https://doi.org/10.17221/197/2020-AGRICECON

Modelling the impact of oil price fluctuations on food price in high and low-income oil exporting countries

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Citation: Chen D., Gummi U.M., Lu S.-B., Mu'azu A. (2020): Modelling the impact of oil price fluctuations on food price in high and low-income oil exporting countries. Agric. Econ. – Czech, 66: 458–468.

Abstract: Oil exporting economies were the most hit by the recent oil price shock that spills on the food market in an increasingly volatile macroeconomic environment. This paper examines and compares sub-samples [before crisis (2000 Q1–2013 Q1) and during crisis (2013 Q2–2019 Q4)] as to the impact of oil price on food prices in high- and low--income oil-exporting countries. We found an inverse relationship between oil and food prices in the long run based on full samples and sub-samples in high-income countries. The story is different during the crisis period: in low-income countries and all the countries combined, oil and food prices co-move in the long run as measured by the Fully Modified Ordinary Least Squares (FMOLS) and Dynamic Ordinary Least Squares (DOLS). Our findings suggest that economic structure and uncertain events (crises) dictate the behaviour and relationship between food and oil markets. Food and oil prices may drift away in the short-run, but market forces turn them toward equilibrium in the long-run. Moreover, low-income countries are indifferent in both periods due to limited capacity to balance the increasing demand for and supply of food items.

Keywords: Dynamic Ordinary Least Squares (DOLS); Fully Modified Ordinary Least Squares (FMOLS); food price; oil price

Oil is an essential source of energy and serves as input for industrial and agricultural production. For oil-exporting countries, oil export is the core mechanism that affects their daily economic activities. The global oil market has witnessed yet another sudden price shock, which started in the second quarter of 2013. The oil price reached a new record low of USD 28 per barrel from an average of USD 100 per barrel in 2012. For oil-exporting countries that rely heavily on oil revenues to finance development, this is a severe threat to their growth and income distribution potentials.

On the contrary, it is an incentive or cost-reducing advantage for oil-importing countries (Chen et al. 2019). However, the revenue shortfall in oil-exporting countries due to a drastic reduction in oil price leads to low income, low investment, low output, and consequently high prices of commodities, especially food items that take away about 30% of households income in these countries. Fluctuations in food prices are of a more significant and more immediate concern than high oil prices because of the uncertainty, distortions, and erosion of purchasing power. Oil price fluctuations affect individual households, and their basic needs indirectly through food inflation. In 2008 when the oil price fell drastically from USD 97 to USD 39, food prices also followed the same trend (correspondingly de-

Supported by Scientific Research Program funded by the Shaanxi Provincial Education Department, Program No. 19JZ051 and by the Scientific Research Program funded by the Institute of Silk Road Studies in Northwest University, Program No. XDSR201701 and by the Nigeria's Petroleum Technology Development Fund (PTDF).

https://doi.org/10.17221/197/2020-AGRICECON

creased), and when the price of oil recovered in 2009, food prices steadily began to rise. To be more precise, oil price co-moved with inflation in general and food price in particular. However, what transcends in the recent oil price shocks deviates from the popular notion of co-movement between oil and food prices as the price index of major food items rises despite the drastic fall in oil price, especially in oil-dependent economies. The trend has drawn policymaker and researcher attention toward effective policies on food security and price stability at both global and regional levels (Zmami and Ben-Salha 2019). Recent data from the Food Security Information Network suggest that 124 million people across 51 countries suffered from food crises in 2017 alone. Indeed, food price instability witnessed during the 2000s exerts a substantial impact on socio-economic well-being by affecting the producer income, consumer purchasing power, and government revenue and expenditure framework. Over the last decades, communities worldwide have faced many challenges regarding food security, though the most pressing among them is the surge in prices (FAO 2016).

Empirical debates on the link between oil price and food price strengthened in 2006 (Aleksandrova 2016), with several studies concluding that higher and unstable food prices would substantially hurt the poor because food usually took a large share of their expenditure (Alghalith 2010; Gilbert and Morgan 2010; Nazlioglu et al. 2013; Minot 2014; Abdlaziz et al. 2016; Tiwari et al. 2018). Other studies (Chang and Su 2010; Alom et al. 2013; Ibrahim 2015; Kalkuhl et al. 2016; Wong and Shamsudin 2017) focus on the price volatility in individual food items. Findings of these studies were inconsistent even for individual commodities, and the transmission mechanisms varied with time. However, in recent years, the rising food price has raised the question of whether the oil market has any explanatory power on the recent food price hikes. Thus, the food-energy nexus has become a controversial issue, though some researchers suggest that oil price fluctuation is the main factor behind the historic shock in agricultural market (Abbott et al. 2008, 2009; Yang et al. 2008; Fowowe 2016), yet to others there is no direct link between oil price and agricultural commodity price (Zhang et al. 2010; Lagi etal. 2015). Nevertheless, Zmami and Ben-Salha (2019) opined that food price fluctuations could have a disturbing impact on adequate purchasing power even if they do not directly affect nominal income per se. Accordingly, recent studies suggest that the energy price is the critical factor that explains the dynamics of agricultural commodity prices worldwide (Pal and Mitra 2017; Salisu et al. 2017; Pal and Mitra 2018).

Moreover, oil-exporting countries are still struggling with the recent surge in oil prices that spills on the food market. What differentiates the current state of food price variability in these countries is the hike in prices of few selected crops and nearly all primary food and feed commodities (FAO 2016) despite the drastic fall in oil prices in the international market. Such price movements affect agricultural productivity and tend to intensify inflationary pressures. It further raised the uncertainty faced by households, farmers, and agribusiness firms. Specifically, the food price index of some oil-exporting countries like Nigeria, Venezuela, Iraq, and Algeria remained high in 2013–2019 due to supply shocks and their reliance on oil revenues from the global market. Although very few researches have focused exclusively on oil-exporting countries, Olayungbo and Hassan (2016) found a long-run positive relationship between food price and oil price in 21 developing oil-exporting countries. Cointegration between price series may diverge in the short-run, but may quickly converge towards equilibrium in the long-run (Barrett and Li 2002; Zhang et al. 2010). Also, prices may drift apart both in the short-run and long-run phenomena due to policy changes, economic structure, and uncertain economic events, but market forces may bring them together in the long run. Recent data on oil-exporting countries' food price index refuted the popular notion of co-movement between oil and food prices in these countries, and the indices vary significantly among them, thus the need to uncover new theoretical and empirical evidence on the dynamic impact of oil price on food price in oil-exporting countries by a dis-aggregate approach.

From this perspective, the pressing questions are: how does food price react to oil price fluctuations in oil-exporting countries, specifically when the oil market is booming and when it is bedevilled by price shock? How does the reaction differ from high-income and low-income oil-exporting countries? The current approach extends the discourse on an Organization of Petroleum Exporting Countries (OPEC) panel concerning 2000 Q1–2019 Q4 based on the available data. OPEC serves as a potential laboratory to revisit the long-established debate on the food price-oil price nexus because the countries share some unique characteristics (heavy reliance on oil, high import bills on food items, and sustained food price hikes in recent years). They also produce more than 40% of oil on the global mar-

https://doi.org/10.17221/197/2020-AGRICECON

ket, making them a key market hub globally. The period is divided into stable oil prices (before the recent price shock (2000 Q1–2013 Q1) and during the crisis (2013 Q2–2019 Q4) to isolate the impact of oil price on food prices in high-income and low-income countries. The idea is to account for the effect of economic structure and price shocks that bedeviled the global oil market starting in 2013 Q2, which saw a drastic drop in the oil price to a new record low of USD 28 per barrel. We further employed Fully Modified OLS (FMOLS) by Pedroni (2004) and Dynamic OLS (DOLS) formulated by Stock and Watson (1993) to examine the long-term dynamics and compare the reliability of our findings. Finally, we tested for short-term dynamics and direction of causality on full samples using the Panel Granger Causality Test (PGT).

Moreover, the study provides new insights in both theory and practice. Theoretically, the study successfully refuted the popular notion of co-movement between food price and oil price using a dis-aggregate approach to isolate the recent oil market crises (drastic surge in oil price). Our main argument is that the relationship of oil price fluctuations with and impact on food prices is influenced by economic structure and uncertain economic events (crises or stability in the oil market). So, given the supply and demand conditions in the food market, oil price does not always positively impact food prices in oil-exporting countries, especially the high-income countries. The study practically utilized short-term and long-term dynamic models to deeply understand the relationship and behaviour of food and oil prices and compare the empirical findings. It is pertinent for effective policy on food security and price stability because much is known in isolation (different regimes) than when the whole sample is examined at a point in time. The study highlights appropriate measures to relieve the consumers from hardship and misery associated with higher food prices or shortage of food items. Accordingly, the paper is organized into four sections, including this introduction. Section two presents the methods used in the paper to achieve its objectives; section three deals with the results and discussion of findings, while section four presents conclusions and recommendations based on the implications of our findings.

METHODS

The study used an aggregate analysis on OPEC based on available data for the sampled period (2000 Q1 to 2019 Q4) (Table 1). The period is divided into pre-crises (2000 Q1–2013 Q1) and crises (2013 Q2–2019 Q4) periods. The former represents the period of a sustained increase in oil prices with a limited number of short-term fluctuations and recovery, which serve as an incentive for the oil-exporting countries. In contrast, the latter period represents the recent and sustained price shock in the global market, which started

Table 1. OPEC member states-low and high-income countries

No.	County	Region	Oil output (mb/d)*	Reserve (mb/d)	GDP (billion USD)	PPP (thousand USD)	Countries' income status
1	Algeria	Africa	1.30	12 200	207.96	6 669.58	low
2	Angola	Africa	1.70	8 423	114.20	5 979.46	low
3	Ecuador	Americas	0.55	8 273	79.80	5 917.02	low
4	Equatorial Guinea	Africa	0.23	1 100	10.21	12 399.23	high
5	Gabon	Africa	0.21	2 000	14.00	7 453.06	low
6	Iran	Middle East	3.90	157 530	514.06	11 665.58	low
7	Iraq	Middle East	4.45	143 063	210.28	3 716.22	low
8	Kuwait	Middle East	2.92	101 500	160.91	52 721.96	high
9	Libya	Africa	0.38	48 363	62.36	14 009.44	high
10	Nigeria	Africa	1.90	37 070	262.61	2 344.26	low
11	Qatar	Middle East	1.50	25 244	171.48	72 027.98	high
12	Saudi Arabia	Middle East	10.41	266 578	711.05	22 939.18	high
13	UAE	Middle East	3.10	97 800	348.59	24 176.98	high
14	Venezuela	America	2.30	299 953	381.29	12 846.07	high

*Data is for a daily average of October 2017; PPP – per capita income

Source: Modified data from World Development Indicators – WDI (2018)

https://doi.org/10.17221/197/2020-AGRICECON

in the second quarter of 2013 and hit the economic hub of these countries hard, limiting their development due to revenue shortfalls. A disaggregated analysis is then used to classify the countries into two groups based on per capita income: Purchasing Power Parity ratings of greater or equal to USD 2 000 (high-income countries) and less than USD 12 000 (low-income countries) based on the United Nations estimates (Table 1). For this reason, a balanced panel of quarterly data set was obtained from International Monetary Fund – IMF (2020) and the Food and Agricultural Organization – FAO (2020) data portals. The choice of the period is dictated by recent price shocks bedevilling the oil market, and by availability of data across the units of analysis and recorded food price hikes and food crises during the period.

We pooled cross-section and time-series data to examine the relationship between food price (dependent variable) and independent variables: oil price, exchange rate, and GDP per capita growth rate (demand shock). As such, the following Equation (1) is stated following Kargbo (2005) and Tadesse et al. (2016):

$$FP = f(OILP, EXCR, GRGDP) \tag{1}$$

where: FP – the food price; $OILP$ – the crude oil price, $EXCR$ – the real exchange rate; $GRGDP$ – the GDP per capita growth rate.

The currency exchange rate represents the supply side of the food equation. It determines the food trade-balance of a country and affects food supply/production through imports (Harri et al. 2009; Nazlioglu and Soytas 2011; Nazlioglu et al. 2013). GDP per capita represents the demand condition in an economy. Changes in GDP per capita level affect the demand side of the food equation and food items (Ibrahim 2015; Tadesse et al. 2016). Accordingly, the variables justify the ability to influence both demand for and supply of food items. The empirical model for Equation (1) is given by Equation (2):

$$FP_{it} = \beta_0 + \beta_1 OILP_{it} + \beta_2 EXCR_{it} + \beta_3 GRGDP_{it} + \varepsilon_{it} \tag{2}$$

where: FP, $OILP$, $EXCR$, $GRGDP$ – defined in Equation (1); β_0 – a constant term; β_1 to β_4 – estimated coefficients in the model; i – a cross-section data for countries referred to; t – a time-series data; ε_{it} – the disturbance (error) term.

The empirical analysis begins with unit root testing before the long-term and short-term estimations follow. Im et al. (2003) developed panel-based unit root tests similar to tests carried out on a single series. The Im et al. (2003) tests employ a null hypothesis of a unit root using the following basic Augmented Dickey-Fuller (ADF) specification:

$$\Delta y_{it} = \alpha y_{it} - 1 + \Sigma\beta_{it}\Delta y_{it} - j + X_{it}\delta + \nu_{it} \tag{3}$$

where: y_{it} – the pooled variable; X_{it} – exogenous variables in the model, such as country fixed effects and individual time trends; ν_{it} – the error terms assumed to be mutually independent disturbances. It assumes that $\alpha = \rho - 1$ is identical across the cross-sections in our model, but the lag order for the different terms across the countries is allowed to vary.

The study utilized the technique proposed by Pedroni (2004) to determine cointegration among the modelled variables. It employs four panel statistics and three group-panel statistics to test the null hypothesis of no cointegration against cointegration's alternative hypothesis. Pedroni (2004) points out the appropriateness of the test in estimating residuals from cointegration regression after normalizing the panel statistics with correction terms. Pedronis' procedures make use of estimated residual from the hypothesized long-run regression of the following form:

$$y_{i,t} = \alpha_i + \delta_i t + \beta_{1i} x_{1i,t} + \beta_{2i} x_{2i,t} + \ldots + \beta_{Mi} x_{Mi,t} + e_{i,t}; \quad \text{for } t = 1,\ldots,T;\ i = 1,\ldots,N;\ m = 1,\ldots,M \tag{4}$$

where: T – the number of observations over time; N – number of cross-sectional units in the panel; M – number of regressors. This setup α_i represents the member-specific intercept or fixed-effects parameter, which varies across individual cross-sectional units. The same is true for the slope coefficients and member-specific time effects $\delta_i t$. Under the alternative hypothesis; Panel ν statistics diverges to positive infinity. Therefore, it is a one-sided test where large positive values reject the null hypothesis of no cointegration. The remaining statistics diverge to negative infinity, which means that large negative values reject the null.

However, asymptotically efficient and consistent estimates in panel series, non-exogeneity, and serial correlation problems are tackled by employing Fully Modified OLS (FMOLS) developed by Pedroni (1999). If the explanatory variables are cointegrated with a time trend, and thus a long-run equilibrium relationship exists among these variables. We proceed to estimate Equation (2) by the method for heterogeneous cointegrated panels through the panel unit root

https://doi.org/10.17221/197/2020-AGRICECON

test and panel cointegration test. The method allows for consistent and efficient estimation of the cointegration vector and addresses the problem of non-stationary regressors and the problem of simultaneity biases. It is well known that OLS estimation yields biased results, mainly if the regressors are endogenously determined in the I (1) case. The OLS formulation is based on the following cointegrated system for balanced panel data:

$$\begin{aligned} y_{it} &= \alpha_i + x'_{it}\beta + e_{it} \\ x_{it} &= x_{i,t1} + \varepsilon_{it} \end{aligned} \tag{5}$$

where: $\xi_{it} = [e_{it}, \varepsilon'_{it}]$ – the stationary with the covariance matrix Ω_i. The estimator β will be consistent when the error process $\omega_{it} + [e_{it}, \varepsilon'_{it}]'$ satisfies the assumption of cointegration between y_{it} and x_{it}.

The limiting distribution of the OLS estimator depends upon nuisance parameters. Following Phillips and Hansen (1990), a semi-parametric correction can be made to the OLS estimator that eliminates the second-order bias caused by the fact that the regressors are endogenous. Pedroni (1999, 2001) follows the same principle in the panel data context and allows for heterogeneity in short-run dynamics and fixed effects. FMOLS Pedroni's estimator is constructed as follows:

$$\begin{aligned} \hat{\beta}_{FM}\,\beta &= [\sum_{i=1}^{N} \hat{\Omega}_{22i}^{2} \sum_{t=1}^{T} (x_{it}\,\bar{x}_t)^2]^{-1} \times \\ &\times \sum_{i=1}^{N} \hat{\Omega}_{11i}^{1}\, \hat{\Omega}_{22i}^{1} [\sum_{t=1}^{T} (x_{it}\,\bar{x}_t)\hat{e}_{it} - T\hat{\gamma}_i] \\ \hat{e}_{it} &= e_{it} - \frac{\hat{\Omega}_{21i}^{1}}{\hat{\Omega}_{22i}^{1}} \Delta x_{it}; \\ \hat{\gamma}_i &= \hat{\Gamma}_{21i} + \hat{\Omega}_{21i}^{0} - \frac{\hat{\Omega}_{21i}^{1}}{\hat{\Omega}_{22i}^{1}} (\hat{\Gamma}_{22i} + \hat{\Omega}_{22i}^{0}) \end{aligned} \tag{6}$$

where: the covariance matrix can be decomposed as $\Omega_i = \Omega_i + \Gamma_i + \Gamma_i$. The Ω_i^0 is the contemporaneous covariance matrix; T_i – a weighted sum of auto-covariances. Also, Ω_i^0 denotes an appropriate estimator of Ω_i^0.

The test statistics constructed from the panel group estimators are designed to test the null hypothesis $H_0: \beta_i = \beta_0$ for all i against the alternative hypothesis $H_A: \beta_i \neq \beta_0$ so that the values for are not constrained to be the same under the alternative hypothesis.

Moreover, the panel Dynamic OLS (DOLS) proposed by Stock and Watson (1993) for estimating long-run equilibria proved useful even with small samples. It is applied to a system with variables integrated of different orders but still co-integrated. The potential simultaneity and small sample biases among the regressors are dealt with by including lagged and led values of the regressors. The formulation in Stock and Watson (1993), as later employed by prominent studies (Masih and Masih 1996; Aydemir and Demirhan 2017), is specified as follows:

$$Y_i = X\beta + Y^*\eta^* + \sum_{j=-\rho}^{\rho} \Delta Y^*_{-j}\gamma_j + vt \tag{7}$$

where: Y_i – the response variable for the cross-sections; X – the vector of independent variables η^* is the co-integrating vector; the DOLS estimator η^* is consistent, asymptotically normally distributed, and efficient. If $(y_{1,t}, y_{2,t}, ..., y_{m,t})$ are cointegrated, the proper equilibrium error process v_t must be I (0). If they are not cointegrated, then v_t must be I (1). It tests the null hypothesis of no cointegration against the alternative of cointegration by performing a unit root test on the equilibrium error process v.

The study also employed the standard Panel Granger Causality Test (PGCT) based on Granger (1969). It shows the direction of causality between food price, oil price, exchange rate, and GDP growth rate. PGCT will be conducted based on the following models:

$$\begin{aligned} \Delta FP_t = \beta_0 &+ \sum_{t=1}^{n} \beta_1 \Delta FP_{t-1} + \sum_{t=1}^{n} \beta_2 \Delta OP_{t-1} + \\ &+ \sum_{t=1}^{n} \beta_3 \Delta EXCR_{t-1} + \sum_{t=1}^{n} \beta_4 \Delta GDPGR_{t-1} + \mu_t \end{aligned} \tag{8}$$

$$\begin{aligned} \Delta OP_t = \alpha_0 &+ \sum_{t=1}^{n} \alpha_1 \Delta OP_{t-1} + \sum_{t=1}^{n} \alpha_2 \Delta FP_{t-1} + \\ &+ \sum_{t=1}^{n} \alpha_3 \Delta EXCR_{t-1} + \sum_{t=1}^{n} \alpha_4 \Delta GDPGR_{t-1} + \mu_t \end{aligned} \tag{9}$$

where: FP and OP – two stationary variables in Equations (8) and (9) observed in N cross-sections and T periods. For each individual i = 1, ..., N at time t = 1, ...,T, n represents the lag orders, which are assumed to be identical for the panels; μ_t – the error term; β_0–β_4 and α_0–α_4 – the coefficients of the variables.

Causality is determined by testing the null hypotheses that:

$$\sum_{t=1}^{n} \beta_2 = 0 \text{ and } \sum_{t=1}^{n} \alpha_2 = 0$$

against the alternative hypotheses:

$$\sum_{t=1}^{n} \beta_2 \neq 0 \text{ and } \sum_{t=1}^{n} \alpha_2 \neq 0.$$

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RESULTS AND DISCUSSION

In Table 2, descriptive statistics of the included series for all the countries (ALLC) is presented. The average quarterly oil price (OP) is USD 81.95, while the quarterly average food price index is 163.04. The skewness of the symmetric series is 0. Food price and exchange rates are positively skewed, while oil prices and GDP growth rates are negatively skewed. Kurtosis measures the peakedness or flatness of the distribution of series. For a normal distribution, the value is 3. The estimated kurtosis values exceed the average distribution value for all the variables. It is further proved by the significant *P*-values of Jarque-Bera statistics of all the series.

Results of the unit root tests show that all the series are not stationary at I (0) level but stationary at the first difference I (1) in ALLC, low-income countries (LIC), and high-income countries (HIC). Table 3 indicates that all the series are integrated of the same order i.e. stationary at the first difference I (1), which satisfies the condition for measuring long-run equilibrium relationship among the variables (Pedroni 2004).

The results of the Pedroni panel cointegration test are presented in Table 4. The test is conducted using both constants and trends. It was found that for ALLC, 6 out of 7 statistics rejected the null hypothesis of no cointegration. However, 5 out of 7 statistics reject the null hypothesis for LIC and HIC at 1% and 5% significance levels. The result confirms the existence of a long-run equilibrium relationship among the variables.

In both the FMOLS and DOLS models, we found a more-than-proportional and significantly positive long-run impact of oil price on food price for the whole sample in ALLC and LIC, but in HIC, oil price is inversely related to food price in the same period (Table 5).

Table 2. Descriptive statistics of the variables

Measures	*FP*	*OILP*	*EXCR*	*GDPGR*
Mean	163.04	81.95	816.78	4.21
Median	157.24	86.21	902.35	5.14
Maximum	312.46	143.21	46 738.01	23.15
Minimum	73.58	22.31	0.72	–103.18
Std. dev.	55.75	26.73	17 614.98	12.83
Skewness	3.61	–1.89	5.09	–3.47
Kurtosis	5.02	6.37	7.48	18.49
Jarque-Bera	23.60	34.09	316.93	2 106.72
Probability	0.0008	0.0021	0.0029	0.0000
Expected sign	+/–	+/–	–	+
Observations	1 064	1 064	1 064	1 064

FP – food price; *OILP* – oil price; *EXCR* – exchange rate (USD rate in domestic currencies); *GDPGR* – growth rate of per capita gross domestic product; + positive; – negative

Source: Authors' computation using E-views (version 9) based on Food and Agricultural Organization (2020) and International Monetary Fund (2020) data

Table 3. Results of the IPS panel unit root test

Group	*FP*		*OILP*		*EXCR*		*GRGDP*	
	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)
ALLC	0.3254	11.6134**	0.6749	7.9236**	2.7412	16.0761**	0.2807	5.7360*
LIC	2.7113	9.1913*	1.0185	10.3012*	1.3384	22.6113**	0.7583	9.0361**
HIC	0.7526	16.4219**	1.6204	14.7128*	2.0628	8.5134*	1.6145	4.8864*

*, **Rejection of the null hypothesis at 5% and 1% significance levels, respectively (95% and 99% confidence intervals); *FP* – the food price; *OILP* – the oil price; *EXCR* – the exchange rate (USD rate in domestic currencies); *GDPGR* – the growth rate of per capita gross domestic product; ALLC – all countries; LIC – low-income countries; HIC – high-income countries;

Source: Authors' computation using E-views software (version 9) based on the Food and Agricultural Organization (2020) and the International Monetary Fund (2020) data

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Table 4. Results of cointegration test

Group		Statistics	Constant + trend values
ALLC	panel	v-statistic	−3.2573*
		rho-statistic	−7.1350*
		PP-statistic	−8.0192*
		ADF-statistic	−11.2928**
	group	rho-statistic	−2.1482
		PP-statistic	−9.4611**
		ADF-statistic	−12.7504**
LIC	panel	v-statistic	6.3967**
		rho-statistic	−8.5180*
		PP-statistic	−9.6364**
		ADF-statistic	−9.0162*
	group	rho-statistic	−0.6873
		PP-statistic	−4.1856*
		ADF-statistic	−7.4619**
HIC	panel	v-statistic	8.4972*
		rho-statistic	−3.3192*
		PP-statistic	−6.0840**
		ADF-statistic	−6.8621**
	group	rho-statistic	0.3965
		PP-statistic	−5.4682*
		ADF-statistic	−9.3677**

*, **Rejection of the null hypothesis of no co-integration at the 5% and 1% levels, respectively; ALLC – all countries; LIC – low-income countries; HIC – high-income countries; ADF – Augmented Dickey-Fuller; PP – Panel P–statistic; all statistics are from Pedroni's (1999) procedure, where the adjusted values can be compared to the N (0, 1) distribution. Pedroni (2004) statistics are a sided test with a critical value of −1.64 ($K < 1.64$ implies the rejection of the null hypothesis)

Source: Authors' computation using E-views software (version 9) based on the Food and Agricultural Organization (2020) and International Monetary Fund (2020) data

In sub-samples, the story is different because, before the recent surge in the oil market, oil price has a positive impact on food prices, except in HIC. A significant co-movement between food price and oil price was recorded for ALLC, HIC, and LIC in the crisis periods. For the whole sample, the findings are in tandem with those of Olayungbo and Hassan (2016) and Tadesse et al. (2016), who found long-run convergence between food and oil prices. The findings are significant during the crisis and reflect the current trend in the food and oil markets. Accordingly, the proportional change in oil price is less than the proportional change in food price for the whole sample and sub-samples except for LIC in the FMOLS results. It is worth noting that before the sudden price shock in the global oil market, oil-exporting countries maximized their revenues from sales of crude oil, and part of that revenues may be channelled to investment, production, and imports of food items, which may increase the supply of food items and stabilize their price indices. So, for oil-exporting countries, stable oil price means stable revenue, stable supply of food, and a stable food price (Pieters and Swinnen 2016). When the oil market is in crisis, oil-exporting countries fall short of revenue inflow, especially LIC; most of the sampled countries have faced economic surges due to dwindling oil rents since 2014, leading to low income, output, investment, and high prices of commodities, especially food.

Nevertheless, even before the crisis, LIC recorded a significant positive impact of oil prices on food prices. The trend is attributed to limited capacity in agricultural production in these countries and demand and supply gaps in the food market (Alghalith 2010; Gilbert 2010). On average, the food price index remains relatively high for these countries in the long run.

EXCR coefficients are significant and negatively related to FP in ALLC, HIC, and LIC for all the sample periods, except for LIC the story was different before the crisis as the exchange rate positively impacted food price in the FMOLS model (Table 5). The results indicate that a 1 % appreciation of domestic currency with respect to US dollar leads to less than a proportional increase in LIC food price for all the sample periods. As domestic currency appreciates (depreciation of US dollar), the implication is that the purchasing power and demand for commodities increases, food items inclusive, *ceteris paribus*. In the DOLS model, the long-run impact of EXCR on FP is positive for LIC in both the whole sample and the sub-samples. However, an inverse relationship was found in ALLC during the crisis period. Currency appreciation or depreciation affects price dynamics and inflation levels through supply channels (Nazlioglu et al. 2013; Salisu et al. 2017). In LIC, currency depreciation suggests a supply shortage of primary commodities through imports, so the inability of food supply to meet up the rising demand for food leads to price hikes, affecting household welfare and food security drive in these countries.

For ALLC, the coefficients of GRGDP (demand shock) exert a positive and significant impact on food prices for both the whole sample and the sub-sample periods (Table 5). It means that demand conditions (changes in the level of income) and food prices move

https://doi.org/10.17221/197/2020-AGRICECON

Table 5. Results of the FMOLS and DOLS regressions; dependent variable: food price (*FP*)

Groups	*OILP*	*EXCR*	*GRGDP*
FMOLS regression			
Full sample (FS)			
LIC	0.6273*** (4.6231)	−6.834E-05 (−0.8747)	0.5715*** (4.3862)
HIC	−2.0372* (−1.7825)	−1.3065** (1.9651)	−1.9302 (−0.2615)
ALLC	0.8136*** (3.0671)	−0.7218** (−2.1051)	2.8074* (1.9101)
Sub-sample: before crisis (BC)			
LIC	7.6138 (0.0824)	0.8263*** (6.0371)	2.8431 (0.6983)
HIC	−3.4869*** (−5.1082)	−0.6950* (−1.7264)	−0.6821 (−0.6491)
ALLC	1.5738** (1.9824)	−0.4825** (−1.9901)	2.6205*** (6.4530)
Sub-sample: crisis period (CP)			
LIC	5.0628*** (11.7492)	−0.6935** (−2.0017)	2.4935* (1.6520)
HIC	0.8637* (1.8034)	−2.9085 (−0.0793)	−0.0637* (−1.7052)
ALLC	2.6157*** (3.9462)	−1.4869* (−1.6831)	0.9519*** (6.3035)
DOLS regression			
Full sample (FS)			
LIC	2.0692*** (9.4827)	0.0781*** (4.5899)	3.7149* (1.6952)
HIC	−1.6404** (−2.1802)	−1.1636** (−2.1047)	−1.5861 (−0.8370)
ALLC	3.9136*** (4.5728)	−2.0853 (−1.0976)	4.1635** (2.2368)
Sub-sample: before crisis (BC)			
LIC	1.6892*** (9.0583)	0.2035** (1.9722)	2.2730 (0.0679)
HIC	−1.8407*** (−2.9308)	0.7359*** (2.8430)	−3.6250** (−2.1731)
ALLC	2.0568* (1.6793)	0.0835** (2.0481)	0.8569*** (4.3309)
Sub-sample: crisis period (CP)			
LIC	3.1046* (1.6825)	0.3017*** (7.6905)	2.4416 (0.0073)
HIC	2.1827*** (9.5185)	0.0872*** (3.2795)	−5.6112 (−0.7499)
ALLC	1.7042* (1.6528)	−0.3392* (−1.6675)	1.8504** (2.2006)

*, **, ***Significance level at 1, 5 and 10% respectively; the null hypothesis for the *t*-ratio is $H_0 = \beta = 0$; values in the parenthesis are *t*-statistics; for the DOLS regression FS: N = 1 064, R^2 adj. = 0.81, *F*-stat = 6.03***; BC: N = 686, R^2 adj. = 0.76, *F*-stat = 4.71**; CP: N = 336, R2 Adj. = 0.54, *F*-stat = 14.26***; for abbreviations see Table 3

Source: Authors' computation using E-views software (version 9) based on the Food and Agricultural Organization (2020) and the International Monetary Fund (2020) data

https://doi.org/10.17221/197/2020-AGRICECON

in the same direction. As income changes (increases or decreases) in LIC, other macroeconomic variables, interest rates, investment level aggregate prices, etc. tend to change. When per capita income increases due to an increase in output, peoples' purchasing power exhibits an upward trend, which leads to high demand for goods and services, and consequently to higher prices if supply does not keep pace with changing demand conditions (Tadesse et al. 2016; Pal and Mitra 2017).

Table 6 presents the panel Granger causality test results for ALLC, LIC, and HIC based on the full samples. Bi-directional causality was found between oil price and food price in ALLC and LIC. Impliedly, in the short run, past values of oil price predict the current and future values of food price and vice versa. For HIC, exchange rate and demand shock granger cause food prices in the short run. These findings signalled the fact that oil price has a significant power to predict food price in oil-exporting countries partly because oil serves as the primary source of income (revenue) and critical input in the production of agricultural output, and also serves as fuel for transporting output from farms to markets for direct consumption. Although food and oil prices may drift away from the equilibrium in the short run due to uncertain economic events, market mechanisms may converge them toward equilibrium in the long run (Zhang et al. 2010).

CONCLUSION

Prominent studies submit to the assertion that oil prices co-move with food prices at global and national levels. Recently, the co-movement debate was criticized based on the notion that economic structure and uncertain economic events significantly affect both markets' behaviour. We revisit the debate using a dis-aggregated approach on oil exporting countries in sub-periods (before the crisis and during the crisis) and isolate low-income countries from high-income countries to better explain the nature of price movements. The conclusion emanating from the empirical findings is that oil price has inverse explanatory power on HIC food prices based on the full sample and before the recently sustained price shock in the oil market. However, there is a long-term co-movement between oil prices and food prices in all the countries during the crisis. It is worth emphasizing that even when the oil market is stable, LIC recorded a positive impact of oil prices on food prices. Also, the short-term dynamics revealed that oil prices could predict current and future values of food prices significantly in oil-exporting countries.

Our findings signal that in isolation, oil price does not always co-move with food prices, especially in oil-exporting countries. Nevertheless, low-income countries are indifferent in both periods (whether the market is stable or in crisis) due to their limited capacity to produce and balance the increasing demand for food

Table 6. Results of the panel granger causality test

Dependent variables	Independent variables							
	Δ*FP*		Δ*OILP*		Δ*EXCR*		Δ*GDPGR*	
HIC								
Δ*FP*	–		0.0681	(0.7863)	0.13022	(0.7186)	0.0597	(0.6884)
Δ*OILP*	0.0961	(0.8726)	–		2.0185**	(0.0263)	0.6496*	(0.0796)
Δ*EXCR*	2.0149***	(0.0038)	0.6259	(0.4112)	–		1.0825	(0.8206)
Δ*GDPGR*	6.3362**	(0.0413)	3.5782***	(0.0046)	2.4175	(1.0043)	–	
LIC								
Δ*OILP*	1.5713**	(0.0267)	–		0.3553	(0.7853)	1.6787	(1.0471)
Δ*EXCR*	1.3529	(0.6890)	2.2716	(0.1903)	–		0.3922	(0.4518)
Δ*GDPGR*	0.8716*	(0.0731)	0.6728	(0.6299)	0.0382	(0.4801)	–	
ALLC								
Δ*FP*	–		2.4309*	(0.0472)	1.8394*	(0.0862)	0.2376	(0.9092)
Δ*OILP*	0.3819*	(0.0714)	–		0.4838	(0.7476)	0.7982**	(0.0056)
Δ*EXCR*	0.1137	(0.3546)	0.3657	(0.6049)	–		0.4208	(0.3567)
Δ*GDPGR*	2.0840***	(0.0052)	3.0952	(0.3186)	0.0494	(0.1108)	–	

*, **Significance level at 5% and 1%, respectively; values in the parenthesis are *P*–values; Δ indicates the first difference; for abbreviations see Table 3

Source: Authors' computation using E-views software (version 9) based on Food and Agricultural Organization (2020) and International Monetary Fund (2020) data

https://doi.org/10.17221/197/2020-AGRICECON

supply. We therefore suggest that based on the significant long-run and short-run effects of oil price on food price, oil-exporting countries need to direct much of their efforts towards attaining food self-sufficiency by implementing and evaluating short-run and long-run policies and strategies aimed at improving their food security drive and be able to produce and feed their teeming population at lower costs efficiently. Long-term agricultural strategies and policies should be implemented to alter both the demand and supply sides of these countries' food equation. On the supply side, supporting contract farming and price insurance will increase food sufficiency and food stock balance, especially during a crisis; while on the demand side, household orientation and consumer focus on the importance of locally produced food items ease the heavy reliance on food imports that often worsened the food price situation in the country.

From this perspective, despite the uncovered fresh evidence on the food price-oil price nexus in oil-exporting countries by the current study, further studies may consider comparing oil-exporting countries with oil-importing countries in terms of food price-oil price nexus, there are also research gaps in the role of asymmetric effects of the oil market on the food market, especially in oil-exporting countries.

Acknowledgement. We thank Rong Yang and Junping Wang for the helpful comments. The stimulating discussions and observations from Mika'ilu Abubakar, Tukur Garba and Murtala Kaura are also appreciated by the authors. We are also thankful to colleagues especially from Xi'an Shiyou University and Sokoto State University for their comments and constructive observations on this piece. All remaining errors are our own.

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Received: May 5, 2020
Accepted: September 17, 2020
Published online: October 29, 2020