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The Wax and Wane of CPO Prices in India: A DCC Approach to Understanding Market Sentiment

Supriya R, Rajesh Mamilla*

VIT Business School, Vellore Institute of Technology, Vellore, Tamil Nadu India. *Corresponding Author's Email: rajesh.mamilla@vit.ac.in

Abstract

This study provides a detailed analysis of Crude Palm Oil (CPO) price dynamics, focusing on the relationship between spot and future prices during significant global events, notably the COVID-19 pandemic and the Ukraine-Russia conflict. Utilizing Dynamic Conditional Correlation (DCC) models, the research examines conditional returns and covariance, as well as the correlation trends in the Crude Palm Oil (CPO) market. The study reveals critical insights into market behavior during these tumultuous times. For instance, sharp increases in covariance during key periods suggest strong movement synchronicity between spot and future prices, potentially driven by market-altering events. The onset of COVID-19 and the escalation of the Ukraine-Russia conflict are identified as significant influencers, disrupting global supply chains and impacting global food supplies, which in turn affect both spot and future Crude Palm Oil (CPO) prices. Additionally, the research finds a dynamic correlation trend between the future and spot prices of Crude Palm Oil (CPO). Starting with a strong positive correlation in 2018, the study observes a gradual decrease in this correlation, especially after 2020. This trend indicates diverging market forces or perceptions, particularly in response to the COVID-19 pandemic and the ongoing Ukraine-Russia conflict. Such fluctuations in correlation suggest varying market sentiments and expectations, which have implications for market risk assessment, hedging strategies, and speculative activities.

Keywords: DCC-GARCH, Commodity Market, Crude Palm Oil , Price Movement, and Spot and Future Prices.

Introduction

The global economy heavily relies on commodity markets, essential for trading primary resources and fundamental items. Commodity Exchange Markets (1), like those in India, are significant components of financial landscapes, trading a variety of commodities such as agricultural products, metals, and energy resources (2). Among these, Crude Palm Oil (CPO) is especially significant, used widely in cooking, food processing, and industrial applications. The Indian commodity market, known for its volatility (3), presents challenges for traders and investors, with CPO being one of the most volatile commodities (4).

CPO's significance in the Indian market is underscored by India's status as one of the largest consumers and importers of palm oil globally. This oil is crucial to India's edible oil industry, addressing the needs of its large population. India mostly imports palm oil from countries like Indonesia and Malaysia due to limited domestic production (5). To manage the risks associated with CPO price volatility, stakeholders in the palm oil sector utilize futures contracts offered on the Multi Commodity Exchange (MCX) and National Commodity and Derivatives Exchange (NCDEX). These contracts provide a mechanism for hedging against price fluctuations. However, global factors like production changes in major producing countries, weather impacts, international trade policies, and global demand significantly influence CPO prices (6). The Indian government also plays a key role in the palm oil market through import tariffs and trade policies aimed at market stability and domestic production support. These measures aim to reduce dependence on imports and promote self-sufficiency in edible oil production.

Conventional methods may have limitations related to labor availability, material costs, and project duration. Given its widespread use, fluctuations in CPO prices significantly impact household budgets

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and food accessibility in India, linking directly to food inflation (7). This makes CPO prices a critical focus for policymakers and economists (8). Additionally, the palm oil industry faces environmental and social challenges, such as deforestation and labor conditions, leading to a growing demand for sustainably produced palm oil in India. In this context, accurate price prediction and market analysis are vital for market participants (9). Advanced econometric models like the Dynamic Conditional Correlation-GARCH (DCC-GARCH) model have emerged as effective tools for forecasting price movements in volatile markets like the Indian CPO market (10).

This model, combining the GARCH model's adaptability with the capability to capture time-varying correlations, allows for comprehensive volatility analysis. Traditional time series models like ARIMA have been used for commodity price prediction, but they often struggle with the complex dynamics of financial time series data (11). In contrast, the DCC-GARCH model, which accommodates time-varying conditional correlations (12), offers more accurate predictions and risk management strategies, acknowledging the interdependence among variables and clustering of volatility (13).

In an era marked by volatility in global commodity markets, this study zeroes in on India's Crude Palm Oil (CPO) prices using a Dynamic Conditional Correlation (DCC) approach. With India being a major consumer and importer, understanding CPO price fluctuations is crucial for economic stability, risk management, and policy making. The innovative DCC method offers nuanced insights into market dynamics, addressing the urgent need for advanced analytical tools in volatile environments.

Amidst the backdrop of COVID-19 disruptions and escalating geopolitical tensions, this study delves into India's Crude Palm Oil (CPO) market fluctuations, employing the Dynamic Conditional Correlation (DCC) model. The suspension of future trading has introduced unprecedented volatility, underscoring the necessity for sophisticated analysis. By examining these variables, this research aims to shed light on the intricate dynamics governing CPO prices, offering pivotal insights for stakeholders navigating these turbulent times.

In this study, the application of the Dynamic Conditional Correlation (DCC) model to the Indian Crude Palm Oil (CPO) market has significantly advanced our understanding of market sentiment and price dynamics (14), particularly under the influence of COVID-19 disruptions, geopolitical tensions, and the suspension of future trading (15).

By employing the DCC approach by using R programming version 4.3.1, we've been able to capture and analyze the time-varying correlations between spot and future CPO prices , revealing how external shocks and market sentiments dynamically influence price movements. Financial markets often exhibit asymmetric dependencies, especially during extreme market conditions. DCC-GARCH models can capture these tail dependencies, providing insights into how spot and future prices of CPO behave under different market scenarios.

This methodology not only sheds light on the intricacies of the Indian CPO market but also has broader implications for global commodity markets, offering a valuable analytical tool for dissecting market behaviors amid volatility. The insights gained underscore the model’s utility in informing risk management strategies, policy-making, and strategic decision-making, thereby addressing both the specific dynamics of the Indian market and its interconnectedness with global market trends.

Previous studies focused on This study evaluates the impact of financial contagion on foreign currency markets in developing and industrialized countries during the U.S. subprime mortgage crisis (16). Identified contagion effects, particularly in emerging markets, underscoring its relevance for monetary policy, risk assessment, and portfolio management, explored (17) the relationship between macroeconomic uncertainty, inflation, and output, noting a shift in the correlation patterns from the late 1990s. This study also delved into the behaviors of commodities futures and stock market indices in terms of price volatility and hedging.

Compared weekly hedging strategies using asymmetric dynamic conditional correlation models (18), finding range-based models superior for hedging purposes. In India examined return and volatility spillovers in base metals from 2011 to 2020 (19), identifying key transmitters and beneficiaries of these spillovers, (20) analyzed return volatility and correlation spillovers in the Bloomberg commodity index from 2000 to 2018, highlighting the impact of metals and energy markets on information processing.

Investigated the transmission of price volatility in agricultural commodities and the effectiveness of self-sufficiency measures in mitigating volatility pass-throughs, used VAR models to examine the influence of stock market indices on exchange rates and oil prices, noting changes in these relationships before and after financial downturns (21).

Research on Indian sovereign bond yield volatility (22) challenged assumptions about oil prices and currency dynamics, showing the influence of fiscal and pandemic response policies on volatility, (23) focused on Thai crude palm oil pricing, documenting its growth and volatility spillovers, and its interconnection with Malaysian crude palm oil prices, (24) analyzed the influence of market activity on return volatility in the Malaysian Crude Palm Oil Futures market. Used a copula-based ARMA-GARCH model to study the relationship between crude oil and palm oil prices, finding a small but positive correlation (25).

Examined the link between price and volume of CPO futures trading, observing changes in correlations during different market conditions (26). Overall, this body of research offers significant insights into market risk management, volatility spillovers, and financial contagion. The findings indicate that financial contagion from the subprime mortgage crisis notably affected emerging markets. Changes over time in the relationship between macroeconomic uncertainty, inflation, and output were observed. For hedging purposes, range-based DCC models were shown to be more effective. The research identified key transmitters and recipients of disturbances in base metal markets. In the realm of commodity indices, sparse DCC-GARCH models were highlighted, with metals and energy markets having a greater influence. The potential impact of a grain autarky regime on agricultural commodities was examined. Malaysian and Thai palm oil prices were found to be interconnected. Market activity in the Malaysian Crude Palm Oil Futures market influenced return volatility. The relationship between crude oil and palm oil prices was found to be weakly positive. The CPO futures market study revealed evolving correlations over time. These findings provide valuable insights for policymakers, investors, and risk management professionals. This study contributes to the literature on DCC-GARCH by applying it to CPO spot and future prices in India, thereby enhancing understanding of dynamic correlations in this specific market. Insights gained provide valuable contributions to risk management, pricing strategies, and market efficiency analysis, filling a notable gap in existing literature.

Methodology

Data Description and Descriptive Statistics**.** Crude Palm Oil (CPO) spot and future price has been collected from Apr 1st 2018 to Mar 31st 2022 from the Multi Commodity Exchange Index.

Table 1: Descriptive Statistics for CPO Spot and Future Price.

	CPO_SPOT	CPO_ FUTURE
Mean	0.000797	0.000843
Median	0.000312	0.000549
Max	0.088417	0.041847
Mini	-0.104680	-0.085778
Std. Dev.	0.010843	0.013186
Skewness	-0.709557	-0.776729
Kurtosis	17.52822	7.090892
Jarque-Bera	8896.212	799.4552
Probability	0.000000	0.000000

The following information is a summary of two variables, as displayed in Table 1. CPO_SPOT and CPO_FUTURE. These statistics provide insights into the composition and properties of the variables. The mean represents the data's average value, and for CPO_FUTURE it is 0.000843, while for CPO_SPOT it is 0.000797. The median is the middle value of the data when arranged in ascending order and is less affected by extreme values than the mean. The median for CPO_SPOT is 0.000312, while for CPO_FUTURE it is 0.000549.
Maximum in a dataset, the maximum value is the highest value that has been recorded. The maximum value for CPO_SPOT is 0.088417, and for CPO_ FUTURE it is 0.041847. The lowest value recorded in the dataset is the minimal value. The minimal value for CPO_SPOT is -0.104680, and for CPO_ FUTURE it is -0.085778. The standard deviation gauges how evenly distributed or variable the data is. It gives an indication of how far apart the values are from the mean. The standard deviation is 0.010843 for CPO_SPOT and 0.013186 for CPO_ FUTURE
Skewness is a measure of the distribution's asymmetry. The data is left-skewing when the skewness is negative. The skewness for CPO_SPOT is -0.709557, while that for CPO_ FUTURE is -0.776729. Kurtosis: Kurtosis assesses the distribution's peak or flatness. A heavy-tailed distribution with more extreme values is indicated by a high positive kurtosis. Kurtosis values for CPO_SPOT and CPO_ FUTURE are 7.090892 and 17.52822, respectively. A test for normalcy called Jarque-Bera. Greater values signify a deviation from the normal distribution. The Jarque-Bera value is 8896.212 for CPO_SPOT and 799.4552 for CPO_ FUTURE. Probability likelihood that the Jarque-Bera test will be positive. Probabilities that are nearly 0 indicate that the data substantially deviates from a normal distribution. Both CPO_SPOT and CPO_ FUTURE have extremely low odds in this situation—nearly nil.
The central tendency, dispersion, skewness, and kurtosis of the CPO_SPOT and CPO_ FUTURE variables can all be learned from these statistics, which, in turn, reveal important information and same represented in Figure 1. Further proof that the data is not likely normally distributed comes from the low probability values in the Jarque-Bera test. To fully comprehend the underlying patterns and traits of these variables, more investigation and modelling may be necessary.

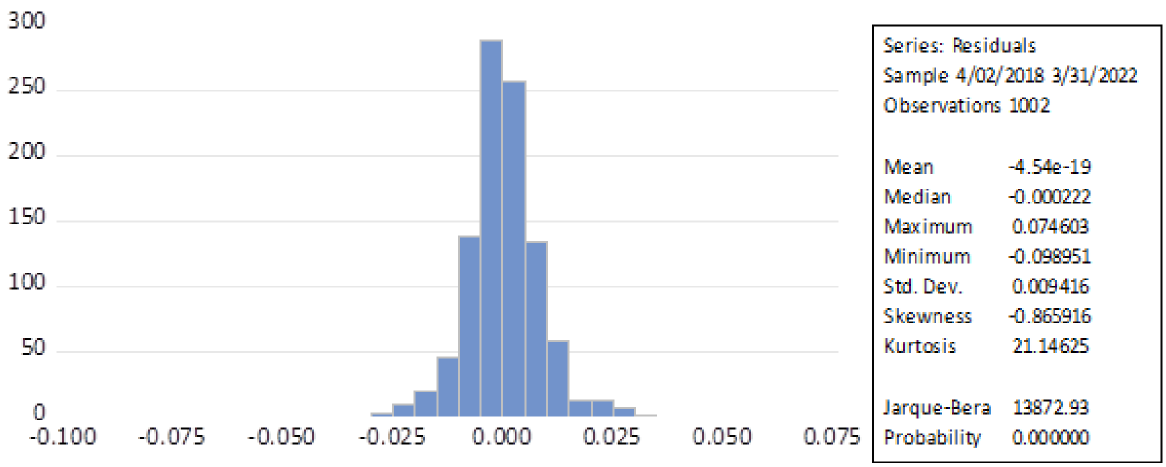

Figure 1: Histogram Normality Test

Stationarity test

The Augmented Dickey-Fuller (ADF) test is a commonly used technique to determine whether a time series is stationary or not. With the help of the ADF test, one can confidently verify the stationarity of the time series (27). The null hypothesis of the ADF test assumes that the time series has a unit root, which indicates non-stationarity, while the alternative hypothesis suggests that the series is stationary.
The ADF test statistic's formula is as follows:
$\Delta Yt=\alpha+\beta t+\gamma Yt-1+\delta 1\Delta Yt-1+\delta 2\Delta Yt-2+\ldots+\delta p\Delta Yt-p+\varepsilon t$
[1]
Where ΔYt is the first difference of the series at time t. α is a constant term (intercept). βt is a trend term.

γY_{t-1} is the lagged level of the series. $\delta_1, \delta_2, ..., \delta_p$ are the coefficients for the lagged differences of the series. ε_t is the error term. p is the number of lagged differences included in the test.

The null hypothesis of non-stationarity is then tested by comparing the ADF test statistic to crucial values at various levels of significance. The time series is non-stationary if the ADF test statistic is less negative than the crucial value and we are unable to reject the null hypothesis.

We reject the null hypothesis and infer that the time series is stationary if, on the other hand, the ADF test statistic is more negative than the critical value. Before analysing time series data, it is crucial to run unit root tests like the ADF test because many time series analysis techniques depend on stationary data to deliver accurate conclusions.

To determine if a time series is stationary or non-stationary, the ADF test is used. This involves comparing the ADF test statistic to critical values at different levels of significance (28). If the ADF test statistic is less negative than the critical value, we cannot reject the null hypothesis of non-stationarity. On the other hand, before analyzing time series data, it is essential to conduct unit root tests such as the ADF test. This is because many analysis techniques rely on stationary data to produce accurate results. If the ADF test statistic is more negative than the critical value, we reject the null hypothesis (29) and conclude that the time series is stationary.

Table 2: Statistical data table (ADF) for unit-root tests

"With Constant" (α)		
	CPO Spot	**CPO Future**
"t-Statistic"	-11.0320	-8.7715
"Prob. value"	0.0000***	0.0000***

The null hypothesis states that the variable has a unit root.

At Ist Difference Level

The ADF test is a reliable method for detecting non-stationarity in time series data by examining the presence of a unit root. In both CPO Spot and CPO Future scenarios, the t-Statistics demonstrate a strong negative trend, providing compelling evidence against the null hypothesis of non-stationarity. The corresponding p-values, marked with "***", indicate statistical significance at typical levels (e.g. 0.05), with values approaching zero. As a result, shown in (Table 2), for both CPO Spot and CPO Future, we reject the null hypothesis of non-stationarity based on the findings of the ADF test. As a result, the time series data for both variables are inferred to be stationary, making them appropriate for additional time series analysis and modelling that call for stationarity assumptions.

Table 3. Correlation Analysis

	Correlation	
	SPOT_PRICE	**FUTURES_PRICE**
SPOT_PRICE_RS__	1.000000	-----
FUTURES_PRICE	0.998245	1.000000
Probability	0.0000	-----

The correlation (Table 3) demonstrates that the spot price and futures price have a very strong positive association. The fact that the spot price and futures price move practically in lockstep suggests that they are closely related and that changes in one can be used to accurately forecast changes in the other. This link is not likely to be a random event given the high correlation and low chance. It is crucial to remember that while correlation demonstrates a connection between two variables, it does not imply causality. To establish any causal relationships between the spot price and futures price, additional research and consideration of other factors are required.

Result and Discussion

The GARCH model is used to capture time-varying volatility in financial markets (30). Its equation can be represented as GARCH (1,1).

$$\sigma t^2 = \omega + \alpha * \varepsilon^2(t-1) + \beta * \sigma^2(t-1) \quad [2]$$

where σt^2 represents the conditional variance or volatility at time t.

ω is the constant term or intercept.

α is the coefficient associated with the lagged squared residual ($\varepsilon^2(t-1)$), which captures the impact of past volatility on current volatility.

β is the coefficient associated with the lagged conditional variance ($\sigma^2(t-1)$), which represents the persistence of volatility over time.

$\varepsilon(t-1)$ represents the standardized residual at time t-1.

The GARCH (1,1) model assumes that the conditional variance at time t is a function of the constant term (ω), the squared residual at the previous time step ($\varepsilon^2(t-1)$), and the conditional variance at the previous time step ($\sigma^2(t-1)$). The model captures the autoregressive nature of volatility by incorporating the lagged values of squared residuals and conditional variances. By estimating the coefficients (α and β) through the use of econometric techniques such as maximum likelihood estimation, the GARCH model provides insights into the volatility dynamics of the CPO commodity market in India.

The DCC-GARCH (Dynamic Conditional Correlation-GARCH) model consists of two main equations: the conditional variance equation and the conditional correlation equation.

Conditional Variance Equation:

The conditional variance equation of the DCC-GARCH model represents the time-varying volatility or fluctuations of the CPO commodity market. It is typically formulated as follows:

$$\sigma t^2 = \omega + \sum(\alpha i * \varepsilon^2(t-i)) + \sum(\beta i * \sigma^2(t-i)) \quad [3]$$

where σt^2 represents the conditional variance or volatility at time t.

ω is the constant term or intercept.

αi and βi are the coefficients associated with the past squared residuals ($\varepsilon^2(t-i)$) and past conditional variances ($\sigma^2(t-i)$), respectively.

$\varepsilon(t-i)$ represents the standardized residual at time t-i.

Conditional Correlation Equation:

The conditional correlation equation of the DCC-GARCH model captures the time-varying correlation between different assets or markets. For the Indian CPO commodity market, it can be expressed as:

$$\rho t = \omega + \sum(\gamma i * \eta(t-i)) + \sum(\delta i * \rho(t-i)) \quad [4]$$

where ρt represents the conditional correlation at time t.

ω is the constant term or intercept.

γi and δi are the coefficients associated with the past standardized residuals ($\eta(t-i)$) and past conditional correlations ($\rho(t-i)$), respectively.

$\eta(t-i)$ represents the standardized residuals at time t-i.

Note: The DCC-GARCH model combines the conditional variance equation and the conditional correlation equation to estimate the time-varying volatility and correlation simultaneously (31). The model iteratively updates these values based on the past information to generate predictive insights (32). The exact specifications of the DCC-GARCH model, including the lag order and distribution assumptions, may vary depending on the specific implementation and research requirements (33).

$$S,t^2 = \omega S + \sum(\alpha S,i * \varepsilon S,t-i^2) + \sum(\beta S,j * \sigma S,t-j^2) + \sum(\gamma S,k * \varepsilon F,t-k^2) + \sum(\delta S,l * \sigma F,t-l^2) \quad [5]$$

Where $\sigma S,t^2$ represents the conditional variance of the spot CPO price (S) at time t.

ωS is the constant term or intercept for the conditional variance of the spot price.

$\alpha S,i$, $\beta S,j$, $\gamma S,k$, and $\delta S,l$ are the coefficients associated with the squared standardized residuals ($\varepsilon S,t-i^2$, $\varepsilon F,t-k^2$) and past conditional variances ($\sigma S,t-j^2$, $\sigma F,t-l^2$) for the spot and futures prices, respectively.

$\varepsilon S,t-i$ represents the standardized residual of the spot price at time t-i.

$\varepsilon F,t-k$ represents the standardized residual of the futures price at time t-k.

$\sigma S,t-j$ represents the conditional variance of the spot price at time t-j.

$\sigma F,t-l$ represents the conditional variance of the futures price at time t-l.

This combined equation captures the dynamics of the spot CPO price (S) by considering the influence of its own past squared residuals and conditional variances, as well as the impact of the squared residuals and conditional variances of the futures CPO price (F). The DCC-GARCH model estimates the coefficients (αS, βS, γS, δS) to provide insights into the time-varying volatility and correlation between the spot and futures prices of CPO.

Table 4: Optimal Parameters for DCC-GARCH (1,1)

	Estimate	Std. Error	t value	Pr(>|t|)
[rspot].mu	0.000579	0.000653	0.88562	0.375823
[rspot].ar1	0.617928	0.251011	2.46175	0.013826
[rspot].ma1	-0.386636	0.306315	-1.26222	0.206870
[rspot].omega	0.000010	0.000001	9.79256	0.000000
[rspot].alpha1	0.173789	0.061913	2.80699	0.005001
[rspot].beta1	0.763506	0.050214	15.20515	0.000000
[rfuture].mu	0.000674	0.000570	1.18271	0.236923
[rfuture].ar1	0.928763	0.048184	19.27542	0.000000
[rfuture].ma1	-0.880835	0.060704	-14.51039	0.000000
[rfuture].omega	0.000001	0.000003	0.52283	0.601093
[rfuture].alpha1	0.039391	0.020794	1.89439	0.058173
[rfuture].beta1	0.953197	0.022692	42.00657	0.000000
[Joint]dcca1	0.010513	0.004467	2.35365	0.018590
[Joint]dccb1	0.989018	0.003913	252.76355	0.000000

The "rspot" variable has a positive AR(1) coefficient, indicating a strong correlation between its current and previous values, and a negative MA(1) coefficient, indicating a past error's negative impact on its current value.

The GARCH model estimates the alpha1 and beta1 coefficients for the "rspot" volatility, with beta1 showing a persistent tendency to cluster over time shown in (Table 4). The "rfuture" variable has a positive AR(1) coefficient and a negative MA(1) coefficient similar to "rspot." The "Joint" model's DCCA1 and DCCB1 coefficients reveal a moderate long-range dependence between the two-time series.

This study showcases in (Figure 2) the dynamics conditional returns of CPO spot and futures. The graphs show the time on the x-axis, representing years, as indicated by 2018 through 2022. The y-axis shows the values of the DCC Conditional Mean, look for spikes or unusual movements that align with major events related to the pandemic or the war. For instance, a spike in early 2020 might coincide with the onset of COVID-19. Examine how the expected future returns ('rfuture') behave before, during, and after these key events. This could provide insights into market sentiment and expectations. Consider how the two lines might be related.

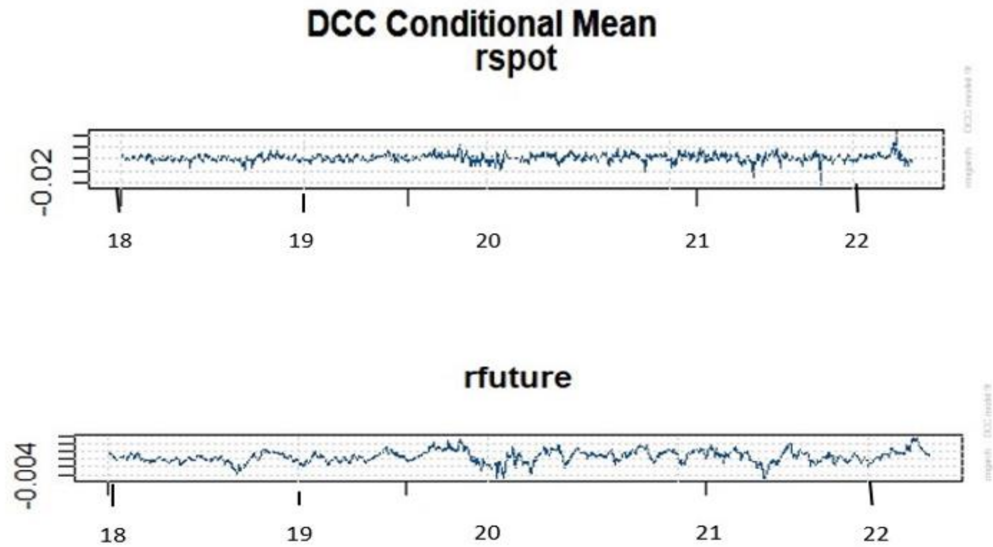

Figure 2: DCC Conditional mean rspot and rfuture

For example, if 'rspot' represents immediate impacts and 'rfuture' represents expectations, one might see a divergence between the two during periods of uncertainty.

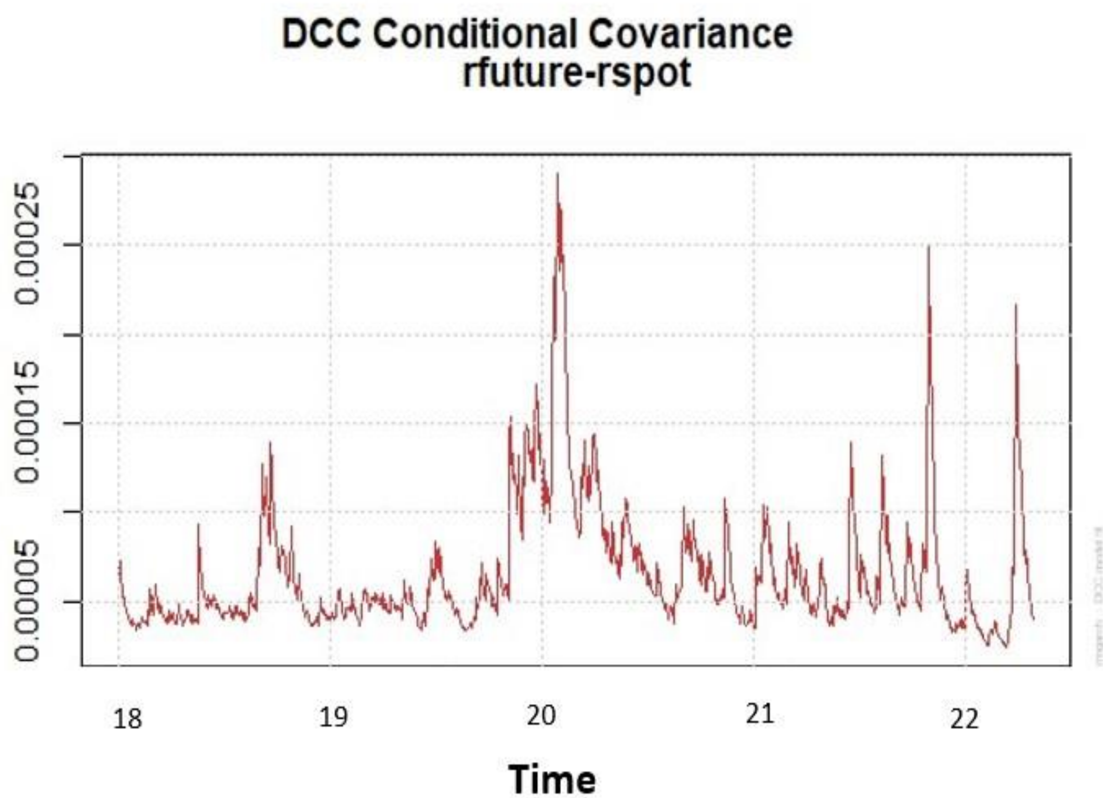

Figure 3: DCC Conditional Covariance rfuture- rspot

Given that the graph (Figure 3) represents the Dynamic Conditional Correlation (DCC) Conditional Covariance of Crude Palm Oil (CPO) prices ('rfuture-rspot'), we can draw some conclusions about the volatility and relationship between spot and future prices of CPO between 2019 and 2021.

- Spikes in Covariance: Sharp increases in covariance, as seen in the graph, suggest periods when the spot and future prices of CPO moved together more strongly than usual. This could be due to market events or news that significantly affect the CPO market.
- Relation to COVID-19: The onset of COVID-19 in early 2020 led to massive disruptions in global supply chains and commodity markets. A spike in covariance during this period might indicate that spot and future prices became more closely linked, possibly due to heightened uncertainty in the market.
- Impact of the Ukraine-Russia War: The escalation of the Ukraine-Russia conflict in 2022 could also have had a substantial impact on global commodity markets, including CPO. The war may have led to concerns about global food supplies, impacting both the spot and future prices similarly and leading to the spikes observed in the graph.
- Market Dynamics: A high covariance between spot and future prices can indicate that the market's expectations (future prices) are closely following the actual market developments (spot prices). This is often the case in markets that are experiencing significant uncertainty or are highly reactive to new information.

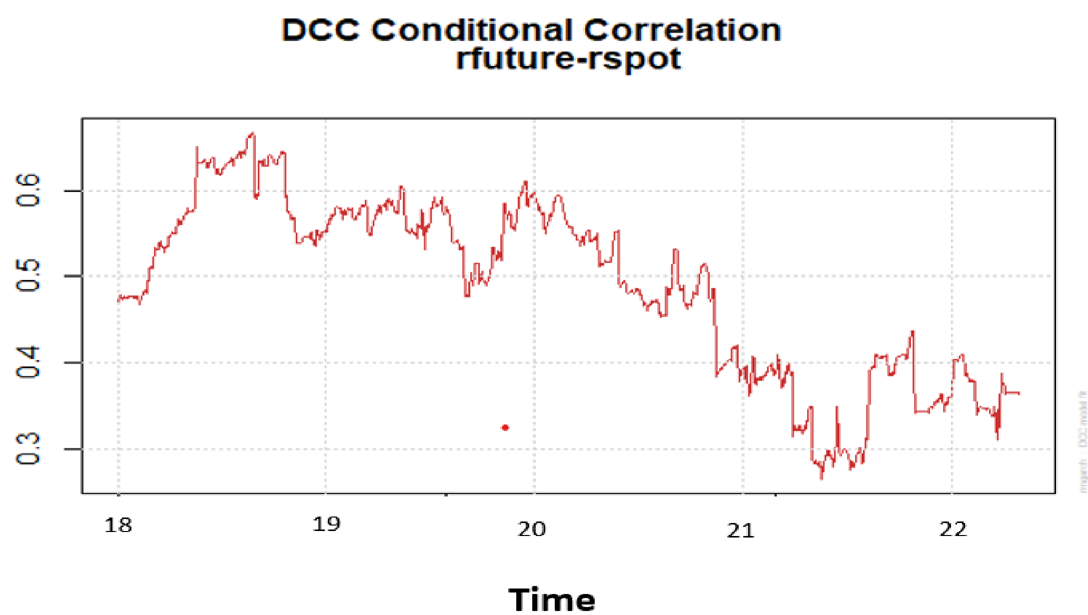

Figure 4: DCC Conditional Correlation rfuture-rspot

The graph (Figure 4) visually displays the average connection between the CPO spot and expected returns.

- Dynamic Correlation Trend: The plot shows the correlation between the future and spot prices of CPO varying over time. It appears that the correlation starts relatively high near 0.6 in 2018, indicating a strong positive relationship between future and spot prices at that time.
- Decreasing Correlation: Over time, the correlation seems to decrease, particularly noticeable after the year 2020, reaching levels as low as 0.3 in later years. A decreasing correlation suggests that the movements in spot and future prices of CPO are becoming less aligned, which might indicate diverging market forces or perceptions affecting spot and future markets differently.

- Impact of External Events: The periods of fluctuation in correlation may correspond to external events. For example, the initial drop around 2020 could potentially be attributed to market disruptions caused by COVID-19, where the future market may have been uncertain about the long-term impact on CPO demand and supply.
- Ukraine-Russia War Influence: The ongoing Ukraine-Russia conflict starting in 2022 may have further influenced the correlation. The conflict has significant implications for global commodity markets, potentially leading to increased volatility and causing future prices to diverge from spot prices due to heightened uncertainty.
- Market Sentiment and Expectations: The correlation reflects how closely future prices of CPO are following the spot prices. A high correlation suggests that market sentiment and expectations are in close alignment with current prices, whereas a lower correlation suggests differing views or uncertainty about future market conditions relative to the present.

This graphical representation of correlation is valuable for market analysts and traders as it illustrates the changing relationship between present and future expectations in the CPO market. It can inform decisions regarding hedging, speculation, and the general assessment of market risk and sentiment over time. Interpreting Dynamic Conditional Correlation (DCC) evaluation results involves understanding how correlation between assets changes over time. High DCC values indicate strong correlation, while low values suggest weak correlation. Fluctuations in riding fees, influenced by factors like supply-demand dynamics, weather conditions, and geopolitical events, impact market participants by affecting pricing strategies, risk management, and investment decisions.

Conclusion

The Indian Crude Palm Oil (CPO) commodity market is a major economic force in the country, driving both the agricultural and finance industries. CPO is a vital component of the edible oil business and is strategically significant on both domestic and international markets. Given its importance, understanding the fluctuating nature of CPO pricing and volatility is essential for market participants, decision-makers, and investors looking to make wise choices and successfully manage risk. With advancements in financial modelling, researchers can now analyze time series data with sophisticated approaches to gain a comprehensive understanding of commodity market behavior. One such approach is the combination of Dynamic Conditional Correlation (DCC) model and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. This DCC-GARCH model allows for the examination of temporal correlations among multiple variables, including spot and future prices, providing insights into volatility patterns.

The purpose of this study is to use the DCC-GARCH model's ability to predict the future to get insightful knowledge about the Indian CPO commodity market. By estimating the DCC-GARCH model and analysing the results, we may analyse volatility patterns, find potential correlations, and better understand the linkages between spot and future prices. The DCC-GARCH model was successfully applied in our study to provide predictive insights into the Indian CPO commodities market. We have learned a great deal about the volatility and behaviour of CPO prices from the thorough investigation of the model outputs.

The computed AR(1) coefficients for "rspot" and "rfuture" have shown that current prices and their corresponding history values are strongly correlated. Market participants can use this result as vital information to forecast price patterns and make more educated decisions. The effect of past error terms on the current rates has also been revealed by the negative MA(1) coefficients for both "rspot" and "rfuture."

This information can be used to better understand the corrective actions performed to bring rates into line with predicted values in reaction to unanticipated variances. The persistence of volatility clustering across time has been brought to light through the analysis of volatility patterns using the GARCH model. Positive alpha1 coefficients demonstrate the impact of squared error terms on the present volatility, whereas a high beta1 value indicates a large influence of historical volatility on the present volatility. Insights from DCC evaluation in the Indian CPO market can inform decision-making by identifying periods of high and low correlation between spot and future prices. This aids in timing investment decisions and implementing hedging strategies effectively. Hazard control strategies benefit from understanding the joint behavior of prices, allowing for better risk mitigation. Additionally, policymakers can use these insights to design appropriate coverage interventions to stabilize the market and support stakeholders during volatile periods.

The DCCA1 coefficient for the "Joint" model also revealed a moderate long-range correlation between the two-time series, suggesting a significant association between the variables being investigated and found there is a dynamic relationship between spot and future prices of CPO. Initially, both market segments moved closely together, as indicated by higher correlation values. Over time, this relationship has become more variable, with the correlation decreasing, suggesting a divergence in the factors influencing spot and future prices. Significant external events such as the COVID-19 pandemic and the Ukraine-Russia war seem to have impacted the CPO market. This is evident from the increased volatility in covariance and the changing correlation patterns during the corresponding periods.

The variation in correlation and covariance over time implies that risk management strategies in the CPO market need to be dynamic. Entities relying on CPO prices must continuously adjust their hedging strategies to account for the changing relationship between spot and future prices. Future studies could explore the CPO market dynamics in comparison to other related commodities which could provide valuable insights into broader economic trends or sector-specific developments. Additionally, it could investigate how macroeconomic indicators or government policies impact the dynamic correlations between CPO spot and future prices in the Indian market.

Abbreviation

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Reference

1. Galanis A, Manouvelos V. The role of Commodity Exchange Markets in the Global Economy. In: Proceedings of the International Conference On Business and Economics Of The Hellenic Open University; 2020 Mar;
2. Inoue T, Hamori S. Market efficiency of commodity futures in India. Appl Econ Lett. 2014;21(8):522-7.
3. Jhunjhunwala S, Suresh S. Commodity and stock market interlinkages: Opportunities and challenges for investors in Indian market. Glob Bus Rev. 2020. doi:0972150920946413.
4. Yanita M, Suandi S. Determinant export volume of crude palm oil (CPO) in Indonesia and Malaysia in the European Union market. Agric Socio-Econ J. 2023;23(1):19-24.
5. Isa MAM, Baharim AT, Mohamed S, Noh MKA, Nasrul F, Ibrahim WMFW, Hassan SS. A study on Malaysian crude palm oil price volatility. Mod Perspect Econ Bus Manag. 2021;6:114-23.
6. Sreenu N, Rao KSS. The macroeconomic variables impact on commodity futures volatility: A study on Indian markets. Cogent Bus Manag. 2021;8(1):1939929.
7. Chodchuangnirun B, Yamaka W, Khiewngamdee C. A regime switching for dynamic conditional correlation and GARCH: application to agricultural commodity prices and market risks. In: Proceedings of the 6th International Symposium on Integrated Uncertainty in Knowledge Modelling and Decision Making, IUKM 2018; 2018 Mar 15-17; Hanoi, Vietnam. Springer; 2018. p. 289-301.
8. Heckman JJ, Pinto R. The econometric model for causal policy analysis. Annu Rev Econ. 2022;14:893-923.
9. Herzog B. Dynamic expectation theory: insights for market participants. J Risk Financial Manag. 2019;12(2):77.
10. Tan X, Wang X, Ma S, Wang Z, Zhao Y, Xiang L. COVID-19 Shock and the Time-Varying Volatility Spillovers Among the Energy and Precious Metals Markets: Evidence From A DCC-GARCH-CONNECTEDNESS Approach. Front Public Health. 2022;10:906969.

11. Reschenhofer E. Unexpected features of financial time series: Higher-order anomalies and predictability. J Data Sci. 2004;2(1):1-15.
12. Ghareeb A. Time Series Forecasting of Stock Price for Maritime Shipping Company in COVID-19 Period Using Multi-Step Long Short-Term Memory (LSTM) Networks. In: Proceedings of the International Conference on Business Excellence. 2023;17(1):1728-47.
13. Ghosh I, Sanyal MK, Jana RK. Co-movement and dynamic correlation of financial and energy markets: An integrated framework of nonlinear dynamics, wavelet analysis and DCC-GARCH. Comput Econ. 2021;57:503-27.
14. Swamy P, Padma K. An empirical examination of correlation dynamics between commodity and equity derivative indices: evidence from India using DCC-GARCH models. Afro-Asian J Finance Accounting. 2020;10(2):207-34.
15. Gabauer D. Volatility impulse response analysis for DCC-GARCH models: The role of volatility transmission mechanisms. J Forecast. 2020;39(5):788-96.
16. Celik S. The more contagion effect on emerging markets: The evidence of DCC-GARCH model. Econ Model. 2012;29(5):1946-59.
17. Jones PM, Olson E. The time-varying correlation between uncertainty, output, and inflation: Evidence from a DCC-GARCH model. Econ Lett. 2013;118(1):33-7.
18. Alshammari S, Obeid H. Analyzing Commodity Futures and Stock Market Indices: Hedging Strategies using Asymmetric Dynamic Conditional Correlation Models. Finance Res Lett. 2023;(104081).
19. Mishra AK, Ghate K. Dynamic connectedness in non-ferrous commodity markets: Evidence from India using TVP-VAR and DCC-GARCH approaches. Resources Policy. 2022;76:102572.
20. Dhaene G, Sercu P, Wu J. Volatility spillovers: A sparse multivariate GARCH approach with an application to commodity markets. J Futures Mark. 2022;42(5):868-87.
21. Tabash MI, Asad M, Khan AA, Sheikh UA, Babar Z. Role of 2008 financial contagion in effecting the mediating role of stock market indices between the exchange rates and oil prices: Application of the unrestricted VAR. Cogent Econ Finance. 2022;10(1). Available from: https://doi.org/10.1080/23322039.2022.2139884.
22. BM L, Chakraborty S, Iyer V, MN N, Ledwani S. Modelling asymmetric sovereign bond yield volatility with univariate GARCH models: Evidence from India. Cogent Econ Finance. 2023 Mar 15;11(1). Available from: https://doi.org/10.1080/23322039.2023.2189589.
23. Songsiengchai P, Sidique SF, Djama M, Hook LS. Volatility spillovers in the Thai palm oil market. Adv Sci Lett. 2018;24(1):543-6.
24. Yeap XW, Lean HH. Trading activities and the volatility of return on Malaysian crude palm oil futures. J Risk Financial Manag. 2022;15(1):34.
25. Kiatmanaroch T, Puarattanaarunkorn O, Autchariyapanitkul K, Sriboonchitta S. Volatility linkages between price returns of crude oil and crude palm oil in the ASEAN region: a copula based GARCH approach. In: Proceedings of the 4th International Symposium on Integrated Uncertainty in Knowledge Modelling and Decision Making, IUKM 2015; 2015 Oct 15-17; Nha Trang, Vietnam. Springer; 2015. p. 428-39.
26. Go YH, Lau WY. The impact of global financial crisis on informational efficiency: Evidence from price-volume relation in crude palm oil futures market. J Commodity Mark. 2020;17:100081.
27. Li J. Comparing Different Permutation Tests with Dickey-Fuller Tests for Unit Root in the Autoregressive Time Series. J Stat Econometric Methods. 2022;11(2):1-11.
28. Worden K, Iakovidis I, Cross EJ. New results for the ADF statistic in nonstationary signal analysis with a view towards structural health monitoring. Mech Syst Signal Process. 2021;146:106979.
29. Zhang S. A test for second-order stationarity of a time series based on the maximum of Anderson–Darling statistics. J Stat Plan Inference. 2021;215:109-26.
30. Mușetescu RC, Grigore GE, Nicolae S. The Use of GARCH Autoregressive Models in Estimating and Forecasting the Crude Oil Volatility. Eur J Interdiscip Stud. 2022;14(1):13-38.
31. Tsiaras K. The Time-Varying Correlation between Crude oil Future and USA Bond Markets During 2005-2020: Evidence from a DCC-GARCH Model. Saudi J Econ Finance. [Year of publication not provided].
32. Idrees SM, Alam MA, Agarwal P, Ansari L. Effective predictive analytics and modeling based on historical data. In: Proceedings of the Third International Conference on Advances in Computing and Data Sciences, ICACDS 2019; 2019 Apr 12-13; Ghaziabad, India. Springer; 2019. Part II, p. 552-64.
33. Nascimento D, Xavier C, Felipe IJD, Neto FL. Dynamic conditional correlation GARCH: a multivariate time series novel using a Bayesian approach. J Mod Appl Stat Methods. 2019;18(1):2-17.