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International price volatility transmission and structural change: a market connectivity analysis in the beef sector

Tetsuji Tanaka¹✉ & Jin Guo¹

Despite the abundance of literature on agricultural price transmissions and unexpectedly disrupted value chains from infectious disease outbreaks such as bovine spongiform encephalopathy and COVID-19, the importance of research on price connectivity in the international beef markets has largely been ignored. To assess agricultural price transmission issues, error correction-type models (ECMs) have been predominantly employed. These models, however, suffer a deficiency in that the method is incapable of depicting time-variant linkages between prices. This article examines the connections between global and local prices, as well as price volatility in the beef sector. Our analysis uses a generalised autoregressive conditional heteroscedasticity (GARCH) model with the dynamic conditional correlation (DCC) specification that enables us to identify market connection intensity dynamics. We pay assiduous attention to structural changes in the overall research processes to enhance the reliability of estimation. For the first time in meat or grain price transmission research, our autoregressive models have been developed with structural break dummy variables for DCC. The principal findings are that (1) local retail prices for Azerbaijan, Georgia, Japan, Kazakhstan, Kyrgyzstan, Tajikistan and the UK showed a structural change in mean or variance, all of which were identified after the global food crisis from 2007–2009, (2) international prices unidirectionally Granger-cause regional prices in Georgia, Tajikistan and the United States in both mean and volatility (accordingly, no country exhibited price or price-volatility transmission from regional to international markets), and (3) volatility liaisons between global and local beef markets are generally weak, but price volatility exhibited closer synchronisation around the 2008 global food crisis, which created structural changes during the period. This finding implies that national governments should shield domestic from global markets by implementing trade restrictions such as quotas or taxes in a global emergency.

¹Department of Economics, Setsunan University, Neyagawa, Japan. ✉email: tetsuji.tanaka@econ.setsunan.ac.jp

Introduction

Price plays an important role in actualising efficient resource allocation in an economy. If high market efficiency is achieved, price oscillations are sensitively conveyed across markets. Price transmission research has long attracted economists seeking to elucidate market mechanisms to improve market efficiency. Consequently, a considerable number of articles on agricultural price transmission have been published, with approximately 500 articles resulting from an AgEcon database search with the keywords 'price transmission' (Kouyaté and vonCramon-Taubadel, 2016). However, relatively fewer publications centre on cross-border linkages (i.e., between global and domestic markets or between local markets in different countries), while the majority analyse price correlations within domestic markets (Ceballos et al., 2017). In particular, almost nothing is understood about the liaisons between international and regional meat markets even though meat value chains have been disrupted by infectious disease outbreaks such as bovine spongiform encephalopathy (BSE) and COVID-19. It is essential to elucidate market linkage mechanisms to mitigate such unexpected shocks to food security.

In past studies, analysis of agricultural price propagation issues predominantly employed error correction-type models (ECMs). These models, however, suffer from a deficiency in that the method is incapable of depicting time-variant links between prices. The dynamic conditional correlation (DCC) that originated from Engle (2002) facilitates observation of the intensity of market connections over time. This methodological process is frequently applied to price and price-volatility spillovers for financial markets such as equities, exchange rates and bond markets (e.g., Basher and Sadorsky, 2016; Gjika and Horvath, 2013; Gomez-Gonzalez and Rojas-Espinosa, 2019; Guo, 2018; Hou et al., 2019; Hwang et al., 2013; Kenourgios et al., 2016; Rizvi and Arshad, 2014; Shahzad et al., 2017; Shahzad et al., 2020; Tamakoshi and Hamori, 2013; Tamakoshi and Hamori, 2014; Tissaoui and Azibi, 2019). Furthermore, the application of DCC to energy issues can be seen in recent studies (e.g., Abdelradi and Serra, 2015; Abdullah and Masih 2016; Kaushik, 2018; Mensi et al., 2013; Mollick and Assefa, 2013; Naeem et al., 2020; Okorie and Lin, 2020; Pan et al., 2016; Sadorsky, 2014; Shiferaw, 2019; Vacha and Barunik, 2012; Xu et al., 2019; Zhang et al., 2017). The dynamic correlation process has never gained popularity in the literature on agricultural price transmissions.

A few articles tackle cereal price co-movement investigations, applying a DCC approach. For instance, Guo and Tanaka (2019) are the first to employ DCC to examine the relationships between world and local agricultural markets. Tanaka and Guo (2020) also utilised DCC to gauge the efficacy of wheat self-sufficiency policy measures for exporting countries. In addition, to the best of our knowledge, Guo and Tanaka (2020) is the only work that applied a time-varying correlation approach to international beef price passthroughs.

The importance of cross-border price co-movement research for the beef industry has been largely ignored, even though value chains (e.g., transport and food processing) have been disrupted by unexpected events such as BSE and COVID-19. However, the literature on price synchronisation within indigenous beef markets (i.e., relationships across farm-gate, wholesale and retail) is copious (Bakucs and Fertő, 2009; Boetel and Liu, 2010; Chang and Griffith, 1998; Dong et al., 2018; Fousekis et al., 2016; Goodwin and Holt 1998; Griffith and Piggott, 1994; Lloyd et al., 2006; Pozo et al., 2013; Saghaian, 2007; Sanjuan and Dawson, 2003). Although Dong et al. (2018) analyse regional market associations among Australia, China, Indonesia and Vietnam, they do not inspect the links with the global market. Ghoshray (2011) is the only work that delves into international beef market liaisons, covering a wide range of commodities and countries.

However, regarding the beef sector, Ghoshray only analyses the Thai domestic market. Therefore, Guo and Tanaka (2020) is currently the only comprehensive analysis focusing on international price or price-volatility transmission for the beef sector.

Managing structural breaks is vital to enhancing the accuracy of estimators in a time-series analysis. Several existing studies on beef price co-movement considered structural breaks in their model estimations (Bakucs and Fertő, 2009; Chang and Griffith, 1998; Fousekis et al., 2016; Hernandez-Villafuerte, 2008; Lloyd et al., 2006; Sanjuan and Dawson, 2003). Cappiello et al. (2006) demonstrated the first application of structural changes to the DCC and asymmetric DCC. However, none of the past price transmission analyses for cereal commodities using the DCC diagnose structural breaks in time-variant correlations (Ceballos et al., 2017; Guo and Tanaka, 2019; Tanaka and Guo, 2020).¹ The present article thoroughly scrutinises the price interconnectivity between world and local beef prices for nine net importing countries, using GARCH-type models with the DCC specification. Our sample period ranges from January 2006 to May 2020. Applying the cross-correlation function (CCF)², we detect Granger causal relationships between global and local prices in both the mean and variance. We pay assiduous attention to structural changes in every estimation process (i.e., the unit root test, the estimation of both GARCH and DCC models) to gain more precise results.

The current analysis contributes to the literature empirically and methodologically. First, we uncovered the directions of cross-border beef market linkage mechanisms, using the Granger causality technique with carefully selected models based on the Bayesian information criterion (BIC) and accounting for structural breaks. Second, to our knowledge, this paper is the first in meat or grain price transmission research to develop autoregressive (AR) models for DCCs with structural breaks. The existing meat price transmission literature has largely adopted conventional methods such as ECM for analysis, which does not allow for visualising the intensity of market liaison dynamics. To resolve this analytical deficiency, we apply the DCC technique to beef price associations.

The paper is organised as follows. The following section explains data used in the analysis. Section 3 describes the specifications of the models we employed. Empirical results obtained from the models are delineated in Section 4. Finally, the paper is summarised with a discussion of the results.

Data description and preliminary analysis

This research concentrates on nine net beef-importing countries (Azerbaijan, Georgia, Japan, Kazakhstan, Kyrgyzstan, Tajikistan, Tunisia, the UK and the United States of America). These nations were selected based on data availability and the criterion that self-sufficiency in beef does not exceed 100% according to data sourced from the Food and Agriculture Organization (FAO) corporate statistical database (FAOSTAT). We collected monthly international and local retail beef price series for each country over the period from January 2006 to May 2020 in US dollar terms. The regional price data series for Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Tajikistan and Tunisia was retrieved from the FAO global information and early warning system (GIEWS).³ Data for Japan, the UK and the United States were acquired from the Agriculture & Livestock Industries Corporation (Japan), the UK Office for National Statistics, and US Bureau of Labor Statistics, respectively. For Japan and the UK, price data for local currencies were converted into US dollar equivalents with exchange rates obtained from Federal Reserve economic data.⁴

To eliminate the influence of seasonal fluctuations, all beef price series are adjusted using the X-13-ARIMA⁵ method. The monthly returns are calculated as the first differences of monthly logarithmic prices $R_t = \ln(P_t) - \ln(P_{t-1})$, where R_t is the monthly beef price return at time t , and P_t is the beef price at time t . The summary statistics for all beef price returns under investigation are displayed in Table 1. According to Table 1, Tajikistan shows the highest returns in mean and median, while Japan displays minimal mean and median values. However, the table indicates that the returns of international beef prices are more volatile than all the domestic prices, evidenced by the largest standard deviation. Meanwhile, Japan's price returns also show relatively higher standard deviation than other countries. Note that the skewness values are all negative except for Tunisia and the United States, indicating there is a longer tail on the left side of the probability density function and a higher probability of observing negative rather than positive returns in most of the price returns. Furthermore, the high values of kurtosis for all the price returns suggests the existence of fat tails in the return distributions. All returns (apart from Tunisia) are not normally distributed, as indicated by the Jarque-Bera statistic. Finally, low and positive unconditional correlations between international and domestic beef prices are revealed, except for Azerbaijan. Specifically, the price return of Tunisia has a relatively high positive correlation and Japan has low correlation with international prices.

The returns of each beef price are plotted in Fig. 1. International and local beef price show considerable variability in the sample period and exhibit different patterns across different countries. For instance, some price returns (e.g., International price (henceforth, IP), Georgia, Japan and Kazakhstan) changed dramatically during turbulent periods, such as the global food crisis and great recession of 2007–2009. Furthermore, significant fluctuations in the price returns of Azerbaijan, Kazakhstan, and Tajikistan have also occurred during other periods, such as 2014–2016. These facts are reflected in beef return figures in periods of high volatility. The insights deduced from beef price returns may be indicative of structural changes in the data series, which will be examined in the analysis below.

Before constructing the econometric model, a stationary process of each price return is tested using the augmented Dickey-Fuller (ADF)⁶ and Kwiatkowski-Phillips-Schmidt-Shin (KPSS)⁷ unit root tests. Table 2 reports the results of the unit root tests, which indicate that all price returns are stationary in their first log-differenced forms.⁸ In addition, the main weakness of traditional unit root tests is that they do not account for endogenous structural breaks. Biased results may be seen when structural breaks impact the data series, as documented above in Fig. 1. Considering this, we apply Zivot and Andrews (1992) and Perron (1997) tests, which have the advantage of allowing for one unknown structural break in the price returns.

Table 2 shows the results of unit root tests with a break and presents the break date endogenously determined by the tests. According to Table 2, results of unit root tests with a break can be detected, which are similar to the usual unit root tests, suggesting that all beef price returns can be deemed as a stationary process. Moreover, turning our attention to the structural break identified for each price return, some estimated break dates correspond to the period of the food crisis and great recession of 2007–2009 (e.g., Georgia, Japan and the UK). The other break dates detected in the test occurred during the period 2014–2016.

In brief, preliminary analysis indicates that these price returns are characterised by non-normal distributions, negative skewness, fat tails, stationarity and an endogenous structural break. Based on these results, it is important to further examine the existence of multiple structural changes in the conditional mean and variance for each price return. GARCH-type models with structural

Table 1 Descriptive statistics and correlations for international and domestic beef price returns.

	Symbol	Mean	Median	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Correlations
International Price	IP	3.559×10^{-3}	3.138×10^{-3}	0.046	-0.125	5.406	41.926***	-
Azerbaijan	AZE	2.847×10^{-3}	3.49×10^{-3}	0.032	-3.403	25.848	4073.009***	-0.020
Georgia	GEO	2.685×10^{-3}	3.784×10^{-3}	0.029	-0.179	6.256	76.902***	0.103
Japan	JPN	0.161×10^{-3}	1.943×10^{-3}	0.038	-0.827	7.901	191.767***	0.000
Kazakhstan	KAZ	2.336×10^{-3}	6.34×10^{-3}	0.034	-3.162	19.264	2182.198***	0.058
Kyrgyzstan	KYR	3.142×10^{-3}	5.573×10^{-3}	0.023	-0.623	4.525	27.780***	0.171
Tajikistan	TJK	4.287×10^{-3}	6.298×10^{-3}	0.025	-0.730	5.117	47.395***	0.084
Tunisia	TUN	1.408×10^{-3}	2.351×10^{-3}	0.022	0.076	3.577	2.553	0.219
United Kingdom	UK	0.614×10^{-3}	2.482×10^{-3}	0.034	-0.249	5.550	48.359***	0.124
United States of America	USA	3.261×10^{-3}	2.93×10^{-3}	0.025	0.618	5.960	73.732***	0.012

***denote statistical significance at the 1% level. The monthly returns are calculated as the first differences of monthly logarithmic prices. Sample size is from February 2006 to May 2020. Std. Dev., standard deviation; the Jarque-Bera test statistic for normality

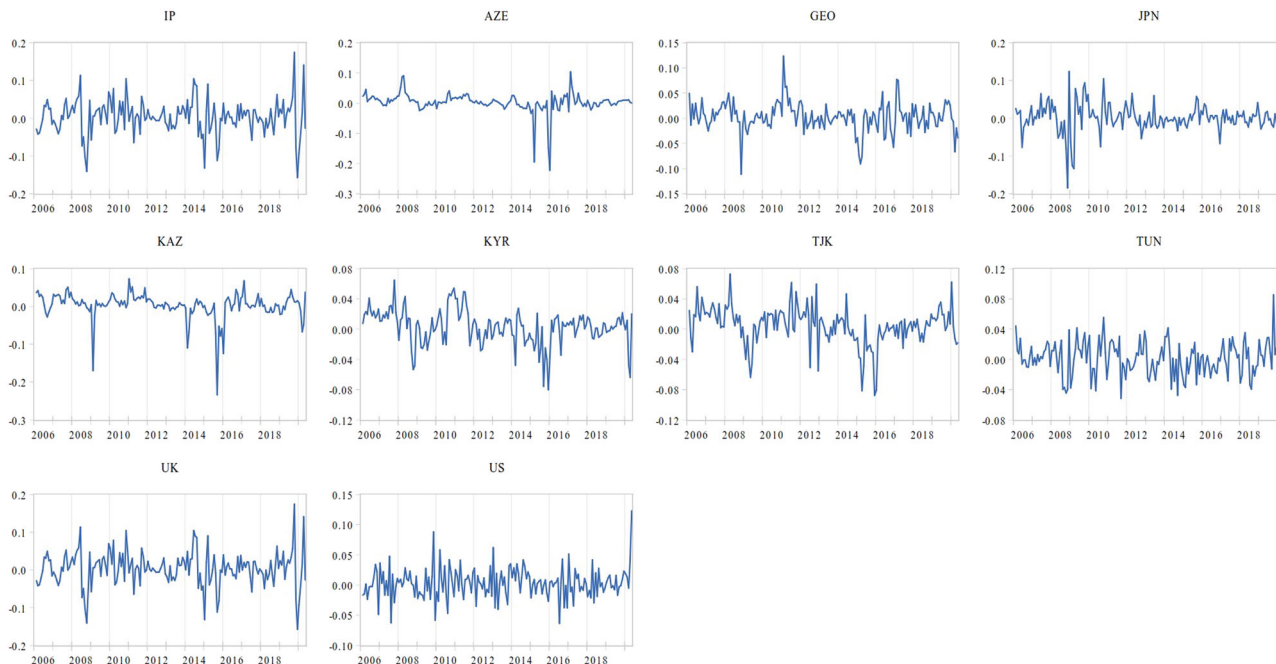


Fig. 1 Time-series plots of monthly beef price returns.

Table 2 Unit root test.

	ADF	KPSS	Ziot-Andrews test		Perron test	
			t-Statistic	Break date	t-Statistic	Break date
IP	-9.547*** (0)	0.032 (3)	-9.853** (0)	09/2014	-4.900 (11)	03/2015
AZE	-8.711*** (1)	0.115 (7)	-4.403*** (10)	10/2016	-5.179*** (10)	01/2016
GEO	-8.379*** (0)	0.060 (7)	-4.974*** (3)	03/2012	-9.035*** (0)	11/2008
JPN	-10.655*** (0)	0.039 (7)	-6.229*** (7)	04/2009	-6.780*** (7)	03/2009
KAZ	-7.642*** (0)	0.084 (8)	8.555*** (0)	02/2016	-10.068*** (0)	09/2015
KYR	-6.788*** (0)	0.088 (7)	-7.746* (0)	02/2016	-8.102*** (0)	12/2015
TJK	-4.044*** (2)	0.117 (8)	-4.131*** (4)	07/2014	-5.536*** (2)	06/2014
TUN	-10.474*** (0)	0.079 (5)	-6.499*** (10)	05/2014	-6.474*** (10)	10/2014
UK	-14.964*** (0)	0.052 (5)	-6.523** (4)	04/2009	-15.781** (0)	10/2008
USA	-14.879*** (0)	0.082 (5)	-3.428*** (10)	08/2015	-15.844*** (0)	12/2014

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Numbers in brackets are the lag length and bandwidth. Lag length selection is based on BIC in the ADF tests. The bandwidth for the KPSS test is determined using the Bartlett kernel and Newey-West bandwidth selection algorithm (Newey and West, 1994). For the Zivot and Andrews (1992) test and Perron (1997) test, one structural break point is detected by a maximised *F*-statistic, assuming breaks in both intercept and trend.

break, CCF and DCC methodology are used to investigate Granger causality and the dynamic interaction between international and domestic beef prices in beef-importing countries.

Methodology

Given two stationary series $\{X_{i,t}\}$, $i = 1, 2$ and $t = 1, \dots, T$ where T is the sample size. Let $\Omega_{i,t}$ be two information sets defined as $\Omega_{i,t} = (X_{i,t-j}, j \geq 0)$, $i = 1, 2$ and $\Omega_t = \Omega_{1,t} \cup \Omega_{2,t}$. Following Hong's (2001) null hypothesis, $X_{2,t}$ Granger-causes $X_{1,t}$ in the mean if:

$$E(X_{1,t} | \Omega_{1,t-1}) \neq E(X_{1,t} | \Omega_{t-1}) \tag{1}$$

Meanwhile, $X_{2,t}$ is considered to cause $X_{1,t}$ in variance if:

$$E\left\{ (X_{1,t} - \mu_{1,t})^2 \middle| \Omega_{1,t-1} \right\} \neq E\left\{ (X_{1,t} - \mu_{1,t})^2 \middle| \Omega_{t-1} \right\}, \tag{2}$$

where $\mu_{1,t}$ is the mean of $X_{1,t}$ conditioned on $\Omega_{1,t-1}$.

To assess Granger causality between international and local beef prices in beef-importing countries, Hong's (2001) non-uniform weighting CCF was applied. One of the key advantages of this

approach is that it can detect the leading and lagging structures of causality, as well as the duration over which causality is exerted.⁹ Specifically, based on the estimated GARCH-type models, the standardised residuals and the standardised squared residuals for international and local beef prices will be estimated, respectively. Next, the sample cross-correlation coefficient $\hat{\rho}_{12}(j)$ between the standardised residuals¹⁰ $\{\hat{\vartheta}_{i,t}, t = 1, \dots, T\}$, $i = 1, 2$ with lag j ($j = 0, \pm 1, \pm 2, \dots, \pm(T-1)$) can be represented as follows:

$$\hat{\rho}_{12}(j) = \begin{cases} \frac{T^{-1} \sum_{t=j+1}^T \hat{\vartheta}_{1,t} \hat{\vartheta}_{2,t-j}}{\sqrt{T^{-1} \sum_{t=1}^T \hat{\vartheta}_{1,t}^2} \sqrt{T^{-1} \sum_{t=1}^T \hat{\vartheta}_{2,t}^2}}, & j \geq 0 \\ \frac{T^{-1} \sum_{t=1-j}^T \hat{\vartheta}_{1,t-j} \hat{\vartheta}_{2,t}}{\sqrt{T^{-1} \sum_{t=1}^T \hat{\vartheta}_{1,t}^2} \sqrt{T^{-1} \sum_{t=1}^T \hat{\vartheta}_{2,t}^2}}, & j < 0 \end{cases}, \tag{3}$$

where $T^{-1} \sum_{t=1}^T \hat{\vartheta}_{1,t}^2$ and $T^{-1} \sum_{t=1}^T \hat{\vartheta}_{2,t}^2$ are the sample variances of $\hat{\vartheta}_{1,t}$ and $\hat{\vartheta}_{2,t}$, respectively. Following Hong (2001), the causality-in-

variance test statistics can be defined as:¹¹

$$\Phi = \frac{T \sum_{j=1}^{T-1} k^2(j/S) \widehat{\sigma}_{12}(j) - \Psi_{1T}(k)}{\{2\Upsilon_{1T}(k)\}^{1/2}}, \quad (4)$$

where

$$\Psi_{1T}(k) = T \sum_{j=1}^{T-1} (1 - j/T) k^2(j/S), \quad (5)$$

$$\Upsilon_{1T}(k) = T \sum_{j=1}^{T-1} (1 - j/T) \{1 - (j+1)/T\} k^4(j/S), \quad (6)$$

$$k(z) = \begin{cases} 1, & |z| \leq 1, \\ 0, & \text{otherwise.} \end{cases} \quad (7)$$

If the test statistic Φ in Eq. 5 is larger than the upper-tailed critical value of $N(0, 1)$, we reject the null hypothesis of no causality-in-mean or causality-in-variance during the first S lags.

Since the results of the CCF approach rely on the correct selection and specifications of the GARCH model applied, in this article we estimate the squared standardised residuals of each variable using three different types of GARCH models. Specifically, besides the univariate GARCH model, our analysis employs both the exponential generalized autoregressive conditional heteroscedastic (EGARCH)¹² and the Glosten, Jagannathan and Runkle-GARCH (GJR-GARCH)¹³ models to capture the presence of asymmetry in volatility. The empirical model for international and domestic beef price returns can be specified as follows:

$$R_t = \theta + \sum_{i=1}^k \omega_i R_{t-i} + v_t, \quad v_t = \sqrt{h_t} \vartheta_t, \quad \vartheta_t \sim N(0, 1), \quad (8)$$

$$h_t = \pi + \sum_{i=1}^p \alpha_i v_{t-i}^2 + \sum_{i=1}^q \beta_i h_{t-i}, \quad (9)$$

$$h_t = \pi + \sum_{i=1}^p (\alpha_i v_{t-i}^2 + \gamma_i \Pi_{t-i}^- |v_{t-i}|) + \sum_{i=1}^q \beta_i h_{t-i}, \quad (10)$$

$$\ln(h_t) = \pi + \sum_{i=1}^p (\alpha_i |\vartheta_{t-i}| + \gamma_i \vartheta_{t-i}) + \sum_{i=1}^q \beta_i \ln(h_{t-i}). \quad (11)$$

Equation (8) specifies the conditional mean equation, where R_t is the beef price return and the error term v_t is assumed to follow a conditionally normal distribution with its conditional variance h_t . Equations (9–11) represent the variance equations specified by the GARCH, GJR-GARCH, and EGARCH models, respectively. The indicator function Π_{t-i}^- in Eq. (10) equals 1 if $v_{t-i} < 0$, and 0 otherwise. q is the number of GARCH terms, and p is the number of ARCH terms that can capture asymmetric effects. We carry out the lag selections using the BIC and determine the optimal univariate model for each price return.

Lamoureux and Lastrapes (1990) suggest that structural breaks in conditional variance may confound the estimation of a GARCH model, and that structural breaks should be incorporated into a GARCH model to obtain certain estimators. Moreover, argue that pre-testing needs to be executed for structural breaks in volatility before examining the causality-in-variance. In this regard, we employ Bai and Perron's (2003) test¹⁴ to identify the structural breaks in mean and variance equations. First, we apply this approach to the AR model and identify the structural break points in the conditional mean equation. Then, the residuals can be obtained from this estimation process. Next, we identify the structural breaks in the variance through the

following equation:

$$\sqrt{2^{-1}\pi} |\widehat{v}_t| = c + u_t, \quad (12)$$

where the transformed residual on the left-hand side indicates the unbiased estimator of the standard deviation of v_t from the conditional mean equation. Moreover, c and u_t are the constant and error term, respectively.

Finally, we use a bivariate GARCH model with a conditional variance-covariance matrix to estimate the DCCs between international and domestic beef prices and examine the volatility transmissions for each price pair. Following Engle (2002), we construct an econometric framework for the GARCH-DCC model, which was formulated as follows:

$$R_t | \Xi_{t-1} \sim N(0, H_t), \quad v_t = H_t^{1/2} \vartheta_t, \quad (13)$$

$$H_t = \Theta_t \Lambda_t \Theta_t, \quad (14)$$

$$\Theta_t = \text{diag}(\sqrt{h_{1,t}}, \sqrt{h_{2,t}}) = \begin{bmatrix} \sqrt{h_{1,t}} & 0 \\ 0 & \sqrt{h_{2,t}} \end{bmatrix}, \quad (15)$$

$$\Lambda_t = \text{diag}\{Q_t\}^{-1/2} Q_t \text{diag}\{Q_t\}^{-1/2} = \begin{bmatrix} 1 & \frac{q_{12,t}}{\sqrt{q_{11,t}q_{22,t}}} \\ \frac{q_{21,t}}{\sqrt{q_{11,t}q_{22,t}}} & 1 \end{bmatrix},$$

where

$$Q_t = \begin{bmatrix} q_{11,t} & q_{12,t} \\ q_{21,t} & q_{22,t} \end{bmatrix} \quad (16)$$

where R_t is a 2×1 vector of returns including the international beef price $R_{1,t}$ and domestic beef price $R_{2,t}$. Ξ_{t-1} is an information set at time $t-1$. $v_t = (v_{1,t}, v_{2,t})'$ is the vector of innovations, H_t is a 2×2 conditional variance-covariance matrix, ϑ_t is a 2×1 independent and identically distributed (i.i.d.) vector of standardised residuals. Θ_t is the diagonal matrix containing the conditional standard deviations of each price return. Λ_t is the time-varying conditional correlation matrix and Q_t is the conditional correlation matrix of the standardised residuals, which can be defined by

$$Q_t = (1 - \alpha - \beta) \bar{Q} + \alpha \vartheta_{t-1} \vartheta_{t-1}' + \beta Q_{t-1}, \quad (17)$$

where parameters a and b are non-negative, with a restriction of $a + b < 1$ to ensure stationarity and a positive definiteness of Q_t . \bar{Q} is the 2×2 unconditional correlation matrix of the standardised residuals ϑ_t . Cappiello et al. (2006)¹⁵ modified the correlation evolution by introducing the presence of asymmetries into the DCC model. The authors constructed an asymmetric generalised DCC (AG-DCC) model, as in the following expression:

$$Q_t = (\bar{Q} - A' \bar{Q} A - B' \bar{Q} B) - G' \bar{N} G + A' \vartheta_{t-1} \vartheta_{t-1}' A + B' Q_{t-1} B + G' \xi_{t-1} \xi_{t-1}' G, \quad (18)$$

where A and B are 2×2 parameter matrices. \bar{N} represents the unconditional matrices of $\xi_t = I[\vartheta_t < 0] \otimes \vartheta_t$ ($I[\cdot]$ is an indicator function equal to 1 if $\vartheta_t < 0$ and 0 otherwise, while \otimes indicates the Hadamard product) and $\bar{N} = E[\xi_t \xi_t']$. The asymmetric DCC (A-DCC) is a special case of the AG-DCC if the matrices are replaced by scalars. Moreover, if matrix G in Eq. (18) equals zero, then the generalised DCC model (G-DCC) can be obtained. Thus, the DCC $\rho_{ij,t}$ can be defined as:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}}, \quad \forall i, j = 1, 2, i \neq j. \quad (19)$$

The parameters of the DCC, A-DCC, AG-DCC, and G-DCC model are estimated by the Gaussian quasi-maximum likelihood estimation (QMLE),¹⁶ assuming conditional multivariate normality with the BFGS¹⁷ optimisation algorithm. Following Engle

Table 3 Structural breaks test for mean and volatility of beef price returns.

	Break in mean			Break in volatility		
	$H_0: L \text{ vs. } H_1: L + 1$	Scaled F-statistic	Break dates	$H_0: L \text{ vs. } H_1: L + 1$	Scaled F-statistic	Break dates
IP	$L = 0$	2.506	No break	0 vs. 1	7.463	No break
AZE	$L = 0$	34.091**	02/2016	$L = 0$	13.127**	03/2015; 04/2017
	$L = 1$	12.813		$L = 1$	37.814**	
				$L = 2$	1.810	
GEO	$L = 0$	9.688**	03/2012	$L = 0$	6.636	No break
	$L = 1$	6.839				
JPN	$L = 0$	2.813	No break	$L = 0$	27.672**	01/2010
KAZ	$L = 0$	13.285**	01/2014; 02/2016	$L = 1$	1.993	No break
	$L = 1$	14.315**		$L = 0$	6.903	
	$L = 2$	3.260				
KYR	$L = 0$	14.392**	10/2011	$L = 0$	3.098	No break
	$L = 1$	5.997				
TJK	$L = 0$	12.353**	07/2012; 08/2014	$L = 0$	3.827	No break
	$L = 1$	23.977**				
	$L = 2$	7.932				
TUN	$L = 0$	2.210	No break	$L = 0$	8.501	No break
UK	$L = 0$	6.079	No break	$L = 0$	8.615**	09/2014
				$L = 1$	1.471	
USA	$L = 0$	6.149	No break	$L = 0$	1.316	No break

We used Bai-Perron's (2003) sequential structural breaks test for the null hypothesis of k breaks vs. $k + 1$ breaks, employing the scaled F -statistics. L denotes the number of determined breaks in each price return. A test sequence is used as L increases and the sequence stops when the null is not rejected. **denotes statistical significance at the 5% significance level.

(2002), the likelihood function can be expressed as:

$$L(\eta, \varsigma) = -\frac{1}{2} \sum_{t=1}^T \left(n \log(2\pi) + \log|\Theta_t|^2 + v_t' \Theta_t^{-2} v_t + \log|\Lambda_t| + \vartheta_t' \Lambda_t^{-1} \vartheta_t - \vartheta_t' \vartheta_t \right). \quad (20)$$

The parameter in matrix Θ_t and matrix Λ_t are denoted as η and ς , respectively. Finally, to determine the best of the four DCC models considered above, we examined the appropriate ability of each model using the BIC.

Empirical results

Identification of structural breaks and estimation of GARCH-type models. As explained in the methodology section, before examining the Granger causality and the dynamic relationship between international and domestic beef prices, the existence of structural breaks in the mean and volatility for each price return needs to be explored. Table 3 reports Bai and Perron's (2003) unknown structural break test for beef price returns. According to Table 3, the scaled F -statistic indicates that there is no structural change in either the mean or variance for IP, TUN¹⁸ and USA. However, it can be verified that GEO or KYR has a single break in the mean, and the identified break dates are March 2012 and October 2011, respectively. Note that two breaks occur in the mean of KAZ (January 2014 and February 2016) and TJK (July 2012 and August 2014). Table 3 also reveals that only one break exists in the variance of JPN (January 2010) and the UK (September 2014). Moreover, for AZE, there is only one break in the mean (February 2016) and two breaks in variance (March 2015 and April 2017).

Interestingly, structural breaks were not detected during the global food crisis (2007–2009), but after the event (i.e., 2010–2017). This may represent that domestic beef markets are less sensitively influenced by external markets. That is, internal factors could have caused the structural changes—at least for the sample countries. As seen in the later experimental outcomes, we demonstrated that the interlinkage between global and local prices in the beef sector is relatively weak. Since the structural break dates are identified in the mean and volatility of

several beef prices, it is reasonable to incorporate their corresponding dummy variables in the estimation of GARCH-type models. Based on the model selection criteria,¹⁹ we choose the best-fitting model for each price return. Table 4 provides the details about the model selection. The specification of the original GARCH (1, 1) model is selected for IP, AZE, KYR, UK, and USA because it had the lowest BIC value and highest log-likelihood ratio. The EGARCH (1, 1) model is selected for GEO, JPN, KAZ, and TJK. The GJR-GARCH (1,1) model is found to be best-suited for TUN.

The parameter estimates for univariate GARCH specifications are summarised in Table 4. Results indicate most of the coefficients of the ARCH (α_1) and GARCH (β_1) are statistically significant, thereby providing evidence of volatility clustering. The results were also confirmed with the near-unity sum of the estimated GARCH and ARCH terms for each price. Moreover, we can see a large magnitude of ARCH terms for TJK and JPN, which indicates that past shocks significantly impact the current conditional volatility in these two countries. However, the GARCH term measures the impact of past volatility on current conditional volatility. A relatively larger magnitude of the GARCH terms can be identified for TUN, UK, GEO, and KYR, which implies the persistence of volatility in these countries. Furthermore, it is noticeable that the asymmetric (γ) terms are statistically significant in the price returns of JPN. This result suggests that the asymmetric effect or 'leverage effect'²⁰ is exerted on Japan's price returns. Furthermore, the dummy variables are statistically significant in mean and variance for AZE, GEO, JPN, KAZ, KYR, TJK, and UK. These findings suggest that the dummy variable accommodates the structural change in the mean and variance of beef prices in these countries. Table 4 also shows the diagnostics of the empirical results for each model. The Ljung–Box statistics and ARCH-LM (Lagrange multiplier) tests show the null hypothesis of no autocorrelation. ARCH effects cannot be rejected at the 1% significance level for all price returns. The well-fitted mean and variance equations described above led us to conclude that our selection of AR-GARCH-type models fit the data reasonably well.

Table 4 Estimation of GARCH-type models with dummy variables.

Model selection	Parameters		Specification tests								
	ω_1	α_1	γ_1	β_1	D_{mean1}	D_{mean2}	$D_{volatility1}$	$D_{volatility2}$	$Q^2(10)$	ARCH	BIC
IP	0.277***	0.428**		0.542***					4.941	0.421	-3.540
AZE	0.728***	0.427*		0.256*	0.002*		0.002**		5.003	0.452	-5.545
GEO	0.341***	0.363*	-0.101	0.709***	-0.006*				1.496	0.141	-4.434
JPN	0.247***	0.545**	-0.297**	0.541***			-0.665**		10.304	1.057	-4.104
KAZ	0.543***	0.491*	0.160	0.508**	-0.009***	0.009***			10.57	0.110	-4.896
KYR	0.499***	0.244**		0.650***	-0.011***				6.439	0.697	-5.105
TJK	0.334***	0.757**	-0.264	0.430*	-0.009***	-0.002*			1.692	0.250	-4.806
TUN	0.250***	-0.037	-0.083	1.037***					6.024	0.729	-4.835
UK	-0.019	-0.072***		0.937***			-0.000**		8.768	1.157	-3.925
USA	-0.212**	0.305*		0.458					2.828	0.388	-4.538

*, **, and ***denote statistical significance at the 10%, 5%, and 1% levels, respectively. The standard error follows Bollerslev and Wooldridge's (1992) robust standard error. The optimal lag length in each mean and variance equation are selected by employing the BIC. Diagnostic test: $Q^2(10)$ is the Ljung-Box (Ljung and Box, 1978) statistics for the null hypotheses of no autocorrelation up to the order of 10 for squared standardised residuals. ARCH denoted the test statistic for testing the ARCH effect up to lag order 10.

Causality-in-mean and Causality-in-variance analysis. Next, we examine the causality-in-mean and variance and lead-lag relationship between international and domestic beef prices by using the standardised residuals obtained from each GARCH-type model. Since the CCF-based approach is typically applied to investigate the causal relationships in a bivariate framework, we present the empirical results for each pair of international and domestic prices. We use Hong's (2001) statistics to test the null hypothesis of no causality from lag 1 to lag M (5, 10, 15) month. The results of causality-in-mean are reported in Table 5. Overall, it is somewhat interesting to ascertain that different causality exists across different countries. We can verify that a unidirectional causality-in-mean runs from IP to domestic prices for GEO, JPN, KAZ, TJK, and the USA. Specifically, IP Granger-causes these domestic prices with a one-month lag up to a 5-month lag, suggesting that the domestic beef market exhibits a speedy reaction to change in the global beef price. In contrast, the reverse causality is not significant, which implies a leading role of the international beef price regarding price transmission. That is, excessive volatility in international beef prices would increase the uncertainty of the domestic beef market in these five countries. However, it can be observed that there are no causality-in-mean effects between IP and domestic prices in AZE, KYR, TUN, and UK. Thus, there is no evidence of price information transmission and contagion between IP and local prices in these four countries

As for the causality-in-variance test, the results are reported in Table 6. Comparing the results with Table 5, we note several interesting findings. First, similar to causality-in-mean, there was no explicit causal relationship between IP and beef prices in AZE and TUN. Thus, information links between international and local prices in these two countries are weak and correlation between them is low. Second, different characteristics of spillover effects from volatility are found between international and domestic prices. Specifically, From Table 6, we can see that there is no statistically significant evidence of causality-in-variance effects between IP and domestic prices in JPN and KAZ, which is different from those in the results of causality-in-mean. Moreover, it is interesting to identify a unidirectional causality-in-variance from IP to domestic prices in KYR and the UK, which does not have causality-in-mean effects. These results provide evidence of one-way lead-lag volatility spillovers from international beef prices to these two countries' local beef prices. Furthermore, IP Granger-causes UK and USA with ten-month and fifteen-month lags, indicating that a delayed reaction and longer time is needed for volatility transmission for these two countries. In sum, our findings confirm the existence of a causal linkage either in mean or in variance from international beef prices to local beef prices in GEO, TJK, and the USA.

Our Granger linkage outcomes indicate that any of the importing nations do not affect the international price of beef, whereas indigenous prices in Georgia, Tajikistan and the United States are influenced by global prices both in mean and variance, which implies closer interconnections with the international market. Note the mean of the beef self-sufficiency rate (SSR) of Georgia, Tajikistan, and the United States during the sample period was 74, 98, and 97%,²¹ respectively, which is not necessarily low²² although it is widely recognised that the food autarky measure contributes to segregating domestic from foreign markets (Guo and Tanaka, 2019; Tanaka and Guo, 2019; Tanaka and Guo, 2020).²³

Time-varying conditional correlations. In the next step, we estimate the time-varying conditional correlations between international and local beef prices. First, we should select the most appropriate model of four DCC specifications²⁴ for each

Table 5 Empirical Results for Granger causality-in-mean test.

Granger causality from international price to domestic price	Test statistic (M = 5)	Test statistic (M = 10)	Test statistic (M = 15)	Granger causality from domestic price to international price	Test statistic (M = 5)	Test statistic (M = 10)	Test statistic (M = 15)
IP → AZE	-0.132	-0.018	0.001	AZE → IP	0.486	0.562	0.583
IP → GEO	3.905***	4.395***	3.343***	GEO → IP	-1.009	-0.944	-0.244
IP → JPN	1.582*	3.370***	1.993**	JPN → IP	-0.502	0.151	0.131
IP → KAZ	1.598*	0.740	0.580	KAZ → IP	-0.379	-0.201	0.552
IP → KYR	0.568	0.142	0.144	KYR → IP	-0.727	-0.939	-1.175
IP → TJK	2.041**	1.908**	1.847**	TJK → IP	0.698	-0.407	-0.739
IP → TUN	-0.793	-1.283	-1.830	TUN → IP	-0.134	-0.245	-0.590
IP → UK	-0.851	-0.095	-0.612	UK → IP	0.463	-0.298	-0.494
IP → USA	5.496***	4.289***	3.168***	USA → IP	-0.752	-0.789	-0.436

IP international beef price, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The arrow indicates the direction of Granger causality. Hong's (2001) test statistic is used to test the null hypothesis of no causality from lag1 to lag M (5, 10, 15), respectively. Lags are measured in months. If the test statistic is higher than the critical value of the standard normal distribution, the null hypothesis is rejected.

price pair. The results of the model selection in Table 7 show that the standard DCC model is selected as the best fit for IP vs. AZE, IP vs. JPN, IP vs. KAZ, and IP vs. KYR and IP vs. TJK. The G-DCC model is selected for the pair of IP vs. GEO, IP vs. UK, and IP vs. USA. However, the A-DCC model is selected for IP vs. TUN, and AG-DCC is not suitable for any price pairs. The parameters for all the selected models are estimated by maximising the log-likelihood functions mentioned in the methodology section.²⁵

Finally, we address the issue of global-local market linkages based on the DCCs between international beef prices and those of nine beef-importing countries. The evolution of DCCs is plotted in Fig. 2 for all the pairs of prices. First, although DCCs exhibit some different patterns across different countries, several similar characteristics of the depicted pairwise correlations are that most of them change visibly over the sample period and show evidence of upward and downward peaks at some common times. Specifically, it can see that DCCs in some countries (e.g., AZE, GEO, JPN, TJK, TUN, and the UK) fluctuated dramatically during 2007–2008, which may be explained by the turmoil characterising the global food and financial crisis over the period. For instance, we observe that DCCs of Japan record an increase almost until the end of 2007, then drop dramatically from early 2008, and return to their path from mid-2009. These features suggest the food crisis had significant impacts on the interrelationship between international beef prices and domestic prices in these countries. Moreover, similar trending patterns are observed in the period of 2014–2015 for AZE, GEO, JPN, and the UK. These countries tended to show sharp declines in the 2014.

Second, we focus on the sign of DCCs between international and domestic prices. Note that the DCCs of JPN, KAZ, and the UK show some negative values throughout the entire sample period and a relatively high level of magnitude. These results can be explained by a lead-lag information transmission across global and local beef markets. Our empirical results in the previous subsection detect a unidirectional causality between international and local prices in JPN, KAZ, and the UK. Therefore, it is reasonable to assume that increases or declines in international beef prices will bring about lagged increases or declines in domestic beef prices in these three beef-importing countries.

Third, as can be observed, the extent of the positive values in DCCs is relatively low in some countries (e.g., GEO, TJK, and the USA). These features indicate weak price transmission and volatility spillovers across the international and domestic beef markets in these countries.

In addition, we report descriptive statistics of DCCs for all countries in Table 8. We find that the magnitude of the mean of DCCs range from -0.099 (JPN) to 0.210 (KYR). Moreover, the median of DCCs range from -0.109 (JPN) to 0.213 (KYR). As can be seen, the maximum value of DCCs is 0.999 for the United States and the minimum value of DCCs is -0.755 for KAZ. These findings reveal different variations of DCCs across various countries. Moreover, DCCs of AZE exhibit larger fluctuations than the other countries, thus demonstrating the highest standard deviation (0.258). In contrast, GEO has the most stable DCCs, evidenced by the lowest standard deviation (0.062). Overall, the results suggest low global-local market linkages between international beef prices and domestic prices in beef-importing countries. These may be explained by the characteristics of SSR and food policy in each country.

Effects of structural breaks on correlations. As documented in Fig. 2, the DCCs seem to be characterised by structural shifts over time in some beef-importing countries. Such findings motivated

Table 6 Empirical results for Granger causality-in-variance test.

Granger causality from international price to domestic price	Test statistic (M = 5)	Test statistic (M = 10)	Test statistic (M = 15)	Granger causality from domestic price to international price	Test statistic (M = 5)	Test statistic (M = 10)	Test statistic (M = 15)
IP → AZE	-0.708	-0.666	-0.929	AZE → IP	-0.921	-0.205	-0.320
IP → GEO	2.618***	0.782	0.623	GEO → IP	-0.588	-0.844	-0.727
IP → JPN	-1.203	-0.671	-0.895	JPN → IP	-0.258	-0.024	-0.377
IP → KAZ	-0.958	-0.293	-1.116	KAZ → IP	-0.991	-0.900	-1.015
IP → KYR	5.582***	3.295***	2.635***	KYR → IP	-0.437	-0.957	-1.316
IP → TJK	9.239***	6.123***	4.448***	TJK → IP	-0.480	-1.285	-1.362
IP → TUN	-0.003	-0.087	-0.325	TUN → IP	1.037	0.301	0.326
IP → UK	0.712	4.439***	3.187***	UK → IP	-0.685	-0.906	-0.951
IP → USA	-1.244	2.498***	1.376*	USA → IP	-1.000	-1.327	-1.285

IP international beef price. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The arrow indicates the direction of Granger causality. Hong's (2001) test statistic is used to test the null hypothesis of no causality from lag1 to lag M (5, 10, 15), respectively. Lags are measured in months. If the test statistic is higher than the critical value of the standard normal distribution, the null hypothesis is rejected.

Table 7 Empirical results of four specifications for DCC models.

	Model selection	BIC
IP vs. AZE	Standard DCC model	-1405.552
IP vs. GEO	G-DCC model	-1311.026
IP vs. JPN	Standard DCC model	-1272.799
IP vs. KAZ	Standard DCC model	-1292.425
IP vs. KYR	Standard DCC model	-1422.739
IP vs. TJK	Standard DCC model	-1388.170
IP vs. TUN	A-DCC model	-1402.486
IP vs. UK	G-DCC model	-1245.463
IP vs. USA	G-DCC model	-1356.488

The best-fitting model is detected by the lowest BIC statistics for each price pairs.

us to conduct a detailed investigation on whether there are structural changes in estimated dynamic correlations and its effects. First, we use Bai and Perron's (2003) structural breaks test to identify the number of break points and their locations in each DCC. Table 9 provided the results and shows that, across all countries, AZE, GEO, JPN, TJK, TUN, UK, and US demonstrate structural breaks in their DCCs. Specifically, a single break point is identified in DCCs for AZE (August 2008), TJK (April 2008), the UK (October 2009), and the US (May 2018). In addition, four significant structural breaks are detected for GEO (August 2008, June 2012, July 2014, and February 2017) and JPN (November 2008, September 2011, October 2015 and November 2017). Five significant breaks were observed in DCCs for TUN (September 2008, November 2010, December 2012, January 2015 and March 2017). These results reveal some close break dates in these countries, suggesting that structural changes for DCCs took place simultaneously around specific periods. In particular, we can allocate these break dates into four groups depending on the common features of the break periods. The first group of break dates corresponds to the period of the 2007–2008 food and financial crisis, when the international beef prices showed violent fluctuations from mid-2007 throughout 2008. The second group of break dates covers the period from 2009 to 2012, which can be recognised as the post-crisis adjustment period. The third group can be considered in the period 2014–2015 and the final group is the most recent period, 2017–2018.

To examine the changing phases of dynamic price transmission, we follow the procedure of Kalbaska and Gatkowski (2012) and apply the AR (1) model with dummy variables, as in the

following equation:

$$D\hat{C}C_t^* = \omega_0 + \omega_1 D\hat{C}C_{t-1}^* + \sum_{l=1}^n \zeta_l DM_{l,t} + \mu_t \quad (21)$$

where $D\hat{C}C_t^*$ is the estimated pairwise correlation coefficient between IP and each domestic price in a beef-importing country. $DM_{l,t}$ is the dummy variable for structural break point l , for $l = 1, \dots, n$ and where n denoted the number of break points detected by the Bai–Perron test in Table 9.

Table 10 reports the estimation results of the AR (1) model. First, except for GEO, the coefficients of AR (1) terms (ω_1) are all positively significant at the 1% level for all the countries. These results indicate that one period past DCCs significantly affects the current DCCs for most countries. Second, we note that the coefficients of the structural change dummies (ζ_l) are statistically significant for all countries. Specifically, for the first group of break dates, the DCCs of AZE and GEO substantially decrease during the 2007–2008 food and financial crisis period, as indicated by the negative estimated coefficient of the dummy variable. In contrast, we can observe the significantly positive structural break dummies for JPN and TUN, suggesting that the DCCs of these two countries substantially increased at the beginning of the crisis period. In the second group, which is considered as the post-crisis adjustment period, DCCs increase in UK and GEO, as witnessed by the positive coefficient of corresponding dummy variables. JPN, however, shows negative DCCs after the second break date. For TUN, there are decreases in DCCs after the second break and an additional increase in DCCs from the third break. As the third group in the period 2014–2015, we can observe that the structural break dummies are negative for GEO and JPN, and these imply that DCCs decrease during this period. The positive dummy variable for TUN indicates a rise in DCCs around the beginning of 2015. Finally, for the most recent break points at 2017 and 2018 in group four, positive dummy variables can be detected for GEO, JPN and the USA, which confirms that DCCs increase in this period. In contrast, we find a negative coefficient of the dummy variable for TJK and TUN, reflecting that DCCs decreased after the first and fifth breaks in these two countries, respectively. Moreover, results of an LM Breusch–Godfrey (B–G) test for assessing residual autocorrelation, and an ARCH test, which evaluates the presence of conditional heteroskedasticity, suggest that the AR (1) model is suitably specified in all cases.

These findings suggest evidence that structural breaks play a crucial role in forecasting the future trends of interaction between global and local beef markets. Many structural changes in DCCs are identified between 2008 and 2009 surrounding the global food

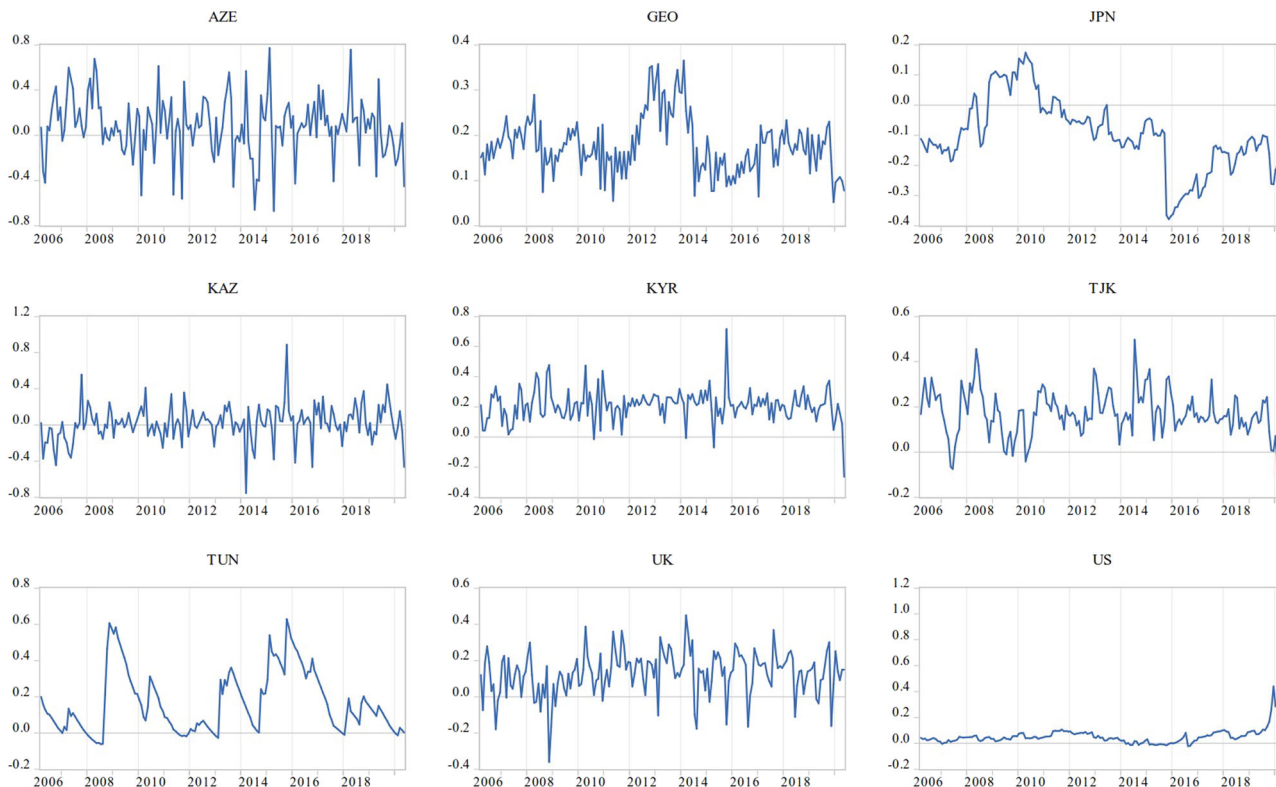


Fig. 2 Plots of time-varying conditional correlations.

Table 8 Descriptive statistics of estimated DCCs of nine beef-importing countries.

	IP vs. AZE	IP vs. GEO	IP vs. JPN	IP vs. KAZ	IP vs. KYR	IP vs. TJK	IP vs. TUN	IP vs. UK	IP vs. USA
Mean	0.080	0.178	-0.099	0.017	0.210	0.169	0.168	0.130	0.058
Median	0.080	0.172	-0.109	0.019	0.213	0.165	0.110	0.147	0.043
Maximum	0.771	0.365	0.175	0.886	0.716	0.497	0.629	0.450	0.999
Minimum	-0.669	0.052	-0.379	-0.755	-0.264	-0.140	-0.062	-0.361	-0.023
Std. Dev.	0.258	0.062	0.120	0.194	0.104	0.101	0.170	0.121	0.095
Observations	171	171	171	171	171	171	171	171	171

Table 9 Detection of break dates in DCCs of nine beef-importing countries.

	Break date 1	Break date 2	Break date 3	Break date 4	Break date 5
IP vs. AZE	08/2008	-	-	-	-
IP vs. GEO	08/2008	06/2012	07/2014	02/2017	-
IP vs. JPN	11/2008	09/2011	10/2015	11/2017	-
IP vs. KAZ	-	-	-	-	-
IP vs. KYR	-	-	-	-	-
IP vs. TJK	04/2018	-	-	-	-
IP vs. TUN	09/2008	11/2010	12/2012	01/2015	03/2017
IP vs. UK	10/2009	-	-	-	-
IP vs. USA	05/2018	-	-	-	-

The significant breaks for each country are examined by applying Bai-Perron's (2003) sequential structural breaks test.

crisis. At that time, the DCCs in beef-importing countries show extreme volatility, reaching high levels during the crisis. This implies that the interconnectivity between international and regional markets is strengthened, and that the lag-lead relationships between international and regional markets are not constant

over time, with DCCs showing both positive and negative values in a short span of time. The regression result with structural change dummy variables suggests that structural breaks affect the inter-linkages between world and local price volatilities positively or negatively, which allows for estimating more accurate DCCs.

Table 10 Estimation of AR model for the estimated DCCs with dummy variables.

	IP vs. AZE	IP vs. GEO	IP vs. JPN	IP vs. TJK	IP vs. TUN	IP vs. UK	IP vs. USA
ω_0	0.173***	0.181***	-0.029***	0.064***	0.002	0.049***	0.023***
ω_1	0.204***	0.065	0.715***	0.645***	0.746***	0.248***	0.408***
ζ_1	-0.132** (08/2008) ¹	-0.034*** (08/2008) ¹	0.052*** (11/2008) ¹	-0.034** (04/2018) ⁴	0.087*** (09/2008) ¹	0.065*** (10/2009) ²	0.074*** (05/2018) ⁴
ζ_2	-	0.114*** (06/2012) ²	-0.047*** (09/2011) ²	-	-0.086*** (11/2010) ²	-	-
ζ_3	-	-0.144*** (07/2014) ³	-0.056*** (10/2015) ³	-	0.046*** (12/2012) ²	-	-
ζ_4	-	0.040*** (02/2017) ⁴	0.030** (11/2017) ⁴	-	0.054*** (01/2015) ³	-	-
ζ_5	-	-	-	-	-0.087*** (03/2017) ⁴	-	-
Adjusted R ²	0.930	0.562	0.905	0.441	0.881	0.648	0.350
B-G test (10)	1.528	2.312	4.263	0.372	2.484	1.410	26.626
ARCH (10)	0.464	1.205	0.134	0.348	1.020	0.632	374.183

, and * statistical significance at the 5% and 1% levels, respectively. The dummy variables refer to the detected break dates for each country in Table 9. Superscript numbers of break dates in brackets denote the groups based on different periods. B-G test denotes the Breusch and Godfrey autocorrelation test statistic up to lag order 10. ARCH denoted the test statistic for ARCH effect up to lag order.

Conclusions and discussions

This work analysed beef price volatility passthroughs between global and local markets for nine importing nations using DCC-GARCH-based models with a focus on identifying structural breaks in the models. The main results are that (1) local beef price returns for Azerbaijan, Georgia, Japan, Kazakhstan, Kyrgyzstan, Tajikistan, the UK and the United States have a structural change in mean or variance, all of which appear after 2010, (2) the global price Granger-causes indigenous prices in both mean and variance for Georgia, Tajikistan, and the United States, and no country showed price or price-volatility transmission from local to global prices, and (3) liaisons across world and regional markets regarding DCC are generally weak, but the intensity of market associations became more volatile around the 2008 global food crisis, which generated structural breaks during the period.

In our Granger linkage experiments, Georgia, Tajikistan, and the United States revealed more intimate connections with global prices. Self-sufficiency in beef for the three nations is not evidently low, and that of Japan is the lowest among the countries selected in our analysis, with 45%. Therefore, the degree of autarky seems to be irrelevant to the degree of interconnectivity between regional and world markets, at least according to these results. Note, however, that these findings are inconsistent with the outcomes in Guo and Tanaka (2020), where price volatility passthrough relies on the self-sufficiency rates of beef. Similarly, Guo and Tanaka (2019) examined the relationship between price volatility transmission and self-sufficiency in wheat. The authors concluded that higher self-sufficiency insulates domestic markets from international markets. Although it is widely believed that autarky policy measures stabilise local markets by protecting them from external shocks, Tanaka and Guo (2019) maintain that if domestic supply is more volatile compared with foreign supply, raising self-sufficiency could exacerbate domestic market steadiness.

Guo and Tanaka (2019) revealed that regional wheat prices in ten importing nations were unidirectionally Granger-caused by global wheat prices, which is consistent with our test results. However, their analysis differs from ours in the number of countries affected by international prices. In the paper, Granger causal relationships were identified for ten wheat importing nations, whereas Granger causality was detected for only five of nine beef-importing nations in our tests. This result may suggest that the interconnection between global and local beef markets is weaker than that of wheat markets. This weak linkage may be revealed in DCCs, whose means for beef and wheat are 0.10 and 0.17, respectively. The weak links for the beef sector also may be attributed to the flexible adjustment of the beef supply. Wheat supply heavily depends on climatic conditions, while beef supply can be more easily controlled by slaughtering domestic animals, which buffers shocks from foreign markets.

We gained the result that the connectivity between global and regional markets is intensified during the food price hikes between 2008 and 2009. This means that local markets are less likely to be affected by global market in the time of peace, but more sensitively receive shocks from a global catastrophe. Assuming that consumers have risk averse preference, national governmental bodies could implement trade restrictions such as export or/and import quotas or taxes to stabilize internal markets only in a stormy market period, which results in enhancing expected utility of consumers. However, they should not impose such regulations for market efficiency gains under usual conditions. This implication derived from the findings would be useful for policy makers who oversee local agricultural markets and market participants who want to procure beef or beef products at a steady price in local markets.

We demonstrated the first application of the time-variant procedure with structural break dummy variables to an

international beef market linkage issue. As stated in the Introduction, though there are many publications concerning agricultural price spillovers, international beef price passthrough mechanisms are not fully understood. Despite this lack of knowledge, advanced econometric techniques have been developed that are helpful in deepening the understanding of agricultural price and price volatility transmissions, which is a topic for future research.

Data availability

The datasets generated and analysed in this study are available in the Global Information and Early Warning System repository: <http://www.fao.org/giews/en/>; and Bureau of Labor Statistics: <https://data.bls.gov/pdq/SurveyOutputServlet>; Office for National Statistics: <https://www.ons.gov.uk/economy/inflationandpriceindices/datasets/consumerpriceindicespiandretailpricesindexrpiitemindicesandprice-quotes>; Agriculture and Livestock Industries Corporation: <https://www.alic.go.jp/english/>; FRED: <https://fred.stlouisfed.org/>. The data that support the findings of this study can be obtained from the corresponding author upon request.

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Notes

- 1 Guo and Tanaka (2019) and Tanaka and Guo (2020) test for structural changes and find that the time-series data used do not have structural breaks.
- 2 The CCF approach developed by Cheung and Ng (1996) and extended by Hong (2001) to test for Granger causality in mean, as well as volatility. This method is widely used in financial and energy market volatility transmissions (e.g., Xu and Hamori, 2012; Guo, 2014).
- 3 <http://www.fao.org/giews/en/>.
- 4 <https://fred.stlouisfed.org/>.
- 5 Developed by the US Census Bureau, X-13-ARIMA (autoregressive integrated moving average) is one of the most popular methods for seasonal adjustment.
- 6 Dickey and Fuller (1979).
- 7 Kwiatkowski et al. (1992).
- 8 We do not report the results of unit root tests for each price in levels for sake of brevity. Both the usual unit root tests and unit root tests with break show that all price series has unit root processes in their levels. These results can be obtained from the authors upon request.
- 9 This empirical technique has been widely applied in the examination of stock and commodity markets (see, e.g.).
- 10 The hats indicate suitable estimates of the corresponding quantities.
- 11 Hong (2001) performed Monte Carlo experiments and suggested that the truncated kernel gives approximately similar power to non-uniform kernels such the Bartlett, Daniell, and QS kernels. In this paper, the truncated kernel was selected, which can provide compact support.
- 12 Nelson (1991) suggested that the EGARCH model not only ensures the nonnegative of coefficients in ARCH terms but also captures the presence of asymmetry in volatility.
- 13 See Glosten, Jagannathan and Runkle (1993) for details of the GJR-GARCH model.
- 14 A standard multiple linear regression model with m breaks (producing $m + 1$ regimes) can be expressed by $Y_t = X_t'\psi + Z_t'\chi_j + \varepsilon_t$. Where $t = T_{j-1} + 1, \dots, T_j$ and $j = 1, \dots, m + 1$. The X_t variables are those whose parameters do not vary across regimes, while the Z_t variables have coefficients that are regime-specific. For each m -partition (T_1, \dots, T_m) , the parameter of ψ and χ_j is estimated by minimising the sum of squared residuals, denoted by $S_T(\hat{T}_1, \dots, \hat{T}_m)$. Then, the estimated break dates $(\hat{T}_1, \dots, \hat{T}_m)$ can be as $(\hat{T}_1, \dots, \hat{T}_m) = \arg \min_{T_1, \dots, T_m} S_T(\hat{T}_1, \dots, \hat{T}_m)$.
- 15 See Cappelli et al. (2006) for an extensive analysis of these models' advantages.
- 16 See Bollerslev and Wooldridge (1992).
- 17 BFGS (Broyden, Fletcher, Goldfarb, and Shannon) is a quasi-Newton optimisation method that uses information about the gradient of the function at the current point to calculate the best direction in which to find a better point.
- 18 Henceforth, the country abbreviation will be used (See Table 1).
- 19 In this study, each model is estimated by using the maximum likelihood method, and we determine the most suitable GARCH-type model according to the lowest SIC value and highest log likelihood ratio. In addition, the lag length k in the AR model, the ARCH term p , and the GARCH term q in the GARCH, GJR-GARCH, and

- EGARCH models are selected from among $k = 1, 2, \dots, 10$, $p = 1, 2$, and $q = 1, 2$, respectively, by applying the SIC and residual diagnostics. Our results suggest that the AR (1) mean equation is chosen for each GARCH model.
- 20 The "leverage effect" is designed to capture the characteristic that the responses of conditional variance to positive and negative innovation differ. Specifically, bad news increases volatility more than good news.
- 21 These were estimated based on data from the FAOSTAT.
- 22 Japan presents the lowest self-sufficiency rate among the countries concerned, which is 45%.
- 23 We discuss more on the relationship between self-sufficiency and DCC in the Conclusion.
- 24 DCC, A-DCC, G-DCC, and AG-DCC model.
- 25 The results of the model estimation were not reported for sake of brevity. The results can be obtained from the authors upon request.

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Author contributions

TT and JG designed the research. TT conceived the study with inspiration from his previous studies. TT also performed the background of the paper and discussed the policy implications of the empirical results. JG constructed the econometric model and edited the program code for analyzing. JG also analyzed and interpreted the data regarding the common determinants of wheat price volatility transmission from international to local markets in wheat-importing countries. The authors equally contributed to this work.

Competing interests

The authors declare no competing interests.

Additional information

Correspondence and requests for materials should be addressed to T.T.

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