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Economic policy uncertainty and the Chinese stock market volatility: Novel evidence☆

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ABSTRACT

In this study, we investigate the impact of global economic policy uncertainty (GEPU) on Chinese stock market volatility. More importantly, for the first time, we explore the effects of directional GEPU based on the changing directions of GEPU and Chinese economic policy uncertainty (EPU). We make several noteworthy findings. First, the in-sample estimated results show that up and down GEPU can lead to substantially high stock market volatility for China. Second, the out-of-sample estimated results support the contention that the GEPU index is helpful for predicting volatility. Moreover, compared to GEPU alone, directional GEPU can provide more useful information that can increase the forecast accuracy. Third, we empirically find that directional GEPU is more effective in predicting Chinese stock market volatility when GEPU and EPU rise in the same month.

1. Introduction

As we know, there is a large body of literature devoted to modeling and forecasting stock market volatility, but how to accurately describe and predict volatility is still a substantial challenge to scholars and practitioners. In this paper, we use macro information that measures the economic and policy uncertainty of China and the world to investigate whether those indicators have influenced Chinese stock market volatility. Why have we done this research? We have three primary motivations.

First, Baker et al. (2016) developed a new index of economic policy uncertainty (EPU) based on newspaper coverage frequency, which can measure economic policy uncertainty. The EPU index has been receiving more attention from scholars, who investigate the links between this index and stock market (or other markets') volatility and returns. Linkages between EPU and volatility (returns) exist, for example, volatility forecasting (Liu and Zhang, 2015; Fang et al., 2017; Ma et al., 2018a) and return predictability (Kang and Ratti., 2013; Wang et al., 2015; Arouri et al., 2016; Phan et al., 2018). Interestingly, the global EPU (GEPU) index is proposed by Davis (2016), and is a GDP-weighted average of national EPU indices for 20 countries that account for two-thirds of global output.[1] To the best of the authors knowledge, few studies have investigated the relationship between GEPU and stock market volatility. Compared to previous works, we not only use the monthly EPU to model and forecast stock market daily volatility in the framework of the GARCH-MIDAS[2] but also consider the impact of monthly GEPU. We will seek to answer the following open question: Is the monthly GEPU index helpful for predicting stock market volatility?

Second, the Chinese stock market is one of the largest and fastest-growing emerging stock markets in the world. By the end of 2017, the total market capitalization of the Chinese stock market had broken 56.62 trillion yuan. More importantly, the Chinese stock market has gradually integrated into the global economy after a series of liberalization policies, such as those of the World Trade Organization (WTO), Qualified Foreign Institutional Investors (QFII) and RMB Qualified Foreign Institutional Investors (RQFII). Considering these factors, the Chinese stock market may be received much more attention from scholars and investors. Naturally, high global economic policy uncertainty can not only lead to the panics of the international investors, but also may result in high

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[1] 20 countries are 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).

[2] The GARCH-MIDAS model has received more attention from Asgharian et al. (2013), Engle et al. (2013), Girardin and Joyeux (2013), Conrad and Loch, (2015), and can be used to model the different frequency data.

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uncertainty for the Chinese investors. Hence, we will investigate the linkages between the GEPU and Chinese stock market volatility using the framework of the GARCH-MIDAS model.

Third, we observe that the monthly EPU of China and GEPU in the same month may have different changes in direction. The first condition is that EPU and GEPU increase in month t, the second situation is that they decrease in month t, and the third situation is mixed ($\text{EPU}_t\uparrow,\ \text{GEPU}_t\downarrow;\text{EPU}_t\downarrow,\text{GEPU}_t\uparrow$). The different changes between them leave us with a series of interesting questions: Does the GEPU index contain different predictive information? Under the different conditions, does GEPU have different impacts on Chinese stock market volatility? To the best of our knowledge, there is no study exploring these related questions. Therefore, this study makes two main contributions to the previous literature with respect to modeling and forecasting stock market volatility.

The first contribution of this paper is that we not only investigate the impacts of Chinese EPU on future volatility but also explore the incremental predictive information of the GEPU index and its effect on Chinese stock market volatility using the GARCH-MIDAS model. Regarding this issue, two works are related to this paper, Fang et al. (2018a) and Yu et al. (2018). However, there are several significant differences. First, Fang et al. (2018a) investigated the impacts of GEPU on the COMEX gold future market volatility, but in this paper we will seek to answer the open question of whether GEPU is still an effective indicator of Chinese stock market volatility. Second, compared to the work of Yu et al. (2018), we not only utilize the individual GEPU information on forecasting volatility but also consider Chinese EPU and GEPU together to investigate their predictive performance. More importantly, both of papers Fang et al. (2018a) and Yu et al. (2018) just explore the impacts of GEPU on volatility, but our study is focused on the directions of EPU and GEPU and investigated those impacts on Chinese stock market volatility. Moreover, the most important model of Fang et al. (2018a) and Yu et al. (2018) is one of our predictive models, and our new proposed model can outperform this model including the GEPU index (equation (4) in Fang et al. (2018a) and equation (4) in Yu et al. (2018)). In addition, in the framework of Fang et al. (2018a) and Yu et al. (2018), we find that GEPU is only one additional explanatory variable, and ignore these effects from the EPU itself. Several works (e.g., Liu and Zhang, 2015; Duan et al., 2018; Mei et al., 2018) have found that the EPU has effect on future volatility. Therefore, this paper is significantly different from those papers (Fang et al., 2018a; Yu et al., 2018).

The second and most important contribution is that we define the new GEPU based on the changes in direction of the Chinese EPU and GEPU, up and down GEPU, and evaluate their predictive ability. Moreover, we further evaluate their forecasting performance and find that our strategies perform differently under three different conditions. Luo and Qi (2017) capture the increasingly positive correlations between the G7 and China's market after 2008. To some extent, this study shows that the Chinese stock market has developed increasingly close ties with the global economy. Therefore, up (down) GEPU can transmit a clear signal that global economic policy is highly (minimally) uncertain and, in the same month, Chinese economic policy is also highly (minimally) uncertain; thus, in this paper, we provide new insights into utilizing the directional GEPU for Chinese stock market volatility forecasting.

The main findings of the paper can be summarized as follows. First, we decompose GEPU into its up, down and mixed components based on the change in direction of the EPU and GEPU, and examine the linkages between them and Chinese stock market volatility. The in-sample estimated results show that, in most cases, up and down GEPU are statistically significant and can lead to high stock market volatility. Compared to the GEPU index alone, the up and down components contain more useful information to increase the forecast's accuracy. Second, the out-of-sample evaluated results indicate that the GEPU index is able to help in forecasting Chinese stock market volatility from a statistical perspective. Moreover, using the combined information of the up and down GEPU can remarkably increase predictive accuracy, which strongly implies that those variables have more useful predictive information than GEPU alone. The results of our robustness tests, such as different forecasting windows and measures, are consistent with our main conclusions. Third, we further analyze whether the up and down GEPU may have different predictive performance under different conditions. We determine that when EPU and GEPU rise in the same month, our strategy can achieve higher forecast accuracy.

The remainder of the paper is organized as follows. The literature review is Section 2. Section 3 presents the GARCH-MIDAS model and other extended models, including the EPU and GEPU indices. Section 4 is the data description. Our empirical results, such as the in-sample estimated results and the out-of-sample forecasting evaluation, are reported in Section 5. Section 6 contains various robustness tests, such as different forecasting windows and different measures of EPU and GEPU. Further analysis is presented in Section 7. In the last section, we provide our main our conclusions.

2. Related literature

In this section, we have paid attentions on the links between the EPU, GEPU and volatility forecasting, so we will review some related literature from two perspectives: (a) EPU and volatility; (b) GEPU and volatility.

First, we review some related literature on the links between the EPU and volatility. Baker et al. (2016) use newspaper coverage frequency to construct the EPU index that can measure economic policy uncertainty. To date, the EPU index has caused attentions by many scholars. Considered our topic, we focus on these studies on the links between the EPU and volatility. For example, Liu and Zhang (2015) use the heterogeneous autoregressive realized volatility (HAR) framework proposed by Corsi (2009) to exploit the predictive ability of EPU on the U.S. stock market. They provide empirical evidence that the EPU index can significantly improve the model's forecasting performance. Chiang (2019) investigate the EPU, risk and stock returns using the G7, and find that lagged EPU innovations have a positive effect in predicting conditional variance. Duan et al. (2018) explore the effects of leverage and EPU on volatility using the Markov-switching models, and find that the predictive models including the EPU and leverage effect can obtain higher forecasts compared to GARCH-class models. Liu et al. (2017) investigate the impacts of EPU on future volatility based on the multifractal insight, and show that the EPU index indeed can increase the forecasts accuracy. Ma et al. (2018a) use the above-threshold EPU to forecast oil futures volatility and find that the HAR-class models including the above-threshold EPU can improve the forecasting. Ma et al. (2018a,b,c) use the AR(3) model to investigate the relationship of the data-rich indices (e.g., EPU) and aggregate oil price volatility, and find that the EPU index can generate higher forecasts compared to the benchmark model.

Second, the global EPU (GEPU) index is proposed by Davis (2016), and is a GDP-weighted average of national EPU indices for 20 countries that account for two-thirds of global output.[3] To the best of knowledge, few studies have investigated the relationship between GEPU and stock market volatility. Yu and Song (2018) investigate the impacts of GEPU on aggregate monthly volatility using Markov-switching model, and find that GEPU can lead to high fluctuation and result in higher forecasts. Yu et al. (2018) exploit the effect of GEPU on the Chinese stock market volatility using the generalized autoregressive conditional heteroscedastic mixed data sampling (GARCH–MIDAS) model, and find that the GARCH-MIDAS model with the GEPU can garner higher predictive performance. Fang et al. (2018a) examine the information of GEPU on the gold futures return variance using the GARCH-MIDAS model, and

[3] 20 countries are 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).

indicate that the GEPU can remarkably forecast the future monthly volatility with respect to gold future markets.

However, the abovementioned studies are investigated the links between the EPU (GEPU) and volatility, but those papers are not considered the common impacts of the EPU and GEPU, especially considering the directions of the EPU and GEPU. Therefore, this study is first to investigate the effects of the direction of the Chinese EPU and GEPU and then evaluate the predictive ability.

3. Volatility models

3.1. The GARCH-MIDAS model

In recent years, the GARCH-MIDAS model has received more attention in academia, such as Engle et al. (2013), Pan et al. (2017), Wei et al. (2017), Fang et al. (2018a, b), and Mo et al. (2018). Following Engle et al. (2013), we first describe the GARCH-MIDAS model and assume the returns (r) on day i in month t can be written as:

$$r_{i,t} = \mu + \sqrt{\tau_t g_{i,t}}\varepsilon_{i,t}, \quad \forall i = i, \dots, N_t, \tag{1}$$

where $\varepsilon_{i,t}|\Phi_{i-1,t} \sim N(0,1)$ with $\Phi_{i-1,t}$ is the information set up on day(i-1) of period t.[4] The volatility component of Equation (1) ($\sqrt{\tau_t g_{i,t}}$) can be expressed in two parts as a short-term component defined by $g_{i,t}$ and a long-term component defined by τ_t. In line with Engle and Rangel (2008), Asgharian et al. (2013), and Engle et al. (2013), we assume that the conditional variance of the short-term component is a daily GARCH (1,1) process as follows:

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

where $g_{i,t}$ is the conditional variance (GARCH component), α and β are the parameters of the ARCH and GARCH components, respectively, and these parameters should be satisfied with $\alpha > 0$ and $\beta > 0$. The long-term component τ_t is generally defined as a smoothed realized variance with an exogenous variable based on a slowly varying weighted function in the framework of the MIDAS model[5]:

$$\log(\tau_t) = m + \theta\sum_{k=1}^{K}\varphi_k(w_1, w_2)\mathrm{RV}_{t-k}, \tag{3}$$

$$\mathrm{RV}_t = \sum_{i=1}^{N_t} r_{i,t}^2, \tag{4}$$

Where RV represents monthly realized variance, N_t is the length of the monthly realized variance, $N_t = 22$. The optimal lag orders of K can be decided by the minimum Bayesian information criterion (BIC) and K is equal to 6 in this study.[6] m is an intercept term and θ is the slope of the weighted effects of lagged monthly RV on the long-term volatility of the Chinese stock market volatility. The weighting scheme used in equation (3) can be calculated by the unrestricted Beta function as follows:

$$\varphi_k(\omega_1, \omega_2) = \frac{(k/K)^{\omega_1-1}(1-k/K)^{\omega_2-1}}{\sum_{j=1}^{K}(j/K)^{\omega_1-1}(1-j/K)^{\omega_2-1}}. \tag{5}$$

Following Engle et al. (2013), Conrad et al. (2014), Su et al. (2017) and Wei et al. (2017), we set the restricted weighting scheme as $\omega_1 = 1$ and the decaying rate is only dependent on the parameter ω_2, and the specification of this function is expressed by:

$$\varphi_k(1, \omega_2) = \frac{(1-k/K)^{\omega_2-1}}{\sum_{j=1}^{K}(1-j/K)^{\omega_2-1}}. \tag{6}$$

The GARCH-MIDAS model is our benchmark in this paper.

3.2. The GARCH-MIDAS model including EPU and GEPU

To investigate the impact of economic policy uncertainty (EPU) on Chinese stock market volatility, we add EPU as an additional variable to equation (3) and the long-term component can be modified as below:

$$\log(\tau_t) = m + \theta\sum_{k=1}^{K}\varphi_k(w_1, w_2)\mathrm{RV}_{t-k} + \gamma\sum_{k=1}^{K}\varphi_k(w_1, w_2)\mathrm{EPU}_{t-k}. \tag{7}$$

We name this new model the GARCH-MIDAS-EPU. To our knowledge, several studies (e.g., Fang et al., 2017; Asgharian et al., 2018; and Su et al., 2018) have investigated the relationship between EPU and stock market volatility in the framework of the GARCH-MIDAS model. However, most of the abovementioned references are not directly involved in the Chinese stock market.

To investigate whether the global EPU (GEPU) index contains useful predictive information for the Chinese stock market, we further add GEPU to equation (7) and construct a new long-term component, named the GARCH-MIDAS-GEPU, and the formulation of this model is expressed by:

$$\log(\tau_t) = m + \theta\sum_{k=1}^{K}\varphi_k(w_1, w_2)\mathrm{RV}_{t-k} + \gamma\sum_{k=1}^{K}\varphi_k(w_1, w_2)\mathrm{EPU}_{t-k} + \delta\sum_{k=1}^{K}\varphi_k(w_1, w_2)\mathrm{GEPU}_{t-k}. \tag{8}$$

In this article, we decompose GEPU into two different components based on the directional EPU. Specifically, assuming EPU and GEPU move in the same direction in the same month t, and in terms of the signed change rates of EPU and GEPU, we construct two new indices, up GEPU (GEPUU) and down GEPU (GEPUD), which are defined as follows, respectively:

[4] When we carefully read the paper of Westerlund and Narayan (2012), and find that our mean equation (equation (1)) is not included additional variable (e.g., EPU, GPU), which is consistent with several papers, such as Engle et al. (2013), Pan et al. (2017), Wei et al. (2017), Fang et al. (2018a, b), and Mo et al. (2018). Additionally, we add explanatory variables to the variance equation, which is consistent with our research object. Therefore, this paper is not used to the GLS estimator method proposed by Westerlund and Narayan (2012).

[5] Following Asgharian et al. (2013), Engle et al. (2013), Conrad et al. (2014), and Pan et al. (2017), to guarantee the non-negativity of the conditional variances, we use the log transformation to do our estimation and prediction.

[6] More importantly, other values of K and N_t are also robust with our conclusions, and the readers can receive available information related to these results by request.

Table 1
Typology of the empirical specifications used in this paper.

Model number	Model name	Eq. number (Main)	Description
Benchmark	GARCH-MIDAS	Eq. (3)	The basic GARCH-MIDAS
Model 1	GARCH-MIDAS-EPU	Eq. (7)	Including Chinese EPU
Model 2	GARCH-MIDAS-GEPU	Eq. (8)	Including Chinese EPU and GEPU
Model 3	GARCH-MIDAS-GEPU-U	Eq. (9)	Including Chinese EPU and up GEPU
Model 4	GARCH-MIDAS-GEPU-D	Eq. (11)	Including Chinese EPU and down GEPU
Model 5	GARCH-MIDAS-GEPU-UD	Eq. (12)	Including the Chinese EPU and up and down GEPU

$$\mathrm{GEPUU}_t = \mathrm{GEPU}_t \cdot I\left(\frac{GEPU_t - GEPU_{t-1}}{GEPU_{t-1}} > 0\right) \cdot I\left(\frac{EPU_t - EPU_{t-1}}{EPU_{t-1}} > 0\right), \tag{9}$$

$$\mathrm{GEPUD}_t = \mathrm{GEPU}_t \cdot I\left(\frac{GEPU_t - GEPU_{t-1}}{GEPU_{t-1}} < 0\right) \cdot I\left(\frac{EPU_t - EPU_{t-1}}{EPU_{t-1}} < 0\right), \tag{10}$$

where $I(\cdot)$ is an indicator function. According to up and down GEPU, we can use them to replace GEPU alone and have three different volatility models, named GARCH-MIDAS-GEPU-U, GARCH-MIDAS-GEPU-D, and GARCH-MIDAS-GEPU-UD, which can be expressed by equations (11) - (13), respectively:

$$\log(\tau_t) = m + \theta \sum_{k=1}^{K} \varphi_k(w_1, w_2)\mathrm{RV}_{t-k} + \gamma \sum_{k=1}^{K} \varphi_k(w_1, w_2)\mathrm{EPU}_{t-k} + \delta_U \sum_{k=1}^{K} \varphi_k(w_1, w_2)\mathrm{GEPUU}_{t-k}. \tag{11}$$

$$\log(\tau_t) = m + \theta \sum_{k=1}^{K} \varphi_k(w_1, w_2)\mathrm{RV}_{t-k} + \gamma \sum_{k=1}^{K} \varphi_k(w_1, w_2)\mathrm{EPU}_{t-k} + \delta_D \sum_{k=1}^{K} \varphi_k(w_1, w_2)\mathrm{GEPUD}_{t-k}. \tag{12}$$

$$\log(\tau_t) = m + \theta \sum_{k=1}^{K} \varphi_k(w_1, w_2)\mathrm{RV}_{t-k} + \gamma \sum_{k=1}^{K} \varphi_k(w_1, w_2)\mathrm{EPU}_{t-k} + \delta_U \sum_{k=1}^{K} \varphi_k(w_1, w_2)\mathrm{GEPUU}_{t-k} + \delta_D \sum_{k=1}^{K} \varphi_k(w_1, w_2)\mathrm{GEPUD}_{t-k}. \tag{13}$$

Table 1 provides a typology of the seven models analyzed in this research.

4. Data source

In this study, we choose the CSI 300 index to do our research. The CSI 300 is a capitalization-weighted stock market index designed to replicate the performance of the top 300 stocks traded on the Shanghai and Shenzhen stock exchanges. There is an important reason that the CSI 300 index is a frequently applied prospect: it is commonly used as a representative index to measure the overall performance of the Chinese stock market (Chen et al., 2013). The raw transaction prices are obtained from the CSMAR database from 8 April 2005 to 31 December2, 017,[7] and we obtain 3098 daily observations. The Chinese EPU index and global EPU index can be freely downloaded from the EPU website (http://www.policyuncertainty.com/), and from them we acquire 153 monthly datapoints.

Table 2 exhibits the statistical description of daily returns on the CSI 300 index. The return series is significantly skewed and leptokurtic at the 1% significance level, suggesting that it has a fat tail. The Jarque-Bera statistic test demonstrates that the null hypothesis of normality is rejected at the 1% significance level, implying that the CSI 300 return is a non-Gaussian distribution. The Ljung-Box test for correlation shows that the null hypotheses of no autocorrelation up to the 5th order is rejected, indicating the existence of a correlation. Furthermore, the augmented Dickey-Fuller test supports the rejection of the null hypothesis of a unit root at the 1% significance level, indicating that this series is stationary and can be modeled directly without further transformations. More importantly, we find that both Chinese and Global EPU rise in 67 of the same months and decline in 55 of the same months. Fig. 1 displays the dynamic change of CSI 300 prices from 8 April 2005 to 31 December 2017. It is clear that the prices of the CSI 300 have huge fluctuations around the 2008 financial crisis and the middle of 2015. Fig. 2 shows the monthly Chinese and global EPU from April 2005 to December 2017. We find that Chinese and global EPU increase over our sample period. Notably, the orange bars in Fig. 2 indicate that Chinese EPU and GEPU increase together in the same month, and the gray bars show that the two indices decline in the same month. From Fig. 2, we find that up and down GEPU at different periods may contain different information with respect to the Chinese stock market.

5. Empirical results

5.1. In-sample estimations

Table 3 presents the estimated results of econometric models during in-sample period (April 8, 2005 to December 15, 2008).[8] From the empirical results of Table 3, we can observe several noteworthy findings. First, the GARCH models of all cases are stable based on parameters α and $\beta (\alpha + \beta < 1)$, and they are statistically significant at the 99% confidence level. Second, most models of the slope parameters θ for the monthly realized volatility specifications of the MIDAS filter are negative. Moreover, in all models, the estimated parameters of γ for Chinese EPU are statistically significant and show that EPU has a remarkably positive impact on future volatility. Uncertainty of economic policy can lead to high stock market volatility with regard to the Chinese stock market. Third, the effects of GEPU on the long-term volatility of China are not significant. Interestingly, most of the parameters for up and down GEPU are significant, and the effects are positive, implying that up and down GEPU can substantially increase the fluctuations of the Chinese stock market.

[7] The CSI 300 index started on 8 April 2005.

[8] Regarding the in-sample period, please see details in Section 5.2.1.

Table 2
Statistical description for the CSI 300 daily return from April 8, 2005 to December 31, 2017.

	Mean	St. dev.	Skewness	Kurtosis	Jarque-Bera	Q(5)	ADF
Return	0.045	1.789	−0.542***	3.751***	1967.670***	21.714***	−20.42***

Notes: We tested the null hypotheses, "Skewness = 0" and "Excess Kurtosis = 3", and the Jarque-Bera statistic test for the null hypothesis of normality for the distribution of series. Q(n) is the Ljung-Box statistic test for up to the 5th order serial correlation. ADF is the Augmented Dickey-Fuller statistic based on the least AIC criterion. Asterisk *** denotes rejections of the null hypothesis at the 1% significance level. In this table, return is calculated by the following equation, return $= 100*(\ln P_{i,t} - \ln P_{i-1,t})$, $P_{i,t}$ represents the closing price of day i in the month t.

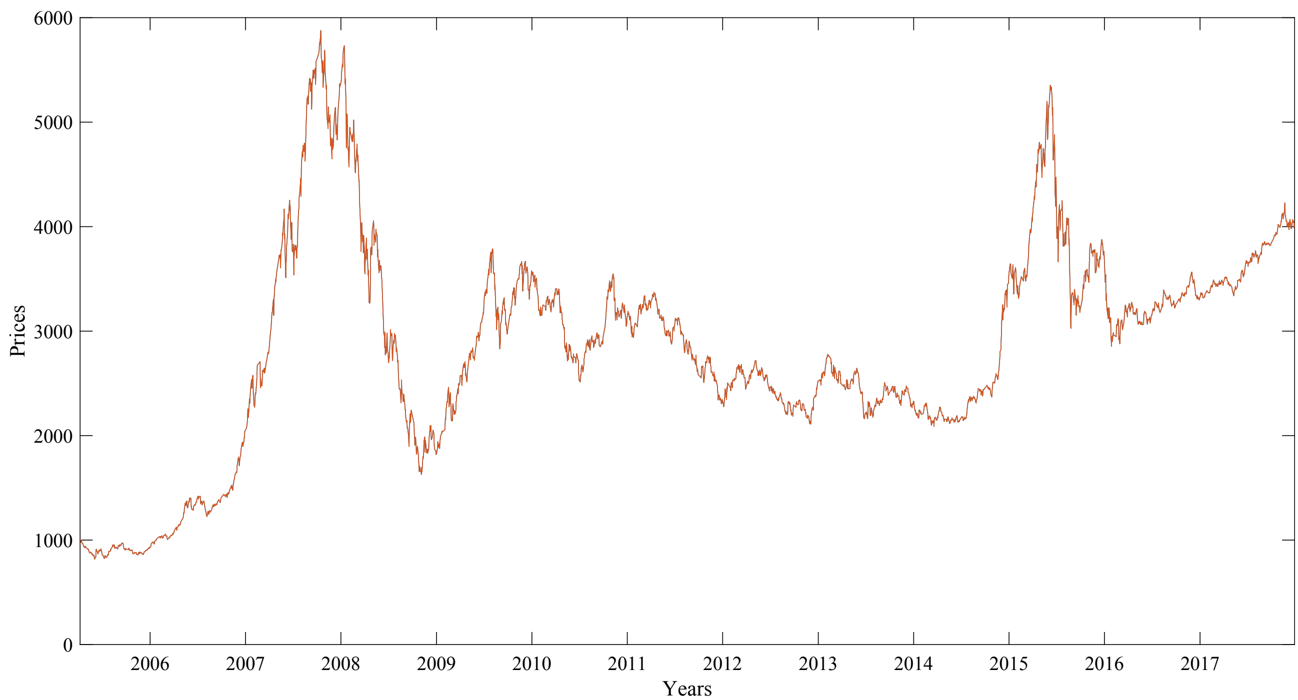

Fig. 1. The prices of the CSI 300 index during the whole sample.

5.2. Out-of-sample evaluation

5.2.1. Evaluated methods

Compared to in-sample performance, the out-of-sample performance of a model (i.e., its predictive ability) is more important to market participants because the participants are more concerned about the model's ability to improve future performance than its ability to analyze past patterns (Wang et al., 2016, 2018, 2019). We divide our whole sample into two components, in-sample and out-of-sample. Specifically, in-sample is used to estimate, and out-of-sample is used to forecast. We use the rolling window method to obtain future volatility. Specifically, we first use for our in-sample the period from April 8, 2005 to December 15, 2008 and use the period from December 16, 2008 to December 31, 2017 as an out-of-sample evaluation period. The first forecasted value (April 9, 2005) is part of the data from April 8, 2005 to December 15, 2008, and the parameters of the forecasting models are re-estimated with fixed lengths. The forecasting process is conducted up through the end of the sample period.

To assess the significant differences between these models, we use the following two loss functions:

$$\mathrm{HMSE} = M^{-1}\sum_{m=1}^{M}\left(1 - \widehat{\sigma}_m^2 \Big/ \sigma_m^2\right)^2, \tag{14}$$

$$\mathrm{HMAE} = M^{-1}\sum_{m=1}^{M}\left|1 - \widehat{\sigma}_m^2 \Big/ \sigma_m^2\right|, \tag{15}$$

where HMSE and HMAE represent the heteroscedasticity-adjusted squared error and the heteroscedasticity-adjusted mean absolute error, respectively. A large body of literature (see, for example, Koopman et al., 2005; Chen et al., 2012; Kristjanpoller and Minutolo, 2016) uses these two popular loss functions to evaluate forecasting performance. $\widehat{\sigma}_m^2$ denotes the out-of-sample volatility forecast obtained by benchmark, individual, and combination forecasts and diffusion models. σ_m^2 is a proxy for actual market volatility in the out-of-sample period, and M is the length of the out-of-sample data.

Notably, the aforementioned loss functions do not provide any information on whether the differences among the models are statistically significant. Therefore, we utilize the model confidence set (MCS) proposed by Hansen et al. (2011) to choose a subset of models that contain all possible superior models from the initial model set. The MCS method has several attractive advantages over conventional tests, such as a superior predictive power (Hansen, 2005) and "reality check" tests. For example, this test does not require the specification of a benchmark model, which is useful in applications without an obvious benchmark. If the MCS p-values of several volatility models are greater than a critical value α, the corresponding models are "surviving" models, implying that those models outperform other models that produce a value lower than α. The higher the p-value of the MCS test, the greater the likelihood that the corresponding model is better than other models. Additionally, following Martens et al. (2009), Rossi and Fantazzini (2014) and Wei et al. (2017), we use the range statistic (T_R) and the semi-quadratic statistic (T_{SQ}) as the MCS statistics to test whether the null hypothesis of equal predictive power for the remaining models is rejected. In this study, we do not give further technical details of the MCS test; more in-depth discussions may be found in Hansen et al. (2011).

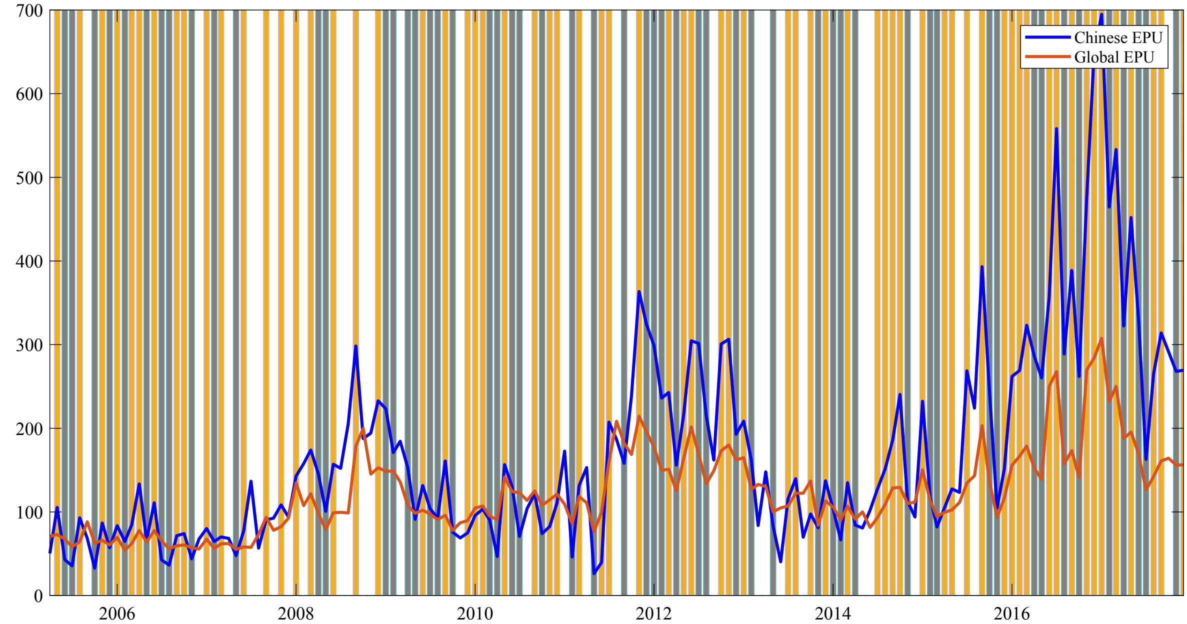

Fig. 2. The Chinese and Global EPU during the sample period.

Table 3
In-sample estimation results of our econometric models.

	Benchmark	Model 1	Model 2	Model 3	Model 4	Model 5
	0.001***	0.001***	0.001***	0.001***	0.002***	0.002***
	0.057***	0.057***	0.059***	0.059***	0.055***	0.059***
	0.943***	0.943***	0.941***	0.941***	0.945***	0.941***
	−20.956	−40.386**	−93.386**	−82.426**	−61.985**	−59.919**
		138.661**	261.813**	244.084**	137.087***	150.379**
			−13.594			
				8.683		60.434**
					121.074***	142.299***
	35.898	28.484	4.632**	5.283**	12.396*	23.746
		3.994*	2.208**	2.176**	11.409*	5.370
			25.813			
				30.064		36.788
					45.662	47.033
m	−9.155***	−10.033***	−10.535***	−10.583***	−10.242***	−10.485***
LLF	1918.228	1922.522	1923.974	1924.022	1926.805	1928.861

Notes: This table reports the estimation results of the benchmark and Models 1–5 during in-sample period (April 8, 2005 to December 15, 2008). The benchmark model is GARCH-MIDAS. Asterisk ***, ** and * denote rejections of the null hypothesis at the 1%, 5% and 10% significance levels, respectively. LLF represents the logarithmic likelihood function value. In our estimation and forecasting, we divide the EPU and GEPU by 10,000, following Liu and Zhang (2015) and Ma et al. (2018a,b,c).

5.2.2. *Is the GEPU index helpful for predicting Chinese stock market volatility?*

In this section, we will seek to answer this question: Is the GEPU index helpful for predicting Chinese stock market volatility? We evaluate the predictive ability between the benchmark and individual models, including EPU and GEPU, using the MCS test. Following Laurent et al. (2012), Martens et al. (2009) and Ma et al. (2018b), we set the critical value at 25%. Specifically, if the MCS p-value of a model is smaller than 0.25, then this model is removed from the initial model set (e.g., the six models in this article). Hence, the remaining models of the initial set have remarkably superior predictive performance from a statistical viewpoint. Table 4 shows the out-of-sample evaluated results under the HMSE and HMAE loss functions. We make several important findings. First, under the range statistic with the HMSE and HMAE loss functions, we find that the MCS p-value of Model 2, which includes the GEPU index larger than 0.25, strongly implies that this model, including GEPU, exhibits higher forecast accuracy. Model 2 contains an additional variable, GEPU, compared to Model 1, and we therefore conclude that the GEPU index can contain useful predictive information to forecast the performance of the Chinese stock market. Second, considering the alternative statistic method, semiquadratic, we find that Model 2 is able to garner higher forecasts than the benchmark and Model 1, which tells us that the GEPU index can further help to increase the forecast accuracy for the Chinese stock market. From these empirical results, we find that the GEPU index is substantially helpful for predicting the performance of the Chinese stock market, and the global economic policy conditions can indeed impact the Chinese stock market.

5.2.3. *The effects of up and down GEPU*

In this paper, we first construct up and down GEPU based on the direction of EPU and GEPU and further evaluate their predictive performance. We use up, down, and up and down GEPU to replace GEPU alone and to construct three models, GARCH-MIDAS-GEPU-U, GARCH-MIDAS-GEPU-D, and GARCH-MIDAS-GEPU-UD, respectively. In Section 4.2.2, we empirically find that the GARCH-MIDAS-GEPU model has superior performance in forecasting Chinese stock market volatility compared to the benchmark and GARCH-MIDAS-EPU models. Therefore, the interesting question of whether these directional GEPU models contain more useful predictive information has been examined in this paper. Table 5 indicates the out-of-sample evaluated results based the

Table 4
Out-of-sample predictive performance using the MCS test.

	Range		Semiquadratic	
	HMSE	HMAE	HMSE	HMAE
Benchmark	0.000	0.000	0.000	0.000
Model 1	0.000	0.000	0.000	0.000
Model 2	**1.000**	**1.000**	**1.000**	**1.000**

Notes: MCS *p*-values are calculated according to the test statistics T_R and T_{SQ}. The MCS *p*-values larger than 0.25 are indicated in bold.

Table 5
Out-of-sample evaluated results.

	Range		Semiquadratic	
	HMSE	HMAE	HMSE	HMAE
Model 2	0.000	0.000	0.000	0.000
Model 3	0.000	0.000	0.000	0.000
Model 4	0.000	0.000	0.000	0.000
Model 5	**1.000**	**1.000**	**1.000**	**1.000**

Notes: MCS *p*-values are calculated according to the test statistics T_R and T_{SQ}. The MCS *p*-values larger than 0.25 are indicated in bold.

MCS test. We make some interesting findings. The most important finding is that, under the range and semi-quadratic statistics, Model 5 exhibits statistically higher predictive accuracy than Model 2, Model 3, and Model 4. From these empirical results, a primary meaningful conclusion is that using up and down GEPU together are more helpful for predicting volatility than GEPU alone or up GEPU, implying that the combination of up and down GEPU contains more useful information to predict stock market volatility. A plausible explanation for why Model 5 performs better is that directional GEPU may contain more useful predictive information than GEPU alone. In addition, the Chinese stock market has gradually integrated into the global economy after a series of liberalization policies, such as those of the World Trade Organization (WTO), Qualified Foreign Institutional Investors (QFII) and RMB Qualified Foreign Institutional Investors (RQFII). With a series of open polices, the international uncertainty cannot be ignored by the investors. In this paper, we consider the change-of-directions of the GEPU and EPU, which is more effective to detect useful information to predict the Chinese stock market volatility. To put it simply, the change rates of Chinese EPU and GEPU have three conditions, up ($EPU_t\uparrow$, $GEPU_t\uparrow$), down ($EPU_t\downarrow$, $GEPU_t\downarrow$) and mixed ($EPU_t\uparrow$, $GEPU_t\downarrow$; $EPU_t\downarrow$, $GEPU_t\uparrow$); up and down GEPU can further enhance economic policy uncertainty of China and may provide clear signals to help investors to make beneficial strategies, which can increase the fluctuations of the Chinese stock market.

6. Robustness checks

6.1. Different forecasting windows

Rossi and Inoue (2012) argue that different estimations and forecasting windows may produce different empirical results. Hence, the forecasting window (out-of-sample period) plays an important role in evaluating these models' predictive abilities. Following Ma et al. (2018b), Wei et al. (2017), we choose two different forecasting windows, 2000 and 2400, as our alternative robustness checks.[9] From the empirical results in Table 6, we find that Model 5, including both up and down GEPU, is capable of generating higher forecast accuracy than the benchmark and other models. Therefore, both up and down GEPU are more useful for predicting the Chinese stock market than GEPU alone or up or down GEPU alone. Our study provides some novel evidence that the GEPU index is able to improve the predictive accuracy of the Chinese stock market.

[9] We follow by the works of Liu et al. (2018), Ma et al. (2019) and among others, we choose the different forecasting windows around 2200 days. More importantly, we choose other forecasting windows, and find that our main findings are also robust.

Table 6
The MCS test results for the out-of-sample model performance using different forecasting windows.

Models	Range		Semiquadratic	
	HMSE	HMAE	HMSE	HMAE
Panel A: $M = 2000$				
Benchmark	0.000	0.000	0.000	0.000
Model 1	0.000	0.000	0.000	0.000
Model 2	0.000	0.000	0.000	0.000
Model 3	0.000	0.000	0.000	0.000
Model 4	0.000	0.000	0.000	0.000
Model 5	**1.000**	**1.000**	**1.000**	**1.000**
Panel B: $M = 2400$				
Benchmark	0.000	0.000	0.000	0.000
Model 1	0.000	0.000	0.000	0.000
Model 2	0.000	0.000	0.000	0.000
Model 3	0.000	0.000	0.000	0.000
Model 4	0.000	0.000	0.000	0.000
Model 6	**1.000**	**1.000**	**1.000**	**1.000**

Notes: MCS *p*-values are calculated according to the test statistics T_R and T_{SQ}. The MCS *p*-values larger than 0.25 are indicated in bold.

Table 7
Out-of-sample predictive performance using the change rates of the EPU and GEPU.

	Range		Semiquadratic	
	HMSE	HMAE	HMSE	HMAE
Benchmark	0.000	0.000	0.000	0.000
Model 1	0.000	0.000	0.000	0.000
Model 2	0.000	0.000	0.000	0.000
Model 3	0.000	0.000	0.000	0.000
Model 4	0.000	0.000	0.000	0.000
Model 5	**1.000**	**1.000**	**1.000**	**1.000**

Notes: MCS *p*-values are calculated according to the test statistics T_R and T_{SQ}. The MCS *p*-values larger than 0.25 are indicated in bold.

6.2. The change rate of EPU and GEPU

Following Fang et al. (2017), we use the change rate of EPU and GEPU ($\Delta EPU_t = (EPU_t - EPU_{t-1})/EPU_{t-1}$, $\Delta GEPU_t = (GEPU_t - GEPU_{t-1})/GEPU_{t-1}$) to replace the original EPU and GEPU and re-evaluate their predictive performance in the out-of-sample period. From the empirical results of Table 7, we find that, under the HMSE and HMSE loss functions, Model 5 contains both up and down GEPU and can survive the MCS test with different statistics, implying that Model 5 can beat the benchmark and other models discussed in this paper in forecasting the Chinese stock market. This finding provides strong evidence that considering both up and down GEPU can contain more useful information than GEPU alone to help with forecasting the Chinese stock market volatility.

6.3. Shanghai Stock Exchange Composite Index (SSEC)

In this section, we use the Shanghai Stock Exchange Composite Index (SSEC) to represent the Chinese stock market and re-evaluate our research on whether the directional of EPU and GEPU have effect on the

Table 8
Out-of-sample predictive performance using the change rates of the EPU and GEPU.

	Range		Semiquadratic	
	HMSE	HMAE	HMSE	HMAE
Benchmark	0.000	0.000	0.000	0.000
Model 1	0.000	0.000	0.000	0.000
Model 2	0.000	0.000	0.000	0.000
Model 3	0.000	0.000	0.000	0.000
Model 4	0.000	0.000	0.000	0.000
Model 5	**1.000**	**1.000**	**1.000**	**1.000**

Notes: MCS *p*-values are calculated according to the test statistics T_R and T_{SQ}. The MCS *p*-values larger than 0.25 are indicated in bold.

Table 9
Out-of-sample predictive performance using the new EPU (Huang and Luk, 2018).

	Range		Semiquadratic	
	HMSE	HMAE	HMSE	HMAE
Benchmark	0.000	0.000	0.000	0.000
Model 1	0.000	0.000	0.000	0.000
Model 2	0.000	0.000	0.000	0.000
Model 3	0.000	0.000	0.000	0.000
Model 4	0.000	0.000	0.000	0.000
Model 5	**1.000**	**1.000**	**1.000**	**1.000**

Notes: MCS *p*-values are calculated according to the test statistics T_R and T_{SQ}. The MCS *p*-values larger than 0.25 are indicated in bold.

Chinese stock market volatility[10]. As we known, the Shanghai Stock Exchange Composite Index (SSEC) has been investigated by several studies, for example, Narayan et al. (2015), Tsai (2017), Gu et al. (2018) and Li et al. (2019). To keep the consistent with our previous data (e.g., CSI 300), SSEC data can be downloaded by WIND database, which spans from 8 April 2005 to 31 December 2017. In addition, the fixed estimated and predictive windows are the same as the CSI index. Table 8 reports the empirical results using the MCS test with the HMSE and HMAE loss functions. The Model 5 model, GARCH-MIDAS-GEPU-UD, can survive in the MCS test, because the MCS p-value of this model is larger than 0.25. Therefore, the GARCH-MIDAS model including up and down GEPU can indeed increase the predictive ability of the benchmark and other models, so we provide new evidence on forecasting Chinese stock market volatility.

6.4. Using new EPU

In this section, we use new EPU index, which is proposed by Huang and Luk (2018). Compared to the EPU of Baker et al. (2016), the EPU of Huang and Luk (2018) uses information from multiple local newspapers, and foreshadows declines in equity price, employment and output. Additionally, Huang and Luk (2018) show that their EPU has several advantages, such as averaging out idiosyncrasies in individual newspapers.[11] To some extent, the EPU of Huang and Luk (2018) is not belonged to the GEPU of Davis (2016). Out-of-sample predictive performance results using the new EPU (Huang and Luk, 2018) are reported in Table 9. In general, considered the information of up and down GEPU together are more helpful for predicting stock market volatility compared to use the GEPU itself, which is supported our main findings.

Table 10
The MCS test results for the out-of-sample model performance under three conditions.

	Range		Semiquadratic	
Models	HMSE	HMAE	HMSE	HMAE
Up ($EPU_t \uparrow$, $GEPU_t \uparrow$)				
Benchmark	0.000	0.000	0.000	0.000
Model 1	0.000	0.000	0.000	0.000
Model 2	0.000	0.000	0.000	0.000
Model 3	0.000	0.000	0.000	0.000
Model 4	0.000	0.000	0.000	0.000
Model 5	**1.000**	**1.000**	**1.000**	**1.000**
Down ($EPU_t \downarrow$, $GEPU_t \downarrow$)				
Benchmark	**1.000**	**1.000**	**1.000**	**1.000**
Model 1	**0.321**	0.217	**0.564**	0.226
Model 2	0.116	0.216	0.208	0.120
Model 3	0.113	0.216	0.121	0.092
Model 4	**0.321**	0.217	**0.564**	0.226
Model 5	0.116	0.216	0.138	0.097
Mixed ($EPU_t \uparrow$, $GEPU_t \downarrow$; $EPU_t \downarrow$, $GEPU_t \uparrow$)				
Benchmark	**1.000**	**1.000**	**1.000**	**1.000**
Model 1	**0.324**	**0.369**	**0.587**	**0.583**
Model 2	**0.324**	**0.472**	**0.589**	**0.597**
Model 3	**0.324**	**0.369**	**0.589**	**0.597**
Model 4	**0.324**	**0.369**	**0.589**	**0.597**
Model 5	**0.324**	**0.369**	**0.573**	**0.552**

Notes: MCS *p*-values are calculated according to the test statistics T_R and T_{SQ}. The MCS *p*-values larger than 0.25 are indicated in bold.

7. Further analysis

Does our proposed model (i.e., Model 5) still outperform the benchmark model under different conditions with regard to predicting Chinese stock market volatility? To the best of our knowledge, this paper is the first to answer this interesting question. Based on the directions of EPU and GEPU, we have three regimes, up ($EPU_t \uparrow$, $GEPU_t \uparrow$), down ($EPU_t \downarrow$, $GEPU_t \downarrow$) and mixed ($EPU_t \uparrow$, $GEPU_t \downarrow$; $EPU_t \downarrow$, $GEPU_t \uparrow$). We then divide the out-of-sample period into three states based on the change rates of the EPU and GEPU and evaluate the predictive performances of the benchmark and Models 1–5 in the three states. From the empirical results of Table 10, we garner several noteworthy findings. First, in $EPU_t \uparrow$ and $GEPU_t \uparrow$, we find that Model 5, including up and down GEPU together, exhibits higher predictive ability, implying that considering the direction of GEPU provides more useful information than GEPU alone. Second, under $EPU_t \downarrow$ and $GEPU_t \downarrow$, we find that the benchmark models are not defeated by our extended models and, in some cases, the benchmark models have higher forecast accuracy, indicating that EPU, GEPU and directional GEPU are useless for increasing the accuracy of Chinese stock market volatility. Third, in the mixed condition, we find that the predictive ability of the benchmark and our extended models have no significant differences. In conclusion, we first find that the effects of GEPU are an effective indicator to predict Chinese stock market volatility and, to some extent, provide empirical explanations for why GEPU can impact Chinese stock market volatility.

8. Conclusions and implications

In this article, we investigate the effects of GEPU on Chinese stock market volatility in the framework of the GARCH-MIDAS. More interestingly, we further distinguish GEPU based on the changing direction of EPU and GEPU into up, down and mixed components and evaluate their

[10] We are very thankful for the reviewer and Prof. Ke Yang.

[11] More details on this EPU index can be found this website, https://economicpolicyuncertaintyinchina.weebly.com/. In addition, using new EPU, we could reduce the impacts of GEPU on the China EPU of Baker et al. (2016). In addition, inspired the work of Rapach et al. (2010), we add the EPU and GEPU alone to the MIDAS-RV model to reduce the multicollinearity of GEPU and EPU, then have two model. And we use the mean combination forecasts to obtain out-of-sample forecasts, which is similar with the studies of Rapach et al. (2010) and Neely et al. (2014). Our empirical results find that our conclusions are robust. We thanks to the comments of the reviewer.

predictive performance using the MCS test. We make several noteworthy findings. First, in-sample estimations show that GEPU alone does not seem to impact the Chinese stock market. However, up and down GEPU have positive influences on stock market volatility and, in most cases, they are statistically significant. Second, our out-of-sample results find that the GEPU index is helpful for predicting Chinese stock market volatility from a statistical perspective. Moreover, combining up and down GEPU can substantially increase the forecast accuracy of the Chinese stock market, implying that they contain more useful predictive information. Our robustness tests strongly support our conclusions. Third, according to the changing directions of EPU and GEPU, we find that, in different conditions, up and down GEPU may perform differently in forecasting volatility. This is especially so when EPU and GEPU rise in the same month, when our strategy can achieve higher forecast accuracy. Our paper provides new insights into utilizing the EPU and GEPU for Chinese stock market volatility forecasting.

"*Measuring, forecasting, and controlling risk are at the heart of financial, economic theory and practice*" (Bollerslev et al., 2018). This is because risk (volatility) is of great importance to hedge strategy design, asset portfolio, derivative pricing and risk management. Therefore, accurately forecast stock market volatility is of great importance to scholars, investors and government decision makers. Specifically, based on our findings, individual and institutional investors should consider the directional GEPU and China EPU, this is because considered these factors are helpful for volatility forecasting, and then they can reduce risk that are came from the unstable stock market. According to our conclusions, the same directional of the GEPU and EPU should be caused special attentions by the policy makers, and they can use some tools (e.g., monetary policy) to reduce the shocks on the Chinese stock market, which can make Chinese stock markets stably.

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