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Using GARCH-MIDAS Model to Research the Impact of Economic Policy Uncertainty on Food Price Volatility: A Case of China

Abstract. *The variability of grain prices is significantly influenced by uncertainty in economic policy. Examining how grain prices fluctuate in response to this uncertainty is crucial to maintaining stability in the grain market. This study utilises the Economic Policy Uncertainty (EPU) index as a proxy variable and analyses daily price data for wheat, corn, early indica rice, and mid-late rice from 2003 to 2023. It introduces the Generalised Autoregressive Conditional Heteroskedasticity Mixed-Frequency Data Sampling model (GARCH-MIDAS) to explore the impact of economic policy uncertainty on grain price fluctuations. Research indicates that the effects of economic policy uncertainty on the prices of various food crops differ. Corn prices experience a strong and significant long-term positive impact. Although the effect on early indica rice prices is smaller than that on corn, it still demonstrates a substantial long-term influence. In contrast, the impact on wheat and mid-late rice prices is significantly less pronounced compared to corn and early indica rice. Long-term fluctuations in wheat prices are minimally affected, while mid-late rice prices are nearly unaffected by economic policy uncertainty.*

Keywords: *food prices, economic policy uncertainty, time series analysis, GARCH-MIDAS model.*

JEL Classification: Q11, E66, C32.

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1. Introduction

Backed by supportive policies, China's total grain output has grown steadily, exceeding 650 million tons for nine consecutive years, with 2023 output projected at approximately 695.4 million metric tons. In 2023, wheat production reached 136.59 million metric tons, surpassing demand of 134.53 million metric tons to

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achieve self-sufficiency; rice output has remained above 200 million metric tons for 13 consecutive years, reducing imports and balancing supply and demand, though both wheat and rice production is declining due to external policies and environmental factors. While 2023 corn output hit 288.84 billion kg, it still fails to meet market demand, with heavy reliance on imports totalling 27.13 billion kg. Alongside shifts in supply-demand relations and support policies for each grain, the price volatility sensitivity of wheat, rice, and corn has evolved: from the 1980s to the early 21st century, China was a net grain importer, and consumption structure upgrading has reduced flour consumption, stabilised food consumption, and lowered forage and industrial consumption, with wheat overproduced for seven consecutive years. Rice is prone to causing supply-demand imbalances; since the 2004 implementation of a minimum rice purchase price policy, its production has generally risen, but slowing population growth has curbed demand, and national rice ration consumption has declined in recent years, while the grain storage system has mitigated price fluctuations, weakening price conductivity for wheat and rice and reducing their volatility under external shocks. In contrast, corn consumption rises annually, with supply growth lagging demand to cause shortages, and despite historical oversupply, its supply-demand dynamics make prices more susceptible to external fluctuations, with more pronounced volatility under shocks. Amid global economic policy uncertainties, analysing their impact on grain price volatility can deepen understanding of product differences, offering insights for food security and stabilising food prices in policymaking.

This paper investigates the impact of fluctuations in grain product prices in response to shocks from economic policy uncertainty. Four crops – wheat, corn, early indica rice, and medium-to-late season rice – are selected for the analysis of grain product prices. The EPU index is utilised as a proxy variable for economic policy uncertainty to explore its effects on grain prices. The remainder of the article is structured as follows. Section 2 reviews the relevant literature and introduces the GARCH-MIDAS model. Section 3 elaborates on the methodology employed in this study. Section 4 presents and discusses the empirical results. Section 5 concludes the study and provides policy implications.

2. Literature review

Definition of economic policy uncertainty. Economic policy uncertainty refers to the unpredictability of whether, when, and how the government will alter its economic policies. This type of uncertainty arises from the inability of economic agents to accurately forecast government behaviour (Gulen & Ion, 2016) and represents an economic risk linked to the lack of clarity surrounding future government policies and regulatory frameworks (Al-Thaqeb & Algharabali, 2019). Factors contributing to economic policy uncertainty include geopolitical tensions, such as the Russia-Ukraine conflict (Saâdaoui et al., 2022), trade restrictions (Hamulczuk et al., 2023), supply chain disruptions, and both capital and financial speculation (Guo and Tanaka, 2022). Economic policy uncertainty itself is not a directly observable variable; therefore, both domestic and international scholars often rely on relevant proxy variables to measure it. Among these, Baker et al. (2016) employed text analysis to create an index of economic policy uncertainty for the world's major economies. This index, known as the Economic Policy Uncertainty (EPU) index, is based on the frequency of news articles that report on the economy, policy, and uncertainty, and it is widely recognised by scholars both domestically and internationally.

Various studies on the impact of economic policy uncertainty on different varieties of food prices. Xiao et al. (2019) highlighted that the responses of various grain prices to uncertainty shocks differ, with the impact on wheat prices being less pronounced than that on corn and soybean prices. Long et al. (2023) further emphasised that the effects of economic policy uncertainty on the prices of corn, wheat, and soybeans are asymmetrical; under varying levels of economic policy uncertainty, these grain products experience different price impacts. Tian et al. (2018) observed that the futures prices of soybeans, wheat, and corn are primarily positively influenced by economic policy uncertainty, with soybean prices being the most affected, followed by wheat prices, and then corn prices. Liu et al. (2024) found that uncertainty related to COVID-19 adversely affects international corn price fluctuations but positively influences changes in corn futures prices.

Research on the impact of the EPU on grain prices frequently employs Vector Autoregression (VAR) models to examine the impulse response relationship between the EPU index and grain prices. Zhou et al. (2021) investigated the influence of economic policy uncertainty specifically on wheat prices using the SV-TVP-SVAR model. Adeosun et al. (2023) employed both linear and nonlinear autoregressive distributed lag models, along with the Granger causality test, to analyse the impact of economic policy uncertainty on food prices in Nigeria. Although traditional VAR models accommodate few variables, hindering effective analysis of larger datasets, enhanced ones handle larger datasets without omitting key information (Koop & Korobilis, 2013), they are applicable only to data with the same frequency. When dealing with mixed-frequency data, these models may downsample high-frequency data, thereby failing to retain the valuable information contained within (Cuoco et al., 2008). Consequently, the key to this research lies in effectively processing mixed-frequency data while ensuring that no essential information is lost.

GARCH-type models offer significant advantages for analysing various time series-related issues, such as capturing the clustering of variable volatility and examining the pathways through which volatility impacts different variables. In agricultural economics research, these models have been extensively applied, including studies on price fluctuations of corn, wheat, and soybeans (Yuan et al., 2020), investigations into the fluctuation characteristics of livestock and poultry meat prices (Luo & Liu, 2011), forecasting volatility in agricultural futures (Hau et al., 2020), and analyses of spillover effects and dynamic correlations between domestic and international grain markets (Kang et al., 2017). Currently, in agricultural economics research utilising GARCH-type models, the primary focus is on using data of the same frequency (Liu & Serletis, 2024). In agricultural economics, handling mixed-frequency data is particularly crucial, as variables often interact across different data frequencies, and downsampling high-frequency data to achieve frequency consistency can lose valuable volatility information, leading to biased parameter estimates.

Based on the aforementioned research, Engle et al. (2013) developed a volatility model from the perspective of volatility component decomposition, integrating the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model with the MIDAS model to create the GARCH-MIDAS model. This model differentiates itself from traditional methods for processing high-frequency data by separating the long-term and short-term components of high-frequency volatility. It utilises low-frequency volatility to characterise the factors influencing the long-term volatility component and employs the MIDAS approach to connect the single factor with the long-term component. This methodology has been widely applied. Tumala et al. (2023) utilised the GARCH-MIDAS model, based on mixed-frequency data, to examine the impact of oil shocks on stock market volatility in Nigeria and South Africa. Furthermore, Wang et al. (2020) constructed a GARCH-MIDAS model to analyse the effects of extreme shocks on stock volatility and to predict short-term stock volatility.

3. Model specification

3.1 Formula of the GARCH-MIDAS Model

The GARCH-MIDAS model effectively assesses the volatility relationship between variables of different frequencies while preserving the valuable information contained in high-frequency data. It is particularly adept at managing mixed-frequency data. Consequently, this paper will utilise the GARCH-MIDAS model to examine the relationship between low-frequency economic policy uncertainty and high-frequency grain prices. The formulation of the GARCH-MIDAS model is as follows:

$$r_{i,t} = \mu + \sqrt{\tau_t \mathrm{g}_{i,t}}\varepsilon_{i,t} | \Phi_{i-1,t} \sim N(0,1) \tag{1}$$

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

$$\tau_t = m + \theta_1 \sum_{k=1}^{K_1} \varphi_{1k}(\omega_{11}, \ \omega_{12})\mathrm{RV}_{t-k} + \theta_1 \sum_{k=1}^{K_2} \varphi_{2k}(\omega_{11}, \ \omega_{12})\mathrm{X}_{t-k} \tag{3}$$

$$\mathrm{RV}_t = \sum_{i=1}^{NT} r_{i,t}^2 \tag{4}$$

Where Equation (1) represents the mean equation, $r_{i,t}$ denotes the return on grain price on the i-th day of month t based on the information set, μ is the conditional expectation of $r_{i,t}$, and $\varepsilon_{i,t}|\Phi_{i-1,\mathrm{t}} \sim \mathrm{N}(0,1)$, where $\Phi_{i-1,\mathrm{t}}$ represents the information set available on the $(i-1)$-th day of month t. $g_{i,t}$ is the short-term high-frequency component of the conditional variance of $r_{i,t}$, such as the prices of wheat, corn, early indica rice, and medium-to-late indica rice. τ_t is the long-term low-frequency component of the conditional variance of $r_{i,t}$, such as the EPU index. The conditional variance of $r_{i,t}$ is the product of the long-term low-frequency component τ_t and the short-term high-frequency component $g_{i,t}$. Equation (2) is the GARCH(1,1) process used to calculate the short-term component, where α and β are parameters. A larger α value indicates that past volatility has a greater impact on current volatility, implying a certain degree of persistence or "memory" in volatility. A larger β value indicates that volatility has longer-lasting persistence, meaning that high volatility in the past is likely to persist into the future. Equation (3) is the part of the MIDAS model that calculates the long-term component. The long-term volatility τ_t in this paper is influenced by the realised volatility RV_t (Equation 4, where T represents the total number of months and N represents the number of days in each month) and the economic policy uncertainty index X. In Equation (3), m is the constant term, and the coefficients θ_1 and θ_2 represent the long-term impact coefficients of X and RV on volatility, respectively. k represents the lag order, and K_1 and K_2 are the maximum lag orders for RV and the exogenous variable X, respectively.

$$\varphi_k(\omega_1, \omega_2) = \frac{\left(\frac{k}{K}\right)^{\omega_1-1}\left(1-\frac{k}{K}\right)^{\omega_2-1}}{\sum_{j=1}^{K}\left(\frac{j}{K}\right)^{\omega_1-1}\left(1-\frac{j}{K}\right)^{\omega_2-1}} \tag{5}$$

In Equation (5), $\varphi_k(\omega_1, \omega_2)$ represents the weight function in the nonlinear weight polynomial function (the Beta-type lag variable weight function), where ω_1 and ω_2 are the parameters of this function. To ensure that the weight of lagged variables decreases as they move further away from the current period (the form of weight decay), it is common to set $\omega_{11} = \omega_{21} = 1$, while the system determines ω_{12} and ω_{22} to govern the degree of decay in the influence of low-frequency data on high-frequency data. The weight function can be simplified as:

$$\varphi_k(\omega_{12}) = \frac{\left(1-\frac{k}{K}\right)^{\omega_{12}-1}}{\sum_{j=1}^{K}\left(1-\frac{j}{K}\right)^{\omega_{12}-1}} \tag{6}$$

In this paper, the maximum likelihood function is used to estimate the multi-factor GARCH-MIDAS model. The log-likelihood function (LLF) is:

$$LLF = -\frac{1}{2}[(2\pi)^{TN} + \sum_{t=1}^{T}\sum_{i=1}^{N}\ln\left(g_{i,t}\tau_t\right) + \sum_{t=1}^{T}\sum_{i=1}^{N}\frac{\left(r_{i,t}-\mu\right)^2}{g_{i,t}\tau_t} \tag{7}$$

3.2 Variable selection and descriptive statistics

In this paper, the daily price data of wheat, corn, early indica rice, and mid-late rice are selected as the raw data (data source: Brake Agricultural Database), and the price yields can directly reflect the changes in the prices of wheat, maize, early indica rice, and mid-late rice, therefore, the yields will be calculated based on the price data and plotted with the fluctuations of the prices of the four food crops. In addition, considering the completeness and availability of data, the time interval of data selection is daily data from April 2003 to September 2023 as the high-frequency component. The sample interval for the Economic Policy Uncertainty Index (EPU Index) is from April 2003 to September 2023, with 246 sets of monthly data as the low-frequency component (data from the Economic Policy Uncertainty website, www.policyuncertainty.com).

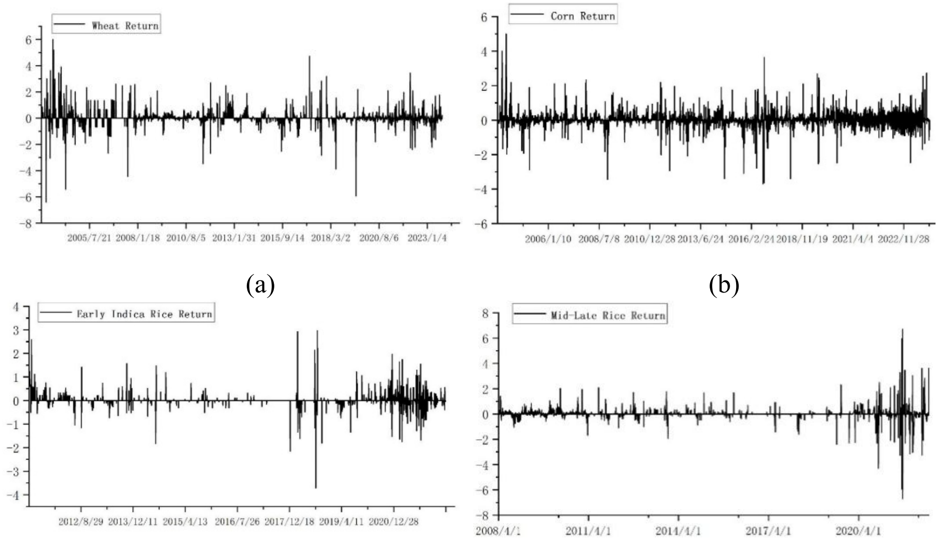
Table 1. Descriptive Statistics of Wheat, Corn, Early Indica Rice, and Mid-Late Rice Prices

	Wheat	**Corn**	**Early Indica Rice**	**Mid-Late Rice**
Average Price (yuan/ton)	2174.89	2039.90	3787.52	3894.84
Minimum Price (yuan/ton)	1134	1063	3180	2622
Maximum Price (yuan/ton)	3297	3036	4022	4477
Standard deviation (yuan/ton)	496.67	524.67	136.50	514.87
Skewness	-0.10	0.08	-1.38	-1.45
Kurtosis	2.29	1.91	4.05	3.79
J-B	112.72***	256.85***	870.81***	1194.1***
ADF	-10.7422***	-10.8825***	-7.6744***	-9.541***
ARCH	4649.1***	4638.7***	2197.6***	2849.1***

Asterisks (*, **, ***) indicate significance levels of 0.1, 0.05, and 0.01. J-B refers to the Jarque-Bera statistic. ADF represents the Augmented Dickey-Fuller unit root test statistic. The ADF test is conducted without a trend term or a constant term. The ARCH effect test is performed using a lagged seventh order after de-meaning the values.

Source: Authors' processing.

According to the descriptive statistics presented in Table 1, the skewness and kurtosis values of the prices for wheat, maize, early indica rice, and middle and late rice reveal the following: the price of wheat exhibits a left-skewed, low-peak distribution; the price of maize displays a right-skewed, low-peak distribution; the price of early indica rice shows a left-skewed, spiky distribution; and the prices of middle and late rice also demonstrate a left-skewed, spiky distribution. This indicates that the majority of wheat, early indica rice, and middle and late rice prices are situated to the right of their respective mean values, while most maize prices are located to the left of their mean value. The Jarque-Bera (J-B) statistics for the prices of these four grains are all significant, suggesting that they do not follow a normal distribution. The data distribution and J-B statistics indicate that the prices of these four food crops are gradually stabilising and converging towards the mean. This trend is closely linked to the ongoing improvements in China's food security policy. The p-value of the Augmented Dickey-Fuller (ADF) test for the prices of the four food crops is 0.01. Based on the ADF statistic, we conclude that the four time series are stationary. Furthermore, the ARCH test reveals a p-value of less than 0.01, indicating that the four sequences exhibit ARCH effects, thereby allowing the establishment of the GARCH model.



(a) (b)

(c) (d)

Figure 1. Fluctuations in return of Wheat (a), Corn (b), Early Indica Rice (c), and Mid-Late Rice Prices (d)

Source: Authors' own creation.

Fig 1 illustrates the price return of wheat, corn, early indica rice, and mid-late rice. The price fluctuations of wheat and corn are significant; however, over time, the fluctuation ranges of their prices gradually diminishes, while the frequency of fluctuations increases. In contrast, the prices of early indica rice and mid-late rice exhibit a shift in fluctuation ranges from small to large as time progresses. Initially, the fluctuation frequency for these rice varieties is very high, but it slows down during the middle stage. Furthermore, following the outbreak of the COVID-19 pandemic in 2020, the frequency of price fluctuations for all four crops increased markedly, with corn experiencing the most pronounced fluctuations.

China's EPU index (as shown in Fig 2), -exhibited significant fluctuations from 2003 to 2023. In particular, these fluctuations were particularly pronounced between 2015 and 2016, as well as between 2019 and 2023. The index reached notable peaks during six distinct periods: 2008, 2012, 2016, 2019, 2020, and 2022. In response to the 2008 financial crisis and the outbreak of the COVID-19 pandemic in 2020, the government implemented a series of economic stimulus policies aimed at revitalising the economy and alleviating the impact of these crises. Analysing the trend line, it is evident that China's EPU index demonstrates an upward trajectory. Furthermore, with the introduction of various measures, the fluctuations in the EPU index have intensified, indicating an increasing level of uncertainty surrounding economic policies.

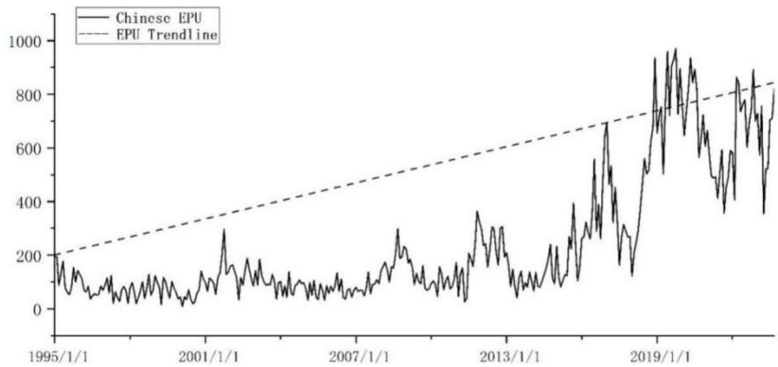


Figure 2. The China's EPU index
Source: Authors' own creation.

4. Results and discussion

The study determines the K value (lag period) for the mixed-frequency volatility model. According to Asgharian (2013), the optimal value of the likelihood function increases with the number of lags and reaches its peak when fitted with data from the past three years. Furthermore, considering that the economic policy uncertainty index exhibits periodicity, the fitting components from both previous and subsequent periods will be included when selecting the lag period. Consequently, the weight coefficients will be estimated using data from the past year, two years, three years, and four years, specifically K = 12, 24, 36, and 48.

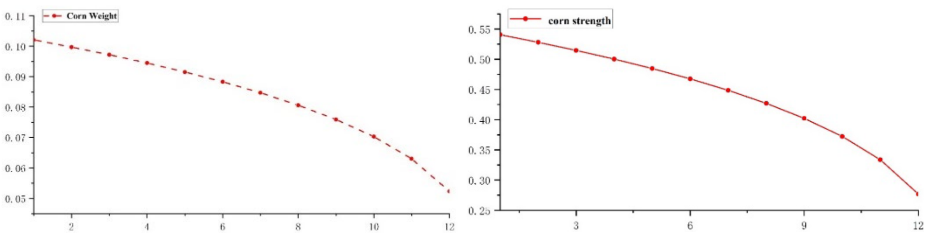
Based on the model output results, this study investigates the impact of the Economic Policy Uncertainty (EPU) index on grain prices. The EPU index, which represents economic policy uncertainty, is classified as a low-frequency variable, whereas the prices of four types of grains are considered high-frequency variables. The short-term component of grain price fluctuations is modelled using GARCH variance, while the long-term component of grain price volatility is characterised using MIDAS. The sum of parameters α and β indicates the effect of past short-term fluctuations in grain prices on current short-term fluctuations. Specifically, parameter α represents the impact of the previous period's de-meaned grain price return on the current grain price short-term fluctuation, while parameter β reflects the impact of past short-term fluctuations on the current short-term fluctuation. Parameter γ represents the extent to which past grain price volatility affects the current volatility. Therefore, the analysis of short-term price fluctuations will be based on the value of $\alpha+\beta$ to assess the influence of past short-term fluctuations on current ones. Parameters ω_{12} and ω_{22} are the optimal estimated coefficients for the weight decay of the low-frequency variable, and coefficients θ_1 and θ_2 reflect the long-term impact of economic policy uncertainty and realised volatility (RV) on volatility, respectively. This study will place greater emphasis on analysing the economic policy uncertainty factor; therefore, the following sections will provide a detailed discussion of this factor. Finally, the results of the model output are presented in Table 2, 3, 4 and 5.

Table 2. Mixed-frequency volatility model estimation results (K=12)

	RV+ EPU index			
	Wheat	**Corn**	**Early Indica Rice**	**Mid-Late Rice**
μ	0.0184**	0.0231***	0.0025	0.0170***
	（0.0049）	(0.0062)	(0.0039)	(0.0048)
α	0.1882	0.1130***	0.1849*	0.1135**
	（0.1374）	(0.0335)	(0.0796)	(0.0442)
β	0.3447	0.8811***	0.6640***	0.7531***
	（0.3586）	(0.0296)	(0.0659)	(0.0485)
γ	-2.3267	0.0059	0.1486	0.2496***
	（0.2196）	(0.0357)	(0.3711)	(0.0889)
m	-0.3019***	0.3406	-2.4573	-0.3623
	（1.9056）	(0.6473)	(1.9082)	(0.7954)
θ_1	0.6957	5.2966**	-4.0893	0.3153
	（1.0811）	(2.1377)	(4.1099)	(0.3321)
θ_2	0.0863***	-0.0824	0.3267**	0.1375***
	(0.0298)	(0.0684)	(0.1385)	(0.0210)
ω_{12}	9.9116	1.2692	1.5236***	89.1252
	（20.9218）	(0.2595)	(0.1703)	(961.5153)
ω_{22}	1.0000	14.1359	2.7525***	1.0000***
	(0.4709)	(20.2314)	(0.9350)	(0.3555)
LLF	-1626.811	-1599.764	452.3835	-64.2626
BIC	3329.769	3275.931	-835.2509	200.4373
VR	56.3186	26.5177	25.2174	39.56023

The values in parentheses in Table 2 represent robust standard errors, specifically t-values. Asterisks (*, **, ***) indicate significance levels of 10%, 5%, and 1%. BIC refers to the Bayesian Information Criterion, and VR denotes the variance ratio. The notes for Tables 3, 4, and 5 are identical.

Source: Authors' processing.



(a) (b)

Figure 3.The Beta function weight (a) and strength (b) for the lagged 12-period corn price volatility

Source: Authors' own creation.

In Table 2, the selected lag period is 12. The values of the price parameters $\alpha+\beta$ for wheat, corn, early indica rice, and mid-late rice are 0.5329, 0.9941, 0.8489, and

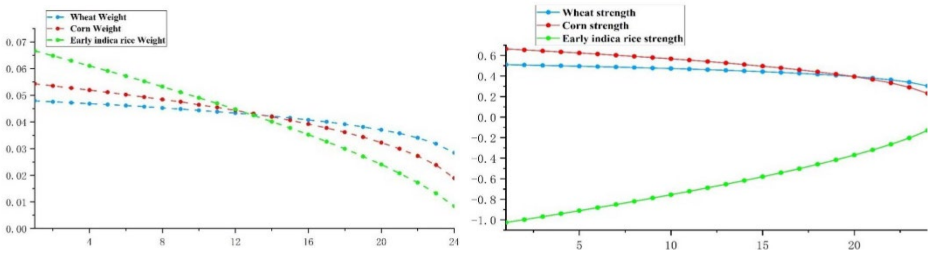
0.8666, respectively. The value of corn prices is the highest and closest to 1, indicating that the persistence of short-term fluctuations in corn prices is stronger than that of wheat, early indica rice, and mid-late rice. The value for wheat prices is the lowest and significantly less than 1, suggesting that the persistence of short-term fluctuations in wheat prices is slightly weaker than that of the other three. Among the impacts of economic policy uncertainty on the prices of these four grains, only the parameter θ_1 for corn prices has a significant positive effect, while the parameters θ_1 for wheat, early indica rice, and mid-to-late season rice prices are not significant. This indicates that an increase in economic policy uncertainty only elevates the long-term component of corn prices, but does not affect the long-term components of wheat, early indica rice, and mid-to-late season rice prices. Fig 3 displays the Beta function weight and strength for corn price volatility. For corn prices, θ_1=5.2966 and ω_{12}=1.2692. Using the Beta function weights $\varphi_k(\omega_{12})$, we can calculate the strength. Specifically, a 1% increase in economic policy uncertainty this month will lead to a 0.5406% increase in the long-term component of corn price volatility in the next month. As the lag period extends from 1 to 12 periods, this effect gradually diminishes. Under the factor of RV, the parameters θ_2 for wheat, early indica rice, and mid-late rice prices are all positive and significant, while it is not significant for corn prices. This suggests that realised volatility has a significant positive impact on the long-term price volatility of these three grains, meaning that each unit increase in realised volatility will lead to an increase in the long-term volatility component of wheat, early indica rice, and mid-to-late season rice, but has no impact on corn price volatility.

Table 3. Mixed-frequency volatility model estimation results (K=24)

	RV+ EPU index			
	Wheat	**Corn**	**Early Indica Rice**	**Mid-Late Rice**
μ	0.0109^{**}	0.0195^{***}	0.0037	0.0138^{***}
	(0.0050)	(0.0053)	(0.0034)	(0.0048)
α	0.2603	0.1265^{***}	0.2003^{**}	0.1046^{**}
	(0.1813)	(0.0426)	(0.1000)	(0.0480）
β	0.3697	0.8580^{***}	0.6650^{***}	0.7704^{***}
	(0.2440)	(0.0766)	(0.0787)	(0.0480)
γ	-0.1123	-0.0103	0.0119	0.2297^{**}
	(0.1364)	(0.0415)	(0.2215)	(0.0915)
m	-2.4543^{***}	-1.1163	-2.9274^{***}	-0.6547
	(0.2932)	(2.3030)	(0.7664)	(0.7936)
θ_1	10.6632^{*}	12.2087^{***}	-15.4022^{**}	0.3128
	(5.5324)	(4.3052)	(6.5097)	(0.3512)
θ_2	0.1206	-0.1016	0.3712^{*}	0.2326^{***}
	(0.0743)	(0.4427)	(0.2167)	(0.0894)
ω_{12}	1.1644^{***}	1.3323^{***}	1.6506^{***}	131.0734
	(0.2471)	(0.2847)	(0.3821)	(1224.0330)
ω_{22}	1.0000	1.0000	4.3697	1.0000
	(2.2147)	(1.3239)	(4.0972)	（0.7187）

	RV+ EPU index			
	Wheat	**Corn**	**Early Indica Rice**	**Mid-Late Rice**
LLF	-1374.146	-1524.772	394.0284	-110.4713
BIC	2823.927	3125.481	-719.58	292.0982
VR	54.5962	30.0273	51.5311	29.34364

Source: Authors' processing.



(a) (b)

Figure 4. The Beta function weights (a) and strength (b) for lagged 24-period wheat, corn, and early indica rice price volatility

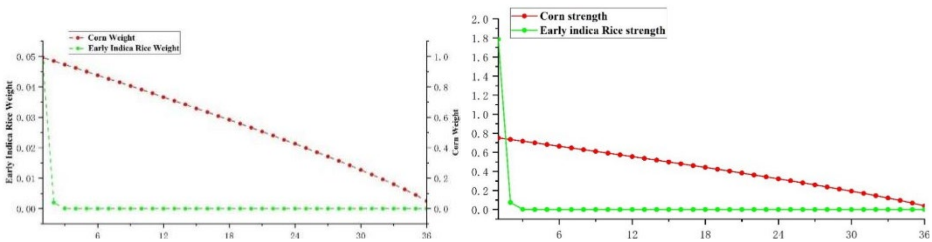
Source: Authors' own creation.

The selected lag period for Table 3 is 24. The parameters α and β for the prices of the four crops are similar to those in Table 2, so the impact of past short-term price fluctuations on current short-term price fluctuations will not be elaborated on for this lag period. Among the price parameters θ1 for wheat, corn, early indica rice, and medium-to-late season rice, only the long-term fluctuation of medium-to-late season rice prices is not significant. The others are all significant, indicating that economic policy uncertainty has an impact on the long-term factors of price fluctuations for wheat, corn, and early indica rice. Specifically, an increase in economic policy uncertainty will lead to an increase in the long-term volatility component of wheat and corn prices, while the long-term volatility component of early indica rice prices will decrease. Fig 4 shows the Beta function weights for price fluctuations of wheat, corn, and early indica rice, with θ_1 values of 10.6632, 12.2087, and -15.4022, respectively, and ω_{12} values of 1.1644, 1.3323, and 1.6506, respectively. If economic policy uncertainty increases by 1% in a given month, the long-term volatility component of wheat and corn prices will increase by 0.5104% and 0.6629%, respectively, in the following month, while the long-term volatility component of early indica rice prices will decrease by 1.025%. This effect gradually diminishes as the lag period extends from 1 to 24 periods. For the RV, only the parameters θ_2 for early indica rice and medium-to-late season rice prices are significant. Therefore, realised volatility has a positive impact on the long-term volatility component of early indica rice and medium-to-late season rice prices, but does not affect the long-term volatility component of wheat and corn prices.

Table 4. Mixed-frequency volatility model estimation results (K=36)

	RV+ EPU index			
	Wheat	**Corn**	**Early Indica Rice**	**Mid-Late Rice**
μ	0.01172	0.0192***	0.0004	0.0106*
	(0.0072)	(0.0060)	(0.0024)	(0.0062)
α	0.3253	0.1435***	0.0266	0.0899***
	(0.2017)	(0.0435)	(0.0182)	(0.0106)
β	0.3149*	0.8309***	0.9697***	0.7855***
	(0.1856)	(0.0467)	(0.0150)	(0.0017)
γ	-0.1026	-0.0195	0.0032	0.2471***
	(0.1733)	(0.0475)	(0.0157)	(0.0178)
m	-2.4531***	-1.8936***	-1.0905	1.4470*
	(0.4377)	(0.6114)	(1.7294)	(0.7995)
θ_1	12.3336	15.1446*	1.8627**	1.2821
	(32.1713)	(7.7632)	(0.8204)	(4.6755)
θ_2	0.1527	0.0944	-1.5305	0.3075**
	(0.1725)	(0.1104)	(1.9714)	(0.1252)
ω_{12}	1.7377	1.8319***	114.0874	3.3750
	(4.8774)	(0.7054)	(174.6378)	(2.7093)
ω_{22}	1.0494	1.0000	1.0000	1.1264*
	(1.9635)	(0.6328)	(0.6390)	(0.6560)
LLF	-1277.248	-1524.433	350.2897	-131.7272
BIC	2629.604	3124.321	-633.1948	333.7512
VR	43.77187	31.56479	100.1948	35.3839

Source: Authors' processing.



(a) (b)

Figure 5.The Beta function weights (a) and strength (b) for lagged 36-period corn and early indica rice price volatility

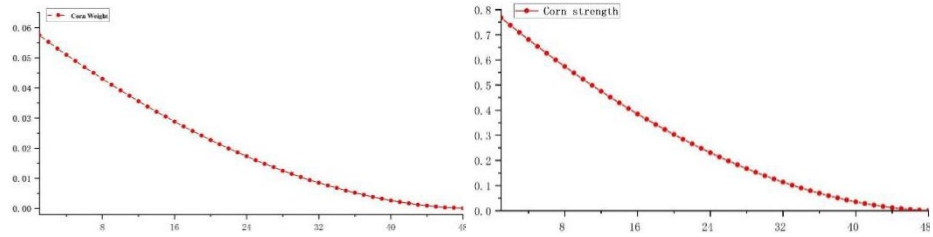
Source: Authors' own creation.

Table 4 selects a lag period of 36. The $\alpha + \beta$ values for the four crops are 0.6402, 0.9744, 0.9963, and 0.8754, respectively. As the number of lag periods increases, the short-term components of price fluctuations for the four crops are increasingly influenced by various factors, particularly evident in the short-term fluctuations of early indica rice prices. Among the parameters θ_1 for the prices of the four crops, the long-term price fluctuations of wheat and mid-to-late season rice are not significant, while those of corn and early indica rice are significant. An increase in economic policy uncertainty leads to an increase in the long-term volatility components of corn and early indica rice prices. Specifically, the parameters θ_1 for corn and early indica rice prices are 15.1446 and 1.8627, respectively, and ω_{12} are 1.8319 and 114.0874, respectively. Fig 5 illustrates the Beta function weights and strength for corn and early indica rice price fluctuations. When economic policy uncertainty increases by 1% in a given month, the long-term components of wheat and early indica rice price fluctuations will increase by 0.752% and 1.786%, respectively, in the following month. Furthermore, as the number of lag periods increases, the impact on the long-term component of corn price fluctuations gradually decreases, while for early indica rice, the impact on the long-term component of price fluctuations becomes zero after a lag of 6 periods. Under the RV, only the parameter θ_2 for mid-to-late season rice prices is significant, indicating that realised volatility positively affects the long-term component of mid-to-late season rice price fluctuations but has no impact on the long-term components of wheat, corn, and early indica rice price fluctuations.

Table 5. Mixed-frequency volatility model estimation results (K=48)

	RV+ EPU index			
	Wheat	**Corn**	**Early Indica Rice**	**Mid-Late Rice**
μ	0.0139^{**}	0.0219^{***}	0.0022	0.0105^{**}
	(0.0043)	(0.0059)	(0.0034)	(0.0049)
α	0.1202^{*}	0.1322^{***}	0.02145^{***}	0.1066^{*}
	(0.0683)	(0.0446)	(0.0060)	(0.0584)
β	0.8099^{***}	0.8363^{***}	0.9742^{***}	0.7769^{***}
	(0.0731)	(0.0682)	(0.0012)	(0.0607)
γ	0.0209	-0.0134	0.0065	0.1993
	(0.0735)	(0.0455)	(0.0127)	(0.1215)
m	-1.5700^{**}	-1.7598^{**}	-0.3398	-1.2867
	(0.7957)	(0.7973)	(0.8957)	(1.0245)
θ_1	13.5281	13.3465^{*}	-11.0926	-1.3277
	(10.0789)	(8.0088)	(13.6559)	(13.1338)
θ_2	-0.0786	0.0317	-2.1854^{**}	0.2764^{**}
	(0.1127)	(0.1549)	(1.0364)	(0.1074)
ω_{12}	2.3064^{**}	2.8413^{***}	2.7938^{***}	1.7881
	(0.9906)	(0.9008)	(0.5351)	(1.6124)
ω_{22}	13.2275^{**}	7.3568^{**}	1.0000^{***}	2.0251^{*}
	(6.3336)	(3.2537)	(0.2840)	(1.0617)
LLF	-1121.46	-1517.259	258.4151	-61.7035
BIC	2317.495	3109.461	-450.6639	192.9231
VR	23.26549	30.9514	144.3283	39.1756

Source: Authors' processing.



(a) (b)

Figure 6. The Beta function weight (a) and strength (b) for the lagged 48-period corn price volatility
Source: Authors' own creation.

Table 5 selects a lag period of 48. The $\alpha + \beta$ values for the four crops are 0.9301, 0.9685, 0.9957, and 0.8835, respectively. As the number of lag periods increases, the short-term fluctuations of wheat prices are most notably affected, with early indica rice experiencing the greatest impact on its short-term fluctuations. Among the parameters θ_1 for the prices of the four crops, only corn prices are significant, while wheat, early indica rice, and mid-to-late season rice prices are not. Therefore, at a lag of 48 periods, economic policy uncertainty has a significant positive impact only on the long-term component of corn prices, with $\theta_1 = 13.3465$ and $\omega_{12} = 2.8413$ for corn prices. Fig 6 illustrates the Beta function weight and strength for corn price fluctuations. When economic policy uncertainty increases by 1% in a given month, the long-term component of corn price fluctuations will increase by 0.767% in the following month, and the impact on the long-term component of corn price fluctuations will gradually diminish and eventually disappear as the number of lag periods increases. Under the RV, the parameters θ_2 for early indica rice and mid-to-late season rice prices are significant, indicating that realised volatility positively affects the long-term components of early indica rice and mid-to-late season rice price fluctuations.

In examining the short-term impacts of own-price fluctuations and economic policy uncertainty (EPU) across crop varieties, corn prices exhibit significant, persistent short-term volatility – evident in Figure 1's consistent cross-period fluctuations – while early indica rice and medium-to-late rice prices display a comparable trend of increasing volatility over time; wheat price fluctuations, initially modest, gradually intensify, particularly at a 48-period lag. Over the long term, corn prices are persistently influenced by realised volatility and EPU, primarily due to its status as a major grain crop with high import dependence (imports exceeding the 20 million-ton quota for three consecutive years), making it susceptible to intense fluctuations from uncertainties. Early indica rice prices, though significantly impacted by uncertainties, see non-persistent fluctuations, as it is a key component of policy-driven reserve procurement with limited market supply – yet annual support prices mitigate long-term impacts. EPU has minimal effects on medium-to-late rice price fluctuations, though their long-term component is significantly influenced by realised volatility. Wheat prices are relatively less affected by own fluctuations and EPU, with only slight EPU impacts at a 24-period lag. Grain price fluctuations intensify under uncertain shocks, with varied responses: experts note China’s abundant grain production coexists with high import volumes and dependence, warning that failure to timely adjust domestic cultivation structures to meet market demand would weaken agricultural price competitiveness internationally, as government price protection measures can only mitigate short-term shocks, not long-term negative impacts from uncertainties. Policy interventions include Hebei and Shandong’s 2006 market price support purchase program (relying on national reserves, marking direct price intervention) and the 2016 abolition of the corn’s minimum support price (shifting to market-driven production structure adjustment), followed by 2016–2017 No. 1 Central Documents emphasising optimised agricultural structures aligned with consumer demand changes, alongside measures to promote sustainable development and enhance market competitiveness.

5. Conclusions

Based on the data characteristics (EPU index as monthly data and grain daily price as daily data), this paper adopts a mixed-frequency volatility model (GARCH-MIDAS model) to study the issue around the impact of economic policy uncertainty on grain prices.

The results show that the EPU strongly affects corn prices' long-term volatility, with past short-term corn price volatility exerting strong persistence on current short-term fluctuations. Early indica rice exhibits similar short-term volatility patterns: past short-term fluctuations show strong persistence, and both realised volatility (RV) and EPU significantly impact its price fluctuations. In contrast, past short-term wheat price volatility has weak persistence on current fluctuations, and EPU has a minor effect on wheat's long-term price volatility components. Medium-late rice displays moderate persistence in its own short-term fluctuations, with its long-term volatility heavily influenced by RV.

As a dual carrier of bioenergy and feed, the supply and demand expectations for corn are susceptible to long-term shocks from policy changes(Condon et al., 2015). In contrast, wheat, as a staple food crop with a high self-sufficiency rate, has its consumption rigidity and policy-based support mechanisms that weaken the transmission effect of policy uncertainties (Li et al., 2020). Unlike the existing literature, this study further reveals that the long-term volatility of early indica rice is simultaneously driven by the Economic Policy Uncertainty index and realised volatility, indicating that rice varieties with both industrial processing uses may face dual sources of volatility from policies and markets. This finding enriches the previous research perspective that focused on single influencing factors.

Economic policy uncertainty exerts heterogeneous impacts across different crops, necessitating differentiated regulatory measures tailored to crop-specific characteristics. As a key feed grain with substantial demand, corn has a high market openness, strong external dependence, and concentrated import sources. Thus, policy efforts should focus on enhancing cultivation support, advancing innovation and promotion in the corn seed industry, and boosting domestic production capacity. Concurrently, it is crucial to leverage international trade policies and global price transmission mechanisms, expand agricultural income insurance coverage, optimise subsidy systems, and implement corn price compensation policies to stabilise market prices. For wheat, early indica rice, and medium-late rice, the priority lies in safeguarding food security through optimised land utilisation and agricultural technological progress. These measures ensure rapid resumption of grain production when required, thereby maintaining supply-demand equilibrium and securing absolute staple food security.

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