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Dynamic Interaction of Coconut Oil and Crude Oil Prices: Insights from a Vector Error Correction Model

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ABSTRACT: Understanding the relationship between commodity prices is paramount for investors, policymakers, and industries reliant on these markets. This study delves into the intricate dynamics between coconut oil and crude oil prices using a Vector Error Correction Model (VECM). The VECM approach allows for exploring these commodities' short-term adjustments and long-term equilibrium relationships. The analysis reveals that while there may not be a strong long-term interdependence between coconut oil and crude oil prices, robust short-term adjustment mechanisms exist. The cointegration rank two (2) highlights the presence of two cointegrating vectors, indicating a stable equilibrium relationship. The alpha and beta coefficients shed light on the speed and direction of adjustments, emphasizing how the system corrects deviations from the equilibrium relationship. Various model selection criteria, including the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), validate the VECM's efficacy in capturing the complexities of these markets while maintaining model simplicity. Moreover, significant error correction terms emphasize the system's self-correcting nature, ensuring long-term stability. Interpreting the coefficients of the lagged terms reveals short-term dynamics, showcasing how coconut oil and crude oil prices mutually influence and respond to changes in one another. The absence of significant autocorrelation in the model's residuals validates the model's accuracy in capturing underlying dynamics.

KEYWORDS: Coconut oil price, Crude oil price, Vector Error Correction Model, Cointegration

INTRODUCTION

Forecasting the price of coconut oil is challenging due to several inherent complexities and uncertainties in the oil market, accompanied by several critical problems associated with forecasting coconut oil prices, such as subjectivity to high volatility and nonlinearity, intensified by various factors such as changes in weather patterns, geopolitical events, global demand-supply dynamics, and fluctuations in other edible oil markets (Mishra, 2018). These characteristics make it challenging to model and predict price movements accurately. Internal factors (local production, processing, and consumption) and external factors (international trade, macroeconomic conditions, and exchange rates) exist, affecting the price of coconut oil. Forecasting coconut oil prices requires a considerably wide range of factors, making the process complex and prone to errors (Abeysekara & Waidyarathne, 2020).

The coconut oil market exhibits seasonal patterns due to seasonal variations in coconut production and harvesting (Sinha et al., 2017). These seasonal fluctuations significantly impact price movements, making it essential to capture and model seasonality effectively. Moreover, accurate and reliable historical data for coconut oil prices are not always readily available or subject to data gaps and inconsistencies. Insufficient or poor-quality data also negatively impact the forecasting accuracy. Posing a more significant challenge in forecasting coconut oil prices are external shocks such as natural disasters (e.g., cyclones affecting coconut plantations), government policies, and changes in global trade agreements (Tolentino, 2020). Forecasting models must account for these unforeseen events, which pose challenges.

Like other commodity markets, the coconut oil market is susceptible to market manipulation, speculation, and price-fixing attempts, making it harder to predict prices accurately (Das & Debnath 2021). Due to the condition, coconut oil prices respond dynamically to changes in demand and supply conditions, leading to rapid price shifts (Sujarwo et al., 2019). These sudden changes make it challenging to predict future price movements.

Developing a forecast model for coconut oil prices is essential for the Philippines due to its position as a significant exporter of coconut oil. Forecasting coconut oil prices is crucial for the country's economy and decision-making. Coconut oil is one of the Philippines' major agricultural exports, contributing significantly to the economy and foreign exchange earnings. As the country heavily relies on the export of coconut oil, price fluctuations substantially affect the overall balance of trade, current account, and economic growth (Guzman et al., 2019).

For the government, coconut oil exports generate substantial revenue through taxes and export duties. Accurate price forecasts help the government formulate appropriate fiscal policies to manage budgetary requirements and national development programs

(Labios, 2019). Further, the coconut industry assumes a crucial role in the rural economy of the Philippines, providing livelihoods to millions of farmers and workers. Price forecasts assist in long-term planning for the agricultural sector, including investments in research, infrastructure, and technology to improve productivity and efficiency (Guzman et al., 2019).

In terms of monetary policy, fluctuations in coconut oil prices affect the Philippine peso's exchange rate, import costs, and the overall stability of the currency. Accurate forecasts help the Bankgo Sentral ng Pilipinas manage foreign exchange reserves and formulate appropriate monetary policies to maintain economic stability (Labios, 2019). Most importantly, coconut oil producers and exporters face price volatility, influencing profitability and financial stability. Forecast models assist them in making informed decisions regarding production levels, inventory management, and hedging strategies to mitigate risks and maximize returns (Guzman et al., 2019). Accurate price forecasts assist suppliers in optimizing the supply chain for coconut oil products, from production and processing to distribution and retail, leading to cost efficiencies and better market responsiveness (Guzman et al., 2019).

Creating a forecasting model for the price of coconut oil based on identified variables presents various challenges due to the complexities of the coconut oil market and the interactions between different factors affecting prices (Indraji, 2016). Multitudes of factors, including coconut production, global demand for edible oils, weather conditions, exchange rates, geopolitical events, and government policies, influence the price of coconut oil (Pang et al., 2021). Integrating all these diverse factors into a single forecasting model is complex and requires extensive data collection.

A significant impediment is that data availability and quality on independent variables pose challenges. Some relevant data might be difficult to obtain or subject to inconsistencies, leading to potential gaps and inaccuracies in the model. Even succeeding in gathering the data, the relationships between the price of coconut oil and its determinants may not be linear. Variables could interact complexly, requiring advanced modeling techniques to capture nonlinearity (Chang et al., 2020). There are instances that some variables might exhibit lag effects, where their impact on coconut oil prices is not immediate but occurs with a time delay. Incorporating such lag effects in the model requires careful consideration and lagged variables.

These considerations are the potential endogeneity which occurs when some independent variables are influenced by the dependent variable (coconut oil price). The situation can lead to biased and inconsistent parameter estimates (Kumar et al., 2018). Choosing the appropriate forecasting model is another critical task.

A robust forecast model for coconut oil prices is essential for the Philippines due to the significant dependence on income from coconut oil exports. Accurate price forecasts impose a far-reaching implication for the country's overall economic performance, agricultural sector, government revenue, trade policies, and risk management for market participants. Reliable forecasting models enable stakeholders to make informed decisions, plan, and navigate the challenges the dynamic global coconut oil market poses. This study intends to determine the presence of a stable long-run relationship between coconut oil prices and crude oil prices.

RELATED LITERATURE

Forecasting the price of coconut oil based on changes in crude oil prices need a relevant approach, as crude oil prices often influence the prices of other edible oils, including coconut oil. Coconut oil and crude oil are commodities with similar macroeconomic factors, such as global demand, geopolitical events, and changes in production levels, which influence their prices. Therefore, changes in crude oil prices might have a spillover effect on coconut oil prices (Kannadhasan & Bala Subramanian, 2016). Further, the relationship between crude oil prices and coconut oil prices is not immediate and exhibit lag effects. Changes in crude oil prices take time to be fully reflected in coconut oil prices, and the strength of the correlation varies over time (Koirala & Mishra, 2017).

While crude oil prices are an essential driver of coconut oil prices, other factors specific to the coconut oil market, such as coconut production, processing, and export trends, may also influence coconut oil prices. The forecasting model must account for these other factors (Leila et al., 2019). For one, crude oil prices are highly volatile due to geopolitical tensions, supply disruptions, and changes in global economic conditions. The high volatility of crude oil prices makes forecasting coconut oil prices based solely on crude oil price changes more challenging (Joshi et al., 2020). Researchers use various econometric techniques and time series models to address developing forecasting challenges to model the relationship between crude oil prices and coconut oil prices.

Limited information exists on the relationship between crude oil prices and coconut oil prices. However, fluctuations in crude oil prices can indirectly affect the price of coconut oil through their impact on the vegetable oil market, which includes coconut oil—according to ChemAnalyst (June 2023), coconut oil prices decreased in the second quarter of 2022 due to weak demand, weakened vegetable oil markets, and falling crude oil prices. Similarly, Procurement Resource provides a price trend and forecast for crude coconut oil tied to the vegetable oil market.

While there is limited research on this relationship, examining other studies reveals the relationship between crude oil prices and food prices in general and the vegetable oil market. Correlation and Co-movement Theory of some studies have found correlations between crude oil prices and food prices, including vegetable oils (Olayungbo, 2021). For instance, a study found a co-integration between soybean oil prices and oil prices during a specific time frame. The study suggests that changes in crude oil prices impact vegetable oil prices, including coconut oil.

Fluctuations in crude oil prices can affect vegetable oil production and transportation costs, including coconut oil. Increasing crude oil prices can lead to higher production costs for coconut oil, which may result in higher consumer prices (Amna et al., 2008). Conversely, if crude oil prices decrease, it can lower production costs and coconut oil prices (Hang, To & Quentin, 2015).

Crude oil prices are influenced by market speculation and investor sentiment. If there is a perception of instability or uncertainty in the crude oil market, it can lead to price volatility. This volatility can spill over into the vegetable oil market, including coconut oil, affecting its prices. It is important to note that these economic theories provide a framework for understanding the relationship between crude oil prices and coconut oil prices. However, other factors, such as regional production, trade policies, and consumer preferences, may influence the relationship.

METHOD

One of the most critical factors affecting the price of coconut oil is the price of crude oil. However, the relationship between the price of crude oil and the price of coconut oil is not always straightforward. This research intended to determine the long-run relationship between coconut and crude oil prices. Hence the Vector error correction model (VECM) was used as the statistical technique to model the long-run and short-run dynamics of a set of cointegrated variables, coconut oil, and crude oil prices. The intention was to determine the presence of a stable long-run relationship. VECM captures this relationship by including an error correction term that measures the deviation from the long-run equilibrium. Also, VECM allows for estimating the short-run adjustments of the variables to changes in other variables or external shocks. The data used for this study is the monthly price of coconut and crude oil from January 1994 to May 2023 obtained from the IndexMundi website.

The Vector error correction model (VECM) was estimated using the Engle-Granger unit-root test procedure. By estimating the error correction term, the VECM measured how quickly the variables in the model return to their long-run equilibrium. Moreover, the VECM helps analyze the relationships between stationary time series variables (Johansen, 1988). Non-stationary time series statistical properties change over time (Engle & Granger, 1987).

Hence depicted in Table 1 was the transformation from non-stationary time-series data on the coconut oil price and crude oil price to stationary time-series data. Once the time series were stationary, VECM was used to estimate the error correction term and identify the long-run relationships between the variables (Granger, 1999).

Table 1. ADF test on Log and 1st Differencing coconut and crude oil prices

ADF Test	coco_log	crude_log	coco_diff1	crude_diff1
tau-stat	0.067535	0.42353	-7.14708	-12.2725
tau-crit	-1.94179	-1.94179	-1.94179	-1.94179
stationary	no	no	yes	yes
aic	-4.07963	-3.65376	-4.08536	-3.65895
bic	-4.02428	-3.62069	-4.04109	-3.63691
lags	4	2	3	1
coeff	3.86E-05	0.000525	-0.6034	-0.78672
p-value	> .1	> .1	< .01	< .01

The log transformation was initiated in converting the crude oil time-series data from non-stationary to stationary before differencing. Taking the logarithm of a time series helped to stabilize its variance, which made it easier to fit statistical models to the data since the logarithm of a time series is often less sensitive to outliers and changes in scale than the original time series (Hyndman & Athanasopoulos, 2018).

While differencing a time series by subtracting successive observations removes the trend and seasonality from the data, which identifies the underlying dynamics of the time series. Differencing removes the data's linear trend and seasonal patterns (Box et al., 2015). Combining log transformation and differencing is a powerful stationary non-stationary time series technique. Log transformation stabilized the variance of the data, whereas differencing removed the trend and seasonality from the data (Chatfield, 2016).

Johansen test examines whether several time series share a common long-run trend. The test estimates the number and form of the cointegrating relationships between coconut and crude oil prices. The test is based on the maximum likelihood estimation of a vector error correction model (VECM), which captures both the time series' short-run and long-run dynamics.

Based on the output in Table 2, the trace and maximum eigenvalue cointegration tests at the 5% significance levels demonstrate cointegration between coco_1 and crude_1. The trace test and the maximum eigenvalue test of one cointegrating vector at the 5% significance level means there is evidence of two cointegrating vectors between coco_1 and crude_1. The renormalized beta matrix shows the coefficients of the cointegrating vectors. The first vector implies that coco_1 is cointegrated with 3.4081 * crude_1, and the second vector implies that crude_1 is cointegrated with -1.8009 * coco_1. Also, the renormalized alpha matrix shows the coefficients of the adjustment vectors, which indicate how fast each variable adjusts to restore the equilibrium when there is a deviation from the long-run relationship. For instance, the first element of alpha (-0.17223) means that when coco_1 is above its long-run level, it decreases by 0.17223% in each period to correct the error. Moreover, the matrix shows the long-run impact of a one-unit change in each variable on itself and the other variable. Wherein the first element of the matrix (-0.47835) means that a one-unit increase in coco_1 leads to a 0.47835% decrease in coco_1 in the long run.

Table 2. Trace and Maximum Eigenvalue Cointegration test

Rank	**Eigenvalue**	**Trace test**	**Lmax test**	**P-value**
0	0.096532	54.349	34.515	0
1	0.056666	19.834	19.834	0

Variable	**Coefficient**	**Renormalized coefficient**		
coco_1	21.268	1		
crude_1	72.485	3.4081		
alpha (coco_1)	-0.0081	-0.17223		
alpha (crude_1)	-0.00853	-0.18132		
beta (coco_1)	76.637	-1.8009		
beta (crude_1)	-42.555	1		
long-run matrix	-0.47835	0.33134	-0.41698	-0.90264

RESULT AND DISCUSSION

The VECM system is a way of modeling the dynamic relationship among a set of cointegrated variables. It combines the short-run effects of changes in the variables with the long-run effects of deviations from the equilibrium relationship. The VECM system depicted in the Table 3 below consists of coconut oil price (the monthly percentage change in the coconut oil price) and crude oil price (the monthly percentage change in the crude oil price). The equation proceeded from the 12 lags of the first differences of the variables as explanatory variables, plus a constant term and an error correction term.

The error correction term is given by the product of alpha and beta matrices, which represent the adjustment and cointegrating vectors, respectively. The cointegrating vector shows the long-run equilibrium relationship among the variables, while the adjustment vector shows how each variable responds to deviations from that relationship. The VECM captures both the short-run and the long-run dynamics of cointegrated variables. A VECM system consists of the cointegrating vectors (beta) and the adjustment vectors (alpha). The cointegrating vectors represent the long-run equilibrium relationships among the variables. In contrast, the adjustment vectors represent the speed and direction of adjustment to restore the equilibrium when there is a deviation from the long-run relationships.

Table 3. Cointegration Rank

Statistic	**Value**	
Cointegration rank	2	
Beta (cointegrating vectors)	[1.0000, 0.00000]	[0.00000, 1.0000]
Alpha (adjustment vectors)	[-0.47835, -0.41698]	[0.33134, -0.90264]
Log-likelihood	1350.9696	
Determinant of covariance matrix	1.21E-06	
AIC	-7.6528	
BIC	-7.0897	
HQC	-7.4284	
Portmanteau test: LB(48)	152.39,	df = 144 [0.3001]

The VECM system was applied to two (2) time series: coco_1 and crude_1, which are the coconut oil and crude oil prices, respectively. The output specified that the cointegration rank is 2, meaning there are two cointegrating vectors between coco_1 and crude_1, with unrestricted constant terms in the model. The log-likelihood value is 1350.9696, which measures how well the model fits the data. The higher the log-likelihood, the better the fit. The determinant of the covariance matrix is 1.2127328e-006, which measures how much variation there is in the residuals. The smaller the determinant, the less variation there is. The Akaike information criterion (AIC), Bayesian information criterion (BIC), and Hannan-Quinn criterion (HQC) are all measures of model selection that balance goodness-of-fit and parsimony. The lower these values, the better the model.

The output in Table 4 is the estimation results for equation 1, the equation for the first difference of coco_1 (d_coco_1). The equation includes 11 lags of d_coco_1 and d_crude_1 and two error correction terms (EC1 and EC2), the lagged residuals from the cointegrating relationships. Based on the output, the constant term is not statistically significant at the 5% level, meaning there is no evidence of drift in d_coco_1. Most of the lagged terms of d_coco_1 and d_crude_1 are statistically significant at the 5% level or lower, meaning that they significantly impact d_coco_1. The coefficients' signs and magnitudes indicate the impact's direction and strength. For instance, the coefficient of d_coco_1_1 is -0.316933, meaning that a one-unit increase in d_coco_1 in the previous period leads to a 0.316933% decrease in d_coco_1 in the current period.

Table 4. VECM Estimate

Variable	Coefficient	Standard error	t-ratio	p-value
const	0.00115918	0.00169787	0.6827	0.4953
d_coco⁺_1_1	-0.316933	0.13231	-2.395	0.0172
d_coco_1_2	-0.366439	0.127723	-2.869	0.0044
d_coco_1_3	-0.20273	0.122957	-1.649	0.1002
d_coco_1_4	-0.123668	0.118281	-1.046	0.2966
d_coco_1_5	-0.0157047	0.114034	-0.1377	0.8906
d_coco_1_6	-0.0612217	0.108922	-0.5621	0.5745
d_coco_1_7	-0.0358192	0.104746	-0.342	0.7326
d_coco_1_8	-0.0794023	0.0974693	-0.8146	0.4159
d_coco_1_9	-0.166193	0.0882151	-1.884	0.0605
d_coco_1_10	-0.140214	0.0730473	-1.919	0.0558
d_coco_1_11	-0.0293393	0.0570227	-0.5145	0.6072
d_crude⁺⁺_1_1	0.450283	0.135735	3.317	0.001
d_crude_1_2	0.38584	0.130521	2.956	0.0034
d_crude_1_3	0.323076	0.123422	2.618	0.0093
d_crude_1_4	0.320087	0.116779	2.741	0.0065
d_crude_1_5	0.237423	0.109743	2.163	0.0313
d_crude_1_6	0.177259	0.100116	1.771	0.0776
d_crude_1_7	0.130233	0.0908251	1.434	0.1526
d_crude_1_8	0.11955	0.0800952	1.493	0.136
d_crude_1_9	0.115113	0.0686027	1.678	0.0943
d_crude_1_10	0.153873	0.0563610	2.730	0.0067
d_crude_1_11	0.0960177	0.0454096	2.114	0.0353
EC1	−0.478349	0.132884	−3.600	0.0004
EC2	−0.416981	0.140437	−2.969	0.0032
Mean dependent var		0.000105		
S.D. dependent var		0.040012		
Sum squared resid		0.298977		
S.E. of regression		0.030808		
R-squared		0.449108		
Adjusted R-squared		0.407135		
rho		−0.007100		
Durbin-Watson		2.013976		

d_coco^{+} = coconut oil price
d_crude^{++} = crude oil price

Both error correction terms are statistically significant at the 5% level or lower, indicating that they have a significant role in adjusting d_coco_1 to restore the long-run equilibrium. The signs and magnitudes of the coefficients signify how fast and in what direction d_coco_1 adjusts. Further, the coefficient of EC1 is -0.478349, meaning that when coco_1 is above its long-run level relative to crude_1, it decreases by 0.478349% in each period to correct the error.

The R-squared value is 0.449108, which measures how much of the variation in d_coco_1 is explained by the model. The higher the R-squared, the better the explanatory power. The adjusted R-squared value is 0.407135, which adjusts for the number of parameters in the model. It penalizes models that are too complex or overfitted. The rho value is -0.007100, which measures the autocorrelation of residuals. The closer rho is to zero, the less autocorrelation there is. The Durbin-Watson statistic is 2.013976, which tests for autocorrelation of residuals. The closer this value is to 2, the less autocorrelation there is. The Portmanteau test is for white noise residuals, meaning they are uncorrelated and normally distributed. The null hypothesis is that there is no autocorrelation up to lag 48. The test statistic is 152.39 with 144 degrees of freedom and has a p-value of 0.3001. This means that at the 5% level and conclude that there is no evidence of autocorrelation in residuals.

Autocorrelation is a measure of how the values of a variable are related to the values of the same variable in previous periods. The output in Table 4 shows the test statistic, the approximate distribution, and the p-value for each lag order from 1 to 12. Based on the output, for all lag orders from 1 to 12, the p-values are larger than 0.05, which shows no autocorrelation at any lag order at the 5% level. The test statistics are also close to 1 for all lag orders, which indicates that the residual variances are similar with and without lagged variables. Therefore, based on this test, the data set is random and exhibits no significant autocorrelation up to lag order.

Table 4. Test for autocorrelation of orders up to 12

	Rao F	Approx dist.	p-value
lag 1	0.461	F(4, 628)	0.7641
lag 2	0.277	F(8, 624)	0.9734
lag 3	0.302	F(12, 620)	0.9891
lag 4	0.282	F(16, 616)	0.9976
lag 5	0.390	F(20, 612)	0.9927
lag 6	0.811	F(24, 608)	0.7245
lag 7	0.799	F(28, 604)	0.7607
lag 8	0.872	F(32, 600)	0.6716
lag 9	0.816	F(36, 596)	0.7698
lag 10	0.798	F(40, 592)	0.8101
lag 11	0.758	F(44, 588)	0.8730
lag 12	0.864	F(48, 584)	0.7309

The impulse response function (IRF) shows how a shock to one variable in a system propagates and affects other variables. In this case, we are interested in the impact of a shock in the price of crude on the price of coconut oil.

Table 5. IRF for a shock to crude

Period	1	2	3	4	5	6	7	8	9	10
coco	0.9394	0.8789	0.8183	0.7577	0.6971	0.6365	0.5759	0.5153	0.4547	0.3941

The IRF shows that the price of coconut oil increases in response to a shock to the price of crude. The increase is largest in the first period and gradually declines. The price of coco returns to its original level after about ten (10) periods. The IRF also shows that the impact of the shock is not symmetrical. The price of coconut oil increases more in response to a positive shock to the price of crude than it decreases in response to a negative shock.

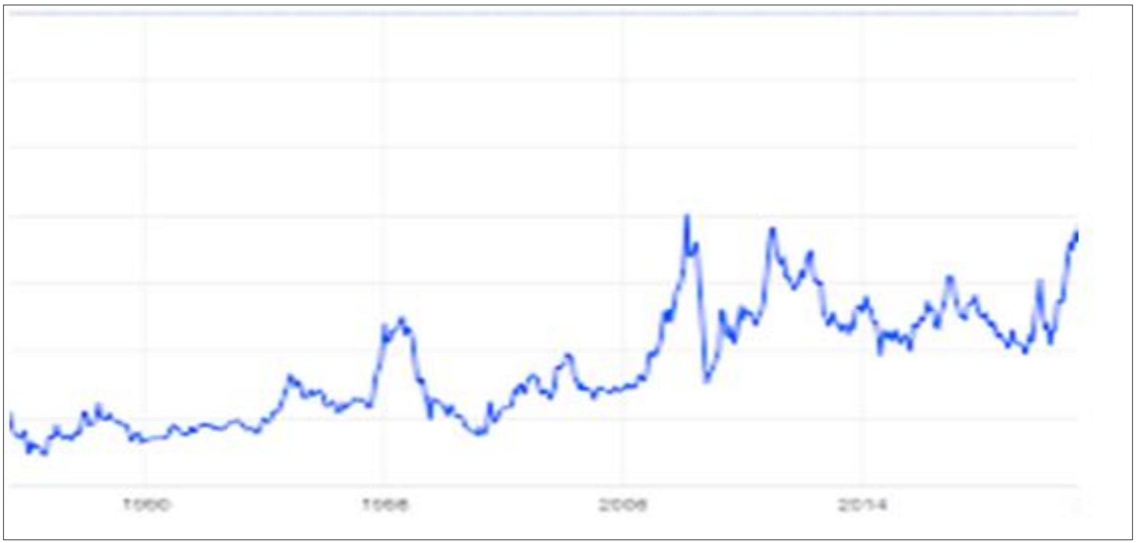

Figure 1. Impulse response function in the crude oil price to coconut oil price

The result of this study confirmed that one factor that affects the price of coconut oil, in the long run, is the price of crude oil. Crude oil is used as an input for producing and transporting coconut oil and manufacturing some of its substitutes, such as palm oil and soybean oil. Therefore, an increase in the price of crude oil may have several effects on the price of coconut oil in the long run. For instance, an increase in the production cost of coconut oil. The higher cost of crude oil may raise the cost of fuel, fertilizers, pesticides, and machinery used in cultivating and processing coconuts which reduce the profitability and supply of coconut oil producers, leading to a higher price of coconut oil (Asiedu & Nketiah-Amponsah, 2019).

An increase in the transportation cost of coconut oil due higher cost of crude oil may also increase the cost of shipping and transporting coconut oil from the producing countries, such as the Philippines and Indonesia, to the consuming countries, such as the US and Europe. The consequence leads to an increase in the price of coconut oil in the international market (Rapsomanikis & Sarris, 2008). Another reason is a change in the demand for coconut oil. The higher cost of crude oil may affect the demand for coconut oil in two ways. On the one hand, it may reduce the demand for coconut oil as a biofuel since it becomes less competitive with other energy sources. On the other hand, it may increase the demand for coconut oil as a food and cosmetic product since it becomes relatively cheaper than some of its substitutes, such as palm oil and soybean oil, which depend on crude oil as an input (Sari & Meyer, 2019).

These effects vary depending on the magnitude and duration of the change in the price of crude oil and on the elasticity and substitution possibilities of coconut oil (Tan & Man, 2002). Moreover, factors such as government policies (Gaskell, 2015), technological innovations (Alouw & Wulandari, 2020), consumer preferences (Hnin et al., C. Z. 2021), and market shocks (Siami-Namini, 2019) may offset or amplify these effects. Therefore, it is impossible to determine precisely a precise relationship between the price of crude oil and coconut oil in the long run. However, based on economic theory and empirical evidence, it is reasonable to expect that an increase in the price of crude oil tends to increase the price of coconut oil in the long run, ceteris paribus.

The asymmetry between the price of crude oil and coconut oil is likely because coconut oil and crude are substitutes. As the price of crude increases, it becomes more economical to use coco as a substitute for crude. This leads to increased demand for coconut oil, increasing the price. The IRF provides a valuable way to visualize the impact of shocks on a system of variables. It can assess the dynamic relationship between variables and identify the channels through which shocks are transmitted.

The IRF also shows that the impact of the shock is not symmetrical. The price of coconut oil increases more in response to a positive shock to the price of crude than it decreases in response to a negative shock. This is likely because the demand for coconut oil is more elastic in the short and long run. In the short run, there are few substitutes for coco, so a crude price shock will significantly impact the demand for coco. In the long run, however, there are more substitutes for coco, so the impact of a shock on the price of crude will be negligible.

Examining cointegration ranks and the derivation of cointegrating vectors have highlighted the absence of a strong long-term relationship between coconut oil and crude oil prices. Instead, the alpha coefficients have illuminated the speed and direction of adjustment mechanisms, indicating how the system rectifies deviations from equilibrium. The dual perspective enriches understanding of how these markets respond to changing conditions and restore stability over time.

The efficacy of the VECM model was underscored through various goodness-of-fit measures, demonstrating its ability to capture the data's complexity while maintaining parsimony. Furthermore, the significant error correction terms emphasize the self-correcting nature of the system, reinforcing the concept of a stable equilibrium relationship.

Interpreting the coefficients of the lagged terms has unveiled the short-term dynamics of these commodities, revealing their mutual influences and responses. Notably, the absence of significant autocorrelation in the model's residuals reaffirms its accuracy and capability to capture the underlying dynamics without systematic patterns.

The VECM framework, incorporating cointegration, adjustment mechanisms, and short-run dynamics, offers a comprehensive perspective on the relationship between coconut oil and crude oil prices. Successfully uncovering both short-term adjustments and long-term equilibrium relationships, the VECM model aids in understanding the complex interactions between these commodities. The presented analysis contributes insights into the dynamics of these markets, facilitating informed decision-making for investors, policymakers, and industry stakeholders.

CONCLUSION AND RECOMMENDATIONS

The conclusion of the error correction model for the relationship between coconut oil price and crude oil price is that the two variables have a stable long-run relationship maintained by error correction mechanisms but also experience short-run variations that depend on their own and each other's past values. The model helps analyze the co-movement and adjustment of coconut and crude oil prices over time.

In practical terms, these findings hold relevance for investors, policymakers, and industry stakeholders who rely on accurate price forecasts and insightful market dynamics. Understanding how these commodities interact, adjust, and achieve equilibrium can inform strategic decisions, risk assessment, and resource allocation in an ever-evolving economic landscape.

The VECM's integrative approach, spanning both short-term fluctuations and long-term equilibriums, contributes to a holistic comprehension of the relationship between coconut oil and crude oil prices. As global economies and the Philippine market continue to evolve, this analysis serves as a valuable resource for navigating the complexities of these interconnected markets and making informed choices that drive sustainable growth and stability.

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