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Natural gas volatility prediction: Fresh evidence from extreme weather and extended GARCH-MIDAS-ES model

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ABSTRACT

This study aims to analyzes the predictability of the natural gas volatility by considering extreme weather information. Based on extended GARCH-MIDAS models, empirical results show that the predictive model adding weather indicators can indeed outperform the model without weather indicators. Importantly, some extreme weather indicators can provide more valuable information to predict the natural gas volatility based on the various out-of-sample tests. Our new weather-related GARCH-MIDAS-ES model can exhibit a new insight on the natural gas volatility forecasting.

1. Introduction

Being a crucial clean energy source, natural gas has received a growing attention because of the serious problems of fossil fuel exhaustion and environmental pollution (Bilgen et al., 2004; Alexopoulos, 2017). Recently, Russia's invasion of Ukraine makes governments and institutions further realize the importance of understanding and forecasting the volatility of the natural gas market under extreme shocks (Ozili, 2022). Moreover, as a common type in extreme shocks, extreme weather is considered as one of the important factors to affect the natural gas market (Cruz and Krausmann, 2013; Cho et al., 2018). For instance, as mentioned in the report of American Gas Association, a North American cold wave leads to a significant volatility in the price of natural gas in the February 2021 (Morales, 2021). By affecting the demand and supply of natural gas, extreme weather often results in large price movements. Therefore, in line with Caporin and McAleer (2010), it is necessary to incorporate extreme weather into the modelling and predicting the natural gas volatility, in order to provide a more detailed knowledge for constructing the econometric model. However, while many studies confirm the close linkage between the natural gas market and weather indicators (Mu, 2007; Nick and Thoenes, 2014a), such as temperature, humidity, and wind speed, the econometric model considering extreme weather is rare. Because the extreme weather-related information shocks may cause the large fluctuations in natural gas market, the information transmission are needed to be taken account in volatility forecasting. Moreover, the forecasting performance of natural gas is largely affected by extreme weather shocks. Hence, extreme weather is one of the major concerns in our study. Based on the above analysis, we conduct the enhancement of predictive ability of the natural gas volatility by adding extreme weather in the GARCH-MIDAS setting. Therefore, understanding the extent of extreme weather information on natural gas market is beneficial to devise new portfolio productions. Analyzing how extreme weather affects the natural gas market is decisive to reduce losses that may occur in the future.

Based on behavioral finance, instead of a rational person, an investor often behaves irrationally in the real world (Basu et al., 2008). Many investors may adopt different investment strategies even when they deal with the same information (Devenow and Welch, 1996). Hence, Daniel et al. (2002) indicate that we should consider individual psychological factor when modelling financial markets. Being an important factor to affect human mood, weather is confirmed to significantly affect financial markets (Jacobsen and Marquering, 2008). For instance, Saunders (1993) argues that sunshine effect measured by cloudiness has a negative effect on stock return based on mood misattribution. Daniel et al. (1998) point out that investors are willing to buy stocks when they are in a good mood under good weather condition. Kamstra et al. (2003) demonstrate the stock markets are strongly seasonal. Besides, the close relationships between weather and stock market (Symeonidis et al., 2010), crude oil market (Cruz and Krausmann, 2013), agricultural market (Overton, 1989) and carbon market (Liu and Chen, 2013) have been verified. Based on the previous studies, we find strong economic evidence that weather may affect natural gas market from the

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behavioral finance perspective (Lucey and Dowling, 2005).

Despite the widely use of GARCH-class models in energy forecasting (Efimova and Serletis, 2014; Liu and Lee, 2021), we intend to introduce the GARCH-MIDAS model proposed by Engle et al. (2013) to analyze the natural gas volatility under extreme weather. The related reasons are following. First, the GARCH-MIDAS model can process the high frequency and low frequency data in a same MIDAS framework (Conrad and Kleen, 2020). This is greatly helpful to solve the problem of different frequencies between natural gas prices and weather indicators. Second, many research verify that the GARCH-MIDAS model including various exogenous variables, such as economic policy uncertainty, macro fundamentals, investor attention, and financial stress indicator, can indeed do an excellent job in predicting the volatility in energy market (Asgharian et al., 2013; Pan et al., 2017). For example, Liu et al. (2021a) and Yu and Huang (2021) confirm the superior predictive power of financial volatility by adding economic policy uncertainty. Salisu et al. (2022) find the significant impact of the global financial cycle on the crude oil volatility prediction. Third, Wang et al. (2020, 2021) develop an extended GARCH-MIDAS model, namely GARCH-MIDAS-ES model, which can capture the evolution of financial volatility in presence of extreme shocks. They demonstrate that extreme shocks have a crucial influence on the crude oil volatility. Hence, motivated by their work, the GARCH-MIDAS-ES model is introduced in our study.

Our research is attractive for three main reasons. First, many studies suggests that weather is a main factor to affect the natural gas market. Mu (2007) discovers a significant weather influence on the conditional volatility of US natural gas futures market. Geng et al. (2016) confirm that temperature changes can lead to the highly fluctuations of Henry Hub Natural Gas Spot Price. However, the work of Hulshof et al. (2016) indicates that the extremely weather in February 2012 hardly has a statistical effect on the TTF gas price. Therefore, the current mixing results motivates us to further examine the impact of weather variables on the natural gas market. More importantly, although whether and how weather information drives the volatility of the natural gas market is widely studied (Fleming et al., 2006; Dergiades et al., 2018; Anđelković and Bajatović, 2020), few studies have carried out whether adding whether variables is beneficial to improve the predictive power of the natural gas volatility. However, more accuracy predictions of the natural gas volatility may provide more strong evidence for risk management and energy security in the future (Pouliasis et al., 2020). Our study aims to fill the gap and empirically analyze the predictive ability of the natural gas volatility under extreme weather by using the GARCH-MIDAS-ES model.

Second, the GARCH-MIDAS model is confirmed to discover the direct link between the financial volatility and exogenous variables (Walther et al., 2019). However, the traditional GARCH-MIDAS model cannot analyze the impact of exogenous variables on the volatility under extreme conditions (Wang et al., 2020). Based on investor's mood, investors may behave abnormally when they are in extreme weather condition (Chesney et al., 2011). According to Bodell (2014), extreme weather, for instance cold snap and hurricane, usually result in the dramatic volatility in the natural gas market. Hence, predicting the natural gas volatility should distinguish the different impacts caused by normal weather and extreme weather. By using the thresholds to capture the extreme and normal impact of extreme shocks (Wang et al., 2020), the GARCH-MIDAS-ES model is verified to yield better predictive results. To obtain better forecasts, we are the first to adopt this model to predict the natural gas volatility in presence of extreme weather information. Besides, compared with Liu and Chen (2013) who demonstrate extreme weather has certain effect on energy market, we further investigate whether extreme weather is useful to enhance the forecasting accuracy of natural gas volatility.

Third, compared with existing studies (Afkhami et al., 2017; Chen et al., 2021; Lu et al., 2022), two types of GARCH-MIDAS model with weather indicators, GARCH-MIDAS-W and GARCH-MIDAS-W-ES, are firstly used in the prediction of natural gas volatility. GARCH-MIDAS-W model denotes the extended GARCH-MIDAS model including weather variables, while GARCH-MIDAS-W-ES model presents the model including extreme and normal weather information separately. On one hand, to examine whether adding weather indicators is helpful to improve the predictive power of natural gas volatility, we compare the traditional GARCH-MIDAS model and two types of MIDAS models including weather information based on several out-of-sample tests (Zhang et al., 2019). On the other hand, the predictive ability between GARCH-MIDAS-W and GARCH-MIDAS-W-ES are analyzed to examine whether extreme weather can offer additional information to predict the natural gas volatility. By using Henry Hub natural gas futures price and weather data including wind speed, temperature, and precipitation, we find strong evidence that the predictive model adding weather indicators can indeed outperform the model without weather indicators. To be more important, some extreme weather can provide valuable information to predict the natural gas volatility from the results of various out-of-sample tests.

The remainder of our study proceeds as follows. The predictive model specifications are provided in Section 2. Section 3 presents our data and descriptive statistics. The related empirical results are shown in Section 4. Section 5 exhibits the results of robustness checks. Section 6 is the conclusion.

2. Literature review

Modelling natural gas volatility is crucial for portfolio and energy risk management. Many studies have examined the volatility characteristics of natural gas prices (Pindyck, 2004; Suenaga et al., 2008). For example, Herbert (1995) finds that historical trading volume has a significant impact on the natural gas price volatility. Serletis and Shahmoradi (2006) demonstrate the seasonal and open interest effects in natural gas futures volatility. Meanwhile, standard GARCH model (Ergen and Rizvanoghlu, 2016), EGARCH model (Lv and Shan, 2013), threshold GARCH model (Cochran et al., 2015), stochastic volatility model (Chan and Grant, 2016), GAS model (Xu and Lien, 2022), GARCH-MIDAS model (Liang et al., 2021) and HAR model (Prokopczuk et al., 2016) are introduced to investigate the volatility in natural gas market.

Moreover, many studies explore what factors drive the natural gas market. Hailemariam and Smyth (2019) verify that demand shocks regarding the natural gas market are the main factors to affect the volatility. Hulshof et al. (2016) point out that gas-market fundamentals have a crucial role on day-ahead gas prices. Besides, supply and demand (Lin and Wesseh Jr, 2013), trading volume (Herbert, 1995), global economic conditions (Wang et al., 2022), uncertainty information (Liang et al., 2021), major political-related events (Karali and Ramirez, 2014) and other energy markets (Asadi et al., 2022) are demonstrated to significantly affect the natural gas volatility. Among all factors, weather information is widely confirmed to have an important effect on the natural gas market. Considine (2000) examines the relationship between US natural gas demand and weather information. The results show that warmer weather conditions indeed reduce US's carbon emissions and natural gas demand. By using heating/cooling degree days as weather variables, Mu (2007) argues that there is a statistical and economic impact of weather variables on the natural gas market. Chan et al. (2009) assume that weather is a short-run demand factor and analyze the role of weather in time-varying volatility in natural gas market. Nick and Thoenes (2014b) adopt a structural VAR method to investigate the main influencing factors of the German natural gas market. They find that temperature and supply shocks have a significant effect on the short-term natural gas prices. Therefore, we can see that there is close connection between natural gas market and weather variables.

Recently, a growing number of literatures carry out the natural gas volatility forecasting. Using seven GARCH-type models, Chkili et al. (2014) conduct the in-sample and out-of-sample volatility forecasting of Henry Hub natural gas. They support that no individual model absolutely outperforms other GARCH models. Baruník and Křehlík (2016) combine realized measures using high frequency data with artificial neural networks approach to examine the forecasting accuracy of natural gas prices. Their work confirms that neural networks yields both statistical and economic forecasts. Lyócsa and Molnár (2018) examine the volatility forecasts of UNG (United States Natural Gas) from a high frequency perspective. They introduce several HAR-type models to describe the volatility of UNG and find that the forecasts obtained by the combination of HAR-type models have better forecasting ability than the forecasts obtained by each single model. Liang et al. (2021) employ GARCH-MIDAS model to analyze whether the uncertainty indices, such as geopolitical risk and equity market volatility, are useful to improve the forecasting power of natural gas volatility. Their results indicate that uncertainty information play a crucial impact on natural gas futures volatility. Chen et al. (2021) show that investor sentiment of Huang et al. (2015) and VIX are difficult to improve the forecasting ability of the natural gas realized volatility. However, VIX and USEPU indeed improve economic values for natural gas futures and spot, respectively. Based on the existing studies, few studies incorporate weather information into the natural gas volatility regardless of the important influence of weather variables on natural gas market.

3. Methodology

3.1. GARCH-MIDAS-ES model

Recently, GARCH-MIDAS model becomes one of the most popular models to detect the linkage between the financial volatility and various exogenous variables (Liu et al., 2021c). Moreover, many studies demonstrate adding the exogenous variables in the long-term volatility component can significantly improve the predictive power of energy volatility (Ma et al., 2021). Comparing to the traditional GARCH-class models with the same frequency data, the GARCH-MIDAS model can employ short- and long-term components to analyze high and low frequency data simultaneously (Liang et al., 2022).

To further examine the effects caused by extreme shocks on the volatility, Wang et al. (2020, 2021) develop the GARCH-MIDAS-ES model by modifying the long-term component in the traditional GARCH-MIDAS model. This extended model can be written as follows:

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

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

$$\tau_t = m + \theta^- \sum_{k=1}^{K} \varphi_k(\omega) RS^-_{t-k} + \theta^+ \sum_{k=1}^{K} \varphi_k(\omega) \mathrm{RS}^+_{t-k} + \theta^* \sum_{k=1}^{K} \varphi_k(\omega) RS^*_{t-k} \tag{3}$$

where $\varepsilon_{i,\ t}|\psi_{i-1,\ t} \sim N(0,1)$ with $\psi_{i-1,\ t}$ is the information set. $g_{i,\ t}$ is short-term component which obeys a GARCH (1,1) process, while τ_t is long-term component within a MIDAS framework. Moreover, $RS^-_{i-k} = \sum_{j=1}^{N'} r^2_{i-j} 1_{\{r_{i-j}<q_1\}}$, $RS^+_{i-k} = \sum_{j=1}^{N'} r^2_{i-j} 1_{\{r_{i-j}>q_2\}}$, and $RS^*_{i-k} = \sum_{j=1}^{N'} r^2_{i-j} 1_{\{q_1 \le r_{i-j} \le q_2\}}$ are realized variance, which denote extremely negative, extremely positive, and normal realized volatility, respectively. $1_{\{\}}$ presents the indicator function which takes 0 or 1, while q_1, q_2 are the thresholds to identify the extreme and non-extreme conditions by using empirical distribution of weather indicators. Additionally, $\varphi_k(\omega)$ is a weighting equation in the form of Beta function. Obviously, we can observe the different impacts of extremely negative, extremely positive, and normal realized volatility on the total volatility of natural gas based on the values of θ^-, θ^+, and θ^*.

3.2. GARCH-MIDAS-ES model including extreme weather

According to behavioral economics, there is close relationship between investor's emotions and their investment decisions (Lucey and Dowling, 2005). Weather effect, proposed by Saunders (1993), is considered as environmental factor to affect the mood and demand of investors, leading to the volatility in the natural gas market. Motivated by Drobetz et al. (2012), we further incorporate the weather indicators into the traditional GARCH-MIDAS model.

3.2.1. Model 1 GARCH-MIDAS-W model

To analyze the effect of macro variables on the volatility in natural gas market, following Salisu et al. (2020), the weather indicators are introduced in the GARCH-MDAS model. We name this model with weather indicators as GARCH-MIDAS-W model. This model can be written as follows

$$r_{i,t} = \mu + \sqrt{\tau_t g_{i,t}}\varepsilon_{i,t} \forall i = 1, \dots, N_t \tag{4}$$

$$g_{i,t} = (1-\alpha-\beta) + \alpha\frac{(r_{i,t}-\mu)^2}{\tau_t} + \beta g_{i-1,t} \tag{5}$$

$$\tau_t = m + \underbrace{\theta \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2) W_{t-k}}_{\text{weather effect}} \tag{6}$$

where W_t in Eq. (3) denotes the weather indicators, such as wind speed and temperature, at time t. Obviously, the GARCH-MIDAS-W model shows that the weather indictors affect the volatility of natural gas on average without considering extreme weather conditions.

3.2.2. Model 2 GARCH-MIDAS-WTS-ES model

In line with Wang et al. (2020), we develop the GARCH-MIDAS-ES model including extreme weather conditions, which is called GARCH-MIDAS-W-ES model. However, since some weather indicators have one-way or two-way extreme effects on the natural gas market, we develop two extended GARCH-MIDAS models including extreme weather.

Some weather indicators, such as temperature, have two extreme levels to affect the natural gas volatility (Cao and Wei, 2005). Specifically, extremely high and low temperature may both have significant impact on the energy market (Song, 2002). Therefore, we incorporate extremely negative and extremely positive components of weather indicators into the long-term volatility of the GARCH-MIDAS-ES model. The proposed model, namely GARCH-MIDAS-WTS-ES (weather two-side extreme shocks), can be following:

$$\tau_t = m + \underbrace{\theta^- \sum_{k=1}^{K} \varphi_k(\omega) W^-_{t-k}}_{\substack{\text{extremely negative}\\ \text{weather effect}}} + \underbrace{\theta^+ \sum_{k=1}^{K} \varphi_k(\omega) W^+_{t-k}}_{\substack{\text{extremely postive}\\ \text{weather effect}}} + \underbrace{\theta^* \sum_{k=1}^{K} \varphi_k(\omega) W^*_{t-k}}_{\substack{\text{normal}\\ \text{weather effect}}} \tag{7}$$

where W_t denotes weather indicators at time t. Meanwhile, $W^-_{i-k} = W_{i-k} \bullet 1_{\{W_{i-k}<q_1\}}$, $W^+_{i-k} = W_{i-k} \bullet 1_{\{W_{i-k}>q_2\}}$, and $W_{i-k}{}^* = W_{i-k} \bullet 1_{\{q_1 \le W_{i-k} \le q_2\}}$ presents extremely negative, extremely positive, and normal weather conditions, respectively. Obviously, this new model can capture the effect of the two extreme cases in weather indicators on the natural gas market.

3.2.3. Model 3 GARCH-MIDAS-WOS-ES model

In addition to the above two-side extreme shocks, some weather indicators such as wind speed, may have one extreme level to affect the natural gas volatility (Shu and Hung, 2009). Considering super wind speed mainly affect the natural gas market (McNeil and D'Asaro, 2007), the extremely positive component of weather indicators can be introduced into the long-term volatility of the GARCH-MIDAS-ES model.

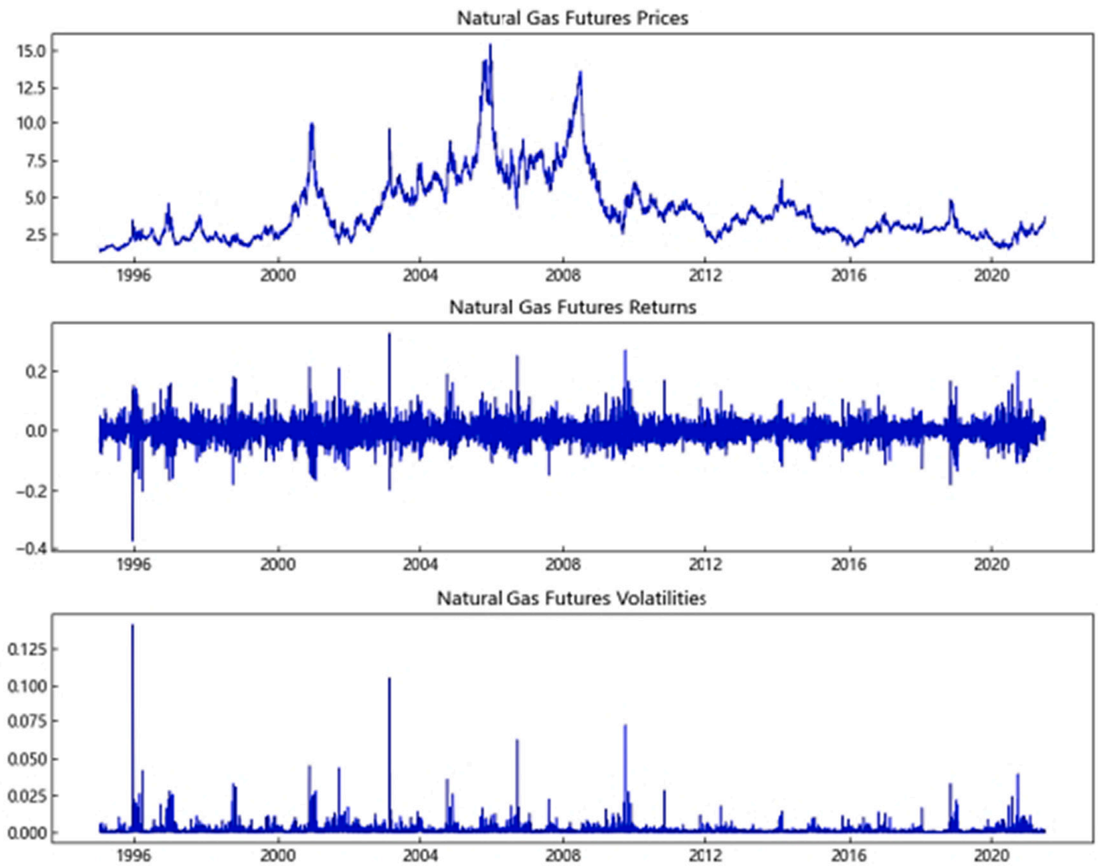

Fig. 1. Daily price, return and volatility of NYMEX.

Hence, the GARCH-MIDAS-WOS-ES (weather one-side extreme shocks) model can be developed as follows:

$$\tau_t = m + \underbrace{\theta^{+}\sum_{k=1}^{K}\varphi_k(\omega)W^{+}_{t-k}}_{\text{extremely postive weather effect}} + \underbrace{\theta^{*}\sum_{k=1}^{K}\varphi_k(\omega)W^{*}_{t-k}}_{\text{normal weather effect}} \tag{8}$$

where W_t denote weather indicators, $W^{+}_{i-k} = W_{i-k} \bullet 1_{\{W_{i-k}>q_2\}}$, and $W_{i-k}{}^{*} = W_{i-k} \bullet 1_{\{W_{i-k}\leq q_2\}}$ denote extremely positive and normal weather conditions, respectively.

Similar to Engle et al. (2013), we adopt QMLE to estimate our new models. The log-likelihood function is as follows

$$LnL = -\frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{N_t}\left[ln(2\pi) + ln\left(\tau_t g_{i,t}\right) + \frac{\left(r_{i,t}-\mu\right)^2}{\tau_t g_{i,t}}\right] \tag{9}$$

For the GARCH-MIDAS-WTS-ES model, τ_t in Eq. (7) can be written as

$$\tau_t = exp\left(m + \theta^{-}\sum_{k=1}^{K}\varphi_k(\omega)W^{-}_{t-k} + \theta^{+}\sum_{k=1}^{K}\varphi_k(\omega)W^{+}_{t-k} + \theta^{*}\sum_{k=1}^{K}\varphi_k(\omega)W^{*}_{t-k}\right) \tag{10}$$

For the GARCH-MIDAS-WOS-ES model, τ_t in Eq. (8) can be written as

$$\tau_t = exp\left(m + + \theta^{+}\sum_{k=1}^{K}\varphi_k(\omega)W^{+}_{t-k} + \theta^{*}\sum_{k=1}^{K}\varphi_k(\omega)W^{*}_{t-k}\right) \tag{11}$$

4. Data

As an important benchmark price, in line with, Henry Hub natural gas 1-month futures price (hereafter, NYMEX) is used to reflect the natural gas market in the world.[1] The used sample is obtained from EIA website and covered from January 1995 to July 2021. Similar to Giot and Laurent (2004), the return is computed by 100 times the logarithmic difference of prices. Fig. 1 reports the evolution of NYMEX in the whole sample period. In addition, NASA Prediction of Worldwide Energy Resources offers the monthly weather indicators, including wind speed, temperature, humidity, precipitation, and Clear-sky insolation index.[2] Considering Henry Hub is located in Louisiana (US) and considered as the price benchmark for natural gas futures on the New York Mercantile Exchange (Mazighi, 2005), the related monthly weather data for New York City and Louisiana is selected in our study. To ensure the comparability of data, suggested by Urolagin et al. (2021), the *Z*-score method is used to scale the raw weather data.

$$X_n = \frac{X-\mu}{\sigma}, \tag{12}$$

where μ, σ, and X_n present the mean, standard deviation, and normalized values of weather variable, respectively. The descriptive statistics are shown in Table 1. All of time series are stationary based on the results of ADF test.

5. Empirical results

To analyze the predictive power of GARCH-MIDAS model in presence of extreme weather, in line with Rapach and Wohar (2006), in-

[1] The natural gas data can be obtained at the website: https://www.eia.gov.
[2] The weather data can be obtained at the website: https://power.larc.nasa.gov/.

Table 1
Summary statistics for natural gas return and weather indicators.

	NYMEX	New York City					Louisiana				
		Wind speed	Temperature	Humidity	Precipitation	CSII	Wind speed	Temperature	Humidity	Precipitation	CSII
Mean	0.0001	−0.2065	-0.0074	−0.0258	0.4231	1.9483	0.2456	0.6249	−0.0577	0.0544	1.3650
SD	0.0352	0.6565	0.6259	0.6831	2.7346	3.8801	1.4399	1.5492	0.4972	1.6729	3.0265
Max	0.3244	3.5650	1.1156	2.1336	34.1830	8.9904	5.8926	8.7268	1.2314	19.4780	5.8926
Min	−0.3757	−0.7218	−1.8703	−1.0286	−1.1778	−6.7680	7.9289	−3.4784	−0.8289	−0.7071	−6.3639
Skewness	0.2001	1.6068	−0.3505	0.6144	3.4664	−0.1230	0.9021	0.1985	0.4881	3.7485	−0.5869
Kurtosis	6.8439	2.2636	−0.8127	−0.6433	18.0845	−1.1956	0.7770	−0.1239	−0.9112	18.9436	−0.8955
JB	13,021.6212***	4281.9727***	319.6646***	533.6159***	103,911.6484***	413.3648***	1069.5451***	47.9983***	494.6919***	114,979.7293***	604.5711***
ADF	−0.1706***	−1.3420***	−9.2082***	−9.1417***	−21.8999***	−12.1286***	−7.8375***	−9.8959***	−8.0711***	−1.7158***	−14.2458***

Notes: Table 1 reports the summary statistics for natural gas return and weather indicators. NYMEX denotes the used natural gas returns, while wind speed, temperature, humidity, precipitation, and clear-sky insolation index (CSII) present the local weather indicators in New York City and Louisiana. JB and ADF denote the statistics for the normal distribution and stationarity, respectively. In addition, *** present rejection of the null hypothesis at the level of 1%.

sample estimation and out-of-sample test are introduced in our study. Specifically, two subsample are obtained for in-sample and out-of-sample analysis, respectively. The in-sample data covers from January 1995 to August 2017, while the remainder sample is served for out-of-sample test. Following Tashman (2000), a rolling window method is used to obtain the volatility forecasts of the natural gas market. In addition, according to Wang et al. (2020), extreme weather is defined as the most negative and positive 10% of weather data. That is, we assume δ_1=0.1 and δ_2=0.9, where $\delta_i(\mathrm{i}=1,2)$ denote the 10th and 90th quantile level of empirical distribution of weather variables. Obviously, the most negative 10% of weather indicator denotes the extreme bad weather condition, while the most positive 10% presents the extreme good weather condition.

5.1. In-sample estimation results

The results of our models including various weather indictors are reported in Table 2. From the in-sample results, we observe some interesting findings. First, for the short-term volatility, except α and β in GARCH-MIDAS-W-ES including humidity variable for Louisiana are insignificant, most coefficients of α and β in our models are statistically significant. This indicates the strong short-term persistence for NYMEX, which is consistent with the work of Jondeau and Rockinger (2006). Second, for New York City, based on the significance of the coefficients θ, we find that temperature, humidity, precipitation, and clear-sky insolation index have significantly impact on the volatility of NYMEX. More importantly, except normal weather condition, we observe that temperature, humidity, and precipitation under extreme condition have important effect on the volatility of NYMEX based on the significance of the coefficients θ^+ and θ^-. Third, for Louisiana, the impact of wind speed, temperature, and precipitation in extreme condition on the volatility of NYMEX are statistically confirmed. Therefore, similar to Considine (2000) and Liu and Chen (2013), it can be concluded that some of weather indicators under extreme condition exhibit a statistical significant effect on the natural gas volatility.

5.2. Out-of-sample forecasting

To analyze the predictive ability of our proposed model, as mentioned in Hong et al. (2022), three wildly used loss functions are introduced, which are as follows:

$$\mathrm{MAE}=\frac{1}{n}\sum_{i=1}^{n}\left|\sigma_i^2-\hat{\sigma}_i^2\right| \tag{14}$$

$$\mathrm{HMSE}=\frac{1}{n}\sum_{i=1}^{n}\left(1-\sigma_i^2/\hat{\sigma}_i^2\right)^2 \tag{15}$$

$$\mathrm{HMAE}=\frac{1}{n}\sum_{i=1}^{n}\left|1-\sigma_i^2/\hat{\sigma}_i^2\right| \tag{16}$$

where σ_i^2 is the actual volatility value of NYMEX, and $\hat{\sigma}_i^2$ is the predictive value obtained by using various extended GARCH-MIDAS models.

Moreover, we adopt Model Confidence Set (MCS) approach proposed by Hansen et al. (2011) to analyze the predictive performance of the NYMEX's volatility. Two related test statistics, the range statistic (T_R) and the semi-quadratic statistic (T_{SQ}), are used in the MCS test. Methodology, based on the pre-specified threshold confidence level, we can determine whether the predictive model belongs to the set of "best" predictive model or not. Additionally, more details of the MCS test can be found in Ma et al. (2019).

Following Wang et al. (2020), a 90% confidence level is determined, which shows that the predictive model with a p-value smaller than 0.10 can be removed from the set of best predictive model. In addition, 10,000 block bootstraps are used to yield the p-values of the MCS test.

Table 2
Estimation of various GARCH-MIDAS models with weather indicators.

	Wind speed		Temperature		Humidity		Precipitation		CSII	
	GARCH-MIDAS-W	GARCH-MIDAS-W-ES	GARCH-MIDAS-W	GARCH-MIDAS-W-ES	GARCH-MIDAS-W	GARCH-MIDAS-W-ES	GARCH-MIDAS-W	GARCH-MIDAS-W-ES	GARCH-MIDAS-W	GARCH-MIDAS-W-ES
Panel A: New York City										
μ	0.0243	0.6151***	0.0163	0.6195***	0.0175	0.6142***	0.0229	0.6210***	0.0243	0.6117***
α	0.1016***	0.4396***	0.0901***	0.4339***	0.0918***	0.0989***	0.1019***	0.2053***	0.0989***	0.4526***
β	0.8771***	0.5040***	0.8739***`	0.5175***	0.8710***	0.8693***	0.8760***`	0.7913***	0.8802***`	0.5019***
θ	0.0002	3.639e-7	2.4296***	2.4414*	2.3240***	2.8476***	0.8693**	3.5238	−0.2869***`	0.7347
θ^{+}		−0.0007		2.3660		−0.0516		−5.3451***		−0.0019
θ^{-}				4.7971***						
ω	26.306***	0.0103***	1.1842***	1.1157	1.2435***	1.1102***	1.8529***	1.5849***	272.09	1.6231
m	2.2217***	3.6857***	−2.1085***	3.9803***	2.1264***	2.3551***	2.1404**	5.5996***	2.1606***	3.9303***
Panel B: Louisiana										
μ	0.0256	0.6084***	0.0218	0.7673***	0.0208	0.6202***	0.0272	0.6196***	0.0209	0.6104***
α	0.1019***	0.4537***	0.1001***	0.4990***	0.0892***	0.4539	0.1007***	0.4562***	0.0918***	0.4473***
β	0.8772***	0.5021***	0.8787***`	0.5010***	0.8766***	0.5062	0.8778***`	0.5045***	0.8839***`	0.4868***
θ	6.940e-7	1.0896***	1.3432***	0.2211***	−2.8680***	6.9133***	−0.0001	−0.5794	1.7729***`	2.7800***
θ^{+}		1.1112***		−0.712***		−0.0005		−0.5988**		−0.6076
θ^{-}				0.0853***						
ω	0.2151***	−1.8840***	1.5718***	2.8115***	1.0000***	1.1182***	4.7979***	−4.4798	1.0000	1.1429***
m	2.2368***	4.0672***	1.9253***	0.0678***	2.2283***	4.8824***	2.2053**	4.2758***	0.5920***	1.4601***

Notes: Table 2 reports the estimation of our GARCH-MIDAS models including weather indicators. Panels A and B denote the used weather variables in New York City and Louisiana, respectively. CSII denotes clear-sky insolation index. In addition, ***,**,* present rejection of the null hypothesis at the level of 1%,5%,and 10%.

Tables 3 and 4 show the results using the weather data of New York and Louisiana, respectively. From the results of Table 3, we observe that the GARCH-MIDAS models including weather or extreme weather exhibit superior predictive power than the GARCH-MIDAS model excluding weather indicators. This conclusion is similar to the work of Wang et al. (2020) which shows that the GARCH-MIDAS model including extreme effect yields more predictive accuracy. Moreover, for New York City, the GARCH-MIDAS models with extreme temperature, humidity, and precipitation perform better than other predictive models, because the MCS *p*-values of the models including extreme variables are all larger than 0.10. Similar to the results of New York City, based on Table 4 by using the weather data of Louisiana, GARCH-MIDAS with extreme weather, such as wind speed, temperature, and precipitation, can survive in the MCS test under all loss functions. In short, we observe that adding weather indictors in the GARCH-MIDAS model can indeed produce more accuracy forecasts, which is similar to Taylor and Buizza (2003), Liang et al. (2021) and Wang et al. (2021). More importantly, we further demonstrate that some weather indictors, such as temperature, humidity, and precipitation, have extreme effect on the out-of-sample prediction for the natural gas volatility, which is not discovered in previous studies.

Furthermore, in line with Marcucci (2005), the success ratio (SR) is also introduced to analyze the predictive power from the perspective of directional precision. Besides, Pesaran and Timmermann (2009) test (PT) is employed to analyze the statistical difference between the success ratio and 0.5. The related results are shown in Table 5. For instance, for New York City, the success ratios of GARCH-MIDAS with extreme weather (wind speed, temperature, humidity, precipitation, and sky insolation index) are 0.6571, 0.7034, 0.7034, 0.7034, and 0.6598, respectively. Moreover, we observe that the success ratios of all models are larger than 0.5, indicating that all GARCH-MIDAS models can obtain statistical directional accuracy. However, the success ratios of the GARCH-MIDAS models including extreme temperature or precipitation variables of New York and Louisiana are the largest among all predictive models. This implies that incorporating extreme temperature or precipitation variables into the GARCH-MIDAS model can obtain more directional accuracy. Finally, the *p*-values in Table 5 imply that our proposed models significantly enhance the predictive accuracy for the NYMEX's volatility change direction. Besides, our findings using monthly weather data is consistent with the work of Mu (2007) using daily data. The same conclusions indicate a significant weather impact on natural gas market. Therefore, our results is robust from a data frequency perspective.

5.3. Discussion

From the in-sample and out-of-sample results, considering the impact of extreme weather in the GARCH-MIDAS model is beneficial for the natural gas volatility prediction. However, why does the GARCH-MIDAS model including extreme weather perform better? We further analyze the reasons as follows.

There are two possible channels through which extreme weather indicators may affect the volatility in the natural gas market. First, extreme weather often increase the uncertainty in economic and financial conditions (Linnenluecke et al., 2012), which largely leads to the changes in natural gas supply and demand based on the changes in consumer expectations. This may further cause natural gas price fluctuations. For instance, huge damages to society caused by hurricanes, droughts, severe floods, snow storms, and other extreme weather events usually induce a surge in uncertainty (Tol, 2005). Specifically, extreme bad weather may largely have a notable negative effect on the production capacity, resident's consumption, supply chains, local labor in the natural gas market (Hatfield and Prueger, 2015; Lee and Olasehinde-Williams, 2021). For instance, the natural gas prices are expected to remain higher in the next few months under the shock of Hurricane Ida. Because of the strong domestic natural gas consumption and the decrease in natural gas production, Henry Hub Spot prices may have a 16% increase from EIA's expectations.[3] Similarly, natural gas prices may exhibit largely volatile during the powerful winter storm when supply and demand can swing sharply.[4] Based on the above considerations, when the supply and demand for natural gas swing sharply under extreme weather, the natural gas market tends to show large fluctuations.

Second, some studies discover that some environmental indicators can be considered as mood-proxy variables for most of investors

[3] More details can be found in "Hurricane Ida contributes to higher natural gas prices" (https://talkbusiness.net/2021/09/).

[4] More details can be found in "Natural gas spikes 16% ahead of winter storm" (https://edition.cnn.com/2022/02/).

Table 3
MCS test for various GARCH-MIDAS models with weather indicators in New York City.

	MAE		HMSE		HMAE	
	T_R	T_{SQ}	T_R	T_{SQ}	T_R	T_{SQ}
Panel A:Wind speed						
GARCH-MIDAS without weather	**0.8854**	**0.8854**	**0.1013**	**0.1011**	**0.1042**	**0.0816**
GARCH-MIDAS with weather	**1**	**1**	**1**	**1**	**1**	**1**
GARCH-MIDAS with extreme weather	0	0	**0.1013**	0.0893	**0.1042**	**0.0816**
Panel B: Temperature						
GARCH-MIDAS without weather	0.0826	0.0501	**0.3097**	**0.3976**	**0.3258**	**0.27420**
GARCH-MIDAS with weather	0.0826	0.0501	**0.4453**	**0.4453**	**0.3645**	**0.3645**
GARCH-MIDAS with extreme weather	**1**	**1**	**1**	**1**	**1**	**1**
Panel C: Humidity						
GARCH-MIDAS without weather	0	0	**0.2060**	**0.2560**	**0.3077**	**0.3655**
GARCH-MIDAS with weather	0.0170	0.0170	**0.5805**	**0.5805**	**0.6124**	**0.6124**
GARCH-MIDAS with extreme weather	**1**	**1**	**1**	**1**	**1**	**1**
Panel D: Precipitation						
GARCH-MIDAS without weather	0	0	**0.1040**	**0.1076**	**0.1419**	**0.1629**
GARCH-MIDAS with weather	**0.9880**	**0.9880**	**0.4359**	**0.4359**	**0.5015**	**0.5015**
GARCH-MIDAS with extreme weather	**1**	**1**	**1**	**1**	**1**	**1**
Panel E: Clear-sky insolation index						
GARCH-MIDAS without weather	**0.6593**	**0.6593**	**0.1549**	0.0968	**0.1463**	0.0981
GARCH-MIDAS with weather	**1**	**1**	**1**	**1**	**1**	**1**
GARCH-MIDAS with extreme weather	0	0	**0.1549**	0.0951	**0.1463**	0.0981

Notes: This table reports the *p*-values of MCS test when using the weather indicators in New York City. GARCH-MIDAS without weather, GARCH-MIDAS with weather, and GARCH-MIDAS with extreme weather denote the standard GARCH-MIDAS model, the GARCH-MIDAS-W model, and the GARCH-MIDAS-W-ES model, respectively. The *p*-values larger than 0.10 are indicated in bold and underlined, indicating that the related model shows better predictive power.

Table 4
MCS test for various GARCH-MIDAS models with weather indicators in Louisiana.

	MAE		HMSE		HMAE	
	T_R	T_{SQ}	T_R	T_{SQ}	T_R	T_{SQ}
Panel A: Wind speed						
GARCH-MIDAS without weather	0	0	0.0894	0.0875	0.0866	0.0847
GARCH-MIDAS with weather	0	0	0.0894	0.0894	0.0866	0.0866
GARCH-MIDAS with extreme weather	**1**	**1**	**1**	**1**	**1**	**1**
Panel B: Temperature						
GARCH-MIDAS without weather	0.0493	0.0493	**0.1026**	**0.1049**	**0.1204**	**0.1319**
GARCH-MIDAS with weather	0.0245	0.0111	**0.4552**	**0.4552**	**0.3857**	**0.3857**
GARCH-MIDAS with extreme weather	**1**	**1**	**1**	**1**	**1**	**1**
Panel C: Humidity						
GARCH-MIDAS without weather	0.0049	0.0049	**0.2455**	**0.1989**	**0.2215**	**0.1885**
GARCH-MIDAS with weather	**1**	**1**	**1**	**1**	**1**	**1**
GARCH-MIDAS with extreme weather	0	0	**0.2455**	**0.1989**	**0.2215**	**0.1521**
Panel D: Precipitation						
GARCH-MIDAS without weather	**0.7074**	**0.7074**	**0.1071**	**0.2097**	**0.1125**	**0.1203**
GARCH-MIDAS with weather	0.0413	0.0280	**0.4526**	**0.4526**	**0.3768**	**0.3768**
GARCH-MIDAS with extreme weather	**1**	**1**	**1**	**1**	**1**	**1**
Panel E: Clear-sky insolation index						
GARCH-MIDAS without weather	**0.6786**	**0.6786**	**0.2331**	**0.2331**	**0.2502**	**0.2468**
GARCH-MIDAS with weather	**1**	**1**	**1**	**1**	**1**	**1**
GARCH-MIDAS with extreme weather	0.0016	0.0048	**0.2072**	**0.2044**	**0.2502**	**0.2025**

Notes: This table reports the *p*-values of MCS test when using the weather indicators in Louisiana. GARCH-MIDAS without weather, GARCH-MIDAS with weather, and GARCH-MIDAS with extreme weather denote the standard GARCH-MIDAS model, the GARCH-MIDAS-W model, and the GARCH-MIDAS-W-ES model, respectively. The *p*-values larger than 0.10 are indicated in bold and underlined, indicating that the related model shows better predictive power.

(Dowling and Lucey, 2005). Based on behavioral finance, Saunders (1993) adopts cloud cover in New York City as a mood-proxy indicator and finds that there is a close linkage between weather variable and the stock market. Similar to his work, many papers employ the following weather indicators as a proxy for investors' mood: temperature (Chang et al., 2006), humidity (Lu and Chou, 2012), sunny days (Kaustia and Rantapuska, 2016), and rain precipitation (Kliger and Levy, 2003). Based on medical knowledge, extreme weather shocks usually significantly affects the cognitive functioning and personal psychological mood. In general, bad weather often lead to significant physical discomfort for people, such as fatigue, exhaustion, depression, and

Table 5
The results of the success ratio.

	Wind speed		Temperature		Humidity		Precipitation		Clear-sky insolation index	
	Success ratio	p_value	Success ratio	p_value	Success ratio	p_value	Success ratio	p_value	Success ratio	p_value
Panel A: New York City										
GARCH-MIDAS-without weather	0.7034	0.0000	0.6560	0.0000	0.6890	0.0000	0.6963	0.0000	0.7034	0.0000
GARCH-MIDAS-with weather	0.7049	0.0000	0.6910	0.0000	0.6880	0.0000	0.7030	0.0000	0.7042	0.0000
GARCH-MIDAS-extreme weather	0.6571	0.0000	0.7034	0.0000	0.7034	0.0000	0.7034	0.0000	0.6598	0.0000
Panel B: Louisiana										
GARCH-MIDAS-without weather	0.7034	0.0000	0.7034	0.0000	0.6936	0.0000	0.7034	0.0000	0.7034	0.0000
GARCH-MIDAS-with weather	0.7049	0.0000	0.7102	0.0000	0.7015	0.0000	0.7049	0.0000	0.7038	0.0000
GARCH-MIDAS-extreme weather	0.7061	0.0000	0.7162	0.0000	0.6504	0.0000	0.7068	0.0000	0.6564	0.0000

Notes: This table shows the results of our models by the success ratio. The Pesaran and Timmermann (2009) (PT) is used to check whether the success probability is less than or equal to 0.5.

anxiety (Cunsolo and Ellis, 2018). Particularly, the occurrence of extreme weather may trigger deteriorations (Maystadt and Ecker, 2014). Yuen and Lee (2003) point out that people are likely to avoid (take) risk in a negative (positive) mood. Hence, extreme weather leads to person's mood changes which is closely related to individuals' investment decisions, price trend evaluation, and mispricing in natural gas market. More seriously, exposure to outside under extreme weather conditions is largely related to the performance of cognitive-related and emotion-related activities. Based on the above analysis, through a psychological and emotional channel, a great negative (positive) change in weather are likely to induce investors to be more pessimistic (optimistic) and then have a negative (positive) effect on the direction and/or magnitude of investment in the natural gas market (Nofsinger, 2005).

Based on the empirical results, we observe some weather indicators such as temperature, humidity, and precipitation are the major weather-related factors to affect the natural gas volatility. On the contrary, wind speed and sky insolation index have a limited effect on the natural gas market. Our findings are consistent with Shahzad (2019), who also demonstrates a mixed influence of different weather indicators on stock volatility. One reasonable explanation suggested by Batten et al. (2021) and Lee et al. (2022) is that the determinants of energy's prices are not fixed over time. Therefore, the weather indicators may exhibit an important, secondary, or unimportant role on the natural gas market in a certain time period. To illustrate this, the used out-of-sample is divided into two parts: the first part covers from August 2017 to January 2020 excluding the coronavirus (COVID-19) pandemic, while the remainder part spans from February 2020 to July 2021 including COVID-19 pandemic. MCS test is used for the two subsample, respectively. Based on Table 6, GARCH-MIDAS models adding weather/extreme weather information produce more predictive accuracy than the standard GARCH-MIDAS model during the period of no pandemic. On the contrary, the extended models including weather indicators exhibit poor predictive accuracy after the outbreak of COVID-19. Specifically, when temperature, humidity, and precipitation are taken account, the standard GARCH-MIDAS model obtain the largest MCS values. This indicates that the normal and extreme weather indictors cannot play an expected role in natural gas volatility prediction under other types of extreme shocks (Lee et al., 2021; Liu et al., 2021b, 2021c; Zhang et al., 2022). Similarly, compared with the impact of the Russian-Ukrainian conflict in 2022 on the natural gas market, extreme weather may not a major factor to affect the volatility in the same period (Zhiznin and Dineva, 2022). Nevertheless, our empirical results confirm that it is necessary to take the extreme weather into account when the natural gas volatility prediction is carried out.

6. Robustness checks

6.1. Different extreme thresholds

Though the extreme weather is determined by using the most negative and positive 10% of weather data. In line with Wang et al. (2020), we also employ different extreme thresholds to analyze the robustness of our new models. Specifically, we assume δ_1=0.2 and δ_2=0.8 for identifying extreme bad and good weather. Tables 7 and 8 reposts the results for New York and Louisiana. It can be seen that a similar empirical conclusion is obtained. GARCH-MIDAS models including weather indicators can achieve better predictive performance than the model without weather indicators. Meanwhile, we observe that the MCS *p*-values of GARCH-MIDAS-W-ES model are largest when temperature, humidity, and precipitation in extreme condition are included. For Louisiana, we also observe that GARCH-MIDAS-W or GARCH-MIDAS-W-ES model exhibit the best predictive power for each weather indicators. This conclusion is similar to Mu (2007) and Nick and Thoenes (2014a) who discover the close connection between natural gas market and weather information. Especially for wind speed, temperature, and precipitation, the predictive model including extreme weather condition outperforms other models. To sum up, similar to the empirical findings in Section 4.3, temperature and precipitation can provide more useful predictive information under extreme shocks to improve predictive power for the natural gas price volatility.

6.2. Different predictive windows

Rossi and Inoue (2012) indicate that the out-of-sample results may depend on the selected predictive window. Inspired by Liang et al. (2022), we employ alternative out-of-sample predictive window to examine the robustness of GARCH-MIDAS-W-ES model. Specifically, different from using 800 observations for out-of-sample test, 1000 observations from December 2014 to July 2021 are employed for the MCS test. The corresponding results for New York City and Louisiana are shown in Tables 9 and 10. For New York City, we find that all models can survive the MCS test under HMSE and HMAE, while GARCH-MIDAS-W or GARCH-MIDAS-W-ES models can survive the MCS test under MAE. However, the GARCH-MIDAS-W-ES models including extreme condition of temperature, humidity, and precipitation are more beneficial for predicting the natural gas volatility than other predictive models. Besides, the similar results of MCS test can be found for Louisiana in Table 10. In short, our results offers some novel evidence that adding extreme weather information into GARCH-MIDAS model can indeed enhance the predictive ability of natural gas volatility.

6.3. Different out-of-sample method

As a standard approach to analyze the forecasting performance, the

Table 6
MCS test before and after COVID-19 pandemic.

	MAE		HMSE		HMAE	
	T_R	T_{SQ}	T_R	T_{SQ}	T_R	T_{SQ}
The period from August 2017 to January 2020						
Panel A: Wind speed						
GARCH-MIDAS	0	0	**0.1540**	**0.1540**	**0.1991**	**0.1991**
GARCH-MIDAS with weather	**1**	**1**	**1**	**1**	**1**	**1**
GARCH-MIDAS with extreme weather	**0.2216**	**0.2216**	**0.1540**	**0.1031**	**0.1739**	**0.0766**
Panel B: Temperature						
GARCH-MIDAS without weather	**0.4352**	**0.4352**	**0.2715**	**0.2579**	**0.2476**	**0.2539**
GARCH-MIDAS with weather	0.0971	0.0668	**0.2715**	**0.2579**	**0.2476**	**0.2539**
GARCH-MIDAS with extreme weather	**1**	**1**	**1**	**1**	**1**	**1**
Panel C: Humidity						
GARCH-MIDAS without weather	**0.3792**	**0.3792**	**0.3393**	**0.4927**	**0.4279**	**0.4276**
GARCH-MIDAS with weather	0.0025	0.0026	**0.5622**	**0.5622**	**0.5406**	**0.5406**
GARCH-MIDAS with extreme weather	**1**	**1**	**1**	**1**	**1**	**1**
Panel D: Precipitation						
GARCH-MIDAS without weather	**0.1453**	**0.1453**	**0.1514**	**0.1743**	0.0998	**0.1144**
GARCH-MIDAS with weather	0.0795	0.0407	**0.1476**	**0.1743**	0.0998	**0.1144**
GARCH-MIDAS with extreme weather	**1**	**1**	**1**	**1**	**1**	**1**
Panel E: Clear-sky insolation index						
GARCH-MIDAS without weather	**0.1928**	**0.1928**	**0.1880**	**0.1880**	**0.2162**	**0.2162**
GARCH-MIDAS with weather	**1**	**1**	**1**	**1**	**1**	**1**
GARCH-MIDAS with extreme weather	0	0	0.0911	0.0910	0.0914	0.0913
The period from February 2020 to July 2021						
Panel A: Wind speed						
GARCH-MIDAS	**0.7303**	**0.7303**	**0.3122**	**0.3122**	**0.1263**	**0.1263**
GARCH-MIDAS with weather	**1**	**1**	**1**	**1**	**1**	**1**
GARCH-MIDAS with extreme weather	**0.1583**	**0.1589**	0.0567	0.0604	0.0023	0.0013
Panel B: Temperature						
GARCH-MIDAS without weather	**1**	**1**	**1**	**1**	**1**	**1**
GARCH-MIDAS with weather	**0.5407**	**0.5407**	**0.8116**	**0.8116**	0.0495	0.0888
GARCH-MIDAS with extreme weather	0	0	0.0043	0.0036	**0.2224**	**0.2224**
Panel C: Humidity						
GARCH-MIDAS without weather	**1**	**1**	**1**	**1**	**1**	**1**
GARCH-MIDAS with weather	**0.2716**	**0.2716**	**0.6966**	**0.6966**	0.007	0.007
GARCH-MIDAS with extreme weather	0	0	0.0005	0.0004	0	0
Panel D: Precipitation						
GARCH-MIDAS without weather	**1**	**1**	**1**	**1**	**1**	**1**
GARCH-MIDAS with weather	**0.5961**	**0.5961**	**0.6110**	**0.6110**	**0.1676**	**0.1676**
GARCH-MIDAS with extreme weather	0.0629	**0.1610**	**0.2725**	**0.3288**	0	0
Panel E: Clear-sky insolation index						
GARCH-MIDAS without weather	**0.6344**	**0.6344**	**0.2864**	**0.2864**	0.0498	0.0498
GARCH-MIDAS with weather	**1**	**1**	**1**	**1**	**1**	**1**
GARCH-MIDAS with extreme weather	**0.1450**	**0.1462**	0.0537	0.0607	0.0037	0.0022

Notes: This table reports the *p*-values of MCS test before and after COVID-19 pandemic. GARCH-MIDAS without weather, GARCH-MIDAS with weather, and GARCH-MIDAS with extreme weather denote the standard GARCH-MIDAS model, the GARCH-MIDAS-W model, and the GARCH-MIDAS-W-ES model, respectively. The *p*-values larger than 0.10 are indicated in bold and underlined, indicating that the related model shows better predictive power.

out-of-sample R^2 (R^2_{oos}) is also introduced to examine the robustness of our out-of-sample results (Zhang et al., 2019). This approach can analyze the enhancement of forecasting power between the forecasting model and benchmark model by using the mean squared prediction errors (MSPE). The related statistic is written as follows:

$$R^2_{oos} = 1 - \frac{MSPE_{modelj}}{MSPE_{bench}}, \tag{17}$$

where $MSPE_{modelj}$ and $MSPE_{bench}$ present the MSPE of the forecasting and benchmark models, respectively. We employ the standard GARCH-MIDAS model excluding weather information as the benchmark model. The fact that $R^2_{oos} > 0$ indicates that the forecasts obtained by the extended model show better predictive accuracy than the ones obtained by the benchmark model. Meanwhile, the MSPE-adjusted statistic is further introduced to determine whether there is statistical difference between the models with and without weather indicators (Clark and West, 2007). The results are shown in Table 11. We observe that the R^2_{oos} of GARCH-MIDAS-W model under all weather indicators are larger than zero, indicating that considering weather information in GARCH-MIDAS model obtains more accuracy forecasts than the benchmark model. Moreover, the GARCH-MIDAS-W-ES models under the extreme condition of temperature and precipitation in both New York City and Louisiana exhibit better predictive accuracy ability than the benchmark model. This implies that volatility model adding extreme or non-extreme weather indicators has a better predictive ability than the model without weather information.

6.4. Using the weather data in Texas

In the above study, to examine the impact of weather indicators on the natural gas market, we choose the weather variables in New York and Louisiana. To check the robustness of our results for weather data in different city, the related weather variables in Texas (US) is also introduced in our study.[5] Using the data of wind speed, temperature, humidity, precipitation, and Clear-sky insolation index in Texas, we further conduct the in-sample estimation and out-of-sample forecasting based on our extended GARCH-MIDAS models with weather information. The

[5] The related data are obtained at the website: https://power.larc.nasa.gov/.

Table 7
MCS test with weather indicators in New York City using different extreme thresholds.

	MAE		HMSE		HMAE	
	T_R	T_{SQ}	T_R	T_{SQ}	T_R	T_{SQ}
Panel A: Wind speed						
GARCH-MIDAS without weather	**0.8818**	**0.8818**	**0.1103**	**0.1089**	**0.1012**	**0.0780**
GARCH-MIDAS with weather	**1**	**1**	**1**	**1**	**1**	**1**
GARCH-MIDAS with extreme weather	0	0	**0.1103**	0.0991	**0.1012**	0.0780
Panel B: Temperature						
GARCH-MIDAS without weather	0.0874	0.0556	**0.3158**	**0.3905**	**0.3133**	**0.2714**
GARCH-MIDAS with weather	0.0874	0.0556	**0.4350**	**0.4350**	**0.3587**	**0.3587**
GARCH-MIDAS with extreme weather	**1**	**1**	**1**	**1**	**1**	**1**
Panel C: Humidity						
GARCH-MIDAS without weather	0.0196	0.0196	**0.2785**	**0.2127**	**0.4620**	**0.3785**
GARCH-MIDAS with weather	0	0	**0.2785**	**0.2127**	**0.4620**	**0.3785**
GARCH-MIDAS with extreme weather	**1**	**1**	**1**	**1**	**1**	**1**
Panel D: Precipitation						
GARCH-MIDAS without weather	0.0908	0.0706	**0.1053**	**0.1047**	**0.1322**	**0.1334**
GARCH-MIDAS with weather	**0.9856**	**0.9856**	**0.4525**	**0.4525**	**0.3833**	**0.3833**
GARCH-MIDAS with extreme weather	**1**	**1**	**1**	**1**	**1**	**1**
Panel E: Clear-sky insolation index						
GARCH-MIDAS without weather	**0.6596**	**0.6596**	**0.3338**	**0.2315**	**0.1898**	**0.1365**
GARCH-MIDAS with weather	**1**	**1**	**1**	**1**	**1**	**1**
GARCH-MIDAS with extreme weather	0	0	**0.3338**	**0.2315**	**0.1898**	**0.1365**

Notes: This table reports the *p*-values of MCS test. GARCH-MIDAS without weather, GARCH-MIDAS with weather, and GARCH-MIDAS with extreme weather denote the standard GARCH-MIDAS model, the GARCH-MIDAS-W model, and the GARCH-MIDAS-W-ES model, respectively. The *p*-values larger than 0.10 are indicated in bold and underlined, indicating that the related model shows better predictive power.

Table 8
MCS test with weather indicators in Louisiana using different extreme thresholds.

	MAE		HMSE		HMAE	
	T_R	T_{SQ}	T_R	T_{SQ}	T_R	T_{SQ}
Panel A:Wind speed						
GARCH-MIDAS without weather	**0.8805**	**0.8805**	**0.1011**	**0.1001**	**0.1032**	0.0781
GARCH-MIDAS with weather	0	0	**0.1011**	0.0923	**0.1032**	0.0781
GARCH-MIDAS with extreme weather	**1**	**1**	**1**	**1**	**1**	**1**
Panel B: Temperature						
GARCH-MIDAS without weather	0.0853	0.0594	**0.3360**	**0.4076**	**0.3088**	**0.2690**
GARCH-MIDAS with weather	0.0853	0.0594	**0.4538**	**0.4538**	**0.3679**	**0.3679**
GARCH-MIDAS with extreme weather	**1**	**1**	**1**	**1**	**1**	**1**
Panel C: Humidity						
GARCH-MIDAS without weather	0.0165	0.0165	**0.2076**	**0.2023**	**0.2149**	**0.2149**
GARCH-MIDAS with weather	**1**	**1**	**1**	**1**	**1**	**1**
GARCH-MIDAS with extreme weather	0	0	**0.2076**	**0.2023**	**0.1588**	**0.1604**
Panel D: Precipitation						
GARCH-MIDAS without weather	0.0635	0.0491	**0.1032**	**0.1044**	**0.1351**	**0.1359**
GARCH-MIDAS with weather	**0.9866**	**0.9866**	**0.4516**	**0.4516**	**0.3698**	**0.3698**
GARCH-MIDAS with extreme weather	**1**	**1**	**1**	**1**	**1**	**1**
Panel E: Clear-sky insolation index						
GARCH-MIDAS without weather	**0.6635**	**0.6635**	**0.1968**	0.0940	**0.1464**	0.0977
GARCH-MIDAS with weather	**1**	**1**	**1**	**1**	**1**	**1**
GARCH-MIDAS with extreme weather	0	0	**0.1968**	0.0933	**0.1464**	0.0977

Notes: This table reports the *p*-values of MCS test. GARCH-MIDAS without weather, GARCH-MIDAS with weather, and GARCH-MIDAS with extreme weather denote the standard GARCH-MIDAS model, the GARCH-MIDAS-W model, and the GARCH-MIDAS-W-ES model, respectively. The *p*-values larger than 0.10 are indicated in bold and underlined, indicating that the related model shows better predictive power.

corresponding results are shown in Table 12. We observe that GARCH-MIDAS models including weather indicators in Texas still exhibit better predictive ability than the standard GARCH-MIDAS model. Additionally, when the extreme temperature and precipitation in Texas are included, the GARCH-MIDAS-W-ES model shows better predictive performance than the GARCH-MIDAS-W model, indicating the necessity of considering extreme weather.

6.5. Using natural gas spot prices

Many studies point out that there is close linkage between the natural gas futures prices and spot prices. However, some studies provide a mixed relationship. Mishra and Smyth (2016) argue that natural gas futures prices cannot predict spot prices, while Zhang and Liu (2018) discover the bidirectional causal link between spot and futures prices. Hence, instead using the futures prices, we further adopt natural gas spot prices obtained by EIA in this subsection.[6] Except for the natural gas data, the used weather data remain unchanged in our study. Based on the results of Table 13, we observe that GARCH-MIDAS models including weather indicators in New York can still produce more accuracy forecasts than the standard GARCH-MIDAS model. Particularly, the GARCH-MIDAS-W-ES model including extreme information of wind

[6] The related data are obtained at the website: https://www.eia.gov.

Table 9
MCS test with weather indicators in New York using different predictive windows.

	MAE		HMSE		HMAE	
	T_R	T_{SQ}	T_R	T_{SQ}	T_R	T_{SQ}
Panel A: Wind speed						
GARCH-MIDAS	0	0	**0.2695**	**0.5831**	**0.1770**	**0.4633**
GARCH-MIDAS with weather	**1**	**1**	**1**	**1**	**1**	**1**
GARCH-MIDAS with extreme weather	0	0	**0.6061**	**0.6061**	**0.8295**	**0.8295**
Panel B: Temperature						
GARCH-MIDAS without weather	0.0471	0.0471	**0.6041**	**0.6041**	**0.8290**	**0.8290**
GARCH-MIDAS with weather	0.0001	0.0004	**0.6033**	**0.6038**	**0.6366**	**0.6364**
GARCH-MIDAS with extreme weather	**1**	**1**	**1**	**1**	**1**	**1**
Panel C: Humidity						
GARCH-MIDAS without weather	**0.2507**	**0.2507**	**0.6054**	**0.6054**	**0.8273**	**0.8273**
GARCH-MIDAS with weather	0.0001	0.0001	**0.3023**	**0.6043**	**0.3361**	**0.6053**
GARCH-MIDAS with extreme weather	**1**	**1**	**1**	**1**	**1**	**1**
Panel D: Precipitation						
GARCH-MIDAS without weather	**0.9953**	**0.9953**	**0.2734**	**0.6001**	**0.1451**	**0.2848**
GARCH-MIDAS with weather	0	0	**0.8531**	**0.8531**	**0.4810**	**0.4810**
GARCH-MIDAS with extreme weather	**1**	**1**	**1**	**1**	**1**	**1**
Panel E: Clear-sky insolation index						
GARCH-MIDAS without weather	0	0	**0.6130**	**0.6127**	**0.8259**	**0.8259**
GARCH-MIDAS with weather	**1**	**1**	**1**	**1**	**1**	**1**
GARCH-MIDAS with extreme weather	0	0	**0.6130**	**0.6127**	**0.6325**	**0.6324**

Notes: This table reports the *p*-values of MCS test when using the weather indicators in New York City under different predictive windows. GARCH-MIDAS without weather, GARCH-MIDAS with weather, and GARCH-MIDAS with extreme weather denote the standard GARCH-MIDAS model, the GARCH-MIDAS-W model, and the GARCH-MIDAS-W-ES model, respectively. The *p*-values larger than 0.10 are indicated in bold and underlined, indicating that the related model shows better predictive power.

Table 10
MCS test with weather indicators in Louisiana using different predictive windows.

	MAE		HMSE		HMAE	
	T_R	T_{SQ}	T_R	T_{SQ}	T_R	T_{SQ}
Panel A: Wind speed						
GARCH-MIDAS without weather	0.0432	0.0432	**0.6086**	**0.6091**	**0.8612**	**0.8608**
GARCH-MIDAS with weather	0	0	**0.6086**	**0.6091**	**0.8612**	**0.8608**
GARCH-MIDAS with extreme weather	**1**	**1**	**1**	**1**	**1**	**1**
Panel B: Temperature						
GARCH-MIDAS without weather	0.0092	0.0241	0.0890	0.0955	0.0963	0.0905
GARCH-MIDAS with weather	**0.7486**	**0.7486**	**0.5157**	**0.5157**	**0.2009**	**0.2009**
GARCH-MIDAS with extreme weather	**1**	**1**	**1**	**1**	**1**	**1**
Panel C: Humidity						
GARCH-MIDAS without weather	0.0224	0.0224	**0.6038**	**0.6059**	**0.8594**	**0.8392**
GARCH-MIDAS with weather	**1**	**1**	**1**	**1**	**1**	**1**
GARCH-MIDAS with extreme weather	0	0	**0.6053**	**0.6059**	**0.8594**	**0.8461**
Panel D: Precipitation						
GARCH-MIDAS without weather	**1**	**1**	**0.6082**	**0.6082**	**0.8341**	**0.8341**
GARCH-MIDAS with weather	0.0971	0.0971	**0.5165**	**0.6076**	**0.4189**	**0.6313**
GARCH-MIDAS with extreme weather	**1**	**1**	**1**	**1**	**1**	**1**
Panel E: Clear-sky insolation index						
GARCH-MIDAS without weather	**0.8168**	**0.8168**	**0.3135**	**0.5816**	**0.1494**	**0.2957**
GARCH-MIDAS with weather	**1**	**1**	**1**	**1**	**1**	**1**
GARCH-MIDAS with extreme weather	0	0.0001	**0.6299**	**0.6299**	**0.6952**	**0.6952**

Notes: This table reports the *p*-values of MCS test when using the weather indicators in Louisiana under different predictive windows. GARCH-MIDAS without weather, GARCH-MIDAS with weather, and GARCH-MIDAS with extreme weather denote the standard GARCH-MIDAS model, the GARCH-MIDAS-W model, and the GARCH-MIDAS-W-ES model, respectively. The *p*-values larger than 0.10 are indicated in bold and underlined, indicating that the related model shows better predictive power.

speed, temperature, and precipitation can do better job than the GARCH-MIDAS-W model. Although the weather variables that significantly improve the predictive power for the natural gas volatility are different when the spot and futures prices are selected, respectively, the results also reveal that the extreme effect of weather indicators can play an important role in predicting the natural gas volatility.

7. Conclusion

There are a great number of studies regarding the volatility in natural gas market. However, few studies attempt to investigate the linkage between the natural gas volatility and extreme weather. Considering the important impact of extreme weather on the natural gas market, we fill this gap by developing extended GARCH-MIDAS models including extreme and normal weather separately. Specifically, the proposed GARCH-MIDAS-W model can capture the average effect of weather indictors on long-term volatility, while the developed GARCH-MIDAS-W-ES model can analyze the effect of extreme and normal weather information on natural gas volatility, respectively. Moreover, in empirical analysis, we conduct in-sample estimation to examine whether the weather-related parameters in our models are statistically significant,

Table 11
The results of out-of-sample R^2.

		R^2 (%)	MSFE adjusted	*p*-values
New York City	Panel A: Wind speed			
	GARCH-MIDAS with weather	0.4907*	1.4112	0.07909
	GARCH-MIDAS with extreme weather	−15.5006	−0.5790	0.71879
	Panel B: temperature			
	GARCH-MIDAS with weather	0.8292**	2.2438	0.01248
	GARCH-MIDAS with extreme weather	2.9919***	3.1868	0.0007
	Panel C: humidity			
	GARCH-MIDAS with weather	0.7483**	2.2276	0.0130
	GARCH-MIDAS with extreme weather	0.2234**	1.7960	0.0363
	Panel D: precipitation			
	GARCH-MIDAS with weather	0.01788*	1.3620	0.0866
	GARCH-MIDAS with extreme weather	0.36888**	1.1554	0.0239
	Panel E: Clear-sky insolation index			
	GARCH-MIDAS with weather	0.3605*	1.3564	0.0878
	GARCH-MIDAS with extreme weather	−16.6292	−0.7390	0.7701
Louisiana	Panel A: Wind speed			
	GARCH-MIDAS with weather	0.4281***	1.3458	0.0891
	GARCH-MIDAS with extreme weather	0.4832***	1.3904	0.0821
	Panel B: Temperature			
	GARCH-MIDAS with weather	0.4690*	1.3546	0.0878
	GARCH-MIDAS with extreme weather	0.5967**	0.7982	0.0124
	Panel C: Humidity			
	GARCH-MIDAS with weather	0.7287**	2.3238	0.0101
	GARCH-MIDAS with extreme weather	−18.8873	−0.4478	0.6729
	Panel D: Precipitation			
	GARCH-MIDAS with weather	0.4749*	1.3837	0.0832
	GARCH-MIDAS with extreme weather	0.4880*	1.3895	0.0824
	Panel E: Clear-sky insolation index			
	GARCH-MIDAS with weather	0.4216*	1.5430	0.0614
	GARCH-MIDAS with extreme weather	−16.0923	−0.6629	0.7463

Notes: This table shows the results of our models by out-of-sample R^2. GARCH-MIDAS with weather and GARCH-MIDAS with extreme weather denote the GARCH-MIDAS-W model and the GARCH-MIDAS-W-ES model, respectively. Additionally, the MSPE-adjusted is used to test the statistical significance of R^2. *, **, and *** mean significance at the 10%, 5%, and 1% levels, respectively.

and out-of-sample test to explore whether our new models can outperform the traditional model. A set of empirical results exhibit that our new model considering weather indicators does an excellent job in predicting natural gas volatility. More importantly, we demonstrate that extreme weather can play a crucial role in volatility forecasting. Specially, GARCH-MIDAS-W-ES models including temperature or precipitation achieve the best accuracy forecasts in natural gas volatility forecasting. This implies that it is necessary to analyze the role of extreme weather in volatility forecasting in natural gas market. Obviously, our new weather-related GARCH-MIDAS-ES model can exhibit a new insight on the natural gas volatility forecasting.

The strong evidence in our study offer several important implications for natural gas market manager and policy makers. First, extreme weather information must be considered when we examine the volatility

Table 12
MCS test with weather indicators in Texas.

	MAE		HMSE		HMAE	
	T_R	T_{SQ}	T_R	T_{SQ}	T_R	T_{SQ}
Panel A: Wind speed						
GARCH-MIDAS without weather	**0.7086**	**0.7086**	**0.1175**	**0.1060**	**0.1044**	0.0691
GARCH-MIDAS with weather	**1**	**1**	**1**	**1**	**1**	**1**
GARCH-MIDAS with extreme weather	0	0	**0.1175**	0.0973	**0.1044**	0.0653
Panel B: Temperature						
GARCH-MIDAS without weather	0.0793	0.0634	**0.3232**	**0.4018**	**0.3500**	**0.2830**
GARCH-MIDAS with weather	0.0793	0.0703	**0.4495**	**0.4495**	**0.3593**	**0.3593**
GARCH-MIDAS with extreme weather	**1**	**1**	**1**	**1**	**1**	**1**
Panel C: Humidity						
GARCH-MIDAS without weather	**0.4311**	**0.4311**	**0.2069**	**0.2054**	**0.1883**	**0.1317**
GARCH-MIDAS with weather	**1**	**1**	**1**	**1**	**1**	**1**
GARCH-MIDAS with extreme weather	0.0011	0.0042	**0.2069**	**0.2054**	**0.1883**	**0.1302**
Panel D: Precipitation						
GARCH-MIDAS without weather	**0.7262**	**0.7262**	**0.1745**	**0.2730**	**0.1194**	**0.1712**
GARCH-MIDAS with weather	0.0789	0.0585	**0.4435**	**0.4435**	**0.3782**	**0.3782**
GARCH-MIDAS with extreme weather	**1**	**1**	**1**	**1**	**1**	**1**
Panel E: Clear-sky insolation index						
GARCH-MIDAS without weather	**0.8930**	**0.8930**	**0.7594**	**0.7594**	**0.8980**	**0.8981**
GARCH-MIDAS with weather	**1**	**1**	**1**	**1**	**1**	**1**
GARCH-MIDAS with extreme weather	0.0107	0.0241	0.0308	0.0224	**0.8980**	**0.8981**

Notes: This table reports the *p*-values of MCS test when using the weather indicators in Texas. GARCH-MIDAS without weather, GARCH-MIDAS with weather, and GARCH-MIDAS with extreme weather denote the standard GARCH-MIDAS model, the GARCH-MIDAS-W model, and the GARCH-MIDAS-W-ES model, respectively. The *p*-values larger than 0.10 are indicated in bold and underlined, indicating that the related model shows better predictive power.

of natural gas market. Our findings indicate that the more extreme weather occur, the more likely the natural gas market will be volatile. Hence, adding extreme weather information is helpful to better understand the dynamic volatility in natural gas market. Second, several weather-related policies should be developed to stable energy market development and thus reduce energy risks, especially under the goal of peak carbon emissions and frequent outbreaks of extreme weather around the world. More importantly, our study is beneficial to green finance that means the financing of investment that combine environmental development with the investment decisions (Wang et al., 2019). From a green investment standpoint, investors should pay more attention on the emergence of extreme weather associated with natural gas

Table 13
MCS test with weather indicators in New York City by using natural gas spot prices.

	MAE		HMSE		HMAE	
	T_R	T_{SQ}	T_R	T_{SQ}	T_R	T_{SQ}
Panel A: Wind speed						
GARCH-MIDAS without weather	**0.1746**	**0.1635**	0	0	0	0
GARCH-MIDAS with weather	**0.2946**	**0.2946**	0	0	0	0
GARCH-MIDAS with extreme weather	**1**	**1**	**1**	**1**	**1**	**1**
Panel B: Temperature						
GARCH-MIDAS without weather	**0.1548**	**0.1634**	0	0	0	0
GARCH-MIDAS with weather	**0.3124**	**0.3124**	0	0	0	0
GARCH-MIDAS with extreme weather	**1**	**1**	**1**	**1**	**1**	**1**
Panel C: Humidity						
GARCH-MIDAS without weather	0.03760	**0.1368**	**0.8665**	**0.8409**	**0.1098**	**0.2488**
GARCH-MIDAS with weather	**1**	**1**	**1**	**1**	**1**	**1**
GARCH-MIDAS with extreme weather	**0.8757**	**0.8757**	**0.8665**	**0.8409**	**0.9855**	**0.9855**
Panel D: Precipitation						
GARCH-MIDAS without weather	**0.1565**	**0.2722**	0	0	0	0
GARCH-MIDAS with weather	**0.6563**	**0.6563**	0	0	0	0
GARCH-MIDAS with extreme weather	**1**	**1**	**1**	**1**	**1**	**1**
Panel E: Clear-sky insolation index						
GARCH-MIDAS without weather	**0.1615**	**0.1426**	0	0	0	0
GARCH-MIDAS with weather	**0.2559**	**0.2559**	0	0	0	0
GARCH-MIDAS with extreme weather	**1**	**1**	**1**	**1**	**1**	**1**

Notes: This table reports the *p*-values of MCS test when using the weather indicators in New York City and natural gas spot prices. GARCH-MIDAS without weather, GARCH-MIDAS with weather, and GARCH-MIDAS with extreme weather denote the standard GARCH-MIDAS model, the GARCH-MIDAS-W model, and the GARCH-MIDAS-W-ES model, respectively. The *p*-values larger than 0.10 are indicated in bold and underlined, indicating that the related model shows better predictive power.

market to develop a more sustainable economy. Our findings support that the notable impact of extreme weather on the natural gas volatility. Based on this fact, investors should take flexible hedging strategies as early as possible to avoid risk from extreme weather. Meanwhile, weather derivatives regarding natural gas can be priced more rationally when extreme weather information is taken account.

Credit author statement

Chao Liang: Software, Formal analysis, Investigation, Writing, Revision. Zhenglan Xia: Methodology, Writing – review & editing. Xiaodong Lai: Data curation, Software, Project administration. Lu Wang: Conceptualization, Writing – review & editing, Revision.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2022.106437.

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