

Article

The Linkages between Crude Oil and Food Prices

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Abstract: This paper aims to indicate the linkages between crude oil prices and selected food price indexes (dairy, meat, oils, cereals, and sugar) and provide an empirical specification of the direction of the impact. This paper reviews the fuel–food price linkage models with consideration to the time series literature. This study adopts several methods, namely the Augmented Dickey–Fuller test, Granger causality test, the cointegration test, the vector autoregression model, and the vector error correction model, for studying the price transmission among the crude oil and five selected food groups. The data series covers the period between January 1990 and September 2020. The empirical results from the paper indicate that there are long-term relationships between crude oil and meat prices. The linkage of crude oil prices occurred with food, cereal, and oil prices in the short term. Furthermore, the linkages between the analyzed variables increased in 2006–2020.

Keywords: food prices; crude oil prices; cointegration; vector autoregressive model; Granger causality

1. Introduction

The role of crude oil in the worldwide economy [1–3] is considered essential as it is one of the most crucial sources of energy, which, in turn, constitutes an essence of the modern global economy. In the past, oil occupied most of the energy area [4], and Rahmas [5] suggested that the oil dominion would extend over the twenty-first century, too.

There were some significant spikes in the price of oil. The first was noticed in May 1974, followed by the Yom-Kippur War in 1973, when imported crude oil's actual price per barrel jumped to 69.64 USD, followed by January 1981, just after the Iranian Revolution in 1979, with the price per barrel hitting 115.81 USD. The central peak during the considered period coincided with the time of the world's financial crisis in 2007 and 2008. Further, in March 2012, another peak was observed when real prices increased up to 126.10 USD per barrel (Figure 1).

Crude oil is a critical input for most services and goods and has a massive impact on people's lives. It has a broad scope of applications, supplying various sectors of economies including agriculture, transportation, and industry, as well as households, because it serves for the production of fuel. Therefore, people's quality of life shifts up and down when the price of crude oil is unbalanced and irrational [6]. Therefore, oil price fluctuation may influence the prices of other products [7].

Recent studies on crude oil price influence mostly influence the stock market. For example, Xu et al. [8] argue the heterogeneous nature of the correlation between the stock market of different countries and the crude oil market. Moreover, the work indicates that, when compared, the short-run correlation between fuel and the stock market is lower than the long-term correlation.

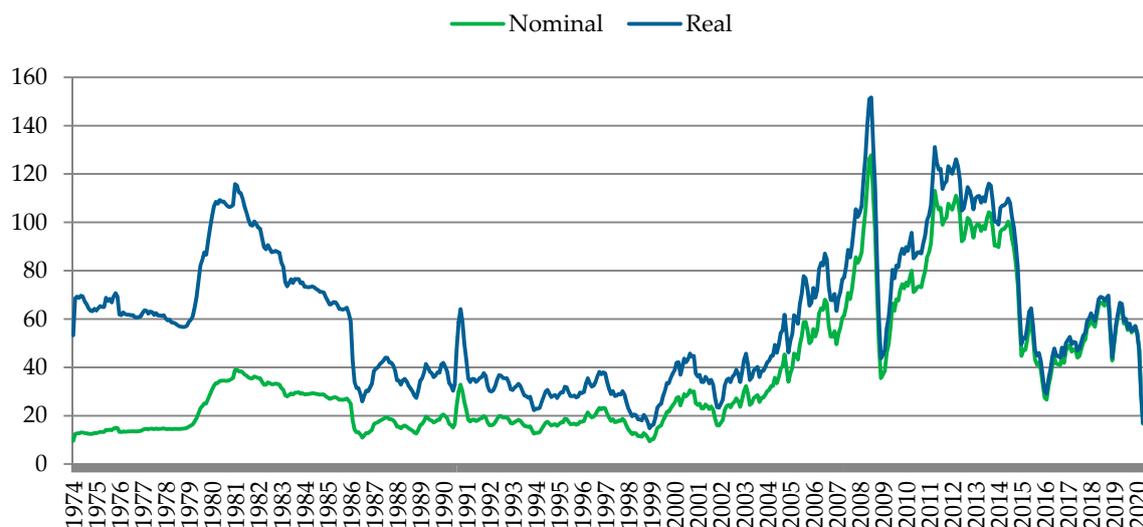


Figure 1. Monthly imported crude oil prices from January 1974 until August 2020 (USD per barrel). Source: own elaboration based on [9].

Research presenting crude oil prices and their relation to GDP level and economic growth constitutes another line of consideration, the results of which indicate the existence of a significant impact of crude oil price on economic growth [6,10–13].

Not only is oil the primary source of energy but it also serves in the production of other forms of energy such as electricity or refinery products, which, in turn, serve for manufacturing various goods or impact transportation processes. Hence, the third field of research is illustrated by the number of studies presenting crude oil price levels with the prices of multiple goods classified as food and nonfood products. The study of Sarwar and Tivari [14] regarding Pakistan demonstrates the nonlinearity of the relationship between the nonfood Consumer Price Index and oil prices. Increases in oil prices lead to increases in prices, whereas there is no such phenomenon in the opposite direction.

Food products are investigated separately as they constitute essential living costs, and numerous studies have been conducted that present food product prices in terms of crude oil prices. There are no studies, however, based on groups of agricultural commodities. Therefore, this paper aims to identify and describe the relations between selected groups of agricultural commodities, such as dairy, meat, oil, cereal, sugar product, and crude oil prices. To aid this process, we have established the short- and long-term linkages between variables and determined the directions of their mutual influence.

The article is structured as follows: Section 2 indicates the literature review, and Section 3 discusses the materials and methods used. Section 4 lays out the outcome of the empirical analysis, and, finally, Section 5 presents the discussion, closing with conclusions.

2. Literature Review

The recent years saw a rise in the number of papers published on the relationship between fuel and food prices (Table 1). Out of these, it is possible to identify three groups of studies. In the first, the researchers were unable to find evidence for the relationship between analyzing data. On the other hand, several studies indicate that there are linkages when investigating this relationship. The final group focuses on discovering studies that point to neutrality between variables in one period but find evidence in the second period. These instances correspond to food (2006) or the financial crisis (2008).

Table 1. Overview of previous studies and results.

Authors, Year	Methods	Data (Source)	Time/Geographical Coverage	Results	
				Neutrality Hypothesis	Crude Oil/Energy Prices Driving Prices of Agricultural/Food Goods
Ding, Zhang (2020) [15]	Spread CRB Index, Dickey–Fuller test	Crude oil, corn, cattle gold, and copper prices daily data (Thomson Datastream)	2005–2018	+	
Hau, Zhu, Huang, Ma (2020) [16]	Model TVP-SVM, Model MCMC estimation	Corn, soybean, bean, strong wheat, cotton, pulp, natural rubber; weekly data	2003–2004, 2007–2011, China	+	
Fowowe (2016) [17]	ECM, Nonlinear causality tests	Maize, sunflower, and soybeans; weekly data (the EIA, the Johannesburg Stock Exchange)	2001–2014, South Africa	+	
Ibrahim (2015) [18]	NARDL model	Food and oil prices annual data	1971–2012, Malaysia	+	
Nazlioglu, Soytaş (2011) [19]	Toda and Yamamoto causality test	Monthly data	1994–2010, Turkey	+	
Gilbert (2010) [20]	Granger causality test, 2SLS, 3SLS OLS,	Quarterly data	1971–2008	+	
Zhang, Lohr, Escalante, Wetzstein (2010) [21]	VECM	Crude oil, soybean, corn, wheat prices, monthly data	1989–2008	+	
Vo, Vu, Vo (2019) [22]	SVAR model IRF model, variance decomposition technique	Crude oil prices, corn, wheat, sugarcane, soybeans, coconut, soybean and palm oil, palm kernel oil, barley, coffee, cocoa, rice, tea, cotton prices; monthly data; WB	January 2000–July 2018, 2000–2006, 2006–2013, 2013–2018		+
Taghizadeh-Hesary, Rasoulinezhad, Yoshino (2019) [7]	Panel-VAR model	Food prices, crude oil and biofuel price, inflation and real interest rate, agricultural land, employment in the agriculture sector, GDP (World Development Indicators, the FAO, the BP, the EIA, Statistical Review of World Energy)	2000–2016, 8 Asian countries		+

Table 1. Cont.

Authors, Year	Methods	Data (Source)	Time/Geographical Coverage	Results	
				Neutrality Hypothesis	Crude Oil/Energy Prices Driving Prices of Agricultural/Food Goods
Su, Wang, Tao, Oana-Ramona (2019) [23]	Vertical market integration model Ciaian and Kancs, bootstrap full-sample causality test, Granger causality test, bivariate VAR models	Crude oil spot price Worldwide; maize and soybeans, tea and cocoa beans, monthly data, (WTI)	1990–2017		+
Pal, Mitra (2019) [24]	DCC model, Pearson correlations	Crude oil, corn, soybeans, wheat, and oat prices, daily spot closing prices, (WTI)	2000–2018; U.S.		+
Pasrun, Rosnawintang, La Ode, La, La Ode (2018) [25]	VAR model, Granger causality test	Crude oil price, rice price, monthly data	January 2000–September 2017		+
Ji, Bouri, Roubaud, Shahzad (2018) [26]	Copula model	Daily data,	2000–2017		+
Al-Maadid, Caporale, Spagnolo, Spagnolo (2017) [27]	Bivariate VAR-GARCH(1,1) model	Crude oil and ethanol prices and coffee, cacao, corn, sugar, soybeans, and wheat prices, daily data (Bloomberg)	January 1st, 2003 to June 6th, 2015		+
Bergmann, O'Connor, Thummel (2016) [28]	VAR model, multivariate GARCH model	Palm oil, butter, and crude oil prices	January 1995–December 2005; EU and World		+
Hamulczuk (2016) [29]	Correlation coefficient	Energy prices and agrifood prices	1995–2015,		+

Table 1. Cont.

Authors, Year	Methods	Data (Source)	Time/Geographical Coverage	Results	
				Neutrality Hypothesis	Crude Oil/Energy Prices Driving Prices of Agricultural/Food Goods
Mawejje (2016) [30]	Cointegration techniques	Energy, meat, dairy, cereal, edible oil, sugar prices, monthly data; the Uganda Bureau of Statistics, Bank of Uganda, FAO	2000–2011		+
Fernandez-Perez, Frijns, Tourani-Rad (2016) [31]	SVAR	Daily data	2006–2016		+
McFarlane (2016) [32]	Dickey–Fuller test, Johansen tests, VAR	Corn, sugar, wheat, and crude oil prices, weekly data	1999–2005, 2006–2012, The U.S		+
Cabrera, Schulz (2016) [33]	Correlation GARCH model, multivariate multiplicative volatility model	Energy, agricultural product prices	2003–2012, Germany		+
Nwoko, Aye, Asogwa (2016) [34]	GARCH (1, 1) model, Dickey–Fuller test, Phillip–Perron test, Granger causality test, VAR model	Oil price (food crop prices (US EIA, Federal Ministry of Agriculture), annual data	2000–2013, Nigeria		+
Zhang, Qu (2015) [35]	ARMA-GARCH	Daily data	2004–2014		+
Koirala, Mishra, D’Antoni, Mehlhorn (2015) [36]	Copula model	Daily data	2011–2012		+

Table 1. Cont.

Authors, Year	Methods	Data (Source)	Time/Geographical Coverage	Results	
				Neutrality Hypothesis	Crude Oil/Energy Prices Driving Prices of Agricultural/Food Goods
Rezitis (2015) [37]	Panel-VAR model, Granger causality tests	US dollar exchange rates, crude oil prices, 5 fertilizer prices, 30 selected agricultural prices, monthly data	June 1983–June 2013		+
Natanelov, Alam, McKenzie, Huylenbroeck (2011) [38]	VECM, TVECM	Monthly data	1989–2010		+
Chang, Su (2010) [39]	EGARCH	Daily data	2004–2008		+
Balcombe, Rapsomanikis (2008) [40]	VECM, AVECM, TVECM	Weekly data	2000–2006		+

Abbreviations: SVAR—structural vector autoregressive model; DCC—dynamic conditional correlation model; VAR—vector autoregression; (V)ECM -(vector) error-correction model; (T)VECM—(threshold) VECM, (A)VECM—(asymmetric) vector error-correction model; ARMA-GARCH—autoregressive moving average with generalized autoregressive conditional heteroskedasticity, EGARCH—exponential GARCH, (N)ARDL—(nonlinear) autoregressive distributed lag model; OLS—ordinary least squares, 2SLS—two-stage least squares, 3SLS—three-stage least squares, ECM—error-correction model, WTI—The West Texas Intermediate; FAO—Food and Agriculture Organization; EIA—the Energy Information Administration; BP—British Petroleum, WB—World Bank.

Some studies show no straight influence of crude oil on groups of food prices. In one example, Ding and Zhang [15] used copper, cattle, oil, corn, and gold data captured between 2005 and 2018. The authors demonstrated the long-term connection between crude oil and industrial metal markets; however, they did not confirm fuel–food linkages. Hau et al. [16] investigated the heterogeneous nature of the relationship between crude oil and China’s agricultural futures. The work of Fowowe [17] featured a cointegration test with nonlinear Granger causality tests. His findings pointed to a lack of a short- or long-term price link between crude oil and food product prices in South Africa. Ibrahim [18] analyzed the case of Malaysia through a nonlinear autoregressive distributed lag model (NARDL) model. No long-term relationship between investigated variables was found as a result of this work. However, he found that, in the short term, agricultural product price inflation is caused by fluctuations in the oil price. In their work, Nazlioglu and Soytas [19] tested for causality between agricultural commodity and crude oil price and the exchange rate with the Toda–Yamamoto procedure but failed to discover any linkages formed between fuel and food prices. The researchers found neither direct nor exchange-rate-driven transmission. Gilbert [20] concluded that the significant correlation between analyzing prices is due to monetary and financial developments and rising demand. The limitations of the usage of agricultural products for biofuel production were not supported by his findings. Zhang et al. [21] insisted that the rising prices of fuel do not directly affect food product prices.

In contrast, numerous researchers point to increasing crude oil prices as the main cause of significant shocks the agricultural markets experienced. The 2007/2008 food crisis was mainly driven by the sharp increase in the prices of agricultural goods as well as crude oil and biofuels. The interaction between agricultural commodities and biofuels was extensively studied. The rising price of energy encouraged policy changes aimed to produce biofuels from corn and soybean. An increase in the prices of agricultural commodities with energy-producing capabilities could be caused by the biofuels segment expansion, resulting in high food prices. Several studies [23,41,42] pointed to the bidirectional causal link between crude oil and food prices. Contrastingly, Vo et al. [22] emphasized the fact that the contribution of individual oil shocks to agricultural price fluctuations is not uniform, and the same is true for the aggregate demand shocks and their effects on the food prices. Their findings present the significance of the fuel market in clarifying variabilities in the prices and related agricultural goods changeability. Taghizadeh-Hesary et al. [7] pointed to a connection between the security of energy and food through price volatility. Because oil price growths have an adverse effect on food security, diversification of the energy usage appears to be a necessity, relinquishing the reliance on fossil fuels in favor of an optimal relationship between energy resources (renewable and nonrenewable). Such a solution will be of great benefit not just for the security of energy but food security as well. Pal and Mitra [24], using three generalized autoregressive conditional heteroskedasticity (GARCH) models, discovered a relatively strong relationship between crude oil and energy crops; however, the value of this index for food crops was relatively low. Su et al. [23] submitted evidence of bidirectional causality existing among oil and food prices over selected subperiods. Ji et al. [26] discovered the tail dependence among food products and energy. Pasrun et al. [25] indicated a lack of long-term connections between the exchange rates and the prices of crude oil and rice. Only a short-term relationship based on the causality test transpired. Al-Maadid et al. [27] studied the nature of relationships between food and energy prices. Their results indicate the existence of outstanding linkages between the prices of agricultural commodities and petroleum products. Bergmann et al. [28] studied the transmission of volatility in the prices of palm oil, butter, and fuel markets with the application of the vector autoregression (VAR) model. The results indicate the spillover of oil prices into butter prices. Mawejje [30] found long-term linkages between agricultural commodities and energy prices in Uganda. McFarlane [32] explored the relationship in the US market between the prices of agricultural goods and oil. He found significant cointegration between the variables in 1999 and 2005 and the second between 2006 and 2012. Cabrera and Schulz [33] showed that prices move together and maintain a long-run balance despite the fact that market shocks appear. However, no evidence was discovered pointing to relations from rapeseed to crude oil in either the long-run or short-run. The study of Fernandez-Perez

et al. [31] puts forward a conclusion that oil prices affect corn, soybeans, and wheat, whereas soybeans and wheat have an effect on ethanol. Hamulczuk [29] confirmed an increasing connection between Brent crude oil and food index prices. There are numerous roots of increase in price relationships, among them a policy of developed economies, the main focus of which is biofuels and their promotion and consumption. Nwoko et al. [34] mainly focused on the effect that oil prices apply on the relation of food prices in Nigeria in 2000–2013. The results obtained revealed a consequential short-term relationship between the volatility of variables. Other authors, based on the research from China [35], pointed to an irregularity in oil price shocks and food products. Koirala et al. [36] found a significant correlation between agricultural commodities and future energy prices. Rezitis [37] concluded that the prices of international agricultural commodities are influenced by crude oil prices and US dollar exchange rates. Chang and Su [39], using a bivariate exponential GARCH (EGARCH) model, pointed to crude oil and its relationship with corn prices. Natanelov et al. [38] presented that biofuels policy mitigates joint oil and corn price developments until a certain price threshold is exceeded. Balcombe and Rapsomanikis [40] used Bayesian techniques to investigate long-run relations, and their study resulted in a long-term balance between ethanol, crude oil, and sugar prices.

Researchers apply various methods to conduct their investigations of agricultural and energy commodities. They are mentioned in Table 1.

3. Materials and Methods

To identify the linkages between crude oil and food prices, we selected 5 groups of food commodities: dairy, meat, oils, cereals, and sugar products. The statistical variables were monthly real crude oil prices [9] and real food price indexes [43]. The time series are shown in Figure 2. Putting the issue into a time perspective, the research covered the period from January 1990 until September 2020. Following Al-Maadid et al. [27] and Vo et al. [22], we divided the full period into two subperiods: (i) 1990–2005 (before the 2006 food crisis) and (ii) 2006–2020 (after the crisis). Table 2 presents the results of Pearson’s correlation with division into subperiods. It should be noted that, in the second period, a moderate correlation occurred between crude oil and food, cereal, and oil prices (logarithms of prices). In the analysis of the first price differences, the prices of food and oils had the highest correlation coefficients.

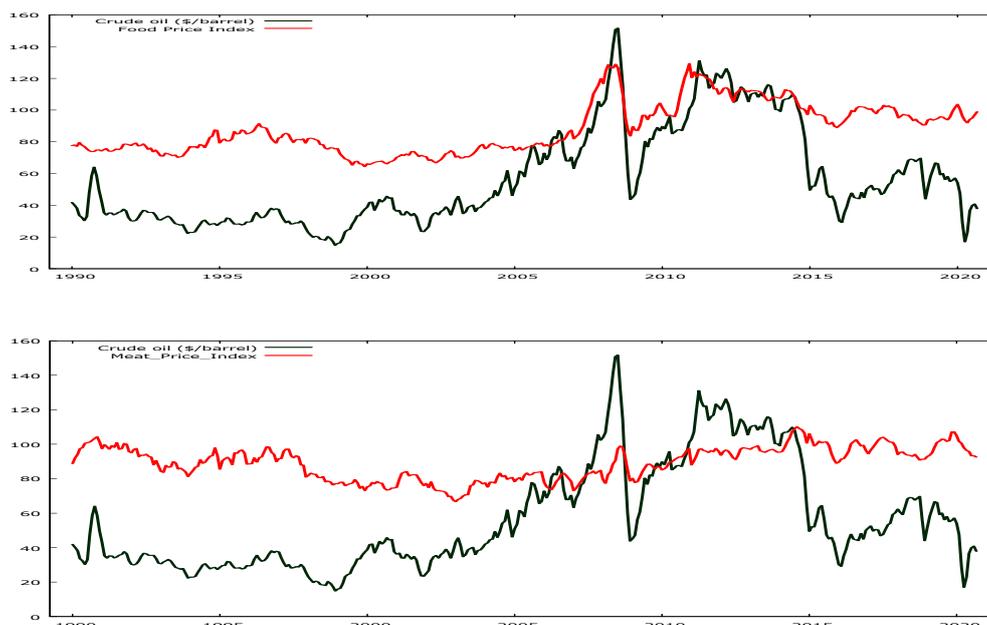


Figure 2. Cont.

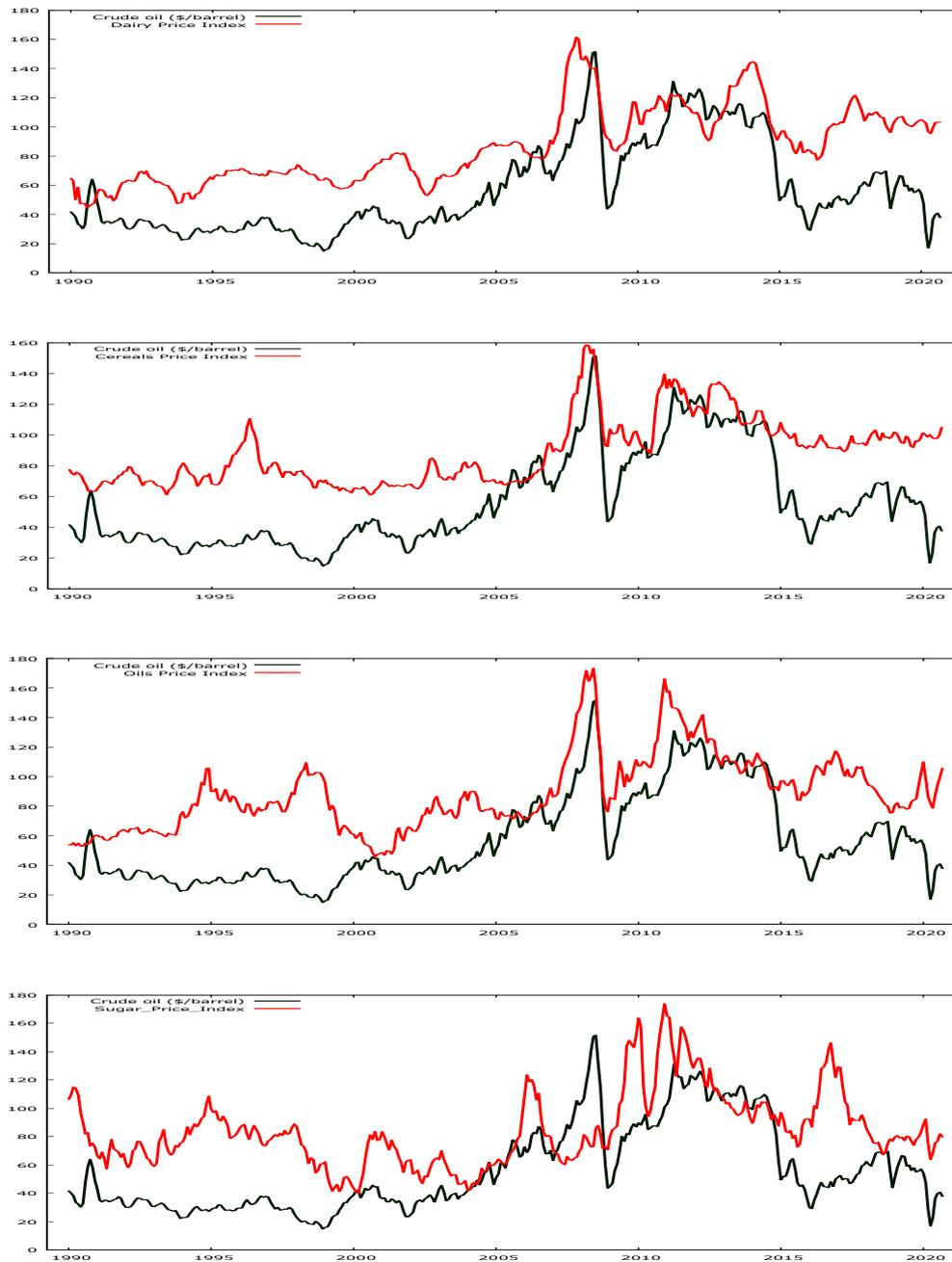


Figure 2. Monthly food price indices. Source: based on [9,43].

Table 2. Correlation coefficients between crude oil and food price indices.

	L_Crude Oil			DI_Crude Oil			
	1999–2020	1990–2005	2006–2020	1999–2020	1990–2005	2006–2020	
l_Food	0.742	−0.125	0.603	dl_Food	0.195	−0.174	0.393
l_Meat	0.275	−0.025	−0.085	dl_Meat	0.159	0.007	0.282
l_Dairy	0.783	0.341	0.557	dl_Dairy	0.124	−0.095	0.293
l_Cereals	0.732	−0.121	0.595	dl_Cereals	−0.001	−0.223	0.137
l_Oils	0.592	−0.353	0.603	dl_Oils	0.202	−0.141	0.436
l_Sugar	0.509	−0.072	0.321	dl_Sugar	0.169	−0.011	0.308

5% critical value: 0.1021 for 1999–2020, 0.142 for 1990–2005 and 2006–2020. Source: own calculations.

Firstly, to select the appropriate research methodology, we used the Augmented Dickey–Fuller test (ADF) [44]. Based on the test results, we chose the methods for analysis (Table 3). The optimal lag for the tests was selected with the Akaike Information Criterion (AIC). The variables are integrated I(1), except for the sugar in the full period.

Table 3. Unit root testing results.

	1990–2020	1990–2005	2006–2020
l_Food	−2.769	−1.768	−2.873
dl_Food	−14.449 ***	−12.984 ***	−8.507 ***
l_Meat	−2.141	−2.525	−2.947
dl_Meat	−10.460 ***	−4.214 ***	−10.082 ***
l_Dairy	−3.021	−2.694	−3.048
dl_Dairy	−14.612 ***	−13.606 ***	−7.020 ***
l_Cereals	−3.260	−3.044	−3.166
dl_Cereals	−13.326 ***	−7.387 ***	−8.957 ***
l_Oils	−3.120	−2.267	−2.989
dl_Oils	−8.043 ***	−5.743 ***	−5.948 ***
l_Sugar	−3.568 **	−2.676	−2.477
dl_Sugar	−12.747 ***	−9.406 ***	−9.494 ***
l_Crude oil	−2.430	−2.335	−2.556
dl_Crude oil	−13.048 ***	−8.923 ***	−9.247 ***

** $p < 0.05$, *** $p < 0.01$. Source: own calculations.

The first step was testing for linear cointegration. According to Engle and Granger [45], “two-time series are cointegrated if their linear combination is stationary series, $I(0)$.” The analysis of cointegration allows to state the existence of a long-run connection between analyzed variables. In order to test the long-run relationship, a Johansen cointegration test was used. The test is based on the VAR [46,47]:

$$X_t = C + \sum_{i=1}^p A_i X_{t-i} + e_t, \tag{1}$$

where: X_t —endogenous variable vector, C —constant vector, A_i —coefficient matrix, e_t —white noise vector which is independently and identically distributed with $e_t \sim \text{IID}(0, \Sigma)$ where Σ is a positive definitive matrix.

If the endogenous variables are cointegrated, then Equation (1) can be shown in a vector error-correction model (VECM) $(p - 1)$ as follows [46,47]:

$$\Delta(X_t) = C + \Pi X_{t-1} + \sum_{i=1}^{p-1} \tau_i \Delta(X_{t-1}) + e_t, \tag{2}$$

where: $\Pi = \sum_{i=1}^{p-1} A_i - I$, I —identity matrix; $\Gamma_i = - \sum_{j=i+1}^{p-1} A_j$; Π —called a long-run matrix coefficient, Γ_i —short-run matrix coefficient. To study cointegration in the Johansen procedure, the order of the Π matrix is used, this corresponds to the sum of independent cointegration vectors. The Johansen test is based on the trace or maximum eigenvalue test:

$$LR_{trace}(r) = -(T - p) \sum_{i=r+1}^k n(1 - \lambda_i) \tag{3}$$

$$LR_{max}(r) = -(T - p) \ln(1 - \lambda_{r+1}), \tag{4}$$

where: T —sample size, λ_i — i -th greatest canonical correlation (eigenvalues of matrix Π). The LR_{trace} tested the H_0 : the number of vectors is equal to r against the H_1 : the number of vectors is equal to n . The LR_{max} tested the H_0 : the number of vectors is equal to r against the H_1 : the number of vectors is equal to $r + 1$.

As a result of using Johansen’s procedure, three options may appear [48]: “(i) the rank of the Π matrix is equal to 0—then model (2) is a VAR model for the increments of variables, in which there is no long-run dependence; (ii) the rank of the matrix Π is bigger than 0 and less than r , then the number of cointegration vectors is equal to this rank; (iii) the matrix Π is of a full order, then the series of variables are stationary and model (2) is a VAR model for the levels of the variables.”

In the next stage, the VAR and VECM models were estimated. If there are relationships in this assessment, then the last step will be the Granger causality test and Impulse Response Function test (IRF). The causality test is used to determine the cause-effect relations, where “variable x is the Granger cause of variable y when the values of variable y can be more accurately foreseen, considering the future value of variable x than when disregarding those values. In the Granger causality test, H_0 is tested: all β_k coefficients equal zero, which is interpreted as a lack of causality.” The Granger causality test can be shown as follows [49]:

$$Y_t = \beta_0 + \sum_{j=1}^m \beta_j Y_{t-j} + \sum_{k=1}^n \beta_k X_{t-k} + u_t, \tag{5}$$

$$X_t = \beta_0 + \sum_{j=1}^m \beta_j X_{t-j} + \sum_{k=1}^n \beta_k Y_{t-k} + u_t, \tag{6}$$

where: Y_t —values of variable Y ; X_t —values of variable X ; β —structural model parameters; t —time variable; u_t —random model element.

4. Results

4.1. Long-Run Analysis

As the variables are $I(1)$, the Johansen cointegration procedure was performed first. The test was used to verify the long-run relationship between crude oil and food index prices. The results of the cointegration test in two subperiods are presented in Table 4. It should be noted that the statistical values of the two tests are smaller than the required critical values (at $p = 0.05$). The exceptions are the results for meat and crude oil in 2006–2020. This demonstrates the long-run connections between these variables. However, in most cases, the long-term relationship between other variables does not exist. This means that the prices of these variables do not follow each other in the long-term. It should be noted that short-term linkages may exist. For that reason, the next step is to identify the short-term link between analyzed variables in the next part. For this purpose, the VAR model (for food, dairy, cereals, oils, and sugar) and the VECM model (for meat) were used.

Table 4. Cointegration results for oil and food price indices.

Rank		1990–2005				2006–2020			
		LR _{trace}		LR _{max}		LR _{trace}		LR _{max}	
		Stat.	<i>p</i> -Value	Stat.	<i>p</i> -Value	Stat.	<i>p</i> -Value	Stat.	<i>p</i> -Value
l_Food	0	8.990	0.171	8.900	0.126	22.300	0.131	11.285	0.497
	1	0.091	0.828	0.091	0.819	11.014	0.088	11.014	0.088
l_Meat	0	20.513	0.204	15.769	0.159	32.632	0.005	21.617	0.020
	1	4.744	0.639	4.744	0.640	11.015	0.088	11.015	0.088
l_Dairy	0	23.120	0.106	15.788	0.158	22.398	0.128	13.481	0.301
	1	7.332	0.321	7.332	0.321	8.916	0.190	8.916	0.190

Table 4. Cont.

Rank	1990–2005				2006–2020				
	LR _{trace}		LR _{max}		LR _{trace}		LR _{max}		
	Stat.	p-Value	Stat.	p-Value	Stat.	p-Value	Stat.	p-Value	
l_Cereals	0	21.006	0.182	14.256	0.246	24.618	0.070	14.345	0.240
	1	6.749	0.382	6.749	0.383	10.273	0.117	10.273	0.117
l_Oils	0	9.395	0.941	5.186	0.973	22.431	0.127	14.123	0.255
	1	4.209	0.713	4.209	0.715	8.308	0.234	8.308	0.234
l_Sugar	0	23.177	0.104	13.759	0.280	19.150	0.278	11.936	0.434
	1	9.417	0.160	9.417	0.160	7.214	0.332	7.214	0.333

Source: own calculations.

4.2. Short-Run Analysis

Due to the lack of cointegration among analyzed variables (except meat), the VAR model was estimated. Using the AIC criterion, it was found that the appropriate lag length was $p = 3$. Since the variables are $I(0)$, the VAR ($p - 1$) model is estimated, and the lag length is two ($p - 1 = 2$). The effects of VAR (2) in the first difference are shown in the Appendix A (Table A1). On the basis of R^2 , it should be concluded that the quality of the model fit is not satisfactory. For example, about 30% of the variation in crude oil is explained by crude oil prices and only 2% by food price.

The results indicate that crude oil price does not have a short-term impact on food, dairy, cereal, oil, and sugar price volatility in the second subperiod; however, food, cereal, and oil prices have a favorable short-term impact on crude oil price volatility. Further proof of the short-run connection between analyzed prices can be inferred from the IRF test. Figure 3 presents only statistically significant impulse responses. The reaction of the price of crude oil to the food, cereal, and oil price is positive. The change in impact occurs after the fourth month for oils and the fifth month for food and cereals.

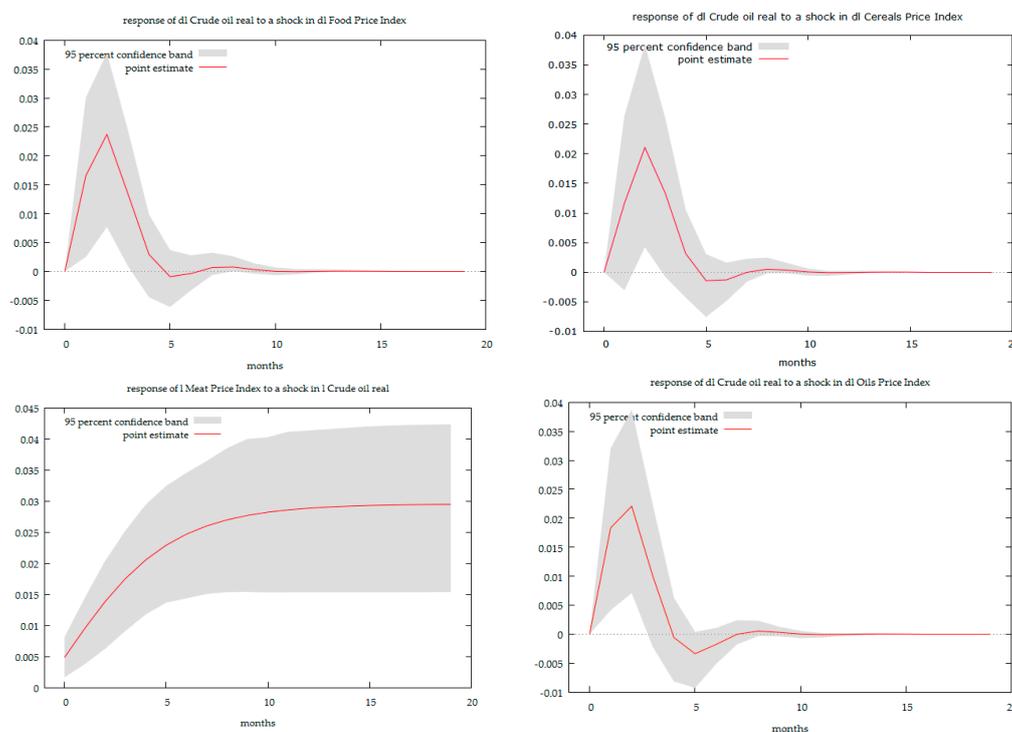


Figure 3. Impulse response function between crude oil price and selected food price volatility. Source: own calculations.

Because there is one cointegrating rank in the relationship between meat and crude oil prices in the second subperiod, the VECM model was used. The result estimation is presented in Table A2 in the Appendix A. The coefficient in the long-term linkage in the VECM model (with the restricted trend and unrestricted constant) is 6.16, which means that a 1% increase or decrease in crude oil price is a response to a 6.16% increase or decrease in meat prices. Therefore, the price of crude oil is an exogenous variable for meat prices. This is evidenced by the significant EC coefficient in the meat price equation. The coefficient for the error correction term in the meat price equation is 0.027, whereas for the crude oil price, the equation is -0.008 . Therefore, the disequilibrium in the price system is revised in one month by 2.7% via the reaction of the meat and by 0.8% via the reaction of crude oil. Moreover, the meat price response is positive and persistent throughout the entire period (Figure 3).

4.3. Causal Relationship

After estimating the VAR and VECM models, the next step is a determination of causality. For this purpose, the Granger causality test was implemented to investigate the mutual influence of the researched prices. (Table 5). The direction of the relationship in the second subperiod can be deduced from the results in Tables A1 and A2. There is only a one-way (\leftarrow or \rightarrow) connection between crude oil and food prices in two subperiods in the short-run. In the first subperiod, in the performed tests approach, we can determine that the food, cereals, and dairy ex-work prices were a Granger cause for crude oil future prices. The food, cereal, and oil future prices were a cause for the crude oil ex-work prices in the second subperiod. It should be noted that crude oil prices are the cause of Granger for meat prices in two subperiods.

Table 5. Granger causality test.

	1990–2005			2006–2020		
	Stat.	p-Value		Stat.	p-Value	
dl_Crude oil \neq > dl_Food	1.151	0.333	Crude	0.020	0.980	Crude
dl_Food \neq > dl_Crude oil	3.359	0.010	oil \leftarrow Food	5.277	0.006	oil \leftarrow Food
dl_Crude oil \neq > dl_Meat	3.344	0.011	Crude	5.185	0.007	Crude
dl_Meat \neq > dl_Crude oil	1.628	0.167	oil \rightarrow Meat	1.020	0.363	oil \rightarrow Meat
dl_Crude oil \neq > dl_Dairy	1.866	0.173	Crude	0.732	0.482	Crude oil x
dl_Dairy \neq > dl_Crude oil	4.697	0.031	oil \leftarrow Dairy	2.140	0.121	Dairy
dl_Crude oil \neq > dl_Cereals	1.176	0.322	Crude	0.497	0.609	Crude
dl_Cereals \neq > dl_Crude oil	2.533	0.041	oil \leftarrow Cereals	3.704	0.027	oil \leftarrow Cereals
dl_Crude oil \neq > dl_Oils	2.137	0.061	Crude oil x	0.571	0.566	Crude
dl_Oils \neq > dl_Crude oil	1.237	0.292	Oils	4.853	0.009	oil \leftarrow Oils
dl_Crude oil \neq > dl_Sugar	0.250	0.617	Crude oil x	0.142	0.867	Crude oil x
dl_Sugar \neq > dl_Crude oil	0.751	0.387	Sugar	0.548	0.579	Sugar

\leftarrow/\rightarrow the direction of causality, x—no causality Source: own calculations.

5. Discussion and Conclusions

The paper showed an empirical examination into the linkages between the prices of crude oil and selected groups of agricultural commodities. We used monthly data from January 1990 until September 2020. The food prices are for the meat, dairy, cereal, oil, and sugar product groups. Except for meat price, the results indicate no evidence of long-term linkages between the prices of crude oil and food products, whereas the Granger causality tests confirmed that the global oil price reacts to the prices of food products (dairy, oil, cereal) in the short term.

Each farm, especially focused on mass animal husbandry, needs specialized machines that make the work faster and more efficient. Animal husbandry with machine utilization is an example of extensive farming implemented in developing and highly developed countries. Regardless of the specific breeding directions, the significant aspect prompting the efficiency of breeding is

the available farm infrastructure with its equipment. For example, feeding cards increase food quality. Likewise, without the support of modernly equipped buildings and safety standards meeting hygiene standards and cleaning machines, it is impossible to keep the costs of breeding at a level that guarantees sufficient income. Additionally, in the case of poultry farming, proper temperature in the boiler is essential. The very strong mechanization of animal farming has a strong relationship with energy use. Vehicles, machines, and heating systems are in use thanks to diesel, which increases the production costs, which, in turn, affects the meat price. There might be enlightenment for the strong correlation between the prices of petroleum and meat products. The results suggest that the development in the mechanization process in the agriculture sector may lead to a situation in which an increase in demand for agricultural commodities will be accompanied by a growth in demand for crude oil [50]. Hence, the surge in food consumption roots a rise in the demand for food and thus may affect the volatility of crude oil prices. Apart from agricultural machinery, crude oil is used for the production of fertilizers, plant protection products, and costs of transport, which can additionally be translated into food prices.

The second explanation may be related to the usage of some groups of agricultural commodities for biofuel production. There has been an important rate change between fuel and food when the Renewable Fuel Standard was enacted in 2005 in the US. Hence, there are noticeably stronger linkages between crude oil prices and volatility in food commodities, which are closely related to biofuel production. These relationships were confirmed by researchers in former studies (e.g., Coronado et al. [51]; Vacha et al. [52]). In March 2020, the price index was lower than in February. However, the decline was not the result, as might be expected, of the fall in demand due to the coronavirus lockdown but the oil price slump. A significant part of the world's crops, e.g., sugar cane in Brazil, maize in the USA, or rape in Poland, is intended for the production of biofuel as an alternative energy source. Therefore, when the crude oil prices fell sharply in the world's markets, biofuel producers also had to adjust their prices. Our results confirm the short-run relationship between the price of crude oil and the prices of cereals and oils.

The lack of long-term dependencies among crude oil and most of the analyzed groups of the prices of agricultural goods was also set, inter alia, by Fowowe et al. [17], Zhang et al. [21], and Pasrun et al. [25]. Furthermore, some authors confirm the long-term relationship between the prices of crude oil and agricultural commodities [30,33]. These studies were based on the analysis of individual products (e.g., wheat, maize, butter, etc.) whereas our analyses concern groups of agricultural commodities; therefore, they are not directly comparable. Mawejje [30], analyzing the groups, agreed that energy prices have long-term cointegrating linkages with food prices. However, it should be noted that the results related to a different research period, 2000–2011, than the adopted research period seems to have a significant impact on the result of this type of calculation and their comparison.

The results obtained have an important practical global context. Firstly, the results should apply to investors involved in hedging prospects between petroleum and food markets. The outcomes can inform them that risk in food markets is not dependent on hazards in the oil market [53]. Moreover, the lack of effect of crude oil price level on the fluctuation in the prices of agricultural goods indicates that agricultural policy relating to mitigating volatility of food prices should be based on other issues rather than fluctuations in crude oil markets [19,54]. Furthermore, there are continuous developments in the biofuel market, hence the production of agricultural commodities for energy purposes is increasing. Therefore, we believe that the analysis of their issues should be continued. To obtain more accurate results, we recommend the analyses of individual agricultural commodities, not their groups.

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Appendix A

Table A1. Selected VARs statistics.

VAR(2)	Coef.	Coef.	Coef.
	dl_Crude Oil		dl_Food
dl_Crude oil (−1)	0.499 ***	dl_Crude oil (−1)	0.001
dl_Crude oil (−2)	−0.328 ***	dl_Crude oil (−2)	−0.004
dl_Food (−1)	0.6444 ***	dl_Food (−1)	0.342 ***
dl_Food (−2)	0.38	dl_Food (−2)	0.105
Constant	−0.004	Constant	0.001
R ²	0.320	R ²	0.153
	dl_Crude oil		dl_Dairy
dl_Crude oil (−1)	0.560 ***	dl_Crude oil (−1)	0.020
dl_Crude oil (−2)	−0.323 ***	dl_Crude oil (−2)	−0.034
dl_Dairy (−1)	0.213	dl_Dairy (−1)	0.521 ***
dl_Dairy (−2)	0.209	dl_Dairy (−2)	−0.002
Constant	−0.003	Constant	0.000
R ²	0.296	R ²	0.279
	dl_Crude oil		dl_Cereals
dl_Crude oil (−1)	0.551 ***	dl_Crude oil (−1)	−0.031
dl_Crude oil (−2)	−0.298 ***	dl_Crude oil (−2)	0.024
dl_Cereals (−1)	0.283 *	dl_Cereals (−1)	0.334 ***
dl_Cereals (−2)	0.261	dl_Cereals (−2)	0.036
Constant	−0.004	Constant	0.002
R ²	0.308	R ²	0.118
	dl_Crude oil		dl_Oils
dl_Crude oil (−1)	0.488 ***	dl_Crude oil (−1)	0.0156
dl_Crude oil (−2)	−0.311 ***	dl_Crude oil (−2)	−0.046
dl_Oils (−1)	0.378 ***	dl_Oils (−1)	0.423 ***
dl_Oils (−2)	0.111	dl_Oils (−2)	−0.041
Constant	−0.004	Constant	0.001
R ²	0.317	R ²	0.174
	dl_Crude oil		dl_Sugar
dl_Crude oil (−1)	0.603 ***	dl_Crude oil (−1)	0.013
dl_Crude oil (−2)	−0.288 ***	dl_Crude oil (−2)	−0.031
dl_Sugar (−1)	−0.052	dl_Sugar (−1)	0.313 ***
dl_Sugar (−2)	−0.074	dl_Sugar (−2)	−0.077
Constant	−0.003	Constant	−0.001
R ²	0.283	R ²	0.097

* $p < 0.1$, *** $p < 0.01$. Source: own calculations.

Table A2. Selected VECMs statistics.

Selected Statistic	Stat.
AIC	−6.421
BIC	−6.242
Long-run relationship	$1 * \ln_Crude\ oil - 6.164 \times \ln_Meat + 0.012 \times time$
EC (ln_Crude oil)	−0.008
EC (ln_Meat)	0.027 ***

*** $p < 0.01$. Source: own calculations.

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