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Article

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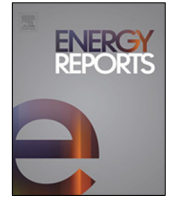
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Research paper

The forecasting power of EPU for crude oil return volatility

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ABSTRACT

Economic policy uncertainty (EPU) has important implications for crude oil market. To explore the implications, this paper investigates the impact of EPU on the crude oil return volatility and which EPU index has the most forecasting power in crude oil market. To this end, we employ the GARCH-MIDAS model which can incorporate lower frequency EPU index variable with higher frequency crude oil return variable effectively. We find that EPU has a positive and significant impact on the crude oil return volatility, but the effect is short-lived and the decay period is about one year. Particularly, our results show that the US EPU index has the best forecasting power for crude oil return volatility over the long-term, whereas China EPU index has the best forecasting performance in the past one year. Our findings have important implications on risk management for investors in crude oil market.

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1. Introduction

As one of the most important commodities in the world, crude oil is not only an energy product, but also a financial asset, which plays an important role in world economy. The crude oil return volatility is essential for many studies such as asset pricing, portfolio allocation and risk management. Modeling and forecasting the volatility of crude oil return has always been a core issue in the financial field, which has received extensive attention from academics, investors and asset managers. However, how to improve a more accurate forecast for crude oil return volatility remains a major challenge both theoretically and practically.

Over the last few decades, researchers have found crude oil return volatility to be responsible for crude oil supply and demand (Kilian and Park, 2009; Conrad et al., 2015), speculative component (Yin and Zhou, 2016), exchange rate (Lu et al., 2018) and Crude Oil Volatility Index (OVX) (Dutta, 2017; Haugom et al., 2014). Since the seminal work of Baker et al. (2013), EPU index has attracted a lot of scholarly attention in exploring the effect on crude oil market and the forecast of crude oil return volatility. The EPU index is constructed from three types

of uncertain components, including policy-related economic uncertainty in newspaper, the number of tax code provisions that will expire in future years and the disagreement among economic forecasters. Baker et al. (2015) point out that there exists significant relationship between EPU index and real macroeconomic variables. Using the EPU index, a large number of studies have examined the linkage between economic policy uncertainty and crude oil market (e.g. Antonakakis et al., 2014; Aloui et al., 2016; Fang et al., 2017; Ma et al., 2017b). For example, Antonakakis et al. (2014) examine the dynamic relationship between economic policy uncertainty and crude oil price changes, they reveal that economic policy uncertainty responds negatively to aggregate demand oil price shocks, and the total spillovers increased and reached unprecedented heights during the years 2007–2009. Aloui et al. (2016) investigate the effect of economic policy uncertainty on crude oil returns. They find that there exists a negative correlation between economic policy uncertainty and crude oil returns over the entire sample period but a positive relationship during the financial crisis period. Ma et al. (2017b) investigate whether and how the EPU index increase the HAR-RV type model's accuracy in forecasting the volatility of crude oil futures. They find significant evidence that the HAR-RV type model including EPU can generate more accurate forecasts in crude oil market, and the forecast accuracy would be better if specific EPU thresholds were set for a range of horizons.

Although previous literature shows that EPU can affect crude oil volatility, it remains unclear how long the EPU's effect will

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last in crude oil market. Furthermore, as Kilian and Park (2009) claim that the price increase of crude oil is mainly driven by demand and China has become the largest crude oil importer in the world, it becomes an interesting issue to be further studied whether the predictive power of EPU index will also shift among countries to reflect this new trend and vary at different length of time horizon. In this paper, we use the EPU index proposed by Baker et al. (2013) to examine the impact of economic policy uncertainty on crude oil return volatility and investigate the predictive performance of different EPU indices.

Regarding the models for forecasting crude oil return volatility, there are two strands of literature. The first strand employs GARCH-family models to capture oil return volatility (e.g. Sadosky, 2006; Kang et al., 2009; Wei et al., 2010). The second strand of literature uses realized volatility models (Tian and Hamori, 2015). However, most of these models have difficulties in dealing with the different frequencies between crude oil return volatility and the macroeconomic covariates. In detail, the frequency of the crude oil return data is on a daily basis, while the macroeconomic covariates are obtained monthly or on a even lower frequency. For solving this problem, Engle et al. (2013) develop the GARCH-MIDAS model. This model allows macroeconomic covariates to be incorporated at different sampling frequencies, and decomposes conditional volatility into a short-run volatility component following the GARCH(1,1) process and a long-run component captured by a mixed-frequency data sampling regression with lower frequency variables. Since the GARCH-MIDAS model can solve the mixed-frequency problem well in volatility forecasting, it has been broadly used in different fields. In this article, we employ GARCH-MIDAS model to examine the impact of the monthly EPU indices on the daily crude oil return volatility.

In the finding, we come up with several noteworthy discovery. First, we find evidence that the economic policy uncertainty contains significant predictive information, and can improve the predictive performance for crude oil return volatility. Second, our results show that the economic policy uncertainty in US is the most powerful in forecasting crude oil return volatility in nearly the last ten years, but economic policy uncertainty in China has started to show a powerful forecasting performance in the recent years since China has become the largest importer of crude oil since 2017. Third, we find that the impact of economic policy uncertainty on crude oil market is short-lived and the decay period is about one year.

This study makes two contributions to the research on forecasting oil price volatility. Most of the literature documents only one EPU index to model and forecast crude oil return volatility, few of them compare the impact that difference EPU index on crude oil return volatility. We focus on a series of important country and region's EPU indices, and investigate which EPU index has the best predictive performance on crude oil volatility. Additionally, we choose three different horizons to test the predictive performance for EPU indices, which can dynamically test the relationship and predictive power between EPU index and crude oil return volatility. From a practical point of view, our results may help investors or policy-makers to select appropriate EPU index, improving the efficiency of asset allocation and manage risk.

The remaining part of the paper is organized as follows. Section 2 presents the methodology. Section 3 introduces the data. Section 4 shows the empirical results. The last section concludes the paper.

2. Methodology

2.1. Model specification

To examine the impact of economic policy uncertainty on crude oil volatility, we employ the GARCH-MIDAS (Mixed data sampling) model of Engle et al. (2013). The crude oil return $r_{i,t}$, can be written as follows:

$$r_{i,t} = \mu + \sqrt{g_{i,t} * \tau_t} \varepsilon_{i,t}, \quad \forall i = 1, 2, \dots, N_t \quad (1)$$

where μ is the daily expected returns, $\varepsilon_{i,t} | \Phi_{i-1,t} \sim N(0, 1)$ with $\Phi_{i-1,t}$ denotes the information set to the day $i - 1$ of period t . Eq. (1) means that the crude oil returns incorporating two components: the long-run fluctuations τ_t and the short-run volatility $g_{i,t}$.

Accounting to Engle et al. (2013), we assume that the short-run volatility component $g_{i,t}$ follows a mean-reverting GARCH (1,1) progress:

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

to maintain the non-negativity and stationarity of the $g_{i,t}$, constraints of $\alpha > 0$, $\beta > 0$, and $1 - \alpha - \beta > 0$ are set to maintain. The long-run component τ_t is measured by EPU indices from different countries or regions in this paper.

Following the spirit of Engle et al. (2013) and Conrad et al. (2015), τ_t can be specified as:

$$\tau_t = m + \theta \sum_{k=1}^K \varphi_k(\omega_1, \omega_2) X_{t-k} \quad (3)$$

where the Beta weighting scheme $\varphi_k(\omega_1, \omega_2)$ in Eq. (3) follows such specification:

$$\varphi_k(\omega_1, \omega_2) = \frac{(k/K)^{\omega_1-1} (1 - k/K)^{(\omega_2-1)}}{\sum_{j=1}^K (j/K)^{\omega_1-1} (1 - j/K)^{(\omega_2-1)}} \quad (4)$$

where ω_1 and ω_2 are the parameters of weighting function, their size determines the rate of decay. A large (small) value of ω_i means a fast (slow) decaying pattern. $\varphi_k(\omega_1, \omega_2)$ attached to past EPU series depends on the coefficients of ω_1, ω_2 , and $\sum_{k=1}^K \varphi_k(\omega_1, \omega_2) = 1$. Following Engle et al. (2013), we take the lag $K = 36$ in our paper. If restrict $\omega_1 = 1$, the restricted long-run component τ_t and $\varphi_k(\omega_1, \omega_2)$ can be rewritten as Eqs. (5) and (6):

$$\tau_t = m + \theta \sum_{k=1}^K \varphi_k(\omega_2) X_{t-k} \quad (5)$$

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

Eqs. (1)–(4) form a GARCH-MIDAS model with the unrestricted weighting scheme and the parameter space is $\Theta = (\mu, \alpha, \beta, \theta, \omega_1, \omega_2)$. Eqs. (1)–(2), (5)–(6) form a model with restricted weighting scheme and the parameter space is $\Theta = (\mu, \alpha, \beta, \theta, \omega_2)$. The parameter θ measures the impact of exogenous explanatory variables on long-run volatility.

We take the quasi-maximum likelihood method to estimate the parameters of GARCH-MIDAS model, and the log-likelihood function (LLF) can be expressed as follows:

$$LLF = -\frac{1}{2} \sum_{t=1}^T \left[\log g_t(\Phi) \tau_t(\Phi) - \frac{(r_t - \mu)^2}{g_t(\Phi) \tau_t(\Phi)} \right] \quad (7)$$

2.2. Performance test

To evaluate the performance of the GARCH-MIDAS models with different sets of low-frequency EPU indices, we use two loss functions to measure the forecasting error: Heteroskedasticity-adjusted mean square error (HMSE) and Heteroskedasticity-adjusted mean absolute error (HMAE). These loss functions are given by Eqs. (8)–(9),

$$HMSE = \frac{1}{N} \sum_{i=1}^N (1 - \hat{\sigma}_i^2 / \sigma_i^2)^2, \quad (8)$$

and

$$HMAE = \frac{1}{N} \sum_{i=1}^N |1 - \hat{\sigma}_i^2 / \sigma_i^2|, \quad (9)$$

where $\hat{\sigma}_i^2$ denotes the predictive volatility, σ_i^2 denotes the actual crude oil return volatility, and N is the number of predictive days.

Since the loss functions cannot distinguish the predictive power among these models in a statistically significant manner, we use the model confidence set (MCS) test developed by Hansen et al. (2011) to test the predictive performance on crude oil return volatility. In recent years, this method has been widely used for evaluating the predictive performance of different models under a defined loss function (Ma et al., 2017a; Nguyen and Walther, 2018). Compared with Superior Predictive Ability test by Hansen and Lunde (2005), MCS test has several advantages. For instance, it does not need a benchmark model, or composite hypothesis test which can greatly reduce the probability of Type I error. Moreover, it allows for multiple best models to appear simultaneously.

The implementation process of MCS test is as follows: First, consider a set $M_0 = 1, 2, \dots, m_0$, where m_0 refers to the number of predictive models. These models are evaluated via a loss function and we denote the loss value that is associated with model i in period t as $L_{i,t}$, $t = 1, 2, \dots, n$. In the situation where a point forecast $\hat{r}_{i,t}$ of r_t is evaluated according to a loss function L , $L_{i,t} = L(r_t, \hat{r}_{i,t})$. We define the relative performance variables as $d_{ij,t} \equiv L_{i,t} - L_{j,t}$, $\forall i, j \in M_0$. Second, the set of superior models is defined by: $M^* \equiv \{i \in M_0 : \mu_{ij} = E(d_{ij,t}) \leq 0, \forall j \in M_0\}$. MCS test procedure is determined by M^* . Through a sequence of significance tests, we can eliminate the poor predictive ability model in set M_0 . The null hypotheses taking the form as: $H_{0,M} = \mu_{ij} = 0, \forall i, j \in M$, where $M \subset M_0$. It means that in a set of models, the Equal Predictive Ability (EPA) is not rejected at a certain confidence level.

MCS procedure is based on equivalence test (δ_M) and elimination rule (e_M). δ_M is used to test the hypothesis $H_{0,M}$, $\forall M \subset M_0$, and e_M is to eliminate those models that reject the null hypothesis. As a convention, $\delta_M = 0$, $H_{0,M}$ is accepted, while $\delta_M = 1$, $H_{0,M}$ is rejected. MCS procedure continues until there is no rejection of the null hypothesis, and the survival model is obtained in the MCS test. For the given model k ($k \in M_0$), the survival condition is that the MCS test's p -value is greater than the significance level Λ . In other words, the higher the p -value, the more accurate prediction the model is.

According to Hansen et al. (2011), we introduce two statistic of MCS test in this paper, the range statistic (T_R) and semi-quadratic statistic (T_{SQ}), they are defined as follow:

$$T_R = \max_{i,j \in M} \left| \frac{\bar{d}_{ij}}{\sqrt{\text{var}(\bar{d}_{ij})}} \right|, T_{SQ} = \max_{i,j \in M} \frac{(\bar{d}_{ij})^2}{\text{var}(\bar{d}_{ij})}, \forall i, j \in M \quad (10)$$

where $\bar{d}_{ij} \equiv \frac{1}{n} \sum_{t=1}^n d_{ij,t}$. The p -value of T_R and T_{SQ} are available to test the hypothesis $H_{0,M}$. If these p -values are larger than

the confidence level Λ , the null hypothesis cannot be rejected. Since T_R and T_{SQ} depend on nuisance parameters (under both the null and alternative conditions), their asymptotic distributions are nonstandard. The nuisance parameter pose few obstacles, so we use bootstrap methods to estimate relevant distributions and implicitly solve the nuisance parameter problem.

3. Data

In this study, we combine daily oil returns with the monthly EPU indices, and the sample period spans from 1 January 1998 to 31 May 2018. Baker et al. (2013) develop EPU index for the world's major economies from three types of sources. One source uses newspaper coverage of policy-related economic change as a proxy for uncertainty. A second source reflects the number of federal tax code provisions that is to expire in future years. The third channel uses different opinions among analysts as the uncertainty index.

We consider eight EPU indices, including two Global EPU indices, three EPU indices from major crude oil import countries/region (e.g. US, Europe,¹ China), and the other three EPU indices from major crude oil export countries. OPEC counties are important crude oil export countries, but due to the lack of the EPU's data, we only select Russia, Canada and Mexico whose data is available to be included in our analysis. These data can be obtained from the economic policy uncertainty website (<http://www.policyuncertainty.com/>). Fig. 1 shows the daily import and export volume for major countries in the past ten years.² We find that in the past decade, the US daily volume of crude oil imports showed a certain decline, while China's imports increased year by year, leading in the breakthrough that China exceeded US and became the world's largest crude oil importing country in 2017. Russia, on the contrary, kept its daily exports volume around 5000 barrels.

We use the Brent crude oil prices to derive crude oil return volatility, the data are obtained from Bloomberg database. We calculate the crude oil return as the first difference of the natural logarithm of crude oil prices and multiplied by 100: $r_t = 100 \cdot \ln(P_t/P_{t-1})$. The graphical representations of crude oil prices and returns are illustrated in Fig. 2. As it shows, higher crude oil price does not mean higher crude oil return volatility. We can find that there exists a clear volatility cluster phenomenon, indicating that the crude oil return series exhibit heteroskedasticity and confirms the appropriateness of using the GARCH-MIDAS model in our study.

The descriptive statistics for these data are reported in Table 1. The mean of crude oil returns is close to zero, and the standard deviation is 1.845. The mean of eight EPU indices is ranged from 94.42 to 143.91, and the standard deviation is ranged from 35.408 to 108.374. All the skewness values of these EPU indices are greater than zero, indicating that their fat tail are on the right and their distributions are right-skewed. The kurtosis values are greater than three, so they are not subject to normal distribution. These indicates that the probability distributions of all series are skewed and leptokurtic, thereby rejecting normality, which is also confirmed by the Jarque–Bera(J–B) statistics. We can find from Table 1 that the China EPU has the largest mean and standard deviation among these EPU indices. On the contrary, the US EPU has relatively smaller mean and standard deviation compared to other countries. The skewness value of crude oil is -0.072 , and Kurtosis value is 8.334 , indicating that its distributions are left-skewed and not subject to normal distribution.

¹ Notes: It includes UK, Germany, France, Italy and Spain, more details can be found at the website of EPU homepage.

² Data is available at the website: <https://www.ceicdata.com>.

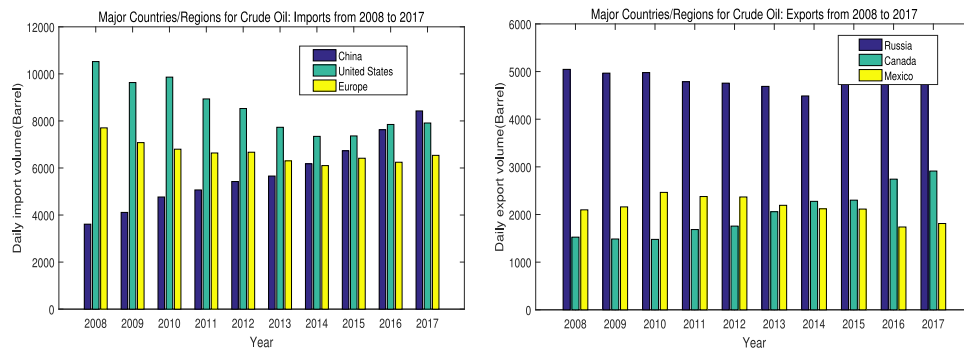


Fig. 1. The import and export of crude oil from major countries in the past 10 years.

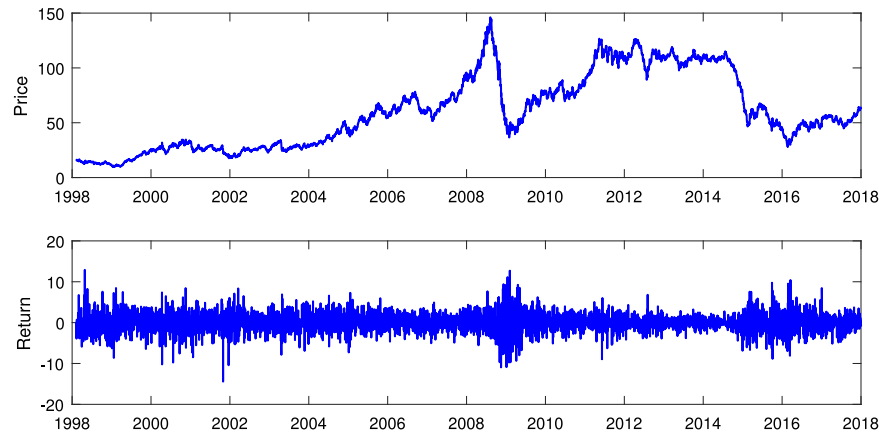


Fig. 2. Plots of Brent oil prices and returns.

Table 1
Descriptive statistics of EPU indices and oil returns series.

	Min.	Max.	Mean.	Std. Dev.	Skewness	Kurtosis	J-B stat.
GEPU current	50.065	283.347	111.187	43.974	1.204	4.811	92.699***
GEPU ppp	51.699	307.609	111.619	46.061	1.336	5.227	123.490***
USA EPU	57.203	245.127	110.620	35.408	0.900	3.315	34.087***
Europe EPU	47.692	433.278	141.464	64.901	1.270	5.649	137.539***
China EPU	9.067	694.849	143.941	108.374	1.989	8.209	438.471***
Russia EPU	12.399	400.017	119.691	76.642	1.152	4.049	65.471***
Canada EPU	30.097	449.624	140.553	83.005	1.099	4.060	60.801***
Mexico EPU	8.509	428.725	94.420	71.910	1.968	7.799	393.2275***
Oil return	−14.437	12.898	0.021	1.845	−0.072	8.334	8845.4***

Notes: This table reports the descriptive statistic of daily crude oil returns and monthly EPU index. The sample covers different countries and regions. J-B stat. is the statistics testing for normal distribution.

***Denotes rejections of null hypothesis at 5% significance level.

4. Empirical results

In Section 4.1, we estimate the GARCH-MIDAS model with EPU indices. Next, in Section 4.2, we examine the predictive performance in three different horizons.

4.1. GARCH-MIDAS estimation

To estimate the volatility of EPU indices, we follow the approach taken by Schwert (1989) and Pan et al. (2017), and fit the autoregressive model with 12 monthly dummy variables to estimate monthly EPU, so we can link the crude oil return volatility to these monthly EPU series.

$$X_t = \sum_{i=1}^{12} \eta_i D_{it} + \sum_{i=1}^{12} \zeta_i X_{t-i} + \varepsilon_t \quad (11)$$

where D_{it} is a monthly dummy variable. The ε_t is the residual from the regression of Eq. (11). Following Engle et al. (2013), we include 36 MIDAS lag months of EPU indices, which is long enough for estimating procedures. Table 2 reports the estimated results.

For the model parameters, all of α and β are positive and significant, in the meantime, $\alpha + \beta < 1$. The most important parameter is the parameter θ , which reflects the relationship between economic policy uncertainty and crude oil return volatility. For all of EPU catalogs, the parameters θ are positive and significant. It indicates that when the EPU index increases, the crude oil return volatility also increases, which will affect the decisions of investors and lead to a greater volatility. To compare the effect of different EPU indices on crude oil return volatility, we employ the indicator of RX, with its arithmetic expression as, $RX = \theta * \sum_{k=1}^{36} \varphi(\omega_2) - 1$, which refers to the percentage change in the long-run volatility of crude oil return caused by

Table 2
Parameter estimation results of the GARCH-MIDAS model with different EPU.

	μ	α	β	θ	ω		LL	BIC	RX
GEPU current	0.0314* (0.0172)	0.0244*** (0.0014)	0.9752*** (0.0014)	0.0653*** (0.0100)	3.0839*** (0.8760)	1.1072* (0.6063)	−14 334.2	28 721.9	1.23
GEPU ppp	0.0313* (0.0172)	0.0244*** (0.0014)	0.9751*** (0.0014)	0.0667*** (0.0104)	3.1339*** (0.8354)	1.1889* (0.6128)	−14 334.9	28 723.4	1.27
US EPU	0.0303* (0.0172)	0.0240*** (0.0014)	0.9755*** (0.0014)	0.0872*** (0.0145)	2.1425*** (0.5562)	−0.0641 (0.8446)	−14 332.7	28 718.9	1.68
Europe EPU	0.0333* (0.0172)	0.0254*** (0.0014)	0.9742*** (0.0014)	0.0440*** (0.0074)	3.0470*** (0.9361)	2.9870*** (0.6842)	−14 340.9	28 735.3	0.83
China EPU	0.0312* (0.0174)	0.0272*** (0.0014)	0.9721*** (0.0014)	0.0153*** (0.0036)	2.2474*** (0.7448)	5.6546*** (0.7405)	−14 353.2	28 759.9	0.28
Russia EPU	0.0327* (0.0175)	0.0286*** (0.0014)	0.9705*** (0.0015)	0.0051** (0.0022)	49.7580 (156.0000)	6.4793*** (0.8645)	−14 357.3	28 768.0	0.29
Canada EPU	0.0315* (0.0171)	0.0239*** (0.0013)	0.9756*** (0.0014)	0.0353*** (0.0058)	2.3875*** (0.7307)	3.8238*** (0.5934)	−14 338.8	28 731.1	0.67
Mexico EPU	0.0336* (0.0177)	0.0257*** (0.0016)	0.9710*** (0.0018)	0.0186*** (0.0022)	1.3816*** (0.3241)	1.9560*** (0.2733)	−14 339.2	28 731.9	0.37

Notes: The table shows the estimation results for crude oil return volatility with the restricted weighting schemes. LL is the Log-Likelihood value and the BIC is the Bayesian Information Criterion. The ratio RX represents a unit EPU change leading to the change in the long-run volatility of crude oil return. Robust standard errors are reported in parentheses.

*Denotes rejections of null hypothesis at 10% significance level.

**Denotes rejections of null hypothesis at 5% significance level.

***Denotes rejections of null hypothesis at 1% significance level.

one percent increase of EPU index. Consider the US EPU, the estimated θ is 0.087, and the restricted weighting function with $\omega_2 = 2.143$ which yields 0.192 on the first lag (which is the maximum weights) of EPU level. It indicates that a one percent increase of US EPU index at the current month will increase the next month's long-run volatility of crude oil return by $0.087 * 0.192 - 1 \approx 0.0168$ or 1.68%. As Table 2 shows, US EPU has the biggest RX value, in other words, the fluctuation of US EPU has the most impact on crude oil return volatility.

The restricted weighting scheme is plotted in Fig. 3. We can see that all of eight EPU indices on the first lags get the largest weight except for Russia, indicating that the effects of EPU on the crude oil return volatilities are short-lived. Russia EPU index gets the largest weight at second lag, and its decaying cycle faster than other EPU indices by one month. This is because its w is larger than others, representing a faster decaying pattern. We can also find this effect disappear after one year. In other words, the news-based information (change of EPU index) can be quickly reflected in the crude oil return volatility, implying the crude oil markets is efficient (Fama, 1965).

Fig. 4 shows the estimated daily total volatility and the long-run volatility of eight GARCH-MIDAS models. The dashed line shows the total daily volatility ($\tau_t * g_t$) and the solid line shows the long-run volatility (τ_t) determined by different EPU indices. As Fig. 4 shows, EPU indices impact crude oil return volatility in different ways. We can see that there exists the lagged effect of EPU indices on the long-run volatility, which is a common phenomenon in financial markets, as it takes time for the changes in asset prices caused by policy changes to materialize. One noteworthy phenomenon is the long-run volatility line corresponding to Russia EPU index is smoother than others. To explore the reason behind it, we notice that the coefficient θ of Russia in Table 2 is smaller than others, indicating that the same amount of change in EPU will lead to a smaller change in the long-term volatility, which explains the smoother line in Fig. 4 and shows that the impact of Russia EPU index on international crude oil long-run volatility is smaller than others.

Except for EPU index, the Crude Oil Volatility Index is also found has predictive power on crude oil return volatility (Haugom et al., 2014; Dutta, 2017). In this section, we try to present further evidence to examine whether combining the information content of OVX with EPU index improves the forecasting performance. The OVX index is an important tool to measure the crude oil

volatility, which is available at the website of CBOE. It takes into account real-time bid/ask quotes for nearby and second nearby options, and weights these options to produce a constant, a 30-day estimate of expected volatility in crude oil prices (Liu and Fan, 2013).

Table 3 presents the estimation results of GARCH-MIDAS with monthly EPU indices and OVX index from June 1, 2010 to May 31, 2018. We choose the lag order of EPU indices and OVX index for estimating procedures follows BIC. We can find that the coefficients θ^{EPU} are positive and significant, except for Mexico EPU. Based on the LL and BIC, the GARCH-MIDAS models results with both EPU indices and OVX index included improve upon those derived from the model with only OVX index, indicating that the GARCH-MIDAS models including EPU index can generate more accurate forecasts.

4.2. Model prediction and evaluation

In this section, we use MCS test to compare the performance of the GARCH-MIDAS models with different EPU indices. Appropriate forecasting horizons is crucial to the forecasting performance of the models. However, there is no consensus on this issue in academia. Hence, we choose three different horizons as our predictive comparison, with the sample periods being the last ten, three and one years, respectively. To examine whether evaluation results of the model are robust and to investigate which EPU index has the best forecasting performance, we follows Tian and Hamori (2015) and set the threshold $\lambda = 0.1$ for MCS test in this paper.

The MCS procedure consists of a sequence of tests which permit to construct a set of “superior” models, where the null hypothesis of Equal Predictive Ability (EPA) is not rejected at a certain confidence level. As described in Section 2.2, the p-values of the MCS test are larger than the threshold λ , implying that those models can survive in the MCS test, and the larger of the p-value, means the better forecasting accuracy by the model.

Table 4 reports the result of the MCS tests for GARCH-MIDAS models with EPU index. We find that many p-values are larger than 0.1, especially in the last one year. Panel A in Table 4 presents the forecasting evaluation for the last ten years under the HMSE and HMAE criteria. Obviously the US EPU has the best predictive performance in all EPU indices, and all of the models can survive in the MCS test. The panel B shows that the US

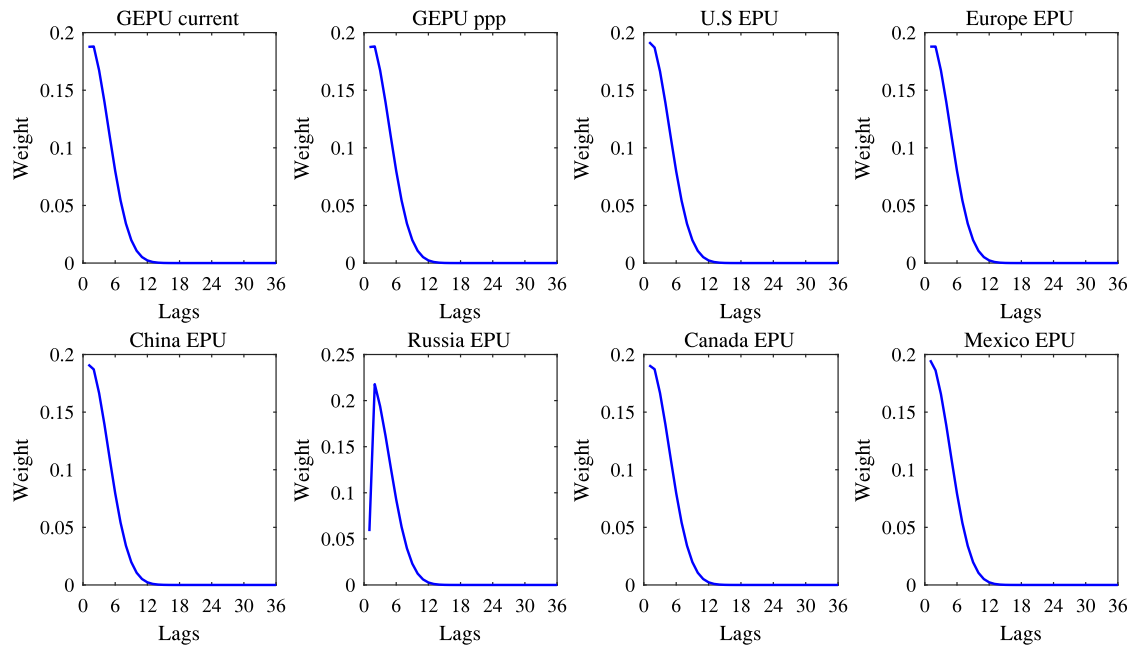


Fig. 3. Restricted weight schemes patterns of EPU indices. Lags refers to the Beta polynomial Lag K , and the weight is the restrict weight ω .

Table 3

The estimation results of GARCH-MIDAS with EPU and OVX.

	μ	α	β	θ^{EPU}	θ^{OVX}	m	LL	BIC
GEPU current	-0.0323 (0.0366)	0.0434*** (0.0138)	0.9037*** (0.0323)	0.0035* (0.0021)	0.0634*** (0.0066)	-1.5004*** (0.3553)	-2474.8	5006.7
GEPU ppp	-0.0313 (0.0366)	0.0423*** (0.0131)	0.9072*** (0.0286)	0.0033* (0.0019)	0.0628*** (0.0068)	-1.4670*** (0.3347)	-2907.2	5872.9
EPU US	-0.0307 (0.0472)	0.0446*** (0.0195)	0.9554*** (0.0244)	0.0055* (0.0029)	0.0509 (0.5380)	0.0796 (0.8847)	-2426.2	4909.2
EPU China	-0.0361 (0.0383)	0.0328** (0.0165)	0.8736*** (0.0457)	0.0017*** (0.0005)	0.0635*** (0.0050)	-1.3808 (0.1811)	-2472.5	5002.0
EPU Europe	-0.0322 (0.0370)	0.0541*** (0.0222)	0.8569*** (0.1010)	0.0024* (0.0014)	0.0645*** (0.0058)	-1.5143*** (0.3217)	-2476.3	5009.7
EPU Russia	-0.0266 (0.0371)	0.0267** (0.0108)	0.9280*** (0.0822)	0.0147*** (0.0042)	0.0467*** (0.0078)	-3.2184*** (0.6254)	-2896.3	5851.1
EPU Canada	-0.0474 (0.0414)	0.0572* (0.0326)	0.5857** (0.2312)	0.0034*** (0.0012)	0.0679*** (0.0044)	-1.8188*** (0.3144)	-2472.9	5002.9
EPU Mexico	-0.0820 (0.0604)	0.0266* (0.0138)	0.9109*** (0.0579)	0.0039 (0.0035)	0.0588*** (0.0052)	-0.8673*** (0.2980)	-2468.2	4993.4
OVX	-0.0309 (0.0351)	0.0353*** (0.0043)	0.9562*** (0.0002)		0.0391*** (0.0113)	-0.3594 (0.3354)	-3328.4	6701.6

Notes: The table shows the estimation results for crude oil return volatility with the restricted weighting schemes. Limited by space, we do not report the estimated result of parameter ω^{EPU} and ω^{OVX} . For two covariates, the long-run component is specified as: $\log(\tau_t) = m + \theta^{EPU} \sum_{k=1}^K \phi_k(\omega^{EPU}) EPU_{t-k} + \theta^{OVX} \sum_{k=1}^K \phi_k(\omega^{OVX}) OVX_{t-k}$. LL is the Log-Likelihood Value and the BIC is the Bayesian Information Criterion. Robust standard errors are reported in parentheses.

*Denotes rejections of null hypothesis at 10% significance level.

**Denotes rejections of null hypothesis at 5% significance level.

***Denotes rejections of null hypothesis at 1% significance level.

EPU has the best predictive performance in the last three years. Finally, Panel C reports the results of the last one year, China EPU has the best predictive performance. The plausible explanation is that China has become the world's largest oil importing country and the second largest economy in the world. Hence, with the economic growth and consumption demand for crude oil, China EPU index will have more powerful performance on the crude oil market.

Table 5 presents the MCS test for models with EPU index and OVX index. We compare eight GARCH-MIDAS with two covariates models and GARCH-MIDAS with OVX. As is shown in Table 5, most of the p -value of models are larger than the threshold $\lambda = 0.1$. We find that US EPU has the best predictive performance in

medium and long term, and China EPU has the best predictive performance in the last one year. This results are consistent with that in Table 4. We also find that most models combine with EPU and OVX have the better performance than the models only with OVX, confirming that the EPU index has a good forecasting power in crude oil return volatility.

In conclusion, our result indicates that EPU has a significant impact on crude oil return volatility. In the long term, the US EPU has an important influence on the crude oil volatility, but in recent year, the China EPU has a stronger influence on crude-oil return volatility.

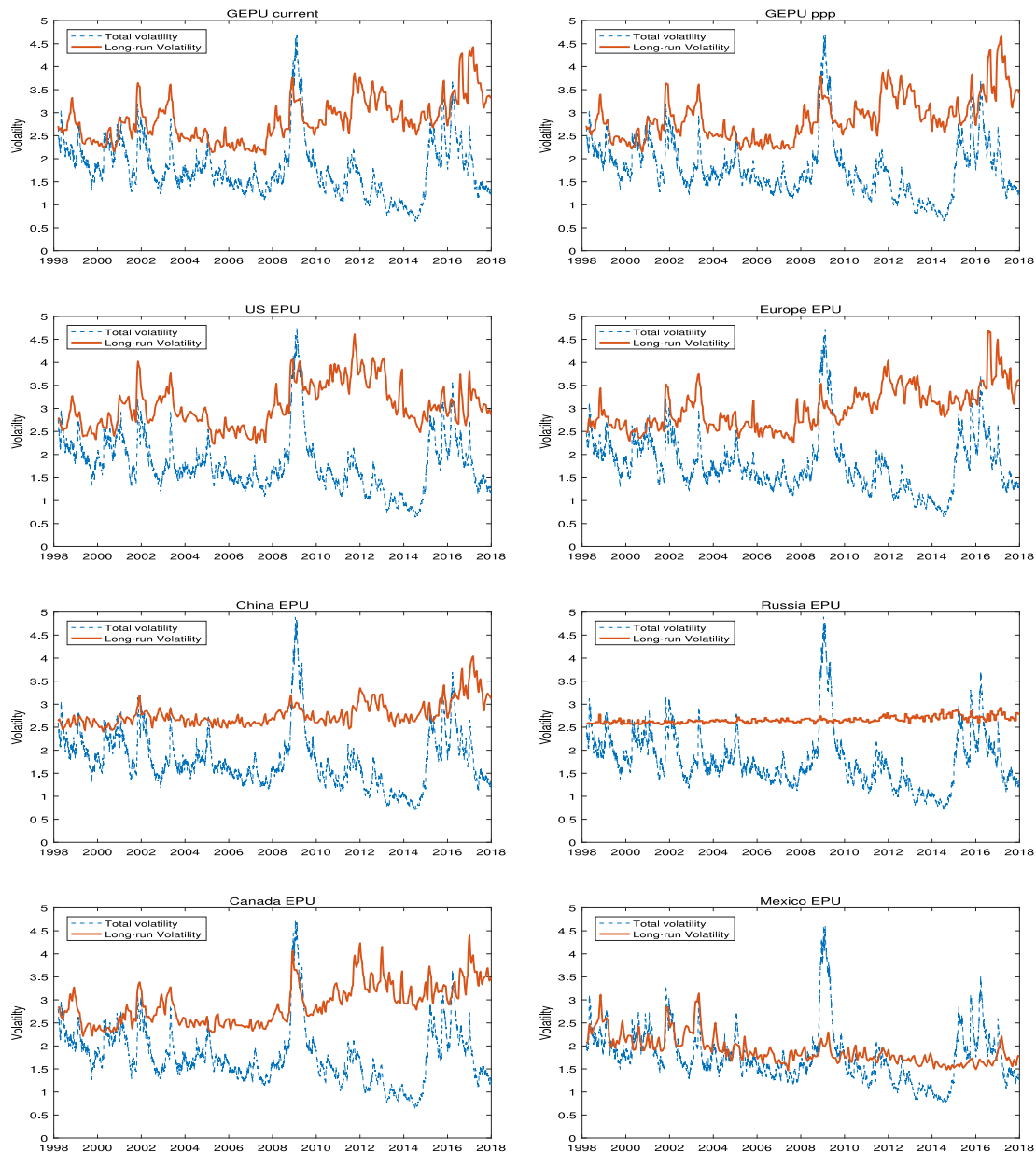


Fig. 4. Estimated total volatility and long-term volatility by different GARCH-MIDAS models. In each picture, the dashed line refers to the total volatility ($\tau_t * g_{i,t}$), the solid line represents the long-run volatility(τ_t).

5. Conclusion

In this paper, we examine the impacts of economic policy uncertainty in different countries on the crude oil return volatility, and investigates which EPU index has the most forecasting power in crude oil market. Our findings show that EPU indices have an important effect on crude oil return volatility forecasting. We also find that US EPU index has the best performance on forecasting crude oil return volatility in the last ten years, but China EPU index has the powerful predictive performance in the past year. Additionally, our research indicates that the effect of EPU on volatility of crude oil return is short-lived and the decay period is about one year.

Our findings have important economic implications for crude oil market participants and policy makers that they should pay more attentions to the change of worldwide economic policy uncertainty. If the long-term effects of EPU is to be examined,

the US EPU index should receive more attention. However, if the recent one year effects of EPU is to be studied, the China EPU index should be more important index to them. For future research, the GARCH-MIDAS model should be modified to contain more macro-level determinants in different frequencies. In addition, a multivariate GARCH-MIDAS model may be considered to explore the impact of EPU on multiple assets volatility.

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Table 4
MCS test results for GARCH-MIDAS with EPU forecasting performance.

	HMSE		HMAE	
	T_R	T_{SQ}	T_R	T_{SQ}
Panel A: 10 years				
GEPU current	0.142	0.162	0.002	0.006
GEPU ppp	0.044	0.067	0.002	0.000
US	1.000	1.000	1.000	1.000
Europe	0.044	0.067	0.002	0.006
China	0.005	0.005	0.000	0.000
Russia	0.005	0.005	0.002	0.000
Canada	0.249	0.216	0.109	0.091
Mexico	0.043	0.067	0.002	0.000
Panel B: 3 years				
GEPU current	0.727	0.752	0.988	0.981
GEPU ppp	0.727	0.752	0.988	0.981
US	1.000	1.000	1.000	1.000
Europe	0.643	0.601	0.988	0.981
China	0.643	0.601	0.955	0.935
Russia	0.643	0.601	0.988	0.981
Canada	0.643	0.601	0.988	0.981
Mexico	0.643	0.601	0.988	0.981
Panel C: 1 years				
GEPU current	0.975	0.980	0.995	0.997
GEPU ppp	0.969	0.980	0.995	0.997
US	0.969	0.980	0.994	0.995
Europe	0.969	0.980	0.995	0.997
China	1.000	1.000	1.000	1.000
Russia	0.984	0.990	0.995	0.997
Canada	0.982	0.990	0.995	0.997
Mexico	0.975	0.980	0.995	0.997

Note: The bold numbers have p-values at 1, indicating that the corresponding model performs the best out of all models. HMSE and HMAE denotes different loss functions, T_R and T_{SQ} refer to different test statistics for MCS.

Table 5
MCS test results for GARCH-MIDAS with EPU and OVX forecasting performance.

	HMSE		HMAE	
	T_R	T_{SQ}	T_R	T_{SQ}
Panel A: 5 years				
GEPU current	0.7765	0.4426	0.8295	0.0000
GEPU ppp	0.8261	0.5076	0.8295	0.0000
US	1.0000	1.0000	1.0000	1.0000
Europe	0.8261	0.5076	0.8295	0.0000
China	0.6549	0.4426	0.7101	0.0000
Russia	0.6549	0.4426	0.8295	0.0000
Canada	0.6549	0.4426	0.7101	0.0000
Mexico	0.8261	0.4426	0.8295	0.0000
OVX	0.6549	0.4426	0.8295	0.0000
Panel B: 3 years				
GEPU current	0.5247	0.5602	0.5515	0.0000
GEPU ppp	0.5939	0.5602	0.6062	0.0000
US	1.0000	1.0000	1.0000	1.0000
Europe	0.5939	0.5602	0.6062	0.0000
China	0.4141	0.5228	0.3529	0.0000
Russia	0.4141	0.5301	0.3529	0.0000
Canada	0.4141	0.5228	0.5515	0.0000
Mexico	0.4141	0.5228	0.3529	0.0000
OVX	0.589	0.5602	0.6062	0.0000
Panel C: 1 years				
GEPU current	0.3693	0.2891	0.3510	0.2435
GEPU ppp	0.3693	0.2541	0.3510	0.0000
US	0.3693	0.2563	0.3510	0.2324
Europe	0.3693	0.2739	0.3510	0.2166
China	1.0000	1.0000	1.0000	1.0000
Russia	0.3693	0.2700	0.3510	0.2435
Canada	0.3693	0.2322	0.3510	0.0000
Mexico	0.5175	0.3995	0.5269	0.3635
OVX	0.5175	0.3995	0.5269	0.4165

Note: The bold numbers have p-values at 1, indicating that the corresponding model performs the best out of all models. HMSE and HMAE denotes different loss functions, T_R and T_{SQ} refer to different test statistics for MCS.

Declaration of competing interest

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

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