Exploring the Dynamics of CPO Spot and Futures Prices in Relation to Global Crude Oil Price: Evidence from India using ARDL Model Approach and Granger Causality Tests

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ABSTRACT: This study examines the connection between Crude Palm Oil (CPO) spot and futures prices, and global crude oil prices using ARDL model and Granger causality tests to analyze data collected between January 2011 and April 2022, including CPO spot and futures prices, MCX, and WTI Crude oil futures. The results from the coefficient estimations show that both CPO future price percentage changes and crude oil price have a statistically significant impact on the CPO spot price. The study also reveals a long-term relationship between the dependent and independent variables in the level's comparison. The study also demonstrates that global crude oil prices can significantly influence the spot and futures prices of CPO. This research provides useful insight for stakeholders in the palm oil industry, policymakers, and investors.

Keywords: Crude Palm Oil, ARDL model, Granger causality tests, spot and futures prices, and crude oil price.

I. INTRODUCTION

The energy industry is a significant contributor to the Indian economy, and crude oil is one of the country's most valuable energy resources which accounts for a sizeable amount of India's overall import bill, is one of the country's most important economic pillars but also one of its most crucially reliant [9]. The unpredictability of crude oil prices on a worldwide scale has a sizeable bearing on India's key macroeconomic indicators, such as the country's inflation rate, currency rate, and budget deficit [28]. The government of India has put into effect a number of different measures in an effort to lessen the negative effects of fluctuating oil prices [32]. These policies include the deregulation of diesel pricing, the introduction of the Goods and Services Tax (GST), and the adoption of the Direct Benefit Transfer (DBT) system for LPG subsidies. In spite of these precautions, the economy of India is still susceptible to fluctuations in the worldwide price of oil [24]. Because India fulfils a substantial percentage of its need for crude oil through imports from international markets, the country is susceptible to swings in the price of crude oil on the international market [31]

According to Ministry of Petroleum and Natural Gas statistics, India's crude oil imports have gradually increased over the last decade, with some volatility owing to economic and geopolitical circumstances. Due to the COVID-19 epidemic[3], India purchased 214.4 MMT of crude oil in 2020-21, down from 227.8 MMT in 2019-20. India's 2011-12–2020-21 crude oil import statistics is shown below in Table 1.

Table 1. India's 2011-12–2020-21 crude oil import statistics.

Fiscal year	Crude oil Import (MMT)	Crude Palm oil Import (MT)
2011-12	171.7	6.32
2012-13	184.7	7.22
2013-14	189.4	8.09
2014-15	189.4	7.15
2015-16	202.8	7.64
2016-17	213.9	8.27
2017-18	220.4	8.64
2018-19	226.5	9.01
2019-20	227.8	9.4
2020-21	214.4	8.4

This data only covers the fiscal year 2020-21, thus the trend may have altered.

Over the last decade, economic and geopolitical variables have affected India's crude palm oil (CPO) imports. As a popular vegetable oil in India, CPO imports have steadily increased. The Solvent Extractors' Association of India reported that India's CPO imports rose from 6.32 MT in 2011-12 to 9.4 MT in 2019-20. The 2020-21 COVID-19 epidemic reduced CPO imports to 8.4 MT. India's 2021-22 crude palm oil (CPO) import data is unavailable. Industry insiders predict that food and FMCG demand would keep India's CPO imports robust in the current financial year. India's CPO imports are likely to exceed 10 million tons in 2021-22, a record.

From January to November 2021, CPO imports in India rose 28% to 8.48 million tones. reduced import taxes, stronger local demand, and reduced worldwide pricing drove 2021 CPO imports. The CPO spot market has been significantly affected by India's restriction on CPO futures trading. Producers, processors, dealers, and consumers all relied heavily on the futures market for price discovery and risk management before the prohibition. The lack of futures trading has forced all price discovery and risk management into the spot market, which has led to more price volatility and uncertainty. It is now more difficult for market participants to initiate and exit positions due to the ban's effect on liquidity. As a result, market players have less ability to hedge risk and alter production and consumption, which has an effect on both supply and demand for CPO. As conclusion, the spot market has been significantly affected by the restriction on CPO futures trading in India, resulting in higher price volatility, less liquidity, and issues for market actors in terms of risk management shown in Figure 1 (data sourced from the Solvent Extractors' Association of India [37] and the Ministry of Petroleum and Natural Gas, Government of India [38]) . However, economic and geopolitical variables may affect India's CPO import trajectory.

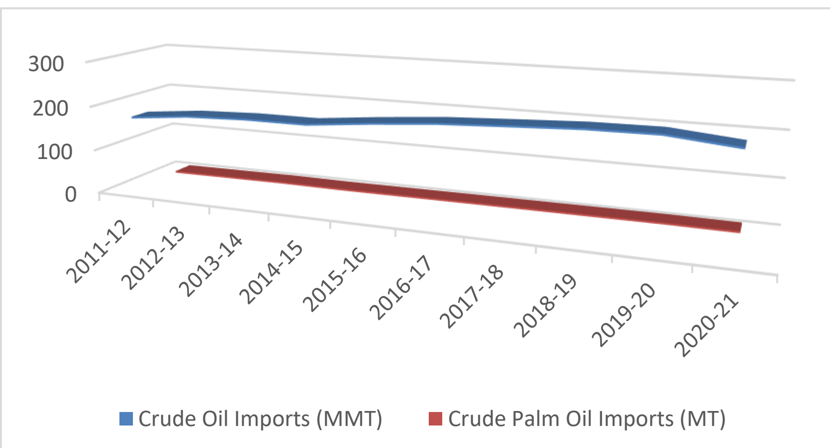

FIGURE 1. Trend in imports of crude oil and crude palm oil.

Despite extensive study into the dynamics of the relationship between the price of crude oil and a range of energy products, the connection between the price of crude oil and commodity futures, such as CPO (crude palm oil), is still not well understood [6]. An important part of the Indian economy is the CPO market, which has a variety of uses, including animal feed, biodiesel, and cooking oil. Along with the dynamics of domestic supply and demand, the price of crude oil in other areas of the world largely determines the price of CPO in India [25]. This makes understanding the relationship between the price of CPO on the spot market, the price of CPO on the futures market, and the global price of crude oil crucial for market participants, policymakers, and other stakeholders in the Indian economy. The goal of this study is to examine the dynamics that exist between the prices of crude oil throughout the world, the prices of CPO on the spot market, and the prices of CPO futures in India [23]. The study also aims to assess the direction of causality between these variables as well as the short- and long-run correlations between them. A number of different energy products, such as petrol, diesel, and natural gas, as well as the price of crude oil have been the subject of prior studies. Most of these studies have found that there is a direct correlation between the cost of crude oil and the cost of energy goods[7]. Furthermore, some of these researches have shown proof of both long-run and short-run causality between these factors [19].

The relationship between the price of crude oil and futures markets for commodities like CPO futures, however, has not received much research. According to a study by [8], there is evidence of a long-term correlation between the price of crude palm oil and the price of international crude oil. The study, however, did not look at the correlation between the prices of CPO futures and those of crude oil in general. Research by [35] that was done in India looked into the relationship between the price of crude oil and the cost of several agricultural products, including palm oil. The study found a favorable correlation between the price of crude oil and the price of palm oil, but it did not thoroughly examine the relationship between those two prices or that between crude oil and the price of CPO futures.

The dynamics between the price of crude oil globally, the spot price of CPO, and the price of CPO futures in India will be investigated in this study using the autoregressive distributed lag (ARDL) model and Granger causality tests. The study will also look into the connections between these three pricing categories. Granger causality tests can determine the direction of a causal relationship between variables, but the ARDL model can examine both long- and short-term correlations between variables[2]. Data from publicly accessible databases will be used for the investigation's aims. The Indian Multi Commodity Exchange. As a result, the interactions between the variables may be fully investigated over a very long-time horizon. The study's time frame extends from 2011 to 2022. And the variations in CPO spot, future and crude oil prices are shown in Figure 2. The goal of this study is to add to the body of knowledge already known about the relationship between the price of crude oil globally, the spot price of CPO, and the price of CPO futures in India. Through the use of the ARDL model and Granger causality tests, this study will shed light on the long- and short-run correlations that exist between these variables, as well as the direction of causation that exists between them. For people who participate in the market, those who formulate economic policy, and other stakeholders in the Indian economy, the findings of this study will have important ramifications.

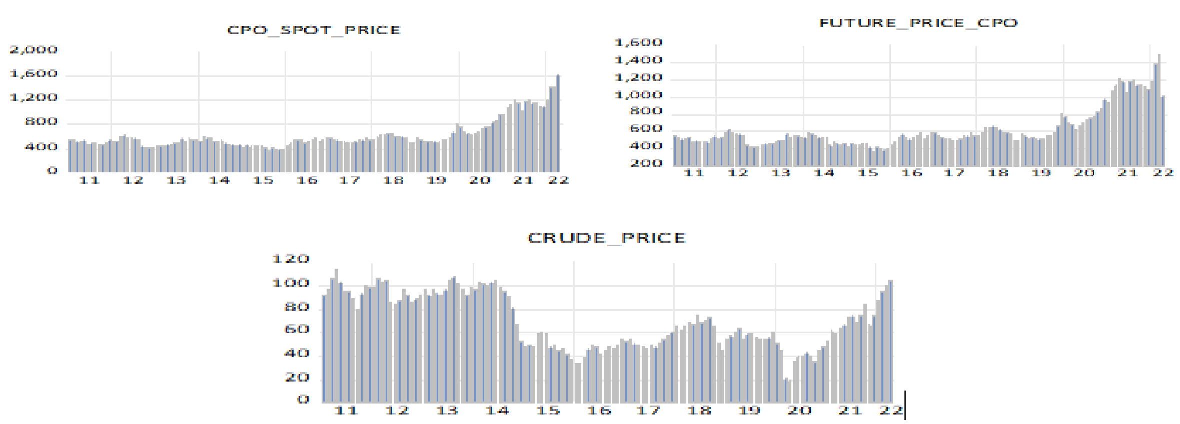

FIGURE 2. Variation in prices

The paper structure: have the Background Theory in Section II, Literature Review, in Section III, discussion in Section IV, the conclusion in section V.

II. LITERATURE REVIEW

Examine long-term and short-term stock, gold, and crude oil price relationships using monthly Turkish data from January 1986 to November 2016.FMOLS, DOLS, and CCR cointegrating equations analyses long-run coefficients, whereas the ARDL model examines cointegration and short-run linkage[42]. Granger causality tests unidirectional gold-stock price connections across short, long, and combination time periods. Gold and stock prices are negatively correlated, whereas crude oil and stock prices are favorably. Gold and crude oil balance stock prices by 0.39%. The new combined cointegration supports the ARDL cointegration limits test and shows the same strong long-term link between variables.]34] explore oil price-stock price relationships in oil-exporting and importing nations. Nonlinear Panel ARDL models provide for relationship nonlinearities and within-group variability. [8] compare linear (symmetric) and nonlinear (asymmetric) Panel ARDL model predictions. Exporters' stock prices are less oil-sensitive than importers. Out-of-sample predictions reveal that integrating positive and negative oil price changes to stock price estimations favors only oil-importing countries. Oil price proxies, lag structure, and in-sample periods yield comparable findings. The method accounts for cross-section variability and oil-stock price nonlinearities. Exporters and importers affect the oil price-stock nexus.

Study in [36] Economists, financiers, and politicians have argued oil price variations' macroeconomic effects for decades. Oil-food costs are a hot topic. The nonlinear link between oil and food prices is less established than the linear one. Brent and WTI oil prices affected global food prices from January 1990 to October 2017. ARDL models are calculated empirically. Positive oil price shocks only affect food prices long-term, perpetuating imbalances. Oil prices affect dairy prices more than reductions. Oil price drops cause short-term imbalances in agricultural commodity pricing. The data suggest symmetric oil-food price relationships are erroneous. [15] utilize a wavelet-based nonlinear autoregressive distributed lags model (W-NARDL) to examine whether US dollar exchange rates of 18 currencies explain crude oil price changes. This model captures short- and long-term nonlinearities and extreme motions while filtering noise. Oil prices depend on currency rates. Long-term currency depreciation affects oil prices more than currency appreciation. Finally, denoising crude oil and exchange rate data is essential before examining their correlations.

The study in [4] examined how oil price variations affect real exchange rates in many Sub-Saharan African nations using NARDL model. Short-term oil price fluctuations exhibited symmetrical effects, whereas long-term swings produced asymmetrical effects, with price hikes having a greater impact than price reductions. [30] used autoregressive distributed lag (ARDL) and nonlinear ARDL (NARDL) to study the short- and long-term impacts of several factors on oil prices. This study examined COVID-19. Salem impacts policy regardless of COVID-19. Study in [13] analyses Malaysian food and oil prices using NARDL. NARDL limitations cointegrate food, oil, and real GDP. NARDL shows food price discrepancy. Long-term oil price hikes affect food costs. Food costs are unaffected by oil price drops. Only medium-term oil price hikes affect food price inflation. Market forces will determine Malaysia's food costs, not oil price decreases.

Study of [26] examines oil-food price cointegration and its causes in food-importing and oil-exporting nations. The study comprises 2001–2015 statistics from 21 nations. I(0) and I(I) stationarity required panel ARDL model. Food and energy prices hurt now but help later. Food prices drive oil prices in the example nation. Agriculture programmers should promote cheap food and alternative energy to safeguard food and oil supply. [14] advise traders, investors, and fund managers to monitor crude oil and soybean futures markets to decrease risk and diversify their portfolios. Since the Asian palm index has a long-term relationship with crude oil futures, they recommend watching it. Long-term relationships advise this. Since the Asian palm index is linked to soybean futures, monitoring crude oil and soybean futures markets is another short-term approach. Empirical data supports their statements, and long-term risk management requires a focus on crude oil futures. The authors feel they have solid evidence. Study of [28] found no correlation between the NCDEX agricultural commodities market and India's FMCG stock index save for barley, cottonseed, jeera, mustard seed, and wheat. Writers highlight wheat, barley, cottonseed, and jeera as exceptions. The authors recommend diversifying into agricultural commodities and fast-moving consumer goods to lessen risk. Both studies recommend financial diversification to reduce risk. Study of [14] propose investing in crude oil and soybean futures, whereas [20] suggest diversification into agricultural commodities and FMCG. Investors must consider risk tolerance, market movements, and commodity price variations.

Study of [16] compare the crude palm oil (CPO) futures trading to the WTI derivatives market to determine efficiency. CPO and WTI futures meet the weak-form efficient market theory despite liquidity disparities. Scaling exponents make CPO futures safer than WTI futures for big gains. The two futures markets are interconnected and share information, supporting our market efficiency findings. We utilize the COVID-19 epidemic's lower petrol consumption to analyses speculation's impact on market integration. COVID-19 updates markets. The results indicates that (i) the CPO market participants should pay attention to the crude oil markets to forecast price shifts, (ii) traders can use the West Texas Intermediate (a future as a hedge tool regarding CPO futures if there is complementary data movement, and (iii) regulators ought to execute the new the CPO futures market strategies cautiously, as asymmetrical shifts in undetermined or imbalances supervision with the West Texas Intermediate (a future market can create market imbalances and uncertainty regarding regulation).

Study of [20] examined palm oil, soybean, and crude oil futures information flow. They suggested ways to enhance vegetable oil markets, notably palm oil futures. The research found interaction cause-effect linkages across the three oil futures markets and their pairings, unlike a Granger causality test. The net information flow was calculated using trade volume and liquidity in the crude oil futures market, the two vegetable oil futures markets, and the soybean and palm oil futures markets. Investment constraints prohibited the palm oil futures market from discovering crude oil and soybean oil futures information first. The authors suggested extending trading hours and using US dollars to develop the palm oil futures market and eliminate market friction.

Study of [29] analysis examined crude oil prices, US dollar exchange rates, and global fertilizer and agricultural prices. Using monthly data from 1983 to 2013, panel VAR and Granger causality analyses showed that crude oil and the US dollar affected fertilizer and other agricultural commodity prices worldwide. Contrary to earlier studies, bidirectional panel causation effects between crude oil, international agriculture prices, and the US dollar were found. Study of [12] stock market and agriculture pricing patterns. 16 agricultural pricing trends and economic discrepancies were examined. Financialization and the financial crisis explained most markets but not global demand, the study found. Farm and stock values rose during financial duress. The study found that financial shocks to agricultural prices should diminish as global financial tensions reduce, but they may rise again if financial instability returns as long as agricultural markets remain financialized. In 2016,[1] examined gold, crude oil, the USD-INR exchange rate, and the Indian stock market using DCC-GARCH models and nonlinear causality tests. Gold and oil plummeted, lowering the Indian Rupee and Sensex.

The research suggests India use gold and oil prices to lower currency rate and stock market volatility. Study of [5] employed a TVP-VAR-based extended joint connectivity technique to study eleven agricultural commodities and crude oil futures prices from July 1, 2005, to May 1, 2020. Economics shook commodities markets. Study [17] on optimum portfolio weights and time-varying hedging ratios in metal and other commodity futures markets found information transmission channels that may enhance investment selection and portfolio investors' trading tactics. Study of [21] crude oil-food price co-movements in 2016 using VAR prediction error correlations. Crude oil and food prices rose together only during the commodities boom. Finally, using connectedness approaches and high-frequency data, [22] examined the realized volatility link between US crude oil futures and five Chinese agricultural commodities futures. Negative US crude oil market volatility drives Chinese agricultural commodity prices more than positive volatility.

III. MATERIAL AND METHOD

Table 2. Data Description.

Description	Data type	Source
CPO Spot price	Monthly data (Jan 2011-Apr 2022)	MCX
CPO Futures price	Monthly data (Jan 2011- Apr 2022)	MCX
Crude Oil	Monthly data (Jan 2011- Apr 2022)	WTI Crude oil future

Data restriction begins in April 2022 as a result of the Multi Commodity Exchange's prohibition on CPO futures trading shown in Table 2.

Table 3. Descriptive Statistics.

	CPO SPOT_PRICE	CPO FUTURE_PRICE	CRUDE_PRICE
Mean	621.7581	617.6353	69.38772
Median	544.5000	545.3500	64.32000
Maximum	1618.000	1485.000	113.9300
Minimum	364.6000	360.6000	18.84000
Std. Dev.	236.2079	223.8126	23.28968
Skewness	2.040724	1.884516	0.154374
Kurtosis	6.709406	5.852943	1.760124
Jarque-Bera	172.3682	126.6210	9.251501
Probability	0.000000	0.000000	0.009796

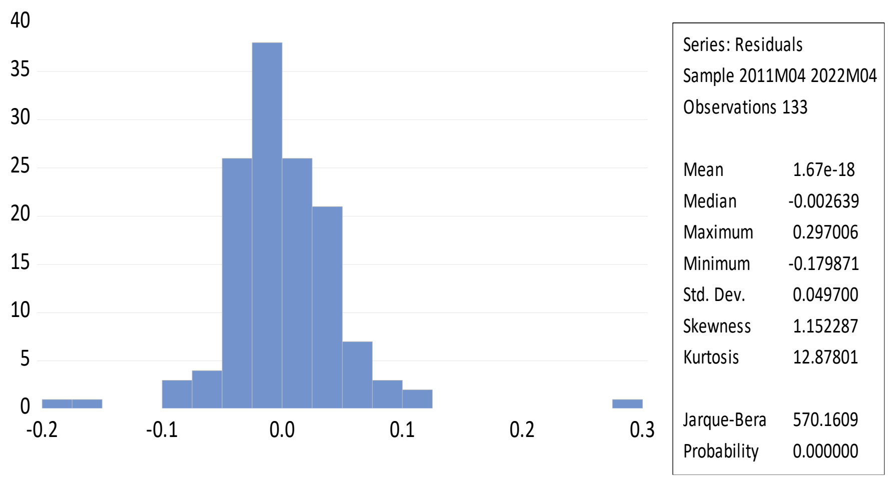

FIGURE 3. Normality Test

Shown in Figure 3 the three variables seem to be strongly skewed, have a positive kurtosis, and not be normally distributed overall, according to the descriptive statistics. The mean and standard deviation of the three variables is greatest for the CPO SPOT_PRICE shown in Table 3. And the process of converting into log form was continued in order to verify stationarity.

1. UNIT ROOT TEST

A stochastic trend in a time series with a root value of one is referred to as a unit root. In other words, a unit root process is one in which the anticipated value of the process fluctuates arbitrarily within a certain range rather than being constant over time. Robert F. Engle, who pioneered the idea of cointegration and introduced the idea of autoregressive conditional heteroskedasticity (ARCH) in econometric modelling, is one of the most prominent writers in the study of unit roots. [10] established that many economic time series have unit roots, which means they have a stochastic trend, in their important study "Co-integration and Error Correction: Representation, Estimation, and Testing.

A statistical technique called the ADF and PP tests are crucial in econometrics for identifying unit roots in time series data. Detecting unit roots is vital because their presence implies non-stationarity, which can lead to spurious regression results and misleading inferences in time series analysis. Stationarity is a fundamental assumption in many time series models, and non-stationary data.

Table 4. Result of Unit root test.

	CPO Spot price		CPO Future price		Crude price	
	At level	**At first Difference**	**At level**	**At first Difference**	**At level**	**At first Difference**
PP test (t-statistics)	0.8368	-10.4998	-0.8814	-10.4119	-1.9365	-9.7539
ADF-test(t-statistics)	0.9040	-10.5140	-0.9565	-10.4171	-1.9560	-9.1709
p-value	0.9944	000	0.7916	000	0.3148	000
Significant value	no	***	no	***	no	***

Notes: (*) Significant at 10%; (**) Significant at 5%; (***) Significant at 1%. and (no) Not Significant. *MacKinnon (1996) one-sided p-values.

The spot price, future price, and crude oil price are not stationary at levels at the 5% level of significance at the first difference I (1) shown in Table 4. At the estimated level, all the variables are converted and represented in their logarithmic form. The roots of the autoregressive (AR) and moving average (MA) polynomials in an ARMA (2,2) model calculated on SPOT_PRICE, FUTURE_PRICE, and CRUDE_PRICE initial differences. The result shows two AR and two MA roots in the model.

Table 5. Inverse Roots of AR/MA Polynomial(s).

AR Root(s)	Modulus
0.588196	0.588196
-0.588196	0.588196
No root lies outside the unit circle.	
ARMA model is stationary.	
MA Root(s)	Modulus
Modulus	0.259608
Modulus	0.259608
No root lies outside the unit circle.	
ARMA model is invertible.	

The Table 5 presents the AR polynomial's reciprocals, or inverse roots. The table displays each root's absolute value and modulus. Both roots are inside the complex plane unit circle since their modulus is less than 1. Cycles are not recorded, hence there are no unit circle roots. Since the AR polynomial has unit circle roots, the ARMA model is stationary and shown in Figure 4.

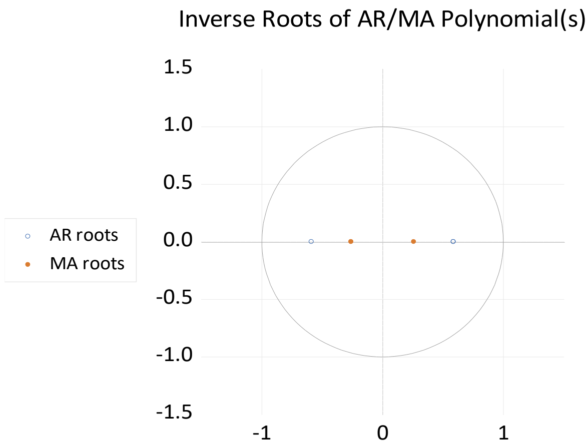

FIGURE 4. Inverse Roots of AR/MA Polynomial(s).

IV. DATA ANALYSIS

1. AUTOREGRESSIVE DISTRIBUTED LAG TEST

This subsection details the statistical methods, software used, and the application of analytical tools to quantify and interpret numerical data. It may include techniques such as regression analysis, ANOVA, correlation, or other statistical tests employed for data interpretation.

The autoregressive distributed lag (ARDL) model, which [27], is a novel technique to cointegration analysis. The ARDL model, a generalization of the conventional error correction model (ECM), allows for the inclusion of both long-run and short-run dynamics in the interaction between two or more time series. In practical research, notably in areas like macroeconomics, finance, and international commerce, the ARDL model has grown in popularity. It has been used to research a variety of subjects, including as the consequences of monetary and fiscal policies, the connection between exchange rates and trade flows, and the factors that influence economic development.

$$\text{Spot Price} = \beta 0 + \beta 1 * \text{Future Price} + \beta 2 * \text{Crude Oil Price} + \varepsilon \quad (1)$$

Equation 2 describes spot Price as the price of the asset in the spot market at a given time. future price: the price of the asset in the futures market at the same time as the spot price. crude oil price: the price of crude oil in the market at the same time as the spot and future prices. *β0*: the intercept of the regression. *β1* and *β2*: the coefficients of the independent variables, representing the effect of changes in the futures and crude oil prices, respectively, on the spot price. ε: the error term, representing the part of the spot price not explained by the model.

$$\Delta Spot_t = \alpha + \beta_1 Spot_{t-1} + \beta_2 \Delta Spot_{t-1} + \beta_3 \Delta Future_{t-1} + \beta_4 \Delta CrudeOil_{t-1} + \beta_5 Future_t + \beta_6 CrudeOil_t + \varepsilon_t \quad (2)$$

Where:

- $\Delta Spot_t$ represents the change in the spot price at time t.

- α is the intercept term.
- $\beta_1,\beta_2,\beta_3,\beta_4,\beta_5,\beta_6$ are coefficients that measure the impact of each respective variable.
- $Spot_{t-1}$ is the spot price at time $t-1$.
- $\Delta Spot_{t-1}$ represents the change in the spot price at time $t-1$.
- $\Delta Future_{t-1}$ is the change in the future price at time $t-1$.
- $\Delta CrudeOil_{t-1}$ is the change in the crude oil price at time $t-1$.
- $Future_t$ is the future price at time t.
- $CrudeOil_t$ is the crude oil price at time t.
- ε_t is the error term, capturing all other factors affecting $\Delta Spot_t$ that are not included in the model.

Another popular econometric model for examining a system's short- and long-term dynamics is the Error Correction Model (ECM). The idea of cointegration between the variables is included in the ECM, which is developed from the ARDL model. The ECM may be expressed in the Equation 4, assuming that the three aforementioned variables are spot, future, and crude oil prices:

$$\Delta Spot_t = \alpha + \beta_1 Spot_{t-1} + \beta_2 \Delta Spot_{t-1} + \beta_3 \Delta Future_{t-1} + \beta_4 \Delta CrudeOil_{t-1} + \beta_5 Future_t + \beta_6 CrudeOil_t + \lambda(ECM_{t-1}) + \varepsilon_t \quad (3)$$

Where:

- $\Delta Spot_t$ represents the change in the spot price at time t.
- α is the intercept term.
- $\beta_1,\beta_2,\beta_3,\beta_4,\beta_5,\beta_6$ are are coefficients for the respective lagged and current variables.
- $Spot_{t-1}$, $\Delta Spot_{t-1}$, $\Delta Future_{t-1}$, $\Delta CrudeOil_{t-1}$, $Future_t$, $CrudeOil_t$ represent the spot price, change in spot price, change in future price, change in crude oil price, future price, and crude oil price at times $t-1$ and t, respectively.
- $\lambda(ECM_{t-1})$ is the coefficient for the error correction term, representing the long-term equilibrium relationship between the variables.
- ε_t is the error term.

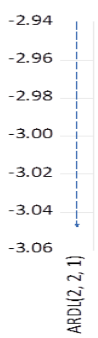

FIGURE 5. Akaike information criterion

The results of an ARDL model using the dependent variable D(CPO_SPOT_LOG,2) are shown in this output. ARDL (2,2,1) shown in Figure 5., with a constrained constant and no trend is the model of choice. There are 133 observations included in the study, and the sample period runs from January 2011 to April 2022. The coefficients, standard errors, t-statistics, and p-values for each independent variable included in the model are shown in the conditional error correction regression results.

Table 6. Autoregressive distributed lag (ARDL) Test

Panel A: Coefficient of ARDL (2.2.1)

Variable	**Coefficient(p-value)**	**Std. error**
c	0.003169 0.4898**	0.004576
Δ (SPOT_PRICE (-1))	-0.510644 0.0042***	0.175315
Δ (SPOT_PRICE (-2))	-0.502505 0.0113***	0.195299
Δ (FUTURE_PRICE)	0.000702 0.0000***	8.32E-05
Δ (FUTURE_PRICE (-1))	0.000715 0.0046***	0.000248
Δ (FUTURE_PRICE (-2))	0.000802 0.0073***	0.000294
Δ(CRUDE_PRICE)	0.001877 0.0104***	0.000722
Δ (CRUDE_PRICE (-1))	0.001403 0.0552**	0.000725

Note: (*) 10%; (**) 5%; (***) 1%. levels of significance, respectively.

Panel B: Diagnostics Test Results

ECTt-1	--2.013149(0.000) ***
Adj. R2	0.697153
Breusch-Godfrey Serial Correlation LM test	-2.548942(0.0823) **
Ramsey RESET Test	0.3402

Note: (*) 10%; (**) 5%; (***) 1%. levels of significance, respectively.

Panel C: Critical values summary for lower and upper bound

Significant	Lower bound test I (0)	Upper bound test I (1)	Test statistics
10%	2.63	3.35	
5%	3.1	3.87	F-statistic
1%	4.13	5	20.26167

Panel D: Long-Run Relation Result

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FUTURE_PRICE)	0.001103	9.83E-05	11.22299	0.0000***
D(CRUDE_PRICE)	0.001629	0.000515	3.165706	0.0019**
C	0.001574	0.002305	0.683056	0.4958

Note: (*) 10%; (**) 5%; (***) 1%. levels of significance, respectively.

The ARDL (2,2,1) model that was used assesses the factors that affect the spot price of crude palm oil (CPO) using data from January 2011 to April 2022 shown in Table 6 under Panel A Coefficient of ARDL (2.2.1). While the fixed regressor is a constant, the dynamic regressors are the first and second lags of the percentage changes in the CPO future price and the price of crude oil. According to the model's coefficient estimations, when all other factors are held constant, a one percent increase in the percentage change in the spot price of CPO results in a 0.0007 percent rise.

Similar to the previous example, keeping all other factors equal, an increase of one percent in the price of crude oil results in an increase of 0.0019 percent in the spot price of CPO. Indicating persistence in the spot price of CPO, the lagged values of the dependent variable are likewise statistically significant. In particular, a 1% drop in the spot price of CPO from the previous period results in a 0.51 % drop in the spot price of CPO in the current period, while a 1% drop from the spot price of CPO from the previous two periods results in a 0.50 % drop in the spot price of CPO in the current period.

The corrected R-squared of 0.43 and the F-statistic, which is significant at the 1% level, both show that the entire model is statistically significant shown in Panel B Diagnostics test. The Breusch-Godfrey Serial Correlation LM test indicates from the findings that the model is devoid of serial correlation. The Ramsey RESET Test is passed by the model, and the model is stable according to the CUSUM test shown as Figure 6.

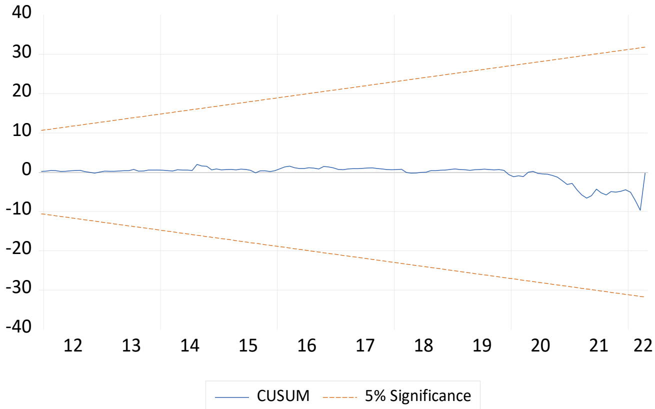

FIGURE 6. CUSUM Test

According to the data, the following variables are statistically significant in explaining the dependent variable: D (CPO_SPOT_LOG (-1)), D (FUTURE_PRICE_CPO (-1)), D (CRUDE_PRICE (-1)), D (CPO_SPOT_LOG (-1),2), D (FUTURE_PRICE_CPO (-1),2), and D(CRUDE_PRICE,2). When the dependent variable is in levels, the levels equation displays the coefficients, standard errors, t-statistics, and p-values for each independent variable in the model. According to the findings, the dependent variable can be explained statistically by D(FUTURE_PRICE_CPO) and D(CRUDE_PRICE) respectively.

The difference between the dependent variable and the product of the coefficients and the independent variables in the levels equation is used to compute the error correction term (EC). The null hypothesis of no levels association is tested using the F-bounds test, and the findings indicate that the null hypothesis may be rejected at a significance level of 1% or below. This suggests that the dependent variable and the independent variables in the level's Equation have a long-term connection.

2. *GRANGER CAUSALITY TEST*

By applying PECM and [10] long run causality test, they found that oil and food prices are related over the long run, even after controlling for other factors. The next step is to determine the direction and causality between the two variables. The observation that oil is an input cost in the production of food, which could affect food prices, led to the idea of conducting research to determine whether or not there is a causal link between the two phenomena, and vice versa, through the biofuel channel. For the relationship between food and oil prices.

Granger Causality Test: This test is not about true causality in a philosophical or physical sense[11]. Instead, it tests whether past values of one variable (*X*) provide statistically significant information about future values of another variable (*Y*), above and beyond the past values of *Y* itself.

$$SpotPrice(t) = \beta_0 + \beta_1 FuturesPrice(t) + \beta_2 CrudePrice(t) + \beta_3 FuturesPrice(t-1) + \beta_4 CrudePrice(t-1) + \beta_5 \times (FuturesPrice(t) \times CrudePrice(t)) + \varepsilon(t) \quad (4)$$

Where:

- *SpotPrice(t)* is the spot price at time *t*.
- β_0 is the intercept term.
- $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ are coefficients estimating the impact of each respective variable.
- *FuturesPrice*(*t*) and *FuturesPrice*(−1) are the futures prices at times *t* and *t*−1, respectively.
- *CrudePrice*(*t*) and *CrudePrice*(*t*−1) are the crude prices at times *t* and *t*−1, respectively.
- *FuturesPrice*(*t*) × *CrudePrice*(*t*) is an interaction term, which models how the combined effect of futures and crude prices at time *t* impacts the spot price.
- *ε(t)* is the error term, capturing all other factors affecting *SpotPrice(t)* that are not included in the model.

Table 7. Granger Causality Test Result.

Null Hypothesis:	Obs	F-Statistic	Prob.
FUTURE_DIFF_CPO does not Granger Cause CPO_SPOT_DIFF	133	0.68336	0.5068
CPO_SPOT_DIFF does not Granger Cause FUTURE_DIFF_CPO		13.9062	3.E-06***
CRUDE_DIFF does not Granger Cause CPO_SPOT_DIFF	133	3.30689	0.0398**
CPO_SPOT_DIFF does not Granger Cause CRUDE_DIFF		3.90189	0.0227**
CRUDE_DIFF does not Granger Cause FUTURE_DIFF_CPO	133	4.06378	0.0194**
FUTURE_DIFF_CPO does not Granger Cause CRUDE_DIFF		2.69501	0.0714*

*Note: (*) 10%; (**) 5%; (***) 1%. levels of significance, respectively.

The findings shown in Table 7 of the paired Granger causality test allow us to draw the conclusion that there is proof of directional causation between some of the model's variables. In particular, the past values of crude oil price differences have statistically significant predictive power on the current and future values of crude palm oil spot price differences as well as the past values of crude palm oil future price differences. The past values of spot crude palm oil price differences and future crude oil price differences, however, do not have any statistically significant predictive power on the current and future values of crude palm oil future price differences, and the past values of spot crude palm oil price differences do not have any statistically significant predictive power on the current and future values of crude oil price differences.

It is crucial to remember that these findings only show the direction of causation between the model's variables, not the actual mechanism driving the link. The findings should also be evaluated in light of the particular data and model that were used, since other variables that were not taken into account by the model could have an impact on the association between the variables. To address this the ARDL model (2,2,1) employed to check the relationship and suggests that the variable as long-run relationship.

V. CONCLUSION

Crude palm oil supply and demand dynamics can be complex and intertwined with those of crude oil. Crude oil has a major impact on the supply and demand of crude palm oil across the world. Crude palm oil demand is influenced by the demand for palm-based biofuels, foods, and other items. However, climate, government policy, and production levels all affect the accessibility of crude palm oil. Global shifts in the price of crude oil have the potential to have a major impact on the supply and demand of crude palm oil. For instance, if the price of crude oil rises, there may be a corresponding rise in demand for biofuels, which may lead to a rise in demand for petroleum palm oil. However, as oil prices drop, demand for biofuels and crude palm oil tends to fall along with them. Crude palm oil supplies are sensitive to fluctuations in the worldwide price of crude oil. The rising cost of crude oil might discourage palm oil farmers from planting and harvesting their crops. Conversely, if crude oil prices fall, it might mean cheaper production costs, which in turn could lead to more output and more supply.

As a result, fluctuations in the price of crude oil might have an effect on the demand and supply dynamics for crude palm oil. Policymakers, merchants, and investors in the crude palm oil market must comprehend these characteristics to make educated selections and proficiently handle risk.

Granger causality tests and the ARDL model both point to a long-term correlation between global crude oil prices and the spot and futures pricing of crude palm oil (CPO) on the Indian market. The ARDL model found that the percentage change in the spot price of CPO increased by 0.0007 percent for every percentage point rise in the price of crude oil, but only increased by 0.0019 percent overall. There was also a statistically significant relationship between the dependent variable's lagged values and the CPO spot price's stability.

Furthermore, Granger causality tests demonstrated that historical crude oil price differentials were a statistically significant predictor of both the present and future crude palm oil spot price differentials. This suggests that there is a cause-and-effect relationship between these factors. However, there was no statistically significant relationship between the differences in spot crude palm oil prices over time and future crude oil prices, and no relationship between the differences in spot crude palm oil prices over time and current values of crude oil price differences. Overall, the data suggests that the global price of crude oil has a positive and reversible effect on the spot and futures pricing of CPO in India. It's important to remember that these findings are tied to a particular model and dataset and may not generalize to other situations or eras. To fully understand the mechanisms behind the observed relationships and to explore the possible effect of factors not included in the model, more study is needed.

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