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Determinants of international price volatility transmissions: the role of self-sufficiency rates in wheat-importing countries

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ABSTRACT From the 1980s until the early 2000s, many developing governments adopted market liberalization policies due to relatively low agricultural prices and the implementation of structural programs by the IMF. Yet, a paradigm shift occurred with the emergence of the 2008 food crisis, which directed food-deficit governmental bodies to protectionist regimes supporting higher food self-sufficiency. Despite the importance of food autarky to shield domestic food markets, its effects have never been fully discussed in a formalized econometric framework. This article analyses wheat price volatility transmissions from global to local markets in 10 wheat importing countries, identifying the causality with conditional correlation functions (CCF), the degree of volatility transmissions using generalized autoregressive conditional heteroskedasticity (GARCH) models with the dynamic conditional correlation (DCC) specification and potential determinants with a panel analysis. The main findings reveal that a significant unidirectional Granger causality runs from international wheat price to local retail flour prices for wheat importing countries with an approximate five-month lag, the volatility correlations from international to local markets were strengthened around the period of the 2007–08 food crisis and a higher self-sufficiency rate plays a role in alleviating volatility passthroughs from international markets. This evidence that increasing the SSR of an agricultural commodity is effective in isolating the domestic market is valuable for policymakers in food importing countries. The primary beneficiaries of implementing the policy measure are risk-averse producers and consumers because their utility or welfare improves as the price volatility of foodstuffs declines.

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Introduction

Between 2006 and 2014, global food price volatilities reduced national food security, particularly in the developing world (Ivanic and Martin, 2008), which caused social and political instability in developing regions, including Africa, Asia and South America (Bellemare, 2014)[1]. For example, in 2008, Haiti's senators fired the prime minister, Jacques Edouard Alexis, because he failed to decrease the price of rice (Delva and Loney, 2008). Global factors behind the food crisis such as poor grain harvests (Headey and Fan, 2008), low levels of grain stocks (Trostle, 2008), decline of investment in agricultural research and grain productivity (International Rice Research Institute, 2008; Von Braun et al., 2008), export restrictions (Von Braun et al., 2008; International Rice Research Institute, 2008; Meyers and Meyer, 2008), biofuel generated from food commodities (Von Braun et al., 2008; Headey and Fan, 2008; Mitchell, 2008; Abbott et al., 2008), energy price hikes (Yang et al., 2008; Headey and Fan, 2008) and financial speculation (Piesse and Thirtle, 2009; Cooke and Robles, 2009) were perceived as major driving forces of domestic food price inflations in importing countries rather than domestic factors. Under such national food insecurity circumstances, governments of importing nations, such as Senegal, India, the Philippines, Qatar and Bolivia, have expressed interest in increasing food self-sufficiency (Clapp, 2017).

Debates over national food autarky policies have long taken place (Hamilton, 1918; Keynes, 1993; Kako, 2009; Bishwajit et al., 2013; Clarete et al., 2013). Governmental administrations aim to enhance food self-sufficiency for various reasons such as concerns about food supply disruption due to war, extremely poor harvests by foreign producers and export restrictions, which could lead to vulnerable positions in diplomatic negotiations, environmental deterioration and the loss of concessions associated with farming or farmers (Clapp, 2015; Yamashita, 2016). However, many economists who espouse modern economic theories argue that agricultural autarky policies distort markets and create resource allocation inefficiencies (Naylor and Falcon, 2010). They also advise that subsidizing farmers or imposing additional import tariffs to hike food self-sufficiency undermine food security in the long term, precluding opportunities for gains in market efficiency (Cramer et al., 1999; Tanaka and Hosoe, 2011).

High food self-sufficiency is broadly regarded as a potent strategy for national food security by policymakers. Such a policy measure could lessen the degree of international price transmissions, which may interest aforementioned governments because this can enhance self-sufficiency rates (Tanaka, 2018). Bouët et al. (2012) discuss the rationales of export duties during global food crises, showing that export taxes contribute to stabilizing local markets.

Despite such an important policy for food security, few studies have examined the usefulness of food self-sufficiency policy using an econometric model, although some studies explore it with a general equilibrium model. Tanaka (2018) analyses the effects of wheat self-sufficiency policies for Egypt with a stochastic computable general equilibrium (CGE) model and Tanaka and Hosoe (2011) scrutinize the impact on households of a free-trade rice policy in Japan. Still, one of the major criticisms of a CGE model is that its parameters are estimated with a single-year dataset called a social accounting matrix (SAM), implying that the parameters are point-estimated and less reliable. On the contrary, an econometric model is established with longer time periods, which overcomes the primary concern of CGE.

Research has not yet fully examined the potential factors influencing the volatility pass-throughs between world and local markets in a formal statistical test. Previous studies primarily focus on the links between domestic markets within developing countries (e.g., Baulch, 1997; Abdulai, 2000; Lutz et al., 2006; Moser et al., 2009; Myers, 2013) and only a few studies examine the transmission of price from world to local markets, including volatility transmissions (Mundlak and Larson, 1992; Conforti, 2004; Minot, 2011; Ceballos et al., 2017; Hatzenbuehler et al., 2017). Most studies adopt an error correction method to examine the relationship between global and domestic prices based on a specific country. Nevertheless, these studies did not explore determining factors of the extent of a spill-over. While, along these lines, no studies explored such factors in a comprehensive manner (such as with a panel analysis), Götz et al. (2013) discovered that Russian and Ukrainian export restrictions during food crises helped to stabilize agricultural domestic prices.

Responding to this gap in the scholarly archive, this research concentrates on examining the relationship between self-sufficiency rates and the extent of spill-over effects from global to local markets (rather than that between food policy changes and the degree of international pass-throughs). More specifically, this article explores the determinants of wheat price volatility transmissions from international to local markets using a generalized autoregressive conditional heteroskedasticity (GARCH) model with dynamic conditional correlation (DCC) specification and three types of panel regressions. We concentrate on whether wheat self-sufficiency weakens international volatility pass-throughs, zooming in on 10 net importer nations that are not self-sufficient in wheat. The analysis was conducted during the period between January 2006 and December 2013. The model testing procedure is as follows. First, the direction of Granger causality was identified and the lead-lag relationships between international and domestic wheat prices using Hong's (2001) conditional correlation function (CCF). Second, the volatility correlation pairs between global and local markets were measured with the GARCH-DCC approach based on the results of leads/lags estimated in the first step. Finally, a panel data analysis was conducted to identify factors that can influence long-term dynamic correlations between international and local wheat prices in wheat-importing countries. After detecting the appropriate causalities and estimations of the three empirical models, it was successfully determined that higher self-sufficiency in wheat effectively insulates domestic markets from international market volatilities.

This article makes several contributions to the existing literature. As stated, Ceballos et al. (2017) offer the only study that investigates international price volatility transmissions of cereals. Whiles Ceballos et al. employ the GARCH-BEKK model, the first international volatility transmission analysis of an agricultural good with a DCC approach was conducted, which enabled the identification of the time variant correlated relationship between global and regional markets. One advantage of using this method is that it more precisely estimates the link between correlated volatilities and underlying factors with an extended sample size, generating yearly correlation outputs differently from a GARCH-BEKK approach. This sort of factor identification econometric testing has never been performed in any prior study. In addition, this study tested the effectiveness of a self-sufficiency measure, one of the most important food security strategies that has not been econometrically examined in the literature. Furthermore, the pass-throughs with an explicit focus on the links between international wheat prices and local retail wheat flour prices were analyzed; in previous studies, it is uncertain whether the commodities focused on were wheat or wheat flour (e.g., Ceballos et al., 2017; Minot, 2011). This study aimed to fill these gaps and provide useful implications not only for policymakers, but also agricultural producers and consumers, assuming that most people are risk-averse with respect to market steadiness (Bar-Shira et al., 1994; Jianakoplos and Bernasek, 1998).

The remainder of this article is organized as follows. Section "Data description" offers a brief description of the data. Section "Econometric methodology" introduces the empirical methods. Section "Empirical" results and interpretations addresses the empirical findings and interprets the results. Section "Conclusion and policy implications discusses the policy implications" of the results and the limitations of the study.

Data description

We used monthly data from the Global Information and Early Warning System (GIEWS), which provides the monthly food commodity prices of various countries and international food prices. Retail flour prices from January 2006 to December 2013 for 10 wheat-importing countries (Afghanistan, Azerbaijan, Brazil, Cameroon, Georgia, Israel, Kyrgyzstan, Mauritania, Peru and Tajikistan) were obtained. While commodity price data are available for a number of countries in the GIEWS, only 10 regions met the study's requirements for available data on the retail prices of wheat flour for a recent time period and of non-self-sufficiency in wheat. Following the literature, the local prices are in US dollars. The international price is the export price of wheat (US No. 2 hard red winter) from the US Gulf Coast, which is also quoted in the GIEWS. To eliminate the influence of seasonal fluctuations, we adjusted all data by using the X-13-ARIMA[2] method. Moreover, for each data series, continuously compounded returns were computed as $\ln(X_t/X_{t-1}) \times 100$, where X_t represents international wheat prices (IWP) and local wheat prices in 10 wheat-importing countries (Afghanistan, Azerbaijan, Brazil, Cameroon, Georgia, Israel, Kyrgyzstan, Mauritania, Peru and Tajikistan). Figure 1 plots the returns of each variable.

Table 1 reports the descriptive statistics of returns on wheat prices (international and domestic markets). Data in this table reveal that most of the mean returns are positive, suggesting a rise in wheat prices during the study period. It is worth noting that the standard deviations of Afghanistan's and Kyrgyzstan's price returns are relatively higher than those of other countries. This indicates that these two countries tend to experience extreme changes in wheat prices more frequently for the two countries. Before proceeding with the causality test based on the CCF approach, it is necessary to check the stationarity of each variable. An augmented Dickey-Fuller (ADF)[3] and Kwiatkowski-Phillips-Schmidt-Shin (KPSS)[4] unit root tests were performed on the return series. The null hypothesis of the ADF test is that the series is nonstationary, whereas that of the KPSS test is that the data series is stationary. The results of the unit root tests presented in Table 1 indicate that all variables are stationary in their first log-differenced forms[5] and integrated of order 1. This allows us to jointly model the price transmission between international and local wheat prices.In addition, Van Dijk et al. (2005) suggest pre-testing for structural breaks before examining causality. Following this, Bai and Perron's (2003) structural change test, which allows for the simultaneous estimation of unknown multiple structural breaks, is applied to identify the structural break points in each wheat price series[6].

The results of Bai and Perron's (2003) structural breaks test in Table 1 show that, across all countries, only Georgia demonstrates a structural break in its price returns. Specifically, one break exists in the wheat price return of Georgia in August 2008.

In the next step, we employ yearly data, including the self-sufficiency rate (SSR) and domestic economic variables, to identify the common factors that could affect wheat price volatility transmission in importing countries. Table 2 provides the definitions of the potential factor variables used and Table 3 displays the summary statistics for the explanatory variables in the panel estimation. First, because a key assumption is that the SSR could be a significant factor in determining the dynamic correlation, the annualized SSR for each country is chosen. The SSR of wheat is defined as $Production/(Production + Import - Export)$. The data source of each component of the SSR is the FAOSTAT[7]. Figure 2 plots the time-series SSR in each country. As Fig. 2 and Table 3 show, the SSR displays different characteristics in wheat-importing countries. For example, Afghanistan, Kyrgyzstan and Tajikistan have relatively high average SSR values, while Cameroon's and Mauritania's SSR display the lowest average values. It is also interesting that the SSRs of some countries (e.g., Afghanistan, Azerbaijan, Brazil and Peru) fluctuated dramatically during the 2007–2008 food crisis. Because SSR data are not available at monthly frequencies, we converted the estimated

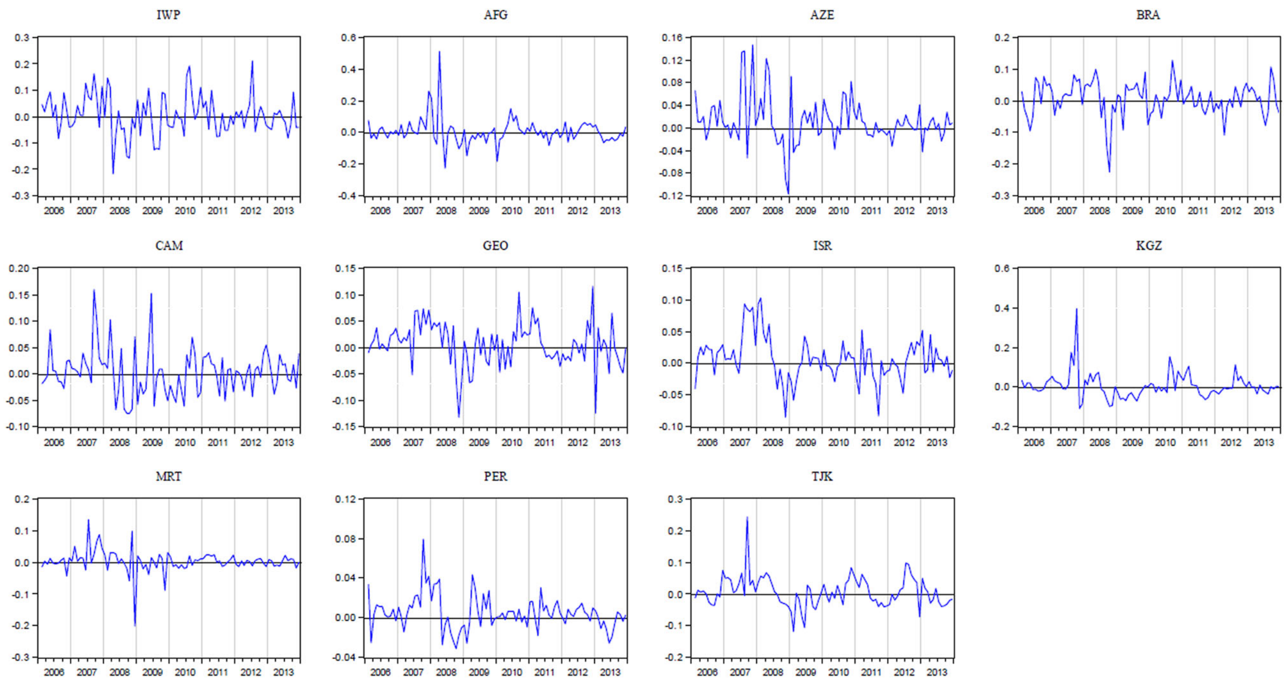

Fig. 1 Time-series plots of continuously compounded returns of international and local wheat prices

Table 1 Summary statistics and pre-test for wheat price returns

	Mean	Std. Dev.	ADF test	KPSS test	Structural break tests
International wheat price	0.006	0.076	−7.609*** (0)	0.072 (2)	No break
Afghanistan	0.006	0.084	−2.950*** (1)	0.056 (4)	No break
Azerbaijan	0.011	0.042	−3.477*** (2)	0.044 (5)	No break
Brazil	0.006	0.054	−6.633*** (0)	0.036 (4)	No break
Cameroon	0.003	0.044	−7.902*** (0)	0.091 (2)	No break
Georgia	0.006	0.041	−4.520*** (1)	0.068 (4)	1 break: 2008:8
Israel	0.007	0.035	−5.185*** (0)	0.075 (6)	No break
Kyrgyzstan	0.006	0.064	−6.952*** (0)	0.073 (4)	No break
Mauritania	0.003	0.035	−11.674*** (0)	0.086 (5)	No break
Peru	0.005	0.017	−4.299*** (6)	0.041 (5)	No break
Tajikistan	0.006	0.048	−3.900*** (1)	0.064 (6)	No break

Notes: (***) denotes rejection of the null hypothesis at the 1% significance level. Numbers in brackets are the lag length and bandwidth. Lag length selection was based on BIC in the ADF tests. The bandwidth for the KPSS test was determined using the Newey-West bandwidth selection algorithm (Newey and West, 1994). We implemented all the unit root tests with intercept and trend terms (this specification has the lowest BIC). We used Bai-Perron's sequential test for the hypothesis of k breaks versus $k+1$ breaks, employing the F-statistics. Lag length selection was based on BIC in the test

Table 2 Definitions of the variables in the panel analysis

Variable names	Definition	Source
$DCC_{i,t}$	Dynamic conditional correlation of wheat between international and country i's domestic price with one lag at time t.	Estimated by Author
$SSR_{i,t}$	Self-sufficiency rate of wheat in country i at time t.	FAOSTAT
$GDP_{i,t}$	Real GDP per capita growth rate in country i at time t.	FAOSTAT
$CPI_{i,t}$	Inflation rate in country i at time t.	World Bank
$MC_{i,t}$	Domestic consumption of maize in country i at time t.	FAOSTAT
$RC_{i,t}$	Domestic consumption of rice in country i at time t.	FAOSTAT

monthly conditional correlations between international and local prices into yearly frequency data[8].

Moreover, it is important to consider the substitutive effects of commodities; therefore, the annualized domestic consumption of maize and rice in each wheat-importing country were selected. Table 4 shows the levels of domestic consumption of wheat, rice and maize in each country. Wheat consumption is typically larger than those of maize and rice in all countries except Cameroon and Peru. In addition, we include macroeconomic factors—the annualized GDP per capita growth rate and annualized inflation rate[9]—to reflect the current economic conditions. The GDP and CPI data are sourced from FAOSTAT and the World Bank's World Development Indicators online database[10].

Econometric methodology

To perform the analysis, we used a three-step econometric methodology. First, we examined the Granger causality and lead-lag relationships between international and local wheat prices by employing the CCF approach. Second, we estimated the price volatility transmission between international and local wheat markets using a GARCH-DCC framework. In the final step, a panel analysis was applied to investigate the common factors that could affect wheat price volatility transmission in wheat-importing countries.

Testing Granger causality using a cross-correlation function. To examine the causality between international and local wheat prices in wheat-importing countries, Hong's (2001) non-uniform weighting cross-correlation function (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[11]. The GARCH used in this model was introduced by Bollerslev (1986)[12] and has been widely used to estimate volatilities for time-series data[13]. Using the residuals obtained from the GARCH model, the standardized residuals $\hat{\tau}_t$ and $\hat{\xi}_t$ were estimated. Next, the sample cross-correlation coefficient at lag m, $\hat{r}_{\tau\xi}(m)$, was calculated from the consistent estimates of the conditional mean and variance for international and local wheat prices. This leaves us with

$$\hat{r}_{\tau\xi}(m) = \hat{c}_{\tau\xi}(m)\left\{\hat{c}_{\tau\tau}(0)\hat{c}_{\xi\xi}(0)\right\}^{-\frac{1}{2}}, \tag{1}$$

where $\hat{c}_{\varepsilon\xi}(m)$ is the m-th lag sample cross-covariance given by

$$\hat{c}_{\tau\xi}(m) = \begin{cases} T^{-1}\sum\limits_{t=j+1}^{T}\hat{\tau}_t\hat{\xi}_{t-j} & \text{for } j \geq 0 \\ T^{-1}\sum\limits_{t=-j+1}^{T}\hat{\tau}_{t+1}\hat{\xi}_t & \text{for } j < 0 \end{cases}, \tag{2}$$

where $\hat{c}_{\tau\tau}$ (0) and $\hat{c}_{\xi\xi}$ (0) are defined as the sample variances of $\hat{\tau}_t$ and $\hat{\xi}_t$, respectively and T is the sample size.

Causality in the mean of international and local wheat prices can be tested by examining $\hat{r}_{\tau\xi}(m)$, the univariate standardized residual CCF. Under the regularity condition[14], the following holds:

$$S = T\sum_{i=1}^{k}\hat{r}^2_{\tau\xi}(i) \xrightarrow{L} \chi^2(k), \tag{3}$$

where $\xrightarrow{L}$ shows convergence in distribution and $\chi^2(k)$ indicates a chi-square distribution with k degrees of freedom. To test for a causal relationship from lag 1 to k, the S-statistic was compared with the chi-square distribution. If the test statistic was higher than the critical value of the chi-square distribution, the null hypothesis. Furthermore, Hong (2001) indicates that the S-statistic weighs each lag uniformly; therefore, it may distort the amount of the presence of causality. Thus, Hong's (2001) method was adopted, incorporating the weighting cross-correlation, which is consistent with the intuition that more recent

Table 3 Summary statistics for the explanatory variables in the panel analysis

	SSR			*GDP*			*CPI*			*MC*			*RC*		
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
AFG	0.774	0.834	0.134	0.058	0.054	0.050	0.080	0.075	0.109	−0.005	0.028	0.129	-0.001	0.001	0.079
AZE	0.540	0.546	0.081	0.091	0.061	0.107	0.080	0.068	0.072	−0.010	−0.107	0.234	0.088	0.023	0.150
BRA	0.433	0.458	0.102	0.028	0.029	0.023	0.052	0.052	0.010	−0.012	−0.006	0.056	0.050	0.052	0.117
CMR	0.002	0.002	0.000	0.011	0.010	0.010	0.029	0.028	0.016	0.063	0.061	0.039	0.056	0.053	0.050
GEO	0.086	0.086	0.019	0.065	0.075	0.047	0.055	0.078	0.047	0.064	0.079	0.260	−0.016	0.037	0.493
ISR	0.077	0.077	0.019	0.020	0.029	0.017	0.025	0.024	0.013	0.046	0.065	0.124	0.017	0.038	0.105
KGZ	0.622	0.622	0.078	0.033	0.031	0.040	0.101	0.074	0.071	0.116	−0.033	0.438	0.032	0.015	0.104
MRT	0.009	0.008	0.005	0.022	0.016	0.055	0.055	0.060	0.017	0.086	0.067	0.104	0.008	0.059	0.229
PER	0.122	0.121	0.007	0.051	0.054	0.024	0.030	0.029	0.014	0.026	−0.025	0.108	0.046	0.053	0.045
TJK	0.612	0.606	0.076	0.038	0.046	0.019	0.100	0.082	0.053	0.063	0.059	0.089	0.015	0.034	0.074

Notes: *SSR*: yearly self-sufficiency rate of wheat. *GDP*: yearly real GDP per capita growth rate. *CPI*: yearly inflation rate. *MC*: yearly growth rate of consumption of maize. *RC*: yearly growth rate of consumption of rice

information should be heavily weighted. The modified test statistics are defined as

$$Q = \frac{S-k}{\sqrt{2k}} \xrightarrow{L} N(0,1). \tag{4}$$

The Q-statistic is assumed to follow an upper-tail normal distribution. This test allowed for more flexible specifications of the innovation and was suitable for analyzing the lead-lag causal relationships between two variables.

Estimating price volatility transmission by applying the GARCH-DCC model. In recent years, multivariate GARCH (MGARCH) models with dynamic covariance and conditional correlation have been shown to be more useful in analyzing volatility spill-over mechanisms[15] and thus this method was used for analysis. The econometric framework of the GARCH-DCC model was formulated as follows: let p_t be a 2×1 vector of returns including the international wheat price $p_{1,f}$ and local wheat price $p_{2,f}$. Thus, an autoregression (AR) model k process for p_t conditional on the information set Ω_{t-1} can be represented as:

$$p_t = \mu + \sum_{i=1}^{k} \phi_i p_{t-i} + u_t = \mu + \sum_{i=1}^{k} \phi_i p_{t-i} + \sqrt{H_t} z_t, \tag{5}$$

$$u_t | \Omega_{t-1} \sim N(0, H_t), \tag{6}$$

$$H_t = E\left[u_t u_t'\right] = D_t P_t D_t, \tag{7}$$

where $\mu = (\mu_1, \mu_2)'$ is the vector of conditional means, ϕ_i is the parameter vector, k is the lag lengths of the mean equations, $u_t = (u_{1,t}, u_{2,t})'$ is the vector of innovations, H_t is a 2×2 conditional variance-covariance matrix, z_t is a 2×1 *i.i.d* vector of standardized residuals, D_t is the diagonal matrix containing the conditional standard deviations on the diagonal and P_t is the conditional correlation matrix given by:

$$P_t = diag(q_{11,t}^{-1/2}, q_{22,t}^{-1/2}) Q_t diag(q_{11,t}^{-1/2}, q_{22,t}^{-1/2}), \tag{8}$$

where Q_t is the conditional correlation matrix of standardized residuals and q is the element of matrix Q_t. Moreover, the matrix D_t can be obtained by estimating a univariate GARCH (p, q) model, with $\sqrt{h_{i,t}}\,(i = 1, 2)$ on the *ith* diagonal as follows:

$$h_{i,t} = \pi_{i,0} + \sum_{p=1}^{p_i} \lambda_{i,p} u_{i,t-p}^2 + \sum_{q=1}^{q_i} \gamma_{i,q} h_{i,t-q}, \tag{9}$$

where $h_{i,t}$ is a 2×1 conditional variance vector of the price series and $\pi_{i,0}$ is a 2×1 constant vector, the lag lengths of variance equations are represented as p and q and λ and γ are the parameters of the GARCH and ARCH terms, respectively

Furthermore, Engle's (2002) DCC model and Cappiello et al.'s (2006) asymmetric DCC (henceforth, A-DCC)[16] model were used to determine the volatility spill-over between international and local wheat prices in wheat-importing countries. Meanwhile, the generalized DCC (henceforth, G-DCC) and asymmetric generalized DCC (henceforth, AG-DCC) models[17] were employed and the best model was selected based on the Bayesian-Schwarz information criterion (henceforth, BIC). According to Engle (2002), the dynamic correlation structure is given as:

$$Q_t = (1 - \alpha - \beta)\bar{P} + \alpha \nu_{t-1} \nu_{t-1}' + \beta Q_{t-1}, \tag{10}$$

where Q_t is a symmetric positive definite matrix in Eq. (8) and $\bar{P}$ is the 2×2 unconditional correlation matrix of the standardized residuals ν_t. The parameters α and β are non-negative, with a sum of less than unity. Therefore, the trend of the G-DCC model can

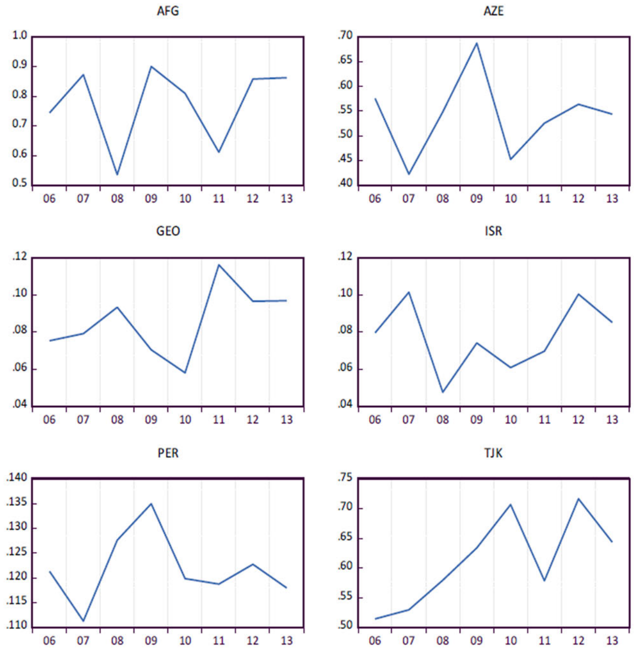

Fig. 2 Time-series plots of SSR for wheat in importing countries

Table 4 Daily per capita caloric consumption of wheat, maize and rice

	AFG	AZE	BRA	CMR	GEO	ISR	KGZ	MRT	PER	TJK
Wheat	1369	1666	384	172	1200	863	1007	818	355	1369
Maize	21	99	240	325	243	99	195	28	185	21
Rice	141	21	326	239	27	165	72	481	519	141

Notes: Data are sourced from FAOSTAT (http://www.fao.org/faostat/en/#data)

be specified as:

$$Q_t = (\bar{P} - A'\bar{P}A - B'\bar{P}B) + A'\nu_{t-1}\nu'_{t-1}A + B'Q_{t-1}B, \quad (11)$$

where A and B are 2×2 parameter matrices and $\bar{P}$ is estimated by using the sample analogue $T^{-1}\sum_{t=1}^{T}\nu_t\nu'_t$. To introduce the presence of asymmetries into the DCC model, Cappiello et al. (2006) modified the correlation evolution equations in the following expression:

$$Q_t = (1-\alpha-\beta)\bar{P} - \delta\bar{N} + \alpha(\nu_{t-1}\nu'_{t-1}) + \beta Q_{t-1} + \delta(\eta_{t-1}\eta'_{t-1}), \quad (12)$$

where $\bar{N}$ represents the unconditional matrices of $\eta_t = I[\nu_t < 0] \otimes \nu_t$, $I[.]$ an indicator function equal to 1 if $\nu_t < 0$ and 0 otherwise and '$\otimes$' the Hadamard product. Equation (12) is a standard A-DCC in which asymmetric terms are included. Thus, the AG-DCC model can be expressed as:

$$\begin{aligned} Q_t = {} & (\bar{P} - A'\bar{P}A - B'\bar{P}B) - G'\bar{N}G + A'\nu_{t-1}\nu'_{t-1}A \\ & + B'Q_{t-1}B + G'\eta_{t-1}\eta'_{t-1}G \end{aligned}, \quad (13)$$

where A, B and N are parameter metrics. In the estimation, $\bar{N}$ is replaced with a sample analogue, $T^{-1}\sum_{t=1}^{T}\eta_t\eta'_t$. It is worth noting that the AG-DCC model in Eq. (13) nests several specifications of these DCC, G-DCC and A-DCC models. In addition, the correlation coefficient ρ_{12} at time t can be defined as:

$$\rho_{12,t} = \frac{q_{12,t}}{\sqrt{q_{11,t}q_{22,t}}}. \quad (14)$$

Finally, the parameters of the DCC, G-DCC, A-DCC, and AG-DCC models were estimated by employing the Gaussian quasi-maximum likelihood estimation (QMLE)[18] with the BFGS[19] optimization algorithm. The joint log-likelihood function $L(\theta, \psi)$ can be written as the sum of a volatility part and a correlation part, expressed as:

$$L(\theta,\psi) = -\frac{1}{2}\sum_{t-1}^{T}\left(N\log(2\pi) + 2\log|D_t| + \log|P_t| + \nu'_tP_t^{-1}\nu_t\right), \quad (15)$$

where T refers to the number of observations and N denotes the number of equations. Moreover, the univariate GARCH parameters in D_t are denoted as θ, where $\theta = (\pi, \lambda, \gamma)$ and the dynamic correlation parameters in P_t are denoted as Ψ, where $\Psi = (\alpha, \beta, \delta)$. The time-varying conditional correlation coefficients are computed based on each GARCH-DCC model.

Identifying factors using panel analysis. In the final step, the underlying factors that influence wheat price volatility transmission from international to local markets in wheat-importing countries were investigated. To tackle the data limitation problems, a panel data approach was taken and wheat-importing countries were regarded as a whole to analyze the factors

Table 5 Empirical results of AR-GARCH model

	Parameters				Specification tests		
	ϕ	λ	γ	Dummy	Ljung-Box (12)	LM test	BIC
International wheat price	0.217**	0.028	0.852***	-	4.947	0.067	−2.160
Afghanistan	0.012	0.298***	0.712***	-	16.301	0.171	−2.290
Azerbaijan	0.046	0.348*	0.607***	-	6.543	0.696	−3.631
Brazil	0.315***	−0.062*	1.039***	-	5.049	0.471	−3.129
Cameroon	0.189**	0.086	0.900***	-	2.284	0.004	−3.331
Georgia	0.194	−0.019**	0.563**	0.448**	6.411	0.117	−3.500
Israel	0.438***	0.363*	0.464**	-	8.173	0.033	−4.058
Kyrgyzstan	0.639***	0.251	0.624**	-	8.198	0.018	−3.403
Mauritania	−0.044	0.550*	0.467**	-	3.581	0.001	−4.356
Peru	0.339***	0.249	0.610*	-	1.826	0.239	−5.491
Tajikistan	0.728***	0.775***	0.012	-	7.053	0.078	−3.426

Notes: (*), (**), and (***) denote statistical significance at the 10%, 5%, and 1% levels, respectively. The lag length k in the AR model, the ARCH term p and the GARCH term q in the GARCH models were selected from among $k = 1, 2, ..., 10$, $p = 1, 2$ and $q = 1, 2$, [23]respectively, by applying the BIC and residual diagnostics[24]. The standard error follows Bollerslev and Wooldridge's (1992) robust standard error. Diagnostic test: Ljung-Box's statistics for the null hypotheses of no autocorrelation up to the order of 12 for standardized residuals (Ljung and Box, 1978). The statistics indicate that the null hypothesis of no autocorrelation up to the order of 12 for the standard residuals cannot be rejected at the 1% significance level. LM test: the Lagrange multiplier (LM) test statistic for ARCH in residuals (distributed as chi-square). The LM test statistic indicates that the null hypothesis of no further ARCH effect in the residuals cannot be rejected

influencing price volatility transmission. Following the specification in Table 2, the following panel regression model was constructed:

$$\mathrm{DCC}_{i,t} = c + \kappa_1 \mathrm{SSR}_{i,t} + \kappa_2 \mathrm{GDP}_{i,t} + \kappa_3 \mathrm{CPI}_{i,t} + \kappa_4 \Delta \mathrm{MC}_{i,t} + \kappa_5 \Delta \mathrm{RC}_{i,t} + \varepsilon_{i,t}, \quad (16)$$

where DCC is the dynamic conditional correlations at yearly frequency; c the constant; $\varepsilon_{i,t}$ is the heteroskedastic error term; GDP and CPI annualized GDP per capita growth rate and inflation rate, respectively; MC and RC the log-transformed values of maize and rice consumption, respectively; Δ the first difference and k the parameters to be estimated. These parameters measure the impact of the common factors that influence the price volatility transmission[20].

Before performing the panel analysis, it was necessary to consider the impact of heteroskedasticity or serial correlation in the error term and any cross-sectional dependence in the cross-country panel. Therefore, a series of pre-tests was applied. Specifically, the modified Wald test (Wooldridge, 2010), Pesaran's test (Pesaran, 2004) and Wooldridge's test (Wooldridge, 2010) were employed for heteroskedasticity, cross-sectional correlation and autocorrelation, respectively. Notably, in a standard panel data estimation, the fixed effect model or random effect model is used to estimate the parameters. Hausman's test was thus used to examine the appropriateness of the fixed effect model relative to the random effect model.

The feasible generalized least-squares (FGLS) regression was used to estimate the panel model. The advantage of the FGLS method is that it allows for heteroskedasticity or autocorrelation in the error term. Moreover, Monte Carlo studies[21] have shown that the FGLS estimator generally yields better estimates than the ordinary least-squares (OLS) estimator. To guarantee the robustness of the empirical results, the Prais-Winsten regression with panel-corrected standard errors (PCSEs) was applied to compare the results. As Beck and Katz (1995) argue, a PCSE model leads to a more accurate estimation than an FGLS model.

Empirical results and interpretations

The causal relationship between global and local wheat prices. As made clear above, in this study, each model was estimated using the maximum likelihood method and the lag lengths of the mean and variance equations were determined based on BIC. The AR (1)-GARCH (1,1) model was chosen for each price series because it had the lowest BIC value[22]. Because structural break dates were identified in Georgia's data, a dummy variable was included in its model. Table 5 shows the parameter estimates for each model and their corresponding statistical significance values. First, we can observe that most of the coefficients of the ARCH (λ) and GARCH (γ) are significant in the GARCH model. Notably, the coefficient of the dummy variables for Georgia is significant at the 5% level. This suggests that the dummy variable accommodates the structural break in Georgia's data. Following the result, this structural break should be interpreted as the military conflict that broke out between Russia and Georgia in August 2008. It strongly suggests that this short war appears to have significantly affected Georgia's wheat market and caused the structural change in domestic wheat products and prices. Furthermore, it is noticeable that the break points in the global wheat price and most local wheat prices in importing countries were not discovered. These results imply that little evidence exists to support the structural changes in the wheat price returns during the 2007–2008 food crisis. In addition, Table 5 shows the diagnostics of the empirical results. All the tests imply that the estimated models adequately fit the data.

Next, based on the CCF approach, the standardized residuals obtained from each GARCH model were used to examine the causal relationship between international and local prices. Table 6 presents the empirical results, which show that international wheat price returns demonstrate a Granger causality in local prices in all wheat-importing countries with a five-month lag[25]. In turn, there is no statistically significant evidence of causality from local price to international price[26]. Therefore, it can be concluded that a unidirectional causality exists from international to local prices in the sample, suggesting that international price can be considered a leading indicator of local price in wheat-importing countries[27]. Based on these results, the local price of each wheat-importing country was lagged by five periods (five months) to capture the information from the global market to the local market with a five-month time lag.

Dynamic conditional correlations between global and local wheat prices. In the second stage, as mentioned in the methodology section, standardized residuals obtained from the GARCH model were used to estimate the conditional cross-correlation coefficient $\rho_{12,f}$ in Eq. (14). Table 7 gives the estimation results of the parameter metrics for all the DCC models. First, the necessary condition of $\alpha + \beta < 1$ holds for nearly every pair of international and local prices in the DCC and A-DCC models, indicating that

Table 6 Results for Hong's (2001) Granger causality test

$m = 5$	Causality-in-mean		Causality-in-variance	
	Q-statistic	**P-value**	**Q-statistic**	**P-value**
IWP → AFG	2.251**	0.024	1.073	0.283
AFG → IWP	−0.045	0.964	−0.329	0.742
IWP → AZE	3.673***	0.000	−0.678	0.498
AZE → IWP	−0.861	0.389	0.551	0.581
IWP → BRA	2.229**	0.026	0.222	0.824
BRA → IWP	0.523	0.601	0.374	0.709
IWP → CMR	2.140**	0.032	2.417**	0.016
CMR → IWP	1.010	0.312	−0.027	0.978
IWP → GEO	2.588**	0.010	0.351	0.726
GEO → IWP	−0.426	0.670	−0.829	0.407
IWP → ISR	3.303***	0.001	0.205	0.837
ISR → IWP	0.086	0.932	0.791	0.429
IWP→ KGZ	3.487***	0.000	2.945***	0.003
KGZ→ IWP	0.371	0.711	−0.544	0.587
IWP→ MRT	2.512**	0.012	−0.397	0.692
MRT→ IWP	0.395	0.693	−0.825	0.409
IWP→ PER	2.391**	0.017	1.073	0.283
PER→ IWP	−0.641	0.521	−0.329	0.742
IWP→ TJK	1.712*	0.080	−1.006	0.315
TJK→ IWP	−0.439	0.847	−0.564	0.573

Notes: IWP: international wheat price. (*), (**), and (***) denote statistical significance at the 10%, 5%, and 1% levels, respectively. The arrow indicates the direction of Granger causality. The *Q*-statistic is used to test the null hypothesis of no causality from lag 1 up to *k* (5). If the test statistic is higher than the critical value of the standard normal distribution, the null hypothesis is rejected. The *Q*-statistics were based on one-sided tests. Lags were measured in months

the dynamic conditional correlations are mean reverting for international and local prices. Second, the parameters, β, were observed to be mostly positive and significant in the DCC and A-DCC models. This indicates that the lagged dynamic conditional correlation significantly affects the current dynamic conditional correlations. Third, the asymmetry coefficients, η, are found to be significant in Afghanistan and Peru in the A-DCC model, thereby providing evidence of an asymmetric response in correlation for the two countries. Next, the most appropriate model for each country was selected based on BIC. Table 8 presents the results of the model selection, which show that the standard DCC model is selected as the best fit to Afghanistan, Georgia, Kyrgyzstan, Peru and Tajikistan and the G-DCC model is chosen for Azerbaijan, Brazil, Cameroon, Israel and Mauritania.

Finally, the dynamic cross-correlation coefficients can be estimated by maximizing the log-likelihood functions in Eq. (15). Figure 3 plots the evolution of the estimated time-varying dynamic correlations of each country. Overall, it is interesting to ascertain that all conditional correlations display considerable variability in the sample period and exhibit different patterns across different countries. Figure 3 visually confirms that almost all the conditional correlation coefficients (except those of Afghanistan, Cameroon, Israel and Tajikistan) are positive throughout the entire sample period. Because the wheat-importing countries' SSRs in the sample are less than 1 (net wheat-importing countries), it is not surprising that global wheat prices significantly affect local wheat prices in these countries. Moreover, it is interesting that some countries' dynamic correlations fluctuated dramatically during the 2007–2008 global food crisis. Specifically, a substantial increase in correlation between global and local wheat markets is apparent at the beginning of the food crisis, offering further evidence of the strong impacts of global wheat prices on local prices in some countries (e.g., Azerbaijan, Brazil, Georgia, Israel, and Mauritania). Since a structural break was found in Georgia, it is necessary

Table 7 Empirical results of four specifications for DCC models

	DCC		A-DCC			G-DCC				AG-DCC					
	α	β	α	β	η	α (I)	α (L)	β (I)	β (L)	α (I)	α (L)	β (I)	β (L)	η (I)	η (L)
AFG	0.360**	0.641***	0.116	0.564**	−0.649***	0.114	0.654***	0.444	0.743***	−0.229*	0.039*	0.970***	0.004	−0.312***	−1.852***
AZE	−0.000	0.791***	−0.000	0.827***	−0.000	0.249***	−0.175***	1.014***	0.749***	0.249***	−0.175	1.014***	0.749***	0.001	−0.001
BRA	−0.000	0.795***	−0.000	0.895***	−0.000	0.139	0.409	0.999***	−0.517	0.085	0.578**	0.985***	−0.465	0.264	0.163
CMR	−0.000	0.753***	−0.000	0.889***	0.000	0.248	−0.312	−0.903***	0.668*	0.137	−0.060	−0.608	0.700	0.645	−0.333
GEO	0.141	0.700	0.141	0.700	−0.000	0.443***	0.105	0.922***	−0.500	0.383**	0.071	0.935***	−0.225	0.072	0.957**
ISR	−0.000	0.836***	−0.000	0.884***	−0.000	0.265***	0.292	1.007***	−0.288	0.202***	0.568***	1.002***	−0.291	0.251**	−0.403
KGZ	0.139	0.863**	−0.000	0.823***	0.363	0.044***	0.602***	1.027***	0.667***	0.044***	0.582***	1.027***	0.689***	−0.001	−0.000
MRT	−0.000	0.822***	−0.000	0.820***	0.135	−0.956***	0.199	−0.114	0.828	−0.925***	0.269	−0.171	0.743*	0.348	0.456
PER	0.141	0.910***	−0.000	0.894***	−0.390**	0.680***	0.032***	0.707***	1.040***	0.686***	0.032***	0.705***	1.040***	−0.003	−0.000
TJK	0.182	0.842***	0.182	0.842***	−0.000	0.107***	0.479***	0.841***	0.920***	0.129***	0.830***	1.000***	0.548***	0.266***	0.220***

Notes: (*), (**), and (***) denote statistical significance at the 10%, 5% and 1% levels, respectively. (I) and (L) indicate the international wheat price and local wheat price, respectively. The parameters of all the models are estimated using QMLE. Specifically, α and β represent the parameter metrics for the DCC and G-DCC models and η is the asymmetric term contained in the A-DCC and AG-DCC models to check whether significant trade policy changes occurred in Georgia during the crisis. Table 9 reports Georgia's import tariff for cereals from 2006 to 2013. It was observed that Georgia's trade tariff rate was lowered from 6.4% to 0.3% in 2007. This policy change seems to have increased the correlation between international and local prices in Georgia. For a country such as Georgia, the autarky rate of which is extremely low[28], one of the best short-term counter strategies to feed citizens is to liberalize food imports rather than to raise import tariffs.

Table 10 provides the descriptive statistics for the 10 wheat-importing countries' dynamic correlations. First, the means of the correlations are positive in all countries. This suggests that increases or declines in the volatility of international wheat prices can cause increases or declines in the volatility of domestic wheat prices in wheat-importing countries. Brazil has the highest average value (0.359) of dynamic correlation coefficients, which broadly indicates that Brazil's domestic wheat price has a high correlation with international wheat prices. On the other hand, Tajikistan has the lowest average value (0.024), which conveys a relatively low correlation. Furthermore, as Table 10 shows, different magnitudes of correlation variability emerge across different wheat-importing countries. In particular, Azerbaijan's correlation coefficients fluctuated more than those of other countries and thus demonstrated the highest standard deviation (0.150). Conversely, Mauritania's dynamic correlation coefficients are the most stable and thus demonstrated the lowest standard deviation (0.011).

Table 8 The model selection of four specifications for DCC models

	BIC criterion			
	DCC	**A-DCC**	**G-DCC**	**AG-DCC**
AFG	−391.117*	−388.464	−383.056	−379.020
AZE	-	−533.733	−537.335*	−528.250
BRA	-	-	−468.264*	−459.710
CMR	-	-	−507.199*	−498.531
GEO	−522.106*	−517.563	−516.417	−508.537
ISR	-	-	−566.537*	−560.248
KGZ	−461.359*	−457.708	−455.269	−446.196
MRT	-	−588.398	−586.404*	−577.758
PER	−704.725*	−702.392	−698.556	−689.479
TJK	−497.645*	−493.102	−489.168	−481.935

Notes: (*) denotes the lowest value of BIC. - denotes that the dynamic conditional correlation cannot be calculated. It is observed that the DCC models demonstrate the lowest BIC values for Afghanistan, Georgia, Kyrgyzstan, Peru, and Tajikistan and that the G-DCC models demonstrate the lowest BIC values for Azerbaijan, Brazil, Cameroon, Israel, and Mauritania

Panel data analysis. To investigate the common factors that impact the price volatility transmission, the panel model was estimated based on Eq. (16). As mentioned in the "Econometric methodology" section of the methods, some pre-tests need to be specified in a preliminary step. Table 11 summarizes the pre-test results. The Hausman test suggests a random effects model for running the panel regression instead of a fixed effects model. Furthermore, the results indicate that the model exhibits heteroskedasticity, serial correlation and cross-sectional dependencies.

Based on the results of the specification tests, a random effects model was employed as the base model.

Table 12 reports the empirical results of the panel regression based on these three model specifications. The empirical results revealed several interesting findings. First, it was verified that the coefficients of *SSR* are negative and significant for all models. These results confirm that the self-sufficiency rate of wheat is a determining factor affecting the dynamic conditional correlation between international and local wheat prices in wheat-importing countries. Furthermore, the negative coefficient indicates that an increase in the *SSR* will decrease the dynamic correlations. This suggests that raising the SSR of wheat can be a reasonable strategy to buffer importing countries from excessive fluctuations in international wheat prices. Second, the panel results show that the coefficients of *CPI* are negative and significant for the PCSEs and FGLS models. Theoretically, an increase in the inflation rate will decrease the real value of currency in local countries, which in

Fig. 3 Plots of dynamic correlations between international and domestic wheat prices

turn weakens purchasing power and amplifies correlation with the global wheat market. One possible explanation for the negative sign of *CPI*s coefficients is that some monopoly or oligopoly exists among wheat importers. They may weaken the price transmission to local wheat markets if international prices decrease. Third, the results show that the coefficients of *GDP* are not robust to model change (k_2 is positive and significant only in the FGLS model). GDP per capita growth represents the livelihood of nationals, which may accelerate volatility pass-throughs because wealthier citizens tend to import more foodstuffs. For instance, Israel has the higher GDP per capita and one of the lowest SSRs[29]. Because the results of *CPI* and *GDP* are not robust against a change in the model selection, they may not be the more important factors in determining the degree of price volatility transmission. Finally, it is interesting that the coefficients of ΔMC and ΔRC are mostly not significant across different estimation methods, implying that a substitutive effect does not exist between wheat, maize and rice. Typically, substituting the consumption of a good that becomes more expensive with one that is relatively cheap could buffer price shocks transmitted from external markets, causing demand for the expensive product to fall. For instance, the high price of wheat induces substitution behavior between cereal goods such as rice and maize, which may partly prevent volatility conveyances. A potential explanation for the findings might be that very different food preferences exist in different countries. Compared with maize and rice, wheat accounts for a huge amount of domestic demand (e.g., as in Afghanistan, Azerbaijan, Israel, Kyrgyzstan, and Tajikistan)[30]. This phenomenon might cause a lower price elasticity of demand in wheat markets. Therefore, it is reasonable to consider that cultural, religious, or demographic factors may be more formative than the price of food in consumers' food choices.

Table 9 Georgia's import tariff for cereal productions

Year	Import tariff (percent)
2006	6.4
2007	0.3
2008	0.3
2009	0.3
2010	0.3
2011	0.7
2012	0.6
2013	0.7

Notes: Data on the import tariffs are available from the WTO (https://data.wto.org/)

Table 10 Summary statistics for dynamic conditional correlations of wheat

	Mean	Median	Maximum	Minimum	Std. Dev.
Afghanistan	0.119	0.115	0.472	−0.166	0.101
Azerbaijan	0.275	0.246	0.996	0.009	0.150
Brazil	0.359	0.363	0.509	0.132	0.066
Cameroon	0.140	0.155	0.402	−0.239	0.101
Georgia	0.267	0.266	0.394	0.199	0.023
Israel	0.212	0.180	0.766	−0.065	0.136
Kyrgyzstan	0.150	0.147	0.228	0.102	0.022
Mauritania	0.095	0.091	0.136	0.085	0.011
Peru	0.101	0.099	0.194	0.017	0.036
Tajikistan	0.024	0.023	0.195	−0.156	0.055

Conclusion and policy implications

This article explored potential factors of international wheat volatility transmissions using econometric methods such as the CCF, GARCH-DCC and panel data analysis. The primary findings are as follows. First, the analysis found a significant unidirectional Granger causality of wheat price running from international to local markets with approximately five months of lag length as the countries analyzed in this article are small wheat producers that cannot influence international prices. Second, the results show positive dynamic conditional correlations between international and local wheat prices for most wheat-importing countries. It is concluded that the international wheat price considerably affects the local price in wheat-importing countries. Third, it was found that the self-sufficiency rate has a significant negative effect on the dynamic correlation between international and local prices in all panel models. This indicates that a high SSR in wheat helps reduce volatility pass-throughs from the global market. Therefore, by adopting practices that increase the level of its wheat self-sufficiency rate, the government of a wheat-importing country can diminish the impact of unexpected excess volatility from international markets on its local markets. A point that that must made here is that this paper focused on the connectivity between the degree of price spill-overs and self-sufficiency in wheat, not between the extent of price pass-throughs and food policy changes. The panel method estimates coefficients, simultaneously comparing results both between regions and years. All 10 selected countries may not have necessarily altered food policy regimes, such as boosting export taxes, although policy information on the subject was not fully available for these nations during the sample period. Accordingly, the outcomes should not be simply interpreted as showing that any autarky policy assists local market stabilization. Nonetheless, it suggests that such policy measures may be useful for reducing price volatilities in domestic markets. For future research, import tariff or a dummy variable might be used as an explaining variable in the model.

This evidence that increasing the SSR of an agricultural commodity is effective in isolating the domestic market is valuable for policymakers in food importing countries. The primary beneficiaries of implementing the policy measure are risk-averse producers and consumers because their utility or welfare improves as the price volatility of foodstuffs declines. While this paper makes these key interventions, several tasks remain. The Arrow-Pratt coefficient, a measure of risk preference intensity, needs to be estimated to gauge the monetary values of the benefit from stabilized price movements[31]. Another subject that needs to be discussed is the cost to raise the SSR. While the potential cost

Table 11 Specification tests of panel estimation

	Hausman test	Modified Wald test for group-wise heteroskedasticity	Pesaran's test of cross-sectional independence	Wooldridge test for autocorrelation
Statistics	0.120	2536.480***	1.973**	15.096***

Note: (**) and (***) denote statistical significance at the 5% and 1% levels, respectively

Table 12 Estimation results of panel data analysis

	Random effects model	Prais-Winsten regression with PCSEs	FGLS model with heteroskedasticity and autocorrelation
SSR (k_1)	−0.072** (0.035)	−0.059* (0.034)	−0.045*** (0.011)
GDP (k_2)	0.051 (0.069)	0.137 (0.130)	0.118*** (0.022)
CPI (k_3)	−0.104 (0.162)	−0.143* (0.081)	−0.161***(0.039)
Δ*MC* (k_4)	0.004 (0.009)	0.014 (0.019)	−0.001 (0.004)
Δ*RC* (k_5)	−0.004 (0.024)	−0.002 (0.018)	0.013 (0.007)
Constant (*c*)	0.208 (0.038)	0.196*** (0.021)	0.193 (0.007)
R^2	0.03	0.179	-
Wald test	6.53	7.61	59.31***
Observations	80	80	80

Notes: (*), (**), and (***) denote statistical significance at the 10%, 5%, and 1% levels, respectively. The values in parentheses are standard errors and the random effect model is adjusted for 10 clusters

to achieve a targeted SSR may vary across countries, it is likely to be substantial in cases in which farmers are continuously given subsidies to stimulate crop production or raise import tariffs and refuse cheaper foreign products. As Tanaka (2018) suggests, a revenue-neutral approach of increasing tax revenues by raising import tariffs that are then expended as subsidies for agricultural production may increase household welfare and lower its variance without hurting the government's budget. However, evidence on this topic has only been obtained for the Egyptian economy and this is not applicable to all nations or regions. Thus, the cost benefit of the policy has not been fully analyzed and therefore calls for future studies. On the other hand, although Bai and Perron's (2003) structural breaks test is used to identify the structural changes in each price return, the main weakness of the GARCH model is that it assumes that conditional volatility is based on only one regime over the sample period. In light of this, it would be interesting to apply a Markov-switching GARCH[32], which has the advantage of allowing for time-varying causality across regime (structural) changes to estimate volatility. This would enable the present study's findings to be compared with the empirical results derived from different models. However, this exercise must be left for a future research project.

Data availability

The datasets generated and analyzed in this study are available in the Global Informationand Early Warning System repository: http://www.fao.org/giews/en/; and World Development Indicators, accessed at: http://www.worldbank.org/data/. The data that support the findings of this study can be obtained from the corresponding author upon request.

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Notes

1 Bellemare (2014) econometrically proves the relationship between food prices and social unrest, such as food riots.
2 X-13-ARIMA is the U.S. Census Bureau's software package for seasonal adjustment.
3 Dickey and Fuller (1979).
4 Kwiatkowski et al. (1992) and Phillips and Perron (1988).
5 The ADF and KPSS unit root tests indicate that all the variables have unit root processes in their levels. These results were not reported for sake of brevity. The results can be obtained from the authors upon request.
6 See Bai and Perron (2003).
7 http://www.fao.org/faostat/en/#home.
8 David and Amir (2017) use the same method to obtain yearly DCC by taking the average of the monthly DCC.
9 Inflation is the annualized growth rate of the consumer price index (CPI).
10 World Development Indicators are available at: http://www.worldbank.org/data/onlinedatabases/onlinedatabases.html.
11 This empirical technique has been widely applied in the examination of stock and commodity markets (see, for example, Tamakoshi and Hamori, 2014).
12 See Bollerslev (1986) for details on the GARCH model.
13 See, for example, the surveys by Bauwens et al. (2006). GARCH models are useful in studying volatility spill-over in financial markets (e.g., Lin et al., 1994; Koutmos and Booth, 1995; Karolyi and Stulz, 1996; Booth et al., 1997; Cha and Jithendranathan, 2009; Guo, 2014) and energy markets (Ewing et al., 2002; Worthington et al., 2005; Sadorsky, 2006; Malik and Hammoudeh, 2007; Elder and Serletis, 2009; Cifarelli and Paladino, 2010; Basher and Sadorsky, 2016).
14 See Cheung and Ng (1996) for details on a two-step procedure to test for causality.
15 See, for example, Chiang et al. (2007), Savva (2009), Lahrech and Sylwester (2011), Antonakais (2012), Apostolakis and Papadopoulos (2014), Basher and Sadorsky (2016), and Guo (2018).
16 The A-DCC model modified the original DCC model by including asymmetries in the correlation dynamics. See Cappiello et al. (2006) for an extensive analysis of these models' advantages. See Tamakoshi and Hamori (2013) for the estimation procedure of the A-DCC mode.
17 The AG-DCC and G-DCC models account for heteroskedasticity when estimating the correlation coefficients.
18 See Bollerslev and Wooldridge (1992).
19 BFGS (Broyden, Fletcher, Goldfarb and Shanno) is a quasi-Newton optimization method that uses information about the gradient of the function at the current point to calculate where to find a better point. All GARCH computations are carried out using WinRATS 8.1.
20 ADF unit root tests, though not reported here, indicated that all variables in Eq. (16) were stationary.
21 See Maddala and Mount (1973) and Baltagi (1981).
22 For details about the model selection, see the note for Table 5. The results of the lag selection are not reported here for the sake of brevity. The results can be obtained from the authors upon request.
23 As suggested by Hansen and Lunde (2005), it is reasonable to include four combinations of lag length $p, q = 1, 2$ for most GARCH models. They also indicated that models with more lag will not result in more accurate forecasts than more parsimonious models. Moreover, Tamakoshi and Hamori (2014) also applied the same lag selection to estimate the AR-GARCH model.
24 The AR (1)-GARCH (1,1) model was chosen for each price series because it has the lowest BIC value.
25 A significant causality was also detected from lag 1 to lags 10 ($m = 10$) and 15 ($m = 15$); therefore, we chose the shortest lag length.
26 There is also no statistically significant evidence of causality from local price to international price at all lags.
27 One of the major advantages of the CCF approach is that it allows researchers to investigate both causality-in-mean and causality-in-variance (Tamakoshi and Hamori, 2014). The squared standardized residuals are used to test the null hypothesis that there is no causality-in-variance. The results of causality-in-variance tests are reported in Table 6. We find significant unidirectional causality-in-variance form international wheat price to local price in Cameroon and Kyrgyzstan. In contrast, no causality-in-variance exists between international and local prices in the other eight countries.
28 Georgia's self-sufficiency rate of wheat in Fig. 2 exhibits a low level.
29 See Table 4 and Fig. 2.
30 See Table 2.
31 See Fox et al. (1999) for detailed explanations on the Arrow-Pratt coefficient.
32 See Hamilton and Susmel (1994) for details.

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Author contributions

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

Competing interests

The authors declare no competing interests.

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