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Potential factors in determining cross-border price spillovers in the pork sector: Evidence from net pork-importing countries

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Although food self-sufficiency is regarded as a potent strategy to secure food supply in the policy circle, the efficacy of policy measures, especially in terms of their quantitative effects, is still not fully understood. We analysed the relationships between international and local prices of pork between January 2001 and December 2018 for 10 net pork-importing countries. The primary outcome obtained in our research is that high self-sufficiency and a small trade volume of pig meat commodities could impair price volatility transmission from the global market. This result does not suggest that a protectionist regime should be established to stabilise the national food supply. It presents useful information to balance the benefit from highly efficient resource allocation and the market steadiness gained from higher self-sufficiency in food, considering the maximisation of the expected utility of economic agents.

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Introduction

Known as an important source of protein, swine meat comprises over one-third of meat products in the world and is, therefore, a critical component of food security (VanderWaal and Deen, 2018). In the same context, a risk factor in pork markets in animal infectious diseases such as African swine fever (ASF), discovered by R. Eustace Montgomery in Kenya in 1921 and spread to other parts of the world (Sanidad Animal Info, 2020). In 2019, the ASF virus killed 180 million pigs in China, equivalent to ~40% of the nation's pig stock (Walters, 2020) and around 18% of the world's pig population. In 2020, a case of ASF was confirmed in Germany, leading to an import ban on German pork by China, South Korea, and Japan (Merco Press, 2020). These events destabilised pork export prices in the chief exporting markets such as the EU, the US, Brazil, and Canada and induced an 86% domestic price increase in China. Infectious disease outbreaks are unpredictable, thus affecting both international and domestic markets, particularly in importing nations.

Food autarky measures are high-priority policies for food-deficit countries such as Egypt, Japan, Senegal, Qatar, and Bolivia. These countries expressed interest in food self-sufficiency policies after the 2008 food price crisis (Clapp, 2017; Tanaka and Hosoe, 2011). While many economists have analysed the effectiveness of food autarky without numerical models (Bishwajit et al., 2013; Clarete et al., 2013; Ghose, 2014; Warr, 2011), only a few studies use econometric models and computable general equilibrium models (Guo and Tanaka, 2019, 2020a; Tanaka, 2018; Tanaka and Guo 2019, 2020; Tanaka and Hosoe, 2011). Although the efficacy of food self-sufficiency policy needs to be clarified for aggravated food security, the literature has not thoroughly explored the extent to which the measure is functional.

The current research is also associated with price transmission analysis. Most of the literature on agricultural price pass-throughs focuses on domestic price links (e.g., Abdulai, 2000; Baulch, 1997; Moser et al., 2009; Negassa and Myers, 2007). Several economists examine international price spillovers (e.g., Conforti, 2004; Minot, 2011; Mundlak and Larson, 1992; Quiroz and Soto, 1995; Robles and Torero, 2010). However, there is a notable knowledge gap in finding potential factors behind cross-boundary price transmissions, particularly the food autarky policy.

To fill the knowledge gaps indicated above, this study focuses on causal relationships and dynamic conditional correlations (DCCs) to identify the volatility spillover between global and local prices for 10 net pork-importing countries with generalised autoregressive conditional heteroskedasticity (GARCH)-type models. Additionally, we test for the effectiveness of self-sufficiency in insulating local markets using panel regression models. The data period spans January 2001 to December 2018. The experimental procedure is as follows: First, we estimate the volatilities of pork prices for the international market and each net importing country of pork. Second, we conduct Granger causality tests to uncover causal directions and lag-lead structures between global and local prices. Third, the time-varying correlations for all pairwise global-local price correlations are described. Finally, based on the panel model, we discover how potential factors, such as self-sufficiency rates and trade volume rates, affect dynamic correlations. We also consider beef consumption as one of the explanatory variables in the panel data analysis, as beef could be a substitute for swine meat, partially absorbing the price spillover effects of imported pork through a decrease or increase in pork demand.

The present study contributes to the literature in several ways. First, we clarify part of the international pork market mechanism, such as the association between global and local prices, using Granger causality and DCC, which has not been understood at all. Second, we highlight the role of self-sufficiency in pork for the

first time. Third, we elucidate the effects of trade volume rate on the intensity of links between global and domestic markets. Finally, we establish that the consumption of a substitute good (beef) impairs international price pass-throughs.

The remainder of this paper is organised as follows. Section "Literature review" contains the literature review. Section "Data and methodology" describes the used data set and application of econometric methodology. Section "Empirical results" presents the empirical results of the analysis. Section "Policy implications and discussions" discusses policy implications based on the outcomes obtained. Section "Concluding remarks" summarises the conclusions and describes some limitations and future investigations.

Literature review

This section provides an overview of previous research on agricultural self-sufficiency and the international price transmission of agricultural commodities. While substantial research has tackled the issue of food autarky policy (Bishwajit et al., 2013; Clarete et al., 2013; Ghose, 2014; Warr, 2011), quantitative methods have rarely been used. Tanaka and Hosoe (2011), Tanaka (2018), and Tanaka and Guo (2019) applied stochastic computable general equilibrium models to analyse the effects of raising or lowering import tariffs for Japan and Egypt to determine the efficacy of a self-sufficiency policy. Guo and Tanaka (2019, 2020a) and Tanaka and Guo (2020) utilised GARCH-type models with DCC to examine links between cross-border price volatility transmissions and the effectiveness of self-sufficiency rates in cereal markets. Over the last two decades, there has emerged a large body of literature using the GARCH type model and DCC to analyse volatility transmissions and time-varying correlations between the financial index and various commodities (e.g., Choi and Hammoudeh, 2010; Du et al., 2011; Guo, 2018; Hammoudeh and Yuan, 2008; Malik and Hammoudeh, 2007; Mensi et al., 2013; Mollick and Assefa, 2013; Naeem et al., 2020; Okorie and Lin, 2020; Pan et al., 2016; Sadorsky, 2014; Xu et al., 2019).

Most studies suggest that higher self-sufficiency is effective in insulating domestic markets from foreign shocks, although Tanaka and Guo (2019) insist that autarky measures could make domestic prices more unstable if a domestic supply is more volatile than foreign supply.

Guo and Tanaka (2020b) is the only study that quantifies the efficacy of meat autarky policy, concluding that a higher level of self-sufficiency is likely to weaken the spillover effects from global to regional markets. To the best of our knowledge, the usefulness of self-sufficiency in swine meat markets is yet to be quantified. As mentioned, swine meat is an essential source of protein and, therefore, an influential factor for food security in low-income households, not only in developing countries but also in developed countries such as the United Kingdom, Canada, Ireland, and the United States (Clendenning et al., 2016; Dowler, 2010; Dowler and O'Connor, 2012; Emery et al., 2013; Lambie-Mumford and Dowler, 2014).

From another perspective, price transmission has attracted the attention of economists for a long time. A large portion of the grain market literature has explored the inter-linkages between local markets within a country, such as farm-gate, wholesale, and retail prices, by scrutinising the symmetry or asymmetry of price movements (e.g., Abdulai, 2000; Baulch, 1997; Moser et al., 2009; Negassa and Myers, 2007). However, relatively few studies have investigated international market connections (e.g., Conforti, 2004; Minot, 2011; Mundlak and Larson, 1992; Quiroz and Soto, 1995; Robles and Torero, 2010;). Similarly, many studies on meat

price co-movement have analysed domestic market associations (Assefa et al., 2017; Dai et al., 2017; Gervais, 2011; Griffith and Piggott, 1994; Jong-Yeol and Brown, 2018; Kuiper and Lansink, 2013; Miller and Hayenga, 2001; Sanjuán and Dawson, 2003; Xu et al., 2012), while few articles have analysed international price liaisons (Guo and Tanaka, 2020b). The cross-border beef market connectivity has been thoroughly scrutinised by Guo and Tanaka (2020b). They identify not only market causal relationships but also the efficacy of high self-sufficiency rates and conclude that high autarky rates are likely to weaken overseas price volatility transmission. Within all these research publications, a gap in the literature is identified: Neither international price co-movement relationships nor the effectiveness of pork self-sufficiency has ever been investigated.

In summary, only a few articles quantify the effects of food self-sufficiency policies using numerical models and identify the determinants of cross-border food price transmissions.

Data and methodology

Monthly data from January 2001 to December 2018 are used for international and local price series for each country. To enhance the trustworthiness of panel data analysis results, yearly data are used as a variable of self-sufficiency, suggesting that the sample size tends to be small. We selected net importing countries of pig meat commodities with a long series of price data, namely China (CHN), Colombia (COL), Japan (JPN), Mexico (MEX), New Zealand (NZL), Peru (PER), the Philippines (PHL), Romania (ROU), South Korea (KOR), the United Kingdom (UK), and international prices (IPP). The price data series for each country were obtained from the Price Monitoring Centre NDRC, National Administrative Statistics Department, Statistics Bureau of Japan, National Institute of Statistics and Geography, Statistics New Zealand, National Institute of Statistics and Information Science, Global Information and Early Warning System (GIEWS), National Institute of Statistics, Statistics Korea, Office of National Statistics, and GIEWS, respectively. Following the existing studies, we converted all the local price data series into US dollar terms, which eliminated the effect of exchange rate volatilities. Exchange rates were retrieved from the Federal Reserve Economic Data for all countries except PER and ROU, which were retrieved from CEIC data. For the panel data analysis, yearly series data for production, consumption, export, and import of pork meat, and beef consumption from 2001 to 2017 were quoted from Food and Agriculture Data-FAOSTAT. Based on the production, import, export, and consumption data, the self-sufficiency rate (SSR) is defined as $(\text{production} - \text{export} + \text{import}) / \text{consumption}$, and the trade volume rate (TVR) is defined as $(\text{export} + \text{import}) / \text{consumption}$.

To eradicate the influence of cyclic fluctuations, all pork price series were adjusted using the X-13-ARIMA (autoregressive integrated moving average) method developed by the US Census Bureau, one of the most useful methods for seasonal adjustment.

The monthly returns are quantified as the first difference of monthly logarithmic prices $r_t = \ln(p_t/p_{t-1})$, where r_t is the monthly pork price return at time t , and p_t is the pork price at time t . Table 1 shows the summary statistics of pork price returns for each country. Negative mean and median values can be observed only for ROU; CHN has the highest mean returns; KOR and NZL show the highest median returns. The table also reveals that NZL's price returns are more volatile than those of the others as evidenced by the largest standard deviation. It is worth noting that the skewness values are all negative except for CHN, PER, and PHL, indicating the existence of fat tails in the return distribution and a higher probability of negative rather than positive returns for most price returns. All price returns exhibit high

kurtosis values, which suggests the existence of fat tails in the return distributions. Finally, Jarque–Bera statistics indicate that, apart from COL, JPN, and NZL, none of the returns were normally distributed.

Figure 1 plots the charts for price returns of each pork price. We can observe that global and local pork prices show variability from January 2001 to December 2018 and exhibit different volatility patterns across pork-importing countries. For instance, some price returns (e.g., KOR and MEX) show similar patterns, with strong trends leading up to the global food and financial crisis of 2007–2009. In contrast, fluctuations of price returns for CHN, COL, and NZL display a fairly strong trend over the sample period. The insights deduced from pork price returns may be indicative of volatility clustering in the data series, which will be examined in the GARCH-type model below.

Before estimating the standardised residuals from GARCH-type models, the stationarity of each price series must be checked using unit root tests. Table 2 reports the results of the standard augmented Dickey–Fuller (ADF) (Dickey and Fuller, 1979) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) (Kwiatkowski et al., 1992), which indicate that all price returns are stationary. All price series have unit root processes in their levels (these results can be obtained from the authors upon request).

We can also observe that the results of the Ljung–Box statistic (Ljung and Box, 1978) for assessing residual autocorrelation, and the Lagrange multiplier for autoregressive conditional heteroskedasticity (LM-ARCH) test, which evaluates the presence of conditional heteroskedasticity, suggest the usefulness and suitability of GARCH-based models. Moreover, considering that the presence of structural breaks or shifts could impact the data series, we employ Bai and Perron's (2003) structural break test to investigate the structural changes in each price return. As shown in Table 2, our results show no structural breaks for all price returns during the sample period. Based on the results of the preliminary test, GARCH-type models without structural breaks will be used to investigate Granger causality and volatility transmission between global and local pork prices in net pork-importing countries.

Table 3 provides definitions of the variables used in the panel analysis. Table 4 displays the summary statistics for the explanatory variables, including SSR, TVR, and beef consumption (BEEF). Table 4 shows that SSR displays a variety of characteristics in different nations. For instance, CHN, COL, PER, and PHL have relatively high average SSR values, while the SSRs of JPN, NZL, and the UK display the lowest average values. In contrast, it is particularly interesting to see that JPN, NZL, and the UK exhibit higher mean and median values of TVR. Theoretically, an increase in SSR will decrease TVR, and vice versa. Furthermore, we can also observe that beef consumption in COL, NZL, and the UK is typically higher than in the other countries.

Granger causality tests for detecting lag-lead structure. To examine whether the occurrence of a change in the global market ($Y_{1,t}$) can help forecast the occurrence of a change in a local market ($Y_{2,t}$), we define the concept in terms of various principles of Granger causality. Let $\Omega_{t-1} \equiv (\Omega_{1,t-1}, \Omega_{2,t-1})$, where $\Omega_{1,t-1} \equiv (Y_{1,t-1}, \dots, Y_{1,1})$ and $\Omega_{2,t-1} \equiv (Y_{2,t-1}, \dots, Y_{2,1})$ are the information sets available at time $t-1$ in global and local markets, respectively. We state that $Y_{2,t}$ does not Granger-cause $Y_{1,t}$ in mean, if the following null hypothesis holds:

$$H_0 : E(Y_{1,t} | \Omega_{1,t-1}) = E(Y_{1,t} | \Omega_{t-1}), \quad (1)$$

and $Y_{2,t}$ Granger-causes $Y_{1,t}$ in mean, if the following alternative

Table 1 Summary statistics for pork price returns.

	Symbol	Mean	Median	Std. dev.	Skewness	Kurtosis	Jarque-Bera
International pork price	IPP	0.001	0.000	0.045	-0.174	4.550	22.594***
China	CHN	0.004	0.003	0.032	1.106	6.473	151.886***
Colombia	COL	0.002	0.003	0.040	-0.235	3.513	4.345
Japan	JPN	0.001	0.002	0.029	-0.059	2.759	0.642
Korea	KOR	0.003	0.004	0.024	-1.444	12.762	928.390***
Mexico	MEX	0.000	0.000	0.028	-0.839	8.577	303.808***
New Zealand	NZL	0.003	0.004	0.051	-0.122	2.684	1.433
Peru	PER	0.003	0.003	0.014	0.246	3.740	7.077**
The Philippines	PHL	0.003	0.003	0.018	0.397	3.877	12.545***
Romania	ROU	-0.005	-0.004	0.032	-0.159	3.792	6.521***
United Kingdom	UK	0.001	0.002	0.035	-0.349	4.620	27.879***

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

Time series plots of pork price returns.

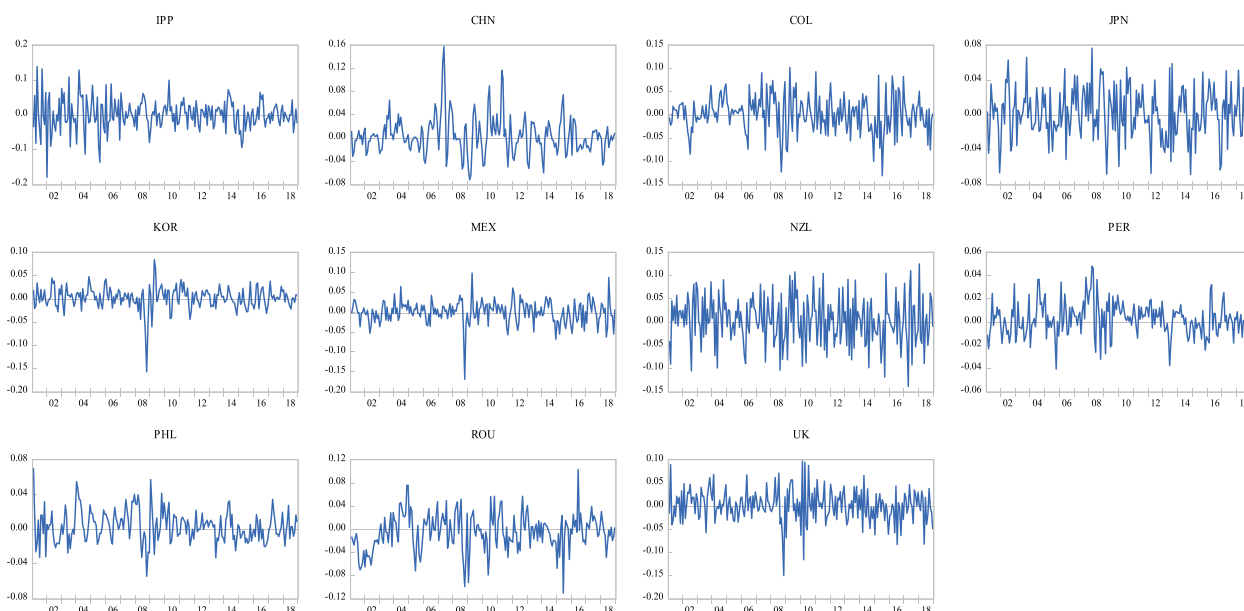


Fig. 1 Time series plots of pork price returns.

hypothesis holds:

$$H_0 : E(Y_{1,t} | \Omega_{1,t-1}) \neq E(Y_{1,t} | \Omega_{t-1}). \tag{2}$$

We can also test for Granger causality-in-variance form $Y_{2,t}$ to $Y_{1,t}$ given the following full and alternative hypothesis:

$$H_0 : E\{ \text{Var}(Y_{1,t} | \Omega_{1,t-1}) \} = \text{Var}(Y_{1,t} | \Omega_{t-1}), \tag{3}$$

and

$$H_0 : E\{ \text{Var}(Y_{1,t} | \Omega_{1,t-1}) \} \neq \text{Var}(Y_{1,t} | \Omega_{t-1}). \tag{4}$$

The first step of our analysis is to use the Granger causality test implemented by Hong (2001) to assess the existence and direction of causal links between international and domestic pork prices in pork-importing countries. Hong’s (2001) approach has more power than Cheung and Ng’s (1996) conventional causality by using the kernel weight function. Such a method is designed to detect whether lagged changes in one variable affect contemporaneous changes in another; thus, the direction of causality between the two variables can be captured. In this study, we simultaneously examine causality-in-mean and causality-in-variance based on two standardised residuals and squared

standardised residuals of $Y_{1,t}$ and $Y_{2,t}$. Using the estimated GARCH-type models, the standardised residuals $\hat{\xi}_t$ for global and $\hat{\varphi}_t$ local pork prices were estimated. The hats indicate suitable estimates of the corresponding quantities and $t = 1, 2, \dots, T$.

Following Hong’s (2001) method, we denote $\hat{\rho}_{\xi\varphi,t}(j)$ the lag j sample cross-correlation coefficient between the standardised residuals as follows:

$$\hat{\rho}_{\xi\varphi,t}(j) = \left\{ \hat{C}_{\xi\xi,t}(0) \hat{C}_{\varphi\varphi,t}(0) \right\}^{-\frac{1}{2}} \hat{C}_{\xi\varphi,t}(j), \tag{5}$$

where $\hat{C}_{\xi\xi,t}(0)$ and $\hat{C}_{\varphi\varphi,t}(0)$ are the subsample variances of $\hat{\xi}_t$ and $\hat{\varphi}_t$, respectively, and $\hat{C}_{\xi\varphi,t}(j)$ is the lag j cross-covariance between $\hat{\xi}_t$ and $\hat{\varphi}_t$ expressed as

$$C_{\xi\varphi,t}(j) = \begin{cases} T^{-1} \sum_{t=1+j}^T \hat{\xi}_t \hat{\varphi}_{t-j}, & j \geq 0, \\ T^{-1} \sum_{t=1-j}^T \hat{\xi}_{t+j} \hat{\varphi}_t, & j < 0. \end{cases} \tag{6}$$

Hong (2001) enables us to capture the bidirectional Granger causality test in time-series pairs by providing a modified test

Table 2 Preliminary tests.

	ADF	KPSS	Q ² (6)	ARCH (6)	Bai-Perron's break test
IPP	-15.484*** (0)	0.0354 (3)	30.857***	4.169***	No break
CHN	-9.713*** (1)	0.102 (1)	40.867***	5.100***	No break
COL	-13.200*** (0)	0.069 (3)	30.837***	4.057***	No break
JPN	-13.835*** (0)	0.061 (5)	2.831	0.449	No break
KOR	-10.526*** (1)	0.043 (3)	49.230***	6.202***	No break
MEX	-11.053*** (0)	0.048 (3)	13.340**	2.418**	No break
NZL	-18.222*** (0)	0.026 (7)	9.272*	2.025*	No break
PER	-10.753*** (0)	0.180 (7)	39.031***	4.594***	No break
PHL	-9.503*** (0)	0.072 (3)	21.441***	3.242***	No break
ROU	-9.300*** (0)	0.102 (8)	6.095	0.942	No break
UK	-17.907*** (0)	0.034 (7)	9.529*	5.336**	No break

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers in brackets are the lag length for the ADF test and the bandwidth for the KPSS test. Lag length selection is based on the Schwarz information criterion, and the bandwidth is determined using the Bartlett kernel and Newey-West bandwidth selection algorithm (Newey and West, 1994). ARCH (6) refers to the Lagrange multiplier (LM) test statistic for conditional heteroskedasticity. Q²(6) is the Ljung-Box statistic for autocorrelations applied to the squared return series. We used Bai-Perron's sequential test for the hypothesis of *k* breaks versus *k* + 1 breaks, employing *F*-statistics.

Table 3 Definitions of the variables in the panel analysis.

Variable	Definition	Source	Frequency
DCC _{<i>i,t</i>}	Dynamic conditional correlation of pork between global and country <i>i</i> 's local price at time <i>t</i> .	Authors' Estimation	Monthly
SSR _{<i>i,t</i>}	Self-sufficiency rate of pork in country <i>i</i> at time <i>t</i> .	FAOSTAT	Yearly
TVR _{<i>i,t</i>}	Trade volume rate of pork in country <i>i</i> at time <i>t</i> .	FAOSTAT	Yearly
BEEF _{<i>i,t</i>}	Domestic consumption of beef in country <i>i</i> at time <i>t</i> .	FAOSTAT	Yearly

Table 4 Summary statistics for the explanatory variables in the panel analysis.

	SSR			TVR			BEEF		
	Mean	Median	Std. dev.	Mean	Median	Std. dev.	Mean	Median	Std. dev.
CHN	0.989	0.991	0.012	0.031	0.029	0.007	1.528	1.538	0.104
COL	0.898	0.933	0.076	0.103	0.067	0.077	2.802	2.800	0.060
JPN	0.488	0.481	0.018	0.513	0.520	0.019	2.186	2.185	0.054
KOR	0.733	0.710	0.091	0.287	0.304	0.072	2.538	2.613	0.155
MEX	0.733	0.730	0.054	0.389	0.402	0.065	2.774	2.795	0.081
NZL	0.519	0.531	0.090	0.497	0.490	0.101	3.209	3.238	0.248
PER	0.966	0.975	0.023	0.034	0.026	0.023	1.433	1.414	0.094
PHL	0.964	0.970	0.021	0.038	0.033	0.022	1.497	1.501	0.047
ROU	0.705	0.700	0.080	0.366	0.393	0.122	1.943	1.976	0.197
UK	0.494	0.482	0.051	0.735	0.742	0.056	2.962	2.948	0.084

The sample data cover the period from 2001 to 2017. The annualised SSR and TVR are calculated as Production/(Production + Import - Export) and (export + import)/consumption, respectively.

statistic as follows:

$$Q_{\xi\varphi} = \{2D_{1T}(k)\}^{-\frac{1}{2}} \left\{ T \sum_{j=1}^{T-1} k^2 \left(\frac{j}{M} \right) \hat{\rho}_{\xi\varphi}^2(j) - C_{1T}(k) \right\} \quad (7)$$

$$D_{1T}(k) = \sum_{j=1}^{T-1} \left(1 - \frac{j}{T}\right) \left\{1 - \frac{j+1}{T}\right\} k^4 \left(\frac{j}{M}\right) \quad (8)$$

$$C_{1T}(k) = \sum_{j=1}^{T-1} \left(1 - \frac{j}{T}\right) k^2 \left(\frac{j}{M}\right)$$

$$k(z) = \begin{cases} 1, & |z| \leq 1 \\ 0, & |z| > 1 \end{cases} \quad (9)$$

Here, *T* is the sample size, *k*(*z*) is the kernel function and *M* is a positive integer. Hong (2001) performed Monte Carlo experiments and suggested that the truncated kernel gives approximately similar power to non-uniform kernels such as the Bartlett,

Daniell and QS kernels. In this paper, the truncated kernel was selected as it can provide compact support.

As in Hong (2001), under the appropriate regularity condition, it can be proven that $Q_{\xi\varphi} \rightarrow N(0, 1)$. If the test statistic $Q_{\xi\varphi}$ is larger than the right tail critical value - the critical value for 1% significance level is 2.33 and for 5% significance level is 1.65—of the normal distribution, we reject the null of no causality in either mean or variance during the first *M* lags. Finally, given the context of the causality test, the estimation of standardised residuals for each price return depends on the appropriate specification of the GARCH-type model. The GARCH model, which was introduced by Engle (1982) and generalised by Bollerslev (1986), is a well-known approach for estimating the volatility of financial data. Nelson (1991) and Glosten et al. (1993) show evidence of asymmetric effects: bad news (negative shocks) tends to be associated with higher volatility rather than good news (positive shocks). As the original GARCH model does not account for asymmetric effects, in this study, we employ the

Glosten–Jagannathan–Runkle (GJR)-GARCH (Glosten et al., 1993) and EGARCH (Nelson, 1991) models simultaneously. The advantage of GJR-GARCH is that it captures the presence of asymmetry in volatility. Conversely, the EGARCH model has a logarithmic form that can either ensure the non-negativity of coefficients or identify the symmetric effects. We use the Schwarz Information Criterion (SIC) to determine the most suitable GARCH-type model and then employ it to estimate the standardised residuals for international and domestic pork price returns. The three types of GARCH models can be described as follows:

$$r_t = \mu + \omega r_{t-1} + \varepsilon_t, \varepsilon_t = \sqrt{h_t} \zeta_t, \zeta_t \sim N(0, 1), \quad (10)$$

$$h_t = \theta + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}, \quad (11)$$

$$h_t = \theta + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I(\varepsilon_{t-1}) + \beta h_{t-1}, \quad (12)$$

$$\log(h_t) = \theta + \alpha |\zeta_{t-1}| + \gamma \zeta_{t-1} + \beta \log(h_{t-1}). \quad (13)$$

Equation (10) explains the conditional mean equation, where r_t is the pork price return, and the error term ε_t is assumed to follow a conditionally normal distribution with its conditional variance h_t . ζ_t is an independent and identically distributed random error. Equations (11)–(13) represent the variance equations specified by the GARCH, GJR-GARCH, and EGARCH models, respectively. The indicator variable $I(\varepsilon_{t-1})$ in Eq. (12) is equal to one if $\varepsilon_{t-1} < 0$ and zero otherwise. The estimate of the coefficients γ captures the asymmetry. Following the estimation of the univariate GARCH-type models, we carry out standardised residuals ζ_t to calculate the conditional correlation parameters.

DCC-MGARCH model for estimating volatility transmission. In the second step, we use a bivariate GARCH model with a conditional variance–covariance matrix to estimate the DCCs between international and domestic pork prices and examine the volatility transmissions for each price pair. Based on Engle (2002), we make an econometric framework for the GARCH-DCC model, formulated as follows:

$$r_t | \Omega_{t-1} \sim N(0, H_t), \varepsilon_t = H_t^{1/2} \zeta_t \quad (14)$$

$$H_t = D_t R_t D_t, \quad (15)$$

$$D_t = \text{diag}\left(\sqrt{h_{1,t}}, \sqrt{h_{2,t}}\right), \quad (16)$$

$$R_t = \left[\text{diag}\{Q_t\}^{-1/2} \right] Q_t \left[\text{diag}\{Q_t\}^{-1/2} \right] \quad (17)$$

$$\text{diag}\{Q_t\}^{-1/2} = \text{diag}\left\{q_{11,t}^{-1/2}, q_{22,t}^{-1/2}\right\},$$

where r_t is a 2×1 vector of returns, including the international pork price $r_{1,t}$ and local pork price $r_{2,t}$. Ω_{t-1} is the information set at time $t-1$. $\varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{2,t})'$ is the vector of the innovations. H_t is a 2×2 conditional variance-covariance matrix, and ζ_t is a 2×1 independent and identically distributed vector of standardised residuals. D_t is a diagonal matrix containing the conditional standard deviations of each price return. R_t is the time-varying conditional correlation matrix, and Q_t is the conditional correlation matrix of the standardised residuals, which can be defined as

$$Q_t = (1 - a - b)\bar{Q} + a\zeta_{t-1}\zeta'_{t-1} + bQ_{t-1}, \quad (18)$$

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 standardised residuals ζ_t . Cappiello et al. (2006) expend the DCC model to an

asymmetric generalised DCC (AG-DCC) model, expressed as follows:

$$Q_t = (\bar{Q} - A'\bar{Q}A - B'\bar{Q}B) - G'\bar{N}G + A'\zeta_{t-1}\zeta'_{t-1}A + B'Q_{t-1}B + G'\psi_{t-1}\psi'_{t-1}G, \quad (19)$$

where A and B are 2×2 parameter matrices. \bar{N} represents the unconditional matrices of $\psi_t = I[\zeta_t < 0] \otimes \zeta_t$ ($I[\cdot]$ is an indicator function equal to 1 if $\zeta_t < 0$ and 0 otherwise, while \otimes indicates the Hadamard product) and $\bar{N} = E[\psi\psi']$. The asymmetric DCC (A-DCC) is a special version of AG-DCC in which the matrices are replaced by scalars. Moreover, if the matrix G in Eq. (19) equals zero, the generalised DCC model (G-DCC) can be obtained. Therefore, the dynamic conditional correlation $\rho_{12,t}$ can be defined as

$$\rho_{12,t} = \frac{q_{12,t}}{\sqrt{q_{11,t}q_{22,t}}}. \quad (20)$$

Following Engle (2002), we employed a two-step maximum-likelihood estimation method for the model. The likelihood function can be expressed as

$$L(\chi, \iota) = -\frac{1}{2} \sum_{t=1}^T \left(n \log(2\pi) + \log|D_t|^2 + \varepsilon_t' D_t^{-2} \varepsilon_t + \log|R_t| + \zeta_t' R_t^{-1} \zeta_t - \zeta_t' \zeta_t \right), \quad (21)$$

where n denotes the number of equations and T refers to the number of observations. This function can be separated into the volatility and correlation parts. χ and ι denote the parameters in the matrix D_t and matrix, respectively, R_t to be estimated. We estimated each parameter of the DCC, A-DCC, AG-DCC, and G-DCC models by the Gaussian quasi-maximum-likelihood estimation (QMLE) (Bollerslev and Wooldridge, 1992), assuming conditional multivariate normality with the Broyden, Fletcher, Goldfarb, and Shannon (BFGS) optimisation algorithm (BFGS 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).

Panel model for identifying potential factors affecting DCC. In the final step, we examine whether self-sufficiency and trade value rates are potential factors that could affect the DCC between global and local pork prices. As the data on SSR and TVR are only available at yearly frequencies, we convert the monthly DCC into a yearly one by taking the average of the monthly DCC (David and Amir, 2017).

Furthermore, to overcome the problem of a small sample size for each country, we combine the 10 pork-importing countries and proceed with a panel approach. This can increase the sample size and degrees of freedom, yielding more precise estimates than those obtained for each country individually. The sample period for panel analysis runs from 2001 to 2017. Based on the definition of the variables in Table 3, the two-panel regression models can be specified as follows:

$$DCC_{i,t} = \omega_i + \varsigma_1 SSR_{i,t} + \varsigma_2 BEEF_{i,t} + e_{i,t}, \quad (22)$$

$$DCC_{i,t} = \eta_i + \delta_1 TVR_{i,t} + \delta_2 BEEF_{i,t} + \nu_{i,t}, \quad (23)$$

where $DCC_{i,t}$ is the dependent variable that presents the dynamic conditional correlation between the global pork price and local pork price in country i at time t . ω_i and η_i are constants, and $e_{i,t}$ is the heteroskedastic error term. $SSR_{i,t}$ and $TVR_{i,t}$ represent the SSR and TVR of pork in country i at time t , respectively. In addition, as the consumption of beef might have substitutive effects on that of pork, it is reasonable to assume that domestic consumption of beef is an important determinant of DCC. For this reason, except for $SSR_{i,t}$ and $TVR_{i,t}$, we choose the explanatory variable, $BEEF_{i,t}$

Table 5 Empirical results of the GARCH model.

Model selection		Parameters for variance equation					Specification tests	
Model	SIC	θ	α	γ	β	Q ² (6)	ARCH (6)	
IPP	GARCH	-3.555	0.000*	-0.063 **		1.043***	5.005	0.864
CHN	EGARCH	-4.648	-1.615***	0.348***	0.170**	0.823***	3.008	0.478
COL	EGARCH	-3.641	-1.161**	0.445***	-0.138*	0.877***	5.397	0.982
JPN	GARCH	-4.192	0.000	0.076***		0.115***	3.105	0.512
KOR	GJR-GARCH	-4.929	0.000*	0.019	0.331***	0.649***	3.084	0.480
MEX	GJR-GARCH	-4.361	0.000***	-0.125***	0.430***	0.672***	9.890	1.794
NZL	GARCH	-3.114	0.000***	-0.092***		1.050***	9.986	1.467
PER	GARCH	-5.685	0.000	0.172*		0.678***	6.496	0.997
PHL	GARCH	-5.435	0.000	0.073*		0.848***	6.105	0.896
ROU	GARCH	-4.129	0.000	0.117**		0.705***	3.719	0.592
UK	GARCH	-3.848	0.000*	0.209***		0.414	0.609	0.111

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Diagnostic test: ARCH (6) refers to the LM test statistic for conditional heteroskedasticity. Q²(6) is the Ljung-Box statistic for autocorrelations applied to the squared return series.

which represents the rate of change of domestic consumption (FAOSTAT, 2020) of beef in country *i* at time *t*. The impact of the determining factors influencing the price volatility transmission is measured by the parameters $\zeta_i(i = 1, 2)$ and $\delta_i(i = 1, 2)$. Though not reported here, the ADF unit root tests indicated that all variables in Eqs. (22) and (23) were stationary.

For robustness, five different types of methodologies are implemented in our panel analysis. The standard pool ordinary least-squares (OLS) model is used as the benchmark. The fixed-effects model, random-effects model, feasible generalised least-squares (FGLS) model (Baltagi, 1981) and Prais-Winsten regression with panel-corrected standard errors (PCSEs) (Beck and Katz, 1995) are applied simultaneously to verify the robustness of our results.

Empirical results

Granger causality test. As noted in the “Data and methodology” section, before examining the Granger causality between global and local pork prices, the appropriate specification for GARCH models should be chosen for each price return. Table 5 provides details on the model selection and estimation. The original GARCH model is selected for IPP, JPN, NZL, PER, PHL, ROU, and the UK because it has the lowest SIC value. The EGARCH model is selected for CHN and COL. The GJR-GARCH model is best suited for KOR and MEX. The parameter estimates for each univariate GARCH specification are presented in Table 5.

The statistical significance of the coefficients of α and β shows evidence of volatility clustering for most price returns. Specifically, a relatively large magnitude of α can be observed for CHN and COL, suggesting that past shocks significantly impacted the current volatility in these two countries. Conversely, a larger magnitude of β can be identified for all the price returns except JPN, suggesting that current conditional volatility is significantly influenced by past volatility in most countries. Notably, the asymmetric terms (γ) are all statistically significant in the price returns for CHN, COL, KOR, and MEX, suggesting that the “leverage effect” (bad news increases volatility more than good news) is exerted on these price returns. Table 5 also shows the results of the Ljung-Box statistics and LM-ARCH tests. We can detect that there is no autocorrelation for the standardised squared residuals and no ARCH effects in any of the models. These results suggest that the selection of GARCH-type models fits the price return series reasonably well.

Next, we investigate the lag-lead structure between global and local pork prices based on standardised residuals from the GARCH-type model estimated above. Table 6 presents the

causality-in-mean test results for international pork prices and each domestic price in the 10 pork-importing countries. Hong (2001) suggests that one can try several different lags or use “rule of thumb” to determine an appropriate lag order. In the causality test, the test statistic values are calculated from 1 to 12 lags. As the lags are measured in months and our interest is mainly focused on the short term, we choose the range of lag length from 1 to 5.

First, we can confirm that there is only a causality-in-mean effect running from international pork prices to domestic prices in CHN, with no feedback effect. In particular, the international pork price Granger-causes CHN’s domestic prices with a one-month lag, indicating that CHN’s domestic pork market exhibits rapid reaction to changes in global pork prices regarding transmission. In contrast, we observe no causality-in-mean effects between international pork prices and all other countries. Second, it is interesting to find that domestic prices in COL, KOR, MEX, PER, PHL, ROU, and the UK Granger-cause IPP. These results suggest that changes in the local prices of these seven countries can help predict changes in global prices. However, the reverse causality-in-mean is not significant, which indicates no evidence of price information transmission from the global to local markets in these countries.

The results of the causality-in-variance tests are presented in Table 7. By comparing the results of the causality-in-mean test, different characteristics of causality-in-variance effects are found. First, our Granger linkage outcomes indicate that the volatility of the local price in COL, KOR, MEX, PER, and PHL does not Granger-cause volatility in the international price, which is different from the results of causality-in-mean. Second, the causal links running from international pork prices to domestic prices in CHN and COL, with no feedback effect, are noteworthy. This evidence reveals that causality-in-mean or causality-in-variance effects exist in the same direction between international pork prices and pork prices in CHN. Third, an interesting bidirectional causality-in-variance effect was noted between international and domestic prices in ROU. This result indicates a two-way information flow between international pork prices and ROU’s local pork prices. Finally, there is a statistically significant indication of causality-in-variance effects running from domestic prices in the UK to international prices, which is similar to the causality-in-mean effects. Furthermore, domestic prices in the UK Granger-cause international prices with 1- and 5-month lags, indicating that the UK’s pork market plays a leading role in the process of price transmission to the international pork market.

Time-varying conditional correlations. Before estimating the parameters of each model, the most appropriate specification of

Table 6 Results for causality-in-mean test.

Causality direction	M = 1	M = 2	M = 3	M = 4	M = 5
IPP → CHN	1.741*	1.016	0.429	0.079	-0.133
CHN → IPP	-0.137	-0.414	-0.707	-0.839	-0.740
IPP → COL	0.475	-0.017	-0.413	0.286	0.143
COL → IPP	-0.290	-0.693	0.924	2.342**	1.831*
IPP → JPN	-0.114	0.869	0.390	-0.014	0.521
JPN → IPP	-0.698	-0.519	-0.774	-0.606	-0.611
IPP → KOR	0.039	-0.280	-0.585	0.008	0.443
KOR → IPP	1.545	0.910	0.532	2.147*	1.694*
IPP → MEX	0.230	-0.290	-0.459	-0.550	-0.055
MEX → IPP	4.953**	3.040**	3.939**	5.075**	4.284**
IPP → NZL	-0.705	-0.992	-1.110	-0.856	-0.929
NZL → IPP	-0.585	-0.911	-1.018	-0.829	-1.056
IPP → PER	1.144	0.592	0.075	-0.018	-0.294
PER → IPP	-0.686	-0.072	1.670*	2.286*	2.363**
IPP → PHL	1.382	0.624	0.348	-0.044	-0.302
PHL → IPP	2.100*	2.046*	2.681**	2.538**	1.991*
IPP → ROU	-0.072	0.263	-0.077	0.660	0.564
ROU → IPP	0.291	1.464	1.919*	2.027*	1.590
IPP → UK	0.749	0.238	-0.187	0.461	1.292
UK → IPP	2.479**	3.472**	2.594**	2.165*	1.633

* and ** denote statistical significance at the 5% and 1% levels, respectively. The arrow indicates the direction of Granger causality.

Table 7 Results for causality-in-variance test.

Causality direction	M = 1	M = 2	M = 3	M = 4	M = 5
IPP → CHN	6.524**	4.139**	3.039**	2.385**	1.889*
CHN → IPP	-0.348	-0.713	-0.984	-0.616	-0.838
IPP → COL	0.054	-0.461	-0.783	3.104**	2.570**
COL → IPP	-0.687	-0.211	1.516	1.228	1.202
IPP → JPN	-0.323	-0.452	0.485	0.160	0.024
JPN → IPP	-0.546	-0.858	-1.107	-1.290	-1.470
IPP → KOR	1.301	0.428	-0.031	1.351	0.893
KOR → IPP	0.060	-0.137	-0.066	-0.386	-0.661
IPP → MEX	-0.704	-0.819	-0.542	-0.823	-0.964
MEX → IPP	-0.484	0.262	0.628	0.236	0.496
IPP → NZL	0.892	0.348	-0.058	-0.359	-0.384
NZL → IPP	-0.271	0.145	-0.029	-0.278	1.042
IPP → PER	-0.699	-0.846	-0.294	-0.403	-0.618
PER → IPP	0.323	-0.260	-0.085	-0.424	-0.568
IPP → PHL	-0.461	-0.471	-0.756	-0.984	-1.063
PHL → IPP	-0.618	0.540	0.070	-0.052	-0.320
IPP → ROU	0.261	-0.023	2.060*	1.443	0.975
ROU → IPP	-0.684	1.338	0.692	2.123*	1.678*
IPP → UK	0.818	0.430	0.032	0.072	0.057
UK → IPP	5.596**	5.011**	4.207**	3.441**	2.799**

* and ** denote statistical significance at the 5% and 1% levels, respectively. The arrow indicates the direction of Granger causality.

Table 8 The model selection for DCC models.

	Model	SIC
CHN	A-DCC	-1634.172
COL	A-DCC	-1629.846
JPN	DCC	-1617.204
KOR	G-DCC	-1758.457
MEX	DCC	1642.599
NZL	A-DCC	-1364.925
PER	G-DCC	-1927.010
PHL	G-DCC	-1845.084
ROU	DCC	-1586.834
UK	G-DCC	-1550.138

The model is selected based on the lowest value of SIC.

the DCC models (i.e., standard DCC, A-DCC, G-DCC, and AG-DCC model for each price pair is determined). Table 8 presents the goodness-of-fit statistics, such as SIC values for each model. The results show that the standard DCC model provides a better fit for JPN, MEX, and ROU compared to others, given minimum SIC values. The asymmetric DCC model is selected for CHN, COL, and NZL, whereas the generalised DCC model is best suited for KOR, PER, PHL, and the UK. The AG-DCC model was not chosen for any price pair based on the information criteria. As mentioned in the section “Data and methodology”, the parameters for each selected model are estimated by maximising the log-likelihood functions.

Next, we focus on the patterns of cross-market linkages between the global market and each pork-importing country to investigate the dynamic correlation structure. Figure 2 depicts the time-varying DCC estimates for each pair of prices from the DCC-MGARCH model. Overall, a visual assessment of the DCC exhibits varied patterns across the 10 pork-importing countries, allowing us to find some interesting features. First, we notice that most of the DCCs fluctuated visibly over our sample period, with the highest magnitude and upward peaks over some turbulent periods. Specifically, we can observe that during a turbulent period, such as the global food crisis and Great Recession of 2007–2009, DCCs in some countries (e.g., CHN, JPN, KOR, and the UK) exhibit significant fluctuations. For example, the KOR’s DCC increased dramatically from early 2007, reaching its peak at the end of the same year. Then, it suffered a huge drop immediately at the beginning of 2008, returning to its average level from mid-2008. This suggests that the food and financial crises of 2007–2009 tended to trigger strong co-movement between international and domestic pork prices in KOR. Second, the DCCs for CHN, COL, and the UK have many negative values throughout the entire sample period, in the sense that an increase in global price causes the local price to decline. Thus, these findings reveal that lag-lead volatility spillover effects exist

Plots of dynamic correlation between global and local pork prices.

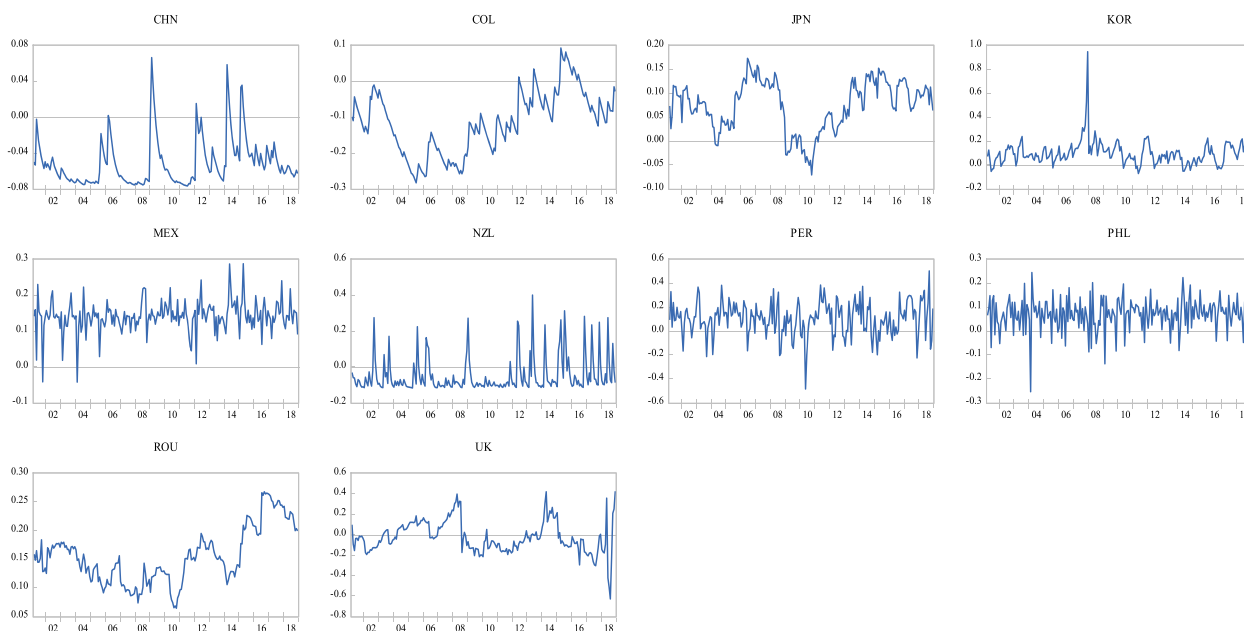


Fig. 2 Plots of dynamic correlation between global and local pork prices.

between global and local pork prices. Recalling the results of the causality-in-variance test in the previous section, a unidirectional causal relationship is identified, running from international prices to local prices for CHN and COL. There is also evidence of a one-way causal relationship running from the local price in the UK to the international price. These results provide a plausible explanation for the negative correlations and demonstrate the existence of delayed information transmission between the global pork market and local markets in CHN, COL, and the UK. Third, the DCCs of MEX, PER, and ROU tended to show almost positive correlations and relatively higher magnitudes during the examination period. These results imply that information interactions between global and local prices are strong in these countries. In contrast, it can be observed that the extent of DCCs is relatively low in some countries (e.g., CHN, JPN, PHL, and the UK), demonstrating weak volatility transmission across international and domestic pork markets.

A summary of the DCC statistics for each pork-importing country is presented in Table 9. Primarily, we can see that the mean value of DCCs ranges from -0.114 (COL) to 0.155 (ROU). Meanwhile, the median DCCs ranged from -0.113 (COL) to 0.149 (ROU). These findings suggest that the correlation levels are generally low between international and domestic pork prices in all countries. In contrast, as shown in Table 9, KOR has the maximum value of DCC (0.948), and the UK has the minimum value of DCC (-0.630). It should be noted that the DCC of the UK shows more fluctuations than other countries because it has the highest standard deviation (0.157). However, CHN has the most static DCC, as evidenced by the lowest standard deviation (0.027). These results reinforce our findings in Fig. 2, which shows that DCCs exhibit different patterns across different countries.

Panel data analysis. In the last stage of our analysis, a panel model is estimated using the SSR and TVR of pork, along with the consumption of beef, as determinants of DCCs in pork-importing countries. As a preliminary check for the presence of heteroskedasticity, serial correlation, and cross-sectional

Table 9 Summary statistics for dynamic conditional correlations of pork.

	Mean	Median	Maximum	Minimum	Std. dev.
CHN	-0.051	-0.059	0.066	-0.077	0.027
COL	-0.114	-0.113	0.093	-0.284	0.086
JPN	0.075	0.082	0.173	-0.071	0.052
KOR	0.097	0.086	0.948	-0.072	0.100
MEX	0.141	0.142	0.288	-0.042	0.043
NZL	-0.047	-0.088	0.400	-0.117	0.101
PER	0.103	0.113	0.504	-0.485	0.141
PHL	0.070	0.076	0.245	-0.253	0.066
ROU	0.155	0.149	0.268	0.064	0.049
UK	-0.025	-0.048	0.425	-0.630	0.157

dependence in panel models, we employ a modified Wald test, Wooldridge’s autocorrelation test, and Pesaran’s cross-sectional dependence test, respectively. Table 10 summarises the results of these pre-tests, which indicate that heteroskedasticity and serial correlations exist, but no cross-sectional dependencies exist in the two-panel regressions of Eqs. (22) and (23). A Hausman test is also applied to choose between the fixed effects and the random effects specification. The Hausman test results shown in Table 10 indicate that the random-effects model is more appropriate than the fixed effects model for each panel regression.

The preliminary test results above allow us to conduct standard panel data estimation methods for empirical analysis. The pooled OLS model and fixed effects model are used as benchmarks. To ensure the robustness of our results, we also apply the random-effects model, the FGLS model, and the PCSE model. The merit of the FGLS model is its ability to account for both heteroskedasticity and serial correlation in the analysis. Baltagi (1981) argues that the FGLS model’s estimator tends to have a much better performance than that of the pooled OLS model. Moreover, Beck and Katz (1995) suggest that the PCSE model is more powerful than the FGLS model because it considers the possible presence of cross-sectional dependence in heterogeneous panels.

Table 10 Preliminary tests of panel data analysis.

	Hausman test	Modified Wald test	Wooldridge's test	Pesaran's test
Preliminary test results of Eq. (22)				
Statistics	0.400	37674.420***	10.314**	0.483
Preliminary test results of Eq. (23)				
Statistics	1.110	35715.900***	9.821**	0.415

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

Table 11 Estimation results of panel data analysis.

	Model 1	Model 2	Model 3	Model 4	Model 5
<i>Panel A: The estimation results of Eq. (22)</i>					
SSR (ζ_1)	-0.216***	-0.233***	-0.220***	-0.119***	-0.128**
BEEF (ζ_2)	-0.091***	-0.058	-0.071**	-0.064***	-0.071***
Constant (ω)	0.408***	0.345***	0.366***	0.279***	0.296***
R ²	0.177	0.136	0.174	-	0.066
Wald test	19.16***	5.82***	13.60***	18.10***	16.17***
<i>Panel B: The estimation results of Eq. (23)</i>					
TVR (δ_1)	0.192***	0.207***	0.180***	0.154***	0.133**
BEEF (δ_2)	-0.094***	-0.035	-0.060**	-0.076***	-0.077***
Constant (η)	0.197***	0.057	0.121**	0.175***	0.173***
R ²	0.193	0.066	0.170	-	0.079
Wald test	21.16***	5.62***	12.79***	26.17***	20.78***
Observations	170	170	170	170	170

Model 1: Pool OLS model. Model 2: Fixed effects model. Model 3: Random-effects model. Model 4: FGLS model with heteroskedasticity and autocorrelation. Model 5: Prais-Winsten regression with PCSEs. ** and *** denote statistical significance at the 5% and 1% levels, respectively.

Table 11 reports the estimation results of the panel data analysis. Specifically, Panel A presents the results of Eq. (22), which includes the explanatory variables SSR and BEEF. Across the different models considered, we can establish that the coefficients measuring the impact of SSR on DCC appear to be statistically significant at the 1% level in all cases. Moreover, we can also identify that the SSR coefficients are very similarly ranged, between -0.119 (FGLS model) and -0.233 (fixed-effects model). These results indicate that the magnitudes of pork's SSR are important drivers of dynamic conditional correlation between global and local pork prices in pork-importing countries, with relatively strong explanatory power. Further, the negative coefficients for all models suggest that a higher SSR is correlated with lower DCC. From the perspective of food security, a high degree of SSR in pork-importing countries is desirable to effectively hedge the risk of excessive fluctuations in the global pork market. These results are consistent with those of Guo and Tanaka (2020b), who noted the increase in SSR and the decline in DCC for the international and domestic beef market. It is also worth mentioning that the estimated coefficients of BEEF are significantly negative in all the models, except for the case of the fixed-effects model. These findings indicate that a substitutive effect exists between the consumption of pork and beef. Therefore, we can suggest that the consumption of beef plays a dominant role in extenuating volatility transmissions from the global to local pork market. This result differs from Guo and Tanaka's (2020b), as they found no evidence of the consumption of pork significantly affecting the DCC between international and domestic beef prices in beef-importing countries. One possible explanation could be that different country selections capture different data properties. Guo and Tanaka's (2020b) study included some Islamic countries (e.g., Tunisia and Mauritania) even though little pork is consumed in these countries. However, all countries selected for this study consume both pork and beef.

Turning to the estimation results of Eq. (23) in Panel B, our results provide interesting insights. First, we observe that the coefficients of TVR are significant and positive for all models. The coefficients of TVR range from 0.133 (PCSE model) to 0.207 (fixed-effects model). These results indicate that an increase in the TVR of pork will increase the value of exports and imports in local countries, which in turn strengthens the correlation between global and local pork markets. This is particularly interesting given that the pork TVR has a potential influence on the DCC. Second, the panel results show that the coefficients of BEEF are negative and significant for all models. Similar to our findings in Panel A, this finding indicates that the impact of BEEF on DCC is robust, suggesting that consumption of beef is an important factor affecting DCC. Furthermore, the high price of pork may induce substitution behaviour between beef, which could buffer volatility transmission between global and local markets.

Additionally, to further investigate whether the effects of factors differ across countries, we proceed with a country-specific analysis based on a random-coefficient linear regression model (Swamy, 1970).

Table 12 presents the estimation results. It can be observed that the SSR and BEEF negatively affect the DCC, while, the TVR positively influences the DCC in most countries, except for CHN and the UK. These results are consistent with the findings of the panel analysis in Table 11, in which all countries are regarded in their entirety. Specifically, it is interesting to note the opposite signs or statistically insignificant values of SSR, TVR, and BEEF in the results of CHN and UK. According to the outcomes of causality, CHN's domestic pork market responds rapidly to global pork price shocks, and the UK's pork market plays a leading role in the international pork market. These unique features are particular to CHN and the UK and differ from other pork-importing countries.

Table 12 The country-specific results based on the random-coefficient regression model.

	The estimation results of Eq. (22)			The estimation results of Eq. (23)		
	SSR (ζ_1)	BEEF (ζ_2)	Constant (ω)	TVR (δ_1)	BEEF (δ_2)	Constant (η)
CHN	0.024	0.063	-0.171	-0.916**	0.112**	-0.192***
COL	-0.064***	-0.324**	1.365***	0.706***	-0.213*	0.408*
JPN	-0.306*	-0.229**	0.714***	0.234**	-0.264*	0.522
KOR	-0.157**	-0.096**	0.452	0.180*	-0.085**	0.259**
MEX	-0.142**	0.005	0.232**	0.140**	0.018**	0.038**
NZL	-0.183*	-0.052**	0.211**	0.170*	-0.050**	0.028
PER	-0.142**	-0.090**	0.366**	0.054**	-0.064**	0.194*
PHL	-0.172*	-0.025**	0.273*	0.186**	-0.016**	0.086
ROU	0.052	-0.098*	0.304*	0.064**	-0.091*	0.305**
UK	0.424	0.425	-1.485	-0.162	0.169	-0.402

The relationship between self-sufficiency and trade volume rates.

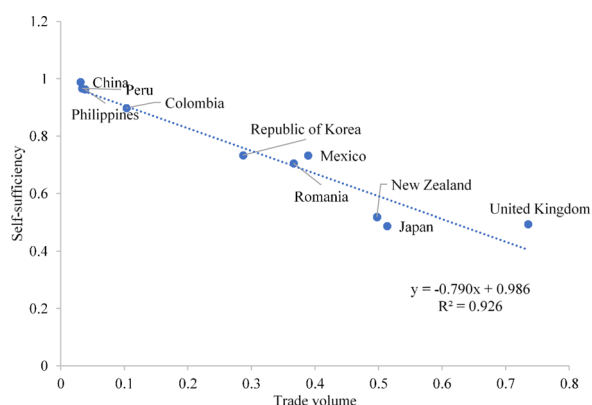


Fig. 3 The relationship between self-sufficiency and trade volume rates.

Policy implications and discussions

The first policy implication derived from the results is that autarky plays a mitigating role in price volatility transmissions from abroad. Namely, a country could increase import tariffs and/or farming subsidies to heighten self-sufficiency and protect domestic markets against unexpected foreign shocks. This must be carefully interpreted. As Tanaka and Guo (2019) demonstrate, the national price could be destabilised if the volatility of domestic supply is greater than that of imports and the ratio of domestic production to total supply is large enough. In addition, the result does not show that protectionist policy improves the market or economy. Policymakers need to identify the balancing points between the benefit from the enhanced efficiency of resource allocation and market stabilisation by raising self-sufficiency in food in terms of the expected utility of economic agents.

We also found that a greater international TVR could facilitate larger price volatility conveyance from global to local markets, which is consistent with the outcome of self-sufficiency obtained in our analysis because a higher autarky rate normally hints at a smaller TVR. However, even if a country reaches a level of total self-sufficiency, it can still be exposed to external markets, with all products domestically produced being exported and an identical amount being imported for internal use. This extreme example illustrates that a country can be self-sufficient in a commodity but hold 200% international trade exposure. Figure 3 shows the trade-off between the mean of self-sufficiency and that of the TVR for the period between 2001 and 2017. Although the UK attains an autarky of around 50%, which is within the range of its counterparts in NZL and JPN, its TVR exceeds that of the other two. Accordingly, the UK could have close ties with overseas markets

relative to NZL and JPN. If policymakers need to reduce their connections with international markets, they should heighten autarky rates and curb exports and imports. Furthermore, net exporting nations would experience mixed effects, as higher self-sufficiency suggests greater trade quantity for the regions. Therefore, higher self-sufficiency does not necessarily alleviate the incoming external shocks.

Our experiments found a role in the consumption of a substitute that mollifies foreign shocks. This indicates that national dietary patterns should be well-balanced with the diversification of food consumption, which may be a rational choice as a preventative policy measure on the grounds of policy implementation costs. Lifting the SSR incurs tremendous financial costs, subsidises farming activities, and sacrifices the benefits from market efficiency. Although changing national dietary habits may take many years, once locals accept new dietary lifestyles, no direct financial cost is required to uphold substitutive options to rarely volatility synchronisation. After World War II, the General Headquarters of the Allied Forces recommended systematic health education and a school lunch programme for Japanese schoolchildren with donated foods such as meat, fish, vegetables, skim milk, and sugar from the United States (Rogers, 2015). Through this assistance, Japanese citizens gradually became accustomed to Western meals, and their daily dietary consumption patterns have since been fundamentally altered from traditional Japanese cuisine.

Concluding remarks

This study employed Granger causality and DCC to examine the relationships between global and local pork meat markets. In addition, we analysed the efficacy of self-sufficiency in the alleviation of international price volatility transmission to local markets. The primary findings are as follows. First, we found that Romania exhibits bidirectional Granger causality between global and domestic prices in variance. China and the United Kingdom present unidirectional linkages from global to domestic markets and from domestic to global markets, both in mean and variance, respectively. Second, high self-sufficiency, or a small TVR of pork meat, mitigates price volatility pass-throughs from foreign markets. Finally, beef consumption plays a preventative role against the transmission of foreign market shocks to local markets.

Comparisons between existing research and this study must also be made. While Guo and Tanaka (2019) identified the unilateral linkages between global and local retail prices for wheat-importing countries, bidirectional relationships were found for pork markets in our research. The Granger causality for beef markets also exhibits bilaterality in Guo and Tanaka (2020b). The difference between wheat and meat (i.e., pork and beef) markets may be attributed to the fact that more importing nations

participate in the global wheat market than in the world's meat markets. In 2018, the cumulative share of the top 10 wheat importers accounted for only 39.7% of total global imports, while the top 10 pork-importing nations accounted for 75.2%, which implies that fewer nations were engaged in the global pork market (FAOSTAT, 2020). Hence, a pork-importing country has a larger market share and greater potential to influence international prices than a wheat-importing country.

The DCCs estimated here should also be compared to those in the existing literature. The mean and median of the time-variant correlations for wheat market pairs in Guo and Tanaka (2019) show positive values for all sample countries. In contrast, this study and Guo and Tanaka (2020b), estimate DCCs to be negative in mean and median for four of ten pork-importing nations and two of ten beef-importing nations, respectively. The difference between cereal and meat may be due to the dissimilar nature of the markets. While cereal production depends crucially on weather conditions, meat production can be adjusted by slaughtering livestock, softening short-term market shocks, and diluting the causal relationship. However, the three studies are consistent from the perspective of more intimate relevance between markets during the global food crisis in 2008.

As mentioned in the previous section, the first limitation is that we did not consider internal price volatility, such as wholesale or producer prices, simply extracting the mitigation effects of self-sufficiency on cross-border pass-throughs. Thus, autarky measures are not always effective in impairing internationally transmitted shocks. Second, our findings are not simply applicable to exporting countries as net exporters' self-sufficiency exceeds 100% with mixed impact (i.e., higher SSR and greater TVR) when self-sufficiency is raised.

Based on our experimental outcomes, an increase in self-sufficiency in pork is likely to stabilise domestic markets. Protectionist measures, such as subsidising domestic production and/or protecting local markets from foreign pig meat products, are the primary methods to raise autarky rates. Steady market prices could reduce the risk of meat production and consumption and improve the expected utility. This is especially beneficial for low-income households in developed and developing countries who suffered severe global food price spikes in 2008, while such protectionist policies worsen market efficiency.

It is essential to analyse the cost-benefit relationship in the policy-making process. Raising self-sufficiency in agricultural commodities at a national level seems to impose a massive economic burden, including both policy implementation costs, such as subsidising farming activity, and the loss of potential benefit from market efficiency with an additional import tariff. To assess the balance between costs and benefits, the reduction in price volatility spillover needs to be converted into a monetary value. It is intrinsic to estimate the Arrow-Pratt measures of risk aversion to express the benefit or cost in monetary value. However, these topics are left for future research.

Data availability

The data that support the findings of this study can be obtained from the corresponding author upon request.

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Competing interests

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Ethical approval

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Informed consent

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Additional information

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