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The Nexus of Crude Oil and Food Prices: Evidence of the Crude Oil Prices Influence on Food Insecurity Problem

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Abstract

Food cost is a fundamental factor in reducing world hunger and minimizing the food insecurity problem. Agricultural commodities prices, especially grains, are determinants of food costs. Therefore, studying the behavior of commodity prices responsible for food security on the planet is essential for economic agents, especially for macroeconomic policy decision-makers. Food production and prices are related to energy prices, mainly through biofuels and fertilizers. Among energy sources, crude oil is one of the main ones in the world's energy matrix. Many studies on crude oil and food prices have been carried out relating energy and food or, more specifically, crude oil and agricultural commodity prices. This work examines the dynamic relationship between oil and grain commodity prices: rice, wheat, corn and soybeans. It also verifies the causality and cointegration between each grain and crude oil price return. Besides that, Autoregressive vector models were estimated to infer the impulse response function and the variance decomposition. The sample period corresponds to the interval between the two biggest crises of the century, the subprime financial crisis and the Covid-19 pandemic sanitary crisis. Thus, the data is not impacted by significant abnormal variations caused by these crises. The inferences show an interaction between crude oil prices practiced in the international market and food commodity prices.

JEL: C32, C58, G15, O13, Q02, Q43

Keywords: food insecurity, food prices, crude oil prices, var models

1. Introduction

According to the Food and Agriculture Organization of the United Nations (FAO) (2020), almost 690 million people go hungry globally, representing 8.9% of the world population. There is a tendency for growth in the number of people affected by the food insecurity problem.

Thus, food cost is a crucial factor in reducing world hunger and minimizing the food insecurity problem. Agricultural commodities, especially grains, are necessary products to feed the world's population and are highly relevant for human survival and hunger reduction. Hence, this reinforces the need to study and understand the factors affecting their prices. Agricultural grain commodities are priced based on international market quotations.

According to the Center for Advanced Medicine (2020), three ingredients are found in most processed foods: wheat, maize, and soya called the "Big Three". In addition, Wright (2011) highlights that rice, wheat, and maize provide the global population with most of its food energy. Rice is among the world's most consumed foods, being strategic economically, and has the world's largest producers in Southeast Asia, according to the IFC Markets (2020) website. Wheat, in turn, is the second most produced grain globally and plays a critical role in food security as it is the primary ingredient of bread and an essential source of nutrition. On the other hand, corn has economic importance, characterized by several uses ranging from animal feed to high-tech industry. Corn can also be used as an energy source in biofuels and is among the main components of poultry, cattle, and pig feed, which are essential animal protein sources. It is interesting to note that grain maize, as animal feed, accounts for most of its consumption. Besides, soya, like maize, can be an energy source for biofuels and an essential component of poultry, cattle, pig feed, and human nutrition. Add rice to the Big Three, and have the four foods responsible for food security.

Regarding emerging or developing economies, it is essential to note that adverse agricultural price shocks have an even more significant negative impact on their economic growth, as pointed out by Todsadee et al. (2014), which thus justifies the study of the agricultural commodity price volatility. In addition, developing countries are generally more economically dependent on commodities exports essential to their trade and payment balances or national accounts. However, as Hespanhol et al. (2010) point out, increased food production in these countries does not solve the hunger and malnutrition problems due to the unavailability of income to purchase them.

The grain commodity prices can be affected by other commodity prices, whether they are grain or other commodity groups. Dawson and White (2002) point out that the association between the prices of commodities traded on international markets can happen for four reasons: (i) macroeconomic variables such as aggregate demand, inflation, and interest rates influence commodity prices; (ii) associations between commodity prices of the same group are observed because they are substitute goods, at least partially, or complementary goods; (iii) correlations between future prices of all commodities; and (iv) similarities between government policies.

Pindyck and Rotemberg (1990), in turn, point to two possible reasons for the similar behavior of commodity markets: (i) informational inefficiency of the markets; (ii) "herd" behavior or similar perception among participants in these markets of information affecting prices. As pointed out by Tang and Xiong (2012), with the financialization of commodity markets, the involvement of financial agents has become a determinant of agricultural commodity prices.

Many papers relate agricultural commodities and energy prices mainly due to biofuels, essential energy sources for preserving the environment. Grain commodity prices can be affected by other commodity prices, whether grain or other groups, such as in the energy commodity segment, especially crude oil. While crude oil influences fuel, fertilizer, and transport prices, grain production competes with biofuel and fossil fuel production. Crude oil and agricultural commodity prices have been the subject of various econometric studies and research because they influenced the world economy and their importance in meeting the world's food needs. The agricultural product prices are affected by energy prices through production and distribution costs and the demand for these products to produce biofuels. The crude oil market is one of the largest among international commodity markets. As Salles (2019) points out, crude oil prices are influenced by several random events such as climate, availability of oil stocks, economic growth, variations in industrial production, political or geopolitical aspects, and currency movements. For Salles (2019), sudden changes in crude oil prices directly influence international financial markets, and these variations bring changes to foreign trade, investments, and productive activities. It is worth mentioning that Guo and Kliesen (2005) work stresses that oil price volatility can temporarily reduce aggregate production as it delays business investment, increases uncertainty, or induces costly reallocation of sectoral resources. Moreover, the rise in crude oil prices impacts different macroeconomic indicators by increasing production and operational costs. An increase in oil prices implies higher production costs, reduces the rate of return on investment, and increases uncertainty. Thus, as Rafiq et al. (2009) point out, it directly influences product prices and, consequently, on demand. It can be inferred that there is a significant relationship between oil prices and economic activity in general and with grain production in particular. This way, oil correlates with food security on the planet.

This work aims to examine the interaction, causality, and cointegration between agricultural commodity prices such as rice, wheat, corn, and soybean and crude oil prices on the international market through bivariate stochastic models, namely autoregressive vector models (VAR) and error corrected vector models (VECM). It seeks to verify how each grain commodity price responds to innovations or shocks in crude oil prices and how they respond to innovations or shocks in each commodity price studied. Finally, it analyzes how each grain price variability influences and is influenced by the crude oil price variability.

The remainder of this article is organized as follows. Section 2 deals with the bibliographic review, where studies and research related to the subject are presented. Section 3 presents the methodological approach used, while Section 4 presents the sample used. Section 5 shows the analysis of the results obtained. Finally, Section 6 introduces the conclusions and final comments, followed by the bibliographical references.

2. Literature Review

Several works seek to study the factors that reverberate in the prices practised in the commodities markets, mainly those associated with variations in the energy commodity prices, particularly crude oil prices in the agricultural commodity prices. Crude oil is essential to the world economy, and its prices may impact other commodity prices and global economic indicators. Hence, in this section, some studies and research that compose the bibliographic review of this work are presented and commented on.

Rafiq et al. (2009) sought to verify the impact of oil price volatility on Thailand's macroeconomic indicators, concluding that volatility has a short-term effect on investment and can explain the unemployment rate. This volatility is caused by uncertainty, delays, restricted investments, and reduced unemployment due to the restructuring of the economy and the reallocation of resources.

In another study, Harri and Hudson (2009) note that the use of inputs from the petrochemical industry in agriculture has been increasingly used over time, and a change in these input prices has a direct relationship with the prices of agricultural activity goods. In addition, agricultural commodities have been increasingly used to produce energy. Thereby, Harri and Hudson (2009) studied the dynamics of variation between agricultural commodity prices and crude oil prices, concluding that this price variability has a causal relationship with corn price variation in the Granger sense. It occurs because of corn-based ethanol and soy biodiesel production growth. Chen et al. (2010) investigated the relationship between crude oil prices and the corn, soybeans, and wheat prices in international markets. The results show that crude oil and other grain price variations from 2005 to 2008 significantly influenced grain price variations. Thus, it implies that grain commodities compete with the derived demand for biofuels by using soy or corn to produce ethanol or biodiesel during high crude oil price periods of those years. Gardebroek and Hernandez (2013) studied the volatility transmission among oil, ethanol, and corn prices in North American markets. They highlighted that the energy market price volatility does not influence the corn market price volatility. Furthermore, Gardebroek and Hernandez (2013) observe that the average return in these markets is influenced only by the lagged return itself, dissociated from the lagged returns of other markets.

When the factors that influence the commodity market price volatility classified into energy and non-energy were investigated, Manera et al. (2013a) studied the prices practiced in these markets, inferring that the price returns volatility was significantly affected by speculation. Short-run speculation positively impacts volatility, while long-run speculation has a negative effect. In another study on the future prices of four energy commodities, namely crude oil, fuel oil, gasoline, and natural gas and five agricultural commodities, namely corn, oat, soy oil, soybean, and wheat, Manera et al. (2013b) show that agricultural markets high volatility corresponds to low volatility in the energy market and vice versa. It must be mentioned that Bakhat and Würzburg (2013) also studied the price transmission between food and energy goods, giving evidence that biofuel production increased the association between food prices and crude oil prices. Most of these complex price relationships were found among the biofuel raw materials, such as sugar cane, soy, sunflower, and palm oil. However, no cointegration relationship between crude oil and corn prices has been found. It must be pointed out that the results of these surveys were not entirely consistent and unanimous.

In a study on commodity price volatility with a capital market approach, in particular, the stock market, Mensi et al. (2013) investigated the associations of returns and the volatility transmission between the North American stock market profitability indices and energy, food, beverage, and gold market profitability indices using a sample covering the first decade of this century, a turbulent period in the world economy. The results shown by Mensi et al. (2013) corroborate previous studies of crude oil price volatility affecting the stock markets.

In research developed to examine the variability of food commodities prices, Todsadee et al. (2014) note that the association of soy and crude oil prices in the international market was weak in the 2007-2013 period. In another relevant study, Bin et al. (2014) examined the effects of crude oil price variations on other commodity prices, inferring that the soy price overreacts to adverse shocks compared to positive shocks of crude oil price changes. Besides that, corn prices react significantly to positive and negative crude oil price shocks. Regarding the Brazilian market, Salles and Oliveira (2020) analyzed the conditional correlation between crude oil price returns and agricultural commodity price returns, namely soy, coffee, and sugar. The authors note a significant correlation between crude oil price returns in the international market and Brazilian crystal sugar export price returns and a weaker but significant association between crude oil price returns in the international market and coffee and soybean Brazilian export prices. Regarding food price expectations, Ahumada and Cornejo (2016) present a food price forecast model and consider the cross-dependence among corn, soy, and wheat. This study demonstrates that the models that use these price interactions bring improvements in achieving future price expectations.

Bernhardt (2017), motivated by population growth, increased wealth, and the fact that using grains as fuel influenced prices in agricultural markets, studied the return and volatility spillover effects in agricultural commodity markets, namely sugar, wheat, soy, and coffee. In the same work, Bernhardt (2017) concludes that risk obtained by volatility plays an important role in commodity agricultural markets concerning the conditional average and conditional volatility. In a contemporary study, Kumar (2017) analyzed the transmission of crude oil price volatility to agricultural commodity market price variation, particularly wheat, corn, cotton, and soybeans. This study shows a crude oil price volatility transmission to selected agricultural commodities, although this does not occur constantly. In order to estimate crude oil prices and exchange rates transmission volatility to corn, rice, and soybeans prices in Ghana and Turkey, Damba et al. (2019) observed transmissions among these three agricultural commodity prices and crude oil prices and exchange rates in the short run. The study by Herwartz and Saucedo (2020) analyzed the role of crude oil price variation on agricultural commodity price uncertainties. This study concluded that crude oil price volatility is a determinant factor of uncertainties in raw material markets.

In general, different conclusions of the works presented here indicate that these works point out the association between energy and food prices and the volatility transmission between these two markets. However, it should be observed that the studies accomplished by

Gardebroek and Hernandez (2013) and Todsadee et al. (2014), with data from North American markets, demonstrated a weak relationship between energy and food markets. The first study, conducted by Gardebroek and Hernandez (2013), does not show evidence that energy market volatility provokes corn price volatility, while in the second study, carried out by Todsadee et al. (2014), the correlation coefficient estimates between the crude oil and soybeans prices showed low values, that is, a weak association.

In recent years, the topic discussed here has remained the focus. Many research works continue to be developed on the relationship between oil and food commodity prices in international markets. Among these works is the work of Gong et al. (2023), which uses sample weekly data from 2000 to 2020 with information on quotes from Brent crude oil and "Big Three" prices. Gong et al. (2023) point out the contagion between prices charged in the crude oil and food commodities markets, highlighting that contagion is evident only in specific periods. The work of Gong et al. (2023) highlights the effect of the 2008 subprime crisis on the markets studied, showing a sudden increase in prices following the outbreak of this financial crisis. Other recent work that refers to the relation of crude oil and food prices is presented by Adeosun et al. (2023), with monthly data from 1990 to 2021 of an extensive sample of commodities in addition to the most representative ones for food security on the planet, studied the hypothesis of causality between the prices of crude oil markets and food commodities and the predictive power of these commodities for crude oil prices. The work of Adeosun et al. (2023) highlights that there is no consensus regarding causality between the prices of these markets, presenting results from Granger causality tests that indicate a two-dimensional causal relationship between the returns on the prices of crude oil and selected food commodities except for wheat and of soybeans whose statistical significance of causality tests only points to a unilateral relationship of wheat and soybeans to crude oil but not of crude oil to these commodities. Finally, it is worth mentioning the work of Dai & Wu (2024), who observed the increase in the financialization of the crude oil market and its significant influence on financial markets and the global economy and highlighted that the impact of volatility contagion between the crude oil market and other commodity markets occurs differently.

3. Methodological Approach Used

The first fundamental assumption tested refers to the normality hypothesis that verifies whether the stochastic processes represented by the time series fit a normal probability distribution. Given the relevance of the normal distribution for the estimates conducted in this work, the asymmetry and kurtosis coefficients of the studied time series were analyzed. The estimates of the asymmetry and kurtosis coefficients are essential to infer how close the data distribution is to a normal distribution. Hence, using the Jarque-Bera (JB) normality test proposed by Jarque and Bera (1973) as described by Gujarati and Porter (2009), the studied time series normality hypothesis was verified.

A fundamental assumption for estimating the stochastic models used in this work refers to stationarity. As noted by Gujarati and Porter (2009), a stochastic process is considered to be stationary if the mean and variance are constant over time and also if the covariance value between two periods depends only on the distance, the gap or the lag between the two periods and not on the real-time when covariance is estimated. If the time series is non-stationary, one can study its behaviour only during the period considered, allowing no inferences beyond the period studied or out of the sample considered. According to Gujarati and Porter (2009), non-stationarity generally results in spurious regressions even if performed using a large sample. Among the possible tests to verify the time series stationarity, the unit roots tests are widely used; in this study, the Augmented Dickey-Fuller (ADF) test, proposed by Dickey and Fuller (1979) as described by Gujarati and Porter (2009), was used in this study.

Another hypothesis statistical test essential for this study is the cointegration test. According to Gujarati and Porter (2009), cointegration refers to the existence of a long-run stochastic relationship between two or more variables or time series. That is, if two-time series are cointegrated, it can be said that there is a long-run relationship between both. The cointegration test proposed by Johansen and Juselius (1990) is suggested to test a long-run relationship between the grain commodity and crude oil price return. Thus, the Johansen and Juselius (1990) cointegration test was chosen for its suitability for estimating the autoregressive vector models presented below. Using a VAR model of order p, or VAR (p), the model applied in the test presented by Johansen and Juselius (1990) can be described as follows:

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + Bx_t + \varepsilon_t \quad , \tag{1}$$

where: y_t is a vector of dimension k of non-stationary variables; x_t is a vector of dimension d of deterministic variables and ε_t is a vector of innovations or stochastic terms. Thus, the above expression can be rewritten as:

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-1} \; Bx_t + \varepsilon_t \quad , \tag{2}$$

where:

$$\Pi = \sum_{i=1}^{p} A_i - \mathrm{I} \quad \text{and} \quad \Gamma_i = -\sum_{j=i+1}^{p} A_j \tag{3}$$

As Salles and Oliveira (2014) observe, Granger's representation theorem states that if the matrix coefficient Π has reduced the complete rank $r < k$, then there are the α and β matrices of dimension $k \times r$, each with a complete rank r so that and are stationary. Since r is the number of cointegration relations, cointegration rank, each column β is designated as a cointegration vector. The elements of α are known as the adjustment parameters in the autoregressive vector model with error correction (VECM) that will be presented ahead. Johansen's method estimates the matrix Π from an unrestricted VAR and tests the rejection of the restrictions applied by the reduced full rank of Π. Furthermore, as highlighted by Johansen (1991), the likelihood ratio hypothesis tests that check the number of characteristic roots statistically different from zero in the coefficient matrix have derived asymptotic distributions and converged to two test statistics: the trace and the maximum eigenvalue of the matrix. In the first test, the null hypothesis enunciates the existence of r cointegration relations, while the alternative hypothesis enunciates k cointegration relations, where k is the number of integrated endogenous variables of order 1, where $r = 0, 1, ..., k - 1$. This test statistic can be described as follows:

$$LR_{tracer}(r|k) = -T\sum_{i=r+1}^{k} log\ (1-\lambda_i) \quad (4)$$

where λ_i represents the largest eigenvalue of the matrix coefficient Π and T is the number of observations in the time series included in the analysis. In the second test, the null hypothesis enunciates the existence of r cointegration relations, while the alternative hypothesis enunciates the existence of $r + 1$ cointegration relations. The expression represents the maximum eigenvalue test statistic:

$$\begin{aligned} LR_{max}(r|r+1) &= -\mathrm{T}\log(1-\lambda_{r+1}) \\ &= LR_{trace}(r|k) - LR_{trace}(r+1|k), \quad r = 0, 1, \ldots, \mathrm{k}-1. \end{aligned} \quad (5)$$

The autoregressive vector model (VAR) proposed by Sims (1980) was used to obtain the inferences necessary to achieve the objectives of this work. From the seminal work presented by Sims (1980), the VAR model has been widely used in macroeconomic studies. Especially to verify the evolution and the interdependencies among economic time series. Developed from the autoregressive vector models, this stochastic model does not distinguish the endogenous and exogenous variables. In addition to verifying these variables' short- and long-run relationships, the autoregressive vector models allow for the relationship study of two or more stochastic variables and the innovation or shocks one variable causes in another. The VAR model can be described by the following system for the VAR model of order 1, or VAR (1):

$$\begin{aligned} Y_t &= \beta_1 + \beta_2 Y_{t-1} + \beta_3 Z_{t-1} + \varepsilon_{1t} \\ Z_t &= \beta_4 + \beta_5 Z_{t-1} + \beta_6 Y_{t-1} + \varepsilon_{2t} \end{aligned} \quad (6)$$

where the variables Y_t and Z_t are stationary and the stochastics terms $\mathcal{E}_{1t}$ and $\mathcal{E}_{2t}$ have an expected value equal to zero and are orthogonal. In this work, Y represents the crude oil prices time series, and Zg represents the grain price times series where g can have values *1*, *2*, *3* or *4*, corresponding to corn, rice, soy and wheat, respectively. For all the estimated models in this study, the constants β_1 and β_4 were not statistically significant and, therefore, were not included in the final models.

The autoregressive vector model with error correction (VECM) is the VAR model in a particular case. It should be used whenever a long-run stochastic relationship exists among variables or time series. This model can be applied when the variables are stationary, cointegrated, and the residues are independent. In this study, all variables are considered endogenous, and if they are cointegrated, the VECM should be used to: (a) test whether crude oil price is useful to predict each food commodity price and conversely; (b) analyze the impulse response function to verify whether an unexpected but temporary change or a shock in the crude oil price time series influences the other variables' time series; (c) Analyze the stochastic term variance decomposition of the time series involved in the model.

In econometric models in which the dependence of one variable on another does not always occur at the same time, it may occur at different times. That is, one variable can influence the other with a time lag. Determining the number of lags is an intrinsic problem of this model's estimation. This number is, in general, determined empirically. Model selection criteria were used to determine each model's lag number. In this work, the Akaike (*AIC*) and Schwarz (*BIC*) information criteria, respectively proposed by Akaike (1974) and Schwarz (1978), were used. According to Gujarati and Porter (2009), the *AIC* and *BIC* criteria can be described as follows respectively:

$$AIC = \left(\frac{SQR}{n}\right) exp\left(\frac{2k}{n}\right), \tag{7}$$

and

$$BIC = \left(\frac{SQR}{n}\right) n^{k/n}, \tag{8}$$

where n is the number of observations, k is the number of estimated parameters and *RSS* is the sum of the squares of the residuals. As decision criteria, the model that minimizes the chosen information criterion will be the most appropriate.

4. The Sample – Data Used

The primary data used in this work is crude oil and grain commodities prices in the international market. Specifically, Brent crude oil weekly closing quotations traded in London on the London Stock Exchange, and rice, wheat, corn, and soybeans weekly closing quotations were traded on the grain markets in Chicago on the Chicago Board Trade. Brent Crude oil data refers to the spot market quotes, while grain commodity data refers to the future contracts quotation prices with the closest maturity, the first contract to expire. The price time series for the selected grains were collected from a Bloomberg terminal, while Brent crude oil prices were obtained from the US Government Energy Agency (EIA) website. All data was collected in US$ to reduce the impact of inflation in different currencies. In addition, the US dollar has international acceptance and is the primary currency reference in international trade.

The collected data covers the period from June 2009 to November 2019, making a sample with 547 observations of the weekly closing quotations obtained from the daily data collected. It must be mentioned that this period was chosen because it lies between two major world crises of this century: the 2008 financial crisis, known as the subprime crisis, and the 2020 sanitary crisis, caused by the Covid-19 pandemic. Thus, the data is not impacted by significant abnormal variations caused by these crises.

Figure 1 shows the weekly price time series behaviour for each of the commodities studied in this work, making it possible to compare the evolution of these prices. Generally, all the price time series have similar variations in specific periods, while the grain price time series appears to follow a similar behaviour. Clearly, the prices time series of the “Big Three”, that is, of corn, wheat and soybeans, present similar behaviors and differ from the crude oil prices time series. Concerning corn and crude oil prices time series, it is possible to verify that one of these commodity prices behaves in the same way as the other commodity in several periods in general. Nevertheless, it is noted that the variations in the periods between 2009 and 2011, when there was an upward movement for both data and at the beginning of 2014 when there was a sharp and long downward movement in the crude oil price, do not occur in the corn prices time series.

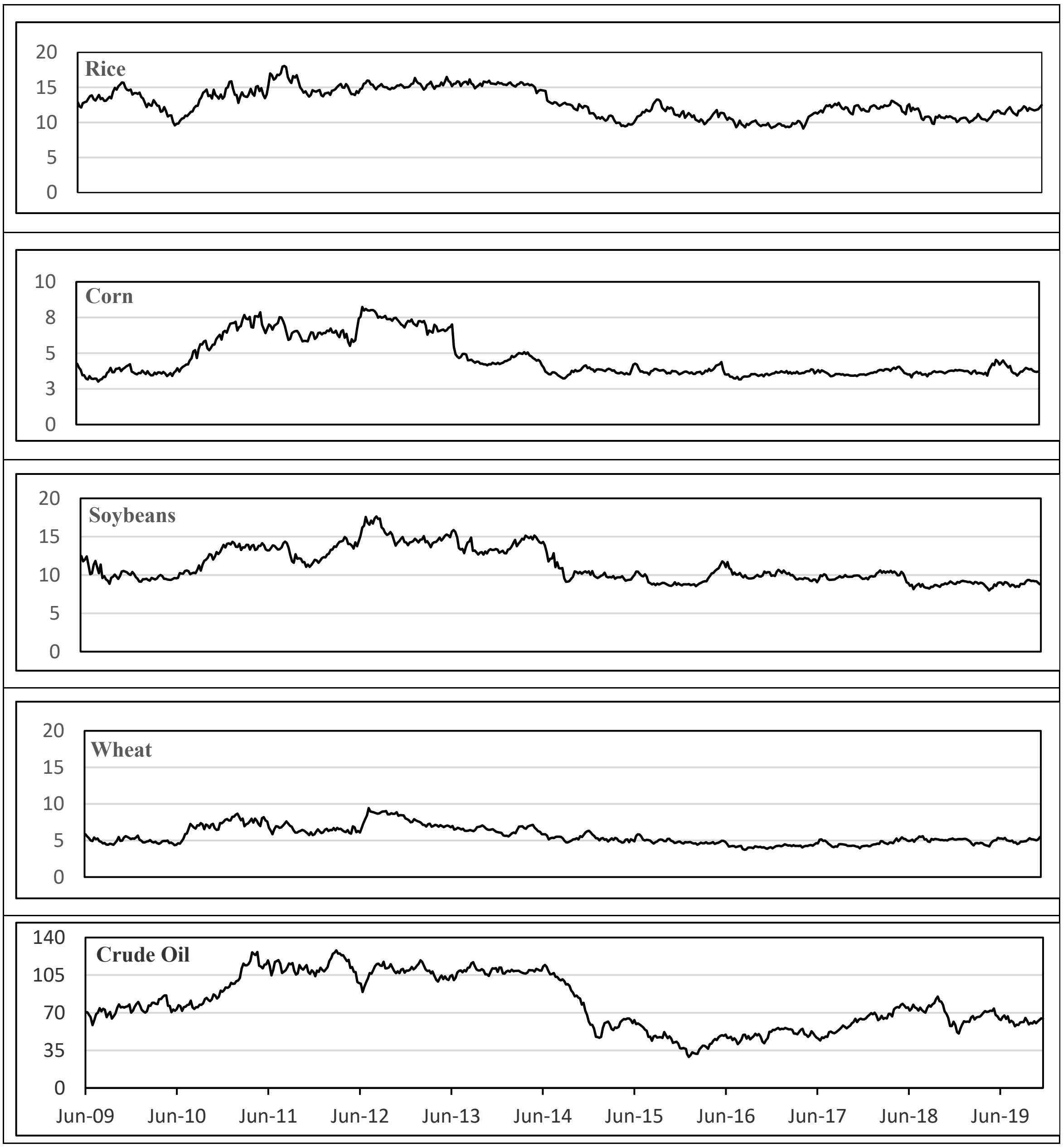

Figure 1. Crude Oil and Grain Prices Plots (US$)

Regarding the time series of soy and crude oil prices, similar movements can be seen between 2011 and 2013. There is a pronounced downward movement in the second half of 2014, which is more pronounced in the crude oil prices time series. A price increase in the first half of 2016 followed, while soybean prices remained constant. Significant wheat and crude oil price variations occur in one commodity, whereas the same is not noticed in price variations of another commodity. In addition, it can be noted that the wheat prices time series do not accompany the sharp fall in crude oil prices in 2014. Concerning the rice and crude oil prices time series, there is no evidence of an association in their movements, except in the mid-2010s, when rice and crude oil prices showed an increasing trend.

Table 1 presents the weekly price time series statistical summary that comprises the sample used in this work. Amid the results presented in Table 1, the average and standard deviation of the price time series allows us to infer that crude oil has the highest average price, followed by rice, soy, wheat, and corn. The crude oil prices time series also has the highest volatility, followed by corn, wheat, soy and rice. Regarding the time series probability distributions, all have an asymmetry coefficient greater than zero, indicating a higher concentration of values above the average. Crude oil prices have an asymmetry coefficient closer to zero, indicating an asymmetry coefficient closer to the normal probability distribution. The same occurs with rice prices. The kurtosis coefficient estimates were less than 3 for all prices in the time series, indicating that the probability distributions are more flattened than the normal probability distribution. The Jarque-Bera test does not allow the acceptance of the normality hypothesis for any time series studied, confirming that the normality of the commodity prices stochastic processes selected for this research cannot be accepted. The stationarity hypothesis was tested using the Dickey-Fuller Augmented unit root or ADF tests. In this test, the null hypothesis enunciates the existence of a unit root in the time series. It is possible to observe in Table 2 that none of the price time series studied show stationarity at a significance level of 5% since the p values present values greater than 0.05.

Table 1. Statistical Summary of Weekly Price and Return Time Series Used

Statistics	Corn Price	Rice Price	Soy Price	Wheat Price	Oil Price	Corn Price Return	Rice Price Return	Soy Price Return	Wheat Price Return	Oil Price Return
Mean	4.593	12.783	11.190	5.655	79.155	-0.0003	0.00002	-0.0006	-0.0002	-0.0001
Median	3.845	12.4150	10.263	5.195	74.580	0.0011	-0.0003	0.0010	-0.0016	0.0017
Maximum	8.245	18.0600	17.645	9.433	128.080	0.1292	0.1038	0.1050	0.1595	0.1621
Minimum	3.005	9.1300	7.970	3.733	28.800	-0.2543	-0.0996	-0.1671	-0.1413	-0.1506
Std Deviation	1.393	2.0865	2.268	1.245	25.596	0.0388	0.0322	0.0326	0.0420	0.0415
Skewness	1.072	0.160	0.712	0.824	0.142	-0.6076	0.0050	-0.7316	0.3146	-0.3130
Kurtosis	2.632	1.859	2.307	2.844	1.699	6.9754	3.6248	5.7881	3.8849	4.1845
Jarque-Bera	107.877	31.995	57.092	62.480	40.385	393.848	8.899	225.977	26.870	40.906
(p value)	0.000	0.000	0.000	0.000	0.000	0.0000	0.0117	0.0000	0.0000	0.000
ADF test	-2.63	-2.57	-2.34	-2.71	-2.04	-10.42	-13.33	-25.01	-8.67	-21.42
(p value)	0.267	0.293	0.412	0.235	0.575	0.000	0.000	0.000	0.000	0.000

Source: Authors estimation with EViews from Bloomberg and EIA data.

The commodity price returns were the data used in constructing the models to obtain the necessary inferences proposed in the objectives of this work. The price returns in the period t given by R_t were calculated as follows: $R_t = ln\ (P_t) - ln\ (P_{t-1})$, where P_t is the closing week price at the period t. These time series statistical summaries are presented in Table 1. Hence, the descriptions of the price returns time series using summary measures of location and scale and the normality and stationarity hypotheses test of each weekly price returns time series are shown in Table 1.

Regarding the price returns time series, it can be observed that rice is the only commodity with a positive average return. The commodity with the lowest average return is soy, followed by corn and wheat in the period studied. It can be observed that crude oil has the highest maximum value return, and among grains, wheat has the highest value return. On the other hand, corn has the lowest minimum return value. It can also be observed that wheat has the most significant standard deviation; that is, it is the commodity whose price returns have a greater weekly volatility in the selected period. Wheat is followed by oil, corn, soy and rice. Rice presents the lowest standard deviation. Therefore, it has the slightest variation in the weekly price returns time series in the selected period. In addition, oil, corn and soy price returns have a negative asymmetry coefficient. Hence, the tail on the left of the probability density function is higher. That is, it has a greater concentration of values below the average. Rice and wheat have a positive asymmetry coefficient. Hence, the tail on the right of the probability density function is higher. That is, it has a higher concentration of values above the average. With an asymmetry coefficient closer to zero, rice price returns have the same normal probability distribution asymmetry.

5. Results Obtained

This section comments on the cointegration hypothesis test between crude oil price returns and each grain commodity price return. Next, the autoregressive vector models estimations and their inferences are presented. Then, the inferences obtained from these estimation procedures, such as causality, impulse response and decomposition of variance, are shown afterwards.

Regarding the cointegration hypothesis tests between each of the agricultural commodities and crude oil price returns in the four cases analyzed, it can be concluded that there is a cointegration relationship between these time series with a significance level of 5%. Hence, the cointegration relationship between crude oil price return and the price returns for the four grains studied cannot be rejected. It confirms a long-run relationship between these variables and states that these variables share the same stochastic properties in the long run. These results have direct implications for the autoregressive vectorial model estimation, which is fundamental to achieving the objectives of this work. It must be highlighted that given the non-rejection of these cointegration hypotheses, an error correction mechanism must be included in the autoregressive vectorial models. That is, turning the VAR model into VEC or VECM models.

Table 2 presents the VECM model estimation results, their estimated parameter, their respective standard errors, the *t* statistics with the associated p-value, and the estimated model's performance metrics. It should be noted that the autoregressive vector model estimated lag was chosen considering the statistical significance of the estimated parameters and the performance metrics optimization for each estimated model. When analyzing Table 2, the following information must be taken into consideration: Y_t represents the crude oil price return in period *t*; Z_{gt} represents each grain commodity price return g in period *t*, where g is 1 to 4, which corresponds to corn, rice, soy and wheat respectively; and ECM represents the error correction mechanism or the cointegrate equation. Table 2 shows the statistical significance of the parameters estimated in each column for the selected grains, namely corn, rice, soybeans, and wheat, each representing one estimated autoregressive vectorial model. As observed for most estimated parameters, a significance level of 5% statistical significance cannot be rejected. However, it should be emphasized that this occurs with a different significant level to some parameters. For example, in Model 3, in the soy return equation, the lagged soy price return variable coefficient has a *t* statistic close to -1.42; in Model 3, in the crude oil price return equation, the lagged soy price return variable coefficient has a *t* statistic close to -1.90; and in Model 2, in the rice price return equation the lagged rice price return variable coefficient has a t-statistic close to -1.27.

Regarding the estimated coefficient signs, it is worth highlighting that in Model 1, the relationship between crude oil and corn price return variables is positive. In contrast, the impact between the variables and their lagged variables is negative.

As can be observed in the Model 2 estimation results, there is a relationship between the variables with the same signs observed in Model 1. An exception is the positive influence of the lagged rice price return on the rice price return. It is interesting to note that a positive variation in the rice price return in period t - 1 causes a slight change in rice price in period t. The relationship obtained in Model 3 estimation that deals with crude oil and soy price returns is similar to Model 2, even though the soy price returns in period t - 1 negatively impact the crude oil price returns in period t. Except for wheat price returns in period t - 1, which negatively impacts the crude oil price returns in period t, all variables in Model 4 positively impact the model estimated.

Table 2 shows all estimated VECM model parameters, which indicate each variable's influence on the interest variable. From the performance metrics listed, it should be noted that the F statistics of all models are large enough to ensure that all parameters are jointly different from zero, demonstrating the model's statistical significance. Regarding the Granger causality test, the F statistic points to the non-rejection of the variable's bidirectional causality hypotheses in the models that relate crude oil price return to commodity price return of corn, rice, soy and wheat. It is essential to highlight that the Wald test for all models does not accept the null hypothesis of these parameters, which are equal to zero. It confirms the long-run relationship between the variables explained by the estimated bivariate models, that is, between the price returns of each food grain and crude oil price returns in the international market. As for the short-run relationship, the statistical significance of the parameters indicates that this hypothesis cannot be rejected. Another relevant inference concerns Granger's causality test. This test points to the no rejection of the bidirectional causality between two indicators, which is confirmed by the Wald exogeneity test. Thus, it can be inferred that there is an interaction in the short and long run between the two variables of interest in each of the four VECM models estimated in this study.

From the response impulse functions obtained through the estimated models, it is possible to analyze how the shock of one variable will persist on the other variable in future periods. The samples considered for each commodity were ten-period or week estimates, and crude oil price returns were analyzed for the impulse response function.

Table 2. The VECM Model Estimation Results

Models	Model 1 - Corn		Model 2 - Rice		Model 3 - Soy		Model 4 - Wheat	
Variable	*r-oil$_t$*	*r-corn$_t$*	*r-oil$_t$*	*r-rice$_t$*	*r-oil$_t$*	*r-soy$_t$*	*r-oil$_t$*	*r-wheat$_t$*
EMC coefficient	-0.316	-4.117	-0.081	-0.169	-0.102	0.343	-0.234	-0.416
Std Error	0.035	0.031	0.015	0.010	0.034	0.023	0.030	0.027
t-Statistic	-8.944	-13.230	-5.386	-17.072	-3.008	15.211	-7.769	-15.149
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
r-oil$_{t-1}$ coefficient	-0.270	0.253	-0.404	0.145	-0.385	-0.126	-0.316	0.278
Std Error	0.040	0.036	0.038	0.025	0.043	0.028	0.040	0.036
t-Statistic	-6.678	7.103	-10.580	5.795	-9.040	-4.428	-7.929	7.668
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
r-grão$_{t-1}$								
coefficient	0.358	-0.182	0.245	0.054	-0.126	-0.062	0.306	-0.081
Std Error	0.045	0.040	0.064	0.042	0.066	0.044	0.045	0.041
t-Statistic	7.903	-4.560	3.809	5.795	-1.903	-1.417	6.846	-1.991
p value	0.000	0.000	0.000	0.000	0.058	0.157	0.000	0.047
DRC	3,66E-06		2,51E-06		2,57E-06		4,25E-06	
R-squared	0.308	0.422	0.233	0.474	0.205	0.509	0.281	0.451
SE of regression	0.047	0.041	0.049	0.323	0.050	0.033	0.048	0.044
F-statistic	120.84	197.83	82.248	243.981	69.989	280.535	105.662	222.725
AkaikeCriterion AIC	-3.279	-3.534	-3.175	-4.021	-3.139	-3.950	-3.239	-3.425
Log likelihood	1864.460		1966.887		1960.674		1823.668	
AIC - Model	-6.813		-7.189		-7.166		-6.663	

To complement the results of the impulse response functions analysis for the four estimated VECM models in ten periods or weeks, the obtained results description from the four estimated VECM models is followed. The results obtained for Model 1 relate crude oil and wheat price returns traded in the international market. Crude oil price returns -- r-oil shocks on agricultural commodity variables are close to 0.01 for all periods. It can also be inferred that crude oil price return response on the variable itself in all models is positive and is higher in the first period, falling in the second and remaining constant at a minimal positive value since then, except for Model 2, which relates crude oil and corn price returns -- r-corn which occurs when the response decreases to close to zero from the third period studied. Concerning the commodity price returns of corn -- r-corn, wheat -- r-wheat and rice -- r-rice into consideration, these variables' impact on crude oil prices returns -- r-oil occurs similarly. It is close to zero in the first period and slightly negative and constant from the second period onwards, followed by equivalent values.

Regarding soy price return -- r-soy, the impact is constantly positive, close to 1%. The agricultural variables' response to themselves is positive for rice and soy. It is more significant in the first period, decreasing to zero from the second period and remaining constant from the fifth. Regarding wheat price return, the impact is positive and more significant in the first period, decreasing to a constant value in subsequent periods. As observed, the impact of corn price return in the first period is more significant, followed by smaller or close values in the subsequent periods.

Using the methodology suggested by Pesaran and Shin (1998), the variance decomposition is used to determine the prediction variance error proportion of a variable, which is explained by its lag as well as by other explanatory variables lags in a specific period. The variance decomposition results differ from the price returns time series studied in the short and long run. Thus, after verifying this difference, 52 periods were also analyzed, in addition to ten-period terms. Concerning Model 1, which relates crude oil and corn price returns, the variance percentage of the crude oil price returns is approximately 80% in the 10th period due to itself. Corn price return variance is impacted by crude oil return price return of 40% in the same period and approaches 60% in the long run. Concerning Model 2 returns, which relate to crude oil and rice price returns, the variation percentage in crude oil price return variance due to itself starting at 100% and nearing 90% after ten periods remains constant over the long run. The variation percentage in rice price returns due to the variation in crude oil price returns starts without any influence. It starts at 0% and increases to approximately 50% in the long run.

Regarding soy price returns, as shown in Model 3, the variation percentage of crude oil price returns to itself remains close to 100% in the long run. The soy price returns variations due to the crude oil price returns variations, which are approximately 60% in ten periods and 80% in the long run, that is, in 52 periods. Concerning Model 4, which relates to crude oil and wheat price returns, the variation percentage of crude oil price returns about itself starts at 100%. It nears 80% after ten periods, remaining constant from then onwards. The variations of wheat price return percentage due to crude oil price returns have no influence initially but nears 40% in the following ten periods and 70% in the long run. Interestingly, within one year, the variance percentage of crude oil price returns that occurs due to agricultural price returns happens increasingly, reaching up to 20% in the case of corn and wheat. Finally, it should be highlighted that the percentage variance of the food commodity price returns caused by crude oil price returns in the same timeframe is much higher, approaching a percentage between 50% and 80%, according to the model estimated for this work.

6. Conclusion and Final Remarks

The primary motivation of this work is the relevance of agricultural commodities for the world population's food security. Food production and prices are linked to energy prices, mainly through fertilizers and biofuel production. Since crude oil is one of the primary energy sources in the world's energy matrix, this study aimed to examine the interaction between crude oil prices and some agricultural commodity prices, namely rice, wheat, corn, and soy. The behaviour and interaction of these prices are essential for economic agents, especially for these commodity market participants and those involved in decision-making related to the macroeconomic policies of national economies.

Statistical hypothesis tests were carried out on the fundamental assumptions for the stochastic models implemented in this work, specifically normality and stationarity, to analyze the time series. The tests of the normality hypothesis performed for this study indicated that the normality hypothesis of the related stochastic processes cannot be accepted except for the rice prices time series. It should be emphasized that this result must be considered when the inferences obtained in this work are observed. A fundamental assumption refers to the time series stationarity of the data used. Concerning the stationarity hypothesis, which generally occurs for all price time series, this hypothesis was not accepted, while the stationarity hypothesis was not rejected for all price return time series. It is a relevant result once the variables used to estimate the autoregressive vectorial models are the commodity price returns. Another determinant hypothesis for estimating autoregressive vector models is the cointegration between the crude oil price returns and each selected food commodities returns time series. Hence, among the cointegration tests available in the econometric literature, the most adequate for these time series used was the Johansen and Juselius test. The results highlighted the non-rejection of the cointegration hypothesis.

Consequently, the error correction mechanisms were added to the autoregressive vector model, transforming the VAR models into VEC models. It was possible to infer the existence of two-dimensional causality for the variables in the VEC models deployed here. Besides that, it was possible to verify the short and long-run interaction between the crude oil price variations and each selected food commodity price variation. The impulse-response functions were obtained by analyzing the dynamic impact on the stochastic terms of the system equations that characterize the VEC model.

The impulse response functions show the behaviour of one of the variables in response to shocks and residual changes in another variable. From the impulse response functions, no significant impact was observed due to crude oil price variation shock on each food commodity price variation and conversely. The estimation of the VEC model also enabled the variance decomposition analysis, that is, how one variable variability can affect another variable variability. The variance decomposition implies that the percentage of the crude oil price return variance caused by food price return variance increases over time.

The inferences show an interaction between crude oil prices practised in the international market and each food commodity price. It must be highlighted that these food commodities form the basis of the planet's food security. Thus, these results demonstrate that the objective of this work was achieved.

In future work, an interesting analysis would be to separately relate crude oil prices to agricultural commodities used for producing biofuels, such as corn and soybeans, and agricultural commodities not used for biofuel production. Also, other research related to this theme should be carried out to expand the crude oil and food prices relationship analysis using different samples and methodological approaches. Among other methodological approaches available in the econometric literature, the possible deployment of methodologies that use classical or Bayesian statistical inferences can improve results, adding relevant conclusions to the studied theme.

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