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Volatility forecasting: Global economic policy uncertainty and regime switching

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HIGHLIGHTS

- I explore the impacts of global economic policy uncertainty on future aggregate monthly volatility.
- Introducing the regime switching in forecasting models, and explore the predictive ability.
- In-sample results show that the GEPU index has a significant impact on one-ahead-step volatility of US stock market.
- The GEPU performs much bigger role on future RV in high volatility regime period than during low volatility regime.
- The GEPU index can increase the forecasts accuracy, especially considering the regime switching.

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ABSTRACT

In this study, I explore the impacts of global economic policy uncertainty on futures aggregate monthly volatility and introduce the regime switching in forecasting models, and analyze the predictive ability. In-sample empirical results show that the GEPU index has a significant impact on one-ahead-step volatility of US stock market. Additionally, the GEPU performs much bigger role on future RV in high volatility regime period than during low volatility regime. The out-of-sample results indicate that the GEPU index can indeed increase the forecasts accuracy, especially introducing the regime switching to the forecasting model. Importantly, the robust test is consistent with the conclusions.
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1. Introduction

As we are known, volatility plays an important role in asset pricing, hedging, portfolio selection and risk measurement [e.g., 1–8]. The volatility of stock market not only has a significant influence on the market itself, but also the real economy [e.g., 9–11]. Thus, modeling and forecasting the volatility of stock market is critical for researchers, market participants, and policymakers.

However, accurately forecasting volatility is still difficult. In this study, I explore the impacts of uncertainty on future volatility, and use the global economic and policy uncertainty index (henceforth GEPU) to represent the uncertainty, and seek to find new evidence to increase the forecasts accuracy. The base of GEPU is EPU index, which is first proposed by Baker et al. [12]. EPU is based on newspaper coverage frequency. Baker et al. [12] use this new measure to investigate the effects of policy uncertainty on stock price volatility and find that policy uncertainty raises stock price volatility. In technical details, GEPU is a GDP-weighted average of national EPU indices for 19 countries that accounting over 50% of total world GDP, for example, US, China, Japan and EU. Each national EPU index reflects the relative frequency of own-country newspaper articles that contain terms pertaining to the economy (E), policy (P) and uncertainty (U). In real world, the sudden change of GEPU

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is also consistent with major events like 9/11, Global Financial Crisis and Trump election, etc. Comparing to EPU, the GEPU covers more information around the world and tracks global uncertainty trend that helps more in forecasting volatility [13]. To best of my knowledge, several studies relate to my study. For example, Liu and Zhang [14] investigate the predictability of economic policy uncertainty (EPU) to stock market volatility, and find that incorporating EPU as an additional predictive variable into the existing volatility prediction models significantly improves forecasting ability of these models. Liu et al. [15] investigate whether economic policy uncertainty (EPU) can affect future volatility based on the multifractal insight, and also find that adding EPU as explanatory variable to volatility models can indeed improve the forecasting performance. Ma et al. [16] also investigate whether economic policy uncertainty (EPU) index can increase the HAR-RV-type models' forecast accuracy with considering the threshold of EPU index, and indicate that the HAR-RV models including above-threshold EPU can further improve the forecast accuracy and yield higher economic values by setting specific thresholds for a range of horizons.

Compared to these existed studies, my paper has three remarkable differences. First, my paper focus on the aggregate stock volatility based on monthly data. Compared to the realized and multifractal volatility using the high-frequency data, the monthly data are more convenient to acquire and apply in real practices. Hence, the monthly aggregate volatility has received more attentions by scholars and investors, who are interested in the asset pricing and return predictability. Second, this paper has paid its attention on GEPU, and explores whether the GEPU has impacts on future volatility of the stock market. To the best of author's knowledge, there are few papers on doing this related research. This is because the GEPU index can be freely used in recent two years. Of course, limited scholars [e.g., 13,17] have just utilized this index to do some research on other markets. However, my paper is in the first group to fill this linkage between the GEPU and volatility forecasting in US market, the most important market. Third, these aforementioned works are all based on the framework of linear models. Previous studies [e.g., 8,18,19] have evidenced that high level of persistence when volatility is low, implying the presence of nonlinearities. Moreover, due to many factors such as business cycle, major events and economic policy, the statistical property of volatility (e.g., volatility persistence) always undergoes structural breaks or switches between different regimes. Therefore, in this study, I explore the impacts of global economic policy uncertainty on futures aggregate monthly volatility and introduce the regime switching in forecasting models, and analyze the predictive ability.

The conclusions of this paper are as below. In-sample empirical results show that the GEPU index has a significant impact on one-ahead-step volatility in the US stock market. The normality test of residuals in each model significantly rejects the null hypothesis that residual meets the normal distribution as the important assumption of linear model. The normality test results indicate that linear model may be not suitable to estimate future RV with these variables. In out-of-sample section, GEPU improves the forecasting power of traditional autoregressive model of volatility. Additionally, the GEPU performs much bigger role on future RV in high volatility regime period than during low volatility regime. The out-of-sample results indicate that the GEPU index can indeed increase the forecasts accuracy, especially introducing the regime switching to the forecasting model. That means the combination of GEPU and regime switching can improve the forecasting accuracy of volatility, which is important in asset pricing, hedging, portfolio selection and risk measurement. Importantly, my robust test is consistent with the conclusions.

The rest of the paper is organized as follows: Section 2 describes the volatility measures and models. The methodology of out-of-sample forecasting and the Model Confidence Set (MCS) test are discussed in Section 3. Section 4 provides the data and some preliminary analysis. The empirical forecasting results are presented in Section 5. Section 6 concludes the paper.

2. Volatility measure and models

2.1. Realized Variance

The primary interest is to measure the monthly variance of stock market, which will be estimated from Realized Variance (RV). RV can measure the actual market volatility more accurate with less trading noise that achieves a balance [20]. In US market, RV is applied in many studies to represent the real volatility [e.g. 21,22]. The monthly RV is calculated by

$$\mathrm{RV}_t = \sum_{j=1}^{N} r_{t,j}^2 \tag{1}$$

where $r_{t,j}$ is the return in month t, day j.

2.2. Forecasting model

As far as I know, the autoregression of RV itself in one lag, AR(1)-RV model, has been used in many studies focusing on forecasting the RV [8]. The AR(1) model of RV archives a balance on model complexity and forecasting accuracy. The AR(1) model of RV is termed as AR(1)-RV and given by

$$RV_{t+1} = a + \beta_1 \times RV_t + \omega_{t+1} \tag{2}$$

With the development of GEPU, many literatures find that GEPU as an indicator of macroeconomy helps in measuring the volatility in financial market [8,14]. Therefore, I add the GEPU to AR(1)-RV model to include the macroeconomy information in forecasting financial market volatility. The updated model with GEPU is displayed below as AR(1)-RV-GEPU

$$RV_{t+1} = a + \beta_1 \times RV_t + \beta_2 \times GEPU_t + \omega_{t+1} \tag{3}$$

In this study, I consider two regimes similar to Wang et al. [21] and Ma et al. [8]. The two regimes can mostly describes the nonlinear and structural break characteristics of financial markets [8,23]. AR(1)-RV-GEPU model with Markov Regime Switching is termed as MS-AR(1)-RV-GEPU and given by

$$RV_{t+1} = a_{s_t} + \beta_{1,s_t} \times RV_t + \beta_{2,s_t} \times GEPU_t + \omega_{t+1} \tag{4}$$

where $\omega_{t+1} \sim N(0, \sigma_{s_t}^2)$. Let s_t be the unobservable state variable. $s_t = 0$indicates the low volatility regime with a smaller conditional variance, suggesting the market is state. In another condition, $s_t = 1$ indicates the high volatility regime with a larger conditional variance, suggesting the market is fluctuating. The observable state variable, s_t is assumed to follow a two-state Markov process with transition probability matrix given by

$$P = \begin{bmatrix} p^{00} & 1-p^{00} \\ 1-p^{11} & p^{11} \end{bmatrix} \tag{5}$$

where, $p^{00} = p(s_t = 0|s_{t-1} = 0)$ and $p^{11} = p(s_t = 1|s_{t-1} = 1)$.

The MS-AR(1)-RV-GEPU model can be estimated by the maximum likelihood function using the filtering procedure proposed by Hamilton [24] that followed by the smoothing algorithm of Kim [25]. The log likelihood function is given by:

$$\ln L = \sum_{t=1}^{T} \ln \left(\frac{1}{\sqrt{2\pi\sigma_{s_t}^2}} \exp(-\frac{RV_{t+1} - \alpha_{s_t} - \beta_{1,s_t} RV_t}{2\sigma_{s_t}^2}) \right) \tag{6}$$

3. Forecasting mode and evaluation

In forecast mode, I briefly apply the rolling window as the out-of-sample forecasting method used in many papers (See e.g. [26]). In this method, the sample data is divided into two groups, one is the in-sample estimation data covering 130 observations from Feb 1997 to Nov 2007. Another group is used for out-of-sample forecasting with 120 trading months from Dec 2007 to Nov 2017. In the forward forecasting, the rolling window mainly adds the most recent month and drops the most distant month. This rule can keep the estimation space for forecasting remains at a fixed length in whole period. The forecast do not overlap as well.

To quantitatively measure the accuracy of forecasting, I introduce six loss functions:

$$MSE = M^{-1} \sum_{t=1}^{M} (RV - \widehat{RV}_t)^2 \tag{7}$$

$$MSE = M^{-1} \sum_{t=1}^{M} |RV - \widehat{RV}_t| \tag{8}$$

$$HMSE = M^{-1} \sum_{t=1}^{M} (1 - \frac{\widehat{RV}_t}{RV_t})^2 \tag{9}$$

$$HMAE = M^{-1} \sum_{t=1}^{M} |1 - \frac{\widehat{RV}_t}{RV_t}| \tag{10}$$

$$QLIKE = M^{-1} \sum_{t=1}^{M} (\ln(\widehat{RV}_t) + \frac{RV_t}{\widehat{RV}_t}) \tag{11}$$

$$R^2LOG = M^{-1} \sum_{t=1}^{M} (\ln(RV_t)/\widehat{RV}_t)^2 \tag{12}$$

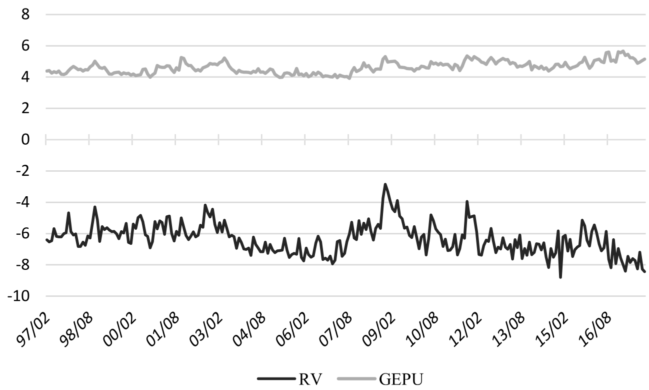

Fig. 1. Monthly RV and GEPU after log transformation.

Table 1
Descriptive statistics of variables.

Variables	Mean	St. dev.	Skewness	Kurtosis	Jarque–Bera	Q(5)	ADF
RV	−6.333	0.975	0.428***	0.480	10.016***	30.494*	−4.571***
GEPU	4.619	0.372	0.374**	−0.363	7.204**	27.258*	−3.726***

Notes: I use the econometric software of the WINRATS to test the null hypothesis, "Skewness = 0" and "Excess Kurtosis = 3". The Jarque–Bera statistic tests are for the null hypothesis of normality for the distribution of the series. Asterisk ***, ** and * denote rejections of null hypothesis at 1%, 5%, and 10% significance levels, respectively.

where $\widehat{RV}_t$ denotes the forecast value of different model. RV_t represents the actual market volatility, and M indicates the out-of-sample size. In my case, $M = 120$.

The disadvantage of these above loss functions is that they cannot provide the significant forecasting evaluation results. Hence, I adopt the advanced test, Model Confidence Set (MCS) proposed by Hansen et al. [27]. MCS test can filter all possible superior models into a subset from the initial set of all models. The MCS test includes several attractive advantages over traditional test like SPA [28]. First, the MCS test do not require any specified benchmark model. This is very useful in some conditions that do not have a clear benchmark model. Second, the MCS test acknowledges the likelihood of outliers in the data, which may cause extreme bias of loss functions. Third, the MCS test allows for the possibility of more than one "best" models.

Following the procedure of MCS test, I apply six statistics to determine all models' P-value. For example, Range statistic and Semi-quadratic statistic, defined as

$$T_R = \max_{u,v\in M} \frac{\left|\bar{d}_{i,uv}\right|}{\sqrt{\mathrm{var}(d_{i,uv})}},\ T_{SQ} = \max_{u,v\in M} \frac{(\bar{d}_{i,uv})^2}{\mathrm{var}(\bar{d}_{i,uv})},\ \bar{d}_{i,uv} = \frac{1}{n}\sum_{t=1}^{n} d_{i,uv,t} \tag{13}$$

If some models' P-values are larger than critical value, alpha, these models can survive in MCS test. The surviving models have a better forecasting performance than the reset models removed from MCS test. Furthermore, the larger P-value (closer to 1) the better the model performs. The technical details of MCS test, other four statistics (T_{max}, T_Q, T_F and T_D) and more in-depth discussion can be referred in [27].

4. Data description

I collect the daily close prices of SP500 index from Yahoo Finance and compute monthly RV. In addition, I obtain data of global Economic Policy Uncertainty (henceforth GEPU) from the website (www.policyuncertainty.com). The GEPU bases on current-price GDP measures that covers more data that other measurement of GEPU. The range of global EPU is matched with RV from Feb 1997 to Nov 2017 with 250 observations.

Many studies [e.g., 29–34] have found that the realized volatility exhibits non-normality. Also, Aït-Sahalia and Mancini [35] point out that the distribution of log-RV can be closer to Gaussian than that of RV. Furthermore, to ensure the volatility values are nonnegative, RV is log transformed. To be consistent with log transformed RV, GEPU is also dealt with log transformation. Fig. 1 illustrates the trend of monthly RV and GEPU with log transformation.

RV behaves more volatile after 2007 with increasing line of GEPU. In addition, at the occurrence of some big events, like 2007 financial crisis and 2012 Euro debt crisis, the sudden flash of GEPU matches the growing RV. Hence, the obvious relationship between GEPU and RV means a good start of the following empirical analysis.

Table 1 shows the descriptive statistics of RV and global GEPU after log transformed.

Table 2
In-sample period estimation of linear models.

	(1)	(2)
lnRV	0.775***	0.568***
	(16.36)	(9.52)
lnGEPU		0.975***
		(4.19)
Constant	−1.360***	−6.952***
	(−4.54)	(−5.31)
Normality test	2.400***	2.603***
N	130	130
Adj. R^2	0.599	0.650

Notes: I have the null hypothesis that coefficients are zeros, for example and so on. Asterisk ***, ** and * denote rejections of null hypothesis at 1%, 5% and 10% significance levels, respectively. t statistics is displayed in the parentheses.

All measures are significantly skewed at least 5% significance level, suggesting that each measure has a skewed distribution other than normal distribution. The Jarque–Bera statistic test further demonstrates that the normality null hypothesis is both rejected at least 5% significance level. The Ljung–Box statistic of autocorrelation shows that the null hypotheses of no autocorrelation up to 5th order are all rejected, indicating the existence of autocorrelation.

5. Empirical analysis

In this section, I first present the estimation results of two linear models and one model with regime witching using in-sample data. Secondly, the forecasting performance of all models is evaluated with MCS test and robustness check.

5.1. In-sample estimation results

Table 2 exhibits the estimation results of two linear models over the in-sample period based on the Newey–West correction, which allows for autocorrelation up to the order of 5. All parameters of two linear models are significant at 1% level, indicating the high persistence in RV and GEPU dynamics. I also find that the positive coefficient of lagged GEPU and declining coefficient of lagged RV in model two, comparing the coefficient of lagged RV in model one. That suggests the additive explaining power of lagged GEPU to RV, along with the growing adjust R square from model one to model two. Furthermore, I observe that adjust R square of each model is larger than 0.5, implying a higher explanation ability to the future realized variance. In final word, the normality test of residuals in each model significantly rejects the null hypothesis that residual meets the normal distribution as the important assumption of linear model. The normality test results indicate that linear model may be not suitable to estimate future RV with these variables.

Table 3 displays the estimation of model three with regime switching. The empirical result shows that the coefficient of lagged GEPU in state 2 is great bigger than this in state 1, along with the declining coefficient of lagged RV from state 1 to state 2. This suggests that GEPU performs much bigger role on future RV in high volatility regime period. This is consistent with the view of the occurrence of big events and their greater effect on fluctuating market like 2007 period. In addition, comparing the translation probability of P^{00} and P^{11}, I find that high volatility regime is short-lived with bigger fluctuation showed in the larger value of sigma2. Finally, I apply the likelihood ratio test to investigate the linearity of model and conclude the model three significantly reject the linear hypothesis, indicating the regime switching models exists.

5.2. Out-of-sample forecasting results

Wang et al. [21] find that the in-sample prediction relationships are not constant but varies over time. Compared with the in-sample performance, the out-of-sample performance of a model (i.e., its predictive ability) is more important to market participants, because they are more concerned about the model's ability to predict the future than its ability to analyze the past.

In this analysis, I apply the MCS test [27] to evaluate the forecasting performance. Based on Martens et al. [36], Hansen et al. [27] and Laurent et al. [37], I set the confidence level alpha of 0.25, which means that if P-value obtained from the MCS test is smaller than 0.25, I can exclude the corresponding model from the set. In other word, the forecasting performance of that model is significantly worse than that of other models in MCS test. The P-values are obtained from 10,000 bootstraps with 2 block length recommended by Hansen et al. [27].

Table 4 reports the MCS test results from the two linear models and one model with regime switching with forecasting window = 120. Under six loss functions (MSE, MAE, HMSE, HMAE, QLIKE and R^2LOG), linear models have the smallest P-value except under MAE loss function. The results of linear models indicate that they have a worse predicting ability than the model including regime switching. In contrast, the model with regime switching survives in MCS test under all six loss functions and have the biggest P-value, implying the best forecasting performance. The results are consistent with the view of Ma et al.

Table 3
In-sample period estimation of model three with regime switching.

GEPU	GEPU	GEPU
lnRV	0.568***	0.534***
	(7.70)	(7.89)
lnGEPU	0.535***	1.189***
	(2.82)	(5.41)
constant	−5.495***	−8.042***
	(−4.20)	(−6.29)
sigma1	0.064***	
	(2.97)	
sigma2		0.544***
		(16.42)
p^{00}	0.449***	
	(2.96)	
p^{11}		0.067*
		(1.87)
Linearity test	8.85**	
N	130	
AIC	503.5	

Notes: I have the null hypothesis that coefficients are zeros, for example and so on. Asterisk ***, ** and * denote rejections of null hypothesis at 1%, 5% and 10% significance levels, respectively. AIC is the Akaike information criterion. Z statistics is displayed in the parentheses.

Table 4
Results of the MCS test.

Statistics	T_R	T_{SQ}	T_{Max}	T_Q	T_F	T_D	T_R	T_{SQ}	T_{Max}	T_Q	T_F	T_D
	MSE						MAE					
Panel A: out-of-sample window = 120												
AR(1)-RV	0.890*	0.890*	0.896*	0.887*	0.888*	0.896*	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***
AR(1)-RV-GEPU	0.819*	0.778*	0.859*	0.744*	0.747*	0.815*	0.714*	0.745*	0.883*	0.735*	0.738*	0.699*
MS-AR(1)-RV-GEPU	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	0.896*	0.896*	0.897*	0.897*	0.897*	0.898*
Panel B: out-of-sample window = 120												
	HMSE						HMAE					
AR(1)-RV	0.176	0.218	0.237	0.321*	0.328*	0.189	0.644*	0.723*	0.669*	0.791*	0.793*	0.776*
AR(1)-RV-GEPU	0.435*	0.435*	0.439*	0.403*	0.405*	0.439*	0.644*	0.723*	0.669*	0.791*	0.793*	0.776*
MS-AR(1)-RV-GEPU	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000**	**1.000***	**1.000***	**1.000***	**1.000***
Panel C: out-of-sample window = 120												
	QLIKE						R^2LOG					
AR(1)-RV	0.862*	0.862*	0.874*	0.858*	0.858*	0.874*	0.616*	0.593*	0.593*	0.625*	0.629*	0.738*
AR(1)-RV-GEPU	0.787*	0.667*	0.791*	0.603*	0.607*	0.725*	0.616*	0.593*	0.593*	0.625*	0.629*	0.738*
MS-AR(1)-RV-GEPU	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***

Note: * indicates a P-value larger than 0.25, which means that the corresponding model survives the MCS test under a specific loss function and test statistic. The bold P-value 1.000 indicates that the corresponding model performs better than other models.

[8], which point out that a regime-switching model may be more suitable for modeling volatility, because of quite common structural breaks in financial market.

5.3. Robustness check

Rossi and Inoue [38] argue that arbitrary choices of window sizes have consequences about how the sample is split into in-sample and out-of-sample portions. Although choosing an appropriate forecasting, window is crucial to the forecasting performance of the models, there seems to be no consensus on how to choose the right forecasting windows. Thus, I also report the results in Table 6 obtained Table 5 from other forecasting windows, such as 96 and 144. The results further validate that my findings are robust, indicating that inclusion of a two-regime switching in model three provides a powerful forecasting ability in the stock market's volatility. Therefore, I can draw a conclusion that, in forecasting of the S&P 500 index volatility, nonlinear regime-switching model with aid of GEPU has a better performance than the linear models alone.

6. Conclusions

Modeling and forecasting the volatility of stock market is critical for researchers, market participants, and policymakers. However, accurately forecasting volatility is still a daunting task. Hence, I investigate the relationship between the uncertainty and volatility, and use the popular uncertainty index of GEPU to represent the global uncertainty, further explore its

Table 5
Results of the MCS test under different out-of-sample windows.

Statistics	MSE						MAE					
	T_R	T_{SQ}	T_{Max}	T_Q	T_F	T_D	T_R	T_{SQ}	T_{Max}	T_Q	T_F	T_D
Panel A: out-of-sample window = 96												
AR(1)-RV	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***
AR(1)-RV-GEPU	0.200	0.206	0.499*	0.233	0.242	0.233	0.161	0.198	0.382*	0.191	0.200	0.162
MS-AR(1)-RV-GEPU	0.625*	0.625*	0.641*	0.627*	0.627*	0.641*	0.536*	0.536*	0.545*	0.547*	0.549*	0.545*
Panel B: out-of-sample window = 144												
AR(1)-RV	0.417*	0.380*	0.427*	0.398*	0.400*	0.427*	0.510*	0.510*	0.507*	0.494*	0.495*	0.507*
AR(1)-RV-GEPU	0.191	0.160	0.238	0.130	0.135	0.304*	0.322*	0.328*	0.342*	0.295*	0.300*	0.418*
MS-AR(1)-RV-GEPU	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***
	HMSE						HMAE					
Panel C: out-of-sample window = 96												
AR(1)-RV	0.525*	0.450*	0.323*	0.420*	0.427*	0.508*	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***
AR(1)-RV-GEPU	0.525*	0.450*	0.323*	0.420*	0.427*	0.508*	0.457*	0.459*	0.808*	0.423*	0.431*	0.484*
MS-AR(1)-RV-GEPU	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	0.974*	0.974*	0.976*	0.976*	0.977*	0.976*
Panel D: out-of-sample window = 144												
AR(1)-RV	0.075	0.057	0.079	0.064	0.068	0.148	0.172	0.192	0.160	0.210	0.216	0.279*
AR(1)-RV-GEPU	0.075	0.057	0.079	0.064	0.068	0.148	0.172	0.192	0.160	0.210	0.216	0.279*
MS-AR(1)-RV-GEPU	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***
	QLIKE						R^2LOG					
Panel E: out-of-sample window = 96												
AR(1)-RV	0.862*	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***
AR(1)-RV-GEPU	0.787*	0.122	0.291*	0.175	0.184	0.159	0.377*	0.260*	0.589*	0.308*	0.316*	0.353*
MS-AR(1)-RV-GEPU	**1.000***	0.412*	0.426*	0.427*	0.429*	0.426*	0.692*	0.692*	0.705*	0.713*	0.714*	0.705*
Panel F: out-of-sample window = 144												
AR(1)-RV	0.379*	0.379*	0.384*	0.359*	0.360*	0.384*	0.243	0.249	0.249	0.228	0.230	0.249
AR(1)-RV-GEPU	0.204	0.101	0.162	0.055	0.059	0.211	0.157	0.127	0.127	0.051	0.056	0.225
MS-AR(1)-RV-GEPU	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***	**1.000***

Note: * indicates a P-value larger than 0.25, which means that the corresponding model survives the MCS test under a specific loss function and test statistic. The bold P-value 1.000 indicates that the corresponding model performs better than other models.

predictive ability with considering the regime switching. Different from previous studies, I focus on the aggregate volatility based on monthly data and investigate the impacts of GEPU on future volatility forecasting. In-sample empirical results show that the GEPU index has a significant impact on one-ahead-step volatility in the US stock market. The normality test of residuals in each model significantly rejects the null hypothesis that residual meets the normal distribution as the important assumption of linear model. The normality test results indicate that linear model may be not suitable to estimate future RV with these variables. Additionally, the GEPU performs much bigger role on future RV in high volatility regime period than during low volatility regime. The out-of-sample results indicate that the GEPU index can indeed increase the forecasts accuracy, especially introducing the regime switching to the forecasting model. Importantly, the robust test is consistent with the conclusions. Based on the results, the government and regulation bureaus can evaluate the effect of global economy uncertainty to stock markets with more accuracy. In addition, the bureau and investors need to know the different impact of global economy uncertainty on market under different fluctuating states, especially the aggregate effect in high violating period.

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