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Predicting natural gas futures' volatility using climate risks

Kun Guo[a,b], Fengqi Liu[a,b], Xiaolei Sun[c], Dayong Zhang[d], Qiang Ji[c,*]

[a] School of Economics and Management, University of Chinese Academy of Sciences, Beijing, China
[b] Research Center on Fictitious Economy & Data Science, Chinese Academy of Sciences, Beijing, China
[c] Institutes of Science and Development, Chinese Academy of Sciences, Beijing, China
[d] Research Institute of Economics and Management, Southwestern University of Finance and Economics, Sichuan, China

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ABSTRACT

In this paper, we examine the tracking and predictive power of two kinds of climate risks—namely, climate policy uncertainty (CPU) and climate-related disasters—on the price volatility of natural gas futures. The GARCH-MIDAS model was adopted to incorporate daily natural gas futures prices with monthly CPU indices and disaster frequencies. The empirical results showed a robust predictive relationship between disaster frequency and natural gas price volatility under both in-sample and out-of-sample scenarios, while combining the CPU index with other predictors could not improve the out-of-sample forecasting performance. We believe these findings could provide insights for traders and market regulators.

1. Introduction

Climate change generates a variety of non-negligible risks in financial markets. The first is physical risk—that is, climate change leads to more frequent extreme weather and natural disasters, and these events can cause significant economic losses and financial market turbulence (van Benthem et al., 2022; Lee et al., 2022; Goldstein et al., 2019; van Aalst, 2006). Another is transition risk, which refers to the uncertainties associated with the low-carbon transition in response to climate change, such as unclear climate policies, changes in outlook for various industries, and shifts in consumer preferences (Griffin and Jaffe, 2022; Ding et al., 2022; Semieniuk et al., 2021; Dafermos et al., 2018).

Since the energy sector is a major contributor to carbon emissions, the energy futures market is more closely linked to climate change than other sectors of the financial market. As a result, the energy futures market is perhaps subject to greater climate risks (Liu et al., 2023; Gupta and Pierdzioch, 2021). In this study, we evaluate the tracking and predictive power of climate policy uncertainty (CPU) and climate-related disasters on natural gas futures price volatility. The empirical strategy we employed was the GARCH-MIDAS model formulated by Engle et al. (2013), which allows for the incorporation of variables at different frequencies into the process of modeling and predicting asset prices. We propose the research framework based on the following considerations: first, considering the importance of natural gas in global energy mix comparable to that of oil and coal, it is reasonable to choose natural gas futures as a proxy for energy futures; second, climate policy uncertainty is part of transition risk, while climate-related disasters are the source of physical risk, so these two factors could provide credible measures of different aspects of climate risks; finally, the GARCH-MIDAS model is suitable for managing monthly CPU indices and disaster frequencies with daily natural gas futures prices.

Existing research has provided a sound theoretical basis for the presence of climate risks in the natural gas futures market. Natural

* Corresponding author.
E-mail address: jqwxnjq@casisd.cn (Q. Ji).

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gas is widely viewed as a transitory option towards a cleaner energy mix and has become one of the focal points of global climate policies due to its lower carbon emissions per unit calorific value (Myhrvold and Caldeira, 2012). In this context, uncertainty in national policies to address climate change could exacerbate volatility in the natural gas market, which is a typical form of transition risk. Relevant empirical evidence could be found in Ren et al. (2023), Guo et al. (2022), and Liu et al. (2022), who explore how the climate policy uncertainty influences natural gas prices. When it comes to physical risk, Auffhammer (2022), Liang et al. (2022), and Speake et al. (2020) provide examples of how natural gas demand responds to extreme weather. Xie et al. (2023) and Cruz and Krausmann (2013) emphasize the vulnerability of natural gas supply to disaster events. The above literature shares similar themes with our work and has inspired us. We believe this paper makes additional contributions in the following aspects: first, we assess not only the in-sample tracking ability of climate risk factors on natural gas futures price volatility but also their performance in out-of-sample volatility forecasts, which is rare in the existing literature. Second, we counted the number of climate-related disasters that occurred globally each month since 1991 as a relatively novel measure of the physical risk of climate change.

2. Methodology

The GARCH-MIDAS model uses a mean reverting unit daily GARCH process to fit the short-lived component of the conditional volatility while exploiting a MIDAS polynomial to depict the secular component driven by some lower frequency variables. The foremost advantage of the GARCH-MIDAS model is that it extracts all the available information from lower-frequency data to provide better predictions of high-frequency variables. The GARCH-MIDAS model has been widely applied to explore the impacts of socio-economic and environmental factors on the price volatility of various financial assets (Raza et al., 2023; Salisu et al., 2022; Fang et al., 2020; Ma et al., 2019). This research focuses on the tracking and forecasting power of two monthly variables—namely, climate policy uncertainty and disaster frequency—on the price volatility of natural gas futures. In this case, the GARCH-MIDAS model fits well into our research, through which we could overcome the bias resulting from data aggregation or disaggregation.

According to Engle et al. (2013), the price return of an energy future on day i in month t can be written as follows:

$$r_{i,\ t} = \mu + \sqrt{\tau_t g_{i,\ t}}\varepsilon_{i,t},\ \forall i = 1,\ 2,\ \cdots,\ N_t \tag{1}$$

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

where μ is the mean of the daily returns conditional on the information set $\psi_{i-1,\ t}$, N_t is the number of days in month t, and $g_{i,t}$ represents the short-term component of the conditional volatility, while τ_t denotes the secular component. The short-term component is assumed to follow a GARCH(1, 1) process:

$$g_{i,\ t} = (1-\alpha-\beta) + \alpha\frac{\left(r_{i-1,t}-\mu\right)^2}{\tau_t} + \beta g_{i-1,\ t} \tag{3}$$

Following the MIDAS regression proposed by Ghysels et al. (2007), the secular/long-term component τ_t in Eq. (1) and Eq. (3) can first be calculated by a function of realized volatility (RV):

$$\log\tau_t = m + \theta\sum_{k=1}^{K_r}\varphi_k(\omega_1,\ \omega_2)RV_{t-k} \tag{4}$$

$$RV_t = \sum_{i=1}^{N_t} r_{i,t}^2 \tag{5}$$

where RV_t is the realized volatility of daily returns in month t, K_r is the number of periods over which the realized volatility is smoothed, and coefficient θ measures the contribution of RV to the secular component. Realized volatility, as a simple and observable volatility measure, is important in describing the dynamics of asset returns (Luo et al., 2022; McAleer and Medeiros, 2008; Anderson et al., 2003; Anderson and Bollerslev, 1998). Settings like Eq. (4), in which RV is a fundamental contributor to the secular component, are relatively common in the existing literature (Chuang and Yang, 2022; Lang et al., 2022; Dai et al., 2022).

In Eq. (4), $\varphi_k(\omega_1,\omega_2)$ is the weighting scheme with a Beta lag structure:

$$\varphi_k(\omega_1,\ \omega_2) = \frac{\left(\frac{k}{K_r}\right)^{\omega_1-1}\left(1-\frac{k}{K_r}\right)^{\omega_2-1}}{\sum_{j=1}^{K_r}\left(\frac{j}{K_r}\right)^{\omega_1-1}\left(1-\frac{j}{K_r}\right)^{\omega_2-1}} \tag{6}$$

It is easily observed that $\varphi_k \geq 0$ for $k = 1, 2, \ldots, K_r$, and $\sum_{k=1}^{K_r}\varphi_k = 1$. The values of parameters ω_1 and ω_2 determine the shape of the weighting scheme. We set $\omega_1 = 1$ here to ensure that more recent observations were assigned higher weights.

The MIDAS regression model in Eq. (4) is flexible to include variables other than RV:

$$\log\tau_t = m + \theta_R\sum_{k=1}^{K_r}\varphi_k(\omega_1,\ \omega_2)RV_{t-k} + \theta_c\sum_{k=1}^{K_c}\varphi_k\left(\omega_{1,c},\ \omega_{2,c}\right)X_{t-k} \tag{7}$$

where X denotes a potential low-frequency predictor and K_c is its maximum lag order; θ_R and θ_c indicate the contributions of RV and X to the long-term price volatility, respectively. In the context of this paper, X is set as the CPU index or the monthly frequency of climate-related disasters. Accordingly, we focus on four GARCH-MIDAS models: the model with RV as the only long-term predictor (basic RV model), the model incorporating RV and CPU index (RV + CPU model), the model with RV and monthly disaster frequency (RV + Disaster model), and the model including all three predictors (RV + CPU + Disaster model).

3. Data

Our sample data includes the daily NYMEX natural gas futures prices, the monthly US Climate Policy Uncertainty (CPU) indices, and the monthly frequencies of climate-related disasters. Data on NYMEX natural gas futures prices were downloaded from the US Energy Information Administration (EIA) website.[1] The CPU index developed by Gavriilidis (2021) is based on the textual analysis of articles published in eight leading US newspapers and provides a new measure of the uncertainty associated with US climate regulations, legislation, and policies.[2] The frequency of climate-related disasters is calculated based on the global disaster records provided by the EM-DAT database.[3] We first downloaded the records of three categories of disasters—namely, meteorological disasters, hydrological disasters, and climatological disasters—which are believed to have correlations with climate change (Utsumi and Kim, 2022; Satoh et al., 2022; Tabari, 2020; Chowdhury et al., 2018; Hirabayashi et al., 2013). We then counted the number of natural disasters occurring in each month according to the recorded start time of each disaster event, which is similar to Chen et al. (2023).

Our sample period was from January 1, 1991, to July 29, 2022, the longest span that could be set given the availability of data. Fig. 1 graphically presents the trends of the three variables, and Table 1 shows the descriptive statistics. It can be observed that the original series of disaster frequency was not stationary, while the original series of the CPU index could only reject the null hypothesis of a unit root at a 10% significance level. To address the concern of spurious regressions, we transformed the original series of the two predictors by taking the first-order difference of their logarithmic forms.[4] According to Table 1, the two transformed series were stationary and thus will replace the original series in our empirical analysis.

4. Empirical results

This section consists of two major parts: the first is the in-sample estimation, which was designed to examine the tracking power of CPU and climate-related disasters on natural gas futures price volatility; the second is the out-of-sample forecast, in which we identified the model with the best predictive performance. The sample data ranging from January 1, 1991, to December 31, 2021, were selected for in-sample estimation, while data after January 1, 2022, were used for evaluating the predictive power of different models. The forecasts in this study were conducted with a rolling-window approach—i.e., using data from January 1, 1991, to December 31, 2021, to project the price volatility on January 1, 2022; using data from January 2, 1991, to January 1, 2022, to project the volatility on January 2, 2022; and so on.

4.1. In-Sample estimation

Table 2 presents the maximum likelihood estimates (MLE) of coefficients in our GARCH-MIDAS models. Notably, the maximum lag orders of long-term predictors—namely, K_r and K_c in Eq. (7)—were determined according to the Bayesian Information Criterion (BIC). It can be observed that the ARCH terms α and GARCH terms β in the four models were all statistically significant, confirming the existence of volatility clustering and persistence in natural gas futures prices. Meanwhile, the sum of α and β in each model was close to 1, indicating a stationary GARCH process.

The significantly positive MIDAS slope coefficients θ_{CPU} and $\theta_{Disaster}$ shown in columns (2)–(3) of Table 2 indicate that the CPU and disaster frequency were positively correlated with the long-term volatility of natural gas futures. That is to say, changing climate policies and frequent disasters make natural gas prices volatile. This result still held when the CPU, disaster frequency, and RV were simultaneously incorporated into a three-variable GARCH-MIDAS model (column [4] of Table 2). Moreover, the values of log-likelihood function (LLF) of all three multi-predictor models are larger than that of the basic RV model, which means both CPU and disaster frequency contain supplementary information for the price volatility of natural gas futures (Zhao, 2022; Yu and Huang, 2021).

Figure 2 plots the in-sample total conditional volatility and secular component derived from each model. Obviously, the total volatility calculated by different models was quite similar while the secular components were relatively different. Specifically, the basic RV model yielded a relatively smooth secular component (Figure 2 [a]), while the RV + CPU model and the RV + Disaster model generated secular components with pronounced fluctuations (Figure 2 [b]–[d]).

Overall, our analysis verified the good tracking power of the CPU and disaster frequency on the in-sample price volatility of natural gas futures. However, such a robust in-sample relationship may not necessarily translate into improved out-of-sample forecasts. Thus, we needed to further ascertain the value of the CPU and disaster frequency as long-term volatility predictors for the out-of-sample

[1] https://www.eia.gov/dnav/ng/ng_pri_fut_s1_d.htm, accessed on January 11, 2023.

[2] http://www.policyuncertainty.com/climate_uncertainty.html, accessed on January 11, 2023.

[3] https://public.emdat.be, accessed on January 11, 2023

[4] Such a transformation is equivalent to calculating the growth rate of the predictor.

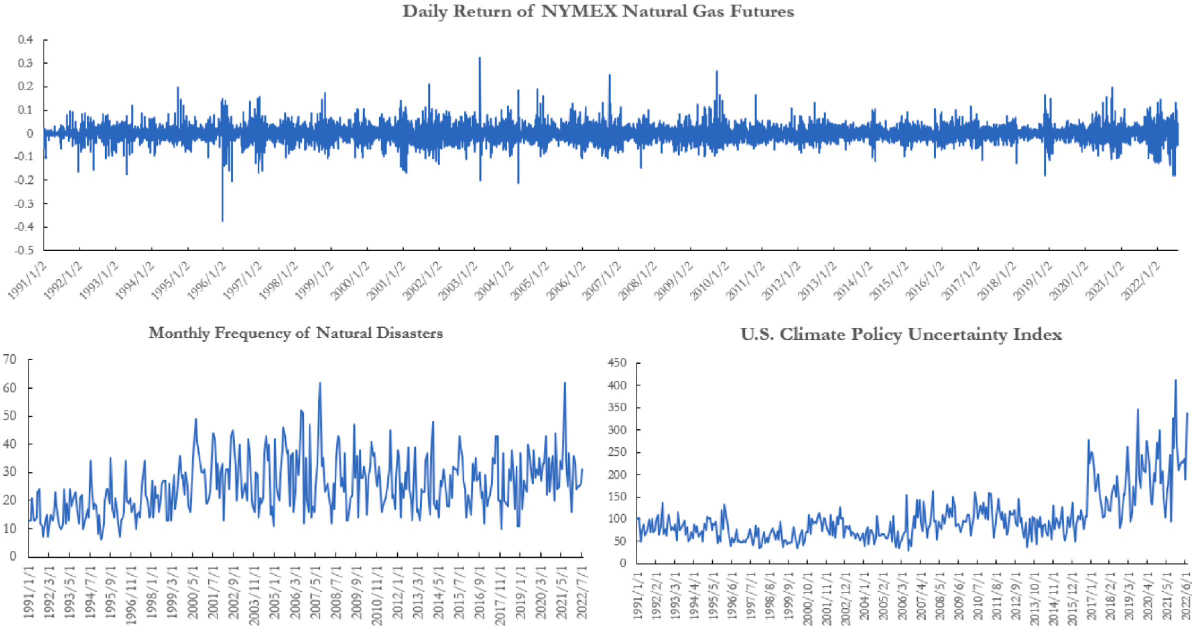


Fig. 1. Trends of the daily return of NYMEX natural gas futures and two climate-related predictors.

Table 1
Descriptive statistics.

Variable	Obs.	Mean	Std.	Min	Max	Skewness	Kurtosis	ADF
Natural gas futures return	8021	0.000	0.035	−0.376	0.324	0.103	9.555	−18.117***
CPU Index	379	102.536	57.212	28.162	411.289	1.929	7.587	0.678
d. CPU Index	379	379	0.004	0.371	−1.701	−0.223	3.787	−18.132***
Natural disasters frequency	379	25.311	9.972	6	62	0.600	3.178	−2.6280*
d. Natural disasters frequency	379	0.002	0.437	−1.447	1.340	−0.027	3.319	−18.014***

Notes: ADF is the t-statistics for the augmented Dickey–Fuller test. The symbol "d." denotes the first-order difference after log-transformation. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

scenario.

4.2. Out-of-Sample evaluation

To assess the predictive power of our GARCH-MIDAS models, we compared the predicted volatility with the true volatility. Two loss functions were adopted as the evaluation criteria—i.e., mean squared error (MSE) and mean absolute error (MAE), which are defined as follows:

$$L_{MSE} = \frac{1}{N_0 - \sum_{t=1}^{E} N_t} \sum_{t=E+1}^{T} \sum_{i=1}^{N_t} \left(\sigma_{i,\ t} - \widehat{\tau}_t \widehat{g}_{i,\ t}\right)^2 \tag{8}$$

$$L_{MAE} = \frac{1}{N_0 - \sum_{t=1}^{E} N_t} \sum_{t=E+1}^{T} \sum_{i=1}^{N_t} \left|\sigma_{i,\ t} - \widehat{\tau}_t \widehat{g}_{i,\ t}\right| \tag{9}$$

where N_0 equals the total number of daily observations; N_t is the number of days in month t; T is the number of months in the entire sample period, while E is the number of months in the in-sample estimation period; $\sigma_{i,t}$ denotes the true volatility of day i in month t; and $\widehat{\tau}_t \widehat{g}_{i,\ t}$ is the daily volatility forecast. Notably, $\sigma_{i,t}$ cannot be directly observed, and thus we used the intraday realized volatility $RV_{i,t}$ as a substitute.[5]

Given that loss functions are susceptible to outliers, we further exploited the model confidence set (MCS) test to select models with

[5] The data of intraday RV can be downloaded from a database maintained by Prof. Dacheng Xiu at the Booth School of Business, University of Chicago: https://dachxiu.chicagobooth.edu/#risklab.

Table 2
In-sample estimation results

	RV	RV + CPU	RV + Disaster	RV + CPU + Disaster
μ	0.0004	0.0003	0.0003	0.0003
	(0.0004)	(0.0004)	(0.0004)	(0.0003)
α	0.0922***	0.0896***	0.0941***	0.0867***
	(0.0131)	(0.0130)	(0.0146)	(0.0140)
β	0.8921***	0.8936***	0.8846***	0.8926***
	(0.0143)	(0.0146)	(0.0182)	(0.0196)
m	-2.1041	-2.2895*	-2.3571	-3.5454*
	(1.4243)	(1.3837)	(1.8393)	(2.0332)
θ_{RV}	1.0885***	1.0541***	1.0594**	0.7724
	(0.3396)	(0.3320)	(0.4414)	(0.4916)
θ_{CPU}		0.3051**		0.4676**
		(0.1393)		(0.2281)
$\theta_{Disaster}$			9.7665***	9.5393***
			(3.0095)	(3.0411)
$\omega_{RV,2}$	1.0000**	1.000***	1.0000	1.0027
	(0.4611)	(0.4213)	(0.8340)	(1.8947)
$\omega_{CPU,2}$		35.7809**		24.6131**
		(15.1146)		(12.3156)
$\omega_{Disasters,2}$			1.000***	1.0000***
			(0.1275)	(0.1345)
LLF/BIC	14495.1348	14499.4019	14640.5884	14645.2893
	-28937.0406	-28927.8317	-29210.1354	-29201.7769
Lag	36	(36, 36)	(33, 33)	(33, 33, 33)

Notes: LLF is the value of the maximized log-likelihood function. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

the best predictive performance. According to Hansen et al. (2011), the p-value of the MCS test reflects the forecasting accuracy of the corresponding model. Models with p-values larger than the threshold are regarded as "survivors" and are supposed to be effective in forecasts. In addition, models with a p-value equal to 1 are considered to have the best predictive power. We set the threshold p-value as 0.1, which is consistent with some previous studies (Wen et al., 2022; Amendola et al., 2019; Wei et al., 2017).

Table 3 shows the prediction errors of different models and the results of the MCS test. When the forecasting horizon was set to less than 30 days, the RV + Disaster model was the only one that survived the MCS test and had the lowest prediction errors. As the forecasting horizon expanded, the RV + Disaster model still performed best, but the RV + CPU model and the RV model also survived the MCS test. This result further verifies that the frequency of climate-related disasters can provide new predictive information additional to that from the RV and can thus become a novel predictor for the long-term volatility of natural gas futures prices.

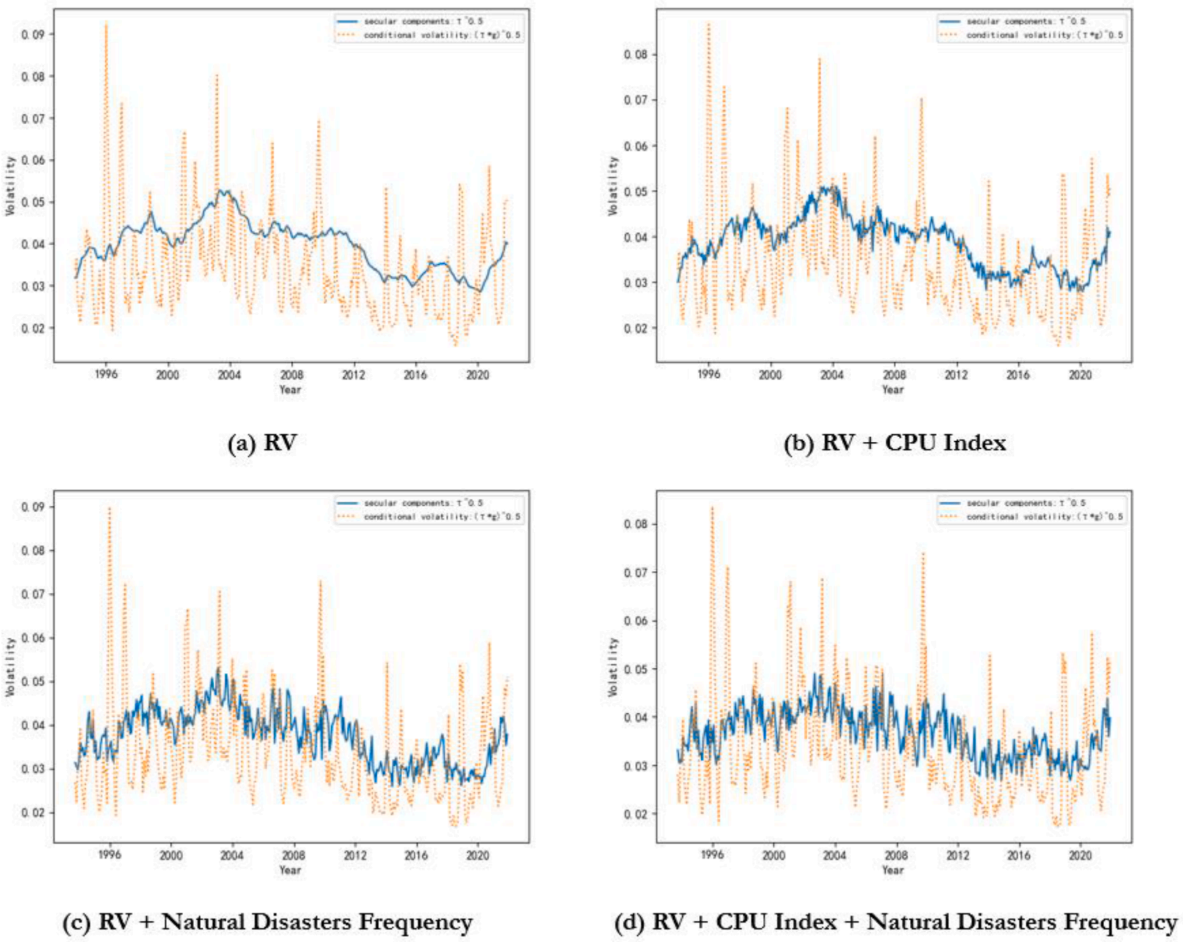
On the other hand, the RV + CPU model had the same p-values as the basic RV model under all the forecasting horizons, which means that including CPU as a predictor in the basic RV model did not improve the forecasting performance. In other words, the CPU index, though showing a significant positive effect on the price volatility in the in-sample analysis, did not have the same out-of-sample predictive power as the disaster frequency did. Worse still, the RV + CPU + Disaster model never survived the MCS test, meaning the CPU index and disaster frequency seemed to interfere with each other in forecasts. In fact, some clues to this phenomenon can be found in Table 2. That is, the absolute value of BIC for the RV + CPU model is the smallest, indicating that the model setup is not concise enough and might be subject to overfitting problem.

The mechanism behind the results of Table 3 could be that it takes a long time to modify existing policies, and thus the risks from changes in climate policies are perceived by investors gradually rather than suddenly. In this case, the impact of CPU on energy markets may have already been captured by the realized volatility, making the combination of RV and CPU unable to provide sufficient additional information for the forecasts. On the other hand, the frequency of climate-related disasters is part of the basis for climate policy formulation, so there may also be an overlap in the information provided by CPU and disaster frequency.

5. Conclusions

The motivation of this paper was to examine whether considering climate risks could improve the prediction of natural gas futures price volatility. Specifically, we identified two kinds of climate risks—climate policy uncertainty and climate-related disasters—and then incorporate them into the GARCH-MIDAS model as two long-term volatility predictors. The empirical results showed that both CPU and disaster frequency had a significant impact on the secular component of natural gas futures price volatility, exhibiting good tracking power on in-sample volatility. However, in terms of the out-of-sample scenario, only disaster frequency could improve the accuracy of volatility predictions.

Conclusions drawn in our work offer useful implications. For traders, it is necessary to pay close attention to weather forecasts and disaster warnings and to improve hedging strategies accordingly. For regulators, timely alerts should be issued to market participants during periods of frequent disasters so as to prevent market disruptions caused by disaster shocks. This paper is deficient in that it only explores the contributions of climate risks to natural gas price volatility. In the future, scholars can further analyze the heterogeneous impact of climate risks on the volatility of different energy futures, as well as the transmission and spillover of climate risks among



(a) RV

(b) RV + CPU Index

(c) RV + Natural Disasters Frequency

(d) RV + CPU Index + Natural Disasters Frequency

Fig. 2. Total conditional volatility and the secular component driven by different combinations of long-term predictors.

Table 3
Evaluation of different models' predictive power

Forecasting horizon	Model	L_{MAE}	L_{MSE}	MCS_{MAE}	MCS_{MSE}
10 days	RV	0.00345	1.2876E-05	0.000	0.000
	RV+CPU	0.003734	1.4919E-05	0.000	0.000
	RV+Disaster	0.002749	9.1583E-06	**1.000***	**1.000***
	RV+CPU+Disaster	0.003345	1.2650E-05	0.000	0.000
30 days	RV	0.003433	1.4565E-05	0.000	0.000
	RV+CPU	0.003511	1.5272E-05	0.000	0.000
	RV+Disaster	0.002667	1.0018E-05	**1.000***	**1.000***
	RV+CPU+Disaster	0.002995	1.1885E-05	0.000	0.000
60 days	**RV**	0.003696	1.5545E-05	**0.265***	**0.429***
	RV+CPU	0.003693	1.5542E-05	**0.265***	**0.429***
	RV+Disaster	0.003385	1.3867E-05	**1.000***	**1.000***
	RV+CPU+Disaster	0.003546	1.4767E-05	**0.117***	0.095
90 days	**RV**	0.004129	1.9072E-05	**0.403***	**0.519***
	RV+CPU	0.004125	1.9063E-05	**0.403***	**0.519***
	RV+Disaster	0.003922	1.7904E-05	**1.000***	**1.000***
	RV+CPU+Disaster	0.004057	1.8813E-05	0.084	0.061
120 days	**RV**	0.004295	2.0983E-05	**0.462***	**0.464***
	RV+CPU	0.00432	2.1253E-05	**0.462***	**0.464***
	RV+Disaster	0.004142	2.0114E-05	**1.000***	**1.000***
	RV+CPU+Disaster	0.004274	2.1097E-05	0.031	0.008

Notes: MCS_{MAE} and MCS_{MSE} denote the p-values of the MCS test based on mean absolute error and mean squared error, respectively. An asterisk* indicates p-value > 0.1, suggesting that the corresponding model survived the MCS test under a special loss function. A p-value of 1.000 indicates a model performing the best out of all models.

various financial assets.

CRediT authorship contribution statement

Kun Guo: Conceptualization, Writing – original draft, Software, Writing – review & editing. **Fengqi Liu:** Conceptualization, Writing – original draft, Data curation. **Xiaolei Sun:** Supervision, Writing – review & editing. **Dayong Zhang:** Supervision, Writing – review & editing. **Qiang Ji:** Supervision, Writing – review & editing, Funding acquisition.

Data availability

Data will be made available on request.

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