Journal of Agricultural and Resource Economics: Preprint ISSN: 1068-5502 (Print); 2327-8285 (Online)

doi: 10.22004/ag.econ.349180

Assessing the Relationship Between Crude Oil and Commodities Prices: Evidence from Tranquil and Crisis Periods

Theodoros Daglis, Anthony N. Rezitis, Ashok K. Mishra

This study investigates the relationship between crude oil and agricultural prices. Specifically, we examine long-term connections and cause-effect relationships, explore dynamic conditional correlations, scrutinize price bubbles, and suggest optimal portfolio ratios. The study uses data from March 4, 2002, to August 1, 2023, and splitting the sample into sub-periods. Findings reveal limited causal connections among commodities during periods of stability. However, crude oil emerges as a critical driver of causal patterns during crises. Bidirectional connections between crude and soybean oil are frequently influenced by biofuel demand and crises. Crude oil shows the most connections with corn, followed by soybean oil and wheat in the long term. Specific periods, like COVID-19 and the war in Ukraine, emphasize connections due to supply disruptions. The dynamic correlation results confirm a robust correlation between crude and soybean oil. Finally, price bubbles exist for all commodities, with varying duration and intensity.

Key words: Causality; long-run relationship; DCC-GARCH; Hedge portfolio; Russia-Ukraine war

Introduction

The agricultural sector is one of the most critical sectors of the global economy because it provides a basic food supply for humans, a livelihood strategy for millions of people around the world, raw materials for other products and income for families and nations through trade. According to the literature, agricultural and energy markets interact on a consistent basis. More specifically, agricultural production, processing, and transportation functions depend on oil prices (Hernandez et al., 2019). A bi-directional causality exists between the oil and agricultural prices over certain sub-periods (Su et al., 2019). Moreover, the cross-correlation between energy and commodity prices exhibits self-affine properties through fractality, explaining how the price relationship behaves across various time scales and demonstrating complex behavior. More importantly, specific global events, such as the COVID-19 pandemic or the war in Ukraine, strengthen the relationship between energy and commodities markets (Wang et al., 2020), which makes such

---

Theodoros Daglis, (thdaglis@aua.gr) PhD, is Post-dcotoral Fellow, Department of Agricultural Economics and Rural Development, Agricultural University of Athens, Greece. Anthony N. Rezitis, (arezitis@aua.gr) PhD, is Professor, Department of Agricultural Economics and Rural Development, Agricultural University of Athens, Greece. Ashok K. Mishra (corresponding author, ashok.k.mishra@asu.edu) is the Kemper and Ethel Marley Foundation Chair in the Morrison School of Agribusiness, W.P. Carey School of Business at Arizona State University.
We thank anonymous referees and the managing editor for useful comments and edits on an earlier version of the paper. The views expressed here are those of the authors and do not necessarily reflect the views of the authors' institution. The usual disclaimer applies.

Review coordinated by Vardges Hovhannisyan.

analysis even more important. Regarding the self-affine properties and fractal behavior of the cross-correlation of the series, we mainly refer to the hidden patterns that exist in the cross-correlation of the time series that emerge at various levels. The cross-correlation indicates a robust long-run relationship between the energy and commodities price series. Furthermore, several studies demonstrate that the characteristics of the relationship are time-variant (Jiang et al., 2019; Shiferaw, 2019) and depend on various dynamics, some of which may be specific events of great importance (e.g., the COVID-19 pandemic, the war in Ukraine). Finally, some studies argue for the hedging efficiency and optimal portfolio allocation regarding the commodities (Zivkov et al., 2020), which are often affected by external factors (Naeem et al., 2022).

The 2008 global financial crisis caused significant changes in international markets, particularly in energy and agricultural sectors. Financialization emerged, leading to commodity price behaviors resembling financial assets and integrating the energy and commodities markets with financial markets (Zhang, 2018). Investors who seek substantial returns often engage in high-risk trading, which in turn leads to speculation in various commodities and other assets (Wang and Kim, 2022). Energy, especially oil futures, shows increased financialization due to its potential for arbitrage and investor interest amid the 2008 financial crisis (Lammerding et al., 2013). Agricultural commodities experienced a similar trend, unprecedented price highs in 2008, followed by crashes and resurgences due to biofuel production and climate change (Adämmer and Bohl, 2015; Mao et al., 2020). Physical events like droughts and geopolitical issues further impacted prices in energy and agricultural sectors, which fostered speculation (Chemeris et al., 2022; Zhou et al., 2023). Geopolitical events, such as wars and pandemics (such as COVID-19), can also increase speculation and affect the oil and agricultural markets in a financial context. In this regard, it is of utmost significance to investigate the presence of price bubbles during various periods, especially during the COVID-19 pandemic and the war in Ukraine.

Therefore, the current study investigates the relationship between crude oil and agricultural commodity prices. Specifically, the study examines long-term connections and cause-effect relationships, explores dynamic conditional correlations, scrutinizes price bubbles, and suggests optimal portfolio ratios. The study uses data from Yahoo Finance for March 4, 2002, to August 1, 2023, splitting the sample into two sub-periods—calm or tranquil and crisis periods. The study employs several methodologies, including multifractal analysis to examine the presence of a long-run relationship in the prices, a dynamic cross-correlation analysis using a Dynamic Conditional Correlation-Generalized Autoregressive Conditional Heteroscedasticity (DCC-GARCH) model, causality analysis, price bubble detection, and hedging strategies to provide evidence for the time-dependent implications that exist in the oil and agriculture nexus. The use of multiple methods and sub-periods is to capture the complexity and variability of relationships between agricultural commodities and energy markets. The relationships are influenced by economic, geopolitical, and market-specific events such as financial crises, the COVID-19 pandemic, and the war in Ukraine. The above approaches provide a deeper understanding of market dynamics. At the same time, the combination of the methods enhances the robustness of the findings by cross-validating results, providing a comprehensive assessment of the evolution of market interactions. The multi-dimensional approach is beneficial to investors and policymakers by highlighting commodity relationships under various market conditions, contributing to optimal hedging strategies, and understanding market behavior during crisis periods. Thus, this approach identifies factors that play an important role in the oil-agriculture relationship and provides evidence of changes during periods of great importance, including the war in Ukraine, a period of high significance that needs to be adequately explored.

This study makes several valuable contributions to the literature. First, the study employs various techniques from the abovementioned disciplines to unveil the dynamics of the relationship between oil and agriculture and their change over time during periods of historical significance, including cross-correlation, causal, and long-run relationship analysis. Second, the study adds to the literature by examining the role of speculation and the influence of speculation in energy and commodities markets. Third, it provides evidence for optimal portfolio strategies and the risk associated with the commodities under scrutiny. It explores changes in the optimal portfolio strategy and risk profiles during different periods, such as calm periods, crises, pandemics, and war.

The findings of this study show persistent long-term relationships between crude oil and agricultural commodities, particularly during the COVID-19 period and the war in Ukraine. Soybean oil demonstrates the strongest correlation with crude oil, followed by corn and wheat, with peaks during crises, suggesting that shocks amplify interconnections between energy and agricultural markets. Likewise, causal relationships between crude oil and agricultural commodities intensify during crises, with crude oil emerging as a primary driver. Hence, the nature of each crisis influences the causal patterns differently, especially in the dynamic between soybean oil and crude oil during the war in Ukraine. Additionally, all commodities exhibit price bubbles at different intensities across crises, with the war in Ukraine having inflated bubbles for soybean oil and wheat, highlighting the role of external factors in influencing price dynamics. Finally, based on the hedging strategies, the results show varying optimal hedge ratios and portfolio weights for crude oil and agricultural commodities. The findings suggest that optimal hedging strategies should adapt to external market conditions.

Literature Review

Numerous studies highlight a lasting connection between oil and agricultural commodities, influenced by crises and geopolitical instability. To begin with, Tiwari et al. (2021) note strong correlations between energy and agricultural markets, affected negatively by geopolitical risks, while Nazlioglu et al. (2013) observed no risk transmission before crises but saw it after. Similarly, Kumar et al. (2021) found that oil crashes coincide with agricultural market drops, with significant risk spillovers during crises. Tiwari et al. (2018) emphasize a long-term relationship affected by crises and geopolitics. Post-2006, this link strengthened, showing different trends before and after that year (Yahya et al., 2019), and COVID-19 notably impacted this relationship, making it more persistent (Wang et al., 2020). Moreover, numerous studies demonstrate a positive correlation between agricultural futures and crude oil, yet outcomes vary under different conditions (Liu et al., 2019). Specifically, Serletis and Xu (2019) highlight a robust link between oil and biofuel feedstock markets, particularly strengthened by ethanol mandates. Pal and Mitra (2019) affirm energy's correlation with the agricultural sector, while Nazlioglu and Soytas (2012) note oil's interconnectedness with various agricultural commodity prices, which are subject to fluctuation due to multiple factors. Literature extensively examines the dynamic correlation between energy and agriculture, employing methods like dynamic correlation analysis (Hou and Li, 2016). Likewise, Mishra and Ghate (2022) use DCC-GARCH to identify interconnectedness among metal commodities, while Yue et al. (2015) examine correlations between Chinese and international nonferrous metal markets. GARCH models have played an important role in analyzing the oil-commodity nexus. For instance, Jiang et al. (2019) investigate the evolving relationship between global oil and Chinese commodities. In contrast, Shiferaw (2019) identifies strong co-movements using a Bayesian framework, and Chen and Qu (2019) detect dynamic correlations between crude oil and various markets. Moreover, Wei et al. (2023) analyze price spillovers across crude oil, agricultural markets, and carbon emissions dynamically, while Yahya et al. (2022) explore dependence between international crude oil, biodiesel, and rapeseed oil markets, noting changes during financial and economic crises using dynamic conditional correlation analysis.

Additionally, multiple studies delve into the causal connections among oil futures, commodities, and financial assets. More precisely, Wang et al. (2022) explore the dynamic relationship between oil prices and China's price index using Granger causality analysis, while Palazzi et al. (2022) note that spikes in heating oil prices correlate with declines in ethanol prices in Brazil. Similarly, Paris (2018) emphasizes how biofuel development amplifies the impact of oil prices on agricultural commodity prices, and Wang et al. (2014) find that the responses of agricultural commodities to oil prices depend on different shocks affecting oil. Similarly, Raza et al. (2022) highlight bidirectional relationships between food and oil prices, primarily influenced by demand and supply shocks. Umar et al. (2017) show increased net return connections between agricultural commodities and oil price shocks during crises. Furthermore, Hernandez et al. (2019) and Jiang et al. (2018) note intricate relationships where oil affects certain precious metals, agricultural commodities, and markets over varying timeframes. Importantly, Su et al. (2019) find bi-directional causality between oil and agricultural prices in specific sub-periods. Hung (2021) observed intensified return spillovers during COVID-19 across different periods, with positive and negative interactions. On the other hand, studies in South Africa (Babajide, 2016) and Turkey (Nazlioglu and Soytas, 2011) report no long-term or causal relationship between oil prices and agricultural commodities.

The detection of price bubbles in energy and agricultural markets holds substantial significance, and the literature presents diverse findings. To begin with, Robles et al. (2009) link speculative activity in agricultural commodity futures to surges and volatility in 2007-2008. Irwin et al. (2009) find limited evidence supporting speculative bubbles causing price fluctuations. Similarly, Gilbert (2010a) emphasizes index investors' impact on food prices and oil, while Gilbert (2010b) detects a soybeans market bubble in 2007-2008, weaker signs in crude oil, and no bubbles in corn and wheat. On the other hand, Sanders and Irwin's investigations (2010, 2011a, 2011b) fail to establish a substantial influence of index funds on commodity futures returns, rejecting the notion that index speculation caused the 2007-08 price surge.

However, recent studies (Mao et al., 2020; Ajmi et al., 2021; Wang and Kim, 2022; Alola, 2022; Oladosu, 2022; Potrykus, 2023) identify bubbles in energy, crude oil, and agricultural commodities, noting transferability among markets and bubble effects in renewable energy equities. Moreover, different approaches explore optimal hedge portfolios, benefiting investors and stakeholders. Specifically, Zivkov et al. (2020) suggest soybeans as a favorable inclusion alongside oil commodities in a portfolio. In a similar framework, Naeem et al. (2022) note crude oil's role as a haven for metals and agricultural commodities before the global financial crisis but not after. In contrast, for the COVID-19 period, stock markets and oil exhibited higher hedging efficiency, indicating oil's potential as a hedge in portfolios. Furthermore, Han et al. (2021) highlight the instability and variability of outcomes in hedging strategies. A review of the literature reveals that the analysis of the oil-agriculture nexus is of great significance to policymakers, investors, and financial markets. However, no study has examined the various aspects of this relationship, investigating various sub-periods, including the war in Ukraine. Our work aims to fill this gap in the literature.

Empirical Methodology

We implement a multi-stage analysis employing many techniques. The study examines the presence of a long-run relationship using a multifractal analysis, followed by a dynamic cross-correlation analysis using a DCC-GARCH model, causality analysis and price bubble detection and hedging strategies.

3.1 Exploring Long-run Relationships

At first, the study examines the long-run relationship between the variables, employing the multifractal detrended cross-correlation analysis (MFDCCA) testing the long-run relationship. The study uses a multifractal method, rather than an econometric one, to derive quantitative and qualitative information regarding the long-run relationships. The multifractal approach, unlike the traditional econometric approach, allows for the detection of long-range dependencies, multifractality, and complex nonlinear interactions in the data, which are often overlooked. Therefore, the use of multifractal analysis provides a richer, better understanding of the market interdependencies that evolve over various periods. Several studies have also employed this approach in financial investigations, among many others, Daglis (2021, 2023). Following Podobnik et al. (2009), He et al. (2016), and He (2017), let x_t and y_t be two-time series and N the number of observations. Then:

$$X(i) = \sum_{k=1}^{i}[x(k) - \bar{x}], i = 1, \dots, N \tag{3.1}$$

and

$$Y(i) = \sum_{k=1}^{i}[y(k) - \bar{y}], i = 1, \dots, N \tag{3.2}$$

$\bar{x}$ and $\bar{y}$ are the mean functions of x and y, respectively.

We divide the profile of the time series $X(i)$ and $Y(i)$ into $N_s = \left[\frac{N}{s}\right]$ non-overlapping windows of equal length, which start from the beginning and also from the end 2 N_s in total, thus, we obtain the detrended covariance for each segment $= 1,2, \dots, N_s$:

$$F^2(s, v) = \frac{1}{s}\sum_{i=1}^{t}|X[(v-1)s + i] - X^v(i)||Y[(v-1)s + i] - Y^v(i)|, \quad v = 1,2, \dots, N_s \tag{3.3}$$

For each segment, $v = N_s + 1, N_s + 2, \dots, 2\ N_s$

$$F^2(s, v) = \frac{1}{s}\sum_{i=1}^{t}|X[N - (v - N_s)s + i] - X^v(i)||Y[N - (v - N_s)s + i] - Y^v(i)|, \quad v = 1,2, \dots, N_s \tag{3.4}$$

where $X^v(i)$ and $Y^v(i)$ are the fitting polynomials with order m in each segment v. Next, we calculate the qth order fluctuation function, squaring and averaging the fluctuations over all segments:

$$F_q(s) = \left\{\frac{1}{2N_s}\sum_{v=1}^{2N_s}[F^2(s, v)]^{\frac{q}{2}}\right\}^{1/q}, q \neq 0 \tag{3.5}$$

$$F_0(s) = exp\left\{\frac{1}{4N_s}\sum_{v=1}^{2N_s} ln[F^2(s, v)]\right\}, q = 0 \tag{3.6}$$

We then capture the power-law relation between the qth order fluctuation $F_q(s)$ and the timescale s:

$$F_q(s) \sim s^{H_{xy}(q)} \tag{3.7}$$

If the generalized cross-correlation exponent $H_{xy}(q)$ depending on q, the cross-correlation of the two series has multifractal properties. If $H_{xy}(q) > 0.5$, the cross-correlation of the two-time series is long-term persistent. If $H_{xy}(q) < 0.5$, the cross-correlation is anti-persistent, and finally, if $H_{xy}(q) = 0.5$, there is no cross-correlation, or the cross-correlation of the two time series is short-term (Wang et al., 2019). The generalized cross-correlation exponent $H_{xy}(q)$ is identical to the Hurst exponent (Wang et al., 2019) in the case of q=2, and we characterize the relationship, as mentioned above. In this work, we examine and characterize the Hurst exponent based on its value.

3.2 Dynamic cross-correlation analysis

Next, we employ the DCC-GARCH model to assess the cross-correlations between agricultural and energy commodities. The DCC-GARCH method is well-suited for analyzing dynamic correlations in volatile markets because it accounts for time-varying correlations and conditional heteroscedasticity. Compared to static models or other correlation models like the constant conditional correlation (CCC) model, DCC-GARCH can track how correlations evolve, capturing the volatility clustering commonly seen in financial and commodity markets. The DC-GARCH is preferred over other methods, such as the BEKK-GARCH, because it balances flexibility, making it suitable for large datasets like the one used in this study. Engle and Sheppard (2001) introduced the dynamic conditional correlation (DCC) generalized autoregressive conditional heteroskedasticity (GARCH) model. Following the notation of Orskaug (2009), the basic idea is that the covariance matrix H_t decomposes into conditional standard deviations, D_t, and a correlation matrix R_t. In the context of a DCC-GARCH model, both D_t and R_t exhibit time-varying properties. Let's now consider a_t the returns on n assets, with expected value 0 and covariance matrix H_t. We may then define the DCC-GARCH model as follows:

(3.8) $$r_t = \mu_t + a_t$$

(3.9) $$a_t = H_t^{1/2} z_t$$

(3.10) $$H_t = D_t R_t D_t$$

where r_t is a nx1 vector of log returns of n assets at time t, a_t is a nx1 vector of mean-corrected returns of n assets at time t, i.e., $E[a_t] = 0$, and $Cov[a_t] = H_t$, μ_t is a nx1 vector of the expected value of the conditional r_t, H_t is a nxn matrix of conditional variances of a_t at time t, and we then obtain $H_t^{1/2}$ through a Cholesky factorization of H_t, D_t, and in this regard, D_t is a nxn diagonal matrix of conditional standard deviations of a_t at time t, R_t a nxn conditional correlation matrix of a_t at time t, z_t a nx1 vector of iid errors such that $E[z_t] = 0$ and $E[z_t z_t^T] = I$.

3.3 Causal investigation

Amornbunchornvej et al. (2021) introduced the concept of Variable-lag (VLT) Granger causality, which, unlike classical causal investigations, does not assume that the causal effect is directed in fixed time delay. Thus, this method can detect causal schemes with variant lag, justifying the reason for its application in financial investigations (Daglis, 2023). To align the cause of a time series X_t to affect time series Y_t, and leverage the power of Granger causality, we employ Dynamic Time Warping (Sakoe and Chiba, 1978). Given the two time series X_t and Y_t, while δ_{max} is the maximum time lag, we can derive the residual $r^*_{Y_t X_t}$ by the following:

(3.11) $$r^*_{Y_t X_t} = Y_t - \sum_{i=1}^{\delta_{max}} \left(a_i Y_{t-i} + b_i X_{t-i} + c_i X_{t-i+1-\Delta_{t-i+1}} \right)$$

where $\Delta_t > 0$ is the time delay constant in the optimal alignment sequence of X_t and Y_t that minimizes the residual of the regression. The coefficients a_i, b_i, c_i optimally minimize the residuals r_{Y_t}, $r_{Y_t X_t}$, and $r^*_{Y_t X_t}$, respectively. In the case that the variance of $r^*_{Y_t X_t}$ is less than the variances of both r_{Y_t} and $r_{Y_t X_t}$ we infer that X_t VL-Granger causes Y_t. Appendix Table A2 provides the estimates of variable-lag causality by commodities and period.

3.4 Price bubble detection

We then investigate for price bubble detection, or explosive bubble behaviors, which are movements in the prices that economic and market fundamentals cannot explain, and we implement two univariate tests (the Sup ADF or SADF by Phillips et al. 2011); the Generalized SADF (GSADF) of Phillips et al. 2015a, b) and a panel test (i.e., the panel GSADF by Pavlidis et al. 2016). Let:

(3.12) $$\Delta p_t = \alpha_{r_1,r_2} + \beta_{r_1,r_2} p_{t-1} + \sum_{j=1}^{k} \psi^j_{r_1,r_2} \Delta p_{t-j} + \epsilon_t, \qquad \epsilon_t \sim N\left(0, \sigma^2_{r_1,r_2}\right)$$

where p_t denotes a time series, Δp_{t-j} with $j=1, \ldots, k$ are lagged first differences of the time series; ϵ_t is the error term; α_{r_1,r_2}, β_{r_1,r_2} and $\psi^j_{r_1,r_2}$ with $j = 1, \ldots, k$ are regression coefficients. The subscripts r_1 and r_2 indicate fractions of the total sample size (of *T* observations) that specify the starting and ending points of a subsample period. We test the null hypothesis of a unit root in y_t, H_0: $\beta_{r_1,r_2} = 0$, against the alternative of mildly explosive behavior, H_1: $\beta_{r_1,r_2} > 0$. The ADF test statistic is:

(3.13) $$ADF_{r_1}^{r_2} = \frac{\widehat{\beta}r_{1},r_{2}}{s.e.(\widehat{\beta}r_{1},r_{2})}$$

The standard ADF test, however, exhibits extremely low power in the case of boom-bust dynamics (Evans, 1991). For this reason, Phillips *et al.* (2011) suggest a recursive procedure that is compatible with a single boom-bust episode that involves the estimation of *ADF* regression in Eq. (3.12) on subsamples of the data. The supremum of this sequence defines the *SADF* statistics as:

(3.13) $$SADF(r_0) = \sup_{r_2 \in [r_0,1]} ADF_0^{r_2}$$

Similarly, the limit distribution of the *SADF* statistic is:

(3.14) $$\sup_{r_2 \in [r_0,1]} \frac{\int_0^{r_2} W dW}{\left(\int_0^{r_2} W^2\right)^{\frac{1}{2}}}$$

When the *SADF* statistic exceeds the right-tailed critical value from its limit distribution, we reject the unit root hypothesis in favor of explosive behavior. Recently, Phillips *et al.* (2015a; 2015b) proposed an extension of the *SADF* test (*GSADF*), which permits both the starting point (r_1) and ending point (r_2) to change and considers a larger number of subsamples than the *SADF* test. In contrast to the *SADF,* the *GSADF* is compatible with multiple boom-bust episodes within a given time series, while the former is compatible only with a single episode. The *GSADF* statistic is as follows:

(3.15) $$GSADF(r_0) = \sup_{r_2 \in [r_0,1], r_1 \in [0, r_2 - r_0]} ADF_{r_1}^{r_2}$$

Following Vasilopoulos *et al.* (2020) and Phillips *et al.* (2015a; 2015b), the *SADF* and *GSADF* procedures can provide a chronology of vitality in the time series in case of null hypothesis rejection. Im *et al.* (2003) and Pavlidis *et al.* (2016) propose an extension of the *GSADF* test procedure to exploit the panel nature of heterogeneous panels and we apply the *SADF* and *GSADF* only in the case of individual time series. The panel counterpart of the *ADF* regression Eq. (3.12) is the following:

(3.16) $$\Delta p_{i,t} = \alpha_{i,r_1,r_2} + \beta_{i,r_1,r_2} p_{i,t-1} + \sum_{j=1}^{k} \psi_{i,r_1,r_2}^{j} \Delta p_{i,t-j} + \epsilon_{i,t}$$

where *i*= 1…, *4* indicates the panel index, while Eq. (3.12) defines the other variables. The null hypothesis of a panel unit root of the panel *GSADF* test is H_0: $\beta_{i,r_1,r_2} = 0$, in all *4* series against the alternative of explosive behavior in a subset of series, H_1: $\beta_{i,r_1,r_2} > 0$ for some *i.* We then construct the panel unit root test through the average of the individual backward SADF (BSADF) statistics at each period:

(3.17) $$\text{panel } BSADF_{r_2}(r_0) = \frac{1}{N} \sum_{i=1}^{N} BSADF_{i,r_2}(r_0)$$

The panel *GSADF* statistic is the supremum of the panel *BSADF,*

(3.18) $$\text{panel } GSADF(r_0) = \sup_{r_2 \in [r_0,1]} \text{panel } BSADF_{r_2}(r_0)$$

Finally, Pavlidis *et al.* (2016) used bootstrap to consider cross-sectional error dependence to compare the panel *BSADF* with the sequence of bootstrap critical values and identified dating episodes of overall exuberance (Pavlidis *et al.*, 2016). Appendix Table A3 provides the results of the bubble detection tests.

3.5 Hedging strategies

Based on Kroner and Sultan (1993), we formulate the most effective hedge ratios based on the conditional volatility approximations captured from the DCC-GARCH model. In the case of a portfolio that includes two commodities, denoted as *i* and *j*. Let a one-dollar positive exposure to commodity *i*, which may be offset by a negative exposure to commodity *j*. We utilize this strategy to minimize the portfolio's risk but keep returns unchanged. The optimal hedge ratio between commodity *i* and commodity *j* is calculated as:

$$\beta_{ij,t} = \frac{h_{ij,t}}{h_{jj,t}} \tag{3.19}$$

where $h_{ij,t}$ is the conditional covariance between commodities *i* and *j* and $h_{jj,t}$ is the conditional variance of commodity *j*. Based on Eq. (3.19), a dynamic hedging strategy consists of a long position of one dollar in commodity *i* and a short position of β dollars in commodity *j*. We establish the optimal portfolio weighting to ascertain the optimal allocation for each commodity within the one-dollar investment portfolio. Based on Kroner and Ng (1998), the optimal portfolio weight for commodity *i* can be expressed as:

$$w_{ij,t} = \frac{h_{jj,t} - h_{ij,t}}{h_{ii,t} - 2h_{ij,t} + h_{jj,t}}, \quad \text{with } w_{ij,t} = \left\{ \begin{array}{ccc} 0, & if & w_{ij,t} < 0 \\ w_{ij,t}, & if & 0 \leq w_{ij,t} \leq 1 \\ 1, & if & w_{ij,t} > 1 \end{array} \right\} \tag{3.20}$$

where $w_{ij,t}$ is the weight of commodity *i* in a dollar portfolio of two commodities (i.e., commodity *i* and commodity *j*) at time *t*, $h_{ij,t}$ is the conditional covariance between commodities *i* and *j* and $h_{jj,t}$ is the conditional variance of commodity *j*, according to the estimation of Eq. (3.19). Note that the weight of the second commodity is 1-$w_{ij,t}$.

Data and Variables

We use data referring to crude oil future prices (CL), KC HRW wheat (KE), corn (ZC), and soybean oil (ZL) in daily frequency between March 04, 2002, and August 01, 2023. We obtained all data from Yahoo Finance. The causal investigation and DCC-GARCH model are in log returns, while the multifractal analysis is in levels. Table 1 presents the descriptive statistics of the variables used in the study and expressed in US dollars.

Table 1 shows that wheat (KE) appears to have the largest variability due to its high standard deviation and range (max-min). Corn (ZC) and crude oil (CL) also exhibit notable variability, whereas soybean oil (ZL) seems to have comparatively lower variability based on its smaller range and standard deviation. In our investigation, we divided the period under consideration (i.e., March 04, 2002, until August 01, 2023) into sub-periods based on essential events to examine the potential relationship between energy and agricultural commodities. The first calm period extends from January 2002 to December 2006, and the period of financial crisis and commodity price increase extends from January 2007 to December 2009. In contrast, the second calm period spans from January 2010 to January 2020. Finally, February 2020 to February 2022 encompasses the COVID-19 pandemic's effects, followed by the war in Ukraine period, March 2022 to August 01, 2023.

Table 1. Descriptive statistics of the time-series data used in the study

	Variable	**CL**	**KE**	**ZC**	**ZL**
Whole Period	Mean	66.985	584.031	426.826	38.482
	Median	64.470	520.500	377.250	33.730
	Standard Deviation	24.261	197.157	160.383	14.190
	Min	10.010	271.250	186.250	15.850
	Max	145.290	1367.750	831.250	90.600
First calm period	Variable	CL	KE	ZC	ZL
	Mean	45.559	379.655	237.898	23.371
	Median	43.250	361.250	230.250	22.670
	Standard Deviation	15.468	62.235	38.282	3.807
	Min	22.500	271.250	186.250	15.850
	Max	77.030	546.000	390.250	34.850
Financial crisis and commodity price increase	Variable	CL	KE	ZC	ZL
	Mean	78.090	680.289	424.763	41.117
	Median	71.970	601.000	390.750	37.180
	Standard Deviation	25.229	189.114	98.088	10.466
	Min	33.870	442.250	293.500	27.700
	Max	145.290	1337.000	754.750	70.400
Second cam period	Variable	CL	KE	ZC	ZL
	Mean	72.680	592.819	464.813	38.792
	Median	71.500	535.625	385.750	34.595
	Standard Deviation	21.811	156.099	140.424	9.582
	Min	26.210	362.000	301.500	26.050
	Max	113.930	988.000	831.250	59.770
COVID-19 pandemic	Variable	CL	KE	ZC	ZL
	Mean	56.123	604.651	487.478	46.575
	Median	58.605	599.625	526.375	46.645
	Standard Deviation	18.878	129.760	124.624	15.081
	Min	10.010	414.000	302.750	24.990
	Max	95.720	963.000	772.750	72.890
War in Ukraine	Variable	CL	KE	ZC	ZL
	Mean	87.122	933.031	673.361	66.572
	Median	81.940	883.250	668.000	66.840
	Standard Deviation	14.360	123.565	67.539	9.700
	Min	66.740	771.250	497.000	46.200
	Max	123.700	1367.750	818.250	90.600

Source: Yahoo Finance

Notes: CL represents crude oil futures prices, KE refers to KC HRW wheat, ZC stands for corn, and ZL represents soybean oil.

Table 2. Hurst Exponent.

Period	Corn & Crude Oil	Soybean Oil & Crude Oil	Wheat & Crude Oil
First calm period	1.3557	1.4065	1.2221
Financial crisis and commodity price increase	1.3617	1.4256	1.4348
Second calm period	1.6026	1.6131	1.515
COVID-19 period	1.8089	1.8717	1.8338
War in Ukraine period	1.6403	1.5503	1.6814
Whole Period	1.18	1.0996	1.0847

The selection of sub-periods is important to understanding the dynamics of the market during different global events, and to do so, we define five sub-periods based on specific economic and geopolitical markers that significantly influenced global markets. Specifically, the rationale for selecting February 2020 as the starting point for the COVID-19 period is derived from early market disruptions in anticipation of the pandemic's global spread, while the study argues for the end of the COVID-19 period in February 2022 to focus on the distinct economic phase before the war in Ukraine, which represents another major case-effect in global markets. The Ukraine war period, starting in March 2022, is known to be followed by geopolitical tensions, supply chain disruptions, and energy price volatility, rendering it an essential milestone for analyzing the subsequent impacts on agricultural commodities and energy markets.

Results And Discussion

5.1 Exploring Long-run Relationships

Table 2 presents the Hurst exponent representing the multifractal detrended cross-correlation analysis for all examined periods. The Hurst exponent is greater than 0.5 in all cases, indicating a positive long-run relationship between the variables.

Multifractal analysis reveals that the most significant long-term relationships occurred during distinct periods: COVID-19, post-Ukraine war, second calm period, financial crisis, first calm period, and overall. These findings stress the importance of scrutinizing sub-periods to understand long-term relationships, fully emphasizing the novelty of our approach. The prevalence of long-term relationships during COVID-19 highlights its profound impact on the global market, particularly on crude oil. The pandemic induced a demand shock, drastically reducing international oil prices (Burghelle et al., 2021), leading to a price collapse with severe market repercussions. This underscores crude oil's pivotal role as a significant global commodity, significantly influencing agriculture (Ezeaku et al., 2020).

Higher Hurst Exponent values indicate more vital persistence in long-term relationships. During the war in Ukraine, wheat and corn exhibited a more robust long-term relationship, attributable to disruptions in Ukraine's export dynamics. The disruptions, impacting supply and trade, prolonged their influence on global market dynamics (Hassen and El Bilali, 2022; Hellegers, 2022), reinforcing their impact on long-term relationships between agricultural commodities and suggesting a strengthening trend in long-term relationships among commodities, aligning with existing literature on financialization (Zhang, 2018). Financialization intensifies linkages, particularly in crude oil, as commodities integrate with financial products like futures, options, and ETFs, fostering higher trading activity and market integration. Globalization and advanced technology accelerate the transmission of market signals, amplifying the impact of changes or shocks in one commodity market on others.

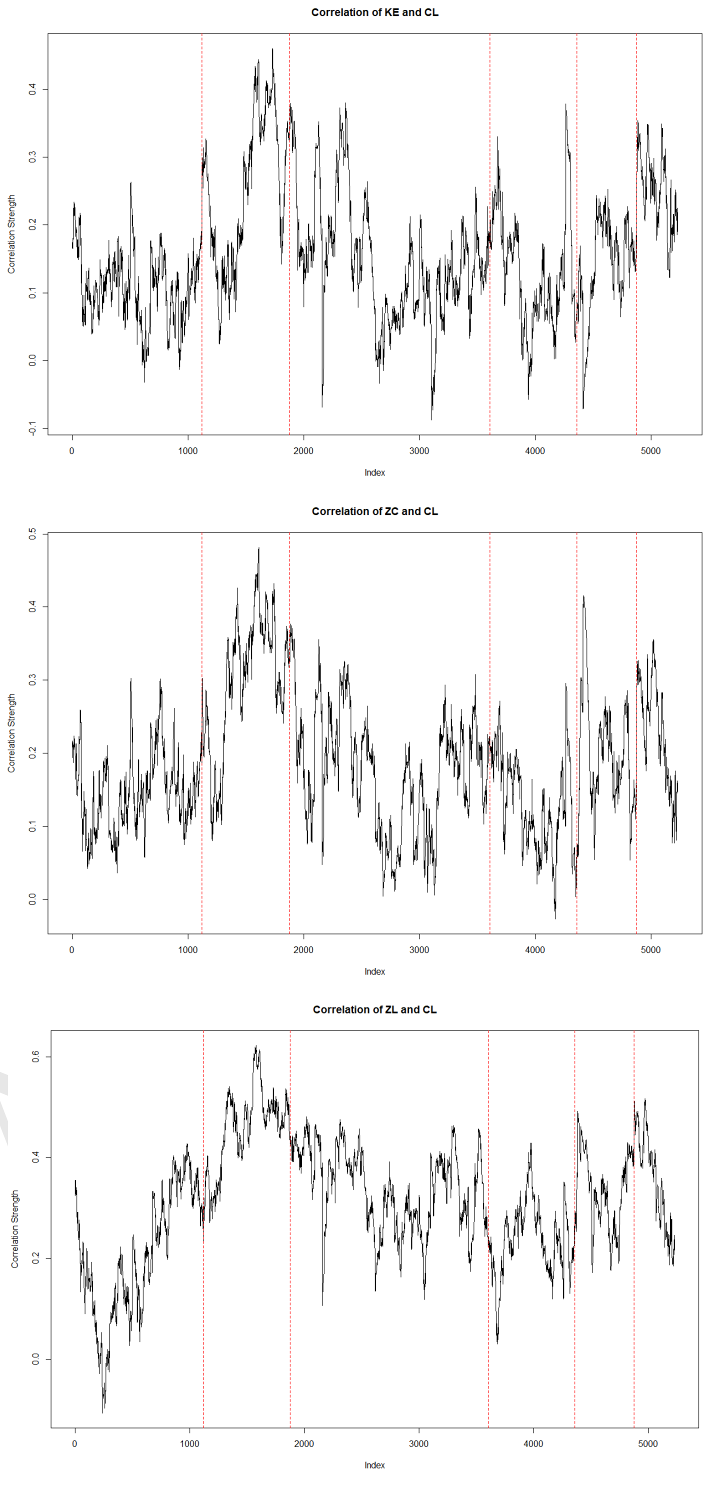

Figure 1. Dynamic Cross-Correlation Plots of Agricultural Commodities and Crude Oil
*Note that the dotted lines indicate the change in the sub-periods examined.

As the literature supports, we confirm the long-term relationship between agricultural and energy markets (Tiwari et al., 2018). However, we show that this relationship varies across specific periods, which aligns with Wang et al. (2020), who emphasize its dynamic nature. Our contribution lies in examining calm and crisis periods to assess each crisis's effect on long-term relationships. Additionally, we employ multifractal analysis, complementing econometric models prevalent in the literature, thereby providing robust results.

5.2 Dynamic cross-correlation analysis

We employ the DCC-GARCH model to analyze the conditional correlation between agricultural commodities and oil. Figure 1 presents the graphs of the dynamic cross-correlations between each one of the agricultural commodities and the crude oil. Appendix Table A1 provides the estimated coefficients of the multivariate DCC-GARCH.

The multivariate DCC-GARCH plots show that crude oil and soybean oil exhibit the most robust correlation. Corn follows this correlation, while wheat indicates the weakest relationship. Wheat demonstrates an average correlation strength of 0.158, corn 0.187, and soybean oil 0.313. The minimum values of the extremes are -0.087 for wheat, -0.027 for corn, and -0.107 for soybean oil. On the other hand, the maximum values are 0.460 for wheat, 0.481 for corn, and 0.623 for soybean oil. Additionally, the plots in Figure 1 show that corn and wheat demonstrate heightened volatility in their correlation with crude oil during the initial calm period. In contrast, soybean oil illustrates an upward trend. In the context of the financial crisis and the period of price increases, all commodities reach their peak correlation with crude oil. During the financial crisis, particularly on June 05, 2009, wheat showed a maximum correlation with crude oil of 0.460, while on December 12, 2008, corn indicated its maximum correlation of 0.481. On October 30, 2008, soybean oil showed a maximum correlation of 0.623 with crude oil.

In the subsequent calm period, there is elevated volatility in the correlation of all commodities with crude oil. Moreover, amid the COVID-19 crisis, mainly corn and soybean oil commodities experienced a peak, while corn displayed the most significant one. Wheat demonstrates a maximum correlation strength with crude oil of 0.252; corn has a value of 0.416, and soybean oil has a value of 0.492. Similarly, the war in the Ukraine period exhibited a peak correlation, and soybean oil registered the highest value. Wheat demonstrates a maximum correlation strength with crude oil (0.354), corn (0.356), and soybean oil (0.517). The outcomes of the multivariate DCC-GARCH analysis unveil a dynamic relationship with volatility between crude oil and agricultural commodities (namely, soybean oil, corn, and wheat). Notably, we identify substantial peaks during periods of crisis, underscoring that crises intensify the interrelationships among commodities and crude oil. The results demonstrate time-varying characteristics and show significant changes during the sub-periods examined.

The finding here is in line with previous studies like Shiferaw (2019), through the DCC framework, suggesting that energy dynamics and time-varying correlations with agricultural commodities demonstrate strong co-movements. Similarly, Yahya et al. (2022) argue that the dynamics of the relationship between crude oil, biodiesel and rapeseed oil markets in Europe change during periods of financial and economic crisis. However, we extend the literature by providing results that suggest that many sub-periods demonstrate significant changes and soybean oil cites the strongest correlation with crude oil than all other agricultural commodities, also addressing the impact of both the war in Ukraine and the COVID-19 pandemic, which underscores the significance of our study, overseen by the literature. Finally, the peaks in corn and wheat are more alike than those in soybean oil, which indicates that soybean oil is an essential commodity in its relationship with crude oil, as it is indeed a significant biofuel, also viewed as a substitute energy source.

Table 3. VLT causality results.

Period	X-Variable	Y-Variable	F-test	P-Value
First calm period	Corn	Crude Oil	1.562	0.058
Financial crisis and commodity price increase	Crude Oil	Wheat	6.477	0.011
Financial crisis and commodity price increase	Crude Oil	Corn	3.747	0.053
Financial crisis and commodity price increase	Crude Oil	Soybean Oil	6.712	0.010
Second calm period	Crude Oil	Wheat	9.583	0.002
COVID-19 period	Crude Oil	Wheat	1.870	0.041
War in Ukraine period	Crude Oil	Wheat	7.301	0.007
War in Ukraine period	Soybean Oil	Crude Oil	6.585	0.011
War in Ukraine period	Crude Oil	Soybean Oil	3.377	0.067
Whole Period	Crude Oil	Wheat	7.493	0.006
Whole Period	Soybean Oil	Crude Oil	3.788	0.052
Whole Period	Crude Oil	Soybean Oil	3.794	0.052

5.3 Causal investigation

The VL-Granger causality analysis is presented in Table 3. The approach allows us to examine whether the causal patterns change over different periods. Table 3 presents the statistically significant results, while the rest of them are included in the Appendix of this work (Table A2).

The causality results suggest that causal relationships increase significantly during crises, and therefore, there is heightened interdependency among commodities. It is essential to highlight that during the financial crisis and commodity price increase period, as well as the COVID-19 era, crude oil emerged as the primary driver behind the identified causal patterns. This finding is in line with existing literature since some studies have consistently underscored the pivotal role of crude oil as a driver of various economies (Rafiq et al., 2009; Wen et al., 2018), thereby carrying economic and financial implications (Huntington, 2005; Lang & Auer, 2020). However, we extend these results by showing how these relationships change over sub-periods of economic, financial, and political importance, including COVID-19 and the war in Ukraine.

During the war in Ukraine, bidirectional causal patterns emerged, mainly revolving around the dynamic between crude oil and soybean oil. This underscores the frequent interconnectedness between these commodities, with soybean oil's role as a primary biofuel source being noteworthy (Dahiya, 2014). Its price tends to inversely relate to crude oil, a relationship susceptible to significant impacts from specific crises (Vatsa and Milikovic, 2021). Our findings align with existing literature, revealing bidirectional causal relationships between crude oil and agricultural futures. However, the nature of this relationship varies across different sub-periods, consistent with prior studies (Umar et al., 2018; Su et al., 2019), which also emphasize the impact of crises on this linkage (Umar et al., 2017). Thus, crises affect the causal relationship differently, highlighting the significance of the crisis's nature and specific attributes in the agricultural-energy causal scheme. This finding extends previous approaches by demonstrating that the nature of a particular crisis, rather than crises in general, influences the causal pattern differently.

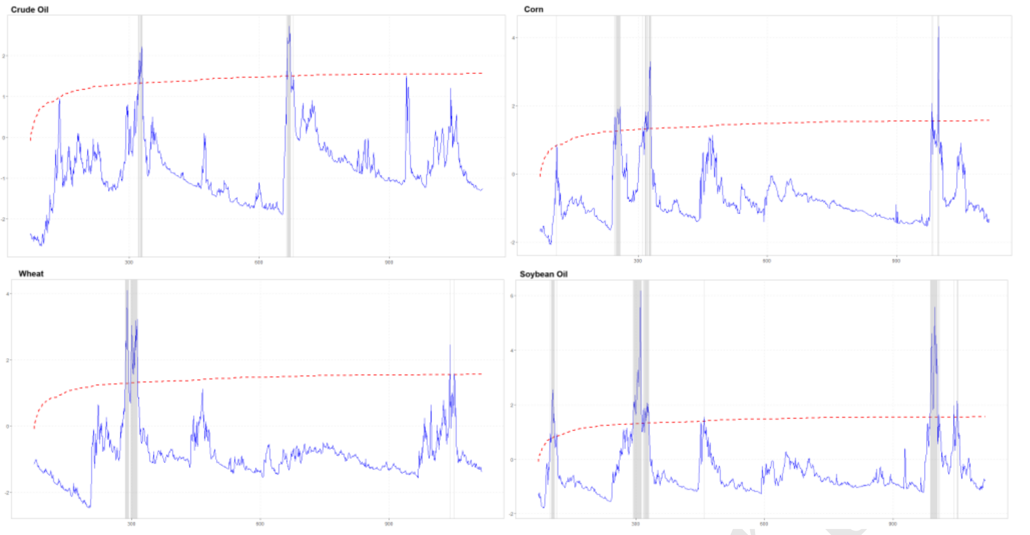

Figure 2. Bubble detection for the four commodities (crude oil, corn, wheat, soybean oil)

5.4 Price bubble detection

Figure 2 presents the results of the price bubble detection. The Appendix provides the statistical tests of this work.

According to the price bubble analysis results, crude oil demonstrated a price bubble during the financial crisis and between the end of 2014 and the beginning of 2015. On the other hand, corn showed more price bubbles of less duration during 2004, during the financial crisis, the COVID-19 pandemic, and, more precisely, in 2021, meaning that the above bubbles were shorter in length compared to other price bubbles. Soybean oil witnessed bubbles during various critical periods: in 2004, during the financial crisis, at the end of 2010 and the beginning of 2011, amidst the COVID-19 pandemic, notably in 2021, and most recently, with the onset of the war in Ukraine. As for the wheat commodity, it demonstrated price bubbles during the financial crisis and the war in Ukraine. Evidence regarding price bubbles in crude oil and agricultural commodities remains contentious. While Gilbert (2010b) found weaker indications of bubble behavior in crude oil markets, recently Ajmi et al. (2021) and Mao et al. (2020) point to the presence of bubbles in energy markets, including crude oil, and highlight the potential for speculative activity to influence price surges and volatility. Similarly, there is an ongoing debate on agricultural commodity bubbles. Robles et al. (2009) suggest speculative activity's significant contribution to excess price surges and volatility in wheat, maize, soybeans, and rice markets during 2007-2008. In contrast, the research by Sanders and Irwin (2011a, 2011b) challenges the hypothesis, which indicates no substantial evidence that links commodity index speculation to the 2007-08 commodity price increase and price levels in agricultural commodity futures markets.

This study contributes to the literature by providing significant empirical evidence and answers to this debate. Remarkably, our results suggest that all commodities we researched (i.e., crude oil, corn, wheat, and soybean oil) exhibit price bubbles. However, the commodities demonstrate price bubbles of different durations and intensities during various periods. For instance, the war in Ukraine inflated a price bubble for soybean oil and wheat but not for crude oil and corn. Thus, the price increase in crude oil is currently occurring not due to speculation but rather due to political events and the market's performance.

Table 4. Hedging optimal portfolio ratios.

Period	Case	b_Average	b_Standard_Deviation
First calm period	CL_KE	0.098	0.040
	KE_CL	0.060	0.022
	CL_ZC	0.150	0.049
	ZC_CL	0.088	0.029
	CL_ZL	0.155	0.064
	ZL_CL	0.086	0.039
Financial crisis and commodity price increase	CL_KE	0.417	0.281
	KE_CL	0.277	0.091
	CL_ZC	0.472	0.245
	ZC_CL	0.346	0.094
	CL_ZL	0.860	0.301
	ZL_CL	0.413	0.110
Second calm period	CL_KE	0.137	0.112
	KE_CL	0.118	0.089
	CL_ZC	0.163	0.112
	ZC_CL	0.121	0.078
	CL_ZL	0.502	0.228
	ZL_CL	0.194	0.073
COVID-19 period	CL_KE	0.233	0.324
	KE_CL	0.106	0.057
	CL_ZC	0.512	0.630
	ZC_CL	0.175	0.114
	CL_ZL	0.760	0.871
	ZL_CL	0.277	0.136
War in Ukraine period	CL_KE	0.343	0.059
	KE_CL	0.274	0.043
	CL_ZC	0.406	0.143
	ZC_CL	0.179	0.131
	CL_ZL	0.370	0.092
	ZL_CL	0.285	0.046
Whole Period	CL_KE	0.195	0.165
	KE_CL	0.141	0.090
	CL_ZC	0.272	0.316
	ZC_CL	0.158	0.092
	CL_ZL	0.512	0.410
	ZL_CL	0.219	0.105

Notes: CL represents crude oil futures prices, KE refers to KC HRW wheat, ZC stands for corn, and ZL represents soybean oil.

Table 5. Hedging Optimal Weights by Period and Commodities

Period	Case	w_Average	w_Standard_Deviation
First calm period	CL_KE	0.371	0.047
	KE_CL	0.629	0.047
	CL_ZC	0.362	0.103
	ZC_CL	0.638	0.103
	CL_ZL	0.335	0.094
	ZL_CL	0.665	0.094
Financial crisis and commodity price increase	CL_KE	0.419	0.238
	KE_CL	0.581	0.238
	CL_ZC	0.420	0.233
	ZC_CL	0.580	0.233
	CL_ZL	0.173	0.229
	ZL_CL	0.827	0.229
Second calm period	CL_KE	0.468	0.159
	KE_CL	0.532	0.159
	CL_ZC	0.443	0.183
	ZC_CL	0.557	0.183
	CL_ZL	0.227	0.145
	ZL_CL	0.773	0.145
COVID-19 period	CL_KE	0.361	0.196
	KE_CL	0.639	0.196
	CL_ZC	0.315	0.254
	ZC_CL	0.685	0.254
	CL_ZL	0.291	0.238
	ZL_CL	0.709	0.238
War in Ukraine period	CL_KE	0.422	0.098
	KE_CL	0.578	0.098
	CL_ZC	0.264	0.217
	ZC_CL	0.736	0.217
	CL_ZL	0.414	0.121
	ZL_CL	0.586	0.121
Whole Period	CL_KE	0.421	0.163
	KE_CL	0.579	0.163
	CL_ZC	0.393	0.195
	ZC_CL	0.607	0.195
	CL_ZL	0.259	0.169
	ZL_CL	0.741	0.169

Notes: CL represents crude oil futures prices, KE refers to KC HRW wheat, ZC stands for corn, and ZL represents soybean oil.

5.5. Hedging strategies

Turning to the financial risk management context, we provide the optimal hedge ratios in Table 4 and the optimal weights in Table 5.

Tables 4 and 5 show that the optimal hedge ratios are relatively low during the first calm period, and the portfolio weights are balanced. During the financial crisis and commodity price increase, the optimal hedge ratios are notably higher than in the first calm period. At the same time, the weights show a strong preference for crude oil (CL) towards soybean oil (ZL), indicating that a more robust hedge between commodities may be better to mitigate risk during turbulent times. Moreover, during the second calm period, the optimal hedge ratios and weights are similar to those in the first quiet period, with some variation. As for the COVID-19 era, we see evidence of varying optimal hedges. Moreover, during the war in Ukraine, the results indicate relatively high hedge ratios and corn (ZC) shows the lead allocation in a portfolio with crude oil (CL), which suggests more substantial hedging during geopolitical uncertainty.

The hedging results suggest that preferences for commodities change based on market conditions. Generally, crude oil (CL) and wheat (KE) often feature prominently in optimal hedge ratios and portfolio weights, while Soybean oil (ZL) shows high ratios during turbulent times. External factors like economic conditions and geopolitical events influence commodity choices. Economic conditions, geopolitics, and supply-demand dynamics alter commodity market preferences. Consequently, commodities respond uniquely to these factors, affecting risk management and investments. Crude oil's sensitivity to geopolitics persists, soybean oil's role in biofuel production and its link to crude oil make it a recurrent choice, and wheat's stability in food supply chains explains its inclusion. At the same time, external forces heavily shape commodity markets, necessitating adaptable strategies for risk management and portfolio optimization.

Our work aligns with past approaches since, according to the literature, certain combinations in the same portfolio are better than others (Yang and Awokuse, 2003; Chihachinda et al., 2019; Zivkov et al., 2020). However, even though our results suggest no uniform case for the hedges examined, specific pairs are better than others, and certain pairs are favored more. In this regard, we extend the literature since, for example, Han et al. (2021) argue that the results for hedging strategies vary, and even though that is the case, through this work, we indicate that certain hedge ratios are generally higher for specific pairs (e.g., corn and soybean oil). It is essential to highlight that various techniques can reveal different facets of price performance and transmission among commodities. In the same context, we have to consider the perception of risk itself and use various techniques since various approaches answer different facets of risk (Capitani and Mattos, 2017). In this regard, the present paper aims to answer these questions and to do so, we employ a multifaceted approach.

Conclusion and Policy Implications

The present paper focuses on four commodities: Crude Oil (CL), Wheat (KE), Corn (ZC), and Soybean Oil (ZL). We divide the study period into different sub-periods based on significant events to reveal probable varying causal relationships and long-run relationships among the commodities. We employ the multifractal analysis and DCC-GARCH model to explore these relationships and correlations and identify dynamics that change during crises. Price bubble analysis further contributed to understanding speculative influences, and the hedging and portfolio allocation results shed light on risk management strategies.

The study underscores the varying levels of volatility and causal relationships among commodities during different periods, especially during crises. Commodities demonstrate stronger interdependencies during crisis periods, suggesting heightened market interconnectedness. Moreover, crude oil consistently emerges as a critical driver of price dynamics and causal relationships, especially during crises, highlighting its significance as a global commodity with far-reaching economic implications. Additionally, this study emphasizes the need for adaptive risk management strategies. Different commodities exhibit varying levels of risk and response to external factors and thus influence optimal hedge ratios and portfolio allocation decisions. As for market responses to crises, the analysis highlights how different commodities respond to specific types of crises since geopolitical events may influence some commodities more than others, while others by supply chain disruptions, economic shifts, or changes in demand. In this regard, the case study of the war in Ukraine unveiled that the commodities examined behave differently, not only before and during the war, but also differently from other commodities.

The dynamic nature of long-run relationships between commodities implies that correlations can evolve, which indicates the need for a nuanced approach to analyze these relationships. Apart from that, the dynamic correlation unveils that the agricultural commodities not only differ in their relation to crude oil, but also this correlation depends on various factors, as shown by their change in behavior during the multiple sub-periods. Turning to the price bubble analysis, the presence of bubbles in different commodities and during various periods suggests that speculative activity plays a role in price surges and volatility. This finding adds to the ongoing debate about the impact of speculation on commodity markets. However, during the war in Ukraine, only soybean oil and wheat demonstrated speculative characteristics, and thus, this played a part in their price increase.

During the war in Ukraine, geopolitical events significantly influence commodity markets. Causal relationships among commodities show distinct patterns; mainly, crude oil (CL) affects wheat (KE) and soybean oil (ZL), forming a bidirectional causal pattern with soybean oil. This interdependency suggests that geopolitical tensions reshape commodity interactions. The DCC-GARCH model indicates heightened correlations between crude oil and agricultural commodities, reinforcing that geopolitical uncertainty amplifies interrelationships among commodities, leading to stronger correlations and higher price volatility. Moreover, the presence of price bubbles in wheat (KE) and soybean oil (ZL) suggests heightened speculative activity and price volatility, which means that speculative activity played a role in commodity price movements during the war period, and market participants must be cautious about the potential impact of speculation on market stability. This underlines how geopolitical events can trigger market distortions and thus impact traders and investors. Despite its strengths, our work demonstrates some limitations, one being the sub-periods chosen since COVID-19 and the war in Ukraine overlapped. However, this did not affect the importance of our results, but future directions could examine for a double effect, utilizing also machine learning or other techniques.

[First submitted April 2024; accepted for publication October 2024.]

References

Adämmer, P., & Bohl, M. T. (2015). Speculative bubbles in agricultural prices, *The Quarterly Review of Economics and Finance*, 55, 67-76. https://doi.org/10.1016/j.qref.2014.06.003

Ajmi, A. N., Hammoudeh, S., & Mokni, K. (2021). Detection of bubbles in WTI, Brent, and Dubai oil prices: A novel double recursive algorithm, *Resources Policy*, 70, 101956. https://doi.org/10.1016/j.resourpol.2020.101956

Alola A. A. (2022). The nexus of renewable energy equity and agricultural commodities in the United States: Evidence of regime-switching and price bubbles, *Energy*, 239, 122377. https://doi.org/10.1016/j.energy.2021.122377

Amornbunchornvej Chainarong, Zheleva Elena, and Berger-Wolf Tanya. (2021). Variable-lag Granger Causality and Transfer Entropy for Time Series Analysis, *ACM Transactions on Knowledge Discovery from Data*, 15, 4, 67. https://doi.org/10.1145/3441452

Babajide, F. (2016). Do oil prices drive agricultural commodity prices? Evidence from South Africa, *Energy*, 104, 149-157. 10.1016/j.energy.2016.03.101

Ben Hassen, T., & El Bilali, H. (2022). Impacts of the Russia-Ukraine War on Global Food Security: Towards More Sustainable and Resilient Food Systems?, *Foods*, 11(15), 2301. https://doi.org/10.3390/foods11152301

Boubaker, H., & Larbi, O. B. (2022). Dynamic dependence and hedging strategies in BRICS stock markets with oil during crises, *Economic Analysis and Policy*, 76, 263–279. https://doi.org/10.1016/j.eap.2022.08.011

Bourghelle, D., Jawadi, F., & Rozin, P. (2021). Oil price volatility in the context of Covid-19, *International Economics*, 167, 39–49. https://doi.org/10.1016/j.inteco.2021.05.00 1

Capitani, D. H. D., & Mattos, F. (2017). Measurement of Commodity Price Risk: An overview of Brazilian agricultural markets, *Revista de Economia e Sociologia Rural*, 55(3), 515–532. https://doi.org/10.1590/1234-56781806-94790550306

Chemeris Anna, Liu Yong, Ker Alan P. (2022). Insurance subsidies, climate change, and innovation: Implications for crop yield resiliency, *Food Policy*, 108, 102232. https://doi.org/10.1016/j.foodpol.2022.102232

Chen, Y., & Qu, F. (2019). Leverage effect and dynamics correlation between international crude oil and China's precious metals, *Physica A: Statistical Mechanics and Its Applications, 534*, 122319. https://doi.org/10.1016/j.physa.2019.122319

Chunhachinda, P., De Boyrie, M. E., & Pavlova, I. (2019). Measuring the hedging effectiveness of commodities, *Finance Research Letters*, 30, 201–207. https://doi.org/10.1016/j.frl.2018.09.012

Daglis, T. (2023). The dynamic relationship of cryptocurrencies with supply chain and logistics stocks – the impact of COVID-19, *Journal of Economic Studies*, 50,4, 840-857. doi:10.1108/JES-03-2022-0190

Daglis, T.(2021). The excessive gaming and gambling during COVID-19, *Journal of Economic Studies*, 49(5), 888 – 901.10.1108/JES-02-2021-0093

Dahiya, A. (2014). *Bioenergy: Biomass to biofuels*, Elsevier, Academic Press. ISBN: 9780124081208

Engle R.F. & Sheppard K. (2001). Theoretical and empirical properties of dynamic conditional correlation multivariate GARCH, *NBER Working Papers*, 8554.

Evans, G.W. (1991). Pitfalls in testing for explosive bubbles in asset prices, *American Economic Review*, 81(4), 922–930.

Ezeaku, H. C., Asongu, S., & Nnanna, J. (2020). *Volatility of international commodity prices in times of Covid-19: Effects of oil supply and global demand shocks, MPRA working paper*. https://mpra.ub.uni-muenchen.de/107544/1/MPRA_paper_107544.pdf

Gilbert, C. (2010a). How to understand high food prices, *Journal of Agricultural Economics*, 61, 398–425. https://doi.org/10.1111/j.1477-9552.2010.00248.x

Gilbert, C.L. (2010b). Speculative influences on commodity prices 2006-2008, *United Nations Conference of Trade and Development*, 197.

Han, L., Jina, J., Wua, L., & Zeng, H. (2020). The volatility linkage between energy and agricultural futures markets with external shocks, *International Review of Financial Analysis*, 68. Doi.org/10.1016/j.irfa.2019.01.011

He H.D., Pan W., Lu W.Z., Xue Y. and Peng G.H. (2016). Multifractal property and long-range cross-correlation behavior of particulate matters at urban traffic intersection in Shanghai, *Stochastic Environmental Research Risk Assessment*, 30, 1515-1523. https://doi.org/10.1007/s00477-015-1162-x

He Hong-di (2017). Multifractal analysis of interactive patterns between meteorological factors and pollutants in urban and rural areas, *Atmospheric Environment*, 149, 47-54. https://doi.org/10.1016/j.atmosenv.2016.11.004

Hellegers, P. (2022). Food security vulnerability due to trade dependencies on Russia and Ukraine, *Food Security*, 14(6), 1503–1510. https://doi.org/10.1007/s12571-022-01306-8

Hernandez J. A., Shahzad S. J. H., Uddin G. S., & Kang, S. H. (2019). Can agricultural and precious metal commodities diversify and hedge extreme downside and upside oil market risk? An extreme quantile approach, *Resources Policy* 62, 588-601. Doi.org/10.1016/j.resourpol.2018.11.007

Hou, Y., & Li, S. (2016). Information transmission between U.S. and China index futures markets: An asymmetric DCC GARCH approach, *Economic Modelling*, *52*, 884–897. https://doi.org/10.1016/j.econmod.2015.10.025

Hung Ngo T. (2021). Oil prices and agricultural commodity markets: Evidence from pre and during COVID-19 outbreak, *Resources Policy* 73, 102236. https://doi.org/10.1016/j.resourpol.2021.102236

Huntington, H. G. (2001). *The Economic Consequences of higher crude oil prices*, EMF SR 9. https://web.stanford.edu/group/emf-research/new-emf.stanford.edu/files/pubs/22457/EMFSR9.pdf

Im, K.S., Pesaran, M.H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels, *Journal of Econometrics*, 115(1), 53–74. https://doi.org/10.1016/S0304-4076(03)00092-7

Irwin, S., Sanders, D.R. & Merrin, R.P. (2009). Devil or Angel? The Role of Speculation in the Recent Commodity Price Boom (and Bust), *Journal of Agricultural and Applied Economics*, 41(2), 377-391. 10.1017/S1074070800002856

Jiang, Y., Lao J., Mo B., & Nie, H. (2018). Dynamic linkages among global oil market, agricultural raw material markets and metal markets: An application of wavelet and copula approaches, *Physica A* 508, 265–279. 10.1016/j.physa.2018.05.092

Jiang, Y., Jiang, C., Nie, H., & Mo, B. (2019). The time-varying linkages between global oil market and China's commodity sectors: Evidence from DCC-GJR-GARCH analyses, *Energy*, *166*, 577–586. https://doi.org/10.1016/j.energy.2018.10.116

Kristjanpoller W. & Minutolo M. C. (2021). Asymmetric multifractal cross-correlations of the price of electricity in the US with crude oil and natural gas, *Physica A* 572, 125830. https://doi.org/10.1016/j.physa.2021.125830

Kroner, K.F., & Sultan, J. (1993). Time dynamic varying distributions and dynamic hedging with foreign currency futures, *Journal of Financial and Quantitative Analysis*, 28(4), 535-551.

Kroner, K.F., & Ng, V.K. (1998). Modeling asymmetric movements of asset prices, *Review of Financial Studies*, 11(2), 844-871.

Kumar, S., Tiwari, K. A., Raheem, Ibrahim, D., & Hille, E. (2021). Time-varying dependence structure between oil and agricultural commodity markets: A dependence-switching CoVaR copula approach, *Resources Policy* 72, 102049. 10.1016/j.resourpol.2021.102049

Lammerding, M., Stephan, P., Trede, M., & Wilfling, B. (2013). Speculative bubbles in recent oil price dynamics: Evidence from a Bayesian Markov-switching state-space approach, *Energy Economics*, 36, 491–502. 10.1016/j.eneco.2012.10.006

Lang, K., & Auer, B. R. (2020). The economic and financial properties of crude oil: A review, *The North American Journal of Economics and Finance*, 52, 100914. https://doi.org/10.1016/j.najef.2019.01.011

Liu, Xiang-dong, Pan, F., Yuan, L, Chen, & Yu-wang. (2019). The dependence structure between crude oil futures prices and Chinese agricultural commodity futures prices: Measurement based on Markov-switching GRG copula, *Energy*, 182, 999-1012. 10.1016/j.energy.2019.06.071

Mao, Q., Ren, Y., & Loy, J. P. (2020). Price bubbles in agricultural commodity markets and contributing factors: Evidence for corn and soybeans in China, *China Agricultural Economic Review*, 13(1), 91–122. 10.1108/CAER-10-2019-0190

Mensi, W., Rehman, M.U., Hammoudeh, S., & Vo, X.V. (2021c). Spillovers between natural gas, gasoline, oil, and stock markets: evidence from MENA countries, *Resources Policy*, 71, 101983. https://doi.org/10.1016/j.resourpol.2020.101983

Mensi, W., Rehman, M.U., & Vo, X.V. (2021a). Dynamic frequency relationships and volatility spillovers in natural gas, crude oil, gas oil, gasoline, and heating oil markets: implications for portfolio management, *Resources Policy*, 73, 102172. https://doi.org/10.1016/j.resourpol.2021.102172

Mensi, W., Rehman, M.U., & Vo, X.V. (2021b). Risk spillovers and diversification between oil and nonferrous metals during bear and bull market states, *Resources Policy*, 72, 102132. https://doi.org/10.1016/j.resourpol.2021.102132

Mensi, W., Sensoy, A., Vo, X. V., & Kang, S. H. (2020). Impact of COVID-19 outbreak on asymmetric multifractality of gold and oil price, *Resources Policy*, 69, 101829. https://doi.org/10.1016/j.resourpol.2020.101829

Mishra, A. K., & Ghate, K. (2022). Dynamic connectedness in nonferrous commodity markets: Evidence from India using TVP-VAR and DCC-GARCH approaches, *Resources Policy*, *76*, 102572. https://doi.org/10.1016/j.resourpol.2022.102572

Naeem, M. A., Hasan, M., Arif, M., Suleman, M. T., & Kang, S. H. (2022). Oil and gold as a hedge and safe-haven for metals and agricultural commodities with portfolio implications, *Energy Economics*, 105, 105758. 10.1016/j.eneco.2021.105758

Nazlioglu, S., & Soytas, U. (2011). World oil prices and agricultural commodity prices: Evidence from an emerging market, *Energy Economics*, 33, 488–496. 10.1016/j.eneco.2010.11.012

Nazlioglu, S., & Soytas, U. (2012). Oil price, agricultural commodity prices, and the dollar: A panel cointegration and causality analysis, *Energy Economics*, 34, 1098–1104. https://doi.org/10.1016/j.eneco.2011.09.008

Nazlioglu, S., Erdem, C., & Soytas, U. (2013). Volatility spillover between oil and agricultural commodity markets, *Energy Economics*, 36, 658–665. 10.1016/j.eneco.2012.11.009

Oladosu, G. (2022). Bubbles in US gasoline prices: Assessing the role of hurricanes and anti–price gouging laws, *Journal of Commodity Markets*, https://doi.org/10.1016/j.jcomm.2021.100219

Orskaug, E. (2009). *Multivariate DCC-GARCH Model-With Various Error Distributions, Norwegian University of Science and Technology*, Department of Mathematical Sciences, https://ntnuopen.ntnu.no/ntnu-xmlui/bitstream/handle/11250/259296/724505_FULLTEXT01.pdf

Pal Debdatta, & Mitra S. K. (2019). Correlation dynamics of crude oil with agricultural commodities: A comparison between energy and food crops, *Economic Modelling* 82, 453–466.

Palazzi, R. B., Meira, E., & Klotzle, M. C. (2022). The sugar-ethanol-oil nexus in Brazil: Exploring the pass-through of international commodity prices to national fuel prices, *Journal of Commodity Markets*, 28 (C). 10.1016/j.jcomm.2022.100257

Paris, A. (2018). On the link between oil and agricultural commodity prices: Do biofuels matter?, *International Economics*, 155 (C), 48–60. 10.1016/j.inteco.2017.12.003

Pavlidis, E.G., Yusupova, A., Paya, I., Peel, D.A., Martınez-Garcıa, E., Mack, A., & Grossman, V. (2016). Episodes of exuberance in housing markets: In search of the smoking gun, *The Journal of Real Estate Finance and Economics*, 53(4), 419–449. 10.1007/s11146-015-9531-2

Phillips, P.C.B, Shi, S., & Yu, J. (2015b). Testing for multiple bubbles: Limit theory of real-time detectors, *International Economic Review*, 56, 1079–1134. https://doi.org/10.1111/iere.12131

Phillips, P.C.B., Shi, S., & Yu, J. (2015a). Testing for multiple bubbles: Historical episodes of exuberance and collapse in the S&P 500, *International Economic Review*, 56(4), 1043–1078. https://doi.org/10.1111/iere.12132

Phillips, P.C.B., Wu, Y., & Yu, J. (2011). Explosive behavior in the 1990s NASDAQ: When did exuberance escalate asset values?, *International Economic Review*, 52(1), 201–226. https://doi.org/10.1111/j.1468-2354.2010.00625.x

Podobnik, B., Grosse, I., Horvatic, D., Llic, S., Ivanoov, P.C. & Stanley, H.E. (2009). Quantifying cross-correlations using local and global detrending approaches, *European Physical Journal*, B 71, 243-250. 10.1140/epjb/e2009-00310-5

Potrykus, M. (2023). Price bubbles in commodity market – A single time series and panel data analysis, *The Quarterly Review of Economics and Finance*, 87, 110–117. 10.1016/j.qref.2022.12.002

Rafiq, S., Salim, R., & Bloch, H. (2009). Impact of crude oil price volatility on economic activities: An empirical investigation in the Thai economy, *Resources Policy*, 34(3), 121–132. https://doi.org/10.1016/j.resourpol.2008.09.001

Raza, S. A., Guesmi K., Belaid, F., & Shah Nida (2022). Time-frequency causality and connectedness between Oil Price Shocks and the World Food Prices, *Research in International Business and Finance*, doi:https://doi.org/10.1016/j.ribaf.2022.101730.

Robles, M., Torero, M., & Von Braun, J. (2009). *When Speculation Matters*, Issue Brief, 57, International Food Policy Research Institute. Washington DC. Available at: http://www.ifpri.org/pubs/ib/ib57.asp. Last access: May, 2021.

Sakoe, H. & Chiba, S. (1978). Dynamic programming algorithm optimization for spoken word recognition, *IEEE Transactions on Acoustics, Speech, and Signal Processing* 26, 1 (1978), 43–49.

Sanders, D.R. & Irwin, S.H. (2010). A speculative bubble in commodity futures prices? Cross-sectional evidence, *Agricultural Economics*, 41(1), 25-32. https://doi.org/10.1111/j.1574-0862.2009.00422.x

Sanders, D.R. & Irwin, S.H. (2011a). New Evidence on the Impact of Index Funds in U.S. Grain Futures Markets, *Canadian Journal of Agricultural Economics*, 59(4), 519-32. http://doi.org/b93j6b.

Sanders, D.R. & rwin, S.H. (2011b). The Impact of Index Funds in Commodity Futures Markets: A Systems Approach, *Journal of Alternative Investments*, 14, 40-49. 10.3905/jai.2011.14.1.040

Serletis, A. & Xu, L. (2019). The ethanol mandate and crude oil and biofuel agricultural commodity price dynamics, *Journal of Commodity Markets*, 15, 100068. 10.1016/j.jcomm.2018.07.001

Shiferaw, Y. A. (2019). Time-varying correlation between agricultural commodity and energy price dynamics with Bayesian multivariate DCC-GARCH models, *Physica A: Statistical Mechanics and Its Applications*, *526*, 120807. https://doi.org/10.1016/j.physa.2019.04.043

Thanh, S.D., Canh, N. P., & Doytch, N. (2020). Asymmetric effects of U.S. monetary policy on the U.S. bilateral trade deficit with China: A Markov switching ARDL model approach, *The Journal of Economic Asymmetries*, 22, e00168. 10.1016/j.jeca.2020.e00168

Tiwari, A. K., Boachie,M. K., Suleman, M. T., & Gupta, R. (2021). Structure dependence between oil and agricultural commodities returns: The role of geopolitical risks, *Energy*, 219, 119584. 10.1016/j.energy.2020.119584

Tiwari, A. K., Khalfaoui, R., Solarin, S. A., & Shahbaz, M. (2018). Analyzing the time-frequency lead–lag relationship between oil and agricultural commodities, *Energy Economics*, 76, 470–494. 10.1016/j.eneco.2018.10.037

Umar, Z., Jareno, F., & Escribano, A. (2021). Agricultural commodity markets and oil prices: An analysis of the dynamic return and volatility connectedness, *Resources Policy*, 73, 102147. https://doi.org/10.1016/j.resourpol.2021.102147

Vasilopoulos, K., Pavlidis, E., & Martínez-García, E. (2020). exuber: recursive right-tailed unit root testing with R. Dallas Fed Working Paper.

Vatsa, P., & Miljkovic, D. (2022). Energy and crop price cycles before and after the global financial crisis: A new approach, *Journal of Agricultural Economics*, 73(1), 220–233. https://doi.org/10.1111/1477-9552.12454

Vo, D. H., Vu, T. N., Vo, A. T., & McAleer, M. (2019). Modeling the Relationship between Crude Oil and Agricultural Commodity Prices, *Energies*, 12(7), 1344. https://doi.org/10.3390/en12071344

Wang, B., Wei, Y., Xing, Y., & Ding, W. (2019). Multifractal detrended cross-correlation analysis and frequency dynamics of connectedness for energy futures markets, *Physica A*, 527, 121194. https://doi.org/10.1016/j.physa.2019.121194

Wang, J., Shao, W., & Kima, J. (2020). Analysis of the impact of COVID-19 on the correlations between crude oil and agricultural futures, *Chaos, Solitons and Fractals*, 136, 109896. https://doi.org/10.1016/j.chaos.2020.109896

Wang, Y., Wang, Z., & Guo, K. (2022). Analysis on the Transmission of International Oil Price to China's Price Index--Baed on Granger Causality Network, *Procedia Computer Science*, 199, 1276-1283. https://doi.org/10.1016/j.procs.2022.01.162

Wang, Y., Wu, C., & Yang, L. (2014). Oil price shocks and agricultural commodity prices, *Energy Economics*, 44, 22–35. 10.1016/j.eneco.2014.03.016

Wang, Z. & Kim, M.-K. (2022). Price bubbles in oil & gas markets and their transfer, *Resources Policy*, 79, 103059. https://doi.org/10.1016/j.resourpol.2022.103059

Wei, Y., Wang, Y., Vigne, S. A., & Ma, Z. (2023). Alarming contagion effects: The dangerous ripple effect of extreme price spillovers across crude oil, carbon emission allowance, and agriculture futures markets. *Journal of International Financial Markets, Institutions and Money*, *88*, 101821. https://doi.org/10.1016/j.intfin.2023.101821

Wen, F., Min, F., Zhang, Y., & Yang, C. (2019). Crude oil price shocks, monetary policy, and China's economy, *International Journal of Finance & Economics*, 24(2), 812–827. https://doi.org/10.1002/ijfe.1692

Yahya, M., Dutta, A., Bouri, E., Wadström, C., & Uddin, G. S. (2022). Dependence structure between the international crude oil market and the European markets of biodiesel and rapeseed oil, *Renewable Energy*, *197*, 594–605. https://doi.org/10.1016/j.renene.2022.07.112

Yahya, M., Oglend, A., & Dahl, R. E. (2019). Temporal and spectral dependence between crude oil and agricultural commodities: A wavelet-based copula approach, *Energy Economics* 80, 277–296. 10.1016/j.eneco.2019.01.011

Yang, J., & Awokuse, T. O. (2003). Asset storability and hedging effectiveness in commodity futures markets, *Applied Economics Letters*, 10(8), 487–491. https://doi.org/10.1080/1350485032000095366

Yue, Y., Liu, D., & Xu, S. (2015). Price linkage between Chinese and international nonferrous metals commodity markets based on VAR-DCC-GARCH models, *Transactions of Nonferrous Metals Society of China*, *25*(3), 1020–1026. https://doi.org/10.1016/S1003-6326(15)63693-7

Zhang, D., Shi, M., & Shi, X. (2018). Oil indexation, market fundamentals, and natural gas prices: an investigation of the Asian Premium in natural gas trade, *Energy Economics*, 69, 33–41. 10.1016/j.eneco.2017.11.001

Zhang, D., Wang, T., Shi, X., & Liu, J. (2018). Is hub-based pricing a better choice than oil indexation for natural gas? Evidence from a multiple bubble test, *Energy Economics*, 76, 495–503. 10.1016/j.eneco.2018.11.001

Zhou, X.-Y., Lu, G., Xu, Z., Yan, X., Khu, S.-T., Yang, J., & Zhao, J. (2023). Influence of Russia-Ukraine War on the Global Energy and Food Security, *Resources, Conservation & Recycling* 188, 106657. 10.1016/j.resconrec.2022.106657

Zivkov, D., Manic, S., & Đuraskovic, J. (2020). Short and long-term volatility transmission from oil to agricultural commodities- The robust quantile regression approach, *Borsa Istanbul Review*, S11-S25. 0.1016/j.bir.2020.10.008

Appendix

Table A1. Summary Estimates of DCC-GARCH Model

Parameter	Estimate	Standard Error	T-stat	p-value
CL.mu	0.001	0.000	2.367	0.018
CL.ar1	0.327	0.715	0.458	0.647
CL.ma1	-0.346	0.710	-0.488	0.626
CL.omega	0.000	0.000	0.962	0.336
CL.alpha1	0.099	0.028	3.508	0.000
CL.beta1	0.887	0.014	63.653	0.000
KE.mu	0.000	0.000	0.425	0.671
KE.ar1	-0.297	1.051	-0.283	0.777
KE.ma1	0.322	1.042	0.309	0.757
KE.omega	0.000	0.000	3.526	0.000
KE.alpha1	0.041	0.004	11.520	0.000
KE.beta1	0.943	0.005	173.606	0.000
ZC.mu	0.000	0.000	0.537	0.591
ZC.ar1	-0.568	0.333	-1.705	0.088
ZC.ma1	0.586	0.329	1.783	0.075
ZC.omega	0.000	0.000	0.746	0.456
ZC.alpha1	0.071	0.021	3.345	0.001
ZC.beta1	0.916	0.016	55.703	0.000
ZL.mu	0.000	0.000	1.242	0.214
ZL.ar1	0.232	0.202	1.148	0.251
ZL.ma1	-0.204	0.203	-1.009	0.313
ZL.omega	0.000	0.000	4.118	0.000
ZL.alpha1	0.040	0.002	24.663	0.000
ZL.beta1	0.956	0.001	877.981	0.000
Jointdcca1	0.015	0.005	3.003	0.003
Jointdccb1	0.976	0.010	100.736	0.000

Notably, “mu” represents the conditional mean for a variable or asset in the model, “ar1” is associated with the autoregressive component of the conditional variance (GARCH). In contrast “ma1” represents the moving average component of the conditional variance. Similarly, “omega” represents the GARCH(0) term, which is the unconditional or constant part of the conditional variance, “alpha1” is associated with the ARCH component of the model, and “beta1” is related to the GARCH component of the model. Finally, “Jointdcca1” and “Jointdccb1” refer to the joint dynamic conditional correlation, which is a part of the DCC-GARCH model and focuses on modeling the time-varying correlation between two or more financial time series.
There are many parameters statistically significant, such as CL.mu, CL.alpha1, CL.beta1, KE.omega, KE.alpha1, KE.beta1, zC.ar1, ZC.ma1, ZC.alpha1, ZC.beta1, ZL.omega, ZL.alpha1, ZL.beta1, Jointdcca1, and Jointdccb1.
Source: Authors’ calculations.

Table A2. Estimates of Variable-Lag Causality by Commodities and Period

Period	X	Y	F-test	p-Value
First calm period	wheat	crude oil	0.377	0.539
First calm period	crude oil	wheat	1.114	0.189
First calm period	corn	crude oil	1.562	0.058
First calm period	crude oil	corn	0.023	0.878
First calm period	soybean oil	crude oil	0.046	0.830
First calm period	crude oil	soybean oil	0.030	0.863
Financial crisis & commodity price increase	wheat	crude oil	0.142	0.706
Financial crisis & commodity price increase	crude oil	wheat	6.477	0.011
Financial crisis & commodity price increase	corn	crude oil	0.270	0.603
Financial crisis & commodity price increase	crude oil	corn	3.747	0.053
Financial crisis & commodity price increase	soybean oil	crude oil	0.392	0.532
Financial crisis & commodity price increase	crude oil	soybean oil	6.712	0.010
Second calm period	wheat	crude oil	0.095	0.758
Second calm period	crude oil	wheat	9.583	0.002
Second calm period	corn	crude oil	0.214	0.644
Second calm period	crude oil	corn	1.601	0.206
Second calm period	soybean oil	crude oil	0.565	0.452
Second calm period	crude oil	soybean oil	0.013	0.908
Second calm period (1st part)	wheat	crude oil	0.008	0.930
Second calm period (1st part)	crude oil	wheat	7.584	0.006
Second calm period (1st part)	corn	crude oil	0.001	0.982
Second calm period (1st part)	crude oil	corn	0.306	0.581
Second calm period (1st part)	soybean oil	crude oil	0.043	0.837
Second calm period (1st part)	crude oil	soybean oil	0.209	0.648
Second calm period (2nd part)	wheat	crude oil	0.194	0.660
Second calm period (2nd part)	crude oil	wheat	1.868	0.172
Second calm period (2nd part)	corn	crude oil	1.470	0.002
Second calm period (2nd part)	crude oil	corn	3.689	0.055
Second calm period (2nd part)	soybean oil	crude oil	4.124	0.043
Second calm period (2nd part)	crude oil	soybean oil	1.490	0.223
COVID-19 period	wheat	crude oil	0.227	0.634
COVID-19 period	crude oil	wheat	1.870	0.041
COVID-19 period	corn	crude oil	0.198	0.657
COVID-19 period	crude oil	corn	0.212	0.646
COVID-19 period	soybean oil	crude oil	0.123	0.726

COVID-19 period	crude oil	soybean oil	0.012	0.912
War in Ukraine period	wheat	crude oil	0.462	0.497
War in Ukraine period	crude oil	wheat	7.301	0.007
War in Ukraine period	corn	crude oil	2.178	0.141
War in Ukraine period	crude oil	corn	2.710	0.101
War in Ukraine period	soybean oil	crude oil	6.585	0.011
War in Ukraine period	crude oil	soybean oil	3.377	0.067
Whole Period	wheat	crude oil	0.001	0.977
Whole Period	crude oil	wheat	7.493	0.006
Whole Period	corn	crude oil	0.690	0.406
Whole Period	crude oil	corn	1.506	0.220
Whole Period	soybean oil	crude oil	3.788	0.052
Whole Period	crude oil	soybean oil	3.794	0.052

Source: Authors' calculations.

Table A3: Estimates of Bubble Detection Tests

Test	**CL**	**ZC**	**ZL**	**KE**	**10% CI**
Adf	-2.620	-2.340	-1.650	-2.600	-0.417
Sadf	2.100	3.270	5.400	3.570	1.300
gsadf	2.720	4.320	6.180	4.100	2.140

Source: Authors' calculations.