https://doi.org/10.17221/318/2023-AGRICECON

Impact of external shocks on international corn price fluctuations

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Citation: Liu S., Liu D., Ge S. (2024): Impact of external shocks on international corn price fluctuations. Agric. Econ. – Czech, 70: 1–11.

Abstract: In recent years, the external shock represented by COVID-19 has caused significant fluctuations in global corn prices. Based on the weekly data on international corn prices from 2020 to 2023, this paper constructs autoregressive conditional heteroskedasticity (ARCH) class and time-varying parameter – vector autoregression (TVP-VAR) models. After analysing the characteristics of corn price fluctuations, it further analyses the influence of external uncertainties such as COVID-19, international finance, the corn futures market, and international exports of corn on corn price fluctuations. The results show that international corn price fluctuations always have significant asymmetry. Nevertheless, the influence of past changes on the future will gradually disappear, and the corn market is not characterised by high risk and high return because of the phenomenon of flat or declining absolute returns during the periods of high volatility. All the selected external shocks also have a time-varying impact on corn price fluctuations, and there are differences in the impact size, impact direction, and impact duration. The external shocks led by COVID-19 had a transmission effect on other factors and then affected corn price fluctuations.

Keywords: autoregressive conditional heteroskedasticity (ARCH) class model; corn futures market; COVID-19; international exports of corn; time-varying parameter – vector autoregression (TVP-VAR) model

Since the outbreak of COVID-19, the global food market has experienced unprecedented challenges. Food security is a fundamental issue related to human survival, and ensuring the stability of food prices is very important. As the world's largest cereal crop and a widely used food staple, corn holds a significant position in the global market. From 2020, global corn prices continued to rise, from USD 168.71/tonne in February 2020 to a maximum of USD 348.17/tonne in April 2022, with a maximum spread of USD 179.46/tonne, although prices fluctuated to USD 298.18/tonne by February 2023. Despite fluctuations, there has been a 74.38% overall increase in the past three years. Food price fluctuations can be caused by various external shocks, such as the price of substitutes, policies implemented by different countries, natural disasters, and global trade flows. Recently, due to the combined effects of COVID-19, trade policies, climate change, energy prices, the conflict between Russia and Ukraine, and other factors, the international price of corn has been increasingly impacted by wide-ranging external uncertainties.

The literature on corn price volatility shows a more pronounced effect of corn futures prices and shows a higher interaction between the ethanol and corn markets when analysing the volatility transmission ef-

Supported by the National Social Science Foundation of China, Project No. 20BJY147.

https://doi.org/10.17221/318/2023-AGRICECON

fects of oil, ethanol and corn prices (Trujillo-Barrera et al. 2012; Fakari et al. 2013; Gardebroek and Hernandez 2013; Haixia and Shiping 2013; Salami and Tahami Pour Zarandi 2015; Saghaian et al. 2018). Other scholars have analysed the relationship among inflation, *per capita* income and agricultural product price volatility based on the X-12 seasonal adjustment method, as well as the Granger causality test (Cudjoe et al. 2010; Bekkers et al. 2017; Gou 2017; Mehdizadeh et al. 2022). Of course, in the study of factors influencing agricultural price volatility, supply and demand aspects, such as production costs, supply and demand gaps, and food stocks, were basically dominant in earlier years domestically and internationally (McPhail et al. 2012; Serra and Gil 2013; Djuric et al. 2015; An et al. 2016). When examining external influences, several factors, such as energy prices, exchange rate movements, cost of capital, trading volume, appropriate facilities, and policies, had an impact on agricultural price volatility (Alam et al. 2012; Otoo 2012; Gardebroek and Hernandez 2013; Hassanzoy et al. 2015; Baffes and Haniotis 2016). Furthermore, Bellemare (2015) used monthly data at the international level and utilised a natural disaster variable to reflect the relationship between food prices and social unrest. In addition, some scholars analysed how COVID-19 affected commodity prices, to which other external factors, such as the economic policy uncertainty index, money supply, and consumer price index, were added for in-depth analysis (Bakas and Triantafyllou 2020).

As an essential source of feed and industrial raw materials, the price volatility of corn significantly affects the security of livestock and industry, affecting the overall food supply situation. Therefore, mitigating price volatility by identifying the factors that affect corn prices can provide valuable lessons for the future of the corn industry and global food security. Extensive research has been conducted in the literature on international agricultural prices; however, the impact of external uncertainties on fluctuations in the price of corn has not been fully taken into account due to the complexity of the international context. Therefore, compared with the previous traditional price volatility research, the academic contribution of this paper is to take various external shock factors as the entry point, use autoregressive conditional heteroskedasticity (ARCH) class model and time-varying parameter vector autoregressive (TVP-VAR) model to analyse the volatility characteristics of international corn prices and the time-varying characteristics of the impact of various external factors on corn price volatility, and finally provide scientific decision-making basis for the development of corn industry.

MATERIAL AND METHODS

ARCH class model. Referring to the interpretation and construction of the model by Engle (1982), the ARCH model contains the following two equations that can confirm the volatility and accumulation of the time series tangibly. Formula (1) is the mean equation. Formula (2) is the variance equation.

$$R_t = X'\gamma_0 + \varepsilon_t \tag{1}$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \tag{2}$$

where: R_t – corn price return, X – only the lag term of (in this paper); h_t – conditional variance of ε_t at t; $\alpha_0 > 0$, $\alpha_i \geq 0$ ($i = 1, \dots, n$) to ensure that $h_t > 0$.

The generalised autoregressive conditional heteroscedasticity model (GARCH model) is an extension of the ARCH model (Bollerslev 1986):

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} \tag{3}$$

where: $\sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2$ – ARCH term, $\sum_{j=1}^{p} \beta_j h_{t-j}$ – GARCH term; p, q – lag orders. If both the ARCH and GARCH terms are significant, it proves that the sequence has very significant fluctuation clustering.

The subsequent addition of a conditional variance term representing expected risk creates a generalised autoregressive conditional heteroscedasticity model with mean values (GARCH-M model) (Engle et al. 1987):

$$R_t = X'\gamma_0 + \lambda h_t + \varepsilon_t \tag{4}$$

where: λ – multiple of the conditional standard deviation.

If λ is positive, the market participants require higher returns due to the increase in risk. This parameter is used to test whether the corn market has the characteristics of high risk and high return.

Then, the threshold autoregressive conditional heteroscedasticity model (TARCH model) is used to describe the asymmetry of the time series (Rabemananjara and Zakoian 1993):

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$$h_t = \alpha_0 + \alpha_1\varepsilon^2_{t-1} + \beta_1 h_{t-1} + \phi d_{t-1}\,\varepsilon^2_{t-1} \tag{5}$$

where: d_{t-1} – dummy variable; if $\varepsilon_{t-1} < 0$, then $d_{t-1} = 1$; otherwise, $d_{t-1} = 0$.

Here, the effect of price increase information ($\varepsilon_t \geq 0$) on conditional variance is α_1, and the effect of price decrease information ($\varepsilon_{t-1} < 0$) is $\alpha_1 + \phi$.

The exponential GARCH model (EGARCH model) and its conditional variance equation is (Nelson 1991):

$$\ln h_t = \alpha_0 + \beta \ln h_{t-1} + \alpha\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| + \gamma\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \tag{6}$$

In Formula (6), the effect of price increase information ($\varepsilon_{t-1} \geq 0$) on $\ln h_t$ is $\alpha + \gamma$, and the effect of price decrease information ($\varepsilon_{t-1} < 0$) is $\alpha - \gamma$.

The TARCH and EGARCH models can describe the time series asymmetry combined with Formula (5) and (6). If $\phi \neq 0$ or $\gamma \neq 0$, it can be proven that the fluctuations are asymmetric. If $\phi > 0$ or $\gamma < 0$, the fluctuation of the price decrease information is greater than the price increase information, and if $\phi < 0$ or $\gamma > 0$, the fluctuation of the price increase information is greater than the price decrease information.

TVP-VAR model. This paper uses a TVP-VAR model to analyse the impact of external uncertainty shocks on international corn price fluctuations. The model is an extension of the VAR model, and its most significant improvement is the assumption that both the coefficient and covariance matrices are time-varying, which helps to portray the nonlinear characteristics of the linkages between the variables in terms of both changes in the magnitude of the shocks and changes in the transmission paths. Referring to Nakajima's (2011) construction of the TVP-VAR model, it can be expressed in the following form:

$$\begin{gathered} y_t = X_t\beta_t + A_t^{-1}\sum t\varepsilon_t \\ t = s+1,\cdots,n,\varepsilon_t \sim N\left(0, I_k\right) \end{gathered} \tag{7}$$

where: t – time; s – number of lag periods; y_t – $k \times 1$-order vector composed of investigated variables; k – number of investigated variables; ε_t – the residual term; $\varepsilon_t \sim N(0, I_k)$; I_k – unit matrix; $X_t = I_k \otimes (y'_{t-1}, \ldots, y'_{t-s})$, where $\otimes$ is the Kronecker product; β_t – $k^2 s \times 1$-dimensional time-varying coefficient variables; A_t, Σt – $k \times k$ -dimensional lower triangular and diagonal matrices.

$$\begin{gathered} A = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ a_{21} & 1 & & \vdots \\ \vdots & & \ddots & 0 \\ a_{k1} & \cdots & a_{k,k-1} & 1 \end{bmatrix} \\ \sum t = \begin{bmatrix} \sigma_{1,t} & 0 & \cdots & 0 \\ 0 & \sigma_{2,t} & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{k,t} \end{bmatrix} \end{gathered} \tag{8}$$

The parameters β_t, A_t, and Σt are time-varying. The time-varying matrix A_t implies that the effect of the variable i shocks on the variable j is time-varying. In the research process, the Bayesian method is used for model estimation, in which the Markov chain Monte Carlo (MCMC) method is used for the posterior estimation of parameters.

Variable selection. The number of new COVID-19 cases (*epi*), stock index, international corn futures price, and international corn exports were selected as the independent variables, and the international corn price (*corn*) was used as the dependent variable. The number of new global COVID-19 cases refers to the number of new confirmed cases worldwide, calculated from the extensive data report published by the World Health Organization. The stock index selects the Standard and Poor's 500 index (*spi*). Using this index as a representative can reflect the rise and decline of the international financial market and was obtained through the Sina financial platform (https://finance.sina.com.cn/). Since the U.S. corn exports accounted for about 33% of global corn exports over the past three years, making it one of the world's largest corn exporters, U.S. corn exports (*exp*) were selected to represent international corn exports, obtained from the USDA database (https://www.usda.gov/). The international corn futures price is captured by the Chicago corn futures price (*fut*) from the United States, and the international corn price is expressed by the customs paid value of Chinese corn imports. The data sources of the price variables are the Brick Agricultural Databases (https://www.agdata.cn/). Data for all variables are weekly data from February 6, 2020, to May 4, 2023. After obtaining the primary data, the fixed base price index was calculated as of February 6, 2020, to reflect the price level change. Finally, all the variables were logarithmically treated to eliminate heteroscedasticity.

Data and descriptive statistics. To deeply analyse the fluctuation characteristics of international corn prices after the outbreak of COVID-19, this paper se-

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Table 1. Descriptive statistics of corn price return

Statistical quantity name	Average value	Standard deviation	Skewness	Kurtosis	JB test statistic	*P*-value
Statistical value	0.002540	0.034118	–0.337102	6.503480	89.63280	0.000000

JB – Jarque-Bera test
Source: Authors' own processing

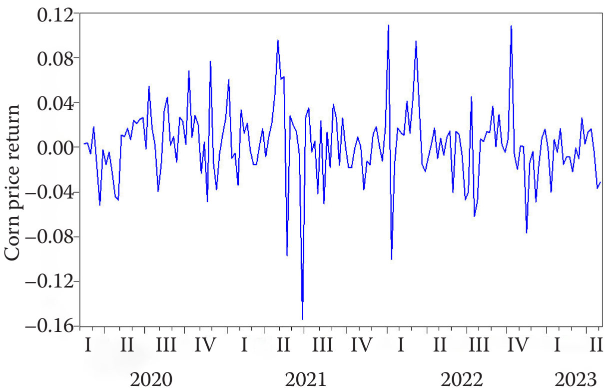

Figure 1. Change chart of corn price return

Source: Authors' own processing

lected the import duty value of Chinese corn to represent the international corn price. It used weekly data from February 6, 2020, to May 4, 2023, to analyse the price fluctuation characteristics. The ARCH model was constructed and took the corn price return as the carrier. The calculation formula was the log-order difference of the corn price in adjacent months, that is, $R_t = \ln p_t - \ln p_{t-1}$, where p_t and p_{t-1} indicate the price of month t and month $t - 1$, respectively. EViews 8.0 was used to regress the ARCH class model. According to Table 1, the mean value of the weekly corn price yield sequence was 0.002540, the standard deviation was 0.034118, and the skewness was –0.337102, indicating that the sequence distribution was left biased; the kurtosis was 6.503480, indicating that the sequence has the characteristics of a thick tail; the Jarque-Bera (JB) statistic was 89.63280, the *P*-value was < 0.05, the null hypothesis was rejected, and the sequence did not obey the normal distribution. Moreover, it can be seen from the change chart of the corn price return (Figure 1) that the fluctuation in corn price returns was concentrated during this period.

RESULTS AND DISCUSSION

Stability test and ARCH effect test

The Augmented Dickey-Fuller (ADF) unit root test was used to test the stationarity of corn price return sequence data, and the results are shown in Table 2. The ADF test value was –12.11833 < –4.013608, indicating that the null hypothesis was rejected at the 1% significance level, and this sequence was stationary.

Subsequently, the Ljung-Box *Q* statistic test was performed on the residual series of corn price return, and the results showed that the autocorrelation coefficient (*AC*) and partial correlation coefficient (*PAC*) were significantly non-zero at lag order 8, and the *Q* statistic was 13.828, which corresponded to a *P*-value of 0.086 < confidence level of 0.1, indicating that there was an 8^{th} order autocorrelation in the series.

The clustering effect of the sequence was tested using the ARCH-LM test method, and the ARMA model was chosen to fit the mean equation. According to the *AIC* and *SIC* minimum criterion, an autoregression AR(2) model is established. When the lag order was order 5, the test probability *P*-value was most significant, and the test results shown in Table 3 indicate that the null hypothesis was rejected at the 10% significance level. There was a significant heterovariance effect, and the ARCH model should be employed.

According to the ARCH effect test, there was a multi-order ARCH effect, which represented the need to estimate multiple parameters, which was problematic. Therefore, this paper chose a low-order GARCH model to replace it, which made it easier to identify and estimate the model.

Characteristics of corn price fluctuations

It can be seen from the estimation results of the GARCH model that in the variance equation for corn price return, of both α_1 and β_1, only β_1 is significant at the 1% level, indicating that there was no solid fluctuating clustering in this sequence. In addition, the sum of α_1 and β_1 is 0.8143 < 1, proving that the impact of past fluctuations on the future gradually disappears. According to the estimation results of the GARCH-M model, in the mean equation for the corn price return, the estimation of λ was –0.6628, but it was not significant, indicating that there was no feature of high risk and high return in the corn market. In the TARCH model, $\phi < 0$, which was significant at 1%; however, in the EGARCH model $\gamma > 0$, and

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Table 2. ADF test results of the corn price return rate

Statistic	ADF test	5% critical value	1% critical value	P-value	Stationary or not
T	–12.11833	–3.436795	–4.013608	0.0000	yes

ADF – Augmented Dickey-Fuller; T – T-statistic, representing corn price return rate
Source: Authors' own processing

Table 3. ARCH-LM test of corn price return

Variable	F statistic	nR^2 statistic
Corn price return	1.9247 (0.0932)	9.4130(0.0937)

ARCH-LM – autoregressive conditional heteroskedasticity – Lagrange multiplier
Source: Authors' own processing

was significant at 1%. The price fluctuation of corn was significantly asymmetric, and the fluctuation generated by the price increase information in the corn market was more significant than the fluctuation generated by the price decline information. The COVID-19 outbreak had little impact on the current fluctuations in international corn prices. There was an asymmetric impact of information on the corn price, with a greater impact of price increase information. Traders in the corn market were making irrational trades, resulting in the corn price fluctuations not having a risk-return certainty (Table 4).

Influencing factors of corn price fluctuations

Stability test. Prior to constructing the model, it was crucial to assess the stationarity of the data. Upon conducting the ADF unit root test on multiple variables (Table 5), it became evident that the initial sequence of international corn prices, stock index, and international corn futures price was nonstationary at the 5% level. However, after applying the first-order difference, no unit root phenomenon was observed, allowing for the construction of the TVP-VAR model.

Determination of the optimal lag order. In general, the optimal lag order of the VAR model was determined by the values of AIC and SIC. Because the difference between the AIC and SIC values of each order was small, the optimal lag order in this paper was 2 (Table 6).

Model estimation results and diagnosis. Before simulating samples and estimating the TVP-VAR model using the MCMC method, we made an initial assignment to the parameters, extracted M = 10 000 sam-

Table 4. Estimation results of the ARCH class model of corn price return

Variable	Estimated value	GARCH	GARCH-M	TARCH	EGARCH
Coefficient of the mean equation	c	0.0014	0.0234	0.0051***	0.0039*
	AR(1)	0.1023	0.1130	0.0476	0.0782
	AR(2)	–0.0232	–0.0181	–0.0322	0.0186
	λ	–	–0.6628	–	–
Coefficients of variance equations	α_0	0.0002**	0.0002**	2.19E–05**	–0.3965**
	α_1	0.0749	0.0943*	0.0124***	–
	β_1	0.7394***	0.7077***	1.0244***	–
	ϕ	–	–	–0.0841***	–
	α	–	–	–	–0.1524**
	β	–	–	–	0.9257***
	γ	–	–	–	0.1532***

*, **, *** P < 0.1, P < 0.05, and P < 0.01, respectively; ARCH – autoregressive conditional heteroskedasticity; GARCH – generalised ARCH; GARCH-M– generalised ARCH in mean; TARCH – threshold ARCH; EGARCH – exponent generalised ARCH; c – costant term; AR(1), AR(2) – vector of coefficients; λ – onditional variance coefficient; α_0 – constant term; α_1 – ARCH terms; β – predicted variance of the GARCH terms of the previous period in the different models; ϕ, γ – coefficients of the asymmetric effects
Source: Authors' own processing

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Table 5. Unit root test for each variable

Variable	Original series				First-order difference series			
	ADF	5%	*P*-value	conclusion	ADF	5%	*P*-value	conclusion
ln*corn*	–1.5349	–2.8785	0.5136	nonstationary	–12.0780	–2.8786	0.0000	stationary
ln*epi*	–5.6152	–2.8787	0.0000	stationary	–8.5826	–2.8787	0.0000	stationary
ln*spi*	–1.3366	–2.8785	0.6119	nonstationary	–9.2854	–2.8786	0.0000	stationary
ln*fut*	–1.3913	–2.8789	0.5855	nonstationary	–9.2455	–2.8789	0.0000	stationary
ln*exp*	–6.1226	–2.8787	0.0000	stationary	–23.3046	–2.8789	0.0000	stationary

epi – number of new COVID-19 cases; *spi* – Standard and Poor's 500 index; *fut* – Chicago corn futures price; *exp* – U.S. corn exports; ADF – augmented Dickey-Fuller test
Source: Authors' own processing

Table 6. Selection of model lag order

Lag	LogL	*LR*	*FPE*	*AIC*	*SIC*	*HQ*
0	9 428.970	NA	2.12e–07	–1.1761	–1.0771	–1.1359
1	1 016.458	1 770.6970	1.73e–12	–12.8949	–12.3007	–12.6535
2	1 094.058	144.0425	8.70e–13	–13.5825	–12.4931	–13.1399
3	1 116.124	39.5155	9.06e–13	–13.5441	-11.9596	–12.9004
4	1 132.685	28.5769	1.02e–12	–13.4338	–11.3541	–12.5890
5	1 149.541	27.9821	1.14e–12	–1 373.3200	–10.7525	–12.2814

LogL – log likelihood ratio; *LR* – sequential modified LR test statistic; *FPE* – final prediction error; *AIC* – Akaike infomation criterion; SIC – Schwarz infomation criterion; *HQ* – Hannan-Quinn information criterion; NA – not applicable
Source: Authors' own processing

ples by the MCMC method, eliminated 1 000 initial samples, and obtained a valid model sample. Table 7 presents the mean, standard deviation, 95% confidence intervals, and convergence statistics for evaluating the posterior distribution of the parameters. The posterior means of the parameters were within the 95% confidence interval, and the Geweke convergence diagnostic values for all parameters failed the significance test at the 5% level, indicating that the parameters converged to the posterior distribution. From the perspective of an invalid factor, all its values were less than 100, indicating that the parameter estimation results of the model were relatively robust.

Equal-interval pulse response. The impulse response of equal intervals refers to a function that represents the shock-induced variables produced by different lag times. The TVP-VAR model can use the parameter calculation point for each variable in various lag periods of the impulse response diagram. We used Matlab 2020a to complete TVP-VAR model. Figure 2 shows the lag of the corn price for 2 weeks, 4 weeks, and 6 weeks for both itself and every external uncer-

Table 7. Results of parameter estimation based on the MCMC algorithm

Parameter	Mean	Standard deviation	95% upper bound	95% lower bound	Geweke test	Invalid factor
*sb*1	0.0023	0.0003	0.0018	0.0029	0.662	94.60
*sb*2	0.0023	0.0003	0.0018	0.0029	0.295	11.61
*sa*1	0.0056	0.0015	0.0034	0.0091	0.684	42.69
*sh*1	0.2068	0.0311	0.1526	0.2744	0.868	301.60
*sh*2	0.5739	0.1048	0.3926	0.7979	0.174	26.67

MCMC – Markov chain Monte Carlo; *sb, sa, sh* – estimated parameters
Source: Authors' own processing

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tainty variable of the interval impulse response. The horizontal axis of Figure 2 represents sample sizes with equal intervals, where January 14, 2021, December 30, 2021, and December 15, 2022, correspond to 50, 100, and 150, respectively, in the time interval. The vertical axis indicates the degree of impulse response. Essentially, the impulse response of equal intervals is a function that depicts the shock-induced variables produced by varying lag times. The TVP-VAR model can utilise the parameter calculation point for each variable within different lag periods of the impulse response diagram.

The international corn price was highly responsive to external factors, with varying impacts over time. The impulse response of corn price fluctuations showed significant chronotropic characteristics. The corn price fluctuation responds positively to variable impact with a lag period of 2, 4, and 6 weeks. The impact of external uncertainty weakens over time. Figure 2A shows that the corn price fluctuation was significantly influenced

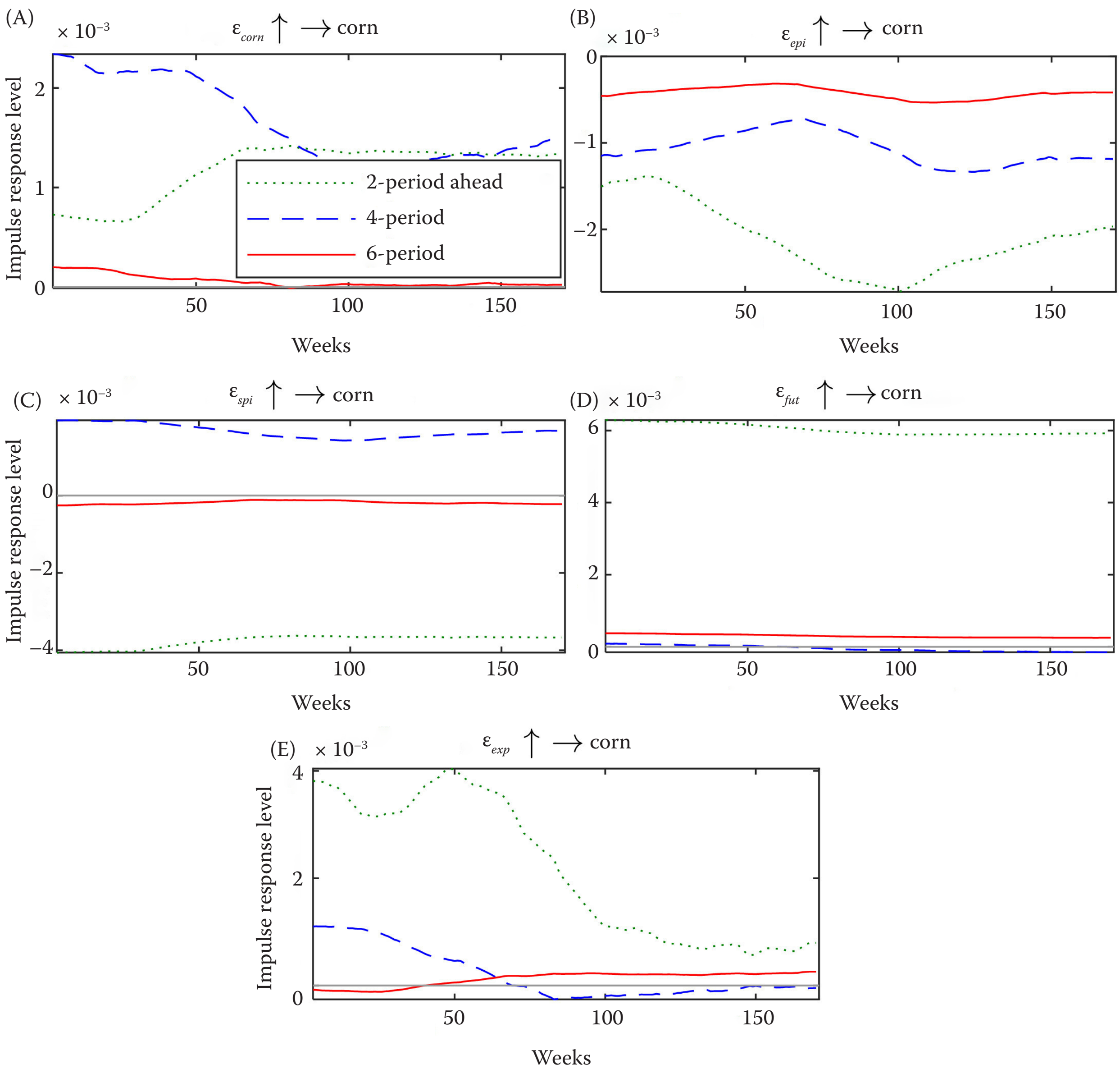

Figure 2. Equispaced impulse response of corn price fluctuations to each variable shock

ε – characterization of corn price volatility; *corn* – on itself; *epi* – in terms of the number of new COVID-19 cases; *fut* – in terms of futures price indices; *spi* – in terms of stock indices; *exp* – in terms of the quantity of corn exported

Source: Authors' own processing

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by itself, but its influence decreases with the increase in the lag period. In Figure 2B, we examined the negative impact of the COVID-19 pandemic on international corn prices. The graph shows that corn prices responded negatively to epidemic changes when the lag time was 2, 4, and 6 weeks, and the impulse response approached 0 with increasing lag time. The pandemic had a prolonged effect on corn prices, leading to severe price fluctuations. Figure 2C shows the correlation between international corn prices and stock indices over time. Changes in stock indices impacted corn prices negatively after a 2-week and 6-week delay but positively after a 4-week delay. The S & P 500 index has shown an upward trend over the last 3 years, but the COVID-19 pandemic caused significant market fluctuations. The Russia-Ukraine conflict that began on February 24, 2022, has led to an energy crisis and food trade protectionism, causing global energy and food prices to rise, production costs to soar, and global inflation to become a critical challenge. Various factors,

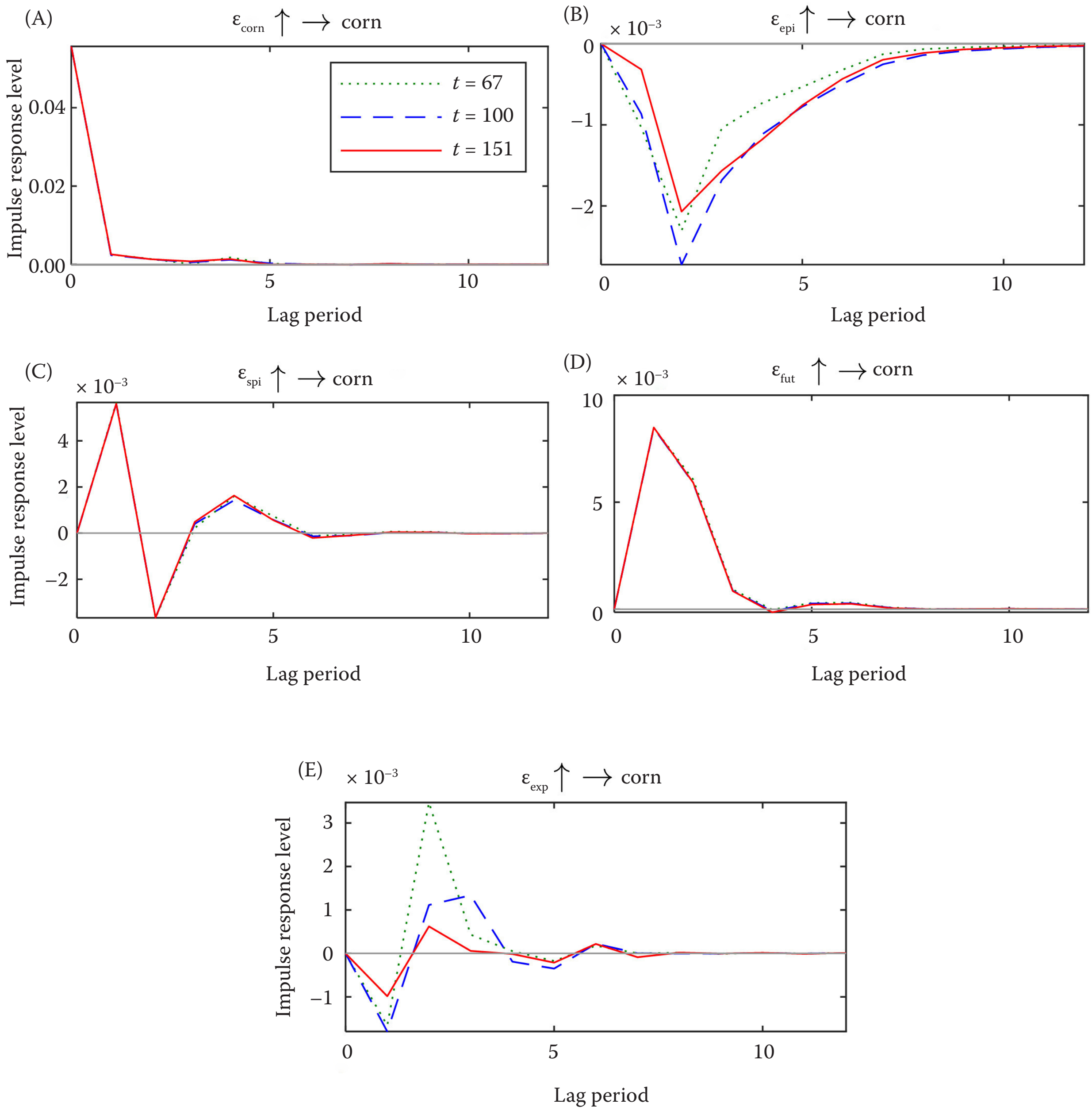

Figure 3. Time-point impulse response of corn price fluctuations to each variable's impact

Source: Authors' own processing

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including the financialisation of commodities, influence corn prices. Figure 2D shows that corn prices reacted positively to changes in the futures price, with lags of 2, 4, and 6 weeks. Due to global events, corn futures prices have been fluctuating and rising in the U.S., causing an increase in demand for corn and creating significant fluctuations in prices. The positive impact of futures prices on corn prices was short-lived, with the effect diminishing as the lag period increased. Figure 2E shows that the corn price responded positively to changes in export volume, especially when the shock occurred two weeks prior. Between 2020 and 2023, U.S. corn export volume fluctuated significantly due to the pandemic and the war in Ukraine, causing unsteady fluctuations in international food prices. However, with the gradual improvement of the international situation in 2023, the import and export of grains began to stabilise. As corn has a high reserve

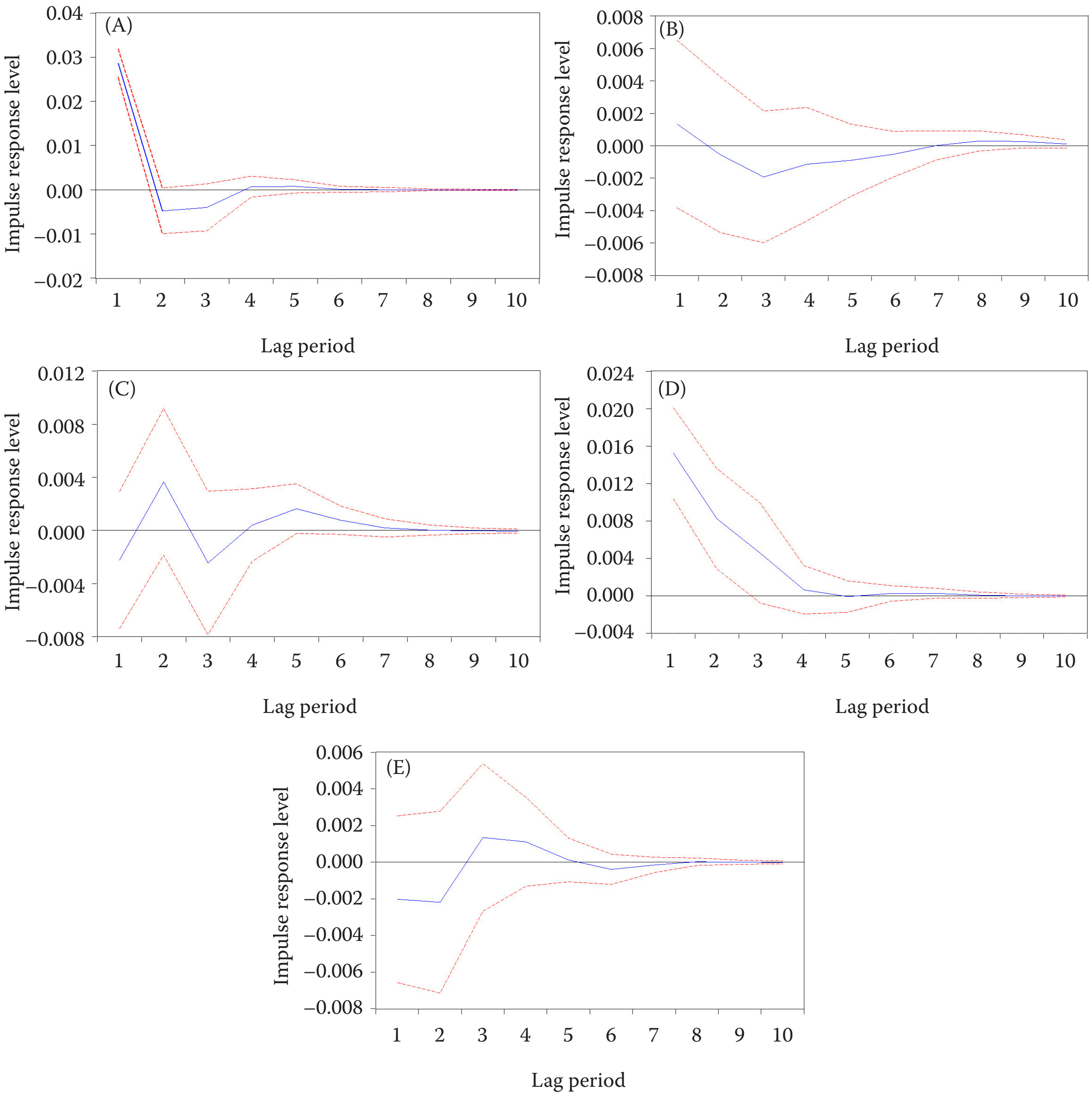

Figure 4. Impulse response of corn price fluctuations to variable shock under the VAR model

VAR – vector autoregression

Source: Authors' own processing

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compared to other food crops, its price was not greatly affected in the later stages.

Time-point impulse response. The impulse responses of a system were observed at different times. The stock index was expected to peak in late 2021 or early 2022, while corn futures and export volume peaked in May 2021. New COVID-19 cases worldwide were expected to peak on December 22, 2022. Three specific dates were chosen to analyse impulse responses: May 13, 2021, December 30, 2021, and December 22, 2022. The results are displayed in Figure 3, with lagged weeks on the horizontal axis and impulse responses on the vertical axis.

The impulse response diagram shows the impact of external factors, which take approximately 5-6 weeks to diminish to zero. Figure 3A shows the impact of international corn price fluctuations on its own. The degree of response was positive, but in these three points in time, its impact was in the lag of 1 week when the lag tended to 0. From the point-in-time impulse response of shock of international corn price volatility on the new number of the COVID-19 cases (Figure 3B), the shocks at the three points in time basically show a certain negative response, and the number of weeks that produce the maximum response is between 2–3 weeks, and a certain point-in-time lag of its negative impact is also consistent with the previous analysis.

Figure 3C shows how fluctuations in international corn prices impacted the stock index over time. There was a positive response for a week, followed by an alternating pattern of positive and negative responses in the second week, and finally, a negative response for two weeks. This confirms that the stock index was influenced by international market turbulence, which indirectly affected domestic corn price fluctuations. Similarly, Figure 3D shows the impact of fluctuations in international corn prices on the international corn futures price index over time. The degree of impact was almost the same at the three time points, with a positive impact in all cases. The impact was the greatest when the lag was between 1 and 2 weeks. Figure 3E shows how fluctuations in international corn prices affected corn export volumes over time. Negative responses occurred with a one-week delay, followed by alternating positive and negative responses in the second week and a positive response in the third week. On May 13, 2021, the international corn export volume peaked, confirming that changes in international corn prices impacted both export volumes and the futures price index.

Robustness test. To strengthen the reliability of the research findings, the VAR model was utilised to verify the correlation between corn prices and other external factors. The impulse response outcomes of the VAR model, as depicted in Figure 4, were in agreement with the empirical analysis outcomes of the TVP-VAR model, confirming that the results of the TVP-VAR model were robust.

In summary, the four external factors affecting corn price volatility discussed in the previous section provide a more comprehensive picture of the impact of sudden shocks on corn price volatility than previous studies, especially the occurrence of COVID-19. However, the impacts of extreme weather, water depletion, natural disasters, and war and conflict are other factors that will have longer-term and more substantial effects and need to be re-collected, reorganised, and re-modelled before further research can be achieved.

CONCLUSION

This study examined the volatility of international corn prices and how external uncertainties impacted them. The data used were weekly data from February 6, 2020, to May 4, 2023. The study found that there was a significant asymmetry in corn price volatility according to the ARCH model. The TVP-VAR model showed that external factors, such as COVID-19, affected corn price volatility and that their impact varied over time. COVID-19 had a negative effect on corn price fluctuations, while the change in the corn futures price had a positive effect. Additionally, all variables weakened as the lag period expanded, and external shocks caused by COVID-19 affected the fluctuation of corn prices. To promote global food security, governments and the United Nations should improve the corn market information system and establish an early warning system for corn. This can be achieved by collecting and analysing information about the corn market and monitoring its supply and demand. They should also ensure the availability of production means and regulate and agree on terms to stabilise global food imports and exports.

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Received: September 25, 2023
Accepted: December 11, 2023
Published online: January 25, 2024