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What factors contribute to the volatility of food prices? New global evidence

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Abstract: The adverse economic and social effects of the recent increases in food prices have prompted policymakers and academics to reconsider the potential causes of such increases. This paper contributes to the existing literature by investigating the causal effects of oil prices, fertiliser prices, global economic activity, and geopolitical risk on international food price volatility between January 1993 and December 2021. The research considers the aggregate food price index and the prices of various specific foods, including cereal, vegetable oils, dairy, meat, and sugar. The Glosten, Jagannathan, and Runkle-generalised autoregressive conditional heteroskedasticity (1,1) [GJR-GARCH(1,1)] model is employed to estimate the food price volatility series, while the causality-in-quantiles test is conducted to identify the drivers of food price volatility for different volatility regimes. The analysis suggests heterogeneous results regarding the significance of causal linkages. More specifically, the aggregate food price volatility is affected by oil prices, global economic activity, and geopolitical risk under different market conditions. The causality analysis also indicates that the volatility of cereal prices is the most sensitive to the four considered variables. Likewise, geopolitical risk is the most critical factor affecting all food commodities during almost all market conditions, while oil prices and global economic activity have limited predictive power. Finally, there is strong evidence that most causal linkages are confirmed during normal market conditions. Policy recommendations are subsequently derived.

Keywords: causality; food commodity price; Glosten, Jagannathan, and Runkle-generalised autoregressive conditional heteroskedasticity (GJR-GARCH); quantiles

Food price fluctuations have been central to academic and political discussions due to their adverse economic and social repercussions. The economies of both food-exporting and food-importing countries have been impacted by price fluctuations over the past few decades, leading to high inflation rates, decreased welfare for consumers and farmers, food insecurity, and social and political unrest (Gregory and Coleman-Jensen 2013; Bellemare 2014; Soffiantini 2020). According to the State of Food Security

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and Nutrition in the World report recently published by the Food and Agriculture Organization of the United Nations (FAO 2022), the number of people globally affected by hunger has increased by 46 million between 2020 and 2021 to reach 828 million in 2021. The situation has worsened further, and food prices became more volatile in 2022 due to the Russian-Ukrainian conflict (Živkov et al. 2023). The price spikes provoked widespread protests in many countries where the population devote a sizeable portion of their income to acquiring food products (Demarest 2015; Rudolfsen 2021). Rising food prices' economic and social implications, particularly poverty, hunger, and economic imbalances, have prompted academics to investigate the causes of food price fluctuations. In this context, many factors, including climate change, oil price fluctuations, liberalisation of trade and international financial markets, the production of biofuels from food products, and the intensification of global risks, have been proven to exacerbate food price fluctuations (Wheeler and Braun 2013; Zmami and Ben-Salha 2019; Chen et al. 2020; Frimpong et al. 2021; Saâdaoui et al. 2022; Szerb et al. 2022). Two main conclusions may be drawn from the existing empirical literature. First, most related works explored the drivers of food price fluctuations at the national level. The second remark stems from the fact that past research on international food price fluctuations did not typically concentrate at the same time on a variety of factors that contribute to such fluctuations, including energy prices and global risks. Finally, most studies, such as Kalkuhl et al. (2016) and Mokni and Ben-Salha (2020), concentrated on the drivers of aggregate food prices, while others considered specific food commodities. Despite the growing corpus of literature on the topic, few studies have provided a comprehensive understanding of how various factors influence the volatility of different food commodity prices.

This study aims to fill this gap by investigating the key factors affecting the volatility of international food prices during the past decades. The effects of energy, economic, and international risk-related factors on food price volatility are empirically investigated. We are especially keen to analyse whether global economic activity, oil prices, fertiliser prices, and geopolitical risk affect food price volatility. The analysis is conducted for the global food price index and five food products between January 1993 and December 2021. The analysis is based on the Glosten, Jagannathan, and Runkle-generalised autoregressive conditional heteroskedasticity (GJR-GARCH) model to derive the food price volatility series and the causality-in-quantiles technique to identify the drivers of food price volatility. Indeed, with the financialisation of food commodity markets, food prices held similar characteristics with financial assets in which some stylised facts should be accounted for when estimating and forecasting volatilities. In these markets, the volatility is found to be time-varying and clustered. Another characteristic is that negative returns (bad news) and positive returns (good news) have different impacts on the volatility of the market (Black 1976; Christie 1982; French et al. 1987). The literature provided a GARCH family model with a threshold feature to effectively capture volatility asymmetry. Regarding this issue, Brownlees et al. (2011) indicated that the GJR-GARCH model is the best among asymmetric GARCH models in volatility forecasting. Therefore, the GJR-GARCH is used in this study to estimate global and sectoral food price volatility. The GJR-GARCH is found to outperform other GARCH models accounting for asymmetry, including the threshold GARCH (TGARCH) and exponential GARCH (EGARCH) models.

On the other hand, the causality-in-quantiles test procedure is used to explore the determinants of food price volatility since it accounts for different volatility regimes when checking causality. Moreover, the causality-in-quantiles test outperforms the conventional causality tests that check whether the causality occurs, regardless of the volatility regime. However, previous studies show that the interaction between financial variables strongly depends on distributional volatility levels.

The study presents three main novelties. First, whereas most previous studies on food price dynamics have concentrated on factors impacting domestic food prices, the determinants of international food price volatility are examined in this research. Second, this study examines the effects of various factors on the volatility of aggregate food prices and the prices of different food products. More specifically, the empirical analysis is carried out for six food price indices provided by the FAO: global food price index, sugar price index, dairy product price index, vegetable oil price index, cereal price index, and meat price index. Such a disaggregation is important as it allows for providing product-specific conclusions. Third, the empirical investigation is based on the causality-in-quantiles test developed by Balcilar et al. (2017). Indeed, quantile-based techniques allow for avoiding

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the problems related to ordinary least squares (OLS)-based techniques, which are inappropriate in non-normally distributed series. The causality-in-quantiles test allows for assessing the impact of each independent variable (global economic activity, oil prices, fertiliser prices, and geopolitical risk) on the food price volatility for different levels of volatility (low, medium, and high).

Brief literature review. Research on international food inflation has increased in recent decades. Undoubtedly, a spike in international food prices will be transmitted to national food prices (Furceri et al. 2016; Alsamara et al. 2018). Given the importance and extent of the pass-through of international food prices on national prices, several works focused on factors affecting international food price volatility. Pal and Mitra (2017) examined the linkages between crude oil prices and international food prices using wavelets between January 1990 and February 2016. The authors confirmed the role of oil prices in explaining international food price fluctuations. These results have been approved by Raza et al. (2022), who suggested that oil prices (both supply and demand shocks) are the key drivers of food price volatility, including meat, dairy, cereals, and sugar. For their part, Tadesse et al. (2013) analysed the main determinants of international food price volatility and concluded that external shocks substantially affected volatility. Sujithan et al. (2014) showed that financial markets, biofuel production, and economic activity affect the volatility of food products, such as wheat, soya, coffee, cocoa, and sugar. Kirikkaleli and Darbaz (2021) employed the spectral causality test to reveal the presence of two-way causality linkages between energy and food prices. The nonlinear and co-links linkages between energy prices and international food prices were analysed by Chowdhury et al. (2021). According to the nonlinear autoregressive distributed lag model (ARDL), the impact of energy prices on food prices is asymmetric, with positive increases in energy prices having a higher impact on agricultural product prices. The wavelets approach suggested that energy prices in the long run affect wheat and corn prices in the long run. Some other works have recently examined the effects of risk-related factors on food price volatility. For instance, Frimpong et al. (2021) implemented the wavelets approach to check the co-movement between economic policy uncertainty (EPU) and prices of five food products: corn, soybeans, cereals, rice, and wheat, during the period January 1997–December 2019. The analysis suggested that global economic policy uncertainty drives agricultural product prices. Finally, Saâdaoui et al. (2022) indicated the critical role of geopolitical risk as a significant contributor to food price fluctuations.

MATERIAL AND METHODS

Measuring food price volatility. There are essentially two approaches for measuring volatility. The first measure considers historical volatility and is based on dispersion metrics, such as the standard deviation and coefficient of variation. The irregularities characterising price series have raised doubts about the suitability of historical volatility. Moreover, historical volatility estimates do not account for the instability caused by fluctuations in time series. Given these limitations, the financial literature provided an alternative approach based on the conditional volatility proposed by Bollerslev (1986) within the context of the GARCH model and its derivatives. The recent trends in measuring price volatility heavily relied on GARCH-type models.

The present study employs the GJR-GARCH model proposed by Glosten et al. (1993) to estimate conditional volatilities of food prices. Let ip_t be the food price returns. To specify the conditional volatility of food price, we consider the following specification [Equations (1) and (2)]:

$$ip_t = \mu_t + \varepsilon_t, \quad \varepsilon_t = \sigma_t; \quad z_t\varepsilon_t \backslash \Omega_{t-1} \sim St(\nu) \tag{1}$$

$$\sigma_t^2 = w + \alpha\varepsilon_{t-1}^2 + \gamma I_{t-1}\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{2}$$

where: $I_t = \begin{cases} 1 \text{ if } \varepsilon_t < 0 \\ 0 \text{ if } \varepsilon_t \geq 0 \end{cases}$;

ip_t – food price return computed as the log difference of the price indices between two consecutive periods; μ_t – term that follows autoregressive moving average [ARMA(p,q)] process that will be specified based on the Akaike information criteria; p, q – ARMA process orders; ε_t – error term; z_t – standardised error term; Ω_{t-1} – information available until t–1; $St(\nu)$ – student distribution with ν degree of freedom; Equation (1) – mean equation; Equation (2) – variance equation that describes the dynamics of conditional volatility; σ^2 – conditional variance; w – constant of the variance equation; α – ARCH term; γ – asymmetry parameter; I_t – dummy variable; β – GARCH term.

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Causality-in-quantiles testing procedure. To investigate the drivers of food price volatility, we use the causality test introduced by Balcilar et al. (2017). This approach is based on the work of Nishiyama et al. (2011) and Jeong et al. (2012). Food volatility is denoted as y_t while x_t denotes the oil price, fertiliser price, world GDP or geopolitical risk logarithmic changes. According to Jeong et al. (2012), x_t does not cause y_t in the θ-quantile (0 < θ < 1) in reference to the lag-vector $\{y_{t-1}, ..., y_{t-p}, x_{t-1}, ..., x_{t-p}\}$ if [Equation (3)]:

$$Q_\theta\left(y_t|y_{t-1}, \ldots, y_{t-p}, x_{t-1}, \ldots, x_{t-p}\right) = \\ = Q_\theta\left(y_t|y_{t-1}, \ldots, y_{t-p}\right) \tag{3}$$

x_t is supposed to cause y_t in the θ-quantile with respect to $\{y_{t-1}, ..., y_{t-p}, x_{t-1}, ..., x_{t-p}\}$ if [Equation (4)]:

$$Q_\theta\left(y_t|y_{t-1}, \ldots, y_{t-p}, x_{t-1}, \ldots, x_{t-p}\right) \neq \\ \neq Q_\theta\left(y_t|y_{t-1}, \ldots, y_{t-p}\right) \tag{4}$$

where: $Q_\theta(y_t.)$ – the θ^{th} quantile of the y_t.

We consider $Y_{t-1} = (y_{t-1},...,y_{t-p})$, $X_{t-1} = (x_{t-1},...,x_{t-p})$, and $Z_t = (X, Y_t)$. $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t|Y_{t-1})$ is the conditional distribution function of y_t given Z_{t-1} and Y_{t-1}. Furthermore, $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ is supposed to be entirely continuous in y_t for approximately all Z_{t-1}. If we define $Q_\theta\left(Z_{t-1}\right) \equiv Q_\theta\left(y_t\middle|Z_{t-1}\right)$ and $Q_\theta\left(Y_{t-1}\right) \equiv Q_\theta\left(y_t\middle|Y_{t-1}\right)$, we obtain $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$ with a probability of one. Consequently, the causality-in-quantiles hypothesis based on Equations (3) and (4) can be formulated as follows [Equations (5) and (6)]:

$$H_0\text{: } P\left\{F_{y_t|Z_{t-1}}\left\{Q_\theta\left(Y_{t-1}\right)\middle|Z_{t-1}\right\} = \theta\right\} = 1 \tag{5}$$

$$H_1\text{: } P\left\{F_{y_t|Z_{t-1}}\left\{Q_\theta\left(Y_{t-1}\right)\middle|Z_{t-1}\right\} = \theta\right\} < 1 \tag{6}$$

Following Jeong et al. (2012), one can use the distance measure:

$$J = \{\varepsilon_t\, E\, (\varepsilon_t|Z_{t-1}) f_Z(Z_{t-1})\} \tag{7}$$

where: ε_t – residual term; E – expectation operator; $f_Z(Z_{t-1})$ – marginal density function of Z_{t-1}.

According to Jeong et al. (2012), the feasible kernel-based causality-in-quantiles test statistic is as follows [Equation (8)]:

$$\hat{J}_t = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1,\, s\neq t}^{T} K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right)\hat{\varepsilon}_t \tag{8}$$

where: $K(.)$ – kernel function; h – bandwidth in kernel estimation; T – sample size; s – index; p – lag-order; $\hat{\varepsilon}_t$ – regression error, which is expressed as Equation (9):

$$\hat{\varepsilon}_t = 1\left\{y_t \leq \hat{Q}_\theta\left(Y_{t-1}\right)\right\} - \theta \tag{9}$$

where: $\hat{Q}_\theta\left(Y_{t-1}\right)$ – estimate of the θ^{th} conditional quantile of y_t given Y_{t-1}.

Based on the kernel approach, the term $\hat{Q}_\theta\left(Y_{t-1}\right)$ may be written as Equation (10):

$$\hat{Q}_\theta\left(Y_{t-1}\right) = \hat{F}^{-1}_{y_t|Y_{t-1}}\left(\theta Y_{t-1}\right) \tag{10}$$

where: $\hat{F}^{-1}_{y_t|Y_{t-1}}\left(y_t Y_{t-1}\right)$ – Nadarya-Watson kernel estimator written as Equation (11):

$$\hat{F}^{-1}_{y_t|Y_{t-1}}\left(y_t Y_{t-1}\right) = \\ = \frac{\sum_{s=p+1,\, s\neq t}^{T} \boldsymbol{L}\left(\frac{Y_{t-1} - Y_{s-1}}{h}\right) 1\left\{y_s \leq y_t\right\}}{\sum_{s=p+1,\, s\neq t}^{T} \boldsymbol{L}\left(\frac{Y_{t-1} - Y_{s-1}}{h}\right)} \tag{11}$$

where: $L(.)$ – kernel function.

To implement the causality-in-quantiles test, it is necessary to determine the following parameters: the bandwidth h, the kernel type for $K(.)$ and $L(.)$, and the lag order p. A lag order of one for the VAR model involving food volatility and different considered factors is chosen using the SIC selection criteria, while h is selected using the leave-one-out least-squares cross-validation. Gaussian kernels are performed to select $K(.)$ and $L(.)$.

Data. This study explores the effects of world economic activity, oil prices, fertiliser prices, and geopolitical risk on food price volatility between January 1993 and December 2021. The data used in the empirical investigation were extracted from different sources. The dependent variable, food price

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volatility, was computed based on the Food Price Index provided by the FAO. The analysis considers six food price indices: the global price index (FOOD), meat (MEAT), dairy (DAIRY), cereals (CEREALS), vegetable oils (OILS), and sugar (SUGAR). For each food price index, we compute the price return series as Equation (12):

$$R_t = 100 \times \ln\left(\frac{P_t}{P_{t-1}}\right) \quad (12)$$

where: R_t – price return series at month t; P_t – value of the food price index at month t.

Then, the volatility series associated with the different food price indices are computed from the conditional volatility of the GJR-GARCH model. The explanatory variables are also collected from different sources. Oil prices (OIL) and fertiliser prices (FERT) are gathered from the World Bank Commodity Price Dataset. The data on world GDP (GDP) is obtained from Nasdaq. Finally, the geopolitical risk (GPR) data comes from Caldara and Iacoviello (2022). Table 1 summarizes descriptive statistics.

Regarding the explanatory variables, we note that the fertiliser price index has the highest mean, followed by oil prices, the world GDP, and the geopolitical risk index. On the other hand, the highest standard deviation is reported for geopolitical risk, then the oil prices. These two variables are relatively more volatile than fertiliser price and world GDP. Regarding the different series of monthly price volatility estimated using the GJR-GARCH model, we note that their average returns are all positive. Based on the Akaike information criterion (AIC), we retain the ARMA(1,1) for the mean equation and the GJR-GARCH(1,1) for the variance equation. The standard deviations of food price volatilities at the disaggregated level (cereals, oils, sugar, meat, and dairy) are all higher than the standard deviation of the global food price index. Therefore, disaggregated product prices are more volatile than the global food price index. The descriptive statistics also show that cereals, oils, and sugar prices are more volatile than meat and dairy. Another important issue that may arise from the Jarque-Bera statistics is that volatility series are nonnormally distributed, representing an argument on the suitability of the quantile-based techniques to analyse the drivers of food price volatility. In addition, Table 1 provides the Ljung-Box statistics 5 for the levels and squared series. The values strongly reject the null hypothesis of serial dependence, supporting the use of the GARCH-type models to fit the data and estimate the volatility.

Figure 1 depicts the evolution of conditional volatility associated with the different food prices at the aggregate and disaggregate levels.

Table 1. Descriptive statistic

Variables	Mean	SD	Skewness	Kurtosis	J-B	Q(5)	Qs(5)
Explanatory variables							
OIL	0.41	9.17	–1.08	7.69	0.00	34.30***	169.03***
FERT	0.52	6.40	0.49	10.02	0.00	34.71***	13.95**
GDP	0.18	1.96	–17.27	313.67	0.00	38.14***	18.14***
GPR	0.05	22.53	2.31	22.22	0.00	28.62***	0.80
Food price volatility							
FOOD	6.05	3.43	2.77	12.29	0.00	1 186.40***	760.39***
MEAT	7.18	4.25	5.07	35.66	0.00	22.99***	114.25***
DAIRY	10.94	6.22	1.64	6.01	0.00	1 001.21***	369.03***
CEREALS	15.01	10.67	1.97	6.96	0.00	1 219.51***	713.50***
OILS	27.98	12.06	2.12	8.65	0.00	950.77***	504.39***
SUGAR	49.58	15.58	0.74	3.16	0.00	1 063.21***	361.37***

, * rejection of the null hypothesis of no autocorrelation at the 5 and 1% levels, respectively; SD – standard deviation; J-B – P-values of the Jarque-Bera normality test; $Q(5)$ – Ljung-Box test statistics in order 5 for returns; $Qs(5)$ – Ljung-Box test statistics in order 5 for squared returns; FERT – fertiliser price; GPR – geopolitical risk

Source: Authors' own calculation

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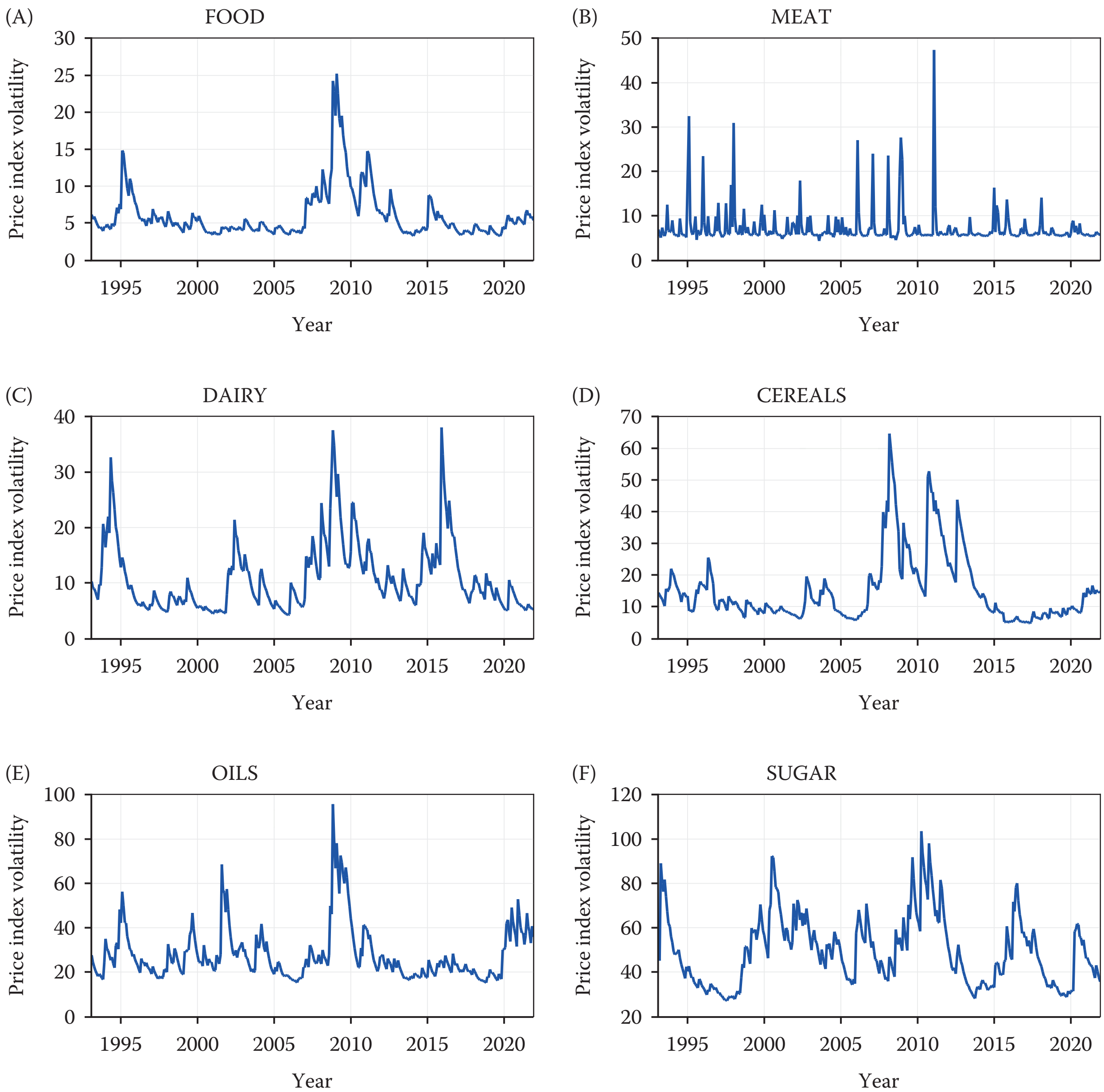

Figure 1. The conditional volatility of the global food price index and different food commodities: (A) FOOD, (B) MEAT, (C) DAIRY, (D) CEREALS, (E) OILS, and (F) SUGAR

Source: Authors' own elaboration

RESULTS AND DISCUSSION

Unit root tests. We used two types of unit root tests to examine the stationary properties. First, we performed the conventional unit root tests, the Augmented Dicky-Fuller (ADF) and Phillips-Perron (PP). As a next step, we implemented Galvao (2009) quantile unit root test. This test has the advantage of assessing the presence of a unit root by considering the various quantiles. The results of conventional unit root tests are reported in Table 2, while Table 3 reports the quantile-based unit root test findings.

The ADF and PP tests reveal that the null of a unit root should be rejected at the 1% level, which confirms that the different variables exhibit a stationary process. The quantile unit root test also confirms these findings, as the null hypothesis is generally rejected for all quantiles and variables. Therefore, it can be confirmed that the explanatory and food price volatility series are stationary.

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Table 2. Conventional unit root tests results

Variables	ADF statistics	PP statistics
FOOD	–3.39***	–3.42**
MEAT	–14.76***	–14.42***
DAIRY	–4.02***	–3.99***
CEREALS	–3.11**	–3.21**
OILS	–3.85***	–4.57***
SUGAR	–4.03***	–3.96***
OIL	–13.26***	–13.77***
FERT	–13.67***	–13.67***
GDP	–5.51***	–59.54***
GPR	–18.37***	–35.06***
Critical values		
1% level	–3.45	
5% level	–2.87	
10% level	–2.57	

, * rejection of the null hypothesis of unit root at the 5% and 1% level, respectively; ADF – Augmented Dickey-Fuller root test; PP –Phillips-Perron unit root test; FERT – fertiliser price; GPR – geopolitical risk

Source: Authors' own calculation

Causality-in-quantiles test results. Results of the causality-in-quantiles test from oil prices, fertiliser prices, world GDP, and geopolitical risk on the food price index volatility and volatilities of the different food price indices (meat, dairy, cereals, vegetable oils, and sugar) are reported in Figures 2–5.

The findings reveal that the causal effects from oil prices on the global food price volatility are observed for lower quantiles (below 0.15) and higher quantiles (above 0.8). Such results indicate that oil prices Granger cause global food price volatility during low and high volatility periods in the food commodity market. In other words, causality from oil prices to food price volatility exists only during extreme low and high volatility in the food markets. Our findings align with Kalkuhl et al. (2016), who concluded the existence of a significant impact of oil prices on aggregate food price volatility using the quantile regression. When considering the different food products, the figure suggests heterogeneous outcomes regarding the significance of causal linkages between the oil and food commodity markets. The quantile causality analysis reveals the existence of causality from oil prices to the volatility of the cereals price index. Specifically, oil prices cause cereal price volatility during normal market conditions. This finding points to the importance of oil as a mandatory input in producing cereal crops. Consequently, oil price changes will be transferred to the cost of producing cereals, which will, in turn, cause swings in cereal prices. However, the originality of our findings is that changes in oil prices will not always be reflected in the volatility of cereal prices but only during normal market conditions. A possible explanation of such findings is that investors are influenced by factors other than oil prices during high volatility in the international cereal market. Furthermore, the quantile causality analysis shows that the relationship between oil prices and the volatility of other food commodity prices, namely meat, dairy, sugar, and vegetable oils, are not affected by oil prices during all food market conditions (low volatility, medium volatility, high volatility). These results partially corroborate those of Nwoko et al. (2016), who concluded that oil prices have no statistically significant causal effects on the price volatility of different food products, including wheat and rice.

Figure 3 summarises the results of the causality-in-quantiles test between the fertiliser price and the different food price volatility series. The fertiliser price does not cause global food price volatility for all market conditions. This result has been previously reached by Ott (2012), who concluded that fertiliser price has no significant impact on the volatility of international food prices. One could note here that the aggregation of food prices in a global food price index may hide the impact of the fertiliser price on the food price volatility.

To deal with this issue, we disaggregate the global food price index into five sub-indices and reconduct

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Table 3. Quantile unit root test results

Quantile	MEAT		DAIRY		CEREALS		OILS		SUGAR		FOOD		OIL		FERT		GDP		GPR	
orders	*t*-stat	CV	*t*-stat	CV	*t*-stat	CV	*t*-stat	CV	*t*-stat	CV	*t*-stat	CV	*t*-stat	CV	*t*-stat	CV	*t*-stat	CV	*t*-stat	CV
0.05	−1.68	−2.60	−2.93	−2.31	−4.00	−2.89	−2.46	−2.62	−4.12	−2.54	−2.23	−2.67	−1.80	−2.31	−2.21	−2.66	−0.10	−2.80	−7.86	−2.31
0.10	−3.91	−2.83	−4.12	−2.63	−6.54	−2.89	−6.07	−2.68	−7.06	−2.79	−6.22	−2.59	−4.30	−2.58	−5.46	−2.83	−0.72	−3.19	−13.13	−2.31
0.15	−6.43	−2.86	−4.98	−2.95	−7.86	−2.93	−7.60	−2.87	−7.91	−2.58	−7.39	−2.88	−5.39	−2.48	−7.97	−2.84	−3.02	−3.09	−18.53	−2.31
0.20	−7.93	−2.84	−5.62	−2.99	−9.29	−2.89	−8.64	−2.85	−11.51	−2.81	−8.45	−2.88	−7.41	−2.58	−9.20	−2.87	−5.64	−3.23	−22.98	−2.31
0.25	−8.55	−2.94	−6.61	−3.08	−10.72	−2.97	−9.99	−2.93	−11.46	−2.94	−9.40	−2.94	−8.31	−2.69	−12.03	−2.90	−8.34	−3.13	−23.70	−2.31
0.30	−10.19	−2.88	−9.76	−3.21	−13.84	−3.03	−12.33	−3.02	−11.28	−2.89	−10.25	−3.01	−7.89	−2.95	−16.02	−2.89	−13.29	−3.11	−23.40	−2.31
0.35	−11.29	−2.81	−10.55	−3.21	−14.17	−3.04	−12.75	−3.14	−10.93	−2.84	−11.45	−3.06	−9.05	−3.09	−15.92	−2.91	−16.52	−3.13	−24.99	−2.31
0.40	−10.92	−2.78	−11.28	−3.19	−13.92	−2.89	−12.03	−3.07	−11.80	−2.91	−11.40	−3.17	−10.79	−3.11	−20.20	−3.00	−18.93	−3.10	−23.49	−2.31
0.45	−12.85	−2.88	−11.72	−3.15	−13.32	−2.95	−11.58	−3.10	−12.44	−2.99	−11.43	−3.26	−12.02	−3.15	−21.28	−3.03	−23.18	−3.10	−21.58	−2.31
0.50	−14.58	−3.03	−13.48	−3.14	−12.17	−2.91	−11.87	−3.14	−12.11	−3.02	−11.46	−3.29	−13.02	−2.93	−20.91	−3.05	−25.05	−3.11	−19.94	−2.31
0.55	−15.76	−3.11	−13.90	−3.24	−12.17	−2.78	−11.96	−3.21	−11.74	−2.98	−12.06	−3.39	−14.90	−2.93	−19.75	−3.07	−22.54	−3.12	−19.16	−2.31
0.60	−15.53	−3.15	−12.35	−3.19	−12.12	−2.78	−10.98	−3.20	−10.52	−3.03	−11.08	−3.34	−17.80	−2.76	−17.95	−3.00	−24.95	−3.11	−19.47	−2.31
0.65	−15.20	−3.06	−11.01	−3.16	−11.99	−2.81	−9.84	−3.14	−11.15	−3.06	−12.04	−3.33	−16.85	−2.76	−16.63	−3.03	−22.58	−3.08	−19.83	−2.48
0.70	−14.75	−3.06	−9.70	−3.18	−10.95	−2.88	−9.41	−3.12	−12.02	−2.99	−11.67	−3.33	−16.09	−2.84	−15.74	−2.97	−21.79	−3.05	−19.92	−2.57
0.75	−13.78	−3.00	−7.98	−3.18	−8.24	−2.85	−9.25	−3.10	−9.67	−3.04	−11.89	−3.25	−16.01	−2.84	−12.79	−3.03	−18.91	−3.00	−20.19	−2.71
0.80	−12.00	−3.04	−6.91	−3.20	−7.85	−2.84	−8.99	−2.97	−9.13	−2.86	−10.44	−3.24	−15.82	−2.84	−11.90	−3.00	−17.07	−2.95	−19.07	−2.66
0.85	−10.36	−2.90	−5.18	−3.02	−5.96	−2.78	−7.92	−2.83	−8.28	−2.77	−8.66	−3.18	−14.01	−2.91	−8.50	−2.86	−20.86	−2.87	−11.33	−2.53
0.90	−9.82	−2.83	−4.25	−2.85	−5.64	−2.90	−6.75	−2.66	−5.29	−2.83	−8.49	−3.01	−12.77	−2.75	−4.39	−2.77	−16.51	−2.83	−7.59	−2.31
0.95	−7.02	−2.33	−2.78	−2.82	−2.31	−2.70	−5.11	−2.63	−4.75	−2.78	−4.30	−2.61	−3.82	−2.46	−1.58	−3.01	−7.57	−2.31	−4.61	−2.31

t-stat – *t*-statistics; CV – critical value; FERT – fertiliser price; GPR – geopolitical risk

Source: Authors' own calculation

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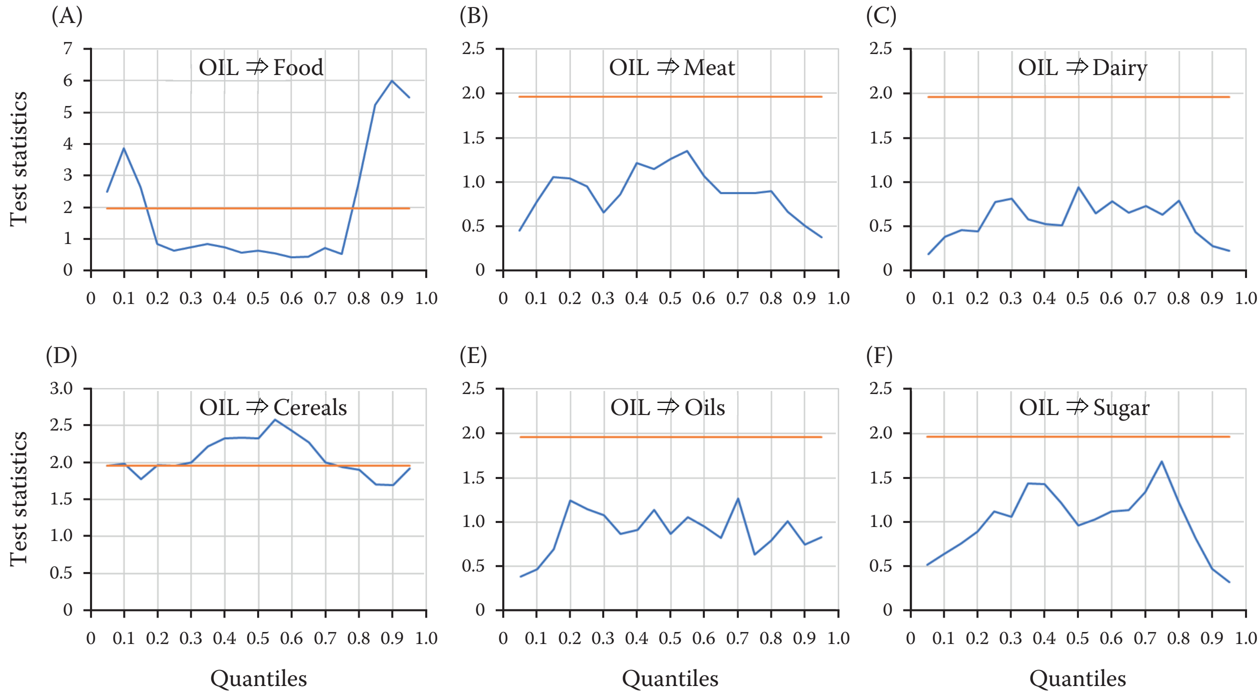

Figure 2. Causality-in-quantiles from oil prices to food price volatility: (A) food, (B) meat, (C) dairy, (D) cereals, (E) oils, and (F) sugar

red line – critical value at the 5% level (critical value = 1.96)
Source: Authors' own elaboration

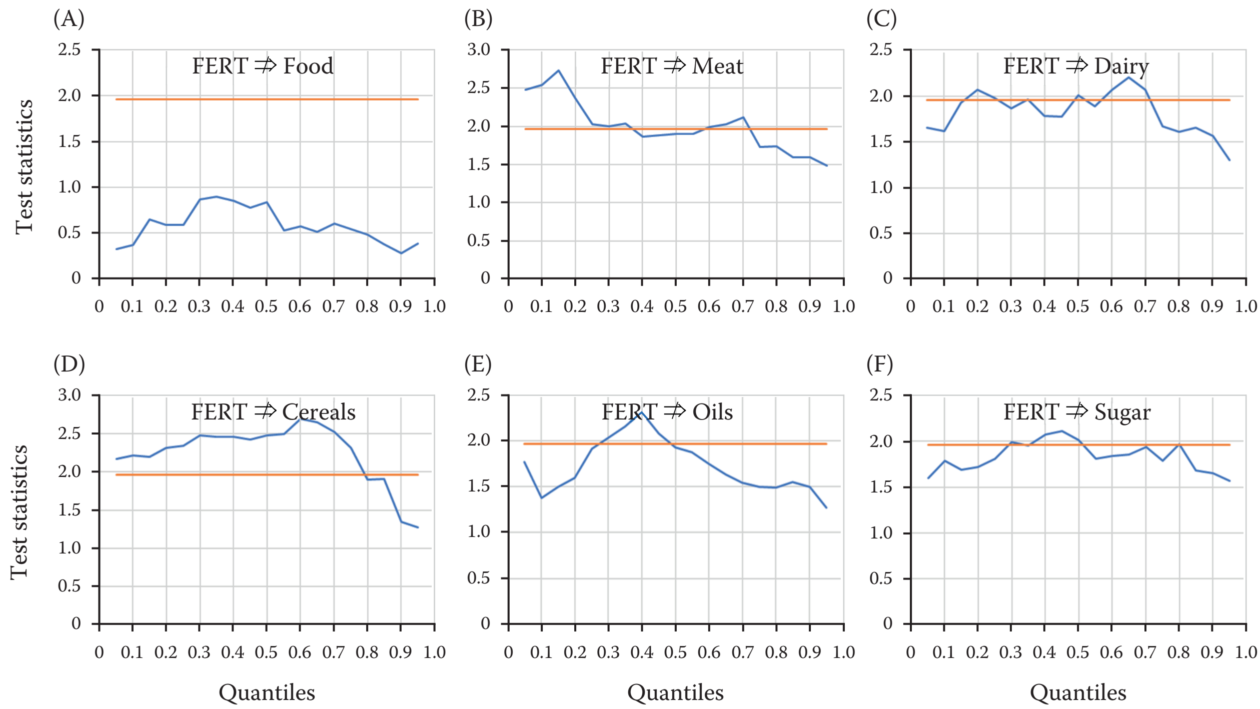

Figure 3. Causality-in-quantiles from fertiliser price to food price volatility: (A) food, (B) meat, (C) dairy, (D) cereals, (E) oils, and (F) sugar

red line – critical value at the 5% level (critical value = 1.96); FERT – fertiliser price
Source: Authors' own elaboration

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the causality-in-quantiles analysis. The figure suggests heterogeneous results regarding the significance of the fertiliser-food causal linkages. The cereal price volatility is the most affected sector by fertiliser price changes. Indeed, the causality-in-quantiles test shows that changes in the international fertiliser price cause cereal price volatility during low and medium volatility in the cereal market. Starting from the quantile 0.8, which corresponds to high price volatility, changes in the fertiliser price will have no significant causal impacts. These results are expected as investors in the cereal market will no longer pay attention to fertiliser price as a driver of cereal price volatility in the presence of high volatility. In this situation, other economic and financial factors may be more important than fertiliser price. Etienne (2016) used data between January 1994 and December 2014, and concluded the significant interconnections between the fertiliser and corn markets. Nonetheless, the researchers noted a relatively poor volatility transmission from the fertiliser to the corn markets from 2006 to 2014, a period marked by considerable volatility in corn prices. The causality-in-quantiles test also indicates similar findings for the sugar and vegetable oils markets. Indeed, the causality from the fertiliser price to the sugar and vegetable oils price volatility is statistically significant for medium quantiles ranging approximately from q = 0.3 to q = 0.5. Therefore, the fertiliser price index significantly causes the volatility of both agricultural commodities only during normal market conditions. On the other hand, the fertiliser price does not allow for predicting the sugar and vegetable oils price volatility in the presence of low/high volatility in the sugar and vegetable oils markets. A close shape is observed when checking the impact of the fertiliser price index on dairy price volatility, as the causality is significant for medium quantiles. Finally, the meat price volatility is affected by fertiliser price volatility only during low price volatility, i.e. the price transmission is confirmed when volatility is relatively low. On the contrary, when volatility exceeds a given level (q = 0.2), fertiliser price changes will not cause meat price volatility. All in all, results show that the fertiliser price index does not cause global food price volatility during all market conditions. However, the causality-in-quantiles test shows heterogeneous findings when considering the different food commodities.

We move to estimate the impact of global economic activity on food price volatility using the causality-in-quantiles test. The findings are reported in Figure 4. The findings suggest that global economic

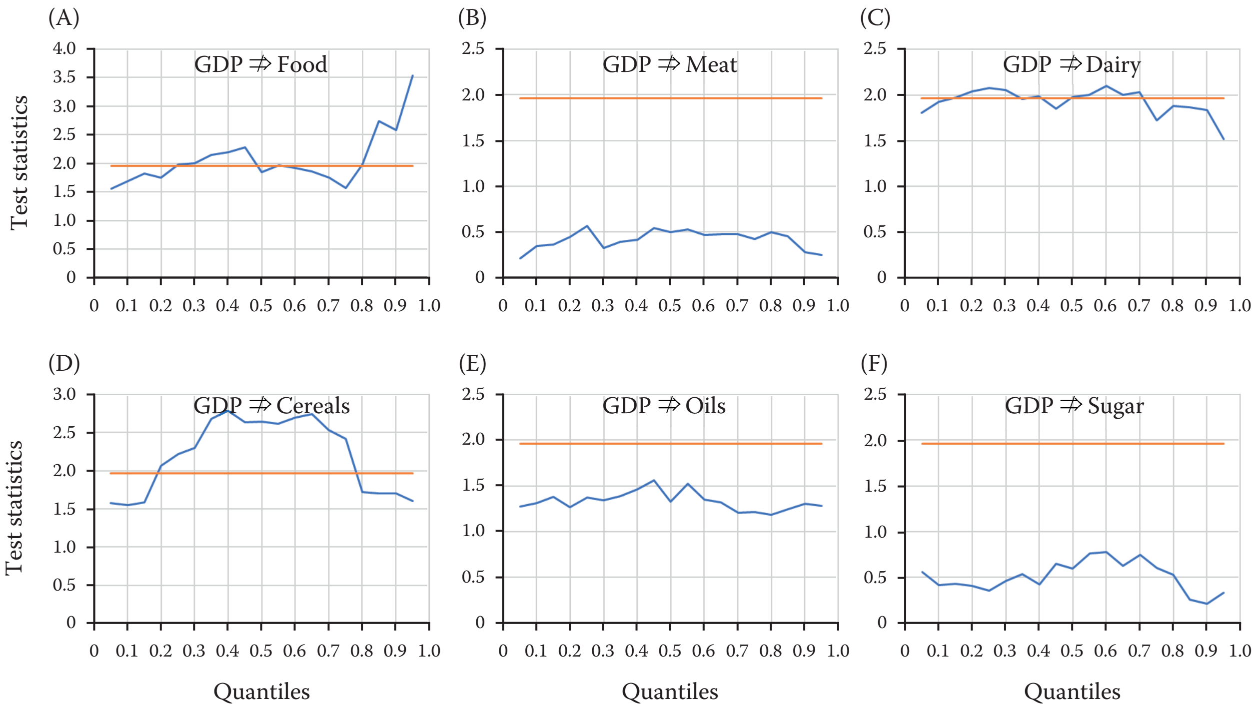

Figure 4. Causality-in-quantiles from world GDP to food price volatility: (A) food, (B) meat, (C) dairy, (D) cereals, (E) oils, and (F) sugar

red line – critical value at the 5% level (critical value = 1.96)
Source: Authors' own elaboration

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activity significantly affects food price volatility during the medium and extremely high volatility in the food commodity market. Such results imply that food price volatility will be sensitive to world GDP changes, mainly when food price volatility is relatively high. One possible explanation is that investors in the food commodity market may pay attention to worldwide demand as a potential driver of food prices when the latter is volatile, in which case investors will be more susceptible to global factors, including world demand. As done previously, we consider the reaction of the various food commodities to global demand. Surprisingly, the findings suggest that for three of the five commodities, namely, meat, sugar, and vegetable oils, there are no statistically significant causal linkages from the global economic activity for all market conditions. Therefore, changes in global economic activity do not affect the fluctuations in meat, sugar, and vegetable oil prices regardless of the market condition.

The figure also shows the presence of weak causality from the world GDP to the dairy price volatility. Indeed, a weak causality is observed during normal market conditions. On the other hand, there is strong evidence of a significant causal impact of world GDP on cereal price volatility for medium quantiles. Therefore, changes in global demand cause volatility in the cereal price only during normal cereal market conditions. These findings are similar to those obtained when we explored the impact of oil prices on cereal price volatility. The cereal price volatility is affected by oil prices and world GDP during normal cereal market conditions. It is worth mentioning that the previous literature confirmed the existence of a closed association between oil prices and global economic activity. He et al. (2010) used monthly data covering the period from January 1988 to December 2007 and concluded the presence of a long-run relationship between crude oil prices and global economic activity as measured by the Kilian economic index. In addition, Dong et al. (2019) revealed a significant short-run association between crude oil prices and global economic activity. The quantile-based analysis conducted in this research suggests that these two factors affect cereal price volatility during normal cereal market conditions. Once volatility is extremely low or high, no predictive power is associated with them.

The final potential driver of food price volatility is geopolitical risk. Figure 5 depicts the causality-in-quantile results at the aggregate and disaggregated levels. Unlike oil prices, fertiliser prices, and global economic

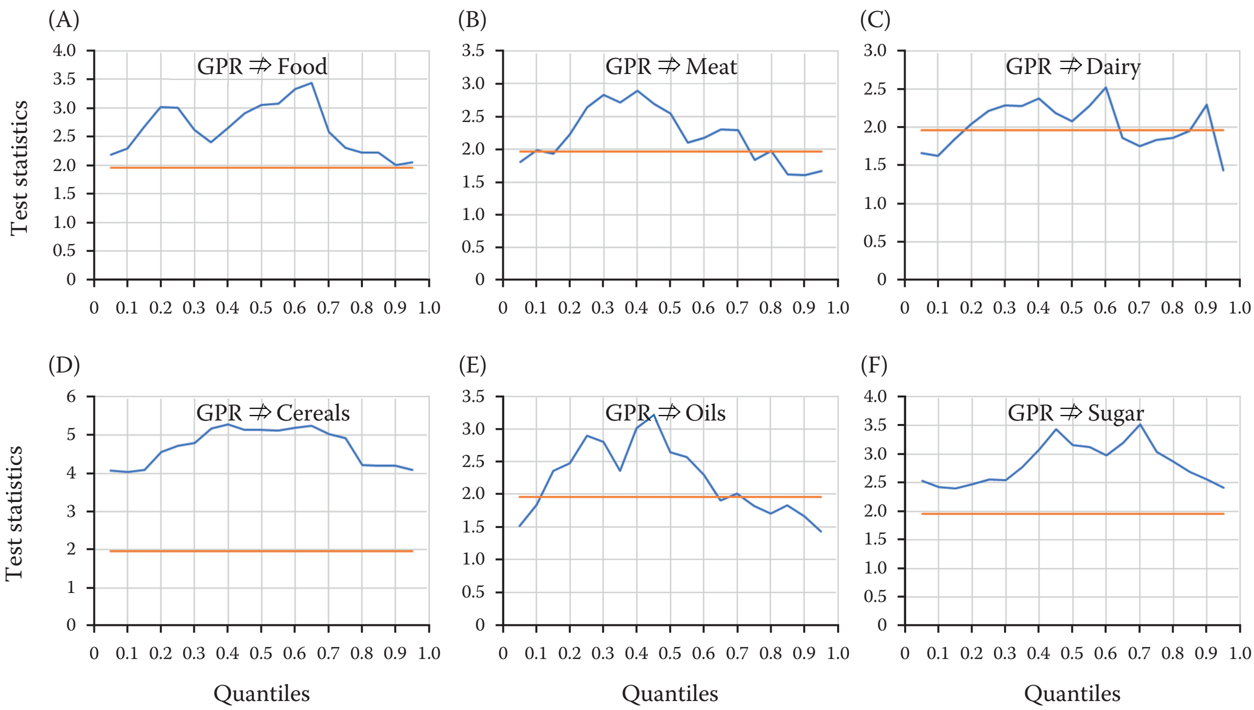

Figure 5. Causality-in-quantiles from geopolitical risk to food price volatility: (A) food, (B) meat, (C) dairy, (D) cereals, (E) oils, and (F) sugar

red line – critical value at the 5% level (critical value = 1.96); GPR – geopolitical risk

Source: Authors' own elaboration

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activity, geopolitical risk is found to cause global food price volatility during all market conditions. These findings align with Saâdaoui et al. (2022), who analysed the effects of the geopolitical risk induced by the Russo-Ukrainian conflict on the food price. The findings revealed the presence of significant causal linkages from geopolitical risk to food price. Moreover, Sohag et al. (2022) concluded that geopolitical risk increased food prices in Western Europe between January 2001 and March 2022.

When moving to the different food commodities, one could note that cereal and sugar price volatilities are caused by geopolitical risk during all market conditions. In other words, regardless of the market condition, cereal and sugar price volatilities will be affected by changes in geopolitical risk. The findings also suggest that the volatilities of meat, dairy, and vegetable oil prices are caused by geopolitical risk during normal market conditions. More specifically, the figure suggests that the significant causal linkages are confirmed for quantiles ranging between q = 0.15–0.20 and q = 0.6–0.7. Therefore, the geopolitical risk does not cause the price volatility of meat, dairy, and vegetable oils during extreme market conditions, particularly during high price volatility in the meat market. Indeed, geopolitical risk will have no significant predictive power during low and high volatility. The critical role of geopolitical risk as a key driver of food price volatility for all commodities during almost all market conditions may be explained by the high-risk volatility during the past decades. Indeed, the descriptive statistics presented in Table 1 indicate that the geopolitical risk index has the highest volatility among all considered factors, with a standard deviation of 22.537, which is 2.5 times higher than the volatility of oil prices, 3.5 times higher than the volatility of fertiliser prices, and 11.5 times higher than the volatility of world GDP.

CONCLUSION

The economic and social consequences of increased food price swings have been the focus of intense debate among policymakers and academics. The present research contributes to this debate by empirically investigating the causal effects of oil prices, fertiliser prices, global economic activity, and geopolitical risk on the volatility of aggregate food prices and food commodity prices, namely cereals, dairy, meat, vegetable oils, and sugar. The empirical investigation is based on monthly data between January 1993 and December 2021. The food price volatility series are calculated using the GJR-GARCH, while the causality-in-quantiles test is performed to explore the causal linkages. The advantage of the used causality test is that it enables the analysis of causality from oil prices, fertiliser prices, global economic activity, and geopolitical risk to the various food price volatility series under different food market conditions (low price volatility, medium price volatility, high price volatility).

The preliminary analysis of the data suggests that volatility series are nonnormally distributed, while the quantile unit root test indicates that all variables are stationary. The causality-in-quantiles test reveals heterogeneous findings regarding the significance of causal linkages. The aggregate food price volatility analysis suggests that the volatility reacts differently to the four considered variables. Indeed, volatility is caused by geopolitical risk during all market conditions, oil prices during low and high volatility, and global economic activity during medium and high volatility in the food market. On the contrary, the fertiliser price has no significant causal impact. Consequently, the findings strongly suggest the critical role of geopolitical risk as a booster of volatility in the food commodity market under all market conditions. While these results provide fresh insights into the determinants of international food price volatility, it only focuses on the aggregate price. As food commodities may have specific characteristics, we conduct the causality-in-quantiles test for the five food commodities. The analysis shows that the four variables affect cereal price volatility most. More specifically, oil prices and global economic activity cause cereal price volatility during periods of low volatility, while the impact of fertiliser prices is significant during low and medium volatility. Finally, geopolitical risk affects cereal price volatility during all market conditions, a conclusion already obtained for the volatility of global food prices. The causality-in-quantiles test also suggests that oil prices have no significant effects on the volatility of other food commodities (meat, dairy, vegetable oils, and sugar) under all market conditions. The same findings are almost reached for global economic activity, which does not exert significant causal effects on meat, vegetable oils, and sugar price volatilities. In contrast, fertiliser price only influences price volatility during periods of low and medium volatilities to a lesser extent. As previously concluded for aggregate and cereal price volatilities, geopolitical risk affects the sugar price volatility under all market conditions, while the meat, dairy, and vegetable oils price volatilities are only affected during normal market conditions. The results indicate the heterogeneity

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of causal effects depending on market conditions and, consequently, the need to account for market conditions by conducting the causality-in-quantiles analysis.

The findings of the present study could potentially inform the development of policy recommendations aimed at promoting food accessibility and upholding global food security. Given that rising food prices significantly contribute to higher overall inflation rates and food insecurity, it is important to design policies to stabilize food prices. At the national level, countries need to implement a number of structural reforms within the agricultural sector to alleviate the escalation of agricultural prices. For example, this could be achieved by protecting agricultural land and promoting investment in the agricultural sector through financial and tax incentives. At the global level, it is imperative for international institutions to implement measures that promote food security by mitigating the adverse effects of food price volatility. Additionally, the United Nations and other international institutions must increase their efforts, intensify dialogue between warring nations, and reach agreements to safeguard international supply and export chains linked to global food transport. For example, the need for more stringent regulation by the World Trade Organisation regarding export restrictions imposed by producing countries is evident. Additionally, the United Nations and other international institutions must increase their efforts, intensify dialogue between warring nations, and reach agreements to safeguard international supply and export chains linked to global food transport.

Although the present research provided some new findings, it still has limitations. The GJR-GARCH model is a parametric estimation method of volatility, which can provide a spurious volatility estimation. Future research could address this issue using the realised volatility measure. Furthermore, the causality-in-quantiles test can be more effective when considering structural breaks. Finally, the scope of the analysis could be broadened to encompass a wide range of food products by considering more disaggregated datasets.

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