theoretically, our study enriches the HAR-type models from the perspective of exploring potential predictors, that is, considering the GFSI information is helpful to predict long-term equity market volatility. And our empirical results based on global stock markets make the applicability and validity of the findings relatively wider and more robust. Second, our findings also have implications for the asset pricing research considering the GFSI. Specifically, our significant findings between the GFSI and equity market volatility seem to guide the potential relationship between the GFSI and equity market returns, if the implied "risk-return" relationship is true for the corresponding asset. Third, this study inspires research on the relationship between the GFSI and asset liquidity's volatility. A higher volatility will not be entirely negative for the market liquidity, because it may amplify asset liquidity's volatility. For some illiquid assets, the character of high liquidity's volatility is positive information for investors (Pereira & Zhang 2010), because investors can wait for a better liquidity timing to trade the assets without a high liquidity cost.

In practice, policy makers of many countries and regional and global investors can benefit from our findings by effectively using the GFSI information. When the predicted volatility of the domestic equity market is extremely high, policy makers should actively formulate corresponding policies to reduce market risks related to global financial stress information. Investors also can use the forecasting model with the GFSI to better predict the long-term volatility of the target equity market, adjust relevant asset positions in their portfolio, and reduce the systemic risk related to the GFSI.

The remainder of the study is organized as follows. Section 2 is a literature review, and Section 3 provides econometric specifications and evaluation methods. Section 4 describes the data, and the results of out-of-sample estimation analysis and robustness checks are shown in Section 5. Extended contents are provided in Section 6, and finally, Section 7 concludes the paper.

2. Literature review

Volatility forecasting is important for both academics and investors (e.g., Mittnik et al., 2015; Zhang et al., 2019), especially RV forecasting. Compared with volatilities based on the parametric GARCH models, the RV based on high-frequency data provides model-free unbiased estimates of the ex-post return variation and has the advantages of reduced noise and easier than conditional volatility (Barndorff-Nielsen & Shephard 2002; Degiannakis & Filis 2017). Recently, Bollerslev (2023), the pioneer of the GARCH model, documents that.

[1] For instance, Gkillas et al. (2020) found that GFSI can improve the forecasting performance of the oil market's RV.

[2] In terms of the short-term forecasting performance of these indicators, although the GFSI still shows a significantly predictive role for some stock markets, it underperforms the VIX.

"…research on GARCH perse has arguably long since reached diminishing returns to scale, being supplanted by analyses related to realized volatility type measures and related procedures."

In terms of modeling and predicting RV, the classical Heterogeneous Autoregressive-Realized Volatility (HAR-RV) model proposed by Corsi (2009) provides the basic structure. Although the HAR-RV model is useful and popular, it still has upper limitations in RV's modeling accuracy, especially the out-of-sample forecasting performance. To better improve the accuracy of RV forecasts, many studies extend the HAR-type models and introduced new predictive factors, such as leverage, jump, overnight-information factors, VIX, and among others (Bekaert & Hoerova, 2014; Wen et al., 2016; Yao et al., 2019; Audrino et al., 2020; Fang et al., 2020; Liang et al., 2021a). Also, some studies consider new predictive methods by introducing popular machine learning methods, such as using component gradient boosting techniques (Mittnik et al. 2015), conducting the cluster group Lasso to select relevant variables (Yao et al. 2019), and others. Improving the prediction accuracy of volatility is still challenging for scholars. In this study, based on the HAR-type model, we focus on the comprehensive role of GFSI as a predictor in forecasting equity RV for global equity markets.

Incorporating economic fundamentals facilitates long-horizon volatility forecasting (Engle et al. 2013). Financial stress index is an important fundamental indicator, which is designed to reflect vulnerabilities in financial intermediation and risks in the financial system and facilitate to monitor financial market conditions. Illing and Liu (2006) have conducted pioneering work in constructing a financial stress index. Financial stress is rapidly contagious through hedging transactions across markets, and it is also transmitted among submarkets in a financial system (Louzis & Vouldis 2012; Park & Mercado 2014). In the context of asset price volatility, we are not the first to consider GFSI information. Many studies have investigated effective impacts of GFSI on oil markets. For instance, Gkillas et al. (2020) find that global and regional measures of financial stress can improve the forecasting performance of the oil market's RV. Das et al. (2022) find the time-variant co-movement between oil implied volatility and financial stress. Additionally, Pang et al. (2023) study the region-based components of GFSI and provide evidence that the US-specific financial stress index is more useful in predicting oil volatility instead of the comprehensive GFSI itself. For the equity markets, Ronald et al. (2018) investigate the volatility relationships within the eurozone economies using multivariate GARCH model and employing the financial stress index as systemic risk metrics. They show the intensive stress transmission in banking and money markets.

Different from these studies focusing on the oil markets and regional economies, we aim to provide a comprehensive analysis for using GFSI, a global economic/financial variable, to predict international equity market volatilities (21 equity market indices). Specifically, under the basis of the HAR-RV model with three endogenous RV components, we further introduce the exogenous predictor of GFSI to construct a predictive model of HAR-GFSI.

We also introduce some important global economic/financial variables to compare their forecasting performance with that of GFSI, including VIX, EPU indices, and GPR. Many studies show the useful predictive information of VIX and EPU in predicting stock market fluctuations (Bekaert & Hoerova, 2014; Liu & Zhang, 2015; Brogaard & Detzel, 2015; Balcilar, et al., 2019). Liu & Zhang (2015) point out that when forecasting the volatility of the S&P 500 stock market, the EPU index has considerable forecasting ability. The predictive role of VIX is significant for asset volatility during the COVID-19 pandemic (Liang et al., 2020; Wang et al., 2020). In terms of GPR, Caldara & Iacoviello (2018) construct a comprehensive GPR index, showing that when GPR undergoes noneconomic changes, it typically decreases stock market returns. Liang et al. (2021b) find that GPR contains considerable information related to changes in natural gas prices in the future. Therefore, in this study, we examine the long-term prediction power of the GFSI, VIX, USEPU, GEPU, and GPR in RVs of the international stock markets.

3. Methodology

3.1. Econometric specifications

RV is defined as the sum of the squares of the intraday return, expressed as follows:

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

where $r_{t,i}$ is the i-th intraday stock market return on day t and M is the number of observations of the intraday stock market return on day t.

The HAR-RV model has become one of the most commonly used forecasting models for RV, as it can effectively consider RV characteristics. The HAR-RV model specification can be expressed as follows:

$$RV_{t+1:t+H} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \varepsilon_{t+1} \tag{2}$$

where

$$RV_{t+1:t+H} = 1/H(RV_{t+1} + RV_{t+2} + \cdots + RV_{t+H}), \tag{3}$$

$$RV_{w,t} = 1/5(RV_t + RV_{t-1} + \cdots + RV_{t-4} \tag{4}$$

$$RV_{m,t} = 1/22(RV_t + RV_{t-1} + \cdots + RV_{t-21} \tag{5}$$

$RV_{t+1:t+H}$ is the H-day-ahead RV on trading day $t+1$; RV_t, $RV_{w,t}$, and $RV_{m,t}$ represent the daily, weekly, and monthly RV, respectively; ε_{t+1} is the disturbance term. The HAR-RV model is treated as the benchmark model to evaluate the performance of the following models with exogenous variables.

For a given predictor of x, we incorporate × into the HAR-RV model to construct a HAR-X model, then examine the predictive role of × in RV. The HAR-X model is expressed below:

$$RV_{t+1:t+H} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \beta_{GFSI} x_t + \varepsilon_{t+1} \tag{6}$$

where x_t is the one predictor of $GFSI_t$, VIX_t, $USEPU_t$, $GEPU_t$, and GPR_t at day t. Therefore, we have five HAR-X models which are the HAR-GFSI, HAR-VIX, HAR-USEPU, HAR-GEPU, and HAR-GPR models.

3.2. Evaluation methods

The quality of out-of-sample prediction is critical for both researchers and market participants. The model confidence set (MCS) test is typically used to evaluate whether statistically significant differences exist in the out-of-sample performance of a proposed model, as stated by Hansen et al. (2011). The MCS test obtains the "best" model set from a large number of models and counts the probability (p) of each model entering this "best" model set. The larger the p value is, the better is the model's prediction performance. Following Ma et al. (2017), Zhang et al. (2019), and Zhang et al. (2020), we let 0.25 be the threshold. If the MCS p value is greater than 0.25, the prediction model is included in the MCS.

This method uses a specific statistic to continuously test the difference in the predictive performance of any two models in the initial model set. Accordingly, it continuously removes the "bad" models from the model set and obtains the "best" model set. This study performs this process using the range statistics given below (Audrino & Hu, 2016; Gong & Lin, 2018; Ma et al., 2019):

$$T_R = \max_{u,v \in M} \frac{\left|\overline{d}_{i,uv}\right|}{\sqrt{var\left(d_{i,uv}\right)}} \tag{7}$$

where $\overline{d}_{i,uv} = \frac{1}{n}\sum_{t=1}^{n} d_{i,uv,t}$, $d_{i,uv}$ is the difference of the losses between model u and v. Since the mean squared error (MSE) and mean absolute error (MAE) loss functions are widely used to evaluate prediction performance (Patton, 2011; Wang et al., 2016; Bekierman & Manner, 2018; Liang et al., 2020; Wang et al., 2020), this study also uses MSE and MAE to measure Eq. (8). MSE and MAE are measured as follows:

$$\text{MSE} = q^{-1} \sum_{t=m+1}^{m+q} \left(\text{RV}_t - \widehat{\text{RV}}_t\right)^2 \tag{8}$$

$$\text{MAE} = q^{-1} \sum_{t=m+1}^{m+q} \left|\text{RV}_t - \widehat{\text{RV}}_t\right| \tag{9}$$

where $\widehat{\text{RV}}_t$ represents the forecasts from a forecasting model, RV_t is the real volatility, and m and q are the in-sample and out-of-sample lengths, respectively. This study sets the initial in-sample length to 3000 observations, i.e., data from February 2, 2000, to before November 10, 2011, are used for the initial in-sample estimation; RVs since November 11, 2011, are used for the out-of-sample prediction evaluation.

We further use the out-of-sample R^2 (R^2_{OOS}) test to comprehensively compare the prediction quality of the models defined above. The R^2_{OOS} measures the differences between the mean squared forecasting error of the target and benchmark models, as follows:

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

where RV_{m+k}, $\widehat{RV}_{m+k}$, and $\widehat{RV}_{m+k,bench}$ are actual RV, predicted RV of the target model, and predicted RV of the benchmark model on the $(m+k)$-th day, respectively, and $m+q$ is the total sample size. If $R^2_{OOS} > 0$, the predictive ability of the target model is better than the benchmark model. Additionally, we introduce the MSFE adjustment statistics proposed by Clark & West (2007) to show the significance of the R^2_{OOS}. Consistent with the Diebold & Mariano (2002) and West (1996) statistics, the MSFE-adjusted statistics have a normal asymptotic distribution. If R^2_{OOS} of a target model is positive and the MSFE-adjusted statistic is significantly positive, the forecasting performance of the benchmark model is inferior to the target model.

We design the following empirical plan. First, we mainly conduct the out-of-sample analysis for the HAR-VIX, HAR-GFSI, HAR-USEPU, HAR-GEPU, and HAR-GPR models. The rolling window method is used to predict the long-term RV in one-step forecasting, and two popular evaluation methods—model confidence set (MCS) and out-of-sample R^2 (R^2_{OOS})—are used to evaluate out-of-sample prediction performance. Second, we examine the forecasting performance of these models during the COVID-19 period. Then, we check the robustness of using another rolling window size. Finally, we also provide the short-term (i.e., 1-day-ahead, 5-day-ahead, and 10-day-ahead) forecasting performance of these models to further show varying degrees of impacts of GFSI in the short- and long-term RV of equity market indices.

4. Data

Many studies use a sampling frequency of five minutes to calculate the RV because this sampling frequency demonstrated a better performance (Liu et al., 2015; Yang et al., 2015; Degiannakis, 2018; Zhang et al., 2020). We also calculate RV by this sampling frequency. The data of GFSI is obtained from the website of the Office of Financial Research (OFR).[3] GFSI is a daily market-based snapshot of stress in global financial markets, constructed from 33 financial market variables, such as yield spreads, valuation measures, and interest rates. The VIX data are from Yahoo Finance, and the data for the USEPU, GEPU, and GPR indices were obtained from the EPU website.[4] These data cover the period from February 2, 2000, to May 4, 2021.

This study focuses on the following 21 international stock indices: the AEX Index (AEX) of the Netherlands, the All Ordinaries Index (AORD) of Australia, the Bell 20 Index (BFX) of Belgium, the BVSP BOVESPA Index (BVSP) of Brazil, the Dow Jones Industrial Average Index (DJI) of the United States, the CAC 40 Index (FCHI) of France, the FTSE 100 Index (FTSE) of the United Kingdom, the DAX Index (GDAXI) of Germany, the HANG SENG Index (HSI) of Hong Kong China, the IBEX 35 Index (IBEX) Spain, the Nasdaq Composite Index (IXIC) of the United States, the KOSPI Index (KS11) of South Korea, the Karachi SE 100 Index (KSE) of Pakistan, the IPC Mexico Index (MXX) of Mexico, the Nikkei 225 Index (N225) of Japan, the NIFTY 50 Index (NSEI) of India, the Russell 2000 Index (RUT) of the United States, the S&P 500 Index (SPX) of the United States, the Shanghai Composite Index (SSEC) of China, the Swiss Stock Market Index (SSMI) of Switzerland, and the EURO STOXX 50 Index (STOXX50E) of the European Union. We chose these 21 indices because they have samples long enough to work with. Figs. 1 and 2 show the trajectories of the RV of the international stock indices and forecast indicators, respectively. The descriptive statistics of these predictive variables and RVs of global equity markets are reported in Table 1. Additionally, during the full sample, GFSI has a correlation of 85.5% with VIX, 32.9% with USEPU, −1.4% with GEPU, and −9.8% with GPR.

5. Empirical results

5.1. MCS test results

This study uses a rolling window method to generate out-of-sample volatility forecasts for international stock indices. For each day, we estimate the parameter of the prediction models using fixed-length previous samples (the rolling window size) and generate the out-of-sample forecast using the estimated parameter. This estimation and prediction process is repeated by removing the earliest data and adding the latest available data to generate the out-of-sample forecast series. In this study, the rolling window size is 3000.

The MCS p values of 22-day-ahead RV forecasts for the 21 international stock indices from the 6 forecasting models mentioned above are reported in Table 2. First, based on the MSE loss function, the HAR-RV model passes the MCS test with a p value larger than 0.25 only in the HSI, KS11, and SSEC markets. While based on the loss function of MAE, the HAR-RV model can enter the MCS only in the AEX market. These results show that the prediction performance of the HAR-RV model is unsatisfactory. Second, in most cases, the HAR-GFSI model can pass the MCS test under the loss function of MSE and MAE. Additionally, in 10 of the international stock markets (AEX, BVSP, DJI, FCHI, GDAXI, IBEX, N225, SPX, SSMI, and STOXX50E), the HAR-GFSI model passes the MCS test with a p value equal to 1.000 under both the loss function of MSE and MAE. This also illustrates the excellent predictive performance of the HAR-GFSI model. Third, in most cases, the HAR-VIX model can also pass the MCS test under the MSE loss function in most cases; in the AORD, BFX, FTSE, IXIC, KSE, MXX, and RUT markets, it passes the MCS test with p values equal to 1.000. Additionally, under the MAE loss function, the HAR-VIX model also passes the MCS test with p values equal to 1.000 in both the IXIC and RUT markets. These also show that the HAR-VIX model has a good predictive ability for some international stock indices. The HAR-USEPU model fails the MCS test under both the MSE and MAE loss functions in all stock markets. The HAR-GEPU model, under the MSE loss function, enters the MCS in 5 international stock markets; under the MAE loss function, it passes the MCS test in 14 international stock markets. Furthermore, in the NSEI and SSEC markets, the HAR-GEPU model passes the MCS test under the MSE and MAE loss functions, with p values of 1. Finally, under the MSE loss function, the HAR-GPR model passes the MCS test only for the SSEC index, whereas under the MAE loss standard, the HAR-GPR model can only pass the MCS test for the IBEX index.

Based on these results, we conclude that the HAR-GFSI and HAR-VIX models are more predictive than the HAR-RV, HAR-USEPU, HAR-GEPU, and HAR-GPR models, indicating that the GFSI and VIX contain more effective forecasting information for the price volatility of most international stock indices. Additionally, the predictive ability of the GFSI performs better than other predictors.

Table 3 shows the MCS p value of 66-day-ahead RV forecasts for the 21 international stock indices from the 6 forecasting models mentioned above. First, the evaluation results based on both the MSE and MAE loss functions show that the HAR-RV model can only predict the HSI and KSE indices' volatility, whereas the HAR-VIX and HAR-USEPU models can only predict the volatility of the HSI index. The results show that the HAR-RV, HAR-VIX, HAR-USEPU, and HAR-GPR models have poor predictive ability for international stock indices. The HAR-GFSI and HAR-GEPU models pass the MCS test in more international stock markets than the other models. The HAR-GFSI model passes the MCS test with p values equal to 1.000 in some international stock markets; under the MSE loss function, the HAR-GFSI model passes the MCS test with p values equal to 1.000 in 15 international stock indices. Similarly, the HAR-GEPU model also passes the MCS test with p values equal to 1.000 in three international stock markets (e.g., KS11, KSE, SSEC) under the MSE function; however, under the MAE function, it enters the MCS with p values equal to 1.000 in 13 out of 21 international stock markets.

[3] https://www.financialresearch.gov.

[4] https://www.policyuncertainty.com/index.html.

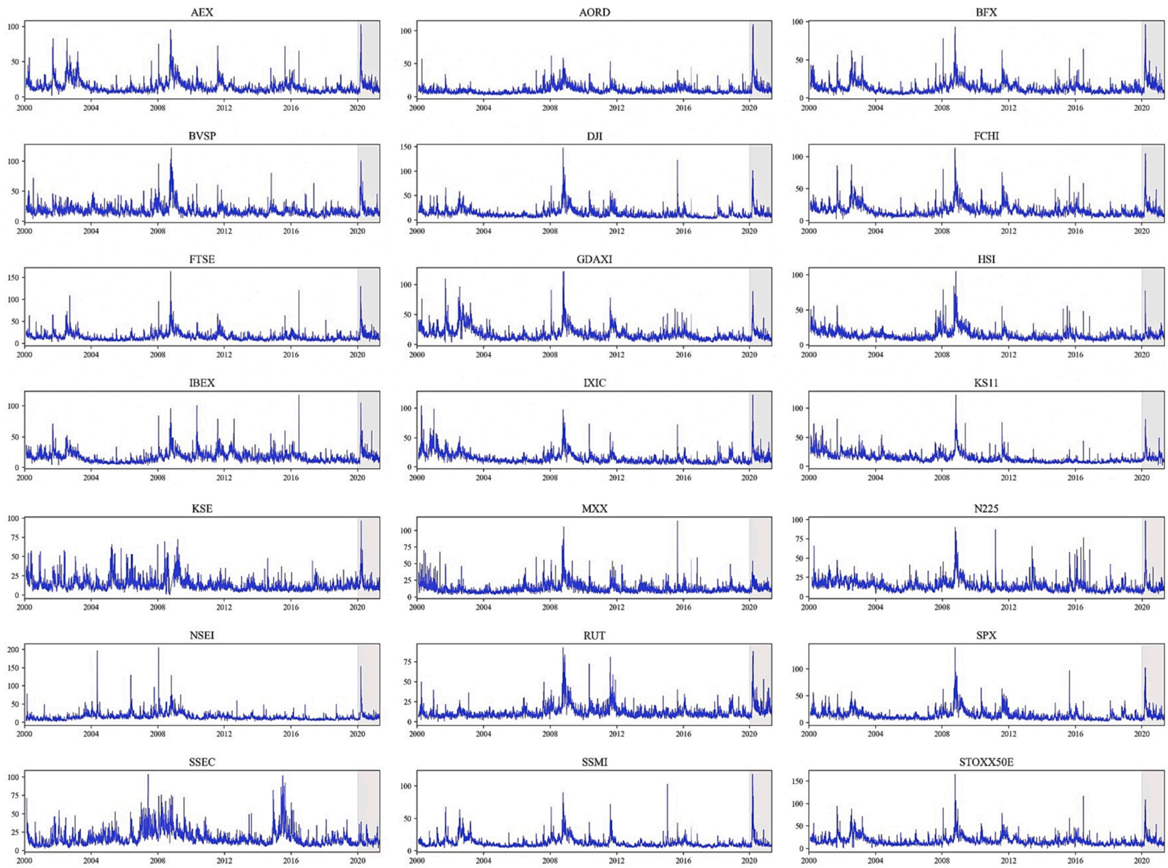

Fig. 1. RVs of International stock markets.

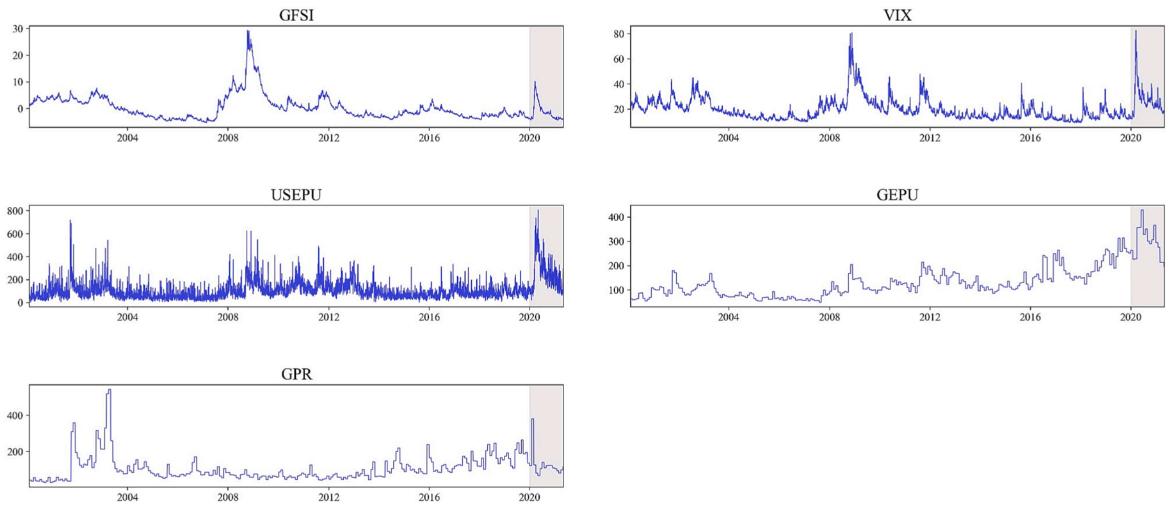

Fig. 2. The time series of predictive variables.

The HAR-GFSI model's excellent forecasting ability demonstrates the strong long-term forecasting ability of the GFSI for international stock indices.

In summary, the global financial stress indices can improve the long-term forecasting accuracy of most international equity indices, whereas the VIX and EPU (USEPU, GEPU, and GPR) index's forecasting abilities are relatively poor. Additionally, the HAR-HFSI model performs better than the HAR-RV, HAR-VIX, HAR-USEPU, HAR-GEPU, and HAR-GPR models. This evidence highlights the strong

Table 1
Descriptive statistics.

	Mean	Std. Dev.	Skewness	Kurtosis
Panel A. Predictive variables				
GFSI	0.262	4.499	2.240	7.869
VIX	19.957	8.904	2.190	7.555
USEPU	108.662	82.333	2.494	9.672
GEPU	133.896	68.789	1.447	2.154
GPR	105.563	70.935	2.685	10.708
Panel B. RVs of international stock markets				
AEX	14.442	9.203	2.842	13.327
AORD	9.656	6.388	4.454	39.013
BFX	13.224	7.585	2.909	15.707
BVSP	17.475	9.316	3.525	20.924
DJI	13.636	9.891	3.597	23.027
FCHI	15.833	9.414	2.833	14.986
FTSE	14.642	9.668	3.828	29.082
GDAXI	17.031	10.729	2.628	11.714
HSI	13.743	7.226	3.268	20.638
IBEX	16.773	8.992	2.477	13.331
IXIC	14.730	9.859	2.709	12.797
KS11	14.702	9.106	2.669	13.338
KSE	13.715	8.338	2.382	8.710
MXX	12.384	7.397	3.589	24.804
N225	14.002	7.837	2.896	16.151
NSEI	14.788	10.326	5.143	59.128
RUT	11.835	7.837	3.595	20.923
SPX	13.499	9.817	3.358	19.534
SSEC	16.941	10.634	2.300	8.414
SSMI	12.478	8.003	4.036	27.787
STOXX50E	16.879	10.717	3.218	20.072

Notes: The table provides descriptive statistics of predictive variables and equity market RVs. GFSI is the global financial stress index obtained from the Office of Financial Research (OFR). VIX is the Chicago Board Options Exchange volatility index. USEPU is the US economic policy uncertainty index. GEPU is the global economic policy uncertainty index. GPR is the geopolitical risk index. Our samples cover the period from February 2, 2000, to May 4, 2021.

Table 2
MCS test results of 22-day-ahead RV forecasts.

	HAR-RV		HAR-GFSI		HAR-VIX		HAR-USEPU		HAR-GEPU		HAR-GPR	
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
AEX	0.128	**0.387**	**1.000**	**1.000**	**0.448**	**0.387**	0.000	0.000	0.000	**0.387**	0.000	0.046
AORD	0.007	0.003	**0.945**	**1.000**	**1.000**	**0.476**	0.000	0.000	0.000	**0.476**	0.000	0.001
BFX	0.001	0.000	**0.362**	**1.000**	**1.000**	**0.722**	0.001	0.000	0.001	0.000	0.001	0.000
BVSP	0.004	0.000	**1.000**	**1.000**	**0.347**	0.025	0.002	0.000	0.004	0.025	0.002	0.000
DJI	0.017	0.004	**1.000**	**1.000**	**0.577**	**0.325**	0.001	0.000	0.017	**0.364**	0.001	0.004
FCHI	0.074	0.083	**1.000**	**1.000**	**0.309**	0.015	0.002	0.000	0.002	0.155	0.002	0.155
FTSE	0.001	0.000	**0.386**	**1.000**	**1.000**	**0.497**	0.000	0.000	0.000	0.036	0.000	0.000
GDAXI	0.058	0.151	**1.000**	**1.000**	0.137	0.002	0.001	0.000	0.008	**0.653**	0.008	0.174
HSI	**0.721**	0.146	**1.000**	**0.729**	**0.721**	**0.637**	0.022	0.001	**0.707**	**1.000**	0.177	0.052
IBEX	0.122	0.012	**1.000**	**1.000**	0.243	0.000	0.005	0.000	0.023	**0.325**	0.005	**0.996**
IXIC	0.000	0.000	**0.400**	**0.307**	**1.000**	**1.000**	0.000	0.000	0.000	**0.307**	0.000	0.000
KS11	**1.000**	0.034	0.047	0.000	**0.728**	0.000	0.014	0.000	**0.730**	**1.000**	0.141	0.046
KSE	0.028	0.000	**0.690**	0.049	**1.000**	0.007	0.000	0.000	**0.690**	**1.000**	0.000	0.000
MXX	0.005	0.000	**0.649**	**1.000**	**1.000**	**0.529**	0.001	0.000	0.005	**0.529**	0.001	0.001
N225	0.040	0.000	**1.000**	**1.000**	**0.314**	0.001	0.002	0.000	0.041	**0.315**	0.002	0.000
NSEI	0.042	0.000	**0.873**	0.000	**0.430**	0.000	0.034	0.000	**1.000**	**1.000**	0.010	0.000
RUT	0.001	0.000	0.149	**0.871**	**1.000**	**1.000**	0.001	0.000	0.001	0.000	0.001	0.000
SPX	0.118	0.017	**1.000**	**1.000**	**0.361**	**0.305**	0.004	0.000	0.040	**0.657**	0.004	0.029
SSEC	**0.778**	0.000	0.208	0.000	0.003	0.000	0.208	0.000	**1.000**	**1.000**	**0.265**	0.000
SSMI	0.012	0.001	**1.000**	**1.000**	**0.384**	0.001	0.006	0.000	0.006	0.011	0.006	0.001
STOXX50E	0.042	0.002	**1.000**	**1.000**	**0.286**	0.002	0.000	0.000	0.001	0.008	0.005	0.011

Notes: The table provides the MCS test for 22-day-ahead RV forecasts. The threshold of the MCS test is 0.25. The numbers greater than the threshold are displayed in bold. The maximum MCS p value is indicated in bold and underlined. The data cover the period from February 2, 2000, to May 4, 2021. The rolling window length is 3000 for out-of-sample forecasting evaluation.

Table 3
MCS test results of 66-day-ahead RV forecasts.

	HAR-RV		HAR-GFSI		HAR-VIX		HAR-USEPU		HAR-GEPU		HAR-GPR	
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
AEX	0.187	0.000	**1.000**	0.227	0.145	0.000	0.187	0.000	0.079	**1.000**	0.079	0.000
AORD	0.076	0.001	**1.000**	**1.000**	0.010	0.000	**0.569**	0.003	0.000	0.000	0.003	0.000
BFX	0.000	0.000	**0.763**	**1.000**	**1.000**	0.050	0.000	0.000	0.000	0.040	0.000	0.038
BVSP	0.001	0.000	**1.000**	**1.000**	0.005	0.000	0.001	0.000	0.001	**0.560**	0.000	0.000
DJI	0.000	0.000	**1.000**	0.187	**0.522**	0.000	0.000	0.000	0.000	**1.000**	0.000	0.000
FCHI	0.088	0.000	**1.000**	0.006	0.088	0.000	0.000	0.000	0.029	**1.000**	0.000	0.000
FTSE	0.004	0.015	**0.784**	**1.000**	**1.000**	0.024	0.004	0.000	0.004	**0.541**	0.004	0.015
GDAXI	**0.588**	0.000	**1.000**	0.000	0.000	0.000	0.000	0.000	**0.588**	**1.000**	0.000	0.000
HSI	**1.000**	**0.405**	**0.354**	**0.405**	**0.354**	**0.380**	**0.354**	**0.405**	0.000	**1.000**	0.000	0.000
IBEX	0.187	0.000	**1.000**	0.000	0.007	0.000	0.000	0.000	0.000	0.088	0.000	**1.000**
IXIC	0.000	0.000	**1.000**	0.008	**0.664**	0.001	0.000	0.000	0.000	**1.000**	0.000	0.000
KS11	**0.736**	0.000	0.000	0.000	0.001	0.000	0.001	0.000	**1.000**	**1.000**	0.137	0.000
KSE	**0.745**	**0.308**	0.149	**0.308**	0.048	0.101	0.000	0.000	**1.000**	**1.000**	0.149	0.162
MXX	0.001	0.000	**1.000**	**1.000**	0.014	0.000	0.001	0.000	0.000	0.024	0.000	0.000
N225	0.005	0.000	**1.000**	0.001	0.008	0.000	0.003	0.000	0.109	**1.000**	0.001	0.000
NSEI	0.063	0.000	**1.000**	0.000	0.067	0.000	0.005	0.000	**0.786**	**1.000**	0.017	0.000
RUT	0.000	0.000	**1.000**	**1.000**	**0.320**	0.020	0.000	0.000	0.000	**0.450**	0.000	0.001
SPX	0.025	0.000	**1.000**	**0.324**	0.172	0.000	0.000	0.000	0.000	**1.000**	0.000	0.000
SSEC	**0.251**	0.000	**0.251**	0.000	0.000	0.000	**0.251**	0.000	**1.000**	**1.000**	0.000	0.000
SSMI	0.019	0.000	**1.000**	**1.000**	0.065	0.000	0.065	0.000	0.004	0.170	0.004	0.000
STOXX50E	0.059	0.001	**1.000**	0.075	0.056	0.000	0.000	0.000	0.028	**1.000**	0.035	0.023

Notes: The table provides the MCS test for 66-day-ahead RV forecasts. The threshold of the MCS test is 0.25. The numbers greater than the threshold are displayed in bold. The maximum MCS *p* value is indicated in bold and underlined. The data cover the period from February 2, 2000, to May 4, 2021. The rolling window length is 3000 for out-of-sample forecasting evaluation.

performance of the HAR-GFSI model, which can significantly improve the accuracy of long-term volatility predictions for international stock indices.

5.2. Out-of-sample R^2 results

Table 4 shows the out-of-sample R^2 results of 22-day-ahead RV forecasts of each prediction model. First, the average out-of-sample R^2 values of the forecasting models (e.g., HAR-GFSI, HAR-VIX, HAR-USEPU, HAR-GEPU, and HAR-GPR models) are 3.863%, 3.257%,

Table 4
Out-of-sample R^2 results of 22-day-ahead RV forecasts.

	HAR-GFSI	HAR-VIX	HAR-USEPU	HAR-GEPU	HAR-GPR
AEX	6.722 ***	2.657 ***	−3.977	−3.158	−4.533
AORD	4.262 ***	4.472 ***	−0.845	−2.038	−4.567
BFX	2.679 ***	6.062 ***	−2.425	−5.132	−5.304
BVSP	6.621 ***	3.405 ***	−3.032	−0.529 ***	−1.894
DJI	5.978 ***	3.704 ***	−4.493	−1.936	−4.897
FCHI	7.613 ***	3.476 ***	−5.649	−3.244 **	−5.546
FTSE	2.425 ***	7.245 ***	−5.569	−2.775 ***	−5.059
GDAXI	6.607 ***	−0.795 ***	−9.579	−1.885 ***	−4.721
HSI	1.891 ***	−1.286 **	−6.103	−1.464 ***	−1.547
IBEX	2.053 ***	0.576 **	−3.776	−5.181 ***	−6.975
IXIC	2.026 ***	5.430 ***	−3.462	−1.680	−4.074
KS11	−13.492	−4.215 *	−13.345	−0.389 ***	−3.150
KSE	2.161 ***	5.895 ***	−3.557	3.284 ***	−3.250
MXX	4.256 ***	5.677 ***	−2.761	−0.510 ***	−3.511
N225	5.283 ***	2.288 ***	−4.663	0.784 ***	−3.516
NSEI	4.710 ***	1.514 **	−2.957	5.149 ***	−6.701
RUT	5.493 ***	11.452 ***	−4.489	−2.140	−5.056
SPX	7.150 ***	2.775 ***	−4.365	−1.905 **	−5.124
SSEC	−0.967	−0.891	−0.548	0.494 ***	−0.397
SSMI	9.608 ***	5.363 ***	−3.395	−1.292 ***	−4.789
STOXX50E	8.054 ***	3.583 ***	−7.756	−4.348 *	−6.012

Notes: The table provides the R^2_{OOS} in percentage for the 22-day-ahead RV forecasts. The corresponding significance is evaluated by the MSFE-adjusted statistic. The benchmark model used for calculating out-of-sample R^2 value in this paper is the HAR-RV model. The data cover the period from February 2, 2000, to May 4, 2021. The rolling window length is 3000 for out-of-sample forecasting evaluation. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

−4.607%, −1.424%, and − 4.315%, respectively. The results show that the HAR-GFSI and HAR-VIX models have significant forecasting power for international stock market indices, whereas the GFSI has stronger predictive power than VIX for international stock indices. Additionally, the out-of-sample R^2 value of HAR-USEPU and HAR-GPR models are negative in all international stock markets. The HAR-GEPU model has significantly positive R^2_{OOS} values for the following 3 of the 21 international stock markets: KSE, N225, and NSEI. The HAR-GFSI model generates significantly positive R^2_{OOS} values for 19 international stock indices. The R^2_{OOS} value for the KS11 index is negative at − 13.492%, and the maximum R^2_{OOS} value generated in the SSMI market is 9.608%. The HAR-VIX model has significantly positive R^2_{OOS} values for 17 international stock indices. In 13 of the 21 international stock markets, the HAR-GFSI model generates the largest R^2_{OOS} value. From these results, the GFSI and VIX have strong predictive power whereas the EPU index has a relatively poor predictive effect on international stock market volatility.

Table 5 shows the out-of-sample R^2 results of 66-day-ahead RV forecasts of each prediction model. First, the average out-of-sample R^2 values of the HAR-GFSI, HAR-VIX, HAR-USEPU, HAR-GEPU, and HAR-GPR models are 4.097%, −0.352%, −1.702%, −4.407%, and − 4.092%, respectively, showing that the HAR-GFSI model has the strongest out-of-sample forecasting power for the volatilities of international stock markets. Second, the out-of-sample R^2 values of the HAR-VIX model are significantly positive in the BFX, BVSP, DJI, FTSE, IXIC, MXX, RUT, SPX, and SSMI markets. Importantly, the out-of-sample R^2 values of the HAR-USEPU, HAR-GEPU, and HAR-GPR models are not significant or negative in most international stock markets. Finally, in 17 international stock markets, the out-of-sample R^2 values of the HAR-GFSI model are significantly positive. The R^2_{OOS} for the FTSE index is the minimum (0.515%), whereas the R^2_{OOS} for the BVSP index is the largest (14.984%). In 15 of the 21 international stock markets, the R^2_{OOS} value of the HAR-GFSI model is larger than that of the other competitive models.

Combining the evidence from the out-of-sample R^2 test of 22-day-ahead and 66-day-ahead forecasts, we can conclude that the GFSI has better forecasting ability than the other predictors.

5.3. Out-of-sample forecasting performance during the COVID-19 pandemic

The COVID-19 pandemic has seriously impacted the global economy, and researchers have gradually paid attention to the pandemic's effect on the stock market (Baker et al., 2020; Gormsen & Koijen, 2020). We further discuss the forecasting ability of the GFSI, VIX, and some classic EPU indices in predicting the volatility of the international stock market during the COVID-19 pandemic.

Table 6 reports the MCS test results of 22-day-ahead RV forecasts for the 21 international stock indices from the 6 forecasting models mentioned above during the COVID-19 pandemic. The larger MCS p values indicate better prediction performance. First, the HAR-RV model can pass the MCS test in KS11, KSE, and MXX markets under both the MSE and MAE loss functions. Second, the HAR-VIX model passes the MCS test with a p value of 1.000 only in the BFT, FTSE, and RUT markets under both the MSE and MAE loss functions. Moreover, in 15 of the 21 international stock markets, the HAR-GFSI model successfully entered the MCS under both the MSE and MAE loss functions with p values larger than 0.25. In contrast, the HAR-USEPU, HAR-GEPU, and HAR-GPR models failed the

Table 5
Out-of-sample R^2 results of 66-day-ahead RV forecasts.

	HAR-GFSI	HAR-VIX	HAR-USEPU	HAR-GEPU	HAR-GPR
AEX	8.507 ***	−0.785 ***	0.745	−3.753 ***	−3.364
AORD	1.826 ***	−2.354	0.688	−11.281	−3.541
BFX	1.313 ***	2.103 ***	−0.015	−14.252	−5.149
BVSP	14.984 ***	2.445 ***	0.124 ***	0.092 ***	−3.498
DJI	5.323 ***	2.391 ***	−0.625	−6.145 ***	−3.960
FCHI	7.203 ***	−0.911 ***	−2.194	−4.085 ***	−4.085
FTSE	0.515 ***	1.810 ***	−0.104	−6.765 ***	−4.492
GDAXI	3.495 ***	−6.112	−3.653	0.282 ***	−3.821
HSI	−1.978 ***	−2.320	−1.036	−11.625 ***	−4.467
IBEX	1.928 ***	−1.878	−2.552	−16.509 ***	−5.776
IXIC	4.958 ***	2.746 ***	0.468 ***	−5.449 ***	−3.534
KS11	–23.075	−6.808	−7.380	1.181 ***	−3.556
KSE	−5.434 *	−6.817	−7.353	0.585 ***	−2.958 *
MXX	10.135 ***	1.937 ***	0.497 ***	−6.301 ***	−4.495
N225	7.586 ***	−0.015 ***	−1.842	2.316 ***	−3.475
NSEI	8.978 ***	−0.403	−4.902	8.082 ***	−1.064 *
RUT	10.326 ***	6.953 ***	−2.244	−6.507 ***	−5.430
SPX	9.535 ***	1.992 ***	−0.884	−4.627 ***	−3.445
SSEC	−0.487	−1.072	0.126	3.719 ***	−8.638
SSMI	13.252 ***	1.233 ***	0.570 ***	−5.842 ***	−3.180
STOXX50E	7.154 ***	−1.521 ***	−4.169	−5.108 ***	−4.003

Notes: The table provides the R^2_{OOS} in percentage for the 66-day-ahead RV forecasts. The corresponding significance is evaluated by the MSFE-adjusted statistic. The benchmark model used for calculating out-of-sample R^2 value in this paper is the HAR-RV model. The data cover the period from February 2, 2000, to May 4, 2021. The rolling window length is 3000 for out-of-sample forecasting evaluation. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 6
MCS test results of 22-day-ahead RV forecasts during the COVID-19 pandemic.

	HAR-RV		HAR-GFSI		HAR-VIX		HAR-USEPU		HAR-GEPU		HAR-GPR	
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
AEX	0.071	0.135	**1.000**	**1.000**	**0.543**	0.135	0.011	0.001	0.011	0.000	0.011	0.000
AORD	0.005	0.011	**0.858**	**1.000**	**1.000**	**0.591**	0.002	0.008	0.001	0.000	0.002	0.000
BFX	0.004	0.043	0.004	**0.352**	**1.000**	**1.000**	0.004	0.043	0.003	0.000	0.003	0.001
BVSP	**0.411**	0.090	**1.000**	**1.000**	**0.594**	0.094	0.022	0.007	0.022	0.013	0.011	0.007
DJI	**0.431**	0.021	**1.000**	**1.000**	**0.630**	0.021	0.014	0.003	0.014	0.003	0.014	0.000
FCHI	0.060	0.015	**1.000**	**1.000**	**0.573**	0.015	0.005	0.015	0.004	0.000	0.004	0.000
FTSE	0.038	0.191	0.038	**0.784**	**1.000**	**1.000**	0.013	0.006	0.013	0.000	0.008	0.000
GDAXI	0.051	0.001	**1.000**	**1.000**	**0.280**	0.000	0.001	0.000	0.001	0.000	0.001	0.000
HSI	0.054	0.001	**1.000**	**1.000**	**0.282**	0.000	0.001	0.000	0.001	0.000	0.001	0.000
IBEX	0.002	0.005	**1.000**	**1.000**	**0.779**	0.043	0.002	0.005	0.002	0.003	0.002	0.001
IXIC	0.002	0.010	**0.622**	**1.000**	**1.000**	**0.919**	0.002	0.001	0.000	0.000	0.000	0.000
KS11	**0.848**	**1.000**	0.052	0.016	**1.000**	0.016	0.043	0.016	0.095	0.108	0.052	0.016
KSE	**0.525**	**0.446**	**0.525**	**1.000**	**1.000**	0.035	0.026	0.010	0.026	0.446	0.026	0.035
MXX	**1.000**	**1.000**	0.027	0.019	**0.852**	0.019	0.065	0.019	0.027	0.071	0.027	0.019
N225	0.173	0.007	**1.000**	**1.000**	0.173	0.000	0.001	0.000	0.001	0.078	0.001	0.000
NSEI	0.065	0.043	**1.000**	**1.000**	**0.408**	0.012	0.019	0.012	0.019	0.012	0.013	0.012
RUT	0.004	0.030	0.101	**0.606**	**1.000**	**1.000**	0.004	0.008	0.004	0.008	0.004	0.000
SPX	**0.502**	0.012	**1.000**	**1.000**	**0.502**	0.005	0.014	0.005	0.014	0.005	0.014	0.001
SSEC	**1.000**	0.130	0.018	0.003	0.014	0.004	0.203	1.000	0.014	0.130	0.095	0.033
SSMI	0.098	0.019	**1.000**	**1.000**	**0.555**	0.003	0.009	0.013	0.009	0.008	0.005	0.000
STOXX50E	0.100	0.009	**1.000**	**1.000**	**0.664**	0.009	0.008	0.000	0.002	0.000	0.002	0.000

Notes: The table provides the 22-day-ahead predicted performance during the COVID-19 pandemic (i.e., from 1 January 2020 to the end of the sample) based on the MCS test. The threshold of the MCS test is 0.25. The numbers greater than the threshold are displayed in bold. The maximum MCS *p* value is indicated in bold and underlined. The total sample covers the period from February 2, 2000, to May 4, 2021. The rolling window length is 3000 for out-of-sample forecasting evaluation.

MCS test in 21 international stock markets. Based on these results, we show that the GFSI has the strongest predictive ability during the COVID-19 pandemic.

Table 7 shows the out-of-sample R^2 values of the 22-day-ahead RV forecasts of each prediction model during the COVID-19 pandemic. The average out-of-sample R^2 values of the HAR-GFSI, HAR-VIX, HAR-USEPU, HAR-GEPU, and HAR-GPR models are 2.933%, 3.493%, −5.946%, −5.714%, and − 8.414%, respectively. Taken individually, the HAR-GFSI model yields significantly positive out-of-sample R^2 values in 16 international stock markets, ranging from 1.992% to 11.689%. The HAR-VIX model generates

Table 7
Out-of-sample R^2 results of 22-day-ahead RV forecasts during the COVID-19 pandemic.

	HAR-GFSI	HAR-VIX	HAR-USEPU	HAR-GEPU	HAR-GPR
AEX	8.679 ***	3.897 ***	−3.639	−4.476	−6.953
AORD	4.541 ***	5.189 ***	−0.658	−2.726	−5.455
BFX	−1.667 *	5.730 ***	−2.054	−5.776	−7.806
BVSP	4.245 ***	1.544 **	−3.653	−3.413	−2.811
DJI	5.344 ***	2.215 ***	−5.551	−4.103	−8.355
FCHI	9.323 ***	5.781 ***	−5.466	−4.603	−10.121
FTSE	−6.241 **	6.004 ***	−5.180	−5.273	−7.782
GDAXI	10.153 ***	1.502 *	−9.625	−3.456	−9.123
HSI	10.153 ***	1.502 *	−9.625	−3.456	−9.123
IBEX	4.401 ***	3.697 ***	−4.458	−11.324	−18.911
IXIC	2.461 **	5.401 ***	−4.500	−4.146	−6.092
KS11	−12.361	1.874 **	−17.260	−2.669	−6.230
KSE	1.992 ***	10.644 ***	−6.490	−3.006	−7.256
MXX	−16.168	−1.863 ***	−6.932	−12.603	−16.510
N225	5.917 ***	−3.503	−10.495	−3.760	−10.064
NSEI	11.689 ***	6.170 ***	−5.297	−2.214	−7.290
RUT	3.239 ***	12.676 ***	−4.801	−3.239	−6.937
SPX	7.263 ***	0.969 ***	−5.379	−3.950	−8.743
SSEC	−8.642	−6.820	−3.456	−28.146	−3.434
SSMI	8.228 ***	4.512 ***	−3.704	−2.497	−6.339
STOXX50E	9.045 ***	6.223 ***	−6.649	−5.168	−11.365

Notes: This table reports the R^2_{OOS} in percentage for the 22-day-ahead RV forecasts during the COVID-19 pandemic (i.e., from 1 January 2020 to the end of the sample). The corresponding significance of R^2_{OOS} is evaluated by the MSFE-adjusted statistic. The benchmark model used for calculating out-of-sample R^2 value in this paper is the HAR-RV model. The total sample covers the period from February 2, 2000, to May 4, 2021. The rolling window length is 3000 for out-of-sample forecasting evaluation. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

significantly positive R^2_{OOS} values in 18 of 21 international stock markets. Comparing these two models, the out-of-sample R^2 value of the HAR-GFSI model is higher than that of the HAR-VIX model in the following 12 international stock markets: AEX, BVSP, DJI, FCHI, GDAXI, HSI, IBEX, N225, NSEI, SPX, SSMI, and STOXX50E. The HAR-VIX model generates relatively large R^2_{OOS} values for the KSE and RUT indices, which are 10.644% and 12.676%, respectively. These results indicate that among all the considered models, the HAR-GFSI and HAR-VIX models have better predictive ability for international stock market volatility during the COVID-19 pandemic.

Tables 8 and 9 show the MCS p values of the 66-day-ahead RV predictions of the 21 international stock indices and the out-of-sample R^2 test results of each prediction model, respectively. We find that under both the MSE and MAE loss functions, the HAR-GFSI model enters the MCS with a p value equal to 1.000 in 10 international stock indices (AEX, AORD, BVSP, FCHI, GDAXI, IBEX, NSEI, SPX, SSMI, and STOXX50EZ). Concurrently, the HAR-GFSI model's out-of-sample R^2 result is also the highest. The out-of-sample R^2 values of the HAR-GFSI model are significantly positive in 14 of the 21 international stock markets, ranging from 2.253% to 19.504%.

In general, during the COVID-19 pandemic, GFSI's long-term forecasting ability is better. During the COVID-19 pandemic, investors and the market are more sensitive to the financial stress index; therefore, the GFSI's forecasting ability is higher than VIX, USEPU, GEPU, and GPR.

5.4. Robustness check

In practical applications, arbitrarily choosing different training window sizes may lead to markedly different out-of-sample results (Rossi & Inoue, 2012; Inoue et al., 2017). Therefore, the robustness check in this subsection is conducted using an alternative rolling window size of 3500.

Table 10 shows the out-of-sample R^2 results of the 5 extended models for 22-day-ahead forecasts when using an alternative predicting window. First, the average out-of-sample R^2 values of the five forecasting models (e.g., HAR-GFSI, HAR-VIX, HAR-USEPU, HAR-GEPU, and HAR-GPR models) are 4.200%, 3.500%, −3.438%, −1.424%, and − 4.780%, respectively, indicating that the HAR-GFSI and HSR-VIX models have stronger predictive ability for international stock indices than the other models. Second, the HAR-GFSI model has significantly positive R^2_{OOS} values for 19 of 21 international stock indices, ranging from 0.466% to 10.297%. Additionally, the R^2_{OOS} values of the HAR-VIX model are significantly positive for 17 international stock indices and the R^2_{OOS} values of 13 stock indices are lower than those of the HAR-GFSI model. We find that the GFSI's predictive ability is better than that of the VIX when using an alternative predicting window. In contrast, the prediction ability of the HAR-USEPU, HAR-GEPU, and HAR-GPR models for 21 international stock indices is inferior to that of the HAR-GFSI and HAR-VIX models.

Table 11 shows the out-of-sample R^2 results for the 66-day-ahead forecasts. The result is notably different than the results in section 5.2. First, the average out-of-sample R^2 values are 5.208%, 0.015%, −0.907%, −5.533%, and − 5.375%, indicating that the HAR-GFSI model has the strongest predictive ability for the volatility of the international stock market. The out-of-sample R^2 values of the HAR-VIX model are also significantly positive for 10 international stock indices. Additionally, the out-of-sample R^2 values of the HAR-USEPU and HAR-GEPU models are only significantly positive for a few international stock indices, whereas the GPR index has no predictive power for the volatility of 21 international stock indices.

In general, GFSI has the strongest predictive ability for the long-term volatility of international stock markets, and the robustness test confirmed this result.

6. Extensions

The empirical results above show that the GFSI outperforms other predictors in terms of long-term stock market volatility forecasts. In this section, we further evaluate the predictive ability of the predictors in terms of 1-day-ahead, 5-day-ahead, and 22-day-ahead volatility forecasts. Tables 12, 13, and 14 show the results of the out-of-sample R^2 test, indicating that the HAR-GFSI and HAR-VIX models have good predictions for the volatility of international stock indices. The average out-of-sample R^2 values of the HAR-GFSI model for 1-day-ahead, 5-day-ahead, and 22-day-ahead volatility forecasts are 0.521%, 1.534%, and 2.463%, respectively, indicating that the GFSI has a good predictive ability for short-term international stock indices. Additionally, the HAR-VIX model yields significantly positive out-of-sample R^2 value for all international stock indices, except for SSEC, in all three forecast horizons. Calculations show that the average out-of-sample R^2 values of the HAR-VIX model for 1-day-ahead, 5-day-ahead, and 22-day-ahead volatility forecasts are 5.107%, 7.421%, and 6.146%, respectively. We find that the short-term forecasting ability of the VIX is excellent. The out-of-sample R^2 values for the HAR-USEPU, HAR-GEPU, and HAR-GPR models are significantly inferior to the other two models.

In short, combining the short- and long-term forecasting results, we show that USEPU, GEPU, and GPR has less effective information in forecasting global equity market volatilities. The HAR-GFSI model also shows significant forecasting performance in the short-term RVs of equity markets, but underperforms the HAR-VIX model, which is the best model among five HAR-type models with exogenous variables. Our results comprehensively demonstrate varying degrees of impacts of GFSI in the short- and long-term RV of equity market indices. The less short-term and excellent long-term forecasting performance of GFSI in RVs of global equity markets is intuitive to the snowball role of financial stress information on the economic/financial system.

Table 8
MCS test results of 66-day-ahead RV forecasts during the COVID-19 pandemic.

	HAR-RV		HAR-GFSI		HAR-VIX		HAR-USEPU		HAR-GEPU		HAR-GPR	
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
AEX	0.144	0.031	**1.000**	**1.000**	0.144	0.031	0.144	0.031	0.000	0.001	0.029	0.031
AORD	0.067	0.040	**1.000**	**1.000**	0.030	0.002	0.588	0.040	0.000	0.000	0.002	0.000
BFX	0.008	0.227	0.008	0.084	**1.000**	**1.000**	0.008	0.227	0.001	0.005	0.008	0.084
BVSP	0.084	0.000	**1.000**	**1.000**	0.084	0.000	0.084	0.001	0.000	0.000	0.000	0.000
DJI	0.000	0.000	**1.000**	0.184	**0.512**	0.000	0.000	0.000	0.000	1.000	0.000	0.000
FCHI	0.042	0.010	**1.000**	**1.000**	0.066	0.010	0.000	0.000	0.000	0.000	0.000	0.002
FTSE	0.199	0.120	0.199	0.023	**1.000**	**1.000**	0.199	0.023	0.055	0.023	0.055	0.023
GDAXI	0.031	0.001	**1.000**	**1.000**	0.031	0.000	0.000	0.000	0.000	0.000	0.000	0.000
HSI	**1.000**	0.139	0.048	**1.000**	0.048	0.068	0.147	0.139	0.000	0.003	0.048	0.052
IBEX	0.002	0.007	**1.000**	**1.000**	0.087	0.041	0.000	0.000	0.000	0.000	0.000	0.007
IXIC	0.001	0.000	**1.000**	**0.621**	**0.840**	**1.000**	0.000	0.000	0.000	0.000	0.000	0.000
KS11	**1.000**	**1.000**	0.007	0.014	0.046	**0.279**	0.007	0.014	0.007	0.014	0.027	0.040
KSE	**1.000**	**1.000**	0.000	**0.671**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.008
MXX	**1.000**	**0.717**	0.001	**1.000**	0.001	0.002	0.001	0.002	0.000	0.000	0.001	0.002
N225	0.028	0.007	**1.000**	0.127	0.001	0.000	0.001	0.003	0.001	1.000	0.001	0.000
NSEI	0.031	0.000	**1.000**	**1.000**	0.031	0.000	0.000	0.000	0.000	0.000	0.000	0.000
RUT	0.000	0.004	**0.297**	**0.348**	**1.000**	**1.000**	0.000	0.000	0.000	0.003	0.000	0.003
SPX	**0.302**	0.058	**1.000**	**1.000**	**0.302**	0.004	0.000	0.004	0.000	0.004	0.000	0.004
SSEC	0.002	0.014	0.001	0.081	0.001	0.014	1.000	1.000	0.001	0.574	0.001	0.001
SSMI	0.061	0.005	**1.000**	**1.000**	0.061	0.001	0.066	0.005	0.002	0.001	0.015	0.001
STOXX50E	0.071	0.012	**1.000**	**1.000**	0.135	0.012	0.000	0.000	0.000	0.000	0.000	0.001

Notes: The table provides the 66-day-ahead predicted performance during the COVID-19 pandemic (i.e., from 1 January 2020 to the end of the sample) based on the MCS test. The threshold of the MCS test is 0.25. The numbers greater than the threshold are displayed in bold. The maximum MCS *p* value is indicated in bold and underlined. The total sample covers the period from February 2, 2000, to May 4, 2021. The rolling window length is 3000 for out-of-sample forecasting evaluation.

Table 9
Out-of-sample R^2 results of 66-day-ahead RV forecasts during the COVID-19 pandemic.

	HAR-GFSI	HAR-VIX	HAR-USEPU	HAR-GEPU	HAR-GPR
AEX	19.504 ***	0.150 ***	1.149 ***	−11.181	−6.113
AORD	2.253 **	−2.199	0.864 ***	−10.757	−3.961
BFX	−6.314 **	1.647 ***	0.137	−18.681	−8.301
BVSP	12.757 ***	−1.272	0.391 ***	−13.133	−6.206
DJI	5.323 ***	2.391 ***	−0.625	−6.145 ***	−3.960
FCHI	14.964 ***	2.129 ***	−2.451	−16.955	−12.034
FTSE	−10.225 ***	1.128 ***	0.233 **	−14.278	−8.104
GDAXI	16.262 ***	−2.040	−4.224	−17.270	−12.884
HSI	−12.106 **	−11.678	−4.223	−70.310	−8.441
IBEX	5.877 ***	2.034 ***	−2.675	−46.618	−29.693
IXIC	5.339 ***	3.336 ***	−0.208	−15.210	−6.976
KS11	−28.839	−7.985	−15.188	−18.512	−11.519
KSE	−11.465	−15.935	−12.445	−4.734	−6.950
MXX	−20.153	−12.565 **	−1.143	−42.829	−30.433
N225	10.800 ***	−9.872	−5.653	−9.287 **	−14.632
NSEI	18.402 ***	0.558	−9.545	−4.047	−8.690
RUT	2.744 ***	8.302 ***	−3.499	−15.217	−11.524
SPX	13.893 ***	−0.067 **	−1.314	−13.538	−11.787
SSEC	−7.087	−4.489	11.567 ***	−26.250 ***	−0.497
SSMI	16.483 ***	0.407 ***	0.621 ***	−9.664	−4.276
STOXX50E	14.489 ***	3.528 ***	−3.342	−19.737	−13.690

Notes: This table reports the R^2_{OOS} in percentage for the 66-day-ahead RV forecasts during the COVID-19 pandemic (i.e., from 1 January 2020 to the end of the sample). The corresponding significance of R^2_{OOS} is evaluated by the MSFE-adjusted statistic. The benchmark model used for calculating out-of-sample R^2 value in this paper is the HAR-RV model. The total sample covers the period from February 2, 2000, to May 4, 2021. The rolling window length is 3000 for out-of-sample forecasting evaluation. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

7. Conclusion

In this study, we discuss the forecasting ability of the GFSI, VIX, and some classic EPU indices on the RV of the 21 international stock indices. Based on the benchmark HAR-RV model, we construct the following five extended models: HAR-GFSI, HAR-VIX, HAR-USEPU, HAR-GEPU, and HAR-GPR. We show that the HAR-GFSI model performs best for the long-term predictive ability by evaluating the MCS and out-of-sample R2 tests. And the HAR-GFSI model is more predictive during the COVID-19 pandemic. Our findings are robust

Table 10
Out-of-sample R^2 results of 22-day-ahead RV predictions using alternative predicting window.

	HAR-GFSI	HAR-VIX	HAR-USEPU	HAR-GEPU	HAR-GPR
AEX	7.969 ***	4.262 ***	−2.759	−1.609	−4.377
AORD	4.507 ***	5.795 ***	−0.726	−2.245	−5.046
BFX	1.594 ***	7.429 ***	−1.585	−3.433	−5.294
BVSP	4.953 ***	2.307 ***	−1.981	0.098 ***	−3.502
DJI	5.392 ***	4.355 ***	−3.042	−1.509	−5.427
FCHI	8.189 ***	4.598 ***	−4.478	−1.691	−5.887
FTSE	2.939 ***	7.431 ***	−3.672	−2.724	−6.087
GDAXI	7.089 ***	−0.832 ***	−7.494	−0.609 ***	−5.444
HSI	1.702 ***	−1.868 *	−4.006	−2.191 ***	−1.884
IBEX	4.306 ***	2.385 ***	−3.881	−6.257	−7.290
IXIC	0.466 ***	4.685 ***	−2.509	−2.085	−4.537
KS11	−8.634	−2.321	−9.175	−0.879 ***	−6.537
KSE	2.630 ***	3.373 ***	−2.267	−0.110 ***	−5.174
MXX	3.301 ***	2.587 ***	−1.793	−3.119 **	−4.262
N225	7.006 ***	1.996 ***	−4.917	1.409 ***	−4.023
NSEI	7.944 ***	4.015 ***	−3.583	3.385 ***	−2.876
RUT	3.153 ***	10.553 ***	−3.152	−2.273	−5.717
SPX	6.406 ***	3.207 ***	−2.921	−1.557	−5.758
SSEC	−0.961	−0.121	0.301	0.665 ***	−0.335
SSMI	10.297 ***	5.745 ***	−2.696	−1.019	−4.983
STOXX50E	7.945 ***	3.912 ***	−5.862	−2.149	−5.937

Notes: This table reports the R^2_{OOS} in percentage for the 22-day-ahead RV forecasts using alternative predicting window of 3500. The corresponding significance of R^2_{OOS} is evaluated by the MSFE-adjusted statistic. The benchmark model used for calculating out-of-sample R^2 value in this paper is the HAR-RV model. The total sample covers the period from February 2, 2000, to May 4, 2021. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 11
Out-of-sample R^2 results of 66-day-ahead RV predictions using alternative predicting window.

	HAR-GFSI	HAR-VIX	HAR-USEPU	HAR-GEPU	HAR-GPR
AEX	12.397 ***	0.848 ***	0.747 ***	−4.932 ***	−3.467
AORD	4.520 ***	−0.841	0.930 ***	−9.806	−5.082
BFX	−2.521 ***	3.703 ***	−0.251	−11.887	−5.997
BVSP	12.238 ***	1.100 ***	1.582 ***	1.116 ***	−3.768
DJI	6.168 ***	2.762 ***	−0.635	−6.229	−5.634
FCHI	8.323 ***	0.259 ***	−1.767	−6.108 ***	−5.536
FTSE	3.418 ***	2.041 ***	0.228 ***	−9.900	−5.786
GDAXI	6.094 ***	−5.384	−4.022	−2.884 ***	−5.142
HSI	−1.858 ***	−2.544	0.955 ***	−11.235 ***	−2.602
IBEX	4.361 ***	−0.133	−2.792	−19.554	−9.442
IXIC	5.938 ***	2.289 ***	−0.691	−7.538	−4.357
KS11	−12.607	−5.478	−3.408	−5.396 ***	−10.967
KSE	−5.273	−5.438	−1.826	−4.684 ***	−8.710
MXX	10.079 ***	−1.997 ***	−0.259	−14.372 ***	−6.383
N225	9.036 ***	−1.628	−2.025	6.516 ***	−3.241
NSEI	4.365 ***	−1.571	−1.632	9.354 ***	−5.055
RUT	10.811 ***	7.464 ***	−1.877	−7.904	−6.538
SPX	10.482 ***	2.020 ***	−0.649	−5.248 ***	−5.155
SSEC	−0.268	0.418	1.347 ***	7.081 ***	−1.321
SSMI	16.127 ***	2.763 ***	0.269 ***	−7.049	−3.958
STOXX50E	7.538 ***	−0.340 ***	−3.274	−7.318 *	−4.728

Notes: This table reports the R^2_{OOS} in percentage for the 66-day-ahead RV forecasts using alternative predicting window of 3500. The corresponding significance of R^2_{OOS} is evaluated by the MSFE-adjusted statistic. The benchmark model used for calculating out-of-sample R^2 value in this paper is the HAR-RV model. The total sample covers the period from February 2, 2000, to May 4, 2021. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

using alternative forecasting window size. Additionally, in terms of short-term (one-, five-, and ten-day-ahead) volatility forecasting, although the HAR-GFSI shows significant predictive ability beyond the HAR-RV model, the HAR-VIX model is more reliable than the HAR-GFSI model. In short, this study shows the excellent predictive performance of the GFSI in long-term volatilities of equity markets for many countries.

Theoretically, our study is meaningful from the following three aspects. First, our study enriches the HAR-type models from the

Table 12
Out-of-sample R^2 results of one-day-ahead RV predictions.

	HAR-GFSI	HAR-VIX	HAR-USEPU	HAR-GEPU	HAR-GPR
AEX	0.478 **	7.073 ***	−0.612	−0.419	−0.204
AORD	−0.880	5.792 ***	−0.430	−0.314	−0.201
BFX	−0.078 *	7.097 ***	−0.273	−0.538	−0.222
BVSP	0.940 ***	3.383 ***	−0.789	−0.215	−0.139
DJI	0.202 ***	9.411 ***	−0.813	−0.247	−0.226
FCHI	1.102 **	5.527 ***	−0.706	−0.615	−0.218
FTSE	−0.319 **	8.855 ***	−1.003	−0.319	−0.119
GDAXI	1.288 ***	3.503 ***	−1.098	−0.354	−0.141
HSI	1.656 ***	3.299 **	−0.512	−0.041 *	−0.023
IBEX	0.480 ***	0.895 ***	−0.257	−0.540	−0.062
IXIC	−0.351 *	6.077 ***	−0.485	−0.126	−0.138
KS11	−0.410 **	6.271 ***	−0.646	−0.114	−0.080
KSE	0.839 ***	2.100 **	−0.563	0.193 ***	−0.098
MXX	0.838 ***	2.143 ***	−0.275	−0.058	−0.047
N225	1.237 ***	3.904 ***	−0.361	0.008	−0.041
NSEI	2.043 ***	4.843 **	−0.526	0.042 *	0.116 ***
RUT	0.294 **	9.410 ***	−0.505	−0.278	−0.156
SPX	0.377 ***	8.548 ***	−0.790	−0.241	−0.189
SSEC	−0.011	0.049	−0.017	0.162	0.038
SSMI	0.110	4.714 ***	−0.692	−0.248	−0.277
STOXX50E	1.097 ***	4.343 ***	−0.845	−0.724	−0.152

Notes: This table reports the R^2_{OOS} in percentage for the one-day-ahead RV forecasts. T The corresponding significance is evaluated by the MSFE-adjusted statistic. The benchmark model used for calculating out-of-sample R^2 value in this paper is the HAR-RV model. The data cover the period from February 2, 2000, to May 4, 2021. The rolling window length is 3000 for out-of-sample forecasting evaluation. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 13
Out-of-sample R^2 results of five-day-ahead RV predictions.

	HAR-GFSI	HAR-VIX	HAR-USEPU	HAR-GEPU	HAR-GPR
AEX	1.688 ***	6.629 ***	−1.748	−2.303	−0.838
AORD	−2.395	9.121 ***	−0.815	−1.360	−0.734
BFX	0.099 **	8.974 ***	−0.941	−2.437	−1.117
BVSP	3.143 ***	5.674 ***	−1.597	−0.761	−0.469
DJI	1.275 ***	10.743 ***	−1.730	−1.292	−0.988
FCHI	2.956 ***	6.944 ***	−2.281	−3.190	−0.842
FTSE	−0.517 ***	14.073 ***	−2.762	−1.957	−0.779
GDAXI	3.138 ***	2.915 ***	−4.178	−2.688	−0.700
HSI	4.173 ***	5.000 ***	−1.648	−0.295 ***	0.036 **
IBEX	1.349 ***	1.346 ***	−1.191	−2.956	−0.511
IXIC	−0.282 **	9.046 ***	−1.395	−0.784	−0.736
KS11	−2.658 ***	8.429 ***	−2.800	−0.859	−0.268 **
KSE	2.840 ***	7.407 ***	−1.044	1.101	−0.244 **
MXX	2.666 ***	5.437 ***	−1.331	−0.267	−0.332
N225	3.171 ***	5.670 ***	−1.239	−0.093 **	−0.229
NSEI	4.953 ***	8.831 ***	−1.252	0.279 ***	0.477 ***
RUT	1.789 ***	16.058 ***	−1.856	−1.480	−0.713
SPX	1.884 ***	9.333 ***	−1.606	−1.324	−1.032
SSEC	−0.348	−0.415	−0.151	0.575 ***	0.181 ***
SSMI	0.169 *	7.328 ***	−1.871	−1.208	−1.067
STOXX50E	3.117 ***	7.290 ***	−3.070	−3.702	−0.768

Notes: This table reports the R^2_{OOS} in percentage for the five-day-ahead RV forecasts. The corresponding significance is evaluated by the MSFE-adjusted statistic. The benchmark model used for calculating out-of-sample R^2 value in this paper is the HAR-RV model. The data cover the period from February 2, 2000, to May 4, 2021. The rolling window length is 3000 for out-of-sample forecasting evaluation. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

perspective of exploring potential predictors in modeling and forecasting realized volatility, that is, considering the GFSI information is helpful to predict long-term equity market volatility. Moreover, our empirical findings are not based on one single market behavior, but on global stock markets. Therefore, the applicability and validity of our empirical findings are relatively wider and more robust.

Second, our findings also have implications for the asset pricing research considering the GFSI. Specifically, our significant findings between the GFSI and equity market volatility seem to guide the potential relationship between the GFSI and equity market returns, if

Table 14
Out-of-sample R^2 results of ten-day-ahead RV predictions.

	HAR-GFSI	HAR-VIX	HAR-USEPU	HAR-GEPU	HAR-GPR
AEX	3.405 ***	4.775 ***	−3.791	−3.252	−1.984
AORD	−1.301 *	7.918 ***	−1.435	−2.136	−1.858
BFX	0.617 ***	8.245 ***	−2.594	−3.930	−2.351
BVSP	4.761 ***	5.139 ***	−2.068	−0.944	−0.768
DJI	2.481 ***	7.193 ***	−3.833	−1.909	−2.158
FCHI	4.677 ***	5.098 ***	−4.910	−4.064	−2.106
FTSE	−0.448 ***	12.265 ***	−5.477	−2.877	−2.081
GDAXI	4.449 ***	1.157 ***	−7.809	−3.506	−1.707
HSI	4.613 ***	3.320 ***	−2.630	−0.712 ***	−0.226
IBEX	1.877 ***	1.306 ***	−3.192	−4.444	−1.685
IXIC	−0.154 ***	7.359 ***	−3.051	−1.255	−1.692
KS11	−5.155 ***	5.121 ***	−6.383	−1.259	−0.702 *
KSE	3.304 ***	8.763 ***	−1.469	2.007 ***	−0.748 **
MXX	3.690 ***	5.941 ***	−3.132	−0.336 ***	−0.865
N225	4.182 ***	4.635 ***	−3.000	−0.122 ***	−0.859
NSEI	7.726 ***	8.005 ***	−2.391	0.900 ***	0.079 ***
RUT	2.836 ***	15.106 ***	−4.101	−2.006	−1.741
SPX	3.305 ***	6.052 ***	−3.818	−1.898	−2.135
SSEC	−0.470	−0.624	−0.274	0.676 ***	0.031 **
SSMI	2.326 **	6.485 ***	−3.421	−1.768	−2.572
STOXX50E	4.997 ***	5.805 ***	−6.163	−5.142	−2.343

Notes: This table reports the R^2_{OOS} in percentage for the 10-day-ahead RV forecasts. The corresponding significance is evaluated by the MSFE-adjusted statistic. The benchmark model used for calculating out-of-sample R^2 value in this paper is the HAR-RV model. The data cover the period from February 2, 2000, to May 4, 2021. The rolling window length is 3000 for out-of-sample forecasting evaluation. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

the implied "risk-return" relationship is true for the corresponding asset. Therefore, the role of the GFSI on asset pricing is a potential research direction, especially from a global perspective (based on our findings) and a cross-asset perspective (because the GFSI also has an impact on the volatility of crude oil and other important financial assets).

Third, this study inspires research on the relationship between the GFSI and asset liquidity, especially focusing on the liquidity's volatility. A higher GFSI intuitively implies a certain absence of liquidity in financial markets. According to our findings, the asset volatility will be higher because of a higher GFSI; however, A higher volatility will not be entirely negative for the market liquidity, because it may amplify asset liquidity's volatility. For some illiquid assets, the character of high liquidity's volatility is positive information for investors (Pereira & Zhang 2010), because investors can wait for a better liquidity timing to trade the assets, without a high liquidity cost (selling at a discount price or buying with a premium). Therefore, the role of the GFSI on the liquidity of global equity assets is another future research direction.

In practice, policy makers of many countries and regional and global investors can benefit from our findings by effectively using the information of the GFSI for the long-term (one to three months) prediction of future equity market volatility. Policy makers should pay full attention to the real-time changes of GFSI and assess the long-term volatility of the domestic stock market. When the predicted volatility is extremely higher, they should actively formulate corresponding policies to reduce market risks related to global financial stress information. And the policy makers should explain the sources of great financial stress and the potential impacts on domestic economics and finance, and actively guide domestic investor sentiment to avoid causing investor panic. Investors themself also can learn from this study. They can use the forecasting model with the GFSI to better predict the long-term volatility of the target equity market, and timely adjust relevant asset positions to reduce the proportion of risky assets in their portfolio. Especially for international investors targeting equity indices of many countries, they can comprehensively assess the systemic risk caused by the GFSI, so as to effectively and pertinently reduce the weight of assets strongly associated with GFSI in the investment portfolio, so as to reduce the overall systemic risk of the investment portfolio.

CRediT authorship contribution statement

Chao Liang: Project administration, Writing – original draft, Data collection, Validation, Supervision. **Qing Luo:** Conceptualization, Writing – Review & Revision. **Yan Li:** Software, Writing – Review & Revision. **Huynh Luu Duc Toan:** Investigation, Methodology, Funding acquisition, Writing – Review & Revision.

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.

Data availability

Data will be made available on request.

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