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Article

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RESEARCH ARTICLE



Global economic policy uncertainty and stock volatility: evidence from emerging economies

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ABSTRACT

We investigate the impact of the global economic policy uncertainty (GEPU) on stock volatility for nine emerging economies (Brazil, Russia, India, China, South Africa, Mexico, Indonesia, South Korea, and Turkey). We employ an expanded GARCH-MIDAS approach to connect low-frequency GEPU data and high-frequency stock data, assuming that GEPU affects stock volatility via the long-run component of total volatility. We not only use DM and SPA tests to statically evaluate the out-of-sample forecasting ability of the extended model, taking traditional GARCH model and GARCH-MIDAS model as benchmarks, but also use the Fluctuation test to examine the time-varyingly relative forecasting performance in the presence of potential instability. From the in-sample estimation results, we find that GEPU has empirically significant impact on stock volatility for the nine emerging economies. The out-of-sample forecasting results show that the GEPU-based model can improve forecasting performance of stock volatility for emerging markets, especially in unstable environments.

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KEYWORDS

Global economic policy uncertainty; GARCH-MIDAS; emerging markets; stock volatility

1. Introduction

The interest in policy uncertainty has been renewed for recent political and economic events. Having a good understanding of the relationship between economic policy uncertainty and stock volatility will enable investors and policy makers to obtain more accurate forecast of stock volatility conditional on policy shocks. Baker, Bloom, and Davis (2016) define EPU as uncertainty regarding monetary, fiscal or regulatory policy, and calculate the EPU index based on the relative frequency of own-country newspaper articles that contain a trio of terms pertaining to the economy (E), policy (P) and uncertainty (U). In this paper, based on Baker's EPU index, we investigate the impact of the global economic policy uncertainty (GEPU)

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on stock volatility for nine emerging economies, including the BRICS countries (Brazil, Russia, India, China, and South Africa) and the MIST countries (Mexico, Indonesia, South Korea, and Turkey).^{1,2,3}

Following Asgharian, Hou, and Javed (2013) and Engle, Ghysels, and Bumjean (2013), we hypothesize that the short-run component of volatility is related to its own earlier information, while the long-run component of volatility is related to macroeconomic fundamentals. We employ an expanded Generalized Autoregressive Conditional Heteroscedasticity Mixed Data Sampling (GARCH-MIDAS) model to divide the stock total volatility into a long-run component and a short-run component, inserting the GEPU variable into the long-term component. In order to investigate whether GEPU has impact on stock volatility for emerging markets, we firstly estimate the expanded GARCH-MIDAS where GEPU variable added and compare its in-sample results with two selected benchmark models, namely, the GARCH (1,1) model and the traditional GARCH-MIDAS model without GEPU. Then, we employ the Superior Predictive Ability (SPA) method, proposed by Hansen (2005) and the DM test, proposed by Diebold and Mariano (1995) to examine whether involving GEPU information in GARCH-MIDAS model can improve the accuracy of out-of-sample forecast for emerging economies' stock volatility. Finally, we use the Clark and West (CW) Fluctuation test, proposed by Giacomini and Rossi (2010), to compare the out-of-sample forecasting performances, investigating whether the GARCH-MIDAS model involving GEPU can outperforms in unstable environments.

The model is estimated for nine emerging markets by using daily stock index data and monthly GEPU data from January 2002 to October 2018. According to the in-sample empirical results, we show that GEPU has impact on stock volatility for emerging markets. Specifically, through horizontal comparisons, the in-sample results empirically reveal that the impact on South Africa, Mexico, South Korea these three markets are relatively more significant, the impact on Turkey, Indonesia and Brazil are relatively non-significant, while China, Russia, and India these three markets are in the medium range. From vertical comparisons based on the information criterions (AIC and BIC), except Brazil and Turkey, the GARCH-MIDAS model with GEPU performs better than either the simple GARCH model or the GARCH-MIDAS model without GEPU. This suggests that stock volatility and global economic policy uncertainty are closely linked. According to the static comparison of out-of-sample forecasting performance via loss functions, the DM test and the SPA test, we show that the GARCH-MIDAS model with GEPU can supply a more accurate forecast for the stock volatility in 6 of 9 selected emerging countries (South Africa, Mexico, Russia, China, South Korea, and India) than the traditional GARCH-MIDAS model without GEPU, implying that GEPU improves the predictive ability. However, when we take the

¹Steven J. Davis constructs the monthly index of Global Economic Policy Uncertainty (GEPU) from January 1997, building on Baker et al. (2016). The GEPU Index is a GDP-weighted average of national EPU indices for 20 countries: Australia, Brazil, Canada, Chile, China, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, the Netherlands, Russia, South Korea, Spain, Sweden, the United Kingdom, and the United States (http://www.policyuncertainty.com/global_monthly.html).

²Gupta.U. (2011). MIST: The next tier of large emerging economies, Institutional Investor. (<https://www.institutionalinvestor.com/article/b150xy57g39b7l/mist-the-next-tier-of-large-emerging-economies?Keywords=MIST>).

³Bates and Buckles (2017). An Examination of Market Entry Perspectives in Emerging Markets. International Journal of Business and Economic Development, 5(3). <https://www.proquest.com/scholarly-journals/examination-market-entry-perspectives-emerging/docview/1970503509/se-2?accountid=14167>

Fluctuation test to analyze the evolution of models' relative performance over time, we find that the relative out-of-sample forecasting performance of the GARCH-MIDAS involving GEPU is time-varying and more accurate than the two benchmark models, namely, the GARCH model and the traditional GARCH-MIDAS model without GEPU. It highlights that GEPU affects the stock volatilities in emerging countries and involving GEPU index in the GARCH-MIDAS model can improve the out-of-sample predictive performance, especially in the presence of potential instability.

This paper proceeds as follows. [Section 2](#) discusses relevant literature. [Section 3](#) introduces the methodologies. [Section 4](#) shows the information on the data and the descriptive statistics. [Section 5](#) presents the empirical results of in-sample data, and [section 6](#) presents the results of the out-of-sample forecasting exercise. [Section 7](#) concludes.

2. Literature review

Recently, the economic policy uncertainty (EPU) index constructed by Baker et al. (2016) has received increasing attention among researchers. There is a growing literature that investigate the linkage of economic policy uncertainty and financial fundamentals from different perspectives. Ko and Lee (2015), Wu, Liu, and Hsueh (2015), Li, Balcar, Gupta, and Chang (2015), Christou, Gupta, et al., (2017), Cheng (2017), Phan, Sharma, and Tran (2018), Mei, Zeng, Zhang, and Hou (2018), Xiong, Bian, and Shen (2018) and Yu, Fang, and Sun (2018) focus on the effects of economic policy uncertainty on stock markets. Specifically, Wu, Liu, and Hsueh (2015) employ a bootstrap panel Granger causality approach the impact of home country EPU on stock markets for eight OECD countries (India, Italy, Spain, United Kingdom, Canada, France, Germany and United States) and China. Christou, Cunado, et al., (2017) employ a restricted Bayesian panel VAR model estimated using the SSSS prior (PVAR-SSSS) to examine the role of home country EPU shocks and United States EPU on stock market returns for Pacific Rim countries (Australia, Canada, China, Japan, Korea, and the US). Bekiros, Gupta, and Kyei (2016) and Caggiano, Castelnuovo, and Figueres (2017) investigate the relationship between United States EPU and American stock market. Xiong et al. (2018) and Yu et al. (2018) use the dynamic conditional correlation generalized multivariate autoregressive conditional heteroscedasticity model (DCC-MGARCH) to investigate the time-varying correlation between Chinese EPU and Chinese stock market returns. There is a string of literature investigating the effects of economic policy uncertainty on other financial markets. For instance, Fang, Chen, Yu, Qian, (2018) focus on futures market, Demir and Ersan (2017) focus on currency market, Reboredo and Naifar (2017) focus on bond market, while Krol (2014) and Beckmann and Czudaj (2017) interest in forex markets. Besides, there is also some literature focusing on the impact of EPU on the relationship of different markets such as stock-bond correlation (Fang, Yu, & Li, 2017), gold-stock correlations (Gao & Zhang, 2016), oil-stock correlation (Fang, Chen, Yu, Xiong, 2018).

Overall, although previous studies tried to explore EPU's impact on stock markets, they paid more attention on developed countries tries but less on emerging countries. Nowadays, economic globalization is one of the most important features in our era and the trend of the economic globalization deepens the economic interdependent and

mutual influence among different countries day by day. The emerging countries are playing increasingly important roles in the world, with large population and the potential opportunities for economic growth. Thus, the stock markets of emerging countries deserve attention, and it is necessary to investigate the impact of the global economic policy uncertainty on emerging stock markets.

In terms of the research methodologies for studying the relationship between economic policy uncertainty and stock markets, most literature employ the models which are suitable for same-frequency data, such as Granger causality approach (Wu, Liu and Hsueh, 2015), Bayesian approach (Christou, Gupta, et al., 2017), SVAR (Bekiros et al., 2016), DCC-GARCH (Xiong et al., 2018), PVAR-SSSS (Christou, Cunado, et al. 2017) and Wavelet approach (Ko & Lee, 2015). The potential reason may be the dilemma that just monthly EPU index data can be obtained. However, the analyses of the time-varying stock volatility are mostly based on daily-frequency or even higher frequency data. Hence, this study employs a mixed data sampling model to measure what influence the global economic policy uncertainty has on emerging markets, aiming to fill the gap and enrich the literature.

3. Empirical methodologies

3.1. GARCH-MIDAS models

We use the GARCH-MIDAS model suggested by Engle et al. (2013) to inset different frequency data in the same model for investigating the relationship between GEPU and stock markets in emerging countries. In the model, the frequency of stock data is daily while that of GEPU data is monthly. The GARCH-MIDAS model can formally be described as below.

We firstly assume that the stock return on day i in month t follows the process as following equation (assuming for notational convenience that it is not the first day of the period).

$$\begin{aligned} r_{i,t} &= \mu + \sqrt{\tau_t \times g_{i,t}} \varepsilon_{i,t}, \quad i = 1, N_t \\ \varepsilon_{i,t} | \Phi_{i-1,t} &\sim N(0, 1) \end{aligned} \quad (1)$$

where $r_{i,t}$ is the log return on day i during month t . The total volatility of daily return can be defined as $\sigma_{i,t}^2 \left(\sigma_{i,t}^2 = \tau_t \times g_{i,t} \right)$, which is divided into two parts: τ_t is the long-term component that are assumed to tell us something about the source of stock market volatility and $g_{i,t}$ is the short-term component which accounts for daily fluctuations that are assumed short-lived (Engle et al., 2013). $\Phi_{i-1,t}$ is the information set up to day $(i-1)$ of period t and N_t is the number of trading days in month t . The volatility dynamics of the short-term component $g_{i,t}$ is a daily GARCH (1,1) process (Bollerslev, 1986):

$$g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \mu)^2}{\tau_t} + \beta g_{i-1,t} \quad (2)$$

The long-term component τ_t can be described by low-frequency variables such as realized volatility or macro variables. In this study, we use two different specifications for the long-term component τ_t while keeping the equation for short-term component

same. In the first model specification, we investigate the effect of realized volatility on the long-term component of the total volatility. τ_t is specified by smoothing realized volatility in the MIDAS regression. The MIDAS filtering is specified as below:

$$\tau_t = m + \theta_{rv} \sum_{k=1}^K \varphi_k(\omega_1) RV_{t-k} \quad (3)$$

where RV_t ($RV_t = \sum_{i=1}^{N_t} r_{i,t}^2$) is denoted as monthly smoothing realized volatility with the fixed-span and K is the number of periods over which we smooth the realized volatility. In the second model specification, we directly bring macroeconomic variables into the long-term component:

$$\tau_t = m + \theta_{rv} \sum_{k=1}^K \varphi_k(\omega_1) RV_{t-k} + \theta_{gepu} \sum_{k=1}^K \varphi_k(\omega_1) GEPU_{t-k} \quad (4)$$

where $GEPU_{t-k}$ is the level of the change rate of monthly global economic policy uncertainty, which is denoted as log difference of GEPU. We use Equation (4) to capture the information explained by both the realized volatility and the economic policy uncertainty and compare it to the basic model where the long-term component does not involve GEPU information. In order to complete the models, the weighting scheme for Equations (3) and (4) is specified by beta lag polynomial (Ghysels, Sinko, & Valkanov, 2007):

$$\varphi_k(\omega_1) = \frac{\binom{k/K}{\omega_1-1}}{\sum_{j=1}^K \binom{j/K}{\omega_1-1}} \quad (5)$$

where the weights in Equation (5) sum up to 1. The beta lag structure is very flexible to accommodate various lag structure and thus it can represent not only a monotonically decreasing or increasing weighting scheme but also a hump-shaped weighting scheme (Engle et al., 2013).

In this paper, we investigate the impact of GEPU on stock volatility. The estimated daily total variance ($\sigma_{i,t}^2$) is used as the precision of total variance (see Equation (1)). We take $r_{i,t}^2$ as the realized total volatility. The forecasting ability of the GARCH-MIDAS model with GEPU (henceforth GARCH-MIDAS-RV+GEPU model), constructed by Equations (1), (2), (4) and (5), is compared with the traditional GARCH-MIDAS model (henceforth GARCH-MIDAS-RV model) which is constructed by Equations (1), (2), (3) and (5). And it is also compared with a simple GARCH (1,1) model (Bollerslev, 1986), which is specified as below:

$$r_t = \mu + \varepsilon_t \quad (6)$$

Where $\varepsilon_t = \sigma_t z_t$, $z_t \sim N(0, 1)$, and the conditional variance process, σ_t^2 , has the form

$$\sigma_t^2 = k + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (7)$$

3.2. Loss function, DM test, and SPA test

We employ a number of loss functions to evaluate the volatility predictability of a specific model, via comparing the estimated predicted variance with the realized volatility. The six loss functions we used in our work can be described as below:

$$MSE = \frac{1}{T} \sum_{i=1}^T (\hat{\sigma}_i^2 - \sigma_i^2)^2 \quad (8)$$

$$MAE = \frac{1}{T} \sum_{i=1}^T |\hat{\sigma}_i^2 - \sigma_i^2| \quad (9)$$

$$MSE_{sd} = \frac{1}{T} \sum_{i=1}^T (\hat{\sigma}_i - \sigma_i)^2 \quad (10)$$

$$MAE_{sd} = \frac{1}{T} \sum_{i=1}^T |\hat{\sigma}_i - \sigma_i| \quad (11)$$

$$RMSE = \sqrt{\frac{1}{T} \sum_{i=1}^T (\hat{\sigma}_i^2 - \sigma_i^2)^2} \quad (12)$$

$$RMAE = \sqrt{\frac{1}{T} \sum_{i=1}^T |\hat{\sigma}_i^2 - \sigma_i^2|} \quad (13)$$

We also employ the Diebold and Mariano (DM) test, suggested by Diebold and Mariano (1995) to compare the prediction accuracy of two different models. The DM test based on the loss differential which is defined as the difference of the squared forecast errors can be described as follows:

$$DM = \frac{\bar{d}}{\sqrt{\frac{1}{T} \cdot \text{var}(d)}} \sim N(0, 1) \quad (14)$$

$$d_t = e_{0,t}^2 - e_{1,t}^2$$

where $e_{0,t}$ and $e_{1,t}$ are the prediction error of the benchmark model and the completing model, respectively. T is the total number of forecasts, \bar{d} is the mean of the time series d_t and $\text{var}(d)$ is the variance of d_t . The null hypothesis of DM test is $E(d) = 0$.

Besides, we also take the GARCH model, the GARCH-MIDAS-RV model and the GARCH-MIDAS-RV+GEPV model into consideration together, using the Superior Predictive Ability test. Hansen (2005) proposed a test of Superior Predictive Ability (SPA), which can examine whether a particular forecasting procedure is outperformed by alternative predicting procedures. The null hypothesis of SPA test is that the benchmark is not inferior to any of the alternatives. The key relative performance variables are defined as below:

$$d_{k,t} = L(\delta_{0,t}) - L(\delta_{k,t}), k = 1, \dots, m \quad (15)$$

where $d_{k,t}$ denotes the performance of model k relative to the benchmark at time t . The vector of the relative performances is d_t , $d_t = (d_{1,t}, \dots, d_{m,t})'$. We use the studentized test statistic for SPA (Hansen, 2005):

$$T_n^{SPA} = \max \left[\max_{k=1, \dots, m} \frac{n^{1/2} \bar{d}_k}{\hat{\omega}_k}, 0 \right] \quad (16)$$

In particular, we employ a stationary bootstrap implementation of the SPA test, which is described in detail by Hansen, along with the procedure as follows:

$$\{d_{b,t}^*\} \equiv \{d_{\tau_{b,t}}\}, b = 1, \dots, B \quad (17)$$

where $d_{b,t}^*$ are the pseudo time series that are resamples of d_t and B is the number of bootstrap resamples, where $\{\tau_{b,1}, \dots, \tau_{b,n}\}$ is constructed by combining blocks of $\{1, \dots, n\}$ with random lengths.

$$\hat{\omega}_{k,B*2} \equiv B^{-1} \sum_{b=1}^B \left(n^{1/2} \bar{d}_{k,b}^* - n^{1/2} \bar{d}_k \right)^2, k = 1, \dots, m \quad (18)$$

where $\bar{d}_{k,B}^* = n^{-1} \sum_{t=1}^n d_{k,\tau_{b,t}}$, by the law of large numbers, this estimator is consistent for the true variance, ω_k^2 .

$$\begin{aligned} Z_{k,b,t}^* &\equiv d_{k,b,t}^* - g(\bar{d}_k), b = 1, \dots, B; t = 1, \dots, n \\ g(\bar{d}_k) &= \bar{d}_k \cdot 1_{\left\{x \geq \sqrt{(\hat{\omega}_k^2/n) 2 \log \log n}\right\}} \end{aligned} \quad (19)$$

where $1_{\{\cdot\}}$ denotes the indicator function. Given assumptions about the test above, we can calculate the $T_{b,n}^{SPA*}$ and the bootstrap p value as below:

$$T_{b,n}^{SPA*} = \max \left[0, \max_{k=1, \dots, m} \frac{n^{1/2} \bar{Z}_{k,b}^*}{\hat{\omega}_k} \right] \quad (20)$$

$$\bar{Z}_{k,b}^* = n^{-1} \sum_{t=1}^n Z_{k,b,t}^*, k = 1, \dots, m \quad (21)$$

$$\hat{p}_{SPA} \equiv \sum_{b=1}^B \frac{1_{\left\{T_{b,n}^{SPA*} > T_{b,n}^{SPA}\right\}}}{B} \quad (22)$$

where the null hypothesis should be rejected for small p values, suggesting that the benchmark model does not outperform for alternative models.

3.3. Fluctuation test

As static comparison methods for forecasting performance, DM and SPA tests evaluate average forecasting gains for the whole forecasting period. However, forecasting gains may be different over time. Focusing solely on the average performance of the model may result in a loss of information. In this line, we further evaluate the relative forecasting

performance by using the Clark and West (CW) Fluctuation test, a time-varying forecast evaluation test proposed by Giacomini and Rossi (2010), to compare the out-of-sample forecasting performances in the presence of possible instabilities. The CW Fluctuation test measures the model's local relative performance as the out-of-sample mean square forecast error differences computed over rolling window, providing critical values for testing the null hypothesis (the relative mean square forecast error difference equals zero) at each point in time rather than on average over the whole sample (Giacomini & Rossi, 2010). The CW Fluctuation test can be specified as blow:

$$\Delta L_t(\hat{\theta}_{t-h,R}, \hat{\gamma}_{j-h,R}) = L^{(1)}(y_t, \hat{\theta}_{j-h,R}) - L^{(2)}(y_t, \hat{\gamma}_{j-h,R}) \quad (23)$$

$$F_{t,m} = \hat{\sigma}^{-1} m^{-1/2} \sum_{j=t-m/2}^{t+m/2-1} \Delta L_j(\hat{\theta}_{j-h,R}, \hat{\gamma}_{j-h,R}) \quad (24)$$

$$\hat{\sigma}^2 = \sum_{i=-q(P)+1}^{q(P)-1} (1 - |i/q(P)|) P^{-1} \sum_{j=R+h}^T \Delta L_j(\hat{\theta}_{j-h,R}, \hat{\gamma}_{j-h,R}) \Delta L_{j-i}(\hat{\theta}_{j-i-h,R}, \hat{\gamma}_{j-i-h,R}) \quad (25)$$

where $m^{-1/2} \sum_{j=t-m/2}^{t+m/2-1} \Delta L_j(\hat{\theta}_{j-h,R}, \hat{\gamma}_{j-h,R})$ is the local relative loss for the two competitive models over rolling window of size m , $\hat{\theta}_{j-h,R}$ and $\hat{\gamma}_{j-h,R}$ respectively the in-sample parameter estimates for each model, $F_{t,m}$ is the test statistic for the Fluctuation test. $\hat{\sigma}^2$ is a HAC estimator of σ^2 and $q(P)$ is a bandwidth that grows with P (Newey & West, 1987). Following Giacomini and Rossi's propose, we substitute $F_{t,m}$ with the test statistic suggested by Clark and West (2006). The null hypothesis is rejected against the one-sided alternative $E[\Delta L_t(\hat{\theta}_{t-h,R}, \hat{\gamma}_{j-h,R})] > 0$ when $\max_t m^{1/2} F_{t,m} > k_\alpha$, where k_α is the critical value for a significant level α (Giacomini & Rossi, 2010).

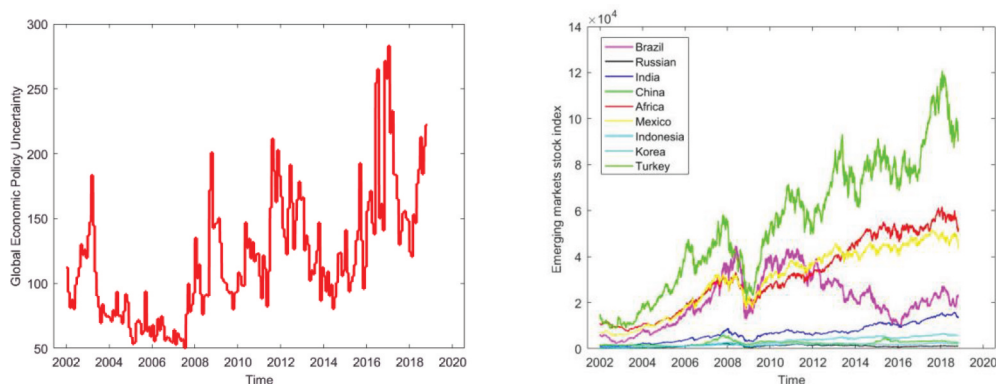
4. Data and descriptive statistics

We choose the monthly GEPU index calculated by Baker et al., which is found to be a good proxy for real-world economic policy uncertainty, being obtained from their website (<http://www.policyuncertainty.com/>). We consider stock markets of nine emerging countries (Brazil, Russia, India, China, South Africa, Mexico, Indonesia, South Korea and Turkey), including the BRICS grouping the MIST grouping, and obtain daily stock market index data from the CEIC Global Database. Table 1 shows the list of selected stock market indexes for each country. According to the availability of the first stock index price data for South Africa, our sample period starts from 1 January 2002 to 31 October 2018, yielding thus 4432 daily stock observations for each country and 202 monthly observations for the global economic policy uncertainty. Figure 1 depicts the monthly evolution of the global economic policy uncertainty index and the daily evolution of stock index series for the nine countries. As we can see in the figure, GEPU captures important economic events such as Global financial crisis (2007–2009), European debt crisis (2011–2012) and Chinese economy fears (2015–2016), along with the corresponding high volatilities of the stock markets.

Table 1. List of emerging countries and stock index series.

Country	Stock index
Brazil	Brazil BOVESPA US\$
Russia	Russia RTS Index US\$
India	Bombay Stock Exchange 500 Index
China	Shanghai Stock Exchange Composite Index
South Africa	FTSE/JSE Index: All Share
Mexico	Mexico Stock Exchange IPC Index
Indonesia	JSX Composite Index
South Korea	KOSPI 100 Index
Turkey	BIST 100 Index

This table reports details on stock market index chosen for each country.

**Figure 1.** Global economic policy uncertainty index and nine stock index series.**Table 2.** Descriptive statistics of GEPU index and stock index series.

Variable	Obs.	Freq.	Mean	Median	Min	Max	Std.	Skew.	Kurt.
GEPU index	202	Monthly	118.34	109.24	50.39	283.09	47.15	0.977	3.943
Brazil	4432	Daily	21,155.66	20,418.34	2160.56	44,616.54	10,989.67	0.160	2.107
Russia	4432	Daily	1168.86	1149.71	267.70	2487.92	500.72	0.197	2.324
India	4432	Daily	6762.79	6688.31	1011.19	15,846.20	3844.18	0.401	2.394
China	4432	Daily	2486.41	2389.10	1011.50	6092.06	934.06	0.786	3.822
South Africa	4432	Daily	31,786.67	29,961.96	7361.15	61,684.77	15,905.53	0.145	1.751
Mexico	4432	Daily	30,425.82	32,471.88	5534.47	51,713.38	14,226.33	-0.385	1.792
Indonesia	4432	Daily	3062.73	2875.78	337.48	6689.29	1865.85	0.065	1.600
South Korea	4432	Daily	1566.00	1726.33	494.43	2591.61	519.36	-0.396	2.095
Turkey	4432	Daily	54,316.75	55,094.58	8627.42	120,845.29	28,063.04	0.106	2.108

This table shows the descriptive statistics of GEPU index and stock index series.

Table 2 shows the descriptive statistics of the nine stock index series data and the GEPU index used in this study. The sample size of stock index series for each country is 4432, where we fill up the null value with the value of the previous day, and there are 202 observations for GEPU index. The data frequency of stock index is daily and that of GEPU is monthly. Table 3 reports the descriptive statistics of relative log stock return series and the log change rate of GEPU, with 4431 observations of stock return for each country and 201 observations for GEPU. From Table 3 we can see that the kurtosis of the

Table 3. Descriptive statistics of GEPU change rate and stock return series.

Variable	Obs.	Freq.	Mean	Median	Min	Max	Std.	Skew.	Kurt.
GEPU	201	Monthly	0.0034	0.0026	−0.5676	0.6554	0.1868	0.3742	4.3232
Brazil	4431	Daily	0.0003	0.0000	−0.1823	0.1961	0.0223	−0.2688	10.0999
Russia	4431	Daily	0.0003	0.0003	−0.2120	0.2020	0.0202	−0.4556	14.4825
India	4431	Daily	0.0006	0.0007	−0.1244	0.1462	0.0136	−0.3911	14.9089
China	4431	Daily	0.0001	0.0000	−0.0926	0.0903	0.0154	−0.4368	8.1857
South Africa	4431	Daily	0.0004	0.0001	−0.0758	0.0683	0.0115	−0.1427	6.7632
Mexico	4431	Daily	0.0004	0.0003	−0.0727	0.1044	0.0116	0.0430	9.7549
Indonesia	4431	Daily	0.0006	0.0004	−0.1095	0.0762	0.0129	−0.7061	11.2416
South Korea	4431	Daily	0.0002	0.0000	−0.1088	0.1154	0.0135	−0.3403	9.0699
Turkey	4431	Daily	0.0004	0.0000	−0.1334	0.1213	0.0176	−0.1545	7.9753

This table shows descriptive statistics of GEPU change rate and stock return series.

Table 4. Statistical properties of GEPU and stock return series.

	DF	ADF	PP	VR	JB	ARCH
GEPU	−16.1277*** (0.001)	−12.5459*** (0.001)	−16.1277*** (0.001)	−5.269*** (0.000)	19.3559*** (0.0028)	0.0179 (0.8937)
Brazil	−62.0121*** (0.001)	−45.972*** (0.001)	−62.0121*** (0.001)	−14.1492*** (0.000)	9359.9054*** (0.001)	109.8977*** (0.000)
Russia	−59.7994*** (0.001)	−45.6744*** (0.001)	−59.7994*** (0.001)	−12.8586*** (0.000)	24,495.7647*** (0.001)	228.8102*** (0.000)
India	−62.0957*** (0.001)	−45.4315*** (0.001)	−62.0957*** (0.001)	−11.8624*** (0.000)	26,296.9283*** (0.001)	392.9771*** (0.000)
China	−65.9103*** (0.001)	−47.4922*** (0.001)	−65.9103*** (0.001)	−17.2436*** (0.000)	5105.8011*** (0.001)	128.2214*** (0.000)
South Africa	−64.7597*** (0.001)	−47.3015*** (0.001)	−64.7597*** (0.001)	−17.6849*** (0.000)	2629.6745*** (0.001)	173.2291*** (0.000)
Mexico	−61.6739*** (0.001)	−46.6045*** (0.001)	−61.6739*** (0.001)	−14.8601*** (0.000)	8425.437*** (0.001)	123.0137*** (0.000)
Indonesia	−60.8692*** (0.001)	−44.3899*** (0.001)	−60.8692*** (0.001)	−14.9223*** (0.000)	12,908.6407*** (0.001)	115.0255*** (0.000)
South Korea	−66.3085*** (0.001)	−47.9037*** (0.001)	−66.3085*** (0.001)	−16.6961*** (0.000)	6887.7287*** (0.001)	120.0438*** (0.000)
Turkey	−66.0426*** (0.001)	−46.0468*** (0.001)	−66.0426*** (0.001)	−16.6494*** (0.000)	4587.705*** (0.001)	112.5617*** (0.000)

The table shows statistical properties of the change rate data of global economic policy uncertainty index (GEPU) and the nine emerging markets' stock return series, including the BRICS countries (Brazil, Russian, India, China and South Africa) and the MIST countries (Mexico, Indonesia, South Korea, Turkey). The numbers in parentheses are the p-values of the tests. 0.000 means that p-value is less than 0.001. ***, ** and * denote significance at 1, 5, and 10% level, respectively.

ten variables is all positive and, except GEPU and Mexico, the skewness of other eight variables are all negative. Table 4 further shows some selected statistical properties of GEPU and

stock return series, including the unit root testing, the Jarque – Bera (JB) test and the ARCH effect test. According to the results of Dickey-Fuller (DF) test, Augmented Dickey-Fuller (ADF) test, Phillips-Perron (PP) test and Vratio (VR) test, all the statistics significantly reject the unit root null hypothesis at 1% level, in favor of the stationary time series. Moreover, all stock return data series and the GEPU data are passed the Jarque-Bera (JB) test at 1% significance level, implying that none of their distributions follows the normal distribution. In addition, Engle (1982)'s ARCH test statistics for stock returns are more than 100 while the critical values of ARCH test at the 1% level is 6.6635, indicating that there are significant heteroskedastic effects.

5. In-sample empirical results

In this section, we cover the estimation of GARCH-MIDAS volatility models and the traditional GARCH model, including the full sample from 2002 to 2018 and the sub-sample from 2002 to 2014, where we take the first subsample (2002–2014) as in-sample data and the remained subsample (2015–2018) as out-of-sample data. we focus on examining whether global economic policy uncertainty has impact on stock market volatility in those emerging stock markets.

Tables A1 and A2 show the full-sample and sub-sample estimates of GARCH models for the nine stock return series, respectively (details in Appendix A section). This table can be seen as three parts, where the first part from 3rd to 11th rows, the second part from 12th to 24th rows and the third part from 25th to the end rows show parameter estimates for the GARCH (1,1) model, the GARCH-MIDAS-RV model and the GARCH-MIDAS-RV+GEPu model, respectively. As shown in the Table A1, except μ , all the other three parameters of the GARCH (1,1) models for nine countries are significant, indicating that GARCH (1,1) model fits the daily data very well. On the estimators for GARCH-MIDAS models, we also find that the mixed data sampling model fits the data well, where the parameter α , β , θ_{rv} , θ_{gepu} are statistically significant. What we are more interested here are the values of θ_{gepu} , which indicate the impact of global economic policy uncertainty on the long-term component of the emerging stock markets' total volatility. As shown in the empirical results for the GARCH-MIDAS-RV+GEPu model, the estimated coefficients θ_{gepu} for Russia, south Africa, Mexico and Indonesia, where θ_{gepu} respectively equals 0.0006, 0.0004, 0.0004, and 0.0003, are empirically significant at 1% level. The estimated coefficients of θ_{gepu} for Brazil, South Korea and Turkey are positively significant at 5%, while that for China and India is significant at 10% level. For the full sample, all results above seem to imply that GEPu plays an important role in emerging countries' stock market. Then we again estimate models with the subsample starting from 2002 and ending in 2014, further investigating whether the analyzing results for full-sample parameters above fit the subsample. As shown in Table A2, we can see that GEPu has empirically significant impact on emerging stock markets for the in-sample data from 2002 to 2014. Except India, the estimated θ_{gepu} for all the other eight emerging economies are statistically significant.

Next, we apply the optimal log-likelihood function (Log-L), the Akaike information criterion (AIC), and the Bayesian information criterion (BIC) to evaluate the models with various specifications, in order to examine whether involving GEPu in the GARCH-MIDAS model can improve the fitness of the model. Table 5 displays the full-sample and in-sample evaluation results of the three different models. For that the evolution results based on AIC, BIC, and Log-L are not always consistent, as long as one model has two or three judgment value optimal, we deem this model performing best. Let us focus first on the full-sample model evaluation results in Table 5. Compared with the traditional GARCH (1,1) model, the GARCH-MIDAS-RV+GEPu model has a better fitness for all the nine emerging stock return data, based on the fact that the AIC values of the latter model are smaller and the Log-L values of the latter model are larger, in spite of the BIC results being inconsistent with AIC (except India and Indonesia). When taking the GARCH-MIDAS-RV model as benchmark, except the BIC values for Brazil, Russia and South Korea, the GARCH-MIDAS-RV+GEPu performs better than the GARCH-

Table 5. Full-sample and in-sample evaluation results for different models.

		Brazil	Russia	India	China	South Africa	Mexico	Indonesia	South Korea	Turkey
2002–2018 GARCH	Log-L	11,027	11,688	13,584	12,841	14,032	14,067	13,557	13,465	11,981
	AIC	-22,045	-23,369	-27,159	-25,674	-28,057	-28,127	-27,106	-26,923	-23,954
	BIC	-22,020	-23,343	-27,134	-25,649	-28,031	-28,101	-27,081	-26,897	-23,928
GARCH-MIDAS-RV	Log-L	11,029	11,692	13,589	12,848	14,033	14,074	13,561	13,472	12,000
	AIC	-22,045	-23,371	-27,166	-25,683	-28,054	-28,135	-27,110	-26,932	-23,988
	BIC	-22,007	-23,333	-27,128	-25,645	-28,015	-28,097	-27,071	-26,894	-23,950
GARCH-MIDAS-RV+GEPU	Log-L	11,033	11,695	13,598	12,854	14,042	14,079	13,573	13,475	12,005
	AIC	-22,051	-23,376	-27,182	-25,693	-28,069	-28,144	-27,132	-26,937	-23,996
	BIC	-22,006	-23,331	-27,137	-25,648	-28,024	-28,099	-27,087	-26,892	-23,951
2002–2014 GARCH	Log-L	8513	8951	10,179	9790	10,738	10,616	10,186	10,037	9025
	AIC	-17,017	-17,894	-20,350	-19,572	-21,469	-21,224	-20,363	-20,065	-18,042
	BIC	-16,992	-17,869	-20,326	-19,547	-21,444	-21,199	-20,339	-20,041	-18,017
GARCH-MIDAS-RV	Log-L	8514	8955	10,199	9796	10,739	10,620	10,191	10,059	9036
	AIC	-17,017	-17,899	-20,385	-19,580	-21,465	-21,228	-20,369	-20,106	-18,060
	BIC	-16,980	-17,862	-20,349	-19,543	-21,428	-21,191	-20,332	-20,069	-18,023
GARCH-MIDAS-RV+GEPU	Log-L	8519	8956	9963	9735	10,743	10,623	10,199	10,060	8932
	AIC	-17,023	-17,897	-19,913	-19,456	-21,472	-21,232	-20,383	-20,107	-17,849
	BIC	-16,980	-17,854	-19,870	-19,413	-21,429	-21,189	-20,340	-20,064	-17,806

This table full-sample and in-sample evaluation results of different models. Three evaluation values are used to compare fitness of the three models, namely AIC, BIC and Log-L. Specifically, Log-L is the optimal log-likelihood function, AIC is the Akaike information criterion and BIC is the Bayesian information criterion.

MIDAS-RV model with larger Log-L value, smaller AIC and BIC values. Next, we turn to the in-sample evaluation results reported in Table 5. Based on AIC criterion, the GARCH-MIDAS-RV+GEPU model performs better than the GARCH (1,1) model and the GARCH-MIDAS-RV model for Brazil, South Africa, Mexico, Indonesia, and South Korea, which are similar to the comparing results with full-sample data. While there is not empirical evidence obtained from AIC criterion that the GARCH-MIDAS-RV+GEPU outperforms for Russia, India, China and Turkey.

In spite that there is not consistent evidence that GEPU-based model outperforms the two constant models for in-sample in all the nine emerging countries, we have already found that the coefficients θ_{gepu} in GEPU-based volatility model for 8 out of 9 countries (Brazil, Russia, China, South Africa, Mexico, Indonesia, South Korea, and Turkey) are positively significant both in full sample and in-sample. The coefficients θ_{gepu} for India is also statistically significant in full sample data. It highlights that the global economic policy uncertainty has impact on stock volatility in the nine countries. Hence, as shown in the next sections, we will further examine the out-of-sample performance of GEPU-based GARCH-MIDAS models for volatility forecasts to study whether GEPU can improve the volatility predictive ability for the nine emerging stock markets.

6. Out-of-sample prediction

In this section, we analyze the forecast performance of the GEPU-based GARCH-MIDAS model for stock volatility. We first use recursive forecasting scheme to generate a series of forecasts for one-step ahead and next compare the predictive results from GEPU-based GARCH-MIDAS model with two selected benchmark specifications: the GARCH model and the GARCH-MIDAS-RV model. A recursive forecasting scheme is one where the initial estimation date is fixed, but additional observations are added one at a time to the estimation period. Our out-of-sample forecast covers the period from January 2015 to October 2018.

To investigate the predictive content of GEPU variable for stock volatility of emerging markets, we consider loss function to examine the out-of-sample predictability of a volatility model. Owing to that the choice of proxy of actual volatility may affect the value of loss function heavily, we do not just refer to only one loss function but choose six loss functions. These six loss functions are given by Equations (8), (9), (10), (11), (12) and (13) mentioned in Section 2. Table 6 reports the performance of the three models in forecasting stock daily total volatility for the nine emerging economies. Let us firstly focus on the loss function values of the GARCH-MIDAS-RV+GEPU models and sort each loss function in order from smallest to largest. On the whole, the sorting order for nine forecast series is Mexico, South Korea, India, South Africa, Indonesia, Turkey, China, Russia, Brazil, in spite that there is different order in a minority of loss function such as MSE and RMSE. These results suggest that the GEPU-based GARCH-MIDAS model has a relatively highest predictive accuracy for Mexico stock market but a relatively lowest predictive accuracy for Brazil.

Next, we turn our attention to the comparing results with respect to the two benchmark models. As shown in Table 6, when comparing with GARCH-MIDAS-RV model, the GARCH-MIDAS model involving GEPU information performs better

Table 6. Results of out-of-sample volatility forecast validation.

Model	MSE	MAE	MSEsd	MAEsd	RMSE	RMAE
Brazil						
GARCH	1.52E-06	0.000462	0.000236	0.011962	0.001234	0.021503
GARCH-MIDAS-RV	1.49E-06	0.000453	0.000231	0.012145	0.001222	0.021281
GARCH-MIDAS-RV+GEPU	1.50E-06 [*]	0.000458 [*]	0.000234 ^{i*}	0.012003 ^{ih}	0.001226 [*]	0.021395 ^{i*}
Russia						
GARCH	5.16E-07	0.000305	0.000146	0.009229	0.000719	0.017452
GARCH-MIDAS-RV	2.51E-06	0.001495	0.000964	0.029585	0.001584	0.038664
GARCH-MIDAS-RV+GEPU	5.16E-07 ^{h#}	0.000306 ^{h#}	0.000146 ^{h#}	0.00924 ^{h#}	0.000719 ^{h#}	0.017493 ^{h#}
India						
GARCH	3.75E-08	0.000087	0.000044	0.005359	0.000194	0.009308
GARCH-MIDAS-RV	3.75E-08	0.000088	0.000045	0.005609	0.000194	0.009395
GARCH-MIDAS-RV+GEPU	3.77E-08 ^e	0.000087 ^{c#}	0.000044 ^{c#}	0.005327 ^{c*#}	0.000194 ^e	0.009301 ^{c*#}
China						
GARCH	4.64E-07	0.000275	0.000139	0.008594	0.000681	0.016587
GARCH-MIDAS-RV	5.54E-07	0.000414	0.000247	0.013832	0.000744	0.02034
GARCH-MIDAS-RV+GEPU	4.62E-07 ^{g*#}	0.000272 ^{g*#}	0.000138 ^{g*#}	0.008519 ^{g*#}	0.00068 ^{g*#}	0.016482 ^{g*#}
South Africa						
GARCH	2.52E-08	0.000096	0.000045	0.005479	0.000159	0.009809
GARCH-MIDAS-RV	2.97E-08	0.000129	0.000066	0.007143	0.000172	0.011364
GARCH-MIDAS-RV+GEPU	2.51E-08 ^{c*#}	0.000096 ^{d#}	0.000044 ^{d*#}	0.005454 ^{d*#}	0.000159 ^{c#}	0.009791 ^{d*#}
Mexico						
GARCH	1.83E-08	0.000072	0.000035	0.004823	0.000135	0.008505
GARCH-MIDAS-RV	2.16E-08	0.000103	0.000055	0.006475	0.000147	0.010132
GARCH-MIDAS-RV+GEPU	1.83E-08 ^{b#}	0.000071 ^{a*#}	0.000034 ^{a*#}	0.004714 ^{a*#}	0.000135 ^{b#}	0.008405 ^{a*#}
Indonesia						
GARCH	3.13E-08	0.0001	0.000051	0.005898	0.000177	0.009994
GARCH-MIDAS-RV	3.21E-08	0.000083	0.000043	0.005131	0.000179	0.009111
GARCH-MIDAS-RV+GEPU	3.14E-08 ^{d#}	0.0001 ^e	0.000051 ^e	0.005867 ^{f*}	0.000177 ^{d#}	0.010003 ^e
South Korea						
GARCH	1.76E-08	0.000079	0.00004	0.005339	0.000133	0.008871
GARCH-MIDAS-RV	1.77E-08	0.000081	0.000042	0.005534	0.000133	0.009008
GARCH-MIDAS-RV+GEPU	1.76E-08 ^{a#}	0.000078 ^{b*#}	0.00004 ^{b#}	0.005249 ^{b*#}	0.000133 ^a	0.008806 ^{b*#}
Turkey						
GARCH	1.10E-07	0.000193	0.000094	0.008072	0.000332	0.013876
GARCH-MIDAS-RV	1.08E-07	0.000181	0.000088	0.007774	0.000329	0.013448
GARCH-MIDAS-RV+GEPU	1.10E-07 ^f	0.00019 ^{f*}	0.000093 ^{f*}	0.007942 ^{e*}	0.000332 ^f	0.013777 ^{f*}

The table shows the out-of-sample forecast validation for total volatility of the three models. The out-of-sample forecast covers the period from January 2015 to October 2018, yielding 1002 forecast values. * and # denote that the GARCH-MIDAS-RV+GEPU model outperforms GARCH model and GARCH-MIDAS-RV model, respectively. ^a, ^b, ^c, ^d, ^e, ^f, ^g, ^h, and ⁱ denote sorting each loss function in order from smallest to largest for the GARCH-MIDAS-RV+GEPU model of the nine countries.

for 4 out of 9 emerging countries (namely Russia, China, South Africa and Mexico) under the criterion of the six loss functions. Although the RMSE criterion values for India and South Korea cannot give comparable information, we can find that the GARCH-MIDAS-RV+GEPU model outperforms from other criterion values, except the MSE criterion for India.

In view of the fact that the six loss functions cannot give consistent compared results, we take an alternative method, the Diebold and Mariano (DM) test, to continue comparing the predictive accuracy of different model. The null hypothesis of the DM test is that two comparing models have the same predictive accuracy. The right panel of [Tables 7 and 8](#) report the DM test results. The GARCH (1,1) model and the GARCH-MIDAS-RV model are used as the benchmark to compute the test statistics, respectively. When taking the GARCH (1,1) model as benchmark, except for Indonesia and Russia, all the other seven statistics are positive, which implies that the model with GEPU give a lower

Table 7. Results of SPA test and DM test for out-of-sample forecasts of stock volatility series.

	SPA test				DM test	
	MSE	MAE	MSE _{sd}	MAE _{sd}	GARCH	GARCH-MIDAS-RV
Brazil						
GARCH	2.0244 (0.0453)	1.1918 (0.1842)	0.8409 (0.3045)	−0.5291 (0.8424)		
GARCH-MIDAS-RV	−0.4950 (0.7573)	−0.7675 (0.8493)	−0.5896 (0.7868)	1.1612 (0.1610)		
GARCH-MIDAS-RV+GEPU	0.5003 (0.3168)	0.7609 (0.4202)	0.5910 (0.4927)	0.5296 (0.5214)	0.7546 (0.4506)	−0.5883 (0.5565)
Russia						
GARCH	−0.0495 (0.5122)	−1.4158 (0.918)	−0.9893 (0.8443)	−0.6281 (0.7352)		
GARCH-MIDAS-RV	33.193 (0.0000)	67.549 (0.0000)	48.2044 (0.0000)	59.2149 (0.0000)		
GARCH-MIDAS-RV+GEPU	0.0498 (0.4884)	1.4350 (0.0803)	0.9853 (0.165)	0.6183 (0.2622)	−0.9802 (0.3272)	48.4613*** (0.0000)
India						
GARCH	0.0391 (0.7534)	0.5102 (0.5438)	1.0548 (0.285)	2.5030 (0.0061)		
GARCH-MIDAS-RV	−0.0393 (0.5354)	0.9597 (0.1841)	0.8767 (0.2081)	3.5951 (0.0003)		
GARCH-MIDAS-RV+GEPU	1.7175 (0.0845)	−0.5038 (0.8572)	−0.8845 (0.9349)	−2.4687 (0.5436)	1.0491 (0.2944)	0.8831 (0.3774)
China						
GARCH	0.5032 (0.3252)	2.3530 (0.0116)	1.7175 (0.0421)	2.491 (0.0074)		
GARCH-MIDAS-RV	5.0160 (0.0001)	17.8399 (0.0000)	16.8526 (0.0000)	23.5454 (0.0000)		
GARCH-MIDAS-RV+GEPU	−0.5089 (0.6821)	−2.3870 (0.5077)	−1.7366 (0.9574)	−2.4700 (0.4944)	1.7052* (0.0885)	16.8737*** (0.0000)
South Africa						
GARCH	0.6897 (0.2427)	1.3693 (0.0898)	1.2936 (0.0978)	2.1911 (0.0166)		
GARCH-MIDAS-RV	7.7370 (0.0000)	17.7844 (0.0000)	16.4043 (0.0000)	17.9151 (0.0000)		
GARCH-MIDAS-RV+GEPU	−0.6856 (0.7617)	−1.3628 (0.9119)	−1.289 (0.9058)	−2.1926 (0.5003)	1.2964 (0.1951)	16.4153*** (0.0000)

The table shows the results of the Superior Predictive Ability (SPA) test and the Diebold and Mariano (DM) test for the different models' out-of-sample forecast performance of the different emerging stock markets. The DM method is applied to examine the null hypothesis of equal forecasting performance while the SPA method examines the null hypothesis that the benchmark model is not inferior to any of the alternatives. The second column of the table lists the benchmark models for SPA-test and the next four columns show the corresponding results of SPA tests based on four different loss functions (MSE, MAE, MSE_{sd} and MAE_{sd}). When we deal with the SPA test, where the sample size $n = 1002$ and the number of resamples $B = 10,000$. The last two columns in the table report the DM test results and each DM statistic in each cell is calculated by the model given in the row comparing with the benchmark model given in the column. The number in parentheses are the p-values of the DM test and SPA test. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

forecast error than the GARCH model for 7 out of 9 countries (Brazil, India, China, South Africa, Mexico, South Korea, and Turkey). However, the test is only significant for China, Mexico, South Korea and Turkey. When taking the GARCH-MIDAS-RV model as benchmark, we find that 6 out of 9 DM statistics are positive (except for Brazil, Indonesia, and Turkey). Among these six countries, except India, all the other positive statistics are statistically significant at 1% level.

We have so far focused on comparing forecasting ability between two models. We next use the Superior Predictive Ability (SPA) test to evaluate the out-of-sample predictability, putting the three models together. We take the GARCH (1,1) model, the GARCH-MIDAS-RV model and the GARCH-MIDAS-RV+GEPU model as the benchmark in

Table 8. Results of SPA test and DM test for out-of-sample forecasts of stock volatility series.

	SPA test				DM test	
	MSE	MAE	MSE _{sd}	MAE _{sd}	GARCH	GARCH-MIDAS-RV
Mexico						
GARCH	-0.0452 (0.5665)	6.5200 (0.0000)	4.4708 (0.0000)	7.8351 (0.0000)		
GARCH-MIDAS-RV	8.7138 (0.0000)	21.3091 (0.0000)	19.2351 (0.0000)	22.1475 (0.0000)		
GARCH-MIDAS-RV+GEPU	0.0448 (0.4322)	-6.5296 (0.5103)	-4.4186 (0.4909)	-7.8288 (0.4984)	4.4373*** (0.00001)	19.1492*** (0.0000)
Indonesia						
GARCH	-0.5681 (0.9514)	8.0505 (0.0000)	4.6762 (0.0000)	8.3320 (0.0000)		
GARCH-MIDAS-RV	0.5693 (0.2828)	-7.7764 (0.4997)	-4.4552 (0.4964)	-7.4766 (0.4909)		
GARCH-MIDAS-RV+GEPU	0.5595 (0.4479)	7.7616 (0.0000)	4.4236 (0.0000)	7.4780 (0.0000)	-0.1413 (0.8876)	-4.4386*** (0.00001)
South Korea						
GARCH	-0.1563 (0.8628)	4.2491 (0.0001)	3.0892 (0.0009)	5.4942 (0.0000)		
GARCH-MIDAS-RV	0.2231 (0.4516)	3.7812 (0.0000)	2.7752 (0.0028)	5.3547 (0.0000)		
GARCH-MIDAS-RV+GEPU	0.1564 (0.5969)	-3.8279 (0.5841)	-2.7768 (0.5954)	-5.3645 (0.6334)	3.0864*** (0.0021)	2.7785*** (0.0056)
Turkey						
GARCH	1.0180 (0.2841)	5.0577 (0.0000)	4.1707 (0.0001)	6.4837 (0.0000)		
GARCH-MIDAS-RV	-1.0035 (0.8668)	-3.4906 (0.4986)	-2.8536 (0.5000)	-1.9664 (0.4983)		
GARCH-MIDAS-RV+GEPU	1.0453 (0.2655)	3.4820 (0.0003)	2.8672 (0.0016)	1.9468 (0.0266)	4.1827*** (0.00003)	-2.8699*** (0.0042)

The table shows the results of the Superior Predictive Ability (SPA) test and the Diebold and Mariano (DM) test for the different models' out-of-sample forecast performance of the different emerging stock markets. The DM method is applied to examine the null hypothesis of equal forecasting performance while the SPA method examines the null hypothesis that the benchmark model is not inferior to any of the alternatives. The second column of the table lists the benchmark models for SPA-test and the next four columns show the corresponding results of SPA tests based on four different loss functions (MSE, MAE, MSE_{sd} and MAE_{sd}). When we deal with the SPA test, where the sample size $n = 1002$ and the number of resamples $B = 10,000$. The last two columns in the table report the DM test results and each DM statistic in each cell is calculated by the model given in the row comparing with the benchmark model given in the column. The number in parentheses are the p-values of the DM test and the SPA test. ***, ** and * denote the significance at 1%, 5% and 10% level, respectively.

sequence. The negative SPA test statistic implies that the benchmark model has lower forecast error under the relative loss function than alternative models. And the null hypothesis of the SPA test is that the benchmark model is not inferior to any of the alternatives. The left panel of [Tables 7 and 8](#) show the SPA test results based on the four loss functions (MSE , MAE , MSE_{sd} , and MAE_{sd}). For China, South Africa, Mexico and South Korea, the GARCH-MIDAS-RV+GEPU model outperforms alternative models, relying on the fact that the SPA test statistics are negative and not significant (except MSE-based SPA test) when taking GARCH-MIDAS-RV+GEPU model as the benchmark, while the SPA test statistics are positive and significant

when taking alternative models as the benchmark. In terms of Brazil, Indonesia and Turkey, similar to the revelation results from loss function and the DM test, we do not find evidence that the GEPU-based model performs best. Interestingly, we cannot get unequivocal information from the SPA test to distinguish which one is best for Russia and India among the three comparing models. We just find that the

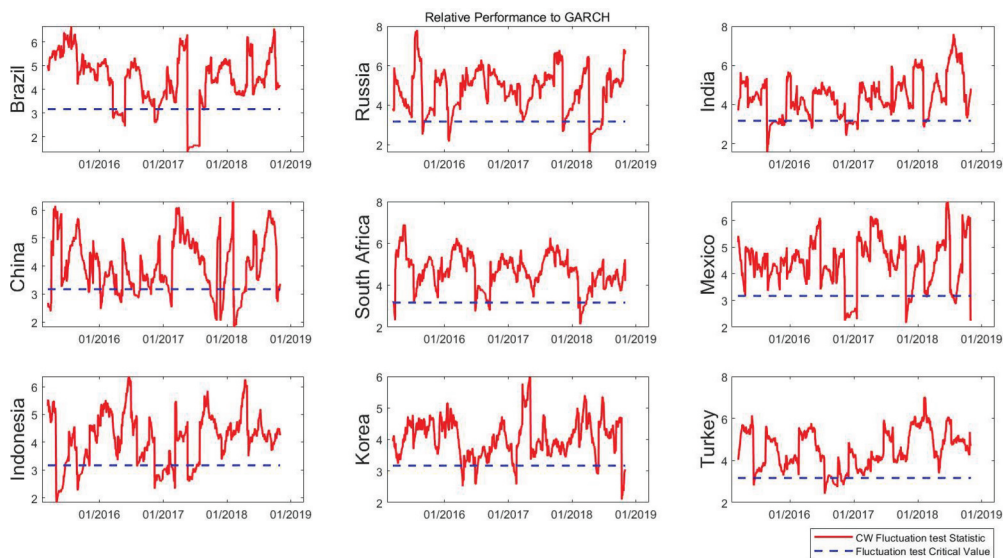


Figure 2. CW Fluctuation test relative to GARCH model for each country. (Notes: Red line depicts Fluctuation test statistics while blue line shows the critical value at significant level 5%. Positive values of the test statistics imply that the GARCH-MIDAS+RV+GEPU model is better than the GARCH model.).

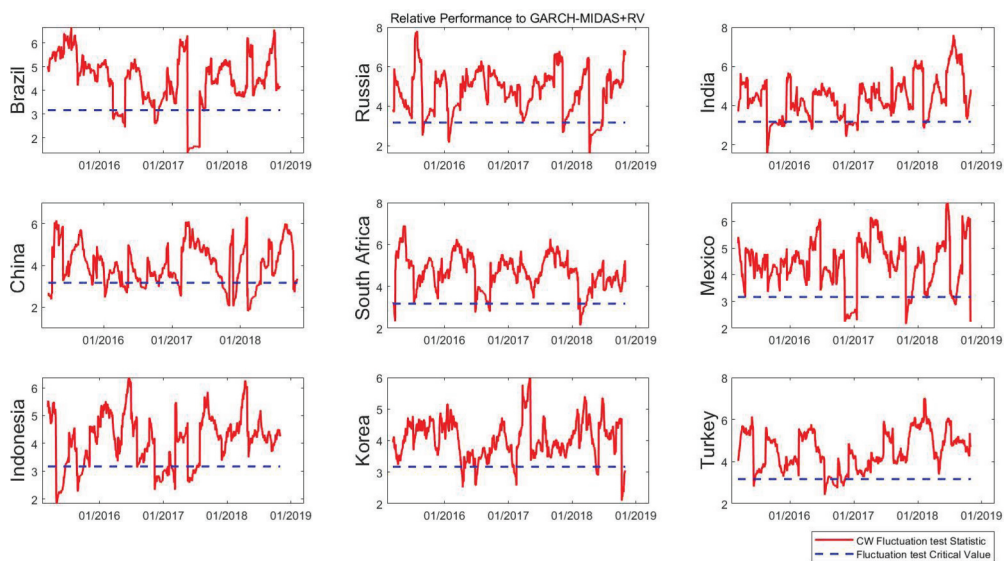


Figure 3. CW Fluctuation test relative to GARCH-MIDAS+RV model for each country. (Notes: Red line depicts Fluctuation test statistics while blue line shows the critical value at significant level 5%. Positive values of the test statistics imply that the GARCH-MIDAS+RV+GEPU model is better than the traditional GARCH-MIDAS model.).

GEPU-based model for India is not inferior to the alternative models based on the fact that the statistic achieved from the MAE_{sd} -based SPA test for GARCH-MIDAS-RV+GEPU model is negative and not significant. As far as Russia is concerned, we find that the GARCH-MIDAS-RV+GEPU model outperforms the GARCH-MIDAS-RV model.

As we know, both DM test and SPA test are static comparison methods for forecasting performance, evaluating average forecasting gains for the whole forecasting period. However, forecasting gains may be different over time and focusing solely on the average performance of the model may result in a loss of information and possibly lead to incorrect forecast selection decisions. With the consideration of this point and the inconsistent comparison results obtained from DM and SPA tests above, we finally use the Fluctuation test to compare their time-varyingly relative out-of-sample forecasting performances.

Figures 2 and 3 report results of the CW Fluctuation test for the GARCH-MIDAS+RV+GEPU model for each country, relative to the GARCH benchmark and the traditional GARCH-MIDAS benchmark, respectively. The CW Fluctuation test statistics are constructed by using a moving window ($m = 50$). Positive test statistic values demonstrate that the GARCH-MIDAS model involving GEPU information is better than the benchmark models. As shown in Figures 2 and 3, the relative forecasting performance of the GARCH-MIDAS+RV+GEPU model to the two benchmark models is time-varying over the whole out-of-sample period. But the Fluctuation test statistics are always positive, in spite that sometimes it is not statistically significant.

Hence, we interpret our empirical results as pointing towards a better performance of the model with GEPU relative to the benchmark models without GEPU information in most out-of-sample periods, to point that GEPU can improve the forecasting performances for the stock market volatility in emerging countries.

7. Summary and concluding remarks

In this paper, we examine the impact of the global economic policy uncertainty (GEPU) on stock volatility of nine emerging markets, paying special attention to the BRICS economies (Brazil, Russia, India, China, and South Africa) and the MIST economies (Mexico, Indonesia, South Korea, and Turkey) for the period January 2002 to October 2018. We use an expanded GARCH-MIDAS approach, which is called the GARCH-MIDAS-RV+GEPU model, to divide the stock total volatility into a long-term component and a short-term component, assuming that GEPU affects the stock total volatility via its long-term component. Besides, we take the GARCH (1,1) model and the GARCH-MIDAS-RV model as benchmarks to study whether GEPU can improve the predictive accuracy of stock volatility for the nine emerging markets.

This study finds a few of interesting empirical results, which can be listed as follows. Firstly, from the in-sample parameter estimation results, we find that the coefficients of GEPU are statistically significant for 9 countries with the full sample data and for 8 of 9 countries (except for India) with the in-sample data, suggesting that the global economic policy uncertainty has impact on their stock volatility. From the comparing results of model evaluation, the GEPU-based model outperforms for 9 countries with respect to the full sample, and for 5 of 9 countries (except for Russia, India, China, and Turkey) with the

in-sample. Secondly, from the results of loss function criterion and the DM test, we find strong evidence that involving GEPU into the GARCH-MIDAS model can improve the out-of-sample predictive ability for 6 of 9 countries (except for Brazil, Indonesia, and Turkey). The SPA test results are similar to the DM test and the loss function criterion results, except Brazil, Indonesia, and Turkey. Finally, taking consideration that both DM and SPA tests are static comparison methods for evaluating average forecasting performance and may result in a loss of information, we use the Fluctuation test to compare their time-varyingly relative out-sample forecasting performances in unstable environments. We find that the GARCH-MIDAS model with GEPU has a statistically significant better out-of-sample forecasting performance than the benchmark models for each country in most recent years. It indicates that GEPU can improve the forecasting accuracy of stock volatility in emerging countries. The findings that the fluctuation of global economic policy uncertainty may lead to the stock volatility for China and Korea are in agreement with Yu et al. (2018) and Cheng (2017), respectively.

One weakness of our study is that we directly extend the GARCH-MIDAS model based on Engle et al. (2013), ignoring comparison of other GARCH series models such as EGARCH, TGARCH, etc. For example, there is possibly another innovation, that is, constructing an EGARCH-MIDAS model, to evaluate if extensions to the traditional EGARCH model are more appropriate to our dataset, which is very challenging. Besides, our data sample is up to 31 October, 2018, the newest data which we can obtain when we started this study at first time. Some following data (especially the data during the COVID-19 pandemic) may be useful for comparing our results. As part of future research, it would be interesting to extend our study to resolve these limitations.

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Appendix A.

Table A1. Full-sample estimates of the three models for nine stock return series.

Variables	Brazil	Russia	India	China	South Africa	Mexico	Indonesia	South Korea	Turkey
GARCH (2002–2018)									
k	1.2e-05*** (1e-06)	9e-06*** (1e-06)	4e-06*** (1e-06)	1e-06** (3e-07)	2e-06*** (1e-06)	2e-06*** (4e-07)	2e-06*** (4e-07)	1e-06*** (4e-07)	7e-06*** (1e-06)
α	0.8912*** (0.0079)	0.8899*** (0.006)	0.848*** (0.0076)	0.9447*** (0.0029)	0.9100*** (0.0069)	0.9068*** (0.0056)	0.8949*** (0.0046)	0.9376*** (0.0046)	0.8963*** (0.0058)
β	0.0838*** (0.0062)	0.0853*** (0.0049)	0.1385*** (0.0077)	0.0543*** (0.0031)	0.0781*** (0.0061)	0.0803*** (0.0053)	0.0938*** (0.0044)	0.0552*** (0.0041)	0.0838*** (0.0052)
μ	0.0008*** (0.0003)	0.001*** (0.0002)	0.001*** (0.0001)	0.0002 (0.0002)	0.0006*** (0.0001)	0.0006*** (0.0001)	0.0008*** (0.0002)	0.0005*** (0.0002)	0.0009*** (0.0002)
GARCH-MIDAS-RV (2002–2018)									
μ	0.0008*** (0.0003)	0.001*** (0.0002)	0.0009*** (0.0001)	0.0002 (0.0002)	0.0006*** (0.0001)	0.0006*** (0.0001)	0.0008*** (0.0002)	0.0004** (0.0002)	0.001*** (0.0002)
α	0.0823*** (0.0059)	0.0912*** (0.0064)	0.1212*** (0.0068)	0.0552*** (0.0033)	0.0803*** (0.007)	0.0923*** (0.0069)	0.113*** (0.0052)	0.0596*** (0.0054)	0.1022*** (0.0074)
β	0.8991*** (0.0071)	0.8667*** (0.0116)	0.8678*** (0.0074)	0.9429*** (0.0032)	0.8999*** (0.0109)	0.871*** (0.0113)	0.8532*** (0.0069)	0.9174*** (0.0097)	0.8216*** (0.0144)
θ_{rv}	-0.0075*** (0.0024)	0.0130*** (0.0027)	0.0158*** (0.0072)	-0.0171* (0.0087)	0.0131* (0.008)	0.0234*** (0.0036)	0.0275*** (0.0037)	0.0258*** (0.003)	0.0313*** (0.0025)
w	2.6194*** (0.9015)	1.9703*** (0.6713)	1.0347*** (0.1277)	4.3672*** (1.6253)	1.1991 (1.1188)	1.6929*** (0.586)	1.9408*** (0.5085)	1.3114** (0.5153)	2.4131*** (0.4663)
m	0.00058*** (0.0007)	0.00022*** (0.0004)	0.00022*** (0.0004)	0.00048** (0.0002)	0.00009*** (0.00002)	0.00005*** (0.00001)	0.00008*** (0.00001)	0.00006*** (0.00000)	0.00009*** (0.00000)
GARCH-MIDAS-RV+GEPV (2002–2018)									
μ	0.0008*** (0.0003)	0.001*** (0.0002)	0.0009*** (0.0001)	0.0002 (0.0002)	0.0006*** (0.0001)	0.0006*** (0.0001)	0.0008*** (0.0002)	0.0004*** (0.0002)	0.001*** (0.0002)
α	0.0781*** (0.0058)	0.0896*** (0.0065)	0.1133*** (0.0062)	0.0541*** (0.0034)	0.0784*** (0.0078)	0.0886*** (0.0073)	0.1221*** (0.006)	0.0576*** (0.0052)	0.102*** (0.0078)
β	0.9019*** (0.0073)	0.8701*** (0.0124)	0.8827*** (0.0063)	0.9444*** (0.0033)	0.8889*** (0.0135)	0.8681*** (0.0124)	0.8148*** (0.0097)	0.9214*** (0.0082)	0.8164*** (0.0156)
θ_{rv}	-0.0058** (0.0026)	0.0109*** (0.003)	-0.0052 (0.0037)	-0.0179* (0.01)	0.0180*** (0.0052)	0.0232*** (0.0033)	0.0257*** (0.0024)	0.0268*** (0.0028)	0.0304*** (0.0025)

(Continued)

Table A1. (Continued).

Variables	Brazil	Russia	India	China	South Africa	Mexico	Indonesia	South Korea	Turkey
θ_{gepu}	0.0010** (0.0004)	0.0006*** (0.0002)	0.0006* (0.0003)	0.0006* (0.0003)	0.0003*** (0.0001)	0.0003*** (0.0001)	0.0004*** (0.0001)	0.0004*** (0.0001)	0.0006*** (0.0002)
w	3.4964** (1.4382)	3.4461*** (1.155)	10.706* (5.4238)	5.8918*** (1.4277)	3.2379*** (1.1173)	2.4517*** (0.5826)	3.2533*** (0.5194)	1.2606*** (0.2936)	2.7305*** (0.5007)
m	0.0006*** (0.0001)	0.0003*** (0.0000)	0.0005*** (0.0002)	0.0006** (0.0003)	0.0001*** (0.0000)	0.0001*** (0.00001)	0.0001*** (0.00001)	0.0001*** (0.0000)	0.0001*** (0.0000)

The table shows the parameter estimates of different models with full sample data for the nine emerging countries. The full sample data spans from 2002 to 2018. The parameter space for GARCH (1,1) model is $\Theta = \{\alpha, \beta, \mu\}$. The parameter space for the GARCH-MIDAS-RV model is $\Theta = \{\mu, \alpha, \beta, \theta_{rv}, w, m\}$. And the parameter space for the GARCH-MIDAS-RV+GEPV model is $\Theta = \{\mu, \alpha, \beta, \theta_{rv}, \theta_{gepu}, w, m\}$. The numbers in parentheses are standard errors. 0.0000 means the number less than 0.0001. *** denotes significance at the 1% level. ** denotes significance at the 5% level. * denotes significance at the 10% level.

Table A2. In-sample estimates of the three models for nine stock return series.

	Brazil	Russia	India	China	South Africa	Mexico	Indonesia	South Korea	Turkey
GARCH (2002–2014)									
k	1e-05*** (1e-06)	1e-05*** (1e-06)	1e-06 (5e-07)	2e-06** (1e-06)	1e-06 (1e-06)	2e-06** (1e-06)	4e-06*** (1e-06)	1e-06 (1e-06)	1e-05*** (1e-06)
α	0.9026*** (0.0086)	0.8747*** (0.0075)	0.9186*** (0.0049)	0.938*** (0.0044)	0.9116*** (0.0078)	0.9003*** (0.007)	0.8724*** (0.0052)	0.895*** (0.0072)	0.8778*** (0.0076)
β	0.0775*** (0.0068)	0.0971*** (0.006)	0.0812*** (0.0047)	0.0536*** (0.004)	0.0781*** (0.0069)	0.0846*** (0.0065)	0.1104*** (0.0057)	0.105*** (0.0077)	0.0991*** (0.0068)
μ	0.0009*** (0.0003)	0.0013*** (0.0003)	0.0010*** (0.0002)	0.0002 (0.0002)	0.0008*** (0.0002)	0.0008*** (0.0002)	0.0011*** (0.0002)	0.0009*** (0.0002)	0.0012*** (0.0003)
GARCH-MIDAS -RV (2002–2014)									
μ	0.0009*** (0.0003)	0.0013*** (0.0003)	0.0011*** (0.0002)	0.0002 (0.0002)	0.0008*** (0.0002)	0.0008*** (0.0002)	0.0012*** (0.0002)	0.0006*** (0.0002)	0.0013*** (0.0003)
α	0.0814*** (0.0075)	0.1047*** (0.0084)	0.1108*** (0.0064)	0.0571*** (0.0046)	0.0771*** (0.0074)	0.0924*** (0.0079)	0.1251*** (0.0067)	0.0668*** (0.0063)	0.1121*** (0.0086)
β	0.8906*** (0.0114)	0.8473*** (0.0148)	0.8847*** (0.0064)	0.9375*** (0.005)	0.9104*** (0.0084)	0.8734*** (0.0128)	0.8394*** (0.0077)	0.9188*** (0.0082)	0.8238*** (0.0145)
θ_{rv}	0.0109** (0.0049)	0.015*** (0.0032)	-0.0253** (0.0102)	-0.0129*** (0.0048)	0.0089 (0.009)	0.0221*** (0.0042)	0.0297*** (0.0065)	0.0267*** (0.0043)	0.0307*** (0.0034)
w	1.001*** (0.0503)	1.8791*** (0.6167)	2.8643** (1.3061)	7.8873** (3.2789)	1.0012*** (0.2852)	1.7283** (0.7243)	1.0093*** (0.0282)	1.0151*** (0.0472)	2.2013*** (0.5134)
m	0.0003*** (0.0001)	0.0002*** (0.00002)	0.0006*** (0.0002)	0.0004*** (0.0001)	0.0001*** (0.00003)	0.0001*** (0.00001)	0.0001*** (0.00002)	0.0001*** (0.00003)	0.0001*** (0.00002)
GARCH-MIDAS -RV+GEPU (2002–2014)									
μ	0.0009*** (0.0003)	0.0013*** (0.0003)	0.0009*** (0.0002)	0.0003 (0.0002)	0.0008*** (0.0002)	0.0008*** (0.0002)	0.0012*** (0.0002)	0.0006*** (0.0002)	0.0008*** (0.0003)
α	0.0814*** (0.0096)	0.1012*** (0.0081)	0.0100*** (0.0015)	0.0100*** (0.0036)	0.0793*** (0.0091)	0.0884*** (0.0082)	0.1300*** (0.0072)	0.0633*** (0.0068)	0.0100*** (0.0028)
β	0.8594*** (0.0223)	0.8555*** (0.0157)	0.9000*** (0.0355)	0.9001*** (0.0586)	0.8897*** (0.016)	0.8753*** (0.0132)	0.8108*** (0.0115)	0.9123*** (0.0127)	0.9001*** (0.0176)
θ_{rv}	0.0179*** (0.004)	0.0098*** (0.0036)	0.0490*** (0.0018)	0.0320*** (0.0018)	0.0201*** (0.006)	0.0213*** (0.0041)	0.0198*** (0.0034)	0.0282*** (0.0035)	0.0275*** (0.0018)
θ_{gepu}	0.0009*** (0.0003)	0.0003** (0.0001)	0.0003*** (0.0002)	0.0003*** (0.0001)	0.0003*** (0.0001)	0.0003** (0.0001)	0.0005*** (0.0001)	0.0004*** (0.0001)	0.0005*** (0.0001)
w	4.3901*** (0.0001)	7.3108** (0.0002)	5.0000*** (0.0002)	4.9992*** (0.0001)	3.5413** (0.0001)	2.1367*** (0.0001)	4.9491*** (0.0001)	2.4108*** (0.0001)	5.0001*** (0.0001)

(Continued)

Table A2. (Continued).

	Brazil	Russia	India	China	South Africa	Mexico	Indonesia	South Korea	Turkey
m	(1.3922) 0.0003*** (0.0000)	(3.2615) 0.0003*** (0.0000)	(0.3926) 0.00001 (0.0000)	(0.7392) 0.0001*** (0.0000)	(1.4813) 0.0001*** (0.0000)	(0.6701) 0.0001*** (0.0000)	(0.9397) 0.0001*** (0.0000)	(0.7322) 0.0001*** (0.0000)	(0.5739) 0.0001*** (0.0000)

The table shows the parameter estimates of different models with in-sample data for the nine emerging countries. The in-sample data spans from 2002 to 2014. The parameter space for GARCH (1, 1) model is $\Theta = \{k, \alpha, \beta, \mu\}$. The parameter space for the GARCH-MIDAS-RV model is $\Theta = \{\mu, \alpha, \beta, \theta_{rv}, w, m\}$. And the parameter space for the GARCH-MIDAS-RV+GEPU model is $\Theta = \{\mu, \alpha, \beta, \theta_{rv}, \theta_{gepu}, w, m\}$. The numbers in parentheses are standard errors. 0.0000 means the number less than 0.0001. *** denotes the significance at 1% level. ** denotes the significance at 5% level. * denotes the significance at 10% level.