Modern Economy, 2025, 16(6), 884-903
https://www.scirp.org/journal/me
ISSN Online: 2152-7261
ISSN Print: 2152-7245

Impact of Climate Policy Uncertainty on Energy Price Volatility: Evidence from China

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How to cite this paper: Duo, J. L. (2025). Impact of Climate Policy Uncertainty on Energy Price Volatility: Evidence from China. *Modern Economy, 16,* 884-903.
https://doi.org/10.4236/me.2025.166042

Received: February 15, 2025
Accepted: June 23, 2025
Published: June 26, 2025

Abstract

Climate change has become one of the most serious challenges facing mankind in the 21st century. Due to the diversity and complexity of climate policies and their dynamic adjustment during implementation, the uncertainty of climate policies has become one of the important factors affecting the market. As the world's largest consumer of commodities, China's climate policy adjustment has an impact on the decision-making process of commodity market participants, which changes the demand structure of commodities and thus affects their yields. In this paper, TVP-SV-VAR and DLNM are used to investigate the nonlinear lagging effects of climate policy uncertainty, energy and agricultural commodity prices in China.

Keywords

Climate Policy Uncertainty, Energy Market, Commodity Market, DLNM, TVP-SV-VAR

1. Introduction

Climate change has become a major global challenge in the twenty-first century, with rising global temperatures and extreme weather events profoundly affecting economic, social and environmental systems. Evidence shows that climate change not only threatens the living environment of human beings, but also poses a serious challenge to the global economic system. Against this backdrop, governments have launched climate policies to promote the energy transition, but the implementation of these policies is subject to multiple uncertainties: differences in policy objectives, asynchronous implementation steps, and unpredictability of detailed adjustments, which together have led to increased volatility in market expectations. The concept of Climate Policy Uncertainty (CPU) was first introduced by Gavriilidis, (2021) to measure the uncertainty associated with the formulation, implementation, and adjustment of climate change-related policies. This uncertainty can impact investor expectations, interfere with corporate production decisions, and change consumption behavior patterns. Especially in the context of globalization, CPU may trigger abnormal price fluctuations in the commodity market (energy, agricultural products, etc.), which are transmitted through the industrial chain and have actually evolved into an important trigger that exacerbates instability in the financial market.

In recent years, as governments and international organizations have gradually increased their policy efforts to address climate change, the uncertainty of climate policy has increasingly become one of the factors affecting the global market. Especially in the process of clean energy transition, the impact of climate policy uncertainty on the energy market is particularly significant. As the global energy structure gradually transforms to renewable energy, the traditional energy sector is facing transformation pressure, and the demand and price of fossil energy such as oil and natural gas are gradually restricted. At the same time, although the rapid development of the new energy market has provided a new growth engine for the global economy, the policy uncertainty it faces makes it difficult for investors and producers to accurately foresee the future direction of the market. In addition to energy markets, the impact of climate policy uncertainty on agricultural markets cannot be ignored. Agricultural production is inherently dependent on climatic conditions, and extreme weather, climate change and natural disasters pose a direct threat to crop growth. At the same time, changes in climate policy may further exacerbate the volatility of agricultural markets by altering agricultural production methods, land-use policies and the global trade environment. In recent years, with the acceleration of global agricultural production and financialization, the volatility of agricultural commodity prices has gradually increased, and climate policy uncertainty has become an important factor affecting agricultural commodity markets. The impacts of climate change on agricultural and energy markets are global, and the implementation of climate policies has implications on an international scale. For example, global emission reduction targets, carbon market mechanisms and renewable energy policies are all relevant to energy and agricultural markets. Therefore, studying the impact of climate policy uncertainty in these two markets can provide a theoretical basis and practical guidance for the formulation of global climate policy and the coping strategies of countries.

In order to reduce carbon emissions, the traditional energy sector faces huge losses, and the lack of preparedness in the new energy sector may lead to the transmission of these risks to financial institutions, thus triggering systemic financial shocks (Stroebel & Wurgler, 2021; Battiston & Martinez-Jaramillo, 2018). The impact of climate policy uncertainty on commodity markets is not only manifested in increased short-term market volatility, but also has important implications for market expectations and investment decisions in the medium to long term. In particular, the impact of climate policy uncertainty is particularly significant in commodity markets such as energy, agricultural products and metals. Specifically, climate policy uncertainty affects price volatility in commodity markets through a number of channels, including changes in policy expectations, the implementation of governments' climate commitments, and market expectations of future policy changes. Together, these factors contribute to a more complex and volatile environment for commodity markets. Therefore, an in-depth study of the impact of climate policy uncertainty on the volatility of commodity markets has both significant academic value and far-reaching implications for investment decisions and policymaking in practice.

In recent years, as global initiatives toward carbon neutrality have accelerated, the influence of climate factors on renewable energy markets has become more apparent. According to Sailor et al. (2008), climate change can substantially reduce wind energy output in summer-by as much as 40%-thereby affecting supply-demand dynamics in the U.S. renewable sector. Similarly, Auffhammer et al. (2017) highlighted that climate-related disruptions in the power industry could account for a significant share of worldwide economic losses in the energy domain. Perera et al. (2020) further demonstrated that extreme weather and climate-driven shifts in weather patterns undermine both energy consumption patterns and the robustness of energy infrastructure. Gernaat et al. (2021) used simulation models to show that renewable energy systems heavily reliant on climatic conditions are particularly susceptible to future climate variability. Additionally, Bouri et al. (2022) identified climate policy uncertainty (CPU) as a key factor differentiating the market performance of green versus traditional energy stocks. Using SVAR modeling, Adeniyi Adeosun et al. (2023) found that rising uncertainty in U.S. climate policies does not significantly affect carbon emissions. (Ren et al., 2022), drawing on data from publicly listed Chinese firms, found that CPU can reduce firms' total factor productivity by constraining access to financial resources. Moreover, several studies (e.g., Diaz et al., 2023; Bartram et al., 2022) point out that abrupt shifts in climate policies tend to trigger notable volatility in energy firm stock prices.

In terms of direct linkages between agricultural commodities and energy markets, climate policy significantly affects agricultural commodity prices through the biofuel demand channel, e.g., an increase in corn futures price volatility with a higher percentage of biofuel blending in the U.S. Renewable Energy Standard (RES). Meanwhile, Kang et al. (2024) find that corn ethanol price volatility affects crude oil futures yields through the fuel substitution effect, suggesting bidirectional spillovers between agricultural and energy markets. In terms of policy transmission mechanisms, Edame et al. (2011) studied the linkage effects of the EU carbon border adjustment mechanism on agricultural and energy markets, and found that carbon price increases would have a one-way spillover effect on wheat prices through fertilizer cost transmission, while energy price volatility affects cotton planting yields through irrigation costs. In terms of the direct linkage between agricultural products and energy markets (Zhang, 2022), based on provincial-level panel data in China, found that the carbon trading pilot policy has a significant impact on wheat and corn prices through the agricultural production cost channel. Li et al. (2023) investigated the impact of photovoltaic (PV) subsidy policy on cotton cultivation, and found that agro-photovoltaic (A-PV) projects have a significant impact on cotton cultivation in the short term by lowering the irrigation tariffs to improve cotton planting returns, but may suppress soybean supply elasticity in the long run due to increased land competition. In terms of the policy transmission mechanism, C. Chen et al. (2021) analyzed the impact of the national carbon market on the power sector, and pointed out that carbon quota trading significantly increased the cost pressure on coal-fired power plants, but there was a lagged effect in the promotion of PV power generation, and this adjustment of the energy structure further affected the energy use pattern of agricultural machinery. In addition, Wang et al. (2023) explored the linkages between agricultural products and energy markets under extreme weather events and found that a surge in energy consumption for agricultural irrigation during drought significantly pushes up electricity demand, which in turn exacerbates the transmission effect of energy price volatility on the cost of agricultural products.

In the energy market, Acemoglu and Rafey (2023) examine the differential impact of carbon tax policies on coal-fired power plants versus photovoltaic power generation, but do not explore their spillover effects on agricultural markets. In terms of agricultural markets, Searchinger et al. (2008) show that biofuel policy significantly affects corn prices through the demand channel, but do not analyze its reverse transmission to energy markets. In terms of financial markets, Chen et al. (2023) explored the impact of carbon markets on stock indices, but did not address the linkages in agricultural markets. F. Zhang et al., (2022) analyzed the impact of carbon trading pilot policies on wheat and corn prices based on Chinese provincial panel data, but did not explore their international spillover effects. Zhong and Pei (2022) used to study the impact of the EU carbon border adjustment mechanism on wheat prices, but did not consider the time-varying character of the policy effect.

The above study provides a valuable perspective for understanding the linkages between climate policy uncertainty and agricultural and energy markets, and the study could be further extended to consider the impacts of additional climate policy instruments (e.g., carbon tax, carbon quota trading, etc.) on the linkages between agricultural and energy markets, especially in the context of the gradual adjustment of the global climate policy framework. In addition, given the time-lag effect of policy uncertainty, more sophisticated dynamic modeling approaches should also be considered to more accurately capture the long-term impact of policy changes on markets.

2. Methodology

2.1. TVP-SV-VAR Model

The time-varying parameter vector autoregressive model (TVP-SV-VAR) used in this paper evolved from the structural vector autoregressive model (SVAR). The main difference with the SVAR model is that in the modeling assumptions, there is no assumption of homoskedasticity in the TVP-SV-VAR model, which is more in line with reality, and it assumes that the coefficient matrices and the covariance matrices change in real time, which is better able to capture the relationships and characteristics of the variables in the context of different market sentiments, avoiding undue smoothing, and is conducive to the delineation of the influence relationships between the variables and the This is conducive to characterizing the influence of variables and their nonlinear features. These features also make the model suitable for measuring the time-varying relationship between climate policy uncertainty and commodity prices.

Since the TVP-SV-VAR model is based on the SVAR model, the structural VAR model is constructed first:

$$Ay_t = F_1 y_{t-1} + F_2 y_{t-2} + \cdots + F_s y_{t-s} + \mu_t,\ t = s+1, s+2, \cdots, n, \tag{1}$$

where s is the number of lags; y_t is an observable variable of order $k \times 1$. $A, F_1, \cdots, F_s$ are parameter matrices of $k \times k$; u_t is used to measure structural shocks and $u_t \sim N(0, \Sigma_t)$.

Assuming that structural shocks obey recursive identification, matrix A is assumed to be a lower triangular matrix of order $k \times k$, which can be obtained by Cholesky decomposition and serves to better identify the economic structure of the model parameters in the form of equation (2):

$$A = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ a_{21} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{k1} & a_{k2} & \cdots & 1 \end{pmatrix} \tag{2}$$

Transform equation (2) by shifting the terms and multiplying both sides of the equation by A^{-1} to obtain equation (3):

$$y_t = B_1 y_{t-1} + \cdots + B_s y_{t-s} + A^{-1} \Sigma \varepsilon_t \tag{3}$$

where $B_i = A^{-1} F_i$, $i = 1, \cdots, s$; $\varepsilon_t \sim N(0, I_k)$; Σ is the standard error matrix and is a diagonal matrix, which is structured as in equation (4):

$$\Sigma = \begin{pmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & 0 \\ 0 & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_k \end{pmatrix} \tag{4}$$

In equation (4), σ is the standard deviation of the structural shock; the model transforms to equation (5) by stacking the row vector elements of the lag coefficient matrix B_i to form a column vector of order $k^2 s \times 1$, β, and setting $X_t = I_k \otimes (y'_{t-1}, \cdots, y'_{t-k})$, $\otimes$ to be the Kronecker product:

$$y_t = X_t \beta + A_t^{-1} \Sigma \varepsilon_t \tag{5}$$

where s is the model lag order and t is the time identity. All parameters in equation (5) are time-varying, and if we assume that β_t, and Σ_t in the model are time-varying variables, we can get TVP-SV-VAR model as equation (6):

$$y_t = X_t\beta_t + A_t^{-1}\Sigma_t\varepsilon_t,\ t = s+1, s+2, \cdots, n, \tag{6}$$

In equation (6), β_t is the vector of time-varying coefficients, A_t is the time-varying parameter matrix, and Σ_t is the covariance matrix of the stochastic perturbation term ε_t. $a_t = \left(a_{21}, a_{31}, a_{41}, \cdots, a_{k,k-1}\right)'$ denotes the stacked vector of lower triangular elements of A_t, where $\sigma_{jt}^2 = \exp\left(h_{jt}\right)$, the stochastic volatility matrix $h_t = \left(h_{1t}, h_{2t}, \cdots, h_{kt}\right)'$, $j = 1, 2, \cdots, k; t = s+1, s+2, \cdots, n$, assumes that the parameters in the model obey mutually independent stochastic wandering processes:

$$\beta_{t+1} = \beta_t + \mu_{\beta t}, a_{t+1} = a_t + \mu_{at}, h_{t+1} = h_t + \mu_{ht} \tag{7}$$

$$\begin{pmatrix} \varepsilon_t \\ \mu_{\beta t} \\ \mu_{at} \\ \mu_{ht} \end{pmatrix} \sim N\left(0, \begin{pmatrix} I & O & O & O \\ O & \Sigma_\beta & O & O \\ O & O & \Sigma_a & O \\ O & O & O & \Sigma_h \end{pmatrix}\right) \tag{8}$$

where $t = s+1, s+2, \cdots, n$, $\beta_{s+1} \sim N\left(\mu_{\beta 0}, \Sigma_{\beta 0}\right)$, $a_{s+1} \sim N\left(\mu_{a0}, \Sigma_{a0}\right)$ and $h_{s+1} \sim N\left(\mu_{h0}, \Sigma_{h0}\right)$. The model has the following assumptions, assuming that the parameters all obey first-order random walks and that the random shocks to the time-varying parameters are uncorrelated, and assuming that Σ_β, Σ_a, and Σ_h are diagonal matrices in order to simplify the estimation of the model. The traditional estimation technique based on the likelihood function is no longer applicable due to the stochastic volatility of the parameters in the model.

This study uses a Markov chain Monte Carlo (MCMC) method based on Bayesian inference to estimate the parameters. The MCMC simulation process is first constructed with samples originating from a multidimensional posterior distribution of the parameters. The sampling method then involves joint sampling using the residual parameter $\beta = \left\{\beta_t\right\}_{t=s+1}^{n}$, $a = \left\{a_t\right\}_{t=s+1}^{n}$, $h = \left\{h_t\right\}_{t=s+1}^{n}$, followed by sampling of β and a using an analog filter. Finally, a state-space simulation is constructed that samples h using multiple shifts. An important advantage of this approach is that it effectively reduces the number of parameters that need to be estimated by modeling the parameters as random walk processes rather than autoregressive processes. This change helps to simplify the model and potentially improve the estimated.

2.2. Distributed Lag Nonlinear Model (DLNM)

In this study, a distributed lag nonlinear model (DLNM) is introduced to analyze the nonlinear and lagged effects of climate policy uncertainty on the markets for bulk agricultural products and energy. The DLNM, which was initially widely used to study the effects of air pollution and temperature changes on health outcomes, is also applicable to characterize the nonlinear and lagged effects among the variables. The main advantages of the DLNM are as follows: firstly, lagged effects, which, in many real-life situations, there may be a certain lag in the effect of exposure factors on outcome events, and DLNM can estimate the effects of exposure factors at different lagged time points, thus revealing the existence of lagged effects and their durations. The second is the nonlinear relationship; the relationship between exposure factors and outcome events may be nonlinear, and DLNM allows the introduction of nonlinear terms in the model to capture the nonlinear relationship between exposure factors and outcome events. Finally, the DLNM employs natural cubic spline smoothing of the exposure factors to capture the effects of the exposure factors over the entire time horizon. This approach eliminates potential confounders and makes the model results more plausible. In this study, the predictor variable is defined as the intensity of CPU in China. In contrast, the response variables are bulk agricultural and energy markets. The cross-basis matrix R is generated through tensor-product interactions, allowing for a comprehensive exploration of the complex, delayed, and nonlinear relationship between policy uncertainty and market spillovers.

$$R = \left[r_1(x,t) \otimes r_2(x,t) \right] \tag{9}$$

where $r_1(x,t)$ denotes the exposure response function based on natural cubic spline (node = 3, AIC optimization), and $r_2(x,t)$ is a polynomial distribution lag function with a maximum lag of $L = 12$ trading months.

The model parameters are estimated using penalized likelihood estimation and the mathematical expression of DLNM is:

$$Y = \alpha + \sum_{j=1}^{J} s_j\left(CPU_{tj};\beta_j\right) + \sum_{k=1}^{K} \gamma_k \mu_{tk} + \varepsilon_t, \tag{10}$$

where t denotes time; x_{tj} is the independent variable, such as China CPU; u_{tk} is the control variable, which has a linear effect on Y. The function s_j represents the nonlinear effect of the independent variable on Y where it is defined by a smooth function, such as a spline function or a polynomial function. The goal is to transform Y into a time series with several different coefficients in order to characterize its nonlinear effect. Using the smoothing function $s\left(CPU_t;\beta\right) = z_t^{\mathrm{T}} \cdot \beta$, the transformation expression is as follows:

$$\begin{cases} CPU_1 \\ \vdots \\ CPU_t \\ \vdots \\ CPU_N \end{cases} \Rightarrow S \Rightarrow \begin{bmatrix} Z_{11} & \cdots & Z_{1j} & \cdots & Z_{1J} \\ & & \vdots & & \\ X_{t1} & \cdots & Z_{tj} & \cdots & Z_{tJ} \\ & & \vdots & & \\ X_{n1} & \cdots & Z_{nj} & \cdots & Z_{nJ} \end{bmatrix}, \tag{11}$$

Here, $Z_{t\bullet}$ denotes the $n \times v_x$ th row vector of the basis matrix Z of dimension t, which is designed to allow the introduction of lagged effects into the model. It is assumed Y to be affected by x_{t-l}, where L denotes the lag period. With this construction, we obtain the $n \times (L+1)$-dimensional matrix Q with the mathematical expression:

$$q_{t\bullet} = \left[CPU_t, \cdots, CPU_{t-l}, \cdots, CPU_{t-L}\right]^{\mathrm{T}}, \tag{12}$$

where L is the maximum lag and hence $q_{1\bullet} = CPU$, which is the first column of

Q. Then, a new DLNM can be constructed and $s(CPU_t;\eta)=q_{t\cdot}^{\mathrm{T}}C\eta$, where C denotes $(l+1)\times v_l$ the matrix of basis variables obtained by applying a specific basis function to the lag vector *l*. For example, if C== 1, it is a moving average model. 22 It is the vector of parameters that should be estimated, and the true coefficients $\hat{\beta}=C\hat{\eta}$.

Compared with the classical VAR model, the DLNM has three key analytical advantages: 1) it is able to identify the threshold of the intensity of policy shocks; 2) it quantifies the cumulative lagged effects and their confidence intervals; 3) it reveals the nonlinear coupling mechanism of "intensity-lag-market response" through the three-dimensional response surface. Thus, the DLNM describes the short- and long-term nonlinear lagged effects of China's CPU on the bulk agricultural and energy markets at different levels.

The selection of the TVP-SV-VAR and DLNM models is based on their distinctive strengths in capturing complex dynamic interactions. Compared to conventional VAR or linear regression models, the TVP-SV-VAR model allows for time-varying coefficients and stochastic volatility, offering a more flexible framework to track structural changes and evolving shock responses. The DLNM model, originally developed in epidemiological research, is particularly effective in analyzing nonlinear and delayed relationships. It accommodates interactions between policy uncertainty intensity and its temporal lag effects, which are crucial to understanding commodity market responses. Nonetheless, both models entail computational intensity and require careful calibration. The robustness of results was ensured through Bayesian inference and sensitivity analyses.

3. Data

The climate policy uncertainty index used in this study was constructed by Ma et al. (2023) based on the news report data published by six mainstream Chinese newspapers (People's Daily, Guangming Daily, Economic Daily, Global Times, Science and Technology Daily, and China News Service) to construct a climate policy uncertainty index for China at the national, provincial, and city levels, which was constructed by integrating the MacBERT deep learning model with a The multi-level semantic characterization framework built by integrating the MacBERT deep learning model effectively overcomes the semantic bias and subjective presupposition problems of traditional keyword matching methods, and provides a quantitative benchmark with high confidence and validity for policy uncertainty research. Its explanatory validity has been tested multidimensionally in the fields of global environmental governance (Wu, 2023) and low-carbon economic transition (Liu et al., 2022). China, as the world's largest "breadbasket" for major agricultural commodities, chose to include futures prices for soybeans, corn, cotton, and wheat obtained from the Zhengzhou Commodity Exchange (ZCE) and the Dalian Commodity Exchange (DME) in China. These major agricultural commodities are closely related to climate policy, with corn and soybeans being the main feedstock for biofuels, which are directly related to the oil industry (Jia et al., 2024). There are two motivations for using commodity futures prices in this paper, one factor is that the price dominance of the futures market determines the spot price of commodities (Ameur et al., 2022), and the other factor is that the volume of futures trading is much larger than the spot market. Energy data choose CSI New Energy Index (NE) and China Daqing Crude Oil (OIL) as proxy variables for China's energy market. The NE index selects 80 listed securities in the Shanghai and Shenzhen markets that are involved in the business of renewable energy production, new energy application, new energy storage, and new energy interactive equipment as the index samples, which can well reflect the overall performance of China's green energy market (Chen et al., 2022); and the price of China's Daqing crude oil is closest to the international oil price, which is more representative (e.g. Chang et al., 2023; Cui & Zou, 2022). The data were selected from January 2016 to December 2022.

The descriptive statistics of the selected variables are given in **Table 1**. The skewness of the data is positive, which implies that it is right skewed and its mean is greater than the median. Moreover, according to the skewness and kurtosis statistics, the climate policy uncertainty index is right-skewed and thick-tailed. The ADF test was first used to validate the smoothness test of the variables and found that all the variables are first-order smooth, and first-order logarithmic differencing was used in this paper for data processing. **Figure 1** and **Table 1** depict the trend of the selected variables.

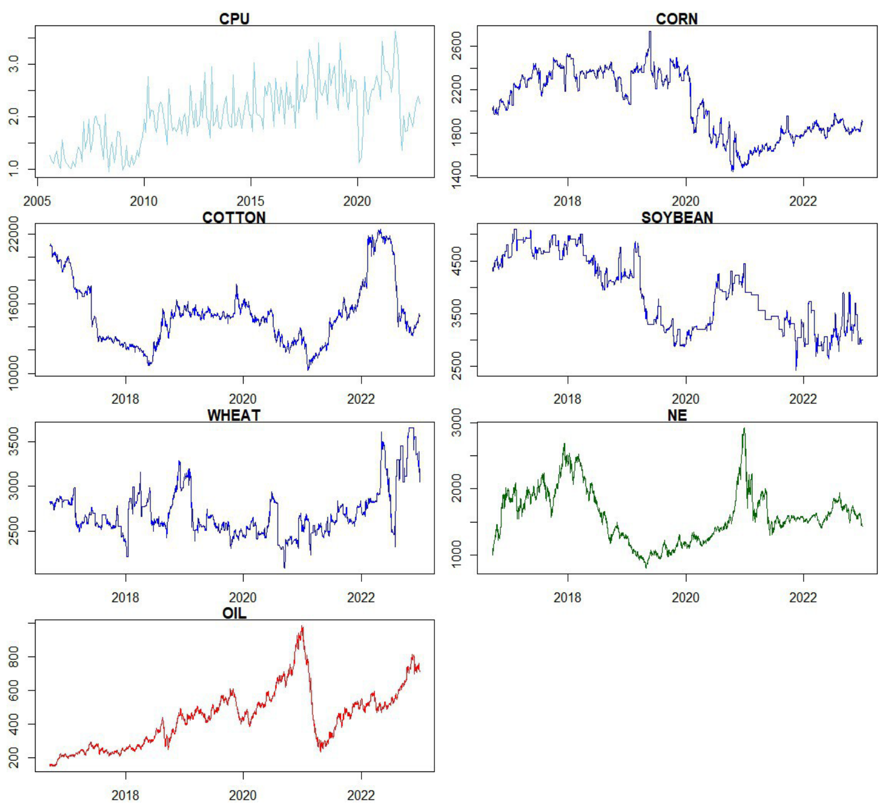


Figure 1. Time series diagram.

Table 1. Results of descriptive statistics.

	Mean	Std. Dev.	Var.	Skewness	Kurtosis	ADF test
CPU	1.758	0.723	0.523	0.184	−0.814	0.005***
Corn	2026.203	449.127	201714.755	0.173	−1.023	0.005***
Cotton	16383.252	4064.359	16519016.334	1.337	2.323	0.005***
Soybean	3912.265	819.821	672106.350	0.043	−0.767	0.005***
Wheat	5496.091	942.328	887982.137	−0.297	0.803	0.005***
NE	1172.486	489.944	0.862	−0.026	214.872	0.005***
Oil	8.229	2.513	0.458	−0.213	577.787	0.005***

Analysis of the time series Figure 1 and descriptive statistics Table 1 shows that the volatility of climate policy uncertainty in China has increased since 2017, reflecting higher market uncertainty due to frequent policy adjustments. The new energy index has grown significantly since 2017, suggesting that policy support and changes in market demand have driven the rapid development of this sector. Meanwhile, crude oil prices have been more volatile, especially during the 2014-2020 period, with sharp fluctuations in the global economy and supply chain leading to dramatic ups and downs in its price, reflecting the energy market's high sensitivity to changes in policy and the global economy. China's markets for major agricultural commodities (corn, soybeans, cotton, and wheat), on the other hand, have been relatively less volatile, especially wheat, whose price fluctuations have been smoother, likely related to the relative stability of domestic production and markets. Prices of maize and soybeans are more volatile, especially during 2019-2020, which is closely related to changes in demand in the international market as well as the impacts of climate change.

4. Empirical results

4.1. Impact of Climate Policy Uncertainty on Bulk Agricultural Commodities

From the equally spaced impulse responses of agricultural futures in Figure 2**,** it can be seen that in the face of the shock of climate policy uncertainty, all four agricultural products receive different impacts of shocks throughout the sample period. Among them, corn, cotton and soybean have less fluctuation and less impact in the short-term, but wheat receives unstable and more volatile short-term shocks throughout the sample period. Corn faces the impact of climate policy uncertainty, and the medium-term and long-term shocks are more volatile at particular points in time, for example, around 2017, the medium-term impact of CPU on corn futures is negative and then positive, on the contrary, the long-term impact is positive and then negative, and both of them reach the peak of the whole sample period; before 2020, the medium-term impact has an obvious positive effect, and in 2022, the long-term impact and the medium-term impact successively In 2022, the long-term and medium-term shocks successively fluctuate significantly, but the short-term shocks are more stable and consistently positive throughout the sample period. Cotton and soybeans, in the face of shocks from climate policy uncertainty, likewise have large fluctuations in medium- and long-run shocks at a few particular points in time, and, as with corn, the medium- and long-run restarts of CPU fluctuate dramatically around 2017, which may be attributed to the establishment of the Paris Agreement, which is exactly the kind of global framework that has been developed to combat climate change, aiming at reducing greenhouse gas emissions, preventing a global temperatures from rising, and increase countries' resilience to climate change. The impulse responses of wheat and the other three agricultural products are slightly different, firstly, the short-term shocks suffered are more volatile over the whole sample period, and the short-term shocks are still larger than the medium- and long-term shocks in 2017, when the rest of the three agricultural products were particularly affected, which may be due to the fact that our country is a large producer of wheat but not a strong producer of wheat, and the share of our wheat production globally is decreasing year by year. Based on the above findings to understand that agricultural products receive different CPU impulse responses at different lags, the DLNM model is next used to observe the trend impacts received by the four agricultural products at different lags and different levels of CPU.

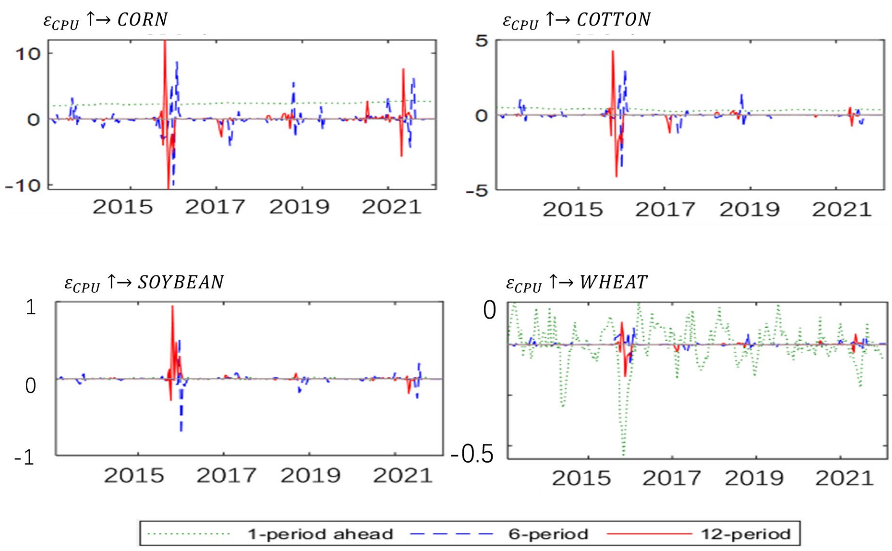
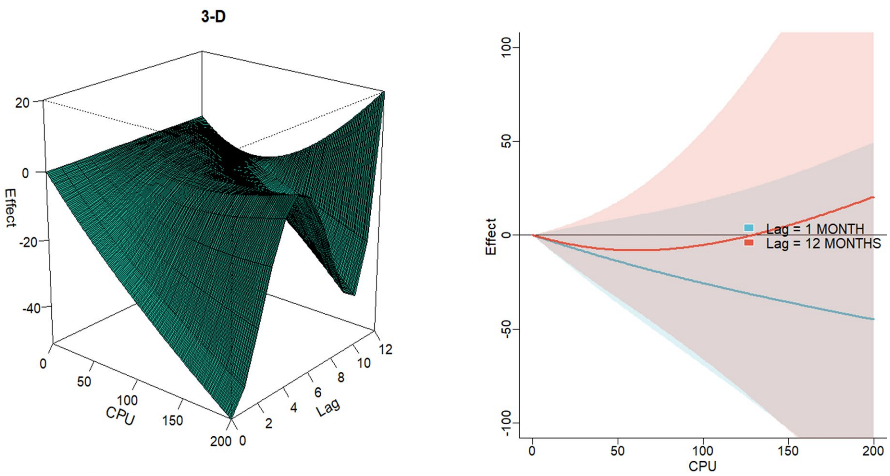


Figure 2. CPU equal-interval impulse for agricultural markets.

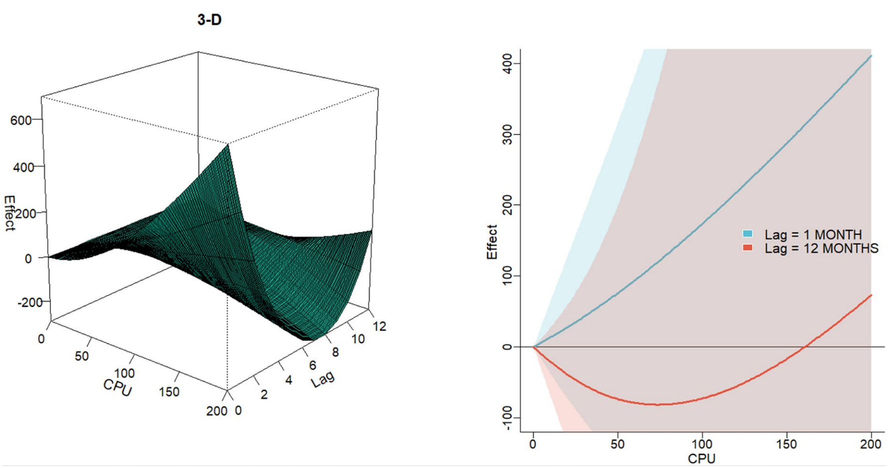
The nonlinear and lagged effects of CPU on corn futures were first investigated. As shown in **Figure 3**, CPU has a significant nonlinear and lagged effect on corn futures prices. The negative effect on corn futures prices only occurs at higher levels of CPU, and this negative effect may strengthen as CPU continues to increase. However, when the lag is about 2 to 6 months, CPU growth has a progressively significant positive effect on corn futures only at high CPU levels. Then, when the lag exceeds 6 months, this effect will again turn to become negative, before the negative effect steepens at a lag of about 10 months, and then turns positive at more than 12 months thereafter. In terms of lagged effects, a rise in CPU will have a negative effect when the lag is about 1 month, and when the lag reaches about 12 months, a low level of CPU may have a significant negative effect on corn futures. However, as the level of CPU increases, the effect of CPU on corn futures prices gradually increases and turns positive. At higher lags, CPU is more likely to have a positive effect on corn futures prices, again at high CPU levels, again positive.

The nonlinear and lagged effects of CPU on cotton futures were then investigated. As shown in Figure 4, CPU has a significant nonlinear and lagged effect on cotton futures prices. The positive effect on cotton futures prices is only observed at higher levels of CPU, and this positive effect may strengthen as CPU continues to increase. However, when the lag is about 8 months, CPU growth has a negative effect on cotton futures prices at high CPU levels. Then, when the lag ranges from 0 to 8 months, CPU at high levels shifts from a positive to a negative effect, and



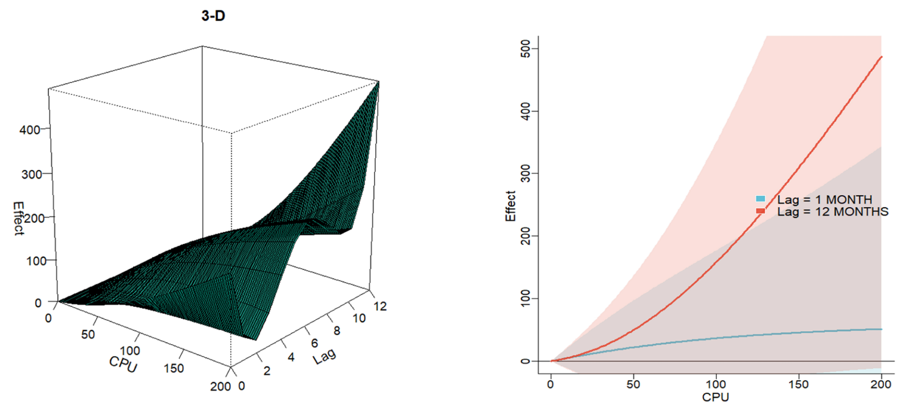
(a) (b)

Figure 3. Impacts of CPU on corn.



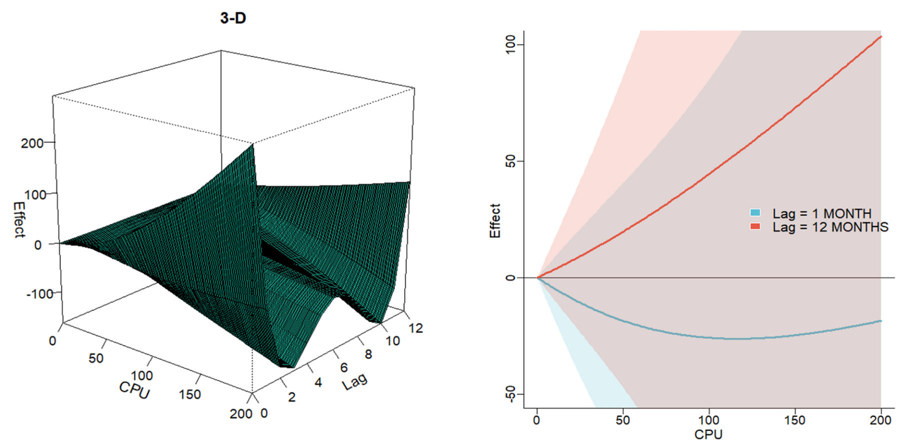
(a) (b)

Figure 4. Impacts of CPU on cotton.



(a) (b)

Figure 5. Impacts of CPU on soybean.



(a) (b)

Figure 6. Impacts of CPU on wheat.

As shown in Figure 5, CPU has a significant nonlinear and lagged effect on soybean futures prices. Unlike corn futures and cotton futures, the effect of CPU on soybean futures prices is positive at both low and high levels of CPU, and likewise with increasing lags. The impact effect has also been increasing at increasing levels of CPU, while it is decreasing between lags of 0 and 2 months, but is in a constant state of growth thereafter. In terms of lagged effects, when the lag period is about 1 month, the increase in CPU will have a positive impact on soybean futures, and when the lag period reaches about 12 months, the increase in CPU is also likely to have a significant positive impact on soybean futures. And the impact effect is stronger when the lag period increases. At higher lags, CPU is more likely to have a positive effect on soybean futures prices, and likewise at high CPU levels. Finally, the nonlinear and lagged effects of CPU on wheat futures are examined. As shown in Figure 6, CPU has a significant nonlinear and lagged effect on wheat futures prices. The positive effect on wheat futures prices is only observed at higher levels of CPU and is likely to strengthen as CPU continues to increase. However, when the lag period is about 0 to 2 months, the increase in CPU has a progressively significant negative effect on wheat futures at high CPU levels. A small increase then occurs, but continues to decline after 6 months and increases after 8 months. In terms of lagged effects, an increase in CPU will have a negative impact when the lag period is about 1 month, and when the lag period reaches about 12 months, the impact of CPU on the price of wheat futures gradually increases as the level of CPU increases and remains positive. At higher lags, CPU is more likely to have a positive effect on wheat futures prices, again at high CPU levels.

4.2. Impact of Climate Policy Uncertainty on Energy Markets

As shown in **Figure 7**, the response of energy markets to shocks to climate policy uncertainty exhibits strong negative shocks, particularly in the 2016-2018 period, indicating that crude oil markets responded more sharply to climate policy uncertainty during this period. The response curves in periods 1 and 6 are relatively small, suggesting that the market reacts more quickly to short-term shocks with greater volatility. The response is smoother up to period 12 (solid line), suggesting that the market gradually adapts to climate policy uncertainty over time, and the impact of the shocks diminishes. The response of the new energy market to climate policy uncertainty shocks exhibits larger negative shocks, especially in 2016 and 2018, which may be related to major adjustments in new energy policy or other related events. The response curves are smaller in periods 1 and 6, but the response of the new energy market to climate policy uncertainty gradually intensifies over time, especially in period 12, when the magnitude of the shock increases. This trend suggests that new energy markets are more sensitive to shocks to climate policy uncertainty and that their impacts gradually increase over time. The sharp reaction of crude oil markets to climate policy uncertainty may be explained by the sensitivity of global energy demand and supply. As one of the major global energy sources, crude oil's price and production are vulnerable to the direct impact of policy changes. 2016-2018 may have experienced changes in international energy policies, climate change agreements, or adjustments in carbon emission policies, making crude oil markets more volatile. In the long term, the crude oil market has become more resilient to climate policies, and its response has gradually smoothed out with the rise of new energy sources and the gradual adaptation of traditional energy markets to the green transition. New energy markets have a relatively larger response to climate policy uncertainty, which may be related to fluctuations in policy support and uncertainty in technology development. New energy markets are often strongly influenced by factors such as government subsidies and green policies, and in particular, uncertainty about climate change-related policies may exacerbate their market volatility. In 2016 and 2018, there may have been key policy changes or major events that led to increased volatility in the new energy market. Over time, as new energy technologies mature and policies gradually stabilize, the market's response tends to level off. Based on the above findings to understand that agri-energy prices receive different CPU impulse responses at different lags, the DLNM model is next used to observe the trend impacts received at different lags and different levels of CPU.

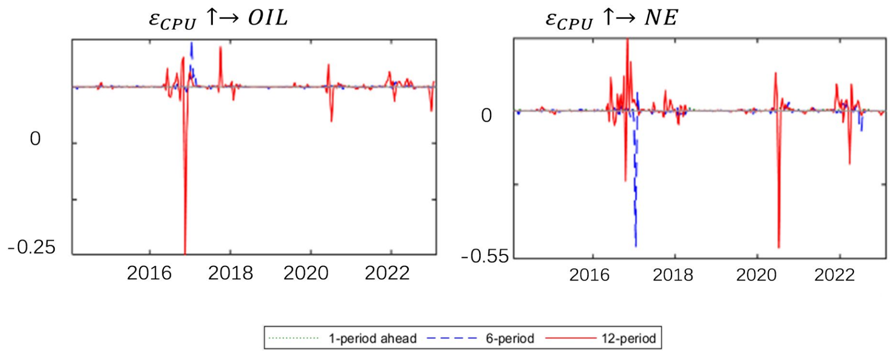
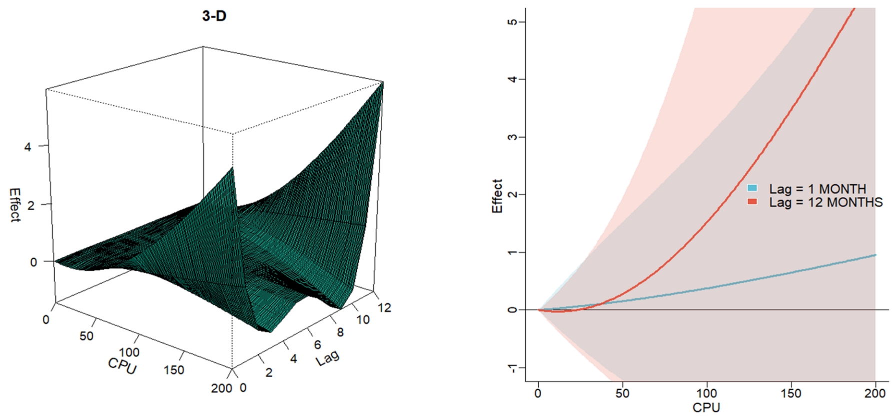
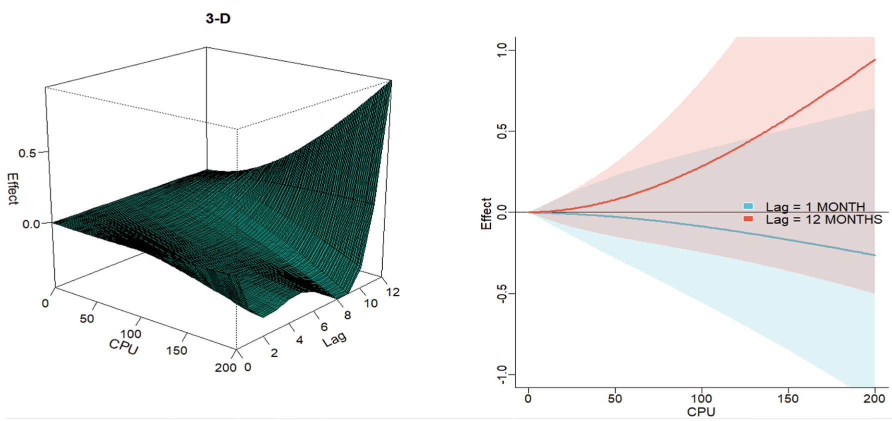


Figure 7. CPU equal-interval impulse for energy markets.



(a) (b)

Figure 8. Impacts of CPU on oil.



(a) (b)

Figure 9. Impacts of CPU on NE.

Figure 8 and Figure 9 present the DLNM results, analyzing the nonlinear and lagged effects of climate policy uncertainty on the two markets, crude oil and new energy, respectively. The left side of the figure shows the nonlinear and lagged effects of the crude oil market on climate policy uncertainty, presenting a three-dimensional surface plot, as well as the nonlinear effects at different lags. The right side of the figure shows a similar analysis for the new energy market, containing the nonlinear effects at different lags. The three-dimensional surface plots in Figure 8 and Figure 9 show the nonlinear impact of climate policy uncertainty on crude oil and new energy markets. The vertical axis represents the market response, and the horizontal axis represents climate policy uncertainty as well as the lag period (number of months). The surface plot shows that when climate policy uncertainty changes, the market response shows a non-linear relationship, which implies that the impact of policy uncertainty on the market is not a simple linear change. The nonlinear response of the crude oil market to climate policy uncertainty suggests that the volatility of crude oil prices or other market variables increases significantly when the CPU changes significantly. In Figure 8 and Figure 9, it can be seen that the impact of higher CPU levels (right part) on the market increases significantly. The nonlinear response of the new energy market shows a similar trend, i.e., the volatility and response of the new energy market increases under the influence of high levels of CPU. In chart (b) for each market, the nonlinear effects are shown at different lags (1 month and 12 months). Here one can see the variation in lag effects, especially the impact of different time horizons on market response. The crude oil market reacts more rapidly with shorter lags (1 month), with the effect diminishing over time. In contrast, at longer lags (12 months), the market response to climate policy uncertainty becomes more persistent and slower. This suggests that crude oil markets may adjust quickly in the short term, but in the longer term the response to policy uncertainty may take longer to materialize. New energy markets show a similar trend, with more pronounced impacts in the short term (1 month) and more sensitive responses, especially at low CPU levels. In a longer lag (12 months), the new energy market's response gradually smoothed out, which may be related to the long-term stability of new energy policies or the market's adaptability. The nonlinear effect of climate policy uncertainty on the market suggests that policy changes will not always affect the market in the same way. Even the same level of climate policy uncertainty may have different levels of impact in different markets and over different time periods. This may be related to the sensitivity of markets to policy changes. Energy markets, especially crude oil markets, typically show a stronger reaction to sudden policy changes. The lag period analysis shows the process of market adaptation to climate policy uncertainty shocks. In the short term, market reactions are usually more dramatic, especially in crude oil and new energy markets. However, long-term lagged effects reveal market adaptation, suggesting that markets gradually absorb the impact of policy changes after the initial shock.

Short-term shocks to crude oil markets are usually large, reflecting the fact that crude oil, as an important component of the global economy, is very sensitive to factors such as policy changes and demand volatility. Over time, however, the market gradually adjusts and adapts, resulting in smaller long-term lagged effects.

The new energy market, on the other hand, has a different response pattern than crude oil. The new energy market usually relies on long-term policy support, such as green energy incentives and carbon emission policies, so while it reacts more in the short term, it is more adaptable in the long term. The lagged response of new energy markets to climate policy uncertainty is more muted. The analysis shows that there are significant differences in the responses of different markets to climate policy uncertainty, and that these responses change gradually over time. Crude oil markets are more volatile in the short term in response to policy uncertainty, while new energy markets are more adaptive, with diminishing effects in the long term.

5. Conclusion

In this paper, we investigate the impact of climate policy uncertainty on China's bulk agricultural and energy markets, focusing on nonlinear and lagged effects. Through the analysis of the DLNM model, it is found that the responses of different agricultural markets to CPU have significant nonlinear and lag effects. Futures prices of corn, cotton, soybean and wheat all exhibit complex responses related to CPU levels and lags. The nonlinear relationship for corn and cotton futures is characterized by a negative effect at higher CPU levels that shifts to a positive effect at lags of two to six months, and then shifts to a negative effect again at lags of more than six months. Soybean futures, on the other hand, show a positive effect at all levels and lags, with the effect gradually increasing as the lag increases. Wheat futures also show a positive effect at high CPU levels, but a negative effect at lags of 0 to 2 months, after which the effect gradually turns positive. These results indicate that there are differences in the way different agricultural futures respond to climate policy uncertainty, with different lagged effects and nonlinear relationships, highlighting the importance of lagged effects and nonlinear analysis in the study of price volatility in agricultural markets.

In the analysis of energy markets, the responses of crude oil and new energy markets to climate policy uncertainty also show obvious nonlinear and lag effects. Crude oil markets responded more to policy uncertainty shocks in the short term, especially during 2016-2018, when market volatility increased significantly. Over time, the market gradually adapted to climate policy uncertainty, and the long-term lag effect diminished. The new energy market, on the other hand, reacted differently from the crude oil market, and although it reacted more to policy uncertainty in the short term, it adapted more, with a gradual decrease in volatility in the long term. The results of this analysis reveal the adaptation process of energy markets, especially crude oil and new energy markets, to policy shocks, and emphasize the nonlinear impact of policy changes on markets as well as the lag effect. Policymakers and market participants should fully consider these complex impact mechanisms in order to better anticipate and respond to the market impacts of climate policy uncertainty.

To mitigate the complex and nonlinear impacts of CPU on commodity markets, policymakers should prioritize the development of transparent, stable, and multi-year climate strategies. Specific recommendations include: 1) Establishing a centralized CPU monitoring system to provide real-time risk indicators; 2) Implementing phased and clearly communicated climate policies to reduce short-term uncertainty; 3) Expanding financial instruments such as climate risk insurance and futures markets tailored to agriculture and energy sectors; and 4) coordinating cross-sectoral tools like carbon pricing and biofuel subsidies to minimize unintended spillovers. These practical steps can help reduce systemic risks, stabilize investor expectations, and enhance the resilience of commodity markets.

While this study provides valuable insights into the impact of climate policy uncertainty (CPU) on China's energy and agricultural markets, the generalizability of its findings to other countries with different policy environments, market structures, and commodity dependencies may be limited. Future research could benefit from comparative multi-country studies to explore potential heterogeneity in CPU responses. Additionally, this study centers on CPU as the primary explanatory variable, whereas other macroeconomic factors such as global supply-demand dynamics, geopolitical risks, and technological advancements in clean energy were not explicitly incorporated. Future extensions may consider these covariates to provide a more holistic analysis of commodity price volatility.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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