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Comparison of crude oil price transmission to food commodities for biofuel source and non-biofuel source

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ABSTRACT

Introduction: World crude oil prices are linked to food commodity prices as input costs for the production distribution and development of biofuels. The relationship between increasing crude oil prices and food prices is in one way; i.e. an increase in worldcrude oil prices will trigger an increase in food prices and not the other way around. This study aimed to analyze and compare price transmission and integration of cross-commodity prices between the price of crude oil and the price of corn (raw material for biofuels) and the price of rice (non biofuels raw material). **Methods:** This study used the VARX (Vector Autoregression with Exogenous variables) method with corn prices and rice prices as the endogenous variables, while crude oil prices as exogenous variables. **Results:** Price transmission and integration of cross-commodity prices occur in crude oil to corn commodities. In contrast, there was no price transmission and price integration between crude oil and rice. Commodities that are directly related to the development of biofuels experience a more significant impact on price changes. **Conclusion:** Energy commodity prices are connected to food commodity prices, particularly corn. Therefore, if crude oil price rises, so does the corn. Highly dependent corn-importing countries have to be aware. Measures engendering food security are key to any country, particularly promoting domestic production and improving food storage and distribution systems to reduce the risk of food price spikes. The policy implications emerging from the one-directional causality between oil and food prices would typically depend on the specific nature of the two markets and the goals of policy intervention.

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INTRODUCTION

Transmission of crude oil prices does not only affect energy commodities but also non-energy commodities, one of which is agricultural commodities (Ji & Fan, 2012). Crude oil plays a role in the distribution and production of agricultural goods and services; so price fluctuations in crude oil will affect various kinds of agricultural commodities, especially food commodities (Olayungbo, 2021; Roman *et al.*, 2020). Crude oil prices fluctuate from year to year. From 2010 to 2020, the highest crude oil price occurred in March 2012 at USD 117.79 per barrel, while the lowest occurred in April 2020 at USD 21.04 per barrel (World Bank, 2022).

The formation of crude oil prices cannot be separated from the mechanism of supply and demand. Based on EIA (2012), in the first half of 2012, from the demand side, high crude oil prices were caused by expectations of changes in global economic growth. High growth in employment in the US, lower interest rates in several European countries, and increased manufacturing activity in China resulted in high expectations of changes in economic growth. So, the price of crude oil goes up. Meanwhile, from the supply side, crude oil production was disrupted because Syria, Sudan, and Yemen reduced crude oil supply by one million barrels per day from the world oil market. Entering April 2020, there was a drastic decline in demand for crude oil due to lockdown policies and travel restrictions almost all over the world as a result of the COVID-19 pandemic. Excess supply caused the price of crude oil to fall to its lowest level in the last decade.

Rising and falling crude oil prices form a pattern of price movements. The patterns that exist in the energy sector and the food sector have similarities (Sholihah & Kusnadi, 2019). Consumer-level prices for food commodities tend to increase when crude oil also increases. The increase in world crude oil prices triggers an increase in production and distribution costs in the agricultural sector so food prices will also rise (World Bank, 2022).

The cross-commodity price relationship between crude oil and food prices is in one way; i.e. an increase in world crude oil prices will trigger an increase in food prices and not the other way around. An increase in food prices can reduce the intake of calories and nutrients needed by the community; even the worst is the food crisis. This happened in 2006 to mid-2008, when the price of crude oil increased, causing people's purchasing power to decline (Darmon & Drewnowski, 2015; Liu *et al.*, 2013; Wijayati *et al.*, 2019).

The transmission of energy commodity prices to food commodities indicates a range where food prices move under energy commodity prices. Generally, the price transmission of energy commodities to food commodities is indirectly connected. Food production uses many inputs related to energy markets, such as the need for fertilizers, the use of agricultural machinery, and the process of distributing agricultural inputs and products (Roman *et al.*, 2020; Wang *et al.*, 2022).

Price transmission is thought to cause price integration between crude oil and food commodities. Two different markets are said to be integrated if price changes in one market are transferred to the other market (Carolina *et al.*, 2016). Such a condition is very likely to occur as price integration (Ravallion, 1986); as already explained the production of food commodities requires production inputs originating from crude oil.

Energy and agricultural commodities are connected with the development of biofuels (Sholihah & Kusnadi, 2019; Su *et al.*, 2019). One of the agricultural commodities used for the development of biofuels is corn. This commodity has a crucial role because it is a source of food and feed in various parts of the world. For example, corn and poultry are highly dependent on one another for supporting food security (Evalia *et al.*, 2022).

Furthermore, the rice commodity is employed in this study to compare the pricing behavior of agricultural commodities related to biofuels and commodities that are just used as food. These products are also freely traded on the world market. Several previous empirical studies have shown that the two food commodities have a positive correlation with shocks from changes in world crude oil (Obadi & Korcek, 2014; Wei & Chen, 2016).

The occurrence of crude oil demand shock like what happened in 2020 caused by the pandemic has disrupted price movements in the global market. According to this statement, it is not enough to only read price movement through fluctuations. However, an analysis of price transmission and price integrations is required. Understanding the effect of crude oil price shocks on agricultural commodities well is important for determining pricing policy strategies, especially during sharp increases or when prices fall, as happened in April 2020 due to the pandemic. If there is an uncontrolled price increase, it will cause welfare losses for producers and consumers of agricultural commodities. Therefore, this study aimed to analyze price transmission and price integration of crude oil to food commodities. Specifically, this study aims at price transmission and cross-commodity price integration between the price of crude oil and the price of corn (raw material for biofuels), and the price of rice.

METHODS

This study used the econometric approach of VAR/VECM (Vector Autoregression/ Vector Error Correction Model) to analyze the transmission and integration of prices between crude oil and food commodities. This study used three main variables, namely: (1) the price of crude oil, (2) the price of corn, and (3) the price of rice; with secondary monthly time series data from January 1960 to December 2021 (744 data series), from the Pink Sheet Data of World Bank. The use of data from 1960 to 2021 can capture the turmoil of the 1073 crisis, the 2008 crisis, and the 2020 recession. Crude oil prices use the average of Brent, Dubai, and West Texas Intermediate ($/bbl). The price of rice used is white rice that has been processed (milled white rice) 5 percent damage refers to fob Thailand ($/mt). The corn commodity uses the commodity price for yellow corn which refers to the US Gulf Port fob ($/mt).

Price transmission is defined as a process in which the price from a higher market (upstream price) will affect the lower market price (downstream price). This study used the price of crude oil as the upstream price because crude oil is an input for the production of food commodities (Roman *et al.*, 2020; Wang *et al.*, 2022); while the price of rice and corn is the downstream price. Furthermore, this study limited the price of crude oil commodities on the exogenous side; assuming that the price increases the relationship between crude oil and food commodities in one way. Apart from that, price transmission and integration of cross-commodity prices for corn and rice are also suspected. Both are fellow carbohydrate commodities that are mutually substitutable. The relationship between food commodities (rice and corn) is thought to be two-way. Thus, this study used the VARX/VECMX (Vector Autoregression with Exogenous variables/ Vector Error Correction Model with Exogenous variables) method.

VARX/VECMX is a form of VAR/VECM that involves exogenous variables in model building. In contrast to VAR/VECM which involves all variables as endogenous variables (Poledna *et al.*, 2023; Septiani *et al.*, 2019; Tsioumas *et al.*, 2017; Usman *et al.*, 2022). To strengthen the formation of the VARX/VECMX model to be used, a Granger causality test was carried out (with $\alpha = 0.05$, and an assumption of 2 lag lengths). A causality test was carried out to determine the direction of the causality relationship between variables in the model; in this case that is the direction of price transmission between the commodities.

Table 1. Granger causality test result

Null hypotheses	F-stat.	Prob.
The price of crude oil does not Granger cause the price of corn	4.263	0.014*
The price of crude oil does not Granger cause the price of rice	6.560	0.001*
The price of corn does not Granger cause the price of rice	14.728	0.000*
The price of rice does not Granger cause the price of corn	5.384	0.005*

Description: *Rejects the null hypothesis, significant at α = 0,05

Based on Table 1, it is known that food prices have a two-way cross-commodity causality relationship. This study assumes that crude oil prices are an exogenous variable. Thus, there are two equations in this study. The linkages between models were tested through the VARX/VECMX models. The models to be used are as follows:

$$PJG_t = \alpha_1 + \sum_{j=1}^{n} \beta_{1j} PJG_{t-j} + \sum_{j=1}^{n} \varphi_{1j} PBRS_{t-j} + \delta_1 PMM_t + \mu_{1t}$$

$$PBRS_t = \alpha_2 + \sum_{j=1}^{n} \beta_{2j} PJG_{t-j} + \sum_{j=1}^{n} \varphi_{2j} PBRS_{t-j} + \delta_2 PMM_t + \mu_{2t}$$

Information:

PJG	=	Corn prices	t	=	Time period
PBRS	=	Rice prices	j	=	Time lag period
PMM	=	Crude oil prices (exogenous)	μ	=	Residual
α	=	Constant			
β, ϕ, δ	=	Variable coefficient			

The VARX/VECMX model above describes price transmission and price integration of cross-commodity. The occurrence of price transmission and integration of cross-commodity prices is possible because it is suspected that crude oil commodities affect food commodities in one direction.

Apart from that, price transmission and integration of cross-commodity prices for corn and rice are also suspected; Both are fellow carbohydrate commodities that are mutually substitutable. It means that the corn commodity can be influenced by the rice commodity and crude oil commodity as well as can also be affected by the corn commodity itself in the previous j lag. The same thing also happened to the rice commodity, where the price of rice can be influenced by corn and crude oil as well as the price of the rice commodity itself in the previous j lag.

The steps taken in building and analyzing the VARX/VECMX model in this study are as follows.

Stationarity testing

Stationarity testing was carried out with the Augmented Dickey-Fuller (ADF) test (with α = 0.05). The function of stationarity is to avoid spurious regression. The ADF test is performed by including trends and constants in the equation because the actual price data normatively contains constants (prices cannot be zero) and trends (there is an inflation factor).

Lag optimum testing

Optimum lag length testing on the VARX model is done with the Schwarz information criterion (SC). The use of lag in the VARX method is only for the endogenous variable which is the dependent variable in the equation, namely the variable price of corn and rice prices. This study used monthly data, so the optimum lag test includes a maximum lag length of 12 lags (1 year) as a hypothesis. Optimum lag testing is useful to find out how much the previous month can affect a variable or can affect other variables.

VARX/VECMX stability testing

Testing the stability of VARX or what is known as the roots of characteristic polynomials is done by calculating the roots of the polynomial function. VARX/VECMX is said to be stable if all absolute values (modulus) roots of a characteristic polynomial are below 1 (<1). The VARX/VECMX stability test aims to evaluate the results of the impulse response function (IRF) and variance decomposition to be carried out valid.

Cointegration testing

Cointegration testing is carried out if it is found that the data is not stationary at the level. Cointegration testing uses the Johansen cointegration test. If the trace statistics value and maximum eigenvalue are greater than the critical value (with α = 0,05), then there is cointegration. Cointegration testing is used to determine the maximum number of cointegration equations (long-term integration) contained in the model.

Whether cointegration exists or not will determine the model used. If the data is not stationary at the level and is detected as having cointegration, the model used is the restricted VAR (Vector Autoregression) model or can be called the VECM (Vector Error Correction Model); in this study uses the VECMX model (Vector Error Correction Model with

Exogenous variables). This model is different from the VAR model because it has additional restrictions and has an error correction term (ECT) variable as the speed of adjustment from the short term to the long term.

VARX/VECMX model analysis

VARX model analysis can be performed after testing the optimum lag, provided that all data is stationary at level. The results of the VARX analysis show price transmission and integration of cross-commodity prices (with α = 0,05); the value of the VARX coefficient indicates the magnitude of price transmission, while the results of the t-test indicate the presence or absence of price transmission and price integration significantly.

Impulse Response Factor (IRF) analysis

Impulse Response Functions are used to study the effects of shocks or impulses in a VAR or VECM system. It traces out one unit or new standard deviation shock to an endogenous variable and its effects on all the endogenous variables in a VAR or VECM, keeping all other variables and shocks constant.

Forecast Error Variance Decomposition (FEVD) analysis

The variance decomposition indicates the amount of information each variable contributes to the other variables in the autoregression. It determines how much of the forecast error variance of each of the variables can be explained by exogenous shocks to the other variables.

RESULT AND DISCUSSION

This research discusses the impact of crude oil prices on food commodities seen through one type of transmission. The transmission used is cross-commodity transmission between crude oil and both food commodities such as rice (not a raw material for biofuels) and corn (a raw material for biofuels).

Result of VARX/VECMX Analysis

Analyzing price transmission and price integration from crude oil to food commodities will help policymakers understand the nature of crude oil prices and food prices. This study limited the price of crude oil commodities on the exogenous side; assuming that the price relationship between crude oil and food commodities is one way. This study used the VARX/VECMX method, with the results of the VARX/VECMX analysis stages as follows:

1. Stationarity test results

Stationarity test results showed that the variable price of crude oil, price of corn, and price of rice are stationary at the level (Table 2). Therefore, there is no need to do differencing on research variables. Thus, the analysis of price transmission and integration of prices from crude oil to food commodities was carried out using the VARX method.

Table 2. Result of the ADF stationarity test

Variable	Level		Conclusion
	T-stat.	Prob.	
Crude oil prices	-3.963	0.010*	Stationer
Corn prices	-3.534	0.036*	Stationer
Rice prices	-3.765	0.019*	Stationer

Description: *Stationary significant with α = 0.05

2. Optimum lag test results

The optimum lag test results using the Schwarz information criterion (SIC) showed that the optimal lag was at lag 3 (Table 3).

Table 3. Optimum lag test result

Lag	*Schwarz information criterion*	Lag	*Schwarz information criterion*
0	21.08798	7	16.09054
1	16.22862	8	16.11341
2	16.04759	9	16.14829
3	16.03740*	10	16.16161
4	16.05745	11	16.19521
5	16.08198	12	16.22225
6	16.10677		

Description: *optimum lag length

Thus, it is determined that the largest lag used in the VARX analysis is lag 3; thus, the VARX model used is as follows:

$$PJG_t = \alpha_1 + \beta_{11} PJG_{t-1} + \beta_{12} PJG_{t-2} + \beta_{13} PJG_{t-3} + \phi_{11} PBRS_{t-1} + \phi_{12} PBRS_{t-2} + \phi_{13} PBRS_{t-3} + \delta_1 PMM_t + \mu_{1t}$$

$$PBRS_t = \alpha_2 + \beta_{21} PJG_{t-1} + \beta_{22} PJG_{t-2} + \beta_{23} PJG_{t-3} + \phi_{21} PBRS_{t-1} + \phi_{22} PBRS_{t-2} + \phi_{23} PBRS_{t-3} + \delta_2 PMM_t + \mu_{2t}$$

Information:

PJG	=	Corn prices	β, ϕ, δ	=	Variable coefficient
PBRS	=	Rice prices	t	=	Time period
PMM	=	Crude oil prices (exogen)	μ	=	Residual
α	=	Constant			

3. VARX stability test results

The results of the VARX stability test showed that the VARX model is classified as stable (Table 4). Hence, the results of the impulse response function (IRF) and the variance decomposition to be carried out are considered valid.

Table 4. VARX stability test results

Roots of characteristic polynomial	Modulus
0.940765	0.940765
0.916099	0.916099
0.511605	0.511605
0.127445 – 0.367259i	0.388744
0.127445 + 0.367259i	0.388744
-0.110893	0.110893

4. VARX model analysis results

The data had stationer at the level then this research skipped Johansen cointegration test and jumped to VARX model analysis. The results of the VARX analysis showed that price transmission and integration of cross-commodity prices significantly occur in crude oil to corn commodities. In contrast, there was no significant price transmission and price integration between crude oil and rice (Table 5).

Table 5. VARX analysis result

Variable	Corn prices	Rice prices
Constant (α)	2.650	6.550
	{0.002}	{0.003}
Crude oil price (PMM_t)	0.074	0.090
	{0.000}*	{0.091}
Corn price t-1 (PJG_{t-1})	1.196	0.365
	{0.000}*	{0.000}*
Corn price t-2 (PJG_{t-2})	-0.227	-0.257
	{0.000}*	{0.080}
Corn price t-3 (PJG_{t-3})	-0.027	-0.068
	{0.468}	{0.476}
Rice price t-1 ($PBRS_{t-1}$)	-0.003	1.317
	{0.815}	{0.000}*
Rice price t-2 ($PBRS_{t-2}$)	0.076	-0.473
	{0.001}*	{0.000}*
Rice price t-3 ($PBRS_{t-3}$)	-0.065	0.110
	{0.000}*	{0.003}*
Adjusted R^2	0.982	0.977

Note : Numbers without brackets are coefficients, and numbers in { } are t-stat probability value

*Significant at α = 0.05

Based on the results of the VARX analysis (Table 5), it is known that the price of corn is significantly influenced by the price of crude oil, the price of corn for the previous one-month period, the price of corn for the previous two months period, the price of rice for the previous two months period, and the price of rice for the previous three months period. Meanwhile, the price of rice was significantly influenced by the price of corn in the previous one-month period, the price of rice in the previous one-month period, the price of rice in the previous two months, and the price of rice in the previous three months.

5. Impulse Response Factor (IRF) analysis

IRF is useful for showing how a variable responds to a shock in the variable itself and other endogenous variables. In identifying the price response of corn and rice in this VAR model, the Cholesky Decomposition standard is used.

Cholesky's Decomposition aims to generate impulse responses that depend crucially on the ordering of variables in the system. The time period used in analyzing the response to corn and rice prices is the next 10 months (Figure 1).

a. Response of maize price to shock of maize price

A corn price shock of one standard deviation in the first month will cause an increase in corn prices of 8 percent. Until the third month, the response to corn price shocks was increased by the price of corn itself, although over time this response decreased. In the fifth month, only 9 percent responded to corn price shocks of one standard deviation. In the tenth month, the response to shocks will decrease by only 7 percent.

b. Response of maize price to shock of rice price

Maize prices were not affected by shocks in rice prices in the first to second months. Maize price responded to rice price shocks at a lag of 2.5. In the fourth month, maize prices experienced the highest increase in response to the rice price shock with an increase of 3 percent. For the next 10 months, maize prices remained stable with a response remaining at 3 percent.

c. Response of rice price to shock of maize price

In the first month, a shock in corn prices of one standard deviation was responded to by an increase in rice prices of 2.5 percent. The highest price increase occurred in the third month, the price of rice increased by 7.5 percent. Furthermore, the response of rice prices to corn price shocks for the fourth to tenth months decreased further. In the tenth month, the increase in rice prices was only around 6 percent.

d. Response of rice price to shock of rice price

A rice price shock of one standard deviation in the first month was responded to by an increase in rice prices of 20 percent. This response is high. Rice prices will increase further in the second month, with an increase of 27 percent. The response to shocks will decrease in the third month, increasing the price of rice on the world market to 26 percent. In the following months, the response to the shock decreased. In the tenth month, the response to shock fell to 17 percent.

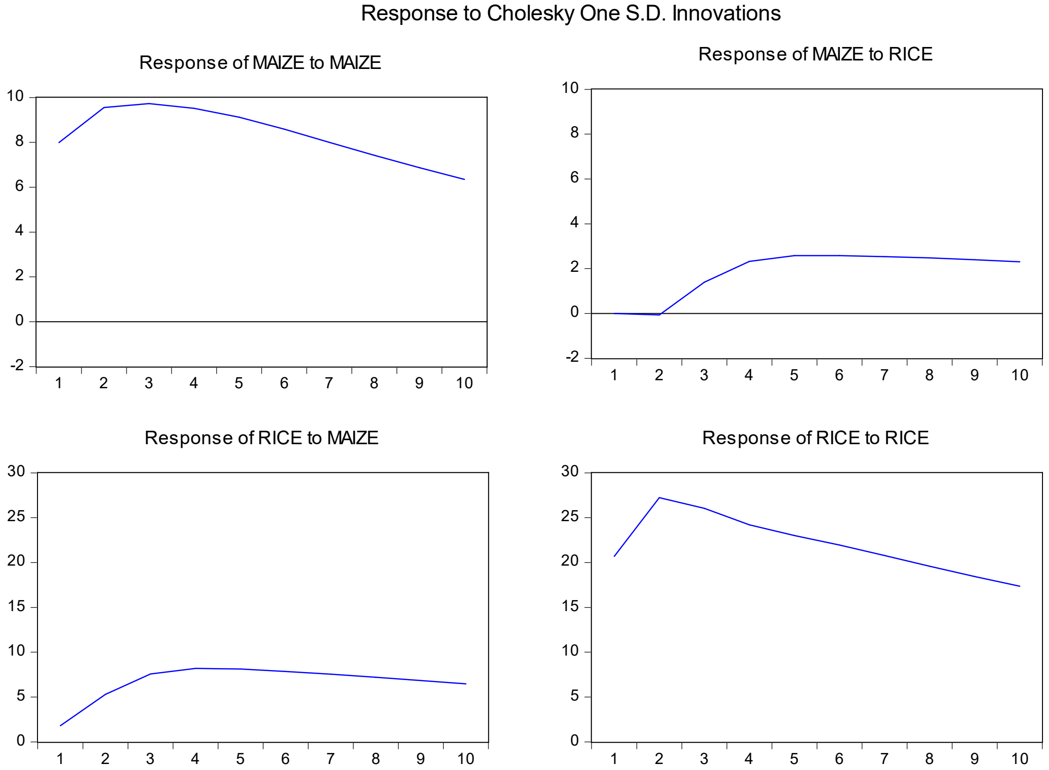

Figure 1. Impulse response factor (IRF) of maize and rice prices

6. Forecast error variance decomposition (FEVD) analysis

FEVD is useful for explaining the contribution of each variable to the shock it causes to the main observed endogenous variable. In other words, FEVD explains the proportion of other variables in explaining the variability of the main endogenous variable of the study. FEVD based on Cholesky Decomposition is sensitive to the ordering of variables and the length of the lag used.

Table 6. Forecast error variance decomposition (FEVD) of maize and rice

Variance decomposition	Period	S.E.	Maize	Rice
Variance decomposition of maize:	1	7.994754	100.0000	0.000000
	2	12.45757	99.99697	0.003032
	3	15.86995	99.22065	0.779346
	4	18.65003	97.88698	2.113018
	5	20.92031	96.79999	3.200011
	6	22.76232	96.00960	3.990401
	7	24.26210	95.39453	4.605474
	8	25.49290	94.88595	5.114052
	9	26.51066	94.45414	5.545862
	10	27.35760	94.08169	5.918308
Variance decomposition of rice:	1	20.76623	0.760730	99.23927
	2	34.66081	2.615763	97.38424
	3	44.01201	4.573938	95.42606
	4	50.89080	6.014370	93.98563
	5	56.43878	6.957325	93.04267
	6	61.06483	7.597291	92.40271
	7	64.94474	8.064922	91.93508
	8	68.21439	8.422473	91.57753
	9	70.99027	8.702323	91.29768
	10	73.36381	8.925626	91.07437
Cholesky ordering: maize rice				

Based on the results of the variance decomposition, it can be concluded that in the first month, corn price fluctuations were caused by shocks in the corn price itself, amounting to 100 percent. However, from the second month to the tenth month, it appears that rice prices begin to influence corn price variability. In the second month, the role of rice prices in explaining corn price fluctuations was 0.003 percent. In the following months, rice prices increasingly influenced fluctuations in corn prices. By the tenth month, rice prices influenced corn price variability by up to 5.92 percent.

The results of the variance decomposition analysis of rice prices show different behavior when compared to corn. In the first month, it appears that the variability in rice prices began to be explained by the corn price variable by 0.7 percent. Starting from the second month to the tenth month, the influence of corn price variability on rice prices becomes greater. It can be seen that up to the tenth month, the variability in rice prices was still explained by the price of rice itself with a proportion of 91.07 percent. Meanwhile, corn prices contributed 8.93 percent. It can be concluded that the variability in corn prices over time will be greater in influencing rice prices.

Price transmission and price integration from crude oil commodities to food commodities

The results of the VARX model analysis showed that price transmission and integration of cross-commodity prices significantly occur in crude oil and corn commodities. In contrast, there was no significant price transmission and price integration between crude oil and rice (Table 5). The results of this study corroborate and are corroborated by empirical results of Su *et al.* (2019), and Sholihah & Kusnadi (2019); that commodities that are directly related to the development of biofuels experience a more significant impact on price changes.

The price of crude oil is transmitted to the price of corn significantly. That is, every increase in the price of crude oil will significantly increase the price of corn in one direction; at the same time indicating the integration of crude oil prices with corn prices. One-way price transmission and integration of crude oil commodity prices into corn commodities significantly indicate that corn prices move under crude oil commodity prices (Carolina *et al.*, 2016; Ravallion, 1986).

Price transmission and integration of cross commodity prices for crude oil commodities to corn commodities are very likely to occur. Corn commodity production also requires production inputs from crude oil; so the increase in crude oil prices directly affects the increase in corn prices (Roman *et al.*, 2020; Wang *et al.*, 2022). In addition, indirectly, corn is used in the development of biofuels (Sholihah & Kusnadi, 2019; Su *et al.*, 2019).

Crude oil prices have a positive trend; indicated by the increase in oil prices over the past 60 years. The scarcity and rising price of crude oil is an incentive for the shift towards alternative energy sources, namely biofuels. The development of food crops (such as corn) as raw materials for alternative energy increases the demand for food commodities as raw materials for biofuels. As a result, there is an increase in food prices around the world.

Determinants of corn prices

This research simultaneously analyzed the factors that influence corn prices based on the results of the VARX model analysis (Table 5). The results of the VARX model analysis showed that the price of corn is influenced by the price of crude oil, the price of corn for the previous one-month period, the price of corn for the previous two-month period, the price of rice for the previous two months period, and the price of rice for the previous three months period. The effect of crude oil prices on corn prices has been discussed previously.

The effect of rice prices on corn prices indicates that there is price transmission and integration of cross-commodity prices. The price of rice in the previous two months had a significant positive effect on the price of corn; that is, each increase in the price of rice in the previous two months will significantly increase the price of corn. Meanwhile, rice prices in the previous three months had a significant positive effect on corn prices. That is, each increase in the price of rice in the previous three months will significantly reduce the price of corn.

The effect of corn prices in the previous period on corn prices shows that there is an autocorrelation. This is based on the autoregression results shown in the VARX model. However, it is beyond the scope of this study to explain whether the trend in corn prices is more influenced by autocorrelation factors or other variables. The price of corn in the previous one-month period had a significant positive effect on the price of corn; that is, each increase in the price of corn in the previous one-month period will significantly increase the price of corn. Meanwhile, the price of corn in the previous two months had a significant negative effect on the price of corn; that is, each increase in the price of corn in the previous one-month period will significantly reduce the price of corn.

Determinants of rice prices

This study also analyzed the factors that influence rice prices based on the results of the VARX model analysis (Table 5). The results of the VARX model analysis showed that the price of rice is influenced by the price of corn in the previous one-month period, the price of rice in the previous one-month period, the price of rice in the previous two months, and the price of rice in the previous three months. The price of rice is not significantly affected by the price of crude oil. However, the price coefficient of crude oil for rice (0.90) is higher than the coefficient for crude oil for corn (0.74). This is possible because the average price of rice is 2.5 times higher than the price of corn.

The effect of corn prices on rice prices indicates that there is price transmission and integration of cross-commodity prices. Corn prices in the previous one-month period had a significant positive effect on rice prices. That is, each increase in the price of corn in the previous one-month period will significantly increase the price of corn. The results of the Granger causality test (Table 1) and the results of the VARX model analysis show that price transmission and cross-commodity price integration between corn and rice commodities are two-way.

The effect of rice prices in the previous period on rice prices also shows an autocorrelation. Nonetheless, the factors that most influence rice price trends are beyond the scope of this study. The price of rice in the previous one-month period had a significant positive effect on the price of rice. That is, each increase in the price of rice in the previous one-month period will significantly increase the price of rice. The price of rice in the previous two months had a significant negative effect on the price of rice; that is, each increase in the price of rice in the previous two months will significantly reduce the price of rice. The price of rice in the previous three months had a significant positive effect on the price of rice; that is, each increase in the price of rice in the previous three months will significantly increase the price of rice.

CONCLUSION

Price transmission and integration of cross commodity prices occur in crude oil to corn commodities. In contrast, there was no price transmission and price integration between crude oil and rice. Commodities that are directly related to the development of biofuels experience a more significant impact on price changes. The increase in crude oil prices can have a multiplier effect on rising corn prices.

The results also show that there is price transmission and integration of cross-commodity prices in two directions the price of corn and the price of rice. Both food commodities were also affected by their prices in the previous period. Food crops as a source of biofuel raw materials, such as corn, have been proven to have a relationship with crude oil. Not only that, the price of corn commodities is also transmitted to rice commodities. The implication is that food commodities that are directly related to biofuels will be more at risk if price shocks occur because they can be transmitted to the other commodity (rice).

Corn prices are correlated with those of energy commodities. Thus, crude oil prices increase in line with those of corn prices. Countries that import a lot of corn must be aware. Any nation that wants to lower the danger of food price surges must take steps to ensure food security, especially by encouraging domestic production and enhancing food delivery and storage infrastructure. The specifics of the two markets and the objectives of policy action will usually determine the policy consequences arising from the one-directional causality between oil and food prices.

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REFERENCES

[EIA] U.S. Energy Information Administration. (2012). *Crude oil prices peaked early in 2012. Today in Energy*. https://www.eia.gov/todayinenergy/detail.php?id=7630

Carolina, R. A., Mulatsih, S., & Anggraeni, L. (2016). Analisis volatilitas harga dan integrasi pasar kedelai Indonesia dengan pasar kedelai dunia. *Jurnal Agro Ekonomi, 34*(1), 47–66. https://doi.org/10.21082/jae.v34n1.2016.47-66

Darmon, N., & Drewnowski, A. (2015). Contribution of food prices and diet cost to socioeconomic disparities in diet quality and health: A systematic review and analysis. *Nutrition Reviews, 73*(10), 643–660. https://doi.org/10.1093/nutrit/nuv027

Evalia, N. A., Harianto, H., Nurmalina, R., & Hakim, D. B. (2022). Price transmission between input and output markets: The COVID-19 effect on laying hens' industry in Indonesia. *Jurnal Manajemen dan Agribisnis, 19*(3), 418–427. https://doi.org/10.17358/jma.19.3.418

Ji, Q., & Fan, Y. (2012). How does oil price volatility affect non-energy commodity markets? *Applied Energy, 89*(1), 273–280. https://doi.org/10.1016/j.apenergy.2011.07.038

Liu, L., Chen, C.-C., & Wan, J. (2013). Is the world oil market "one great pool"?: An example from China's and international oil markets. *Economic Modelling, 35*, 364–373. https://doi.org/10.1016/j.econmod.2013.07.027

Obadi, S. M., & Korcek, M. (2014). Are food prices affected by crude oil price: Causality investigation. *Review of Integrative Business & Economics Research, 3*(1), 411–427.

Olayungbo, D. O. (2021). Global oil price and food prices in food importing and oil exporting developing countries: A panel ARDL analysis. *Heliyon, 7*(3), e06357. https://doi.org/10.1016/j.heliyon.2021.e06357

Poledna, S., Miess, M. G., Hommes, C., & Rabitsch, K. (2023). Economic forecasting with an agent-based model. *European Economic Review, 151*(104306), 1–26. https://doi.org/10.1016/j.euroecorev.2022.104306

Ravallion, M. (1986). Testing market integration. *American Journal of Agricultural Economics, 68*(1), 102–109. https://doi.org/10.2307/1241654

Roman, M., Gorecka, A., & Domagala, J. (2020). The linkages between crude oil and food prices. *Energies, 13*(24), 6545. https://doi.org/10.3390/en13246545

Septiani, A., Sumertajaya, I. M., & Aidi, M. N. (2019). Vector autoregressive X (VARX) modeling for Indonesian macroeconomic indicators and handling different time variations with cubic spline interpolation. *International Journal of Scientific Research in Science, Engineering and Technology, 6*(1), 175–180. https://doi.org/10.32628/IJSRSET196145

Sholihah, F., & Kusnadi, N. (2019). Dampak pengembangan biofuels terhadap volatilitas harga beberapa komoditas pangan di pasar dunia. *Jurnal Agro Ekonomi, 37*(2), 157–170. https://doi.org/10.21082/jae.v37n2.2019.157-170

Su, C. W., Wang, X.-Q., Tao, R., & Oaria-Ramona, L. (2019). Do oil prices drive agricultural commodity prices? Further evidence in a global bio-energy context. *Energy, 172*, 691–701. https://doi.org/10.1016/j.energy.2019.02.028

Tsioumas, V., Papadimitrou, S., Smirlis, Y., & Zahran, S. Z. (2017). A novel approach to forecasting the bulk freight market. *The Asian Journal of Shipping and Logistics, 33*(1), 33–41. https://doi.org/10.1016/j.ajsl.2017.03.005

Usman, M., Loves, L., Russel, E., Ansori, M., Warsono, Widiarti, & Wamiliana. (2022). Analysis of some energy and economics variables by using VECMX model in Indonesia. *International Journal of Energy Economics and Policy, 12*(2), 91–102. https://doi.org/10.32479/ijeep.11897

Wang, Y., Wang, X., & Guo, K. (2022). Analysis on the transmission of international oil price to China's price index--Based on Granger causality network. *Procedia Computer Science, 199*, 1276–1283. https://doi.org/10.1016/j.procs.2022.01.162

Wei, C.-C., & Chen, S.-M. (2016). Examining the relationship of crude oil future price return and agricultural future price return in the US. *EconJournals, 6*(1), 58–64.

Wijayati, P. D., Harianto, & Suryana, A. (2019). Permintaan pangan sumber karbohidrat di Indonesia. *Analisis Kebijakan Pertanian, 17*(1), 13–26. https://doi.org/10.21082/akp.v17n1.2019.13-26

World Bank. (2022). *World Bank commodity price data (The pink sheet)*. World Bank Group. https://www.worldbank.org/en/research/commodity-markets