



Macroeconomic Uncertainty and Crude Oil Futures Volatility—Evidence from China Crude Oil Futures Market

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This paper investigates whether the macroeconomic uncertainty factors can explain and forecast China's INE crude oil futures market volatility. We use the GARCH-MIDAS model to investigate the explaining and predicting power of the macroeconomic uncertainties. We considered various geopolitical risk (GPR) indices, economic policy uncertainty (EPU) indices, and infectious disease pandemic (IDEMV) indices in our model. The empirical results suggest that the geopolitical risk, the geopolitical act risk, the global economic policy uncertainty, the economic policy uncertainty from the United Kingdom, and the economic policy uncertainty from Japan comprehensively integrate the information contained in the rest factors, and have superior predictive powers for INE crude oil future volatility. These findings highlight the importance of the impact of macroeconomic uncertainty factors has on the crude oil futures market, and indicate that the macroeconomic uncertainties need to be considered when explaining and forecasting crude oil futures market volatility.

Keywords: crude oil price, realized measures, GRACH-MIDAS models, macroeconomic uncertainty, volatility forecast

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INTRODUCTION

China is the world's largest importer and the second largest consumer of crude oil and established its own crude oil futures market in the Shanghai International Energy Exchange Center (INE) on March 26, 2018. Over the past two years since its listing, the INE crude oil futures market has experienced various extreme events at home and abroad, and now playing a positive role in promoting the formation of crude oil benchmark prices in Asia. The establishment of the INE crude oil futures market has the following significance. Firstly, like the petrodollar system, the internationalization of a country's sovereign currency must begin with the function of pricing and settlement of commodity trade. Since the INE crude oil futures price was denominated in RMB, the internationalization of the INE crude oil futures market has put the process of RMB internationalization at a new historical starting point. Secondly, it is necessary to use the crude oil futures market for risk management in China. In the current international environment of deglobalization and anti-free trade, the probability of extreme events will increase, which will lead to huge fluctuations in crude oil prices, and the crude oil futures markets can hedge this kind of risk. Thirdly, although Asia is the world's largest market for crude oil demand, it does not have its crude oil pricing system, and thus causes the well-known "Asian Premium." The development of the INE crude oil market can shed lights on the formation of benchmark prices in the Asia-Pacific region.

TABLE 1 | Descriptive statistics.

	Mean	Max	Min	Std	Skewness	Kurtosis
PR	434.528	597.300	210.600	76.524	-1.116	3.830
RETURN	-0.058	9.732	-11.203	2.254	-0.291	6.397
RV	1.608	7.115	0.477	0.792	2.119	9.920
GPR	133.239	285.756	63.554	41.849	1.196	6.082
GPRS	15.409	152.517	0	29.088	3.201	14.833
GPA	52.112	264.458	15.627	41.621	3.891	20.106
GPT	188.565	408.964	72.725	69.771	0.759	4.016
GEPU _{GDP}	244.088	411.959	150.749	60.022	0.806	3.429
GEPU _{PPP}	259.433	423.313	157.958	61.142	0.544	3.105
EPU _{Canada}	358.443	678.817	250.537	101.208	1.494	4.801
EPU _{China}	331.636	649.073	195.706	101.162	1.007	4.420
EPU _{Japan}	123.666	204.657	76.567	32.064	1.012	3.418
EPU _{Russia}	323.784	793.635	69.941	187.206	1.281	3.788
EPU _{UK}	188.181	309.972	102.287	54.663	0.378	2.410
EPU _{US}	156.143	350.460	98.737	60.664	1.672	5.170
IDEMV	6.025	50.215	0.112	13.253	2.297	6.940
IDEMVS	4.515	44.191	0	11.384	2.457	7.788

Notes: PR is the daily price of the INE crude oil futures. RETURN is the daily returns of the INE crude oil futures. RV is the realized variance. GPR is the geopolitical risk index. GPRS is a serious geopolitical risk index calculated by Eq. 10. GPT is the geopolitical threat risk index. GPA is the geopolitical act index. GEPU_{GDP} is the global economic policy uncertainty weighted as current-price GDP. The GEPU_{PPP} is the global economic policy uncertainty weighted and that with purchasing power parity (PPP) adjusted GDP weights. EPU_{Canada}, EPU_{China}, EPU_{Japan}, EPU_{Russia}, EPU_{UK}, and EPU_{US} are the economic uncertainty policy index in Canada, China, Japan, Russia, United Kingdom, United States. IDEMV is the Infectious Disease Equity Market Volatility Tracker index. IDEMVS depicts the serious infectious disease pandemic calculated by Eq. 11. For the sake of numerical stability, we multiply the log returns and the realized volatility by 100, and all these macroeconomic uncertainty factors are normalized.

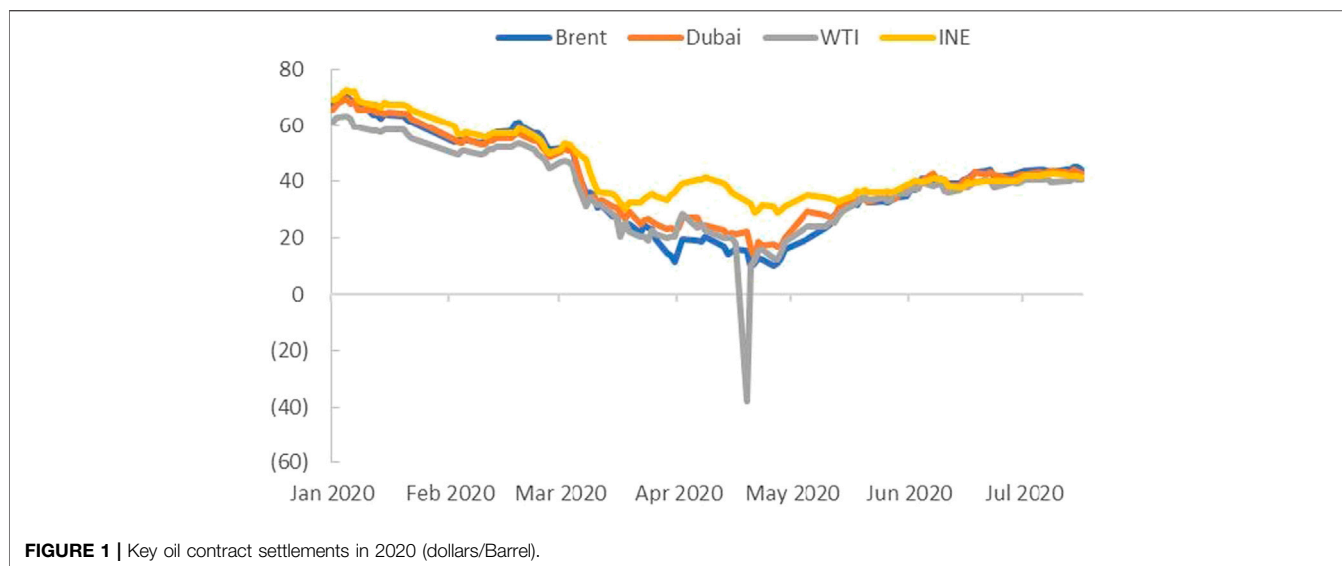
Along with the establishment of the crude oil futures market in 2018, global macro uncertainty events have generally shown an upward trend (Sheng et al., 2020), especially for the economic policy uncertainty (EPU) and the geopolitical risk (GPR). These two macroeconomic uncertainty factors have long been regarded by investors as the key factors affecting investment decisions in the crude oil futures market (Aloui et al., 2016; Antonakakis et al., 2017; Balcilar et al., 2017; Dees et al., 2017; Escribano and Valdes, 2017; Wei et al., 2017; Cunado et al., 2019; Plakandaras et al., 2019; Brandt and Gao, 2019; Geng et al., 2020; Hu et al., 2020). The rising geopolitical risk and economic policy uncertainty greatly increase panic among investors (Tsai, 2017; Ji et al., 2018; Ji et al., 2020; Li and Zhong, 2020), and the rapid transfer of international capital among countries leads to severe fluctuations in the crude oil futures market. Furthermore, since crude oil has long been regarded as a political weapon for many governments (Escribano and Valdes, 2017), it has a geopolitical nature that distinguishes itself from other commodities and financial assets (Hu et al., 2020). Numerous studies have shown that geopolitical risk leads to oil market uncertainty and price fluctuations (Miao et al., 2017; Caldara and Iacoviello, 2018; Gkillas et al., 2018; Brandt and Gao, 2019). During our sample period, the Middle East, as one of China’s largest oil importers, witnessed several geopolitical events such as the Syrian tensions on April 01, 2018, the United States-Iran tensions on July 01, 2018 and the United States—Iran tensions on June 01, 2019. On the one hand, these geopolitical events might affect China’s crude oil importers and cause crude oil supply uncertainty and price volatility. On the other

hand, the geopolitical risk would affect economic activity to a certain extent and thus cause oil demand uncertainty (Liu j. et al., 2019). Since geopolitical risk could result in expectation differences about the INE crude oil futures prices, it is reasonable to consider the role of geopolitical risk in explaining and forecasting the INE crude oil futures market volatility. Furthermore, the recent Coronavirus (COVID-19) outbreak pandemic has further magnified the complexity of the global economic and political environment (Bai et al., 2020), at the same time, the surge in Chinese buying also highlighted China’s importance as a global crude oil price-setter. Thus, accurately understanding and forecasting the INE crude oil future volatility is crucial to effectively reduce the impact of macroeconomic uncertainties on excessive volatility in the INE crude oil market and promote the steady and healthy development of the global economy, which is important to market participants as well as the government policymakers.

Based on the discussion above, we will focus on the following questions from the perspective of quantitative analysis. Do these uncertainties matter in explaining crude oil price volatility? If so, how can we use them to accurately forecast the oil price volatility? Answering these questions can help investors and decision makers better understand China INE crude oil futures market and provide some inspiration for different market participants.

We address the above issues as follows. First, we analyze the impact of economic policy uncertainty, geopolitical, and public infectious disease pandemic on the crude oil volatility by constructing the GARCH-MIDAS model that incorporates several macroeconomic uncertainty factors, respectively. Concerning the economic policy uncertainty, we use two GEPU indices and six country-specific EPU indices. These countries are three major crude oil consumers, United States, China and Japan, and three major crude oil exporters, United Kingdom, Canada and Russia. Concerning the geopolitical risk, we use the GPR index and its variation, the GPT index, and the GPA index. In addition, Liu J. et al. (2019) found that the effect of common geopolitical risk on crude oil price volatility is limited because it does not constantly attract investors’ attention. However, the serious geopolitical risk may cause oil supply disruptions and result in serious oil price fluctuation. Thus, we also construct a serious geopolitical risk (GPRS) index by filtering the GPR index for values larger than the average. Concerning the public infectious disease pandemic, we use the IDEMV index. We also consider the serious public infectious disease pandemic factor and construct the IDEMVS index as mentioned in Section *GARCH-MIDAS Models with Macroeconomic Uncertainty*. Second, in the out-of-sample analysis, we forecast the crude oil futures volatility based on these extended GARCH-MIDAS models and then evaluate the model’s predictive ability by employing the approved model confidence set (MCS) (Hansen et al., 2005). The MCS allows us to examine these macroeconomy uncertainties’ predicting ability of crude oil future volatility and makes a comparison with each other.

We make the following contributions. First, although Asia is the world’s largest market for crude oil demand, it has not established its own crude oil pricing system yet (Shi and Sun,



2017). This causes the well-known “Asian Premium” (Zhang et al., 2018). Therefore, the quantitative analyses on the macroeconomic uncertainty contributions on the INE crude oil futures volatility process can help provide important reference information for establishing the pricing system for Asia crude oil market. Second, as an important way to help different market participants understand the China crude oil futures market, the influence of macroeconomic uncertainties have on INE crude oil futures market has not been studied by scholars. By using the currently available information of the INE crude oil futures market, we conduct a first ever analysis on the uncertainty determinants of INE crude oil futures volatility. The results, yet to be improved with more data though, hope to shed light on the effects of macroeconomic uncertainties have on China’s new crude oil futures for investors, regulators, and academia. Third, to the best of our knowledge, we are the first to consider various GPR indices, and we analyze the different impacts of GPT and GPA have on the China crude oil futures volatility. In addition, we also consider various EPU indices, such as the two version GEPU indices ($GEPU_{GDP}$ and $GEPU_{PPP}$) and the country-specific EPU indices from major oil consumers and exporters, and we test the infectious disease pandemic’s impact on permanent volatility of crude oil volatility.

The empirical results of this paper present solid evidence of the influence and predictability of macroeconomic uncertainty factors on crude oil volatility. The in-sample estimation results show that the economic policy uncertainty, the geopolitical risk, and the public infectious disease pandemic factors have a different impact on the crude oil volatility. First, the EPU from China has a significantly negative impact on the long-term volatility, whereas the EPUs from United States, United Kingdom, Japan, Canada, and Russia have a significantly positive effect on the long-term volatility. In addition, the EPU from the United Kingdom. has the largest average effect on the long-term volatility of oil futures prices among all of the EPU indices, whereas EPUs in the United States

and Russia are less informative in determining oil futures volatility. Second, with regard to the geopolitical factors, the GPRS and the GPT indices have a significant negative impact on the long-run component of INE crude oil futures volatility, whereas the GPA’s impact is significantly positive. Third, the public infectious disease pandemic factors IDEMV and IDMMVS indices also have a positive effect on long-term volatility. The out of sample evaluation results suggest that the GARCH-MIDAS models with macroeconomy uncertainty factors can provide a more accurate prediction. Specifically, the models with the GPR index, the GPA index, the global EPU index, the EPU index from the United Kingdom, and the EPU index from Japan pass the MCS test under MSFE and MASE criterion with both statistics. This implies that these macro-level uncertainty factors contain useful information that the government decision makers and investors need to pay attention to, and have superior ability to predict the crude oil futures volatility.

The rest of this paper is structured as follows. Section *Literature Review* presents a brief literature review. Section *Econometric Methodology* describes the GARCH-MIDAS model and its extensions, as well as the forecast evaluation. Section *Data* discusses the data. Section *Empirical Results* analyzes the empirical results. Section *Robustness Check* reports a series of robustness tests. Section *Conclusion* concludes this study.

LITERATURE REVIEW

In this section, we will review the literature on the subject and laid the foundation for analyzing the determinants of INE crude oil volatility. From the perspective of economic relations between commodity supply and demand and the oil prices, previous literature have shown that demand, supply, and speculation are the driving forces of oil price volatility (Narayan and Narayan, 2007; Mu and Ye, 2011; Kilian and Murphy, 2014;

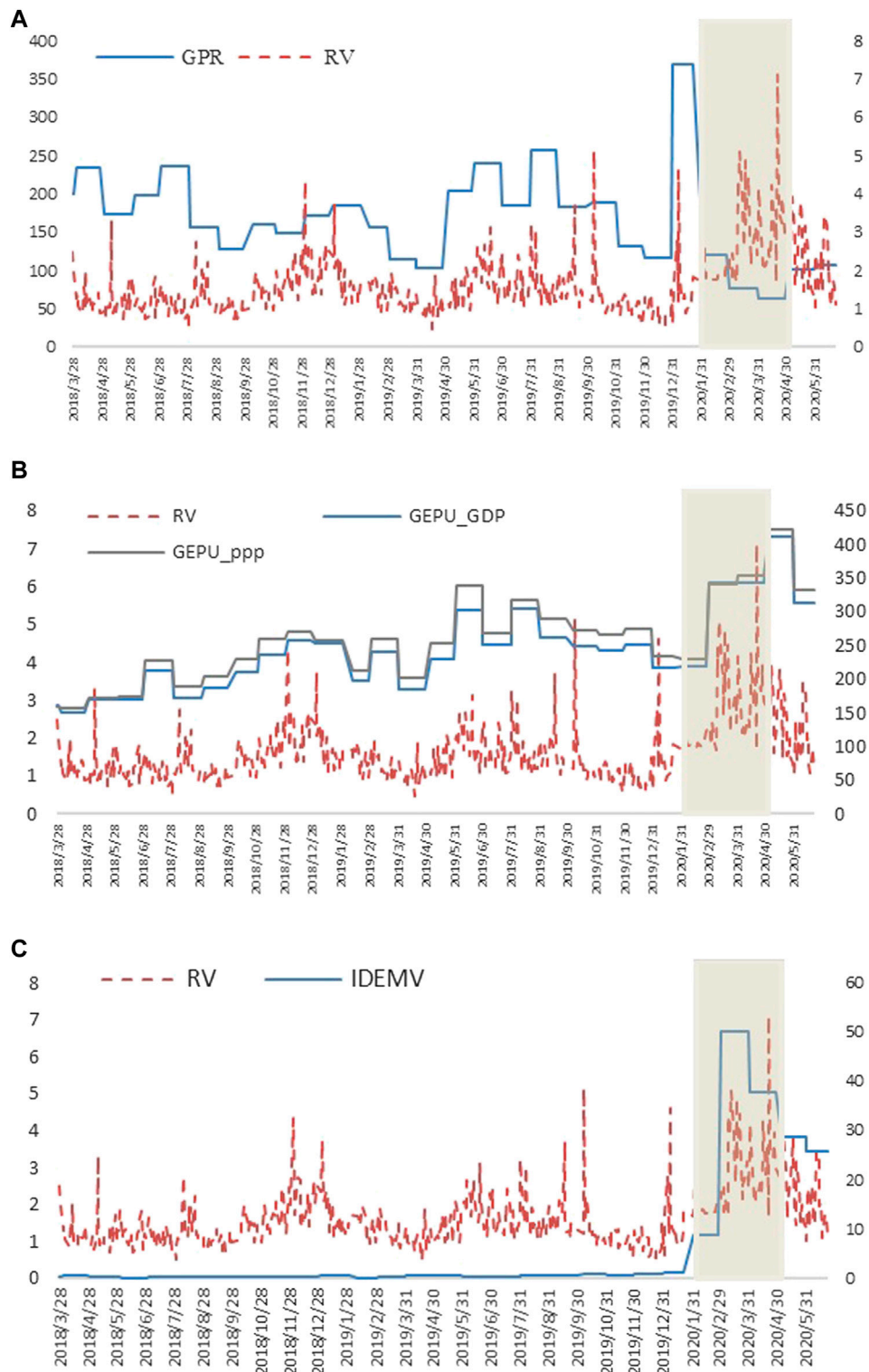


FIGURE 2 | The trends of INE crude oil futures volatility, the GPR index, the GEPU index and the IDEMV index. Panel (A) The trends of INE crude oil futures volatility and the GPR index. Panel (B) The trends of INE crude oil futures volatility and the GEPU index. Panel (C) The trends of INE crude oil futures volatility and the IDEMV index.

TABLE 2 | Estimation GARCH-MIDAS models with geopolitical risk.

	RV	GPR	GPRS	GPT	GPA
μ	0.200 (0.213)	0.006 (0.101)	0.000 (0.099)	-0.001 (0.099)	0.004 (0.110)
α	0.100* (0.055)	0.065 (0.044)	0.065 (0.040)	0.066* (0.040)	0.086** (0.052)
β	0.840*** (0.061)	0.137 (0.084)	0.113 (0.084)	0.108 (0.085)	0.000 (0.474)
γ	0.120 (0.085)	0.538** (0.213)	0.544** (0.219)	0.546** (0.224)	0.321* (0.184)
m	-1.099 (1.401)	0.923 (0.659)	0.150* (0.338)	1.621* (0.916)	-1.280 (0.800)
θ_1	-0.475 (0.564)	0.796*** (0.155)	0.841*** (0.149)	0.819*** (0.149)	0.590*** (0.164)
ω_1	1.000 (2.864)	11.112** (4.803)	10.874** (4.504)	11.287** (4.641)	15.469 (13.085)
θ_2		-0.005 (0.003)	-0.008* (0.005)	-0.008* (0.004)	0.034* (0.018)
ω_2		11.898** (5.449)	4.470*** (1.620)	4.277*** (1.505)	1.349*** (0.364)
Log_Lik	-673.560	-687.146	-686.308	-685.867	-685.869
BIC	1387.024	1426.235	1424.559	1423.677	1423.680
VR	9.558	54.425	56.421	56.788	71.612

Notes: The numbers in parentheses are the standard errors of the estimated parameters. The Asterisks indicate statistical significance at the 1% (***) , 5% (**) or 10% (*) level. Log_Lik is the logarithm maximum likelihood function value. BIC is the Bayesian information criterion. The variance ratio $VR(X) = \text{var}(\log(\tau_M^X))/\text{var}(\log(\sigma_M^X))$ is calculated on monthly aggregates.

TABLE 3 | Estimation GARCH-MIDAS models with economic policy uncertainty.

	GEPU _{GDP}	GEPU _{PPP}	EPU _{China}	EPU _{US}	EPU _{UK}
μ	0.011 (0.103)	0.015 (0.104)	0.004 (0.105)	-0.008 (0.102)	-0.002 (0.104)
α	0.059 (0.048)	0.066 (0.049)	0.091* (0.047)	0.035 (0.044)	0.048 (0.040)
β	0.105 (0.130)	0.096 (0.133)	0.072 (0.193)	0.108 (0.126)	0.056 (0.385)
γ	0.460** (0.187)	0.460** (0.190)	0.399** (0.200)	0.462** (0.182)	0.434** (0.181)
m	-1.143 (1.604)	-0.882 (1.530)	2.532* (1.406)	-0.299 (0.372)	-5.611** (2.666)
θ_1	0.808*** (0.161)	0.826*** (0.166)	0.735*** (0.153)	0.642*** (0.142)	0.756*** (0.133)
ω_1	10.261* (5.504)	9.812* (5.456)	11.728* (6.089)	15.776 (10.188)	11.435 (7.758)
θ_2	0.005 (0.007)	0.004 (0.006)	-0.007* (0.004)	0.004** (0.002)	0.029** (0.013)
ω_2	1.467*** (0.523)	1.062*** (0.299)	2.547*** (0.587)	95.937*** (11.764)	2.187*** (0.269)
Log_Lik	-688.874	-689.022	-687.035	-686.138	-685.695
BIC	1429.692	1429.988	1426.012	1424.220	1423.334
VR	57.885	57.941	62.698	61.862	65.336

Notes: The numbers in parentheses are the standard errors of the estimated parameters. The Asterisks indicate statistical significance at the 1% (***) , 5% (**) or 10% (*) level. Log_Lik is the logarithm maximum likelihood function value. BIC is the Bayesian information criterion. The variance ratio $VR(X) = \text{var}(\log(\tau_M^X))/\text{var}(\log(\sigma_M^X))$ is calculated on monthly aggregates.

Pan et al., 2017; Yi et al., 2018; Liao et al., 2019). However, as a commodity that is traded globally, the crude oil market faces a much more complicated economic environment and might be

TABLE 4 | Estimation GARCH-MIDAS models with economic policy uncertainty and infectious disease pandemic.

	EPU _{Canada}	EPU _{Russia}	EPU _{Japan}	IDEMV	IDEMVS
μ	-0.006 (0.104)	-0.010 (0.107)	0.001 (0.104)	-0.004 (0.102)	0.044 (0.101)
α	0.058 (0.041)	0.051 (0.041)	0.050 (0.045)	0.053 (0.050)	0.097* (0.056)
β	0.071 (0.158)	0.010 (0.283)	0.139 (0.097)	0.136 (0.117)	0.428* (0.245)
γ	0.462** (0.193)	0.448** (0.210)	0.487** (0.192)	0.440** (0.184)	0.451** (0.224)
m	-1.834 (1.211)	-0.684 (0.536)	-0.693 (0.537)	0.441 (0.493)	2.941*** (0.687)
θ_1	0.737*** (0.146)	0.709*** (0.139)	0.690*** (0.140)	0.500 (0.314)	-1.071** (0.454)
ω_1	12.411** (6.216)	14.925 (9.437)	13.800* (7.147)	24.675 (61.107)	1.000*** (0.356)
θ_2	0.006* (0.004)	0.003* (0.002)	0.008** (0.004)	0.025* (0.013)	0.090** (0.039)
ω_2	1.000*** (0.320)	1.769*** (0.389)	94.997*** (10.808)	97.278*** (22.283)	10.550 (8.778)
Log_Lik	-687.234	-687.329	-686.953	-685.161	-689.812
BIC	1426.411	1426.600	1425.849	1422.265	1431.568
VR	60.226	64.166	57.336	62.470	39.229

Notes: The numbers in parentheses are the standard errors of the estimated parameters. The Asterisks indicate statistical significance at the 1% (***) , 5% (**) or 10% (*) level. Log_Lik is the logarithm maximum likelihood function value. BIC is the Bayesian information criterion. The variance ratio $VR(X) = \text{var}(\log(\tau_M^X))/\text{var}(\log(\sigma_M^X))$ is calculated on monthly aggregates.

driven by other macroeconomic factors beyond its supply and demand. After the economic policy uncertainty (EPU) index was constructed by Baker et al. (2016), many studies have turned their attention to the EPU's explanatory power and forecasting power on the crude oil market when modeling oil market volatilities. Existing literature provides some arguments explaining the possible relation between EPU and oil price volatility, and states that the uncertainty of economic policy affects the economic conditions, and then causes oil price volatility as well (Aloui et al., 2016; Hailemariam et al., 2019). Balcilar et al. (2017) show that EPU has significant predictive power for oil price volatility, Wei et al. (2017) also confirm the EPU's predictive power on crude oil volatility and argue that EPU may be a comprehensive reflection of various economic information such as global oil demand and supply shocks, financial crisis, and political events.

Since crude oil has long been regarded as a political weapon for many governments (Escribano and Valdes, 2017), it has a geopolitical nature that distinguishes itself from other commodities and financial assets. After the geopolitical risk (GPR) index and its variation, geopolitical threat risk index (GPT) and geopolitical act index (GPA) was proposed by Caldara and Iacoviello (2018), various studies have found that the changes in GPR index generally have a significant impact on oil returns (Antonakakis et al., 2017; Demirer et al., 2018b; Cunado et al., 2019; Plakandaras et al., 2019). Existing literature found that GPR indices also have a significant impact on other aspects of crude oil price movement. Brandt and Gao (2019) found that geopolitical events can strongly affect the oil prices in a short period, Liu J. et al. (2020) found that the

TABLE 5 | MCS test with monthly RVs.

	MFSE		MASE	
	Tmax	TR	Tmax	TR
GPR	1.000	1.000	1.000	1.000
GPRS	1.000	0.890	1.000	0.000
GPT	0.510	0.417	0.867	0.120
GPA	1.000	1.000	1.000	1.000
<i>GEPU_{GDP}</i>	1.000	1.000	0.962	0.591
<i>GEPU_{PPP}</i>	0.423	0.356	0.951	0.249
<i>EPU_{China}</i>	0.664	0.417	0.880	0.201
<i>EPU_{US}</i>	0.000	0.000	0.000	0.000
<i>EPU_{UK}</i>	1.000	1.000	1.000	1.000
<i>EPU_{Canada}</i>	0.000	0.000	0.000	0.000
<i>EPU_{Russia}</i>	0.000	0.000	0.000	0.000
<i>EPU_{Japan}</i>	1.000	1.000	1.000	1.000
IDEMV	0.000	0.000	0.000	0.000
IDEMVS	0.000	0.000	0.000	0.000
RV	0.802	0.574	0.983	0.347

Note: We use bold number stands for p-values of the model that larger than 0.25, indicating that the corresponding model passes the MCS test under the MAFE loss function and the MSFE loss function, with the Tmax and TR statistic. The p-value of 1.000 indicates that a model has the best performance among all the testing models. MSFE refers to the mean squared forecast error and MAFE refers to mean absolute forecast error. The lags of the RV are set to 22.

TABLE 6 | MCS test with bimonthly RVs.

	MFSE		MASE	
	Tmax	TR	Tmax	TR
GPR	1.000	0.956	1.000	1.000
GPRS	1.000	0.047	1.000	0.000
GPT	0.839	0.278	1.000	0.004
GPA	1.000	1.000	1.000	0.965
<i>GEPU_{GDP}</i>	0.374	1.000	1.000	0.126
<i>GEPU_{PPP}</i>	1.000	0.028	1.000	0.911
<i>EPU_{China}</i>	0.635	0.246	1.000	0.495
<i>EPU_{US}</i>	0.000	0.000	1.000	0.515
<i>EPU_{UK}</i>	1.000	0.943	1.000	0.907
<i>EPU_{Canada}</i>	0.253	0.047	1.000	0.017
<i>EPU_{Russia}</i>	1.000	1.000	0.425	0.007
<i>EPU_{Japan}</i>	1.000	1.000	1.000	1.000
IDEMV	0.000	0.000	0.283	0.938
IDEMVS	0.000	0.000	0.000	0.000
RV	0.998	0.647	1.000	0.495

Note: We use bold number stands for p-values of the model that larger than 0.25, indicating that the corresponding model passes the MCS test under the MAFE loss function and the MSFE loss function, with the Tmax and TR statistic. The p-value of 1.000 indicates that a model has the best performance among all the testing models. MSFE refers to the mean squared forecast error and MAFE refers to mean absolute forecast error. The lags of the RV are set to 44.

serious geopolitical risk can improve the model fitting and forecasting performance concerning crude oil volatility.

In addition to the uncertainty caused by the above macroeconomic policy environment and geopolitical risk, public health events can also cause uncertainty to the macroeconomy. Notably, the COVID-19 outbreak in December 2019 has brought shock to global financial markets. Intuitively, the crude oil market may also react to the shock of such a public health event (Demirer et al., 2018a). The COVID-19 pandemic did cause server distortions and fluctuations in the crude oil markets. In April 2020, the benchmark price for crude oil of the May futures in the United States even fell to negative \$37.63. In this context, Baker et al. (2020) constructed the Infectious Disease Equity Market Volatility Tracker index (IDEMV) index to quantitatively measure the magnitude of an infectious disease pandemic, which is available from January 1985 to the present. This helps investors and academia better understand the impact of the epidemic panic on economic fundamentals. Based on the IDEMV index, recent literature confirms that the eruption of COVID-19 causes greater price fluctuations in commodities and financial assets such as stock, gold, and cryptocurrency, than in days before that (Corbet et al., 2020; Haroon and Rizvi, 2020; Ji et al., 2020; Zhang et al., 2020). Therefore, this paper also considers the uncertainty brought from the public health events, and to observe how the INE crude oil futures market reacts to this uncertainty.

Previous efforts have been made to predict the volatility of oil prices by employing GARCH-class models (Sadorsky, 2006; Nomikos and Pouliasis, 2011; Wang and Wu, 2012; Chan and Grant, 2016) and realized GARCH-class models (Haugom et al., 2014; Sévi, 2014). However, the imputing data of both GARCH-class models and realized GARCH-class models are strictly restricted at the same frequency. They are all failed to explaining the macroeconomic determinants at different sampling frequencies, which is crucial for investors and

government policymakers to understand the market (Engle and Rangel, 2008). Ghysels et al. (2004) proposed mixed data sampling (MIDAS) regression models, and Colacito et al. (2011) and Engle et al. (2013) applied the MIDAS technique into the GARCH model and constructed the GARCH-MIDAS model, and the GRACH-MIDAS model successfully addresses the problem of mismatching data frequency. After that, many macroeconomic factors have been applied to investigate underlying economic factors of asset volatility (Conrad et al., 2014; Liu J. et al., 2020; Sheng et al., 2020), and verified the superiority of predictive ability of GARCH-MIDAS model (Ghysels et al., 2019). Therefore, we construct the benchmark GARCH-MIDAS model with realized volatility (RV) and 15 individual GARCH-MIDAS models with various macroeconomy uncertainty determinants.

To compare the forecast performance of different models, we use the MCS test proposed by Hansen et al. (2005) to identify the most informativeness factor among our macro uncertainties. The current research has not yet considered the relation between macro uncertainty factors and INE crude oil market, to the best of our knowledge, we are the first to consider the effect of various macro uncertainty factors on the INE crude oil market. With the rising international status of China and the expanding scale of its crude oil market, it is necessary to understand and forecast the movement of INE crude oil futures price.

ECONOMETRIC METHODOLOGY

The GARCH-MIDAS Model

Since the MIDAS technique allows using macroeconomic fundamental data at lower frequencies, the GARCH-MIDAS model is widely used to predict daily crude oil futures

volatility. Therefore, this paper uses the benchmark GARCH-MIDAS model (Liu J. et al., 2019) and extends it by incorporating macroeconomic uncertainty factors as our explanatory variable.

The GARCH-MIDAS model is composed of two parts: one is to model the short-term component of volatility, and the other is to model the long-term component of volatility. The short-term component is a GARCH (1,1) process, while the latter is determined by the history of the realized volatility or macroeconomic variables weighted by the MIDAS polynomials. The GARCH-MIDAS model is constructed as follows. Suppose the return of the crude oil future is written as

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

$$\varepsilon_{i,t} | \Phi_{i-1,t} \sim N(0, 1) \quad (2)$$

where $r_{i,t}$ refers to INE crude oil futures return on day i in month t , $\Phi_{i-1,t}$ is the information set, μ refers to the conditional mean of returns on day $i-1$. The volatility component, $\sqrt{\tau_t} g_{i,t}$, of Eq. 1 is divided into a short-term component, $g_{i,t}$, and a long-term component, τ_t . Following Liu J. et al., 2019, $g_{i,t}$ is assumed to follow a mean-reverting unit-variance GJR-GARCH (1,1) process (Glosten et al., 1993) as:

$$g_{i,t} = (1 - \alpha - \gamma/2 - \beta) + \left(\alpha + \gamma 1_{\left\{ \frac{r_{i,t-1} - \mu}{\sqrt{\tau_{t-1}} g_{i,t-1}} \varepsilon_{i,t-1} < 0 \right\}} \right) \frac{(r_{i,t-1} - \mu)^2}{\tau_t} + \beta g_{i-1,t} \quad (3)$$

The long-term component τ_t , is defined as Eq. 4,

$$\tau_t = m + \theta \sum_{k=1}^K \varphi_k V_{t-k} \quad (4)$$

where m is the intercept, and θ refers to the weighted effects, with the weighting scheme function as $(\sum_{k=1}^K \varphi_k)$, of lagged variables, V_{t-k} , on the long-term oil volatility. Following Engle et al. (2013), we use the log transformation to guarantee the nonnegativity of the conditional variances in our estimation and prediction.

We define the benchmark model when lagged variable V_{t-k} equals RV_{t-k} , and its logarithmic form as follows:

$$\log(\tau_t) = m + \theta \sum_{k=1}^K \varphi_k(\omega_1, \omega_2) RV_{t-k} \quad (5)$$

$$RV_t = \sum_{i=1}^{N_t} r_{i,t}^2 \quad (6)$$

Where RV is the realized volatility calculated by intraday high-frequency data using Eq.6, k is the lagged value of the RV , the lags of the RV are set to 224,466 in Section *Out-of-Sample Evaluation* and Section *Robustness Check* following Engle et al. 2013 and Liu J. et al. (2019). The weighting scheme (Ghysels et al., 2004; Engle et al., 2013) used in Eq. 4 and Eq. 5 are the unrestricted Beta function defined as below:

$$\varphi_k(\omega) = \frac{(k/K)^{\omega-1}}{\sum_{j=1}^K (j/K)^{\omega-1}} \quad (7)$$

TABLE 7 | MCS test with quarterly RV.

	MFSE		MASE	
	Tmax	TR	Tmax	TR
GPR	1.000	0.980	1.000	1.000
GPRS	1.000	0.132	1.000	0.001
GPT	1.000	0.816	1.000	1.000
GPA	1.000	1.000	1.000	0.969
GEPU _{GDP}	1.000	0.461	1.000	0.926
GEPU _{PPP}	1.000	0.236	1.000	0.297
EPU _{China}	1.000	0.308	1.000	0.288
EPU _{US}	1.000	0.355	0.952	0.153
EPU _{UK}	1.000	1.000	1.000	1.000
EPU _{Canada}	1.000	0.002	1.000	0.005
EPU _{Russia}	1.000	0.003	0.500	0.001
EPU _{Japan}	1.000	0.995	1.000	1.000
IDEMV	1.000	0.904	0.234	0.918
IDEMVS	0.377	1.000	0.000	0.000
RV	1.000	0.533	1.000	0.697

Note: We use bold number stands for p-values of the model that larger than 0.25, indicating that the corresponding model passes the MCS test under the MAFE loss function and the MSFE loss function, with the Tmax and TR statistic. The p-value of 1.000 indicates that a model has the best performance among all the testing models. MSFE refers to the mean squared forecast error and MAFE refers to mean absolute forecast error. The lags of the RV are set to 66.

$$\varphi_k(\omega_1, \omega_2) = (k/K)^{\omega_1-1} (1 - k/K)^{\omega_2-1} / \sum_{j=1}^K j/K^{\omega_1-1} (1 - j/K)^{\omega_2-1} \quad (8)$$

where the parameter ω_1 is the weighting scheme, and ω_2 is the decaying rate of the Beta function.

GARCH-MIDAS Models With Macroeconomic Uncertainty

To investigate the effect of macroeconomic uncertainty have on oil future market volatility, we add the macroeconomic uncertainty factors (MU) we mentioned above into Eq. 5. Therefore, we get the GARCH-MIDAS-MU model. The long-term component, $\log(\tau_t)$, can be updated as

$$\log(\tau_t) = m + \theta_1 \sum_{k=1}^K \varphi_k(\omega_1, \omega_2) RV_{t-k} + \theta_2 \sum_{k=1}^K \varphi_k(\omega_1, \omega_2) MU_{t-k} \quad (9)$$

Where the MU we choose the geopolitical risk indices (Antonakakis et al., 2017; Plakandaras et al., 2019), economic policy uncertainty indices (Balcilar et al., 2017), and infectious disease pandemic indices as the determinants.

To further examine whether serious geopolitical risk and infectious disease pandemic is informative to improve the predictive accuracy for oil futures volatility, we define the GPRS and IDEMVS as follows:

$$GPRS_{t-k} = GPR_{t-k} \times I(GPR_{t-k} > GPR^{mean}) \quad (10)$$

$$EMVS_{t-k} = EMV_{t-k} \times I(EMV_{t-k} > EMV^{mean}) \quad (11)$$

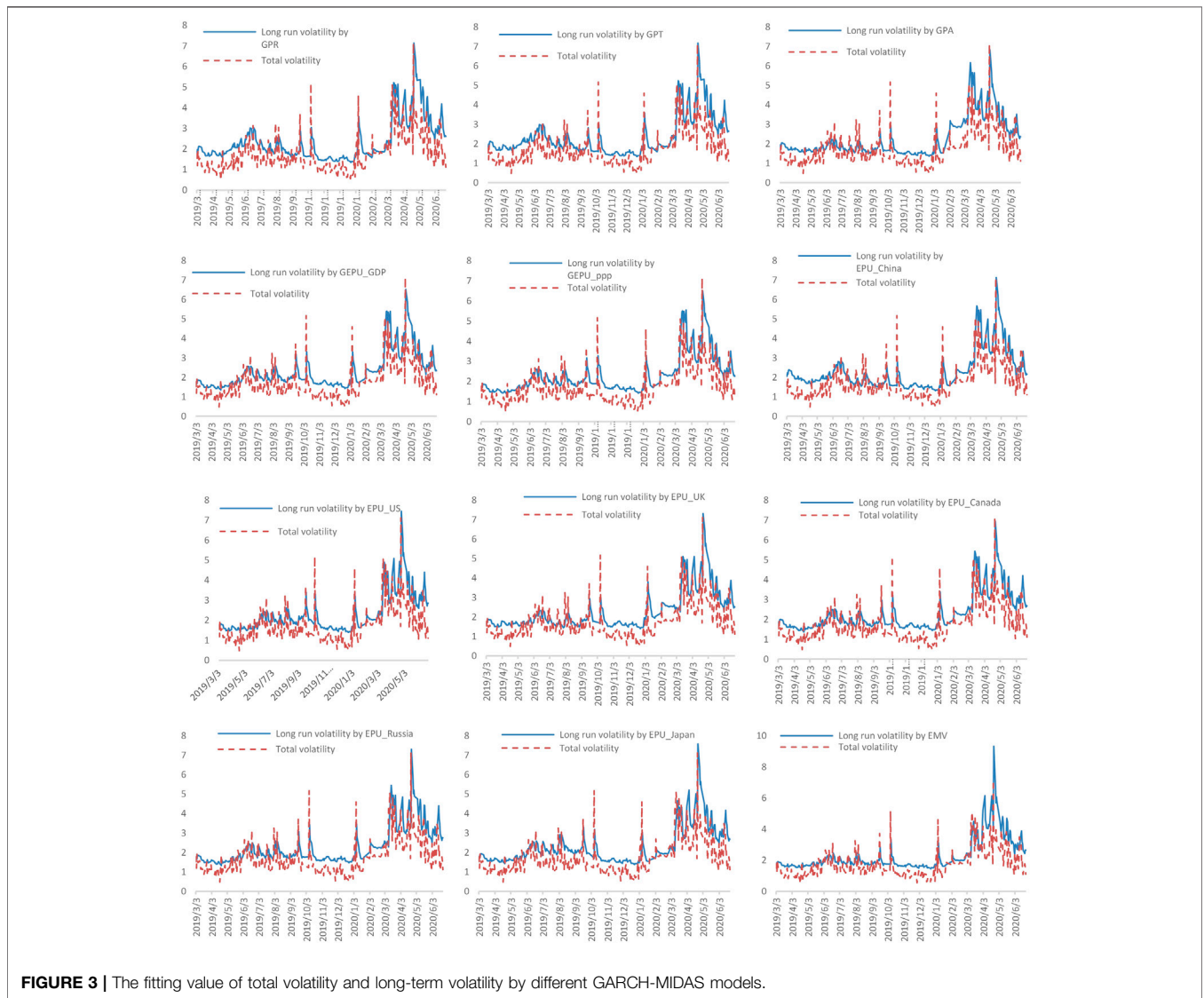


FIGURE 3 | The fitting value of total volatility and long-term volatility by different GARCH-MIDAS models.

Forecast Evaluation

To make a comparison of forecasting performance with the different GARCH-MIDAS-MU models, we use MCS test with two popular loss functions as our evaluation criteria. The loss functions are the mean squared forecast error function (MSFE) and the mean absolute forecast error function (MAFE), and are defined as follow:

$$MSFE = M^{-1} \sum_{t=1}^M (y_t - \hat{y}_t)^2 \tag{12}$$

$$MAFE = M^{-1} \sum_{t=1}^M |y_t - \hat{y}_t| \tag{13}$$

where y_t is the actual daily crude oil futures volatility on day t , and we use RV in day t that measures the actual daily crude oil futures volatility, \hat{y}_t is the predicted value obtained from different GARCH-MIDAS models and M is the number of predicted values.

DATA

The sample data used in this paper are as follows: the intraday INE crude oil high-frequency data, the daily INE crude oil futures prices, and the monthly macroeconomic uncertainty factors of oil futures price volatility. Following Sévi (2014), we use the 5-minute data as our sample data to calculate the RV, and get the intraday 5-min high-frequency data from the Shanghai International Energy Exchange. The monthly dataset consists of three GPR indices, two GEPU indices, six country-specific EPU indices and the IDEMV and IDEMVS indices. The monthly GPR¹ indices were proposed by Caldara and Iacoviello (2018), and are the key indicators that demonstrate risk from geopolitical events such as wars and terrorism. To isolate the effects of pure geopolitical risk, we also consider the two related

¹The GPR index can be downloaded from <http://www.policyuncertainty.com/gpr.html>.

indexes: the geopolitical threats index (GPT) and the geopolitical acts (GPA) index. The GPT index depicts the geopolitical threat, while the GPA index depicts the geopolitical adverse events. With regard to the economic policy uncertainty factors, we use the EPU² indices constructed by Baker et al. (2016). The GEPU indices have two versions with different calculations: one is calculated by current-price GDP measures (denoted as $GEPU_{GDP}$) and the other is calculated by PPP-adjusted GDP (denoted as $GEPU_{PPP}$). We selected three major oil consumers (i.e., the United States, China, and Japan) and three major oil exporters (Russia, Canada, and the United Kingdom) as our country-specific EPU indices. With regard to the infectious disease pandemic of public health events, we use the monthly data is of the Infectious Disease Equity Market Volatility Tracker (IDEMV) index constructed by Baker et al. (2020). For model comparison of fitting and forecasting performance, we make all these macroeconomic uncertainty indices have the same monthly frequency. We obtain the INE crude oil futures high-frequency data from the CSMAR database and the monthly macroeconomic uncertainty indices from the Economic Policy Uncertainty website. The data covered from 27th March 2018 to 24th June 2020 with 305,004 intraday 5-min observations, 545 daily observations, and 28 monthly observations.

Table 1 shows the descriptive statistics of the variables. First, compared with the standard deviation, the sample mean of the INE crude oil futures return is relatively small, suggesting that we can use a constant when we modeling the volatility of crude oil futures prices (Sadorsky, 2006; Narayan and Narayan, 2007). The RV of the crude oil futures price is skewed to the right and exhibit high kurtosis. Second, among the GPR indices, the standard deviation of GPT and the GPA is either larger and smaller than the GPR index, indicating that the GPT changes more frequently and violently and GPA is relatively stable. Third, the mean of IDEMV and IDEMVS is relatively small compared with their standard deviation, indicating that they are both volatile.

Figures 1–3 show the time series of INE crude oil futures and the GPR, EPU, and IDEMV factors. Due to the impact of the epidemic and the international political and economic situation, the overnight trading of INE futures in China was suspended on February 3, 2020, and resumed on May 6, 2020, the shade is the period that the oil futures are suspended from overnight trading.

Figure 2 shows the general relationship among the crude oil futures volatility, the GPR index, the GEPU index, and the IDEMV index. As can be seen from panel (A), before the COVID-19 broke out, changes in GPR index and RV tend to be consistent, presenting potential co-movements there. However, during the COVID-19 broke out periods, the GPR index is relatively stable, and the investors are shocked by the wild swings of the crude oil futures market. With regard to the GEPU indices, there are obvious co-movements between the crude oil future RV and the two GEPU indices. With regard to the IDEMV index, the crude oil future volatility is co-movement with the

IDEMV index only during the COVID-19 broke out periods. This indicates that when GEPU and IDEMV would increase the volatility of the crude oil futures market, the GPR index might decrease the volatility of the crude oil futures market.

EMPIRICAL RESULTS

In-Sample Estimation Results

Before estimating the impact of macro uncertainty indicators on crude oil futures volatility, the variations of the benchmark GARCH-MIDAS model with long-run RVs were estimated as a comparative reference for the extended models and then we further apply the macro uncertainty indicators in our extended models.

Tables 2–4 show the benchmark GARCH-MIDAS model and the extensions with geopolitical risk (Antonakakis et al., 2017; Plakandaras et al., 2019), economic policy uncertainty (Balcilar et al., 2017), and infectious disease pandemic factors (Baker et al., 2020) as the determinants. We use the maximum likelihood estimation method to obtain the parameters of the GARCH-MIDAS model. The lag length $k = 22$ for long run RVs, and $k = 12$ for monthly macro factors and are following Conrad et al. (2014) and Gkillas et al. (2018). Interestingly, concerning the parameter estimates among all these models, the GARCH-MIDAS models with monthly macroeconomic factors have lower estimates β than the model with single daily long run RVs. While for the models with monthly τ_1 the estimates of α are close to zero. In addition, for all models, $\alpha + \beta < 1$, which means all the GARCH-MIDAS models are stable.

Consistent with previous literature (Conrad and Kleen, 2020), the γ parameter is statistically significant and provides strong evidence for the asymmetry effect of the volatility movement. Based on the loglikelihood value and the BIC value, the models with macro factors have better fitting performs than the benchmark GARCH-MIDAS model. These are in line with findings in the previous literature.

Since the main focus of our paper is to investigate whether the macroeconomic uncertainties have an impact on the long-term volatility of the crude oil futures, we pay more attention to the value of parameters θ_1 and θ_2 in **Eq. 9**. The parameters θ_1 and θ_2 stand for the effect of monthly macroeconomic uncertainties on the long-term volatility of INE crude oil futures prices. The parameters θ_1 and θ_2 reflect the long-term impact of realized volatility and macro uncertainty on volatility respectively. If the value of parameters θ_1 and θ_2 are positive, then a high level realized volatility and macro uncertainty factors would cause serious divergence in the expectations of crude oil market participants and thus affects the crude oil futures volatility. The parameter ω_1 and ω_2 are the optimal estimated coefficients for the constrained weighting scheme function -BETA functions. According to the coefficients θ and ω , the influence of low frequency monthly factors on the long-term component of volatility can be estimated. As in **Tables 1–3**, except for the benchmark GARCH-MIDAS model, the θ_1 is significantly positive at 1%, which means higher levels of financial volatility tend to increase long-term volatility of the crude oil futures market. While the θ_2 among these models are different, and we will discuss it as follow.

²The EPU index can be found at http://www.policyuncertainty.com/global_monthly.html.

Table 2 reveals the empirical results of the geopolitical risk factors. First, the results show that geopolitical risk contributes to the crude oil futures volatility in different ways. In column (2)-column (3), both the GPR and the GPRS have a negative impact on the long-run component of INE crude oil futures volatility, which is consistent with Antonakakis et al. (2017) and Mei et al. (2020). This indicates that when a geopolitical risk shock occurs, the crude oil futures market participants synchronize their trading activity in the same direction by reducing the volatility. However, the impact of the GPR is not significant, whereas the impact of GPRS is significant. This can be explained by Liu J. et al. (2019), that although the government policymakers and the oil market participants concern about the geopolitical risk, they are used to common geopolitical risk and are only sensitive to the serious geopolitical risk. Second, we further investigate the categorical GPR index. In column (4)–(7), both the threat related index and the act related index have a significant impact on the crude oil futures volatility. The GPT is significantly negative whereas the GPA is significantly positive. This indicates that although the geopolitical threat makes market participants synchronize their trading behavior, the geopolitical act causes divergence in the expectations of oil futures market participants and increases the crude oil futures volatility.

Tables 3, 4 reveal the empirical results of the EPU indices and the infectious disease pandemic factors. As shown in **Tables 3, 4**, two GEPU indices do not have statistically significant impacts on long-term volatility, whereas the country-specific EPU indices do have impacts on the long-term volatility in different ways. The EPU in China has a significantly negative impact on the long-term volatility, whereas the EPUs in United States United Kingdom, Japan, Canada, and Russia have a significantly positive effect on the long-term volatility. Specifically, the EPUs from the United Kingdom, with a θ_2 value of 0.029, indicates that compared with other major crude oil trading countries, the economic policy uncertainty in the United Kingdom has the greatest impact on the volatility of China's crude oil futures. Besides, EPUs from Canada and Japan also have a great influence on the crude oil futures volatility followed by the United Kingdom. However, the EPUs in the United States and Russia do not have a statistically significant impact on the crude oil futures volatility. **Table 3** column (4)–(5) shows that both the IDEMV and IDEMVS have a positive effect on the long-term volatility. The IDEMV with a θ_2 value of 0.025, whereas the IDEMVS with a θ_2 value of 0.09, indicates that the market participants are more sensitive to the serious public health events.

Figure 3 plots the fitting value of total daily volatility and long-term volatility of the 12 GARCH-MIDAS models. Since the trend of GPRS and IDEMV is similar to that of GPR and IDEMVS, so this paper will not show the figures for them. The orange dashed line represents the total daily volatility and the blue line represents the long-term volatility calculated by the GARCH-MIDAS model with different macroeconomic uncertainty factors. It is clear that the daily total volatility in all 12 subfigures of **Figure 3** are similar, but the long-term volatilities with different monthly macroeconomic uncertainty factors are quite different. **Figure 3** suggests that GPR indices, EPU indices, and infectious disease pandemic have different influences on long-term oil volatility. In the next section, we mainly discuss which

macroeconomic uncertainty factors are most informative in forecasting the daily volatility of crude oil futures prices.

Out-of-Sample Evaluation

In this section, we employed the out-of-sample rolling method to evaluate the predictability of the above models. Considering the sample sized of our data and to ensure that our conclusions are reliable, we set out window size as 430 days³, and we get 115 out of sample predicted values. This paper compared the models' out-of-sample predictability by using the MCS test.

The p -values of loss functions in the MCS test are the indicator of the models' forecasting performance. If the p -values greater than a specific threshold, which is also called MCS alpha, the corresponding model is supposed to have better predictability than the others (Hansen et al., 2005). However, there is no consensus on the specific value of the threshold p -value in MCS tests, and different literatures set the different MCS alpha values (Tian and Hamori, 2015; Pu et al., 2016). **Table 5** reports the p -values of the MCS tests for GARCH-MIDAS-MU models. To clearly distinguish the most informative macroeconomic uncertainty factor contributing the long-term volatility, we follow the most related studies of Liu J. et al. (2019), which investigate the oil market volatility and set the threshold p -value to be 0.25 in **Tables 5–7**.

First, **Table 5** shows the results of out-of-sample forecasting performance with the monthly RVs. Under the MSFE criterion, the model with GPR, GPRS, GPT, GPA, $GEPU_{GDP}$, $GEPU_{PPP}$, EPU_{China} , EPU_{UK} , EPU_{Japan} , pass the MCS test with p -values larger than 0.25 for both test statistics. Under the MAFE criterion, the models with GPR, GPA, $GEPU_{GDP}$, EPU_{UK} and EPU_{Japan} also pass the MCS test under both statistics. Overall, the model with GPR, GPA, $GEPU_{GDP}$, EPU_{UK} , EPU_{Japan} pass the MCS test under MSFE and MASE criterion with both statistics.

Interestingly, whereas the GARCH-MIDAS-GPRS model fails to predict more accurately in our sample, the GARCH-MIDAS-GPRS model's predictability is proved to be superior in forecasting oil prices (Liu J. et al., 2019). After including the GPR and GPA indices, the forecast accuracy of GARCH-MIDAS model is significantly improved. This indicates that government policymakers and INE crude oil futures market participants pay attention to geopolitical risk and the geopolitical adverse events, which cause increased oil price volatility. However, our results show that the GPRS index is not informative in predicting the volatility.

The results in **Table 5** also show that EPU indices, in general, are more informative than the rest of the macroeconomic uncertainties when predicting the volatility of crude oil futures. Furthermore, among all kinds of EPU in our sample, the $GEPU_{GDP}$, the EPU_{UK} , and the EPU_{Japan} indices are the most informative macroeconomic uncertainty factors in forecasting crude oil futures volatility. First, we find that $GEPU_{GDP}$ is more informative than the $GEPU_{PPP}$ in predicting the volatility of crude oil futures price. This indicates that the crude oil futures market participants are paying more attention to nominal economic indicators than to real ones. Second, among the six major crude oil consumers and exporters,

³The data covered from 27th March 2018 to 31st December 2019.

EPU_{UK} , and the EPU_{Japan} indices are the most informative. It might be the following reasons. First, the origin of crude oil in China and United Kingdom is similar. Both China's crude oil and Brent's crude oil comes mainly from the Middle East and North Africa, thus China's crude oil spot pricing mainly refers to the Brent crude oil price⁴. A previous study shows that China's crude oil market is more correlated with the Brent market compare with other major crude oil markets (Zhang and Ma, 2020), Yang et al. (2020) shows that Brent markets have a unidirectional Granger causality relationship with the INE crude oil futures market. Furthermore, Antonakakis et al. (2014) shows that there are spillover effects between oil prices changes and EPU index, Ma et al. (2019) shows that the EPU from Europe, which including the United Kingdom, increases the volatility in Brent futures, which is the benchmark of the China's crude oil spot price. Thus, the EPU in United Kingdom, might contain more information concerning the supply and demand of the INE crude oil market. Second, EPU from Japan might contain more information about the supply and demand of its importers and global crude oil demand. Similar to China, Japan's crude oil comes mainly from the Middle East, followed by the United Arab Emirates and Saudi Arabia, and Rehman (2018) shows that oil specific demand shock has a significant impact on EPU from Japan compared with other countries. The similarity of the crude oil importers between China and Japan, and the sensitivity of EPU_{Japan} to the global oil demand shock might contribute to the superior predictive power of EPU_{Japan} compared with other countries. Third, compared with other countries, previous literature shows the EPU from Japan and United Kingdom are closely related to Chinese economic conditions such as the financial conditions (Liu Z. et al., 2019; Li and Zhong, 2020; Ahmadi et al., 2020), monetary aggregate (Han et al., 2016), exchange rate (Chen et al., 2020; Zheng and Kaizoji, 2019), and market uncertainty (Ji et al., 2020; Smales, 2020). These factors are closely related to the crude oil market (Ahmadi et al., 2020; Yousefi and Wirjanto, 2004; Ratti and Vespignani, 2013), thus it is reasonable that the EPUs from these two countries may contain information of the future volatility of the INE crude oil futures market. The superior predictive power of EPU_{UK} , and the EPU_{Japan} also suggest that INE crude oil futures market is not only following the international crude oil market, it also reflecting the special characters in Asia. It is interesting that EPU_{China} does not pass the MCS test with MASE criterion with TR statistic, even though China is where China's Shanghai crude oil futures market is located at. As the world's second largest economy and crude oil consumer country, the economic conditions in China should influence crude oil future prices. Previous literatures also found empirical evidence that China's economic condition plays a crucial role in the global oil market with respect to crude oil prices (Yuan et al., 2008) and oil price variation (Liu et al., 2016). However, in our results, the EPU in China do not have superior predictive power than other macroeconomic uncertainty factors. Wei et al. (2017) provide some

insights for our results. China's priority, for now, is to maintain stable economic growth, especially under the recent complex environment. Thus, the fiscal and monetary policy, in this case, is unlikely to cause severe volatility in crude oil futures price.

ROBUSTNESS CHECK

Since different lags of RV (RV_{t-k}) in Eqs 4, 5 may result in different accuracy in forecasting the volatility and further affect the predictive power of exogenous macroeconomic uncertainty factors. Previously study of Engle et al. (2013) addresses this issue with the monthly, biannual, and quarterly lags of RV in the GARCH-MIDAS models. Following Engle et al. (2013), this paper also considers the bimonthly and quarterly lags of RV instead of the monthly RV in Eqs 4, 5 in robustness check. We investigate whether macroeconomic uncertainty factors could still have a more accurate forecast of RV with different lags of RV. Tables 6, 7 present the MCS testing results with bimonthly RVs, the p -values of the GPR, GPA, $GEPUGDP$, EPU_{UK} , EPU_{Japan} , pass the MCS test with p -values larger than 0.25 for all four test statistics. Thus, our results are robust with different lags of RVs.

CONCLUSION

As a political commodity, crude oil is closely bound up with the national strategy, global politics, and national economic strength and China's rise is playing an increasingly important role in the global crude oil market. Therefore, it is important for policymakers and investors to accurately understand and predict China crude oil futures volatility. Recent literature have found that many macroeconomic uncertainty indicators have great effects on crude oil volatility. Among the various uncertainty factors, the geopolitical risk and the economic policy uncertainty have traditionally been considered the most powerful. In addition, the Coronavirus (COVID-19) outbreak in December 2019 has brought great pains to the global economy and financial markets. Thus, we analyze the impact of uncertainty factors have on the futures volatility such as traditional uncertainty factors GPR and EPU, and also consider the IDEMV, that the uncertainty comes from the public health event. We use the GARCH-MIDAS model with these macroeconomic uncertainties respectively, and we identified which macroeconomic uncertainty factor is more informative when predicting the crude oil futures volatility.

With regard to the model fitting results, first, we find that geopolitical risk significantly influences the crude oil futures market prices. Especially, the GPR and the GPRS have a significant negative impact on the long-run component of INE crude oil futures volatility, and the GPT is significantly negative whereas the GPA is significantly positive. Second, the EPU in China has a significantly negative impact on the long-term volatility, whereas the EPUs in United States, United Kingdom, Japan, Canada, and Russia have a significantly positive effect on the long-term volatility. Specifically, the EPU from the United Kingdom, makes the largest contribution to the long-term volatility of oil futures prices among all of the EPU indices, whereas EPUs in the U.S. and Russia are less informative in determining oil volatility. Third, the infectious disease pandemic factor also has a positive effect on long-term volatility.

⁴In 2008, the National Development and Reform Commission issued "Administrative Measures for Oil Prices (For Trial Implementation)," the program rules that China domestic crude oil prices are base on the price in Brent, Dubai and Minas, coupled with the domestic cost of import tariffs, refining, distribution of costs and profits.

With regard to the model forecasting results, the model with GPR, GPA, $GEPUGDP$, EPU_{UK} , EPU_{Japan} pass the MCS test under MSFE and MASE criterion with both statistics. This implies that these macroeconomic uncertainty factors contain useful information and the government policymakers and oil market investors pay attention to these factors, which cause increased oil price volatility.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

AUTHOR CONTRIBUTIONS

AY made substantial contributions to the conception of the work. YL acquired the data. MY analyzed and interpreted the data for

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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