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Geopolitical risk uncertainty and oil future volatility: Evidence from MIDAS models☆

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ABSTRACT

Using a textual analysis based geopolitical risk (GPR) index, this paper exploits the effects of geopolitical risk uncertainty on oil futures price volatility within a mixed data sampling (MIDAS) modeling framework. With a variety of MIDAS specifications, our in-sample estimation results suggest that the short-term (e.g. one-day-ahead) oil realized volatility is positively associated with GPR uncertainty, and our out-of-sample forecasting exercise indicates that the GPR index is useful for improving short-term oil futures volatility prediction. In addition, we find that the categorical GPR index: GPR action related index (GPA), contributes more to the long-term oil volatility forecasting, compared with GPR threat related index (GPT).

1. Introduction

Geopolitics, economic uncertainty, and the risks and benefits of new technologies dominate the current energy conversation. Facing with the recent geopolitical tenses: US-China trade wars, Iran sanctions, the role of Russia, the future of shale, oil markets are having a turbulent time, and that shows no sign of ending. Though oil prices have recovered from dramatic lows in 2014 and 2015, recent volatility driven by countervailing geopolitical and geo-economic trends have left many wondering: “what is going on with the oil price volatility?” We surprisingly found there is very less literature addressing this question, and hence, we try to fill the gap to study how the geopolitical risk uncertainty will influence the future oil volatility.

As a commodity, oil is closely tied to national strategy, global politics and power. As a typical representative of nonrenewable energy, oil price volatility has an intimate correlation to monetary policy, investment decisions, economic activity, stock markets, and others (e.g., Jo, 2014; Hamilton, 2003; Kilian and Park, 2009). Therefore, it is sensible to forecast oil prices volatility by exploring their links with these exogenous shocks. More importantly, with the advent of the oil future high frequency data, many papers have investigated oil volatility from high-frequency perspectives (e.g., Haugom et al., 2014; Degiannakis and Filis, 2017; Ma et al., 2018c; Gong and Lin, 2018a; Chen et al., 2019), in this paper, we follow these literatures by using 5-min crude oil E-Mini futures contract to describe and predict oil future realized volatility.

The distinct research of Caldara and Iacoviello (2018) follows the methodology of Baker et al. (2016) by using the contracting economic policy uncertainty (EPU) index and constructs a proxy measure for geopolitical risk named the GPR index. The GPR index focuses on risks that are closely associated with wars, terrorism, and tensions among states (Caldara and Iacoviello, 2018). It measures the frequency of related articles in major newspapers discussing rising geopolitical tensions. GPR can be both replicated and audited, as both algorithms and audit guides are publicly available (http://www.policyuncertainty.com/gpr.html). Moreover, GPR exhibits high variability and can be seen over many years. Therefore, based on work of Caldara and Iacoviello (2018), we can first explore the links between GPR and oil price realized volatility from a quantitative perspective, investigating its predictive ability on forecasting oil market volatility. Moreover, we also investigate the

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effects of GPR itself and its category indices (the geopolitical threats and the geopolitical acts).

Obviously, the GPR index involves special uncertainty compared to other uncertainty indices. Interestingly, few studies have investigated the impacts of GPR on oil volatility forecasting, especially from a high-frequency perspective. Consequently, an open question leaves us: is GPR helpful for forecasting oil volatility? To address this question, we use the MIDAS model to model and forecast oil futures volatility using high-frequency data. To the best of our knowledge, there is only one study that use this model to forecast oil prices volatility (Degiannakis and Filis, 2018). Thus, in this paper, we provide some insights on forecasting oil prices realized volatility, and can enrich this research on predicting volatility in oil future markets.

We have several main conclusions as follows: (a) during in-sample, we find that realized measures (e.g., realized volatility and continuous sample path) can remarkably lead to high fluctuations in the future. The effects of jumps and GPR are significant particularly on short-term (e.g. one-day-ahead) oil volatility; (b) out-of-sample results show, the GPR index can help to predict short-term oil futures realized volatility. Specifically, the MIDAS-CJ-GPR model can outperform the benchmark and other competing models discussed in this paper; (c) we further assess the impacts of the GPR and its category indices, finding that the GPR action related sub-index contributes more to improve long-term oil futures volatility prediction, compared with GPR threat related sub-index; (d) we find that, the GPR index can improve the economic performance when forecasting short-term oil volatility.

Our study contributes the literature from two perspectives. First and the most, our work contributes to the literature that studies the links between uncertainty and oil volatility. Haugom et al. (2014) demonstrate that the inclusion of the CBOE VIX significantly improves the oil volatility forecasting. Gong and Lin (2018a) show that the investor fear gauge (IFG) contains incremental information content for forecasting the volatility of crude oil futures; they indicate that the IFG can help improve the performance of almost all existing volatility models. Here, we employ the daily indicator of geopolitical risk (GPR) based on a tally of newspaper articles covering geopolitical tensions proposed by Caldara and Iacoviello (2018) to study whether geopolitical risk uncertainty is useful to predict oil future volatility. Caldara and Iacoviello (2018) define, "*the risk associated with wars, acts of terrorism, and tensions between states that affect the normal and peaceful course of international relations. Geopolitical risk captures both the risk that these events materialize and the new risks associated with an escalation of existing events*".

Second, our work links with the oil future volatility forecasting using mixed frequency model. Previous literature mainly focus on the oil volatility forecasting using high frequency data, for example, Sévi (2014), Degiannakis and Filis (2017), Ma et al. (2018a, 2018b, 2018c), Gong and Lin (2017), Gong and Lin (2018b), Chen et al. (2019), Liu et al. (2018), Wen et al. (2016) study oil price or future realized volatility using the HAR model of Corsi (2009). However, Ghysels et al. (2006, 2009b) deem that HAR is a special case of Mixed-Data Sampling (MIDAS) with a step function. In addition, some works (e.g., Audrino et al., 2019; Baker et al., 2016) show that the lag structure (1, 5, 22) of HAR may not the optimal choice. Another important reason is that, to date, rarely few studies (e.g., Degiannakis and Filis, 2018) use this model to model and forecast oil volatility. Therefore, in this paper, we use the mixed data sampling (MIDAS) model proposed by Ghysels et al. (2006) to model and forecast oil futures volatility using intraday data. We augment the MIDAS model with the recent GPR index to study how the GPR index will impact on the high frequency (daily) oil future volatility. This provides new insights about how exogenous shock will influence the oil price volatility, and how we can use it to improve oil price volatility forecasting.

We design the framework of this paper as follows. The econometric models, including the key variables' definitions, MIDAS and its extended models presents in Section 2. Some simple descriptions on oil futures high-frequency and GPR index are showed in Section 3. The section 4 is our in-sample estimations. The section 5 provides out-of-sample evaluations. The section 6 is a set of robustness tests. The section 7 is the conclusion.

2. Econometric models

2.1. Realized variance measure

As the seminal contributions of Merton (1980) and Andersen and Bollerslev (1998), the realized volatility (RV) is received much attention by scholars and then used to measure latent market fluctuations. In our paper, we use high frequency data of the oil future prices to construct oil RV. The RV is defined as:

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

where $r_{t,\,i}$ is the i-th interval return of day t, Δ is the sampling frequency, and $\mathrm{M} = 1/\Delta$ indicates the no. of intraday intervals. Barndorff-Nielsen and Shephard (2004) indicate that, RV can be satisfied when $\Delta \to 0$:

$$\mathrm{RV}_t = \int_0^t \sigma^2(s)ds + \sum\nolimits_{0<s\le t}\kappa^2(s), \tag{2}$$

where $\int_0^t\sigma^2(s)ds$ is integrated volatility, which can be approximately calculated by realized bi-power variation (BPV). The BPV is defined,

$$\mathrm{BPV}_t = u_1^{-2}\sum_{i=1}^{M} |\ r_{t,i}||r_{t,i-1}\ |, \tag{3}$$

where $u_1 \cong 0.7979$. $\int_0^t\sum_{0<s\le t}\kappa^2(s)$ is the jump component. We use the Z-ratio test statistic test (Barndorff-Nielsen and Shephard, 2006; Huang and Tauchen, 2005) to obtain jumps components at the threshold significance level, which has better power property of the works of Andersen et al., 2007, Sévi (2014), among others. The formulation of the Z-ratio test is,

$$Z_t = \Delta^{-1/2}\frac{(\mathrm{RV}_t - \mathrm{BPV}_t)\mathrm{RV}_t^{-1}}{\sqrt{\left(\frac{\pi^2}{4}+\pi-5\right)\max\left(1,\frac{\mathrm{TQ}_t}{(\mathrm{BPV}_t)^2}\right)}}, \tag{4}$$

where TQ_t represents realized tri-power quarticity. In line with the work of Andersen et al., 2007, we can obtain the continuous sample path (CRV) and jumps components (CJ) at the α significance level, and define them as,

$$\mathrm{CRV}_t = I(Z_t \le \Phi_{t,\alpha})\cdot\mathrm{RV}_t + I(Z_t > \Phi_{t,\alpha})\cdot\mathrm{BPV}_t, \tag{5}$$

$$\mathrm{CJ}_t = I(Z_t > \Phi_{t,\alpha})\cdot\ \max(\cdot\mathrm{RV}_t - \mathrm{BPV}_t, 0), \tag{6}$$

where $\Phi_{t,\,\alpha}$ is statistical value at the α significance level, which follows normal distribution.

2.2. MIDAS model specifications

At first, we introduce a standard MIDAS model to describe and forecast oil RV, referred to as **MIDAS-RV (labelled as Model 0)**, which have been used in many previous studies (e.g. Ghysels et al., 2007; Ghysels and Sohn, 2009; Santos and Ziegelmann, 2014; Ma et al., 2019). The specification of the model is defined as,

$$\mathrm{RV}_{t,t+h} = \beta_0 + \beta_1\sum\nolimits_{k=1}^{k^{max}} b\left(k,\theta^{\mathrm{RV}}\right)\mathrm{RV}_{t-k} + \varepsilon_{t+h}, \tag{7}$$

where RV_{t-k} is lags (t-k) of RV. The subscript h=1 (5 and 22), implying that we focus on one-day (one-week and one-month) ahead RVs, where $\mathrm{RV}_{t,t+h} = {}^1/_h(\mathrm{RV}_{t,t+1} + \mathrm{RV}_{t+1,t+2}\ldots + \mathrm{RV}_{t+h-1,t+h})$. Following up the studies of Santos and Ziegelmann (2014) and Ghysels and Sohn (2009), in this paper, we set k^{max} to be 66.[1] Following Ghysels et al. (2007) and Santos and Ziegelmann (2014), we define the weighting function, $b(k,\theta^{RV})$, as

$$b\left(k,\theta^{RV}\right) = f\left(\frac{k}{k^{max}},\theta_1,\theta_2\right) / \sum_{k=1}^{k^{max}} f\left(\frac{k}{k^{max}},\theta_1,\theta_2\right), \tag{8}$$

where $f(z,a,b) = z^{a-1}(1-z)^{b-1}/\varphi(a,b)$ and $\varphi(a,b)$ is defined as $\varphi(a,b)=\Gamma(a)\Gamma(b)/\Gamma(a+b)$, which imposes different weights on different RV lags. As suggested by Ghysels et al. (2006), these weighted values, $b(k,\theta^{RV})$, have to all positive to ensure that the RVs are nonnegative. This model (MIDAS-RV) is the benchmark in this article, and then, we augment it with GPR index information to study the effects of geopolitical risk on oil future RV.

We also consider other popular alternative MIDAS specifications, including the one focusing on asymmetric effect of positive and negative past RVs, named as **MIDAS-RS (Model 1)**, and the one distinguishing the effects of continuous and discrete (or jump) movements of past RVs, named as **MIDAS-CJ (Model 2).** The **MIDAS-RS** model is inspired by Barndorff-Nielsen et al. (2008), Chen and Ghysels (2010), Patton and Sheppard (2015), aiming to capture the asymmetric effect of past volatility:

$$RV_{t,t+h} = \beta_0 + \beta_1 \sum_{k=1}^{k^{max}} b\left(k,\theta^{RV^+}\right) RV^+_{t-k} + \beta_2 \sum_{k=1}^{k^{max}} b\left(k,\theta^{RV^-}\right) RV^-_{t-k} + \varepsilon_{t+h}, \tag{9}$$

where $RV^+_t = \sum_{i=1}^{M} r^2_{t,i} I(r_{t,i}>0)$ and $RV^-_t = \sum_{i=1}^{M} r^2_{t,i} I(r_{t,i}<0)$. Including the semi-variance measures: RV^+_{t-k} and RV^-_{t-k}, helps to dig out the asymmetric effect of past positive and negative RVs on future oil volatility. Our second alternative is **MIDAS-CJ** model, which is defined as

$$RV_{t,t+h} = \beta_0 + \beta_1 \sum_{k=1}^{k^{max}} b\left(k,\theta^{CRV}\right) CRV_{t-k} + \beta_2 \sum_{k=1}^{k^{max}} b\left(k,\theta^{CJ}\right) CJ_{t-k} + \varepsilon_{t,t+h}, \tag{10}$$

where CRV_t is continuous sample path and CJ_t is significant jump component. More details relating to this model can be found in Andersen et al., 2007.

2.3. Augmenting MIDAS model using GPR

The MIDAS model offers an ideal ground to study the relationship between series sampled at not only the same frequencies, but also at different frequencies. Therefore, we can use MIDAS model to exploit the effects of geopolitical risk uncertainty (GPR) on oil future price volatility across different time horizons. We extend the benchmark MIDAS model by augmenting it with GPR index as an explanatory variable. The coefficient of GPR index allows us to measure the impact of low frequency GPR on high frequency oil future RV. The extended model specifications are listed as follows:

MIDAS-RV-GPR (Model 3):

$$RV_{t,t+h} = \beta_0 + \beta_1 \sum_{k=1}^{k^{max}} b\left(k,\theta^{RV}\right) RV_{t-k} + \gamma_1 \sum_{k=1}^{k^{max}} b\left(k,\theta^{GPR}\right) GPR_{t-k} + \varepsilon_{t,t+h}. \tag{11}$$

MIDAS-RS-GPR (Model 4):

$$RV_{t,t+h} = \beta_0 + \beta_1 \sum_{k=1}^{k^{max}} b\left(k,\theta^{RV^+}\right) RV^+_{t-k} + \beta_2 \sum_{k=1}^{k^{max}} b\left(k,\theta^{RV^-}\right) RV^-_{t-k} + \gamma_1 \sum_{k=1}^{k^{max}} b\left(k,\theta^{GPR}\right) GPR_{t-k} + \varepsilon_{t,t+h}. \tag{12}$$

MIDAS-CJ-GPR (Model 5):

$$RV_{t,t+h} = \beta_0 + \beta_1 \sum_{k=1}^{k^{max}} b\left(k,\theta^{CRV}\right) CRV_{t-k} + \beta_2 \sum_{k=1}^{k^{max}} b\left(k,\theta^{CJ}\right) CJ_{t-k} + \gamma_1 \sum_{k=1}^{k^{max}} b\left(k,\theta^{GPR}\right) GPR_{t-k} + \varepsilon_{t,t+h}. \tag{13}$$

3. Data and summary statistics

3.1. Crude oil high-frequency data

Our crude oil high-frequency data are garnered from the Thomson Reuters Tick History (TRTH), which is based on crude oil *E*-Mini futures contract. The oil futures are traded from 6:00 p.m. of day t to 5:15 p.m. of the next day $(t+1)$ with a 45-min break. Following up previous studies (e.g., Haugom et al., 2014; Degiannakis and Filis, 2017; Gong and Lin, 2018a; Chen et al., 2019; Ma et al., 2019; Zhang et al., 2019), the 5-min is relatively suitable frequency sampling, and can strike the trade-off between the market microstructure noise and estimation accuracy.

3.2. Geopolitical risk index

Geopolitical risk is hard to quantify from the historical literature and, for a long time, little research has been devoted to quantifying the macroeconomic and financial impact of geopolitical risks. Fairly recently, Caldara and Iacoviello (2018) provide a monthly indicator of geopolitical risk (GPR) based on a tally of newspaper articles covering geopolitical tensions.[2]

The GPR index reflects automated text-search results of the electronic archives of 11 national and international newspapers, including the Boston Globe, Chicago Tribune, The Daily Telegraph, Financial Times, The Globe and Mail, The Guardian, Los Angeles Times, The New York Times, The Times, The Wall Street Journal, and The Washington Post. Caldara and Iacoviello (2018) calculate the index by counting the number of articles related to geopolitical risk in each newspaper for each month (as a share of the total number of news articles). The index is then normalized to average a value of 100 in the 2000–2009 decade. In our study, we focus on the daily GPR index to study its relationship with oil future volatility.

Specifically, Caldara and Iacoviello (2018) explained that the text-search identifies articles containing references to six groups of words: Group 1 includes words associated with explicit mentions of geopolitical risk, as well as mentions of military-related tensions involving large regions of the world and a U.S. involvement. Group 2 includes words directly related to nuclear tensions. Groups 3 and 4 include mentions related to war threats and terrorist threats, respectively. Finally, Groups 5 and 6 aim at capturing press coverage of actual adverse geopolitical events, such as terrorist acts or the beginning of a war. Based on the search groups above, Caldara and Iacoviello (2018) further disentangle the direct effect of adverse geopolitical events from the effect of pure geopolitical risks by constructing two indexes. The Geopolitical Threats (GPT) index only includes words belonging to Search groups 1 to 4 above. The Geopolitical Acts (GPA) index only includes words belonging to Search groups 5 and 6.

3.3. Summary statistics

The oil futures price sample covers from January 1, 2007 to July 15, 2016, having 2378 effective trading days. We drop trading days that only have a few transactions. Table 1 reports summary statistics on realized measures and GPR. We observe that consistent with existing studies (e.g., Liu et al., 2018; Chen et al., 2019; Ma et al., 2019), all variables are skewed and leptokurtic at the 99% confidence level.

[1] We also consider other lags in our robust tests.

[2] The data source, https://www2.bc.edu/matteo-iacoviello/gpr.htm#data.

Table 1
Statistical description (e.g., RV, CRV and CJ).

Variables	Mean	Std. dev.	Skewness	kurtosis	Jarque-Bera	Q(5)
RV	5.69	10.69	17.25***	516.43***	26432241***	2254.16***
RS^+	2.97	8.54	27.85***	1044.72***	107995231***	489.18***
RS^-	2.72	3.71	3.83***	20.07***	45542***	5937.23***
CRV	5.32	7.08	3.71***	17.99***	37398***	6715.96***
CJ	0.37	7.19	38.35***	1627.32***	261868186***	0.06
GPR	86.46	60.04	2.30***	9.62***	11216***	2313.12***

Notes: Variables, such as RV, RS^+, RS^-, CRV and CJ, are multiply by 10, 000. Std. dev. is standard deviation. Jarque-Bera is the normality distribution by Jarque-Bera test. Q(5) is the Ljung-Box statistic test (lags 5). The superscript symbol, ***, implies that the null hypothesis should be rejected by corresponding statistical tests at the 1% significance level.

Furthermore, Jarque-Bera test results show that these series are deviated from the normality distribution. Additionally, the empirical results of Ljung-Box statistic test suggest that those series exist the autocorrelations.

Fig. 1 depicts the time series of crude oil futures RV and GPR index from January 1, 2007 to July 15, 2016. We find that during the global financial crisis, oil futures market exhibits dramatic turbulence, but GPR index is relatively stable. Moving to the recent years from 2015 onwards, both GPR index and oil future RV increase significantly, implying obvious co-movements there.

4. The effect of geopolitical risk on oil future volatility

In this section, we conduct in-sample estimation analysis to investigate the effect of geopolitical risk on oil future volatility. Existing studies (Ma et al., 2017, 2019) as well as our data evidence shows that oil realized volatility measures are not followed the normal distribution, and hence, we take logarithm of these measures to make them close to the normarity. Meanwhile, taking logarithm is able to ensure positivity of the forecasted values from the model after transforming with exponential functions. We report the estimation results of benchmark and augmented MIDAS models in Table 2. These results provide several interesting findings. First, consistent with previous studies (e.g., Gong and Lin, 2018a; Ma et al., 2019), we found strong self-persistence in oil realized volatility measures over different time horizons (shown by β_1 in Model 0 and 3). The short-run (e.g. one-day-ahead), mid-run (e.g. one-week-ahead) and long-run (e.g. one-month-ahead) RV measures are all increasing with the increase of past oil future volatility. Second, jumps (β_2 in Model 2 and 5) have significant imapct on short-run (one-day-ahead) but not mid- and long-run (one-week- and one-month-ahead) oil future volatilites. Third, regarding the effects of GPR index on oil future volatility, we find that its impact is more significant for mid- and long-run oil future volatilities, reflecting by γ_1 in Model 3–5 when $h = 5$ and $h = 22$. While γ_1 shows significantly positive in Model 3–5 when $h = 5$, implying that one-week-ahead oil future volatility increases when geopolitical risk unceratinty is high, and γ_1 appears significantly negative in Model 3–5 when $h = 22$, suggesting that one-month-ahead oil future volatility decreases when geopolitical risk unceratinty is high.

In summary, based on our in-sample estimation results, we confirm that the geopolitical risk significantly influences oil future volatilities, so next, we conduct out-of-sample exercise to evaluate the predictive ability of GPR index on oil future volatilities.

5. The predictive power of GPR index on oil future volatility

In this section, we conduct out-of-sample forecasting exercise to investigate the predictive power of geopolitical risk on oil future volatility.

5.1. Evaluation methods

We divide our sample (January 1, 2007–July 15, 2016) into in-sample estimation periods, including oil RV measures from January 1, 2007 to January 8, 2013, and out-of-sample forecasting period, containing the rest of oil RV observations from January 9, 2013 to July 15, 2016. We start with the first 1500 observations to estimate the models, and produce the one-day- ($h = 1$), one-week- ($h = 5$), and one-month-ahead ($h = 22$) RV forecasts. We keep this procedure each time when a new observation coming, and produce the forecasts for the whole out-of-sample periods.

Following the studies of Kristjanpoller and Minutolo (2016), Gong and Lin (2018b), Chen et al. (2019), Ma et al. (2019), Zhang et al. (2019), we also rely on two loss functions, HMSE and HMAE, to assess models' out-of-sample predictive ability,

$$\mathrm{HMSE} = \frac{1}{N}\sum_{n=1}^{N}\left(1-\hat{\sigma}^2_{j,n}/\mathrm{RV}_n\right)^2, \tag{14}$$

$$\mathrm{HMAE} = \frac{1}{N}\sum_{n=1}^{N}\left|1-\hat{\sigma}^2_{j,n}/\mathrm{RV}_n\right|, \tag{15}$$

where N represents the length of out-of-sample periods. $\hat{\sigma}^2_{j,n}$ denotes the out-of-sample volatility forecasts from model j. RV_n is the actual oil futures realized volatility. These loss functions are useful to conduct pairwise model comparison. Existing literatures have also used these loss functions to evaluate the predictive ability, for example, Kristjanpoller and Minutolo (2016), Chen et al. (2019), Zhang et al. (2019).

To further rank the model performance, we utilize the recently popular method, Model Confidence Set (MCS) proposed by Hansen et al. (2011), along with these loss functions (those are, HMSE and HMAE defined in Eqs. (14) and (15)) to check the best set of models. Following up the studies of Laurent et al. (2012), Ma et al. (2017, 2019), Zhang et al. (2019), we set up 75% confidence level (which corresponds to p-value of 0.25) and then choose the best model set. Simply, if a model can survive in the best model set, its MCS p-value should be bigger than the threshold value of 0.25. Therefore, these models in the best model set remarkably beat the removed models in predicting oil futures volatility.

5.2. Out-of-sample forecasting: Baseline results

Table 3 shows the MCS test results of the benchmark and the GPR index augmented models.[3] Several findings are revealed here. First, when forecasting short-run (that is, one-day-ahead) oil future volatility ($h = 1$), we find that the MIDSA-CJ-GPR model outperforms all the other models by achieving MCS p-values equal to 1 under both HMSE and HMAE loss functions. This conveys a clear message that the GPR index is helpful for predicting oil future volatilities. Second, when forecasting oil volatility over longer horizons, such as one-week and one-month-ahead volatilities, we find that the GPR index is not useful to improve the model performance, because the best model shown by the MCS test is MIDSA-CJ and MIDSA-RS, respectively, in which the GPR index is not included.

Generally speaking, the GPR index can help improving the one-day-ahead oil futures volatility forecasting based on the MIDAS framework, but the improvement is not such obvious for mid- and long-run oil volatility forecasting.

[3] In this paper, we explore this open question: Is Geopolitical risk index unique? We use a simple way to resolve this question. Considered existing findings, we regress the GPR and EPU (Baker et al., 2016), VIX and OVX, respectively, and find that the EPU, VIX and OVX is less explanation, because the adjust R-square are all <0.05. To some extent, the GPR index has unique ability on future oil futures volatility.

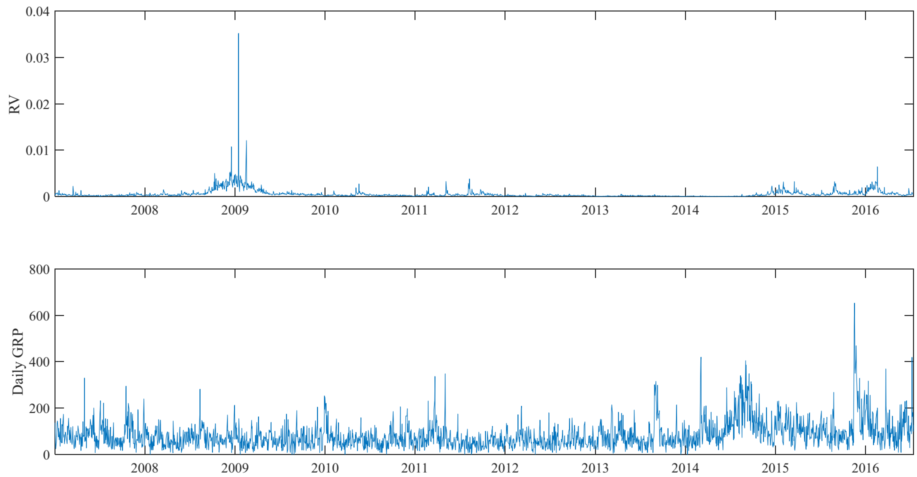

Fig. 1. The time series plot of Oil futures RV (top) and GPR (bottom) during the sample period (January 1, 2007–July 15, 2016).

5.3. Out-of-sample forecasting: further analysis

The GPR index can be further decomposed into two sub-indices in terms of whether the geopolitical risk news words related to potential risk or the actual adverse events. Caldara and Iacoviello (2018) defined the two sub-indices as the geopolitical threats index (GPT) and the geopolitical acts (GPA) index. The GPT index is constructed by searching articles that include words directly mentioning risk, and the GPA index searches only for news words mentioning adverse events. Therefore, we conduct a further analysis to investigate the impacts of the GPT and GPA on oil price volatility Simply, we use the GPA and GPT to replace the GPR index in all the augmented models, and then, reforecast the out-of-sample oil volatilities over different horizons. Table 4 reports the out-of-sample forecasting evaluation results based on the MCS test. First, when forecasting one-day-ahead volatility, we find that the MCS p-values of MIDAS-CJ-GPR model is once again equal to one, indicating that this model outperforms other models for short-run oil volatility forecasting. Second, for one-week-ahead forecasting horizon ($h = 5$), we still find the MIDSA-CJ model performs the best. Last but not the least, in terms of long-run oil volatility forecasting ($h = 22$), the MIDSA-CJ-GPA model outperforms all the others, becoming the best model. This indicates that instead of including the entire GPR index, incorporating the geopolitical risk relating to actual adverse events (GPA) can improve the oil volatility forecasting.

Moreover, this paper furtherly exploits the effects of expected GPR and shocked GPR on oil futures volatility, which is fully consistent with the work of Caldara and Iacoviello (2018). Specifically, we use a

Table 2
The estimated coefficients of the benchmark and its augmented MIDAS models.

	Model 0	Model 1	Model 2	Model 3	Model 4	Model 5
			$h = 1$			
β_0	7.251^{***}	-1.022^{***}	3.648^{***}	2.907^{***}	-0.576^{***}	9.296^{***}
β_1	1.927^{***}	0.109^{***}	1.458^{***}	1.141^{***}	0.214^{***}	1.743^{***}
β_2		0.684^{***}	-98.208^{**}		0.814^{***}	-45.148
γ_1				-0.448	0.378	-0.847
$h = 5$						
β_0	-1.932^{***}	0.045^{***}	-6.261^{***}	-6.536^{***}	-2.780	-5.199^{***}
β_1	0.748^{***}	0.546^{***}	0.189^{***}	2.224^{***}	0.242^{***}	0.2846^{***}
β_2		0.369^{***}	204.72		0.415^{***}	109.32^{**}
γ_1				0.232^{***}	0.009^{*}	-0.004^{***}
$h = 22$						
β_0	10.178^{***}	1.292	1.096^{***}	1.938^{***}	-0.893^{***}	-2.046^{***}
β_1	2.2797^{***}	0.296^{***}	1.125^{***}	1.205^{***}	0.560^{***}	0.715^{***}
β_2		0.764^{***}	-63.736		0.215^{***}	132.51^{***}
γ_1				-0.057	-0.059^{***}	-0.019^{***}

Notes: We report the main parameters results. For the coefficients of the weigh function (e.g., θ^{RV}, θ^{CRV}, θ^{GPR}), the readers can be requested by authors, this is because we report all coefficients in this table, it will too large. Model 0, Model 1, Model 2, Model 3, Model 4 and Model 5 represents MIDAS-RV, MIDAS-RS, MIDAS-CJ, MIDAS-RV-GPR, MIDAS-RS-GPR, MIDAS-CJ-GPR, respectively. In addition, the superscript symbol, ***, ** and * imply that the null hypothesis should be rejected by corresponding statistical tests at the 1%, 5% and 10% significance level, respectively.

Table 3
The out-of-sample evaluations using the MCS test.

Models	$h = 1$		$h = 5$		$h = 22$	
	HMSE	HMAE	HMSE	HMAE	HMSE	HMAE
MIDSA-RV	0.030	0.021	0.008	0.001	0.140	0.095
MIDSA-RS	0.030	0.481	0.008	0.001	1.000	1.000
MIDSA-CJ	0.030	0.021	1.000	1.000	0.140	0.095
MIDSA-RV-GPR	0.007	0.001	0.008	0.001	0.140	0.030
MIDSA-RS-GPR	0.030	0.021	0.008	0.001	0.140	0.095
MIDSA-CJ-GPR	1.000	1.000	0.008	0.016	0.140	0.095

Notes: MIDAS-RV, MIDAS-RS and MIDAS-CJ are existing models, and the rest of models are included the GPR. "$h = 1$", "$h = 5$" and "$h = 22$" are represented short, middle and long predictive horizons, respectively. The numbers of this table are the MCS p-values, and the threshold value is 0.25. If the MCS p-value is larger than 0.25, implying that a corresponding model outperforms other models.

Table 4
The out-of-sample evaluations with the GPR, GPA and GPT.

Types	**Models**	HMSE	HMAE	HMSE	HMAE	HMSE	HMAE
		$h = 1$		$h = 5$		$h = 22$	
Existing models	MIDSA-RV	0.010	0.002	0.017	0.002	0.317	0.223
	MIDSA-RS	0.055	0.212	0.017	0.002	0.712	0.645
	MIDSA-CJ	0.055	0.032	1.000	1.000	0.317	0.223
GPR	MIDSA-RV-GPR	0.010	0.002	0.017	0.002	0.317	0.121
	MIDSA-RS-GPR	0.010	0.002	0.017	0.002	0.317	0.121
	MIDSA-CJ-GPR	1.000	1.000	0.017	0.072	0.706	0.223
GPA	MIDSA-RV-GPA	0.010	0.002	0.017	0.016	0.706	0.170
	MIDSA-RS-GPA	0.055	0.043	0.017	0.002	0.706	0.223
	MIDSA-CJ-GPA	0.138	0.212	0.024	0.072	1.000	1.000
GPT	MIDSA-RV-GPT	0.010	0.002	0.017	0.002	0.190	0.121
	MIDSA-RS-GPT	0.055	0.683	0.017	0.002	0.317	0.223
	MIDSA-CJ-GPT	0.138	0.212	0.034	0.134	0.706	0.223

Notes: MIDAS-RV, MIDAS-RS and MIDAS-CJ are existing models, and the rest of models are included the GPR, GPA and GPT. "$h = 1$", "$h = 5$" and "$h = 22$" are represented short, middle and long predictive horizons, respectively. The numbers of this table are the MCS p-values, and the threshold value is 0.25. If the MCS p-value is larger than 0.25, implying that a corresponding model outperforms other models. "-GPA" and "-GPT" represent these models including the GPA and GPT, not the GPR.

Table 5
The out-of-sample evaluations using the Expected GPR(EG), Shocked GPR(SG) and GPR.

Types	Models	HMSE	HMAE	HMSE	HMAE	HMSE	HMAE
		$h=1$		$h=5$		$h=22$	
Existing models	MIDSA-RV	0.034	0.029	0.006	0.001	0.208	0.173
	MIDSA-RS	0.034	0.485	0.005	0.001	1.000	1.000
	MIDSA-CJ	0.034	0.029	1.000	1.000	0.208	0.173
GPR	MIDSA-RV-GPR	0.007	0.001	0.006	0.001	0.208	0.072
	MIDSA-RS-GPR	0.034	0.029	0.006	0.001	0.208	0.173
	MIDSA-CJ-GPR	1.000	1.000	0.006	0.063	0.208	0.173
Expected GPR (EG)	MIDSA-RV-EG	0.007	0.001	0.005	0.001	0.194	0.072
	MIDSA-RS-EG	0.034	0.001	0.005	0.001	0.208	0.173
	MIDSA-CJ-EG	0.034	0.040	0.006	0.006	0.208	0.173
Shocked GPR (SG)	MIDSA-RV-SG	0.034	0.029	0.006	0.006	0.194	0.072
	MIDSA-RS-SG	0.034	0.040	0.006	0.063	0.208	0.173
	MIDSA-CJ-SG	0.034	0.029	0.014	0.063	0.194	0.072

Notes: MIDAS-RV, MIDAS-RS and MIDAS-CJ are existing models, and the rest of models are included the GPR. "$h=1$", "$h=5$" and "$h=22$" are represented short, middle and long predictive horizons, respectively. The numbers of this table are the MCS p-values, and the threshold value is 0.25. If the MCS p-value is larger than 0.25, implying that a corresponding model outperforms other models. "-EG" and "-SG" represent these models including the Expected GPR and Shocked GPR, not the GPR.

simple AR (1) model (e.g., $\text{GPR}_t = \upsilon_1 + \upsilon_2\text{GPR}_{t-1} + \varepsilon_t$) and then obtain the estimated GPR_t as the expected geopolitical risk and the residuals (ε_t) as the shocked geopolitical risk. Table 5 exhibits the empirical results of the existing models and Augmenting MIDAS model using GPR, Expected GPR(EG) and Shocked GPR(SG). First, when forecasting one-day-ahead volatility ($h=1$), we find that the MCS p-values of MIDSA-CJ-GPR model is equal to one, implying that this model has the superiority of predictive ability for short-term oil volatility forecasting compared to other models. Second, the MIDSA-CJ model outperforms the best for one-week-ahead forecasting horizon ($h=5$). Third, in terms of long-run oil volatility forecasting ($h=22$), the MIDSA-RS model outperforms all the others, which clearly indicates that the Expected GPR (EG), Shocked GPR (SG) and GPR seem not to improve the predictability of oil futures market.

5.4. Economic value analysis

In this section, we analyze the economic value of our new model using an out-of-sample trading strategy. Specifically, we focus on an investor with a mean-variance utility function who allocates his or her assets between oil futures and a risk-free asset. Following Guidolin and Timmermann (2006), Rapach et al. (2010), Wang et al. (2016) and Zhang et al. (2018), the utility is defined as

$$U_t(\widehat{r_t}) = E_t(w_t^*\widehat{r_t} + r_{t,f}) - \frac{1}{2}\gamma Var_t(w_t^*\widehat{r_t} + r_{t,f}), \tag{16}$$

where w_t^* is the optimal weight of oil futures in this portfolio, $\widehat{r_t}$ is the excess return ($\widehat{r_t} = r_t - r_{t,f}$), r_t is the oil futures return, and $r_{t,f}$ is risk-free rate[4]) and γ is a risk aversion coefficient. The portfolio returns (R) is $w_t^*\widehat{r_t} + r_{t,f}$. We calculate the ex ante optimal weight of oil futures at day $t+1$,

$$w_t^* = \frac{1}{\gamma}\left(\frac{\widehat{r_{t+1}}}{\widehat{\sigma_{t+1}^2}}\right), \tag{17}$$

where $\widehat{r_{t+1}}$ are the excess return forecasts of oil futures on day $t+1$. We use last year history average to predict the future oil futures

[4] Following existing works, we use the 3-Month Treasury bill to represent the risk-free rate, which can be downloaded from this website: https://fred.stlouisfed.org/series/TB3MS. We match the same trading day between two markets.

Table 6
Economic values of each model discussed in this paper.

Models	$\gamma=3$	$\gamma=5$	$\gamma=8$
	R	R	R
MIDSA-RV	0.365	0.251	0.187
MIDSA-RS	−0.005	0.030	0.049
MIDSA-CJ	0.705	0.455	0.315
MIDSA-RV-GPR	1.145	0.650	0.437
MIDSA-RS-GPR	1.160	0.727	0.485
MIDSA-CJ-GPR	0.876	0.578	0.392

Notes: This table reports the portfolio return (R) in percentage for a mean-variance investor who allocates assets between oil futures and risk-free bills using various volatility forecasts. The four considered values of the investor's risk aversion coefficient (γ) are 3, 5, and 8. The portfolio return (R) is equal to $w_t^*\widehat{r_t} + r_{t,f}$.

return. $\widehat{\sigma_{t+1}^2}$ are the forecasts of the excess return volatility on day $t+1$, which can be obtained from our six volatility models discussed in this study. Following the study of Zhang et al. (2018), we relax the weight constraint to lie between −1.5 and 1.5.[5]

Table 6 shows the resulting portfolio returns using both our new model and other competing models for oil future volatility forecasting. We choose three risk aversion coefficients ($\gamma = 3, 5$ and 8), and discover that the models including GPR index have gained larger portfolio returns than other models without GPR index. Therefore, generally, when forecasting short-term oil volatility, the GPR index can offer economic value for trading in the oil futures market.

6. Robustness checks

6.1. Different forecasting windows

In this section, we choose different fixed windows to estimate the parameters of all discussed models and then forecast oil futures RV, and further assess the forecasting performance of these models. Regarding this robustness check, this is Rossi and Inoue (2012) indicate that different estimated windows may lead to different out-of-sample predictive ability. Therefore, we use different estimated windows as our alternative robust tests (e.g., the lengths of estimated window are 1200 and 1800), which is similar with Liu et al. (2018), Ma et al. (2019), Zhang et al. (2019). Tables 4 and 5 show the empirical results based on the in-sample windows of 1200 and 1800, respectively. First, From Table 4, we find that when forecasting one-day volatility, the MCS p-values of the MIDSA-CJ-GPR model are larger than the benchmark and other extended models, to some extent, which is supported our findings that the GPR index is useful to predict one-day oil futures volatility, and also can be supported by Table 7. Second, compared to Tables 7 and 8, the MCS p-values of the benchmark and extended models once gain show that the GPR index seems not to improve the models' long predictive performance.

6.2. Different lags

As the lag length is one of most important tuning parameter in MIDAS model, in this section, we consider different max lags (k^{max}) of the benchmark and extended models, such as 22 and 44, to test for the robustness of our previous results. The empirical results are indicated in Tables 9 and 10. We find several findings as follows: a) from Table 9, we find that when $h=1$, the MIDSA-CJ-GPR model is the only one whose p-value is larger than 0.25, implying that this model can achieve higher forecasts accuracy, which once again confirms the

[5] In this section, we only report the economic values on short-term horizons of six volatility models, this is because GPR index is not helpful for predicting oil futures volatility.

Table 7
Out-of-sample evaluations (The length of in sample period is 1200).

Models	$h=1$		$h=5$		$h=22$	
	HMSE	HMAE	HMSE	HMAE	HMSE	HMAE
MIDSA-RV	0.079	0.111	0.150	0.032	0.056	0.059
MIDSA-RS	0.662	0.927	0.150	0.107	1.000	1.000
MIDSA-CJ	0.662	0.927	1.000	1.000	0.056	0.044
MIDSA-RV-GPR	0.386	0.392	0.033	0.020	0.056	0.059
MIDSA-RS-GPR	0.034	0.047	0.150	0.032	0.056	0.160
MIDSA-CJ-GPR	1.000	1.000	0.150	0.028	0.056	0.059

Notes: MIDAS-RV, MIDAS-RS and MIDAS-CJ are existing models, and the rest of models are included the GPR. "$h=1$", "$h=5$" and "$h=22$" are represented short, middle and long predictive horizons, respectively. The numbers of this table are the MCS p-values, and the threshold value is 0.25. If the MCS p-value is larger than 0.25, implying that a corresponding model outperforms other models. The length of in sample period is 1200.

Table 8
Out-of-sample evaluation (The length of in sample period is 1800).

Models	$h=1$		$h=5$		$h=22$	
	HMSE	HMAE	HMSE	HMAE	HMSE	HMAE
MIDSA-RV	0.001	0.001	0.056	0.044	0.022	0.026
MIDSA-RS	0.719	0.622	1.000	1.000	1.000	1.000
MIDSA-CJ	0.719	0.936	0.687	0.608	0.022	0.026
MIDSA-RV-GPR	0.001	0.151	0.006	0.001	0.022	0.026
MIDSA-RS-GPR	0.001	0.001	0.056	0.211	0.022	0.026
MIDSA-CJ-GPR	1.000	1.000	0.056	0.211	0.022	0.026

Notes: MIDAS-RV, MIDAS-RS and MIDAS-CJ are existing models, and the rest of models are included the GPR. "$h=1$", "$h=5$" and "$h=22$" are represented short, middle and long predictive horizons, respectively. The numbers of this table are the MCS p-values, and the threshold value is 0.25. If the MCS p-value is larger than 0.25, implying that a corresponding model outperforms other models. The length of in sample period is 1800.

superiority of the GPR index on short-term (e.g. one-day-ahead) oil futures volatility forecasting. Moreover, this finding can also be supported by the MCS test of Table 10. Second, forecasting longer horizons forecasts, we find that in general, the best forecasting model is not included the GPR index based on the magnitudes of the MCS p-values. The empirical results of Tables 9 and 10 still support our previous finding that the GPR index doesn't exhibit superiorly in forecasting one-week and one-month oil futures volatilities. Overall, our empirical findings are not sensitive to the lag length used in the MIDAS modeling framework.

6.3. Sub-sample predictive ability

Our sample spans from January 1, 2007 to July 15, 2016, and it is likely that there are some accidents or breaks (e.g. financial crisis) _influencing the result of this paper. We therefore divide our whole sample to two sub-groups: the first subsample spans from January 4, 2007 to December 30, 2010 (pre-crisis) and the second covers January

Table 9
Out-of-sample evaluated results ($k^{max}=22$).

Models	$h=1$		$h=5$		$h=22$	
	HMSE	HMAE	HMSE	HMAE	HMSE	HMAE
MIDSA-RV	0.010	0.001	0.008	0.021	0.007	0.008
MIDSA-RS	0.010	0.001	0.797	0.950	1.000	0.990
MIDSA-CJ	0.019	0.001	1.000	1.000	0.007	0.008
MIDSA-RV-GPR	0.010	0.001	0.001	0.004	0.007	0.008
MIDSA-RS-GPR	0.019	0.001	0.790	0.949	0.846	1.000
MIDSA-CJ-GPR	1.000	1.000	0.260	0.460	0.007	0.142

Notes: MIDAS-RV, MIDAS-RS and MIDAS-CJ are existing models, and the rest of models are included the GPR. "$h=1$", "$h=5$" and "$h=22$" are represented short, middle and long predictive horizons, respectively. The numbers of this table are the MCS p-values, and the threshold value is 0.25. If the MCS p-value is larger than 0.25, implying that a corresponding model outperforms other models.

Table 10
Out-of-sample evaluated results ($k^{max}=44$).

Models	$h=1$		$h=5$		$h=22$	
	HMSE	HMAE	HMSE	HMAE	HMSE	HMAE
MIDSA-RV	0.170	0.075	0.134	0.059	0.031	0.130
MIDSA-RS	0.135	0.004	0.037	0.032	1.000	1.000
MIDSA-CJ	0.365	0.397	0.798	0.945	0.802	0.709
MIDSA-RV-GPR	0.076	0.004	0.130	0.032	0.031	0.130
MIDSA-RS-GPR	0.365	0.397	0.798	0.945	0.317	0.675
MIDSA-CJ-GPR	1.000	1.000	1.000	1.000	0.514	0.709

Notes: MIDAS-RV, MIDAS-RS and MIDAS-CJ are existing models, and the rest of models are included the GPR. "$h=1$", "$h=5$" and "$h=22$" are represented short, middle and long predictive horizons, respectively. The numbers of this table are the MCS p-values, and the threshold value is 0.25. If the MCS p-value is larger than 0.25, implying that a corresponding model outperforms other models.

1, 2010 to July 15, 2016 (post-crisis). And then, we evaluate the predictive ability of our new model based on two subsamples separately. The empirical results of the MCS test are reported in Table 11. We obtain several interesting findings. First, from the Panel A of Table 11, for forecasting short-term (one-day) volatility, this model including continuous sample path, jumps and GPR can obtain higher MCS p-values, which can also can be supported by Panel B of Table 11, implying that the GPR index is useful to predict one-day oil futures volatility. Second, compared to Panel A and B of Table 11, the MCS p-values of the benchmark and extended models once gain show that the GPR index seems not to improve the models' long predictive performance. Overall, the superior predictive ability of our model in the original full sample is preserved in the two subsamples.

7. Conclusions

This paper explores the impacts of the GRP index on oil futures price volatility based on the MIDAS framework from high-frequency perspective. Compared to existing studies, we find some interesting conclusions. First, in-sample estimated results show that realized measures (e.g., RV and CRV) have significantly impacts on different forecasts horizons and models. The effects of significant jumps and GPR are mixed in different models and horizons. Second, our out-of-sample results indicate that when forecasting short-term (one-day) volatility, the GPR index is helpful for predicting oil futures volatility based on the MIDAS-CJ model. The MIDAS-CJ-GPR model can outperform the benchmark and other competing models. Third, when forecasting longer horizons volatilities, the GPR index is useless to help increasing the models'

Table 11
Out-of-sample evaluated results of two subsamples.

Models	$h=1$		$h=5$		$h=22$	
	HMSE	HMAE	HMSE	HMAE	HMSE	HMAE
Panel A: 2007.01.04–2010.12.30						
MIDSA-RV	0.128	0.142	0.230	0.027	0.062	0.118
MIDSA-RS	0.357	0.728	0.532	0.367	0.105	0.226
MIDSA-CJ	0.357	0.728	1.000	1.000	0.793	0.916
MIDSA-RV-GPR	0.052	0.069	0.230	0.039	0.105	0.226
MIDSA-RS-GPR	0.357	0.728	0.079	0.009	1.000	1.000
MIDSA-CJ-GPR	1.000	1.000	0.316	0.294	0.769	0.511
Panel B: 2011.01.03–2016.07.15						
MIDSA-RV	0.080	0.026	0.094	0.036	0.455	0.474
MIDSA-RS	0.267	0.685	0.775	1.000	0.001	0.000
MIDSA-CJ	0.005	0.003	0.094	0.036	0.792	0.793
MIDSA-RV-GPR	0.086	0.026	0.115	0.059	0.316	0.474
MIDSA-RS-GPR	0.005	0.003	0.319	0.392	0.316	0.349
MIDSA-CJ-GPR	1.000	1.000	1.000	0.811	1.000	1.000

Notes: MIDAS-RV, MIDAS-RS and MIDAS-CJ are existing models, and the rest of models are included the GPR. "$h=1$", "$h=5$" and "$h=22$" are represented short, middle and long predictive horizons, respectively. The numbers of this table are the MCS p-values, and the threshold value is 0.25. If the MCS p-value is larger than 0.25, implying that a corresponding model outperforms other models.

accuracies. Fourth, we further assess the impacts of the GPR and its category indices, we find that the GPR itself is also more powerful to predict short-term oil futures volatility. However, the GPR action is effective to forecast long horizons volatility. Finally, we find that, the GPR index can improve the economic performance when forecasting short-term oil volatility.

Authors' contributions

Prof. Mei, Prof. Ma, Prof. Liao and Prof. Wang have discussed this paper each other. Prof. Mei provided an updated high-frequency oil futures data by data company and proofread our paper by special institution. Prof. Mei and Prof. Ma wrote the empirical results and conducted all statistical analyses, especially for revising this paper. Prof. Liao wrote another parts of this paper, revised this paper and replied the comments by reviewers. Prof. Wang provided the empirical code for this paper. All authors reviewed the final manuscript.

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Appendix A. Supplementary data

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References

Andersen, T.G., Bollerslev, T., 1998. Answering the skeptics: yes, standard volatility models do provide accurate forecasts. Int. Econ. Rev. 885–905.

Andersen, T.G., Bollerslev, T., Diebold, F.X., 2007. Roughing it up: including jump components in the measurement, modeling, and forecasting of return volatility. Rev. Econ. Stat. 89 (4), 701–720.

Audrino, F., Huang, C., Okhrin, O., 2019. Flexible HAR model for realized volatility. Studies in Nonlinear Dynamics & Econometrics. 23, 1–22.

Baker, S.R., Bloom, N., Davis, S.J., 2016. Measuring economic policy uncertainty. Q. J. Econ. 131 (4), 1593–1636.

Barndorff-Nielsen, O.E., Shephard, N., 2004. Power and bipower variation with stochastic volatility and jumps. Journal of Financial Econometrics 2, 1–37.

Barndorff-Nielsen, O.E., Shephard, N., 2006. Econometrics of testing for jumps in financial economics using bipower variation. Journal of Financial Econometrics 4 (1), 1–30.

Barndorff-Nielsen, O.E., Kinnebrock, S., Shephard, N., 2008. Measuring downside risk-realised semivariance. *CREATES Research Paper*, (2008–42).

Caldara, D., Iacoviello, M., 2018. Measuring geopolitical risk. Available at SSRN https://ssrn.com/abstract=3117773.

Chen, X., Ghysels, E., 2010. News—good or bad—and its impact on volatility predictions over multiple horizons. Rev. Financ. Stud. 24 (1), 46–81.

Chen, Y., Ma, F., Zhang, Y., 2019. Good, bad cojumps and volatility forecasting: new evidence from crude oil and the US stock markets. Energy Econ. 81, 52–62.

Corsi, F., 2009. A simple approximate long-memory model of realized volatility. Journal of Financial Econometrics 7 (2), 174–196.

Degiannakis, S., Filis, G., 2017. Forecasting oil price realized volatility using information channels from other asset classes. J. Int. Money Financ. 76, 28–49.

Degiannakis, S., Filis, G., 2018. Forecasting oil prices: high-frequency financial data are indeed useful. Energy Econ. 76, 388–402.

Ghysels, E., Sohn, B., 2009. Which power variation predicts volatility well? J. Empir. Financ. 16 (4), 686–700.

Ghysels, E., Santa-Clara, P., Valkanov, R., 2006. Predicting volatility: getting the most out of return data sampled at different frequencies. J. Econ. 131 (1–2), 59–95.

Ghysels, E., Sinko, A., Valkanov, R., 2007. MIDAS regressions: further results and new directions. Econ. Rev. 26 (1), 53–90.

Gong, X., Lin, B., 2017. Forecasting the good and bad uncertainties of crude oil prices using a HAR framework. Energy Econ. 67, 315–327.

Gong, X., Lin, B., 2018a. The incremental information content of investor fear gauge for volatility forecasting in the crude oil futures market. Energy Econ. 74, 370–386.

Gong, X., Lin, B., 2018b. Structural breaks and volatility forecasting in the copper futures market. J. Futur. Mark. 38 (3), 290–339.

Guidolin, M., Timmermann, A., 2006. An econometric model of nonlinear dynamics in the joint distribution of stock and bond returns. J. Appl. Econ. 21 (1), 1–22.

Hamilton, J.D., 2003. What is an oil shock? J. Econ. 113 (2), 363–398.

Hansen, P.R., Lunde, A., Nason, J.M., 2011. The model confidence set. Econometrica 79 (2), 453–497.

Haugom, E., Langeland, H., Molnár, P., Westgaard, S., 2014. Forecasting volatility of the US oil market. J. Bank. Financ. 47, 1–14.

Huang, X., Tauchen, G., 2005. The relative contribution of jumps to total price variance. Journal of Financial Econometrics 3 (4), 456–499.

Jo, S., 2014. The effects of oil price uncertainty on global real economic activity. J. Money Credit Bank. 46 (6), 1113–1135.

Kilian, L., Park, C., 2009. The impact of oil price shocks on the US stock market. Int. Econ. Rev. 50 (4), 1267–1287.

Kristjanpoller, W., Minutolo, M.C., 2016. Forecasting volatility of oil price using an artificial neural network-GARCH model. Expert Syst. Appl. 65, 233–241.

Laurent, S., Rombouts, J.V., Violante, F., 2012. On the forecasting accuracy of multivariate GARCH models. J. Appl. Econ. 27, 934–955.

Liu, J., Ma, F., Yang, K., Zhang, Y., 2018. Forecasting the oil futures price volatility: large jumps and small jumps. Energy Econ. 72, 321–330.

Ma, F., Wahab, M.I.M., Huang, D., Xu, W., 2017. Forecasting the realized volatility of the oil futures market: a regime switching approach. Energy Econ. 67, 136–145.

Ma, F., Wei, Y., Liu, L., Huang, D., 2018a. Forecasting realized volatility of oil futures market: a new insight. J. Forecast. 37 (4), 419–436.

Ma, F., Wahab, M.I.M., Liu, J., Liu, L., 2018b. Is economic policy uncertainty important to forecast the realized volatility of crude oil futures? Appl. Econ. 50 (18), 2087–2101.

Ma, F., Zhang, Y., Huang, D., Lai, X., 2018c. Forecasting oil futures price volatility: new evidence from realized range-based volatility. Energy Econ. 75, 400–409.

Ma, F., Liao, Y., Zhang, Y., Cao, Y., 2019. Harnessing jump component for crude oil volatility forecasting in the presence of extreme shocks. J. Empir. Financ. 52, 40–55.

Merton, R.C., 1980. On estimating the expected return on the market: an exploratory investigation. J. Financ. Econ. 8 (4), 323–361.

Patton, A.J., Sheppard, K., 2015. Good volatility, bad volatility: signed jumps and the persistence of volatility. Rev. Econ. Stat. 97 (3), 683–697.

Rapach, D.E., Strauss, J.K., Zhou, G., 2010. Out-of-sample equity premium prediction: combination forecasts and links to the real economy. Rev. Financ. Stud. 23 (2), 821–862.

Rossi, B., Inoue, A., 2012. Out-of-sample forecast tests robust to the choice of window size. J. Bus. Econ. Stat. 30 (3), 432–453.

Santos, D.G., Ziegelmann, F.A., 2014. Volatility forecasting via MIDAS, HAR and their combination: an empirical comparative study for IBOVESPA. J. Forecast. 33 (4), 284–299.

Sévi, B., 2014. Forecasting the volatility of crude oil futures using intraday data. Eur. J. Oper. Res. 235 (3), 643–659.

Wang, Y., Ma, F., Wei, Y., Wu, C., 2016. Forecasting realized volatility in a changing world: a dynamic model averaging approach. J. Bank. Financ. 64, 136–149.

Wen, F., Gong, X., Cai, S., 2016. Forecasting the volatility of crude oil futures using HAR-type models with structural breaks. Energy Econ. 59, 400–413.

Zhang, Y., Ma, F., Shi, B., Huang, D., 2018. Forecasting the prices of crude oil: an iterated combination approach. Energy Econ. 70, 472–483.

Zhang, Y., Ma, F., Wei, Y., 2019. Out-of-sample prediction of the oil futures market volatility: a comparison of new and traditional combination approaches. Energy Econ. 81, 1109–1120.