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Research on Forecasting International Energy Price Volatility based on Model Combination

Bingbing Chen *

School of Economics and Management, Nanjing University of Science and Technology, Nanjing, China

* Corresponding Author Email: 2252489486@qq.com

Abstract. As an important support for the national economy, the volatility of international energy price is of great importance to the stability of the national economy, the maintenance of social stability and the protection of national security. The modeling and forecasting of international energy market price volatility based on many forecasting factors have attracted more and more attention. The model combination method, which can integrate the strengths of various models, is widely used in the field of financial forecasting. In view of this, based on the monthly volatility data of international energy market, macroeconomic variables, uncertainty index and AR extended model from January 1994 to December 2022, this paper adopts five model combination forecasting methods for the prediction of international energy price volatility, and the adaptability of the model combination to different predictors and its performance in predicting the volatility of different energy markets are discussed. Through empirical study, it is found that the forecasting ability of single macroeconomic variable is not satisfactory when forecasting international energy price volatility, but the model combination forecasting method can significantly improve the forecasting accuracy of international crude oil market volatility, and the model combination forecasting based on the uncertainty index performs well in both the crude oil market and the natural gas market. Therefore, this paper can provide some empirical basis for international energy market investors to carry out risk management and portfolio optimization, and also help policy makers grasp the timing of policy issuance and implementation.

Keywords: International energy markets; Volatility forecasting; Model combination; Macroeconomic variables; Uncertainty index.

1. Introduction

Volatility in international energy prices exerts far-reaching impacts on macroeconomic stability, social order maintenance, and national energy security. Driven by geopolitical conflicts, shifts in global economic cycles, adjustments in supply-demand dynamics, and financial-market speculation, major energy commodities such as crude oil and natural gas have experienced frequent and drastic price swings over the past decades. These fluctuations pose substantial challenges for risk management among market participants and policy design for regulatory authorities. Against the deepening financialization of global energy markets, accurate volatility forecasting has emerged as a practically important research issue. Nevertheless, international energy price volatility is characterized by prominent nonlinearity and time-varying properties. Single-model forecasts built upon a limited set of predictors often yield unstable out-of-sample performance and fail to fully exploit diverse predictive information contained in macroeconomic indicators and uncertainty indices. By synthesizing outputs from multiple individual forecasting specifications, model-combination techniques mitigate forecast uncertainty and enhance prediction accuracy, and have been widely applied in financial forecasting research.

This paper investigates volatility forecasting for international crude-oil and natural-gas markets using model-combination approaches. Using monthly data covering January 1994 to December 2022, we construct autoregressive-extended (AR-extended) forecasting specifications with two sets of predictors: conventional macroeconomic variables and a suite of uncertainty indices. Five widely-adopted combination strategies are employed to produce pooled forecasts, including the mean combination, median combination, trimmed-mean combination, and two variants of the discounted

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mean squared prediction error (DMSPE) method. We empirically evaluate the adaptability of model combinations across different predictors, as well as their forecasting performance in crude-oil and natural-gas markets, through both in-sample estimation and out-of-sample forecasting exercises. The empirical results reveal that individual macroeconomic variables exhibit limited predictive power for international energy price volatility, whereas model combinations markedly improve forecast accuracy for crude-oil market volatility. Furthermore, combination forecasts built on uncertainty indices deliver satisfactory predictive performance for both crude-oil and natural-gas markets. Robustness checks that alter the out-of-sample evaluation window and lag order further validate the reliability of these findings.

This study makes two main marginal contributions to the existing literature. First, prior studies predominantly focus on single-model specifications or a small subset of influencing factors for one specific energy market. By contrast, this paper compares the predictive power of an extensive set of macroeconomic variables and uncertainty indices across multiple energy markets, adding new empirical evidence to the literature on international energy-volatility forecasting. Second, we systematically examine how five model-combination techniques adapt to different categories of predictors. Our results confirm that model combinations can extract useful predictive signals from multi-source indicators, offering fresh empirical insights for improving forecasting performance using diverse predictors in energy-volatility research. Additionally, our findings provide practical references for investors concerning risk management and portfolio optimization, as well as for policymakers regarding the timing of policy formulation and implementation.

2. Literature Review

Against the growing complexity of international energy markets, conventional single-model frameworks can hardly generate high-accuracy forecasts for international energy price volatility. Given the rising technical demands for volatility forecasting research, model-combination methods have developed rapidly and produced abundant research outcomes. This section first reviews studies on drivers of international energy price volatility. Next, it summarizes practical applications and recent advances of various model-combination techniques in financial forecasting. Finally, it provides a critical review of existing literature.

2.1. Research on influencing factors of international energy price volatility

International energy price volatility has attracted considerable attention from researchers and policymakers. A broad body of literature confirms that energy price swings stem from the joint effects of multiple factors. Key drivers include supply-demand conditions, political stability, exchange-rate movements and technological progress. This subsection reviews relevant studies from fundamental and non-fundamental perspectives.

Many scholars hold that energy carries basic commodity attributes. Its production, consumption and pricing follow general economic rules. Much research focuses on how supply and demand shifts shape energy price fluctuations. He and Wang [1] construct an error-correction model to explore the link between global crude-oil output and international crude-oil prices. Their results verify long-run cointegration between the two variables and identify global crude-oil output as one Granger-causality source of oil-price volatility. Wang et al. [2] adopt a time-varying dynamic model-averaging (DMA) framework to quantify determinants of North American natural-gas prices. They find that oil prices play a shrinking role in gas pricing, while supply- and demand-side conditions become dominant drivers of natural-gas prices. Xing et al. [3] examine natural-gas futures pricing. They document seasonal differences in gas demand among industrial and residential consumers, which further trigger price volatility.

Inventory changes also exert notable impacts on international energy price volatility, beyond supply-demand dynamics. Xie et al. [4] build a multi-variable structural vector autoregressive (SVAR) model based on global oil-price and inventory data from 2002 to 2017. They show that global

petroleum inventories serve as a core driver of international oil prices and impose significant negative effects on crude-oil prices. Li et al. [5] points out that petroleum inventories represent a special influencing factor. Inventories affect oil-price movements and meanwhile receive negative feedback from oil-price changes. A bidirectional causal interaction exists between the two variables. Liu and Huang [6] combine network analysis with wavelet transformation for multi-scale analysis of North American natural-gas price volatility. Their evidence suggests active price dynamics and significant inventory effects on natural-gas price swings.

Most international energy products are denominated in US dollars. Accordingly, US-dollar exchange-rate movements constitute another major source of energy-price volatility. Roger and Andre [7] apply cointegration analysis to oil prices and the US-dollar exchange rate. They detect nonlinear effects: oil prices rise distinctly when the US-dollar exchange rate falls below a certain threshold. Han et al. [8] adopt ordinary least squares (OLS), vector autoregression (VAR) and vector error-correction models (VECM) using data spanning 1983-2015. Their findings support negative correlations between the US-dollar index, speculative ratios and oil prices. Wang et al. [9] employ threshold regression on daily WTI crude-oil and US-dollar exchange-rate data from 1983 to 2019. They demonstrate obvious time-varying features in the oil-dollar nexus.

Geopolitical risks cannot be overlooked for international energy price movements. Li et al. [10] construct geopolitical-hazard, geopolitical-risk and geopolitical-action indices using daily returns of Brent and WTI crude-oil futures. Based on a mixed-data-sampling GARCH model, they report significantly positive impacts of geopolitical risks on crude-oil volatility. Such impacts differ across oil varieties and appear stronger for Brent crude-oil futures. Mei et al. [11] estimate a MIDAS-RV model with geopolitical-risk and crude-oil futures-price data. In-sample outcomes show positive co-movement between short-run realized oil volatility and geopolitical-risk indices. Out-of-sample evidence further validates the predictive power of geopolitical-risk indices for short-term crude-oil futures volatility. Yang et al. [12] also regard geopolitical risk as a core driver of crude-oil futures volatility. Its influence exhibits clear asymmetry and helps predict realized crude-oil volatility.

Speculative activities also affect energy-price volatility alongside global financial-market development and energy-futures-market expansion. Wang et al. [13] investigate how investor sentiment shapes WTI crude-oil futures volatility using 1994-2018 data. Investor sentiment improves volatility forecasts. Strong dynamic causal links emerge across different frequencies, with more pronounced short-run causal effects. Feng et al. [14] adopt a multi-scale complex-system approach. They analyze interactions between uncertainty indices and crude-oil futures markets across different frequencies, time horizons and price levels. The VIX market-fear index imposes significant negative influences on crude-oil price volatility.

2.2. Applications of model combination methods in financial forecasting

Model combination techniques are widely recognized as best-practice forecasting tools. A large volume of literature confirms their superior forecasting performance relative to single model approaches. The core logic of model-combination forecasting lies in generating separate predictions from multiple individual specifications. Researchers then combine these outputs appropriately. This process makes full use of information embedded in each standalone model and improves overall forecasting accuracy [15]. Since its proposal, the model combination framework has drawn wide scholarly attention and been applied to diverse forecasting contexts. Relevant applications in stock and energy markets are summarized below.

Model combination methods enjoy broad applications for stock market prediction. Lv and Qi [16] forecast stock market returns with conventional macroeconomic variables. Their empirical results reveal better out-of-sample performance from combined forecasts compared with individual models. Ren et al. [17] develop a novel hybrid stock price forecasting model that integrates decomposition-reconstruction tools with machine-learning algorithms. The proposed hybrid model yields high forecasting accuracy, strong generalization ability and good practical value for stock-price

prediction tasks. Kim and Won [18] merge EWMA, GARCH and EGARCH volatility models to build a hybrid specification for realized-volatility forecasting of the KOSPI 200 index. Their hybrid model produces smaller forecast errors than single alternatives. Lin et al. [19] combines BP neural networks, Elman neural networks, support-vector regression (SVR), autoregressive (AR) and heterogeneous autoregressive (HAR) models with the CEEMDAN decomposition technique. Their forecast realized volatility for the S&P 500, STOXX 50 and CSI 300 indices. CEEMDAN-assisted combined models outperform corresponding single models. Robustness tests further verify the advantages of model combinations for stock-index realized-volatility forecasting.

Model-combination forecasting often delivers competitive performance for energy-market research. Zhang and Zhou [20] build a hybrid ARIMA-SVR-POT model. This specification integrates support-vector regression (SVR), the peaks-over-threshold (POT) extreme-value-theory approach and ARIMA. They forecast market risk for WTI crude-oil futures. The hybrid model effectively captures tail-distribution features and produces highly reliable VaR estimates for WTI crude-oil futures. Zhao and Xue [21] construct a hybrid model merging LSTM, SVM, transfer networks (TN) and link prediction (LP). For medium- and long-run forecasting, this hybrid model outperforms standalone LSTM and SVM specifications. Zhang et al. [22] propose a combined forecasting method that merges dynamic error-correction and multi-scale-analysis techniques. Empirical tests on Brent crude-oil spot-price volatility show that this combination significantly enhances forecasting accuracy and generalization capacity for crude-oil volatility. Abrishami and Varahrami [23] combine GMDH neural networks with genetic algorithms for natural-gas-volatility forecasting. During financial-crisis episodes, their combined model generates better forecasting outcomes than standalone GMDH or MLF neural-network models. Yang et al. [24] construct an NHMM-FIEGARCH-GED hybrid model optimized via a mutation-based hybrid particle-swarm algorithm. It delivers more accurate out-of-sample forecasts for crude-oil volatility. Liang et al. [25] extend the GARCH-MIDAS framework and incorporate extreme-weather information to explore natural-gas-volatility predictability. Their GARCH-MIDAS-ES combined model achieves strong forecasting performance. Specifications including weather indicators outperform counterparts without weather-related inputs.

2.3. Critical review of existing literature

Overall, most existing studies focus on single-model setups or a small number of influencing factors for one specific international-energy-market segment. Many papers compare forecasting effects from limited drivers such as economic-policy uncertainty, geopolitical risk or stock-market volatility, mostly targeting crude-oil or natural-gas markets.

Nevertheless, few studies comprehensively compare forecasting performance across numerous macroeconomic and uncertainty indicators for multiple international energy markets. Although model-combination approaches are widely adopted within financial forecasting, limited evidence verifies how such combination techniques adapt to different predictor categories. Considering the merits of model-combination forecasting and the complexity of international energy markets, this study adopts multiple combination-forecasting strategies. It conducts volatility-prediction exercises for several international energy markets drawing on rich macroeconomic and uncertainty-index information.

3. Methodology

3.1. Measurement of realized volatility

This study aims to improve the predictability of international energy price volatility using a large set of predictive factors. We first measure monthly realized volatility of energy markets. Next, we introduce benchmark forecasting model and model-combination strategies. Finally, we describe the evaluation metrics for forecasting performance. We calculate monthly realized volatility by summing the squared daily returns of energy assets [26, 27]. The calculation formula is specified as:

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

Where RV_t denotes the realized volatility in month t, N_t is the number of trading days in month t, and $r_{t,i}$ represents the daily return on energy assets for the i-th trading day of month t. The raw realized volatility series typically exhibits leptokurtic and non-Gaussian distributions, which may bias ordinary least-squares (OLS) estimation results. To address this issue, we take the natural logarithm of realized volatility, denoted as $LV_t = \ln(RV_t)$. The logarithmic realized volatility LV_t approximately follows a normal distribution [28, 29], and we adopt LV_t for subsequent modelling and forecasting of international energy price volatility.

3.2. Benchmark forecasting model

We employ the autoregressive (AR) model as the benchmark for volatility forecasting, which is widely applied in existing relevant literature [27, 28]. The AR model is expressed as:

$$LV_{t+1}=\beta_0+\sum_{i=1}^{I}\beta_i LV_{t+1-i}+\varepsilon_{t+1} \tag{2}$$

Where LV_{t+1} is the logarithmic realized volatility, ε_{t+1} refers to the error term, and the optimal lag order I is determined by the Akaike Information Criterion (AIC).

We further extend the baseline AR specification by incorporating one potential predictive variable to examine the predictive power of individual predictors for energy price volatility:

$$LV_{t+1}=\beta_0+\sum_{i=1}^{I}\beta_i LV_{t+1-i}+\gamma X_{j,t}+\varepsilon_{t+1} \tag{3}$$

Where $X_{j,t}$ stands for the observation of predictor j in month t. The coefficient γ captures the predictive effect of $X_{j,t}$ on future realized volatility. The null hypothesis assumes that the predictor X has no predictive power, i.e., $\gamma = 0$, in which case Equation (3) degenerates into the benchmark AR model. Under the alternative hypothesis, γ is non-zero, implying that X contains useful predictive information. We apply the Newey-West t-statistic to test the null hypothesis.

3.3. Model combination forecasting

A series of individual forecasts can be generated from the AR extension models with macroeconomic variables or uncertainty indices. As documented in prior research [30], out-of-sample predictability derived from a single model tends to be unstable. By contrast, mode combination approaches aggregate valid information from multiple individual forecasts to enhance overall forecasting accuracy [27, 29, 31]. Five popular model combination strategies are adopted in this paper: the mean combination, median combination, trimmed-mean combination, and two versions of the discounted mean squared prediction error (DMSPE) method.

(1) Mean combination (Mean): Assign equal weights to forecasts from N individual models, so as to mitigate the influence of extreme forecast values. The weight for each individual model is $\omega_i=1/N$.

(2) Median combination (Median): Sort N individual forecast values and select their median as the combined forecast output.

(3) Trimmed-mean combination (TMean): Discard the maximum and minimum values among N individual forecasts and compute the equally-weighted average of the remaining forecasts. The weights for the maximum and minimum forecasts are set to $\omega_i = 0$.

(4) Discounted means squared prediction error (DMSPE): Produce combined forecasts via weighted averaging of individual forecasts. The weight of each individual forecast is determined as follows:

$$\omega_{i,t}=\phi_{i,t}^{-1}/\sum_{j=1}^{N}\phi_{j,t}^{-1} \tag{4}$$

$$\phi_{j,t}=\sum_{s=M+1}^{t}\theta^{t-s}\left(LV_s-\widehat{LV}_{j,s}\right)^2 \tag{5}$$

Where LV_s is the logarithmic realized volatility, M represents the length of the initial in-sample training period, and θ is the discount factor. Consistent with previous studies, we set two values for the discount factor: θ=1.0 and θ=0.9. The two corresponding combination approaches are denoted as DMSPE (1.0) and DMSPE (0.9).

3.4. Forecast evaluation metrics

We implement out-of-sample forecasting using an expanding estimation window. To assess the out-of-sample performance of AR-extended models and model combination strategies, we adopt the out-of-sample R^2 (R_{os}^2) metric [27,32]. R_{os}^2 measures the percentage reduction in the mean squared forecast error (MSFE) of a candidate forecasting model relative to the benchmark AR model. Its formulas are given below:

$$R_{os}^2=1-\frac{MSPE_{model}}{MSPE_{bench}} \tag{6}$$

$$MSPE_{model}=\frac{1}{T-M}\sum_{t=M+1}^{T}\left(LV_t-\widehat{LV}_t^m\right)^2 \tag{7}$$

$$MSPE_{bench}=\frac{1}{T-M}\sum_{t=M+1}^{T}\left(LV_t-\widehat{LV}_t^b\right)^2 \tag{8}$$

Where LV_t denotes logarithmic realized volatility in month t, M is the length of the initial in-sample period, and T is the total sample size. $\widehat{LV}_t^m$ and $\widehat{LV}_t^b$ represent forecast values from the candidate AR extension model and the benchmark AR model, respectively. A positive R_{os}^2 indicates that the candidate model yields a lower MSFE than the benchmark, signalling superior volatility-forecasting performance. In addition, the Clark-West (CW) test is employed to examine whether the out-of-sample predictive improvement is statistically significant.

4. Data and Descriptive Statistics

4.1. Data

This study focuses on two international energy markets: NYMEX natural gas futures and WTI crude-oil futures. Daily price data for both markets are obtained from the official website of the U.S. Energy Information Administration (EIA). The full sample spans from January 1994 to December 2022, yielding 348 monthly observations in total.

Table 1. Variable definitions

Variable	Descriptions	Sample
RV1	Realized volatility of WTI Oil Futures	1994:01-2022:12
RV2	Realized volatility of Natural Gas Futures	1994:01-2022:12

DP	Dividend-price ratio	1994:01-2022:12
DY	Dividend yield	1994:01-2022:12
EP	Earning-price ratio	1994:01-2022:12
DE	Dividend-payout ratio	1994:01-2022:12
SVAR	Stock return variance	1994:01-2022:12
BM	Book-to-market ratio	1994:01-2022:12
NTIS	Net equity expansion	1994:01-2022:12
TBL	Treasury bill rate	1994:01-2022:12
LTY	Long-term yield	1994:01-2022:12
LTR	Long-term return	1994:01-2022:12
TMS	Term spread	1994:01-2022:12
DFY	Default yield spread	1994:01-2022:12
DFR	Default return spread	1994:01-2022:12
INFL	Inflation	1994:01-2022:12

Fourteen conventional macroeconomic variables are selected to explore the predictability of international energy price volatility [33, 34]. These variables include the dividend-price ratio (*DP*), dividend yield (*DY*), earnings-price ratio (*EP*), dividend-payout ratio (*DE*), stock return variance (*SVAR*), book-to-market ratio (*BM*), net equity expansion (*NTIS*), treasury-bill rate (*TBL*), long-term yield (*LTY*), long-term return (*LTR*), term spread (*TMS*), default yield spread (*DFY*), default return spread (*DFR*), and inflation (*INFL*). The dataset is downloaded from Amit Goyal's website. Table 1 presents detailed definitions, abbreviations and sample periods for all macroeconomic variables.

4.2. Descriptive Statistics

Table 2 summarizes descriptive statistics for the realized volatility series of energy markets and the fourteen macroeconomic variables. Several variables (*DY*, *EP*, *BM*, *NTIS*, *DFR* and *INFL*) display negative skewness, while the remaining series are right-skewed. Except for *BM*, *TBL*, *LTY* and *TMS* whose kurtosis values are below 3, all other time-series show leptokurtic distributions. The Jarque-Bera (JB) test rejects the null hypothesis of normality for all series except *DP* and *DY*.

Augmented Dickey-Fuller (ADF) unit-root test results suggest that both *RV1* (WTI crude-oil futures) and *RV2* (natural gas futures) are stationary. Nevertheless, seven macroeconomic variables (*DP*, *DY*, *BM*, *NTIS*, *TBL*, *LTY* and *TMS*) are non-stationary at levels. Their first-difference transformations are stationary. Therefore, first-differenced series are adopted in subsequent empirical analysis.

Table 2. Descriptive statistics for realized volatility and macroeconomic variables

	Mean	Std.	Max.	Min.	Skew.	Kurt.	JB	ADF
RV1	0.015	0.045	0.778	0.001	14.542	238.768	818269. 500***	-12.319***
RV2	0.028	0.031	0.293	0.003	3.933	25.903	8502.632***	-11.447***
DP	-4.000	0.218	-3.281	-4.524	0.054	3.417	2.698	-2.278
DY	-3.994	0.218	-3.968	-4.531	-0.023	3.325	1.567	-2.286
EP	-3.141	0.351	-2.566	-4.836	-2.078	9.645	890.738***	-4.598***
DE	-0.858	0.390	1.380	-1.244	3.429	17.696	3813.713***	-5.435***
SVAR	0.003	0.006	0.073	1.503e-04	7.844	79.955	89437.921***	-10.870***
BM	0.267	0.069	0.446	0.121	-0.105	2.362	6.535**	-1.959
NTIS	0.002	0.019	0.045	-0.056	-0.520	3.009	15.714***	-2.366
TBL	2.215	2.073	6.170	0.010	0.415	1.576	39.401***	-2.007
LTY	4.275	1.784	8.090	0.620	0.018	2.117	11.334***	-1.508
LTR	0.489	3.055	14.430	-11.240	0.059	4.765	45.399***	-14.341***
TMS	2.059	1.299	4.530	-0.630	0.095	1.958	16.280***	-2.325
DFY	0.958	0.394	3.380	0.550	3.100	16.373	3150.168***	-4.385***
DFR	0.055	1.784	7.370	-9.760	-0.810	10.027	754.097***	-17.845***
INFL	0.206	0.356	1.374	-1.915	-0.553	7.158	268.371***	-11.450***

Note: Mean, Std., Max., Min., Skew., and Kurt. refer to the sample average, standard deviation, maximum value, minimum value, skewness coefficient, and kurtosis coefficient, respectively. JB refers to the Jarque-Bera normality test statistics. ADF denotes the Augmented Dickey-Fuller unit-root test statistics. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

5. Empirical Results

5.1. In-sample Estimation Results

In-sample estimation refers to model estimation using full-sample data, followed by prediction for partial or all observations within the sample. To test whether each macroeconomic variable contains valid predictive information for international energy market volatility and whether it can significantly improve the in-sample fitting performance of AR extension models, this paper estimates 14 AR extension models incorporating macroeconomic variables with the full dataset. Table 3 reports the in-sample estimation results of AR extension models specified in Equation (3). The table reports the estimated coefficient of each macroeconomic variable, the corresponding Newey-West t-statistic, and the percentage increase in the R^2 of the AR extension model (ΔR^2). Only coefficients of macroeconomic variables are presented, while coefficients of AR lag terms are omitted to highlight the predictive performance of selected macroeconomic variables for international energy price volatility.

Table 3. In-sample estimation results for WTI Oil Futures and Natural Gas Futures markets.

	WTI Oil Futures			Natural Gas Futures		
Model	β	t-stat	ΔR^2(%)	β	t-stat	ΔR^2(%)
DP	2.694***	3.106	2.074	1.370**	1.733	0.530
DY	1.836***	2.425	0.935	1.083*	1.373	0.326
EP	-0.242***	-2.538	0.826	-0.208**	-1.947	0.688
DE	0.139**	1.810	0.360	0.144*	1.466	0.441
SVAR	30.999***	4.290	3.809	11.991***	3.520	0.726
BM	7.681***	3.271	1.871	2.123	0.924	0.143
NTIS	0.264	0.039	1.491e-04	-1.921	-0.233	0.008
TBL	-0.197	-0.766	0.200	0.022	0.140	0.002
LTY	-0.345***	-2.331	0.970	-0.082	-0.611	0.052
LTR	0.030***	2.489	1.211	0.004	0.343	0.017
TMS	-0.161*	-1.306	0.289	-0.068	-0.618	0.051
DFY	0.184**	1.970	0.568	0.141*	1.547	0.435
DFR	-0.085***	-3.589	3.063	0.011	0.599	0.052
INFL	0.091	0.933	0.147	-0.049	-0.597	0.041

Note: This table summarizes the in-sample estimation results of forecasting models with macroeconomic variables. It reports the estimated coefficients, t-statistics, and percentage increases in R^2 (ΔR^2). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

The in-sample results show that most macroeconomic variables provide useful predictive information for both the WTI crude oil futures and natural gas futures markets, but their predictive abilities vary. All ΔR^2 values in Table 3 are positive. This finding indicates that the selected macroeconomic variables carry useful information for volatility prediction of WTI crude oil futures and natural gas futures. For the WTI crude oil futures market, 11 of the 14 predictors have statistically significant regression coefficients. The *SVAR* model produces the largest improvement in fit among the competing models, with an in-sample ΔR^2 of 3.809%. For the natural gas futures market, only 6 of the 14 predictors have statistically significant coefficients. The *SVAR* model again produces the largest improvement in fit, with a significant coefficient estimate of 11.991. This implies that past

stock return variance may lead to higher natural gas futures price volatility in the next month. Moreover, five macroeconomic variables (*DP*, *DY*, *EP*, *SVAR* and *DFY*) exert significant influences on both international energy markets. Except for *EP*, these variables show positive effects on the two energy markets. By contrast, *NTIS*, *TBL* and *INFL* exhibit insignificant impacts on both markets.

5.2. Out-of-sample Predictive Results

5.2.1. Forecasting results of AR extension models

Out-of-sample forecasting estimates a model at a given point in time using only historical information. The estimated model is then used to forecast some or all subsequent observations. Although the preceding analysis provides in-sample estimates, good in-sample performance does not necessarily imply good out-of-sample performance. Out-of-sample forecasting better evaluates model generalization, reduces the risk of overfitting, improves forecast accuracy, and provides a more realistic model assessment [31, 35]. We therefore use an expanding estimation window to examine the predictive ability of individual economic variables. Forecast performance is evaluated using the out-of-sample R^2. Table 4 reports the out-of-sample results for the two energy markets. The sample period runs from January 1994 to December 2022, and the out-of-sample evaluation period runs from December 2008 to December 2022.

Table 4. Out-of-sample forecasting results of AR extension models

	WTI Oil Futures		Natural Gas Futures	
Model	R_{os}^2 (%)	CW	R_{os}^2 (%)	CW
DP	5.220***	2.552	0.404	0.748
DY	1.014*	1.397	-0.487	-0.029
EP	-1.540	0.524	1.013	1.235
DE	-1.870	0.241	-0.128	0.571
SVAR	7.666*	1.313	1.509*	1.325
BM	4.504***	2.456	-0.046	0.107
NTIS	-0.422	-2.354	-0.347	-0.313
TBL	-0.437	-0.605	-0.253	-1.036
LTY	1.832**	1.684	-0.210	-0.252
LTR	2.342**	1.842	-0.455	-0.513
TMS	0.229	0.422	-0.054	-0.110
DFY	-1.769	-0.121	0.748	1.099
DFR	7.490***	2.590	-1.090	0.033
INFL	-0.282	-0.329	-1.104	-0.709

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

The results show that, compared with the in-sample estimates, only a few macroeconomic variables continue to deliver superior out-of-sample forecasts. The 14 macroeconomic variables perform better in forecasting WTI crude oil futures volatility than natural gas futures volatility. For the natural gas futures market, only the AR extension model containing *SVAR* generates a significantly positive R_{os}^2 value of 1.509 %. All other competing models fail to produce significantly positive R_{os}^2. This result implies that among the 14 macroeconomic variables, only *SVAR* can generate reliable out-of-sample forecasts for natural gas futures volatility. For WTI crude oil futures, seven AR extension models (with *DP*, *DY*, *SVAR*, *BM*, *LTY*, *LTR* and *DFR* respectively) produce significantly positive R_{os}^2 values of 5.220%, 1.014%, 7.666%, 4.504%, 1.832%, 2.342% and 7.490%. These seven macroeconomic variables thus exhibit good out-of-sample predictive performance for WTI crude oil futures volatility. Furthermore, R_{os}^2 values and Clark-West (CW) test statistics demonstrate heterogeneous out-of-sample predictive power across macroeconomic variables for international energy market volatility. *DP* and *DFR* stand out as two powerful predictors for WTI crude oil futures price volatility.

5.2.2. Model combination forecasting

Individual macroeconomic variables capture distinct predictive signals. We therefore use five popular combination methods to forecast international energy price volatility from a comprehensive perspective. In theory, combination methods help reduce the mean squared forecast error. Table 5 reports the combination forecast results. The five combination methods perform well in forecasting WTI crude oil futures volatility. In the natural gas futures market, however, only the simple mean combination passes the CW test at the 10% level. The other combination methods do not reduce the mean squared forecast error and thus fail to improve forecast accuracy for natural gas futures volatility. In the WTI crude oil futures market, all combination methods except Median have similar R_{os}^2 values, and all have significant R_{os}^2 values. The combination methods based on macroeconomic variables also produce comparable predictive performance for crude oil volatility and consistently outperform the benchmark model and individual AR extension models.

Several factors may account for these results. First, many studies show that oil price volatility is highly sensitive to macroeconomic events. Most of the 14 traditional macroeconomic variables considered here significantly improve the forecast accuracy of crude oil volatility, leading to better combination forecasts [31, 35]. In the international natural gas market, however, price changes and volatility are more strongly affected by weather, supply and demand, and geopolitics [36, 37]. Consequently, single models based on macroeconomic variables cannot effectively forecast natural gas price volatility, and combination methods cannot fully exploit their advantages. Second, Liang et al. [38] show that the U.S. equity market volatility index (EMV) and the geopolitical risk index (GPR) are important drivers of natural gas futures volatility. For the natural gas futures market, therefore, most macroeconomic variables considered here may be noise, which weakens the performance of combination forecasts.

Table 5. Out-of-sample R^2 test results of combination forecasts

	WTI Oil Futures		Natural Gas Futures	
	R_{os}^2(%)	CW	R_{os}^2(%)	CW
Mean	2.759***	2.481	0.491*	1.297
Median	1.388***	2.852	0.111	0.595
TMC	2.338***	2.859	0.295	0.966
DMSPE (1.0)	2.759***	2.494	0.441	1.180
DMSPE (0.9)	2.785***	2.508	0.475	1.251

Note: * and *** denote statistical significance at the 10% and 1% levels, respectively.

6. Extended Analysis and Robustness Checks

To further examine the performance of model combination in forecasting international energy price volatility, this section extends the analysis to other international energy markets. It also uses uncertainty indices as predictors. Finally, it conducts robustness checks on the preceding empirical results.

6.1. Forecasting Volatility of Other International Energy Markets

To provide a more comprehensive analysis of international energy price volatility forecasting from a model combination perspective, this subsection introduces two additional international energy markets: the Brent crude oil spot market and the WTI crude oil spot market. For each market, we conduct out-of-sample forecasts using AR extension models based on macroeconomic variables and then generate combination forecasts. The sample period runs from January 1994 to December 2022. The out-of-sample evaluation period runs from December 2008 to December 2022.

6.1.1. Out-of-sample predictions of AR extension models

Table 6 reports the out-of-sample R^2 test results for the two international crude oil spot markets. The empirical results show the following. First, the traditional macroeconomic variables produce almost identical out-of-sample forecasts for the two crude oil spot markets. For the Brent crude oil spot market, models with seven macroeconomic variables—*DP*, *DY*, *SVAR*, *BM*, *LTY*, *LTR*, and *DFR*—produce significantly positive R_{os}^2 values. These seven variables therefore have superior out-of-sample predictive ability for Brent crude oil spot volatility. For the WTI crude oil spot market, except for *DY*, models with *DP*, *SVAR*, *BM*, *LTY*, *LTR*, and *DFR* produce significantly positive R_{os}^2 values of 4.176%, 6.612%, 3.720%, 1.396%, 1.884%, and 6.596%, respectively. Second, the R_{os}^2 values and CW test statistics show that the macroeconomic variables perform unevenly in forecasting volatility in the Brent and WTI crude oil spot markets. For example, *DFR* performs well in out-of-sample forecasts of monthly volatility in both markets, whereas *SVAR* performs poorly. For both markets, the models with *DFR* and *SVAR* produce significantly positive R_{os}^2 values, but they pass the CW test at the 1% and 10% significance levels, respectively.

Table 6. Out-of-sample forecasting results of AR extension models.

	Brent Oil Spot		WTI Oil Spot	
Model	R_{os}^2 (%)	CW	R_{os}^2 (%)	CW
DP	3.260**	1.852	4.176***	2.449
DY	2.388**	1.928	0.538	1.112
EP	-2.983	-0.779	-1.784	0.682
DE	-2.827	-1.698	-1.550	0.479
SVAR	6.249*	1.288	6.612*	1.306
BM	2.926**	1.936	3.720***	2.377
NTIS	-0.269	-1.329	-0.349	-2.508
TBL	-0.052	0.216	-0.306	-0.428
LTY	3.755***	2.389	1.396*	1.537
LTR	4.770***	2.860	1.884*	1.625
TMS	0.786	0.847	0.053	0.240
DFY	-2.507	-1.745	-1.523	-0.132
DFR	6.642***	2.503	6.596***	2.611
INFL	-0.207	-0.516	-0.424	-0.690

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

6.1.2. Model combination forecasting

We use the five combination methods described above to generate monthly volatility forecasts for the Brent and WTI crude oil spot markets. Table 7 reports the out-of-sample combination forecast results for the two international energy markets. The five combination methods perform well in forecasting monthly volatility in both the Brent and WTI crude oil spot markets. All methods significantly improve forecast accuracy for international energy price volatility. For both markets, all five combination methods produce R_{os}^2 values that are significantly positive and pass the CW test at the 5% level. In addition, except for the Median method, the other four combination methods produce similar R_{os}^2 values in both crude oil spot markets. The combination methods based on macroeconomic variables therefore produce comparable predictive performance for crude oil monthly volatility and consistently outperform the benchmark model and individual AR extension models. Most of the 14 traditional macroeconomic variables considered here can significantly improve the forecasting performance of monthly volatility in international crude oil markets [31, 35, 39]. This allows the combination methods to exploit their predictive advantages.

Table 7. Out-of-sample R^2 test results of combination forecasts

	Brent Oil Spot		WTI Oil Spot	
	R^2_{OS}(%)	CW	R^2_{OS}(%)	CW
Mean	2.567***	2.425	2.267***	2.421
Median	1.542**	1.969	1.111***	2.524
TMC	2.215***	2.567	1.886***	2.761
DMSPE (1.0)	2.884***	2.670	2.240***	2.509
DMSPE (0.9)	2.887***	2.664	2.271***	2.535

Note: ** and *** denote statistical significance at the 5% and 1% levels, respectively.

6.2. Forecasting International Energy Price Volatility Based on Uncertainty Indices

The preceding results show that the combination forecasting framework based on traditional macroeconomic variables has superior predictive performance for international energy price volatility. To further examine whether the results obtained through model combination are reliable, this subsection uses alternative predictors to construct new AR extension models. A large body of literature focuses on improving the forecasting performance of energy market volatility by exploring potential predictors and improving models [40, 41, 42]. Since Baker et al. [43] first proposed the economic policy uncertainty (EPU) index, a series of new uncertainty indices have emerged, such as the U.S. equity market volatility index (EMV), the geopolitical risk index (GPR), and the risk aversion index (RA). The modeling and forecasting of international energy price volatility has attracted considerable attention. There is also extensive theoretical support for the predictive relationship between increasingly popular uncertainty indices and international energy market price volatility [44, 45]. We therefore use uncertainty indices as new predictors to forecast international energy price volatility. This allows us to further examine whether the good performance of model combination in forecasting international energy price volatility still holds.

We use 10 uncertainty indices that are popular in the relevant literature to examine the predictability of international energy price volatility. These indices are: (1) the U.S. equity market volatility index (*EMV*) [44]; (2) the U.S. economic policy uncertainty index (*EPU*) [43]; (3) the U.S. monetary policy uncertainty index (*MPU*) [46]; (4) the risk aversion index (*RA*) [47]; (5) the economic uncertainty index (*EU*) [47]; (6) the geopolitical risk index (*GPR*) [44]; (7) the CBOE volatility index (*VIX*) [48]; (8) the real economic uncertainty index (*RU*) [49]; (9) the macroeconomic uncertainty index (*MU*) [49]; and (10) the financial uncertainty index (*FU*) [49]. The research objects are the monthly volatility of the WTI crude oil futures market and the NYMEX natural gas futures market. The sample period runs from January 1994 to December 2022. Below, we report the main forecasting results, including in-sample estimation results, out-of-sample forecasts from AR extension models based on uncertainty indices, and combination forecasts.

6.2.1. In-sample estimation results

To test whether each uncertainty index has predictive power for future international energy price volatility and whether it improves the in-sample fit of the monthly volatility model, we estimate 10 AR extension models, each including one uncertainty index, using the full sample. Table 8 summarizes the in-sample estimation results based on uncertainty indices. The table reports the estimated coefficient of each uncertainty index, the corresponding Newey–West t-statistic, and the percentage increase in the in-sample R^2 of the AR extension model (ΔR^2). As before, to highlight the predictive ability of the uncertainty indices, the table reports only the coefficients of the uncertainty indices and omits the estimated coefficients of the AR lags.

The in-sample results show that most uncertainty indices provide useful predictive information for both the WTI crude oil futures market and the natural gas futures market, but their predictive abilities vary. All ΔR^2 values are positive. This indicates that all uncertainty indices considered here contain useful predictive information for monthly volatility forecasting in both markets. For the WTI crude

oil futures market, 9 of the 10 predictors have statistically significant regression coefficients. The AR extension model with *VIX* produces the largest improvement in fit, with an in-sample ΔR^2 of 4.629%. For the natural gas futures market, 9 of the 10 predictors also have statistically significant regression coefficients. The AR extension model with *FU* produces the largest improvement in fit. The estimated coefficient of *FU* is significantly positive at 0.604. This implies that past *FU* may lead to higher natural gas futures price volatility in the next month.

Table 8. In-sample estimation results for the WTI Oil Futures and Natural Gas Futures markets.

	WTI Oil Futures			Natural Gas Futures		
Model	β	t-stat	ΔR^2(%)	β	t-stat	ΔR^2(%)
EMV	0.015***	2.973	1.724	0.009***	2.382	0.788
EPU	8.202e-05	0.099	0.003	0.001**	1.920	0.457
MPU	0.001*	1.541	0.641	0.002***	2.419	0.937
RA	0.278***	4.410	4.349	0.137***	2.949	1.340
EU	0.666***	3.365	2.476	0.278**	1.781	0.530
GPR	0.001**	1.713	0.558	-2.362e-04	-0.435	0.037
VIX	0.027***	4.173	4.629	0.014***	3.245	1.516
RU	0.692*	1.339	0.945	0.633***	2.489	0.887
MU	1.434***	2.976	3.076	0.841***	3.040	1.339
FU	1.153***	4.649	4.490	0.604***	3.223	1.613

Note: This table summarizes the in-sample estimation results of volatility forecasting models based on uncertainty indices. It reports the estimated coefficients of the uncertainty indices, t-statistics, and percentage increases in model R^2. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

6.2.2. Out-of-sample predictions of AR extension models

Table 9 reports the out-of-sample forecast results based on AR extended models. The aim is to examine the out-of-sample predictive ability of individual uncertainty indices for international energy market volatility. When generating out-of-sample forecasts, we exclude the *RU*, *MU*, and *FU* indices. These three indices are constructed via principal component analysis and may suffer from look-ahead bias [31].

The empirical results show that, for the WTI crude oil futures market, most uncertainty indices continue to provide good out-of-sample forecasts. However, *MPU* and *GPR* no longer generate statistically significant forecasts of crude oil volatility. For the natural gas futures market, only *RA* and *VIX* continue to provide good forecasts of natural gas volatility. The R^2_{os} and CW values in the table show that the out-of-sample predictive performance of uncertainty indices for international energy price volatility is uneven. *RA* and *VIX* perform well in forecasting monthly volatility in both international energy markets.

Table 9. Out-of-sample forecasting results of AR extension models.

	WTI Oil Futures		Natural Gas Futures	
Model	R^2_{os} (%)	CW	R^2_{os} (%)	CW
EMV	3.553**	1.882	0.570	1.016
EPU	-4.206	-1.448	-2.010	-0.464
MPU	-0.276	0.246	0.959	1.201
RA	6.171***	2.551	3.271**	2.135
EU	1.824*	1.339	1.098	1.197
GPR	0.135	0.710	-0.288	0.156
VIX	8.325***	2.576	4.091***	2.665

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

6.2.3. Model combination forecasting

Table 10 reports the out-of-sample combination forecast results for international energy market volatility based on the 10 uncertainty indices. The five combination methods perform well in forecasting monthly volatility in both international energy markets. All methods significantly improve the forecast accuracy of international energy price volatility. For the WTI crude oil futures market, the five combination methods produce similar R_{os}^2 values, and all pass the CW test at the 5% significance level. For the natural gas futures market, the five combination methods also produce significantly positive R_{os}^2 values. This result again shows that the combination methods consistently outperform the benchmark model and individual AR extension models.

Table 10. Out-of-sample R^2 test results of combination forecasts.

	WTI Oil Futures		Natural Gas Futures	
	R_{os}^2(%)	CW	R_{os}^2(%)	CW
Mean	3.332**	1.977	1.662**	1.802
Median	3.332**	1.742	1.378*	1.491
TMC	3.442**	1.976	2.010**	2.095
DMSPE (1.0)	3.392**	2.020	1.494**	1.741
DMSPE (0.9)	3.570**	2.074	1.541**	1.773

Note: *, and ** denote statistical significance at the 10%, and 5% levels, respectively.

6.3. Robustness checks

6.3.1. Altering the out-of-sample evaluation period

The length of the forecast window is crucial for testing predictive ability. We therefore change the out-of-sample evaluation period to demonstrate the advantages of combination forecasts and to verify the robustness of the main empirical results. Specifically, we adjust the out-of-sample evaluation period to cover December 2014 to December 2022. We then recalculate the out-of-sample R^2 for each combination method and perform the CW test.

Table 11 reports the out-of-sample performance evaluation results under the new evaluation period. The five combination methods still show superior predictive performance for WTI crude oil futures volatility. For natural gas futures volatility, however, none of the combination methods reduces the mean squared forecast error. They therefore fail to significantly improve the forecast accuracy of natural gas futures volatility. For WTI crude oil futures volatility, the five combination methods produce R_{os}^2 values of 3.551%, 1.704%, 2.881%, 3.637%, and 3.654%, respectively. All pass the CW test at the 1% significance level. In addition, the combination methods based on traditional macroeconomic variables produce comparable predictive performance for crude oil monthly volatility and consistently outperform the benchmark model and individual AR extension models. Overall, the empirical results in Table 10 are consistent with the main conclusions. They show that combination forecasts can significantly improve the forecast accuracy of WTI crude oil futures volatility.

Table 11. Out-of-sample R^2 test results of combination forecasts under the new evaluation period.

	WTI Oil Futures		Natural Gas Futures	
	R_{os}^2 (%)	CW	R_{os}^2 (%)	CW
Mean	3.551***	2.352	0.116	0.296
Median	1.704***	2.860	0.211	0.745
TMC	2.881***	2.661	-0.064	-0.072
DMSPE (1.0)	3.637***	2.372	0.122	0.304
DMSPE (0.9)	3.654***	2.371	0.137	0.332

Note: *** denotes statistical significance at the 1% levels.

6.3.2. Altering the lag order

The conclusions in the main text are based on optimal lag orders of k=2 and k=11 for the log volatility series of WTI crude oil futures and natural gas futures, respectively. These orders are determined by the AIC. In this subsection, we increase the lag orders to 6 and 14, respectively, on the basis of the optimal lag orders. We then re-examine international energy price volatility forecasting and test the predictive ability of the combination methods for monthly volatility in the WTI crude oil futures and natural gas futures markets.

Table 12. Out-of-sample R^2 test results of combination forecasts under the new lag order

	WTI Oil Futures		Natural Gas Futures	
	R^2_{os}(%)	CW	R^2_{os}(%)	CW
Mean	2.873***	2.434	0.490	1.213
Median	1.440***	2.552	0.105	0.517
TMC	2.382***	2.740	0.324	0.980
DMSPE (1.0)	2.954***	2.462	0.427	1.077
DMSPE (0.9)	2.969***	2.461	0.458	1.139

Note: *** denotes statistical significance at the 1% levels.

Table 12 reports the out-of-sample R^2 test results for WTI crude oil futures and natural gas futures volatility after changing the lag order. The empirical results show that the combination methods exhibit superior predictive ability for WTI crude oil futures volatility and consistently outperform single forecasting models. However, they perform poorly in forecasting monthly natural gas futures volatility. The out-of-sample R^2 results for the two international energy markets show the following. For WTI crude oil futures volatility, all five combination methods produce R^2_{os} values that pass the CW test at the 1% significance level. For natural gas futures volatility, none of the R^2_{os} values passes the CW test at the 10% significance level. In addition, for WTI crude oil futures volatility, except for the Median method, the other four combination methods produce similar R^2_{os} values.

7. Summary

7.1. Conclusions

Accurate forecasting of international energy price volatility is an important tool for achieving sustainable development, rational resource allocation, and safeguarding national economic security. This paper therefore focuses on the international natural gas and crude oil markets and examines international energy price volatility forecasting from a model-combination perspective. Using monthly energy volatility data, macroeconomic variables, and uncertainty indices from January 1994 to December 2022, we adopt the AR model as the benchmark model for energy market volatility. We conduct in-sample estimation and out-of-sample forecasts based on AR extension models. On this basis, we construct five combination methods to generate out-of-sample forecasts of international energy market volatility. We further examine the adaptability of model combination to different predictors and whether its superior predictive performance holds across different energy markets. Finally, we conduct robustness checks by changing the out-of-sample evaluation period and the lag order of the log volatility series. The main conclusions are as follows.

First, the in-sample estimation results show that *SVAR* has a significant positive effect on the monthly volatility of both international crude oil and natural gas futures. Most uncertainty indices also have significant positive effects on the volatility of both markets. Although most macroeconomic variables have insignificant effects on natural gas futures volatility, all selected macroeconomic variables and uncertainty indices produce in-sample R^2 values no lower than that of the benchmark model. Second, *DP* and *DFR* have relatively robust out-of-sample predictive ability for international crude oil market volatility. For natural gas futures volatility, only *SVAR* produces a significantly positive out-of-sample R^2. For both international crude oil and natural gas futures markets, most uncertainty indices

continue to provide good out-of-sample forecasts. Finally, whether based on macroeconomic variables or uncertainty indices, all five combination methods perform well in forecasting international crude oil market volatility. They consistently outperform the benchmark model and individual AR extension models, and their forecasting performance is almost identical. In addition, for natural gas futures volatility, combination forecasts based on uncertainty indices better highlight the superior predictive performance of model combination than those based on macroeconomic variables.

7.2. Recommendations

The conclusions of this paper can help policymakers formulate more reasonable and sustainable energy policies. They can also help investors in international energy markets improve risk management and optimize investment strategies.

First, the international energy market has both commodity and financial attributes. Its price volatility is driven not only by macroeconomic fundamentals but also by non-fundamental factors. When formulating strategies in response to international energy price volatility, relevant decision-makers should fully consider the factors that affect this volatility. They should pay close attention not only to traditional macroeconomic indicators but also to changes in uncertainty indices.

Second, China's energy market is closely linked to international energy markets. However, international energy price volatility is largely affected by U.S. and global macroeconomic factors and uncertainty indices. Against the current complex and volatile international economic and political backdrop, Chinese policymakers should seize favorable opportunities in international energy markets and strive to enhance China's influence in these markets.

Finally, information provided by a single predictor can hardly produce stable out-of-sample forecasts. When using volatility forecasts for risk management, investment strategy optimization, and energy policy formulation, international energy market investors and policymakers should ideally combine the predictive information of multiple influencing factors. They should fully consider the effects of macroeconomic variables and uncertainty indices on international energy market volatility.

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