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

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This study investigates the relationship between crude oil and agricultural prices. 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. 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, DCC-GARCH, hedge portfolio, long-run relationship, 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 bidirectional causality exists between the oil and agricultural prices over certain subperiods (Wei 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, Shao, and Kim, 2020), which makes such 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. Further, 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 that hedging efficiency and

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optimal portfolio allocation regarding commodities (Živkov, Manić, and Đurašković, 2020) 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 those financial assets and integrating the energy and commodities markets with financial markets (Zhang, Chevallier, and Guesmi, 2017). Investors who seek substantial returns often engage in high-risk trading, which in turn leads to speculation in various commodities and other assets (Wang, Wang, and Guo, 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, Ren, and Loy, 2020). Physical events like droughts and geopolitical issues further impacted prices in energy and agricultural sectors, which fostered speculation (Chemeris, Liu, and Ker, 2022; Zhou et al., 2023). Geopolitical events, such as wars and pandemics (e.g., 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.

This study investigates the long-term connections and cause-effect relationships, explores dynamic conditional correlations, scrutinizes price bubbles, and suggests optimal portfolio ratios between crude oil and agricultural commodity prices. Using data from Yahoo Finance for March 4, 2002, to August 1, 2023, we split the sample into two subperiods—tranquil (or calm) 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 heteroskedasticity (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. Using multiple methods and subperiods allows us to capture the complexity and variability of relationships between agricultural commodities and energy markets, which are influenced by economic, geopolitical, and market-specific events (e.g., financial crises, the COVID-19 pandemic, and the war in Ukraine). These approaches provide a deeper understanding of market dynamics, and 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. By highlighting commodity relationships under various market conditions, contributing to optimal hedging strategies, and understanding market behavior during crisis periods, this multidimensional approach is beneficial to investors and policy makers. We identify factors that play an important role in the oil–agriculture relationship and provide 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 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 (e.g., tranquil periods, crises, pandemics, and war).

We find evidence for 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. 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 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. Tiwari et al. (2021) note strong correlations between energy and agricultural markets, affected negatively by geopolitical risks, while Nazlioglu, Erdem, and Soytas (2013) observe risk transmission *after* crises but not before. Similarly, Kumar et al. (2021) find 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. After 2006, this link strengthened, exhibiting different trends before and after that year (Yahya, Oglend, and Dahl, 2019); the COVID-19 pandemic notably impacted this relationship, making it more persistent (Wang, Shao, and Kim, 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, which was 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. The 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, Liu, and Xu (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 comovements using a Bayesian framework, and Chen and Qu (2019) detect dynamic correlations between crude oil and various markets. Moreover, Wei et al. (2023) dynamically analyze price spillovers across crude oil, agricultural markets, and carbon emissions, 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.

Multiple studies delve into the causal connections among oil futures, commodities, and financial assets. More precisely, Wang, Wang, and Guo (2022) explore the dynamic relationship between oil prices and China's price index using Granger causality analysis, while Palazzi, Meira, and Klotzle (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, Wu, and Yang (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, Jareño, and Escribano (2021) show increased net return connections between agricultural commodities and oil price shocks during crises. Further, 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, Wei Su et al. (2019) find bidirectional causality between oil and agricultural prices in specific subperiods. Hung (2021) observes intensified return spillovers during the COVID-19 pandemic across different periods, with positive and negative interactions. However, studies in South Africa

(Fowowe, 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, Torero, and von Braun (2009) link speculative activity in agricultural commodity futures to surges and volatility in 2007–2008. Irwin, Sanders, and Merrin (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; 2011b; 2011a) fail to establish a substantial influence of index funds on commodity futures returns, rejecting the notion that index speculation caused the 2007–2008 price surge.

However, recent studies (Mao, Ren, and Loy, 2020; Ajmi, Hammoudeh, and Mokni, 2021; Wang, Wang, and Guo, 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, Živkov, Manić, and Đurašković (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. Further, Han et al. (2020) 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 policy makers, investors, and financial markets. However, no study has examined the various aspects of this relationship, investigating various subperiods, including the war in Ukraine. Our work aims to fill this gap in the literature.

Empirical Methodology

We implement a multistage 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.

Exploring Long-Run Relationships

First, the study examines the long-run relationship between the variables, employing the multifractal detrended cross-correlation analysis 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. Unlike the traditional econometric approach, the multifractal 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 (see, among many others, Daglis, 2022, 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,

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

and

$$Y(i) = \sum_{k=1}^{i} [y(k) - \bar{y}],\ i = 1, \ldots, N, \tag{2}$$

where $\bar{x}$ 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 $N_s = \left[\frac{N}{s}\right]$ nonoverlapping windows of equal length, which start from the beginning and from the end $2N_s$ in total; thus, we obtain the detrended covariance for each segment $= 1, 2, \ldots, N_s$:

$$F^2(s,v) = \frac{1}{s} \sum_{i=1}^{t} \left|X[(v-1)s+i] - X^v(i)\right| \left|Y[(v-1)s+i] - Y^v(i)\right|, \quad v = 1, 2, \ldots, N_s. \tag{3}$$

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

$$F^2(s,v) = \frac{1}{s} \sum_{i=1}^{t} \left|X[N-(v-N_s)s+i] - X^v(i)\right| \left|Y[N-(v-N_s)s+i] - Y^v(i)\right|, \quad v = 1, 2, \ldots, N_s, \tag{4}$$

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:

$$F_q(s) = \left\{ \frac{1}{2N_s} \sum_{v=1}^{2N_s} \left[F^2(s,v)\right]^{\frac{q}{2}} \right\}^{1/q},\ q \neq 0, \tag{5}$$

$$F_0(s) = \exp\left\{ \frac{1}{4N_s} \sum_{v=1}^{2N_s} \ln\left[F^2(s,v)\right] \right\},\ q = 0. \tag{6}$$

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

$$F_q(s) \sim s^{H_{xy}(q)}. \tag{7}$$

If the generalized cross-correlation exponent, $H_{xy}(q)$, depends on q, then the cross-correlation of the two series has multifractal properties. If $H_{xy}(q) > 0.5$, then the cross-correlation of the two time series is long-term persistent. If $H_{xy}(q) < 0.5$, then the cross-correlation is anti-persistent. Finally, if $H_{xy}(q) = 0.5$, then 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 article, we examine and characterize the Hurst exponent based on its value.

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 heteroskedasticity. Compared to static models or other correlation models (e.g., the constant conditional correlation 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 (e.g., BEKK-GARCH) because it balances flexibility, making it suitable for large datasets like the one used in this study. Engle and Sheppard (2001) introduce the dynamic conditional correlation (DCC) generalized autoregressive conditional heteroskedasticity (GARCH) model. Following 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. 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:

(8) $$r_t = \boldsymbol{\mu}_t + a_t\,,$$

(9) $$a_t = H_t^{1/2} z_t\,,$$

(10) $$H_t = D_t R_t D_t\,,$$

where $\boldsymbol{r}_t$ is an $n \times 1$ vector of log returns of n assets at time t, $\boldsymbol{a}_t$ is an $n \times 1$ vector of mean-corrected returns of n assets at time t (i.e., $E[a_t] = 0$), and $Cov[a_t] = H_t$, while $\boldsymbol{\mu}_t$ is a $n \times 1$ vector of the expected value of the conditional r_t, and $\boldsymbol{H}_t$ is an $n \times n$ matrix of conditional variances of a_t at time t. We then obtain $H_t^{1/2}$ through a Cholesky factorization of H_t, D_t; in this regard, $\boldsymbol{D}_t$ is an $n \times n$ diagonal matrix of conditional standard deviations of a_t at time t, $\boldsymbol{R}_t$ is an $n \times n$ conditional correlation matrix of a_t at time t, and z_t is an $n \times 1$ vector of *i.i.d.* errors such that $E[z_t] = 0$ and $E[z_t z_t^T] = I$.

Causal Investigation

Amornbunchornvej, Zheleva, and Berger-Wolf (2021) introduce the concept of variable-lag (VL) 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 assess 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, we can derive the residual $r^*_{Y_t X_t}$ using the following equation:

(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 $\delta_{\max}$ is the maximum time lag and $Delta_t > 0$ 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, and c_i optimally minimize the residuals r_{Y_t}, $r_{Y_t X_t}$, and $r^*_{Y_t X_t}$, respectively. When 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 A3 provides the estimates of variable-lag causality by commodities and period.

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. We implement two univariate tests—the supremum augmented Dickey-Fuller (SADF, Phillips, Wu, and Yu, 2011) and the generalized SADF (GSADF, Phillips, Shi, and Yu, 2015a,b)—and a panel GSADF (Pavlidis et al., 2016). Let

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

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; and 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 augmented Dickey–Fuller (ADF) test statistic is

$$ADF^{r_2}_{r_1} = \frac{\widehat{\beta} r_1, r_2}{\text{s.e.}\ \left(\widehat{\beta} r_1, r_2\right)}. \tag{13}$$

The standard ADF test, however, exhibits extremely low power in the case of boom–bust dynamics (Evans, 1991). For this reason, Phillips, Wu, and Yu (2011) suggest a recursive procedure that is compatible with a single boom–bust episode that involves the estimation of ADF regression in equation (12) on subsamples of the data. The supremum of this sequence defines the SADF statistics as

$$SADF\,(r_0) = \sup_{r_2 \in [r_0, 1]} ADF^{r_2}_{0}. \tag{14}$$

Similarly, the limit distribution of the SADF statistic is

$$\sup_{r_2 \in [r_{0,1}]} \frac{\int_0^{r_2} W dW}{\left(\int_0^{r_2} W^2\right)^{\frac{1}{2}}}. \tag{15}$$

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. Phillips, Shi, and Yu (2015a,b) propose an extension of the SADF test (GSADF), which permits both the start (r_1) and end (r_2) points to change and considers a larger number of subsamples than the SADF test. Unlike the SADF, the GSADF is compatible with multiple boom–bust episodes within a given time series. The GSADF statistic is as follows:

$$GSADF\,(r_0) = \sup_{r_2 \in [r_0, 1], r_1 \in [0, r_2 - r_0]} ADF^{r_2}_{r_1}. \tag{16}$$

Following Vasilopoulos, Pavlidis, and Martínez-García (2022) and Phillips, Shi, and Yu (2015a,b), the SADF and GSADF procedures can provide a chronology of vitality in the time series in case of null hypothesis rejection. Im, Pesaran, and Shin (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 in equation (12) is

$$\Delta p_{i,t} = \alpha_{i,r_1,r_2} + \beta_{i,r_1,r_2} p_{i,t-1} + \sum_{j=1}^{k} \psi^j_{i,r_1,r_2} \Delta p_{i,t-j} + \epsilon_{i,t}, \tag{17}$$

where $i = 1, \ldots, 4$ indicates the panel index and the other variables are as defined in equation (12). The null hypothesis of a panel unit root of the panel GSADF test is H$_0$: $\beta_{r_1 r_2} = 0$, in all 4 series against the alternative of explosive behavior in a subset of series, H$_1$: $\beta_{r_1 r_2} > 0$ for some i. We then construct the panel unit root test through the average of the individual backward SADF (BSADF) statistics at each period:

$$\text{panel } BSADF_{r_2}\,(r_0) = \frac{1}{N} \sum_{i=1}^{N} BSADF_{i,r_2}\,(r_0). \tag{18}$$

The panel GSADF statistic is the supremum of the panel BSADF:

$$\text{panel } GSADF(r_0) = \sup_{r_2 \in [r_0, 1]} \text{panel } BSADF_{r_2}(r_0). \tag{19}$$

Finally, Pavlidis et al. (2016) use bootstrapping to consider cross-sectional error dependence to compare the panel BSADF with the sequence of bootstrap critical values and identify dating episodes of overall exuberance (Pavlidis et al., 2016). Appendix Table A2 provides the results of the bubble detection tests.

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 i and j, a \$1 positive exposure to commodity i 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 commodities i and j is calculated as

$$\beta_{ij,t} = \frac{h_{ij,t}}{h_{jj,t}}, \tag{20}$$

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 equation (20), a dynamic hedging strategy consists of a long position of \$1 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 \$1 investment portfolio. Based on Kroner and Ng (1998), the optimal portfolio weight for commodity i can be expressed as

$$w_{ij,t} = \frac{h_{jj,t} - h_{ij,t}}{h_{ii,t} - 2h_{ij,t} + h_{jj,t}}, \text{ with } w_{ij,t} = \left\{ \begin{array}{ccc} 0, & \text{if} & w_{ij,t} < 0 \\ w_{ij,t}, & \text{if} & 0 \leq w_{ij,t} \leq 1 \\ 1, & \text{if} & w_{ij,t} > 1 \end{array} \right\}, \tag{21}$$

where $w_{ij,t}$ is the weight of commodity i in a dollar portfolio of two commodities (i and 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 equation (20). Note that the weight of the second commodity is $1 - w_{ij,t}$.

Data and Variables

We use daily data for crude oil future prices (CL), KC hard red wheat (KE), corn (ZC), and soybean oil (ZL) from March 4, 2002, and August 1, 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. Wheat (KE) appears to have the largest variability due to its high standard deviation and range (maximum minus minimum). Corn (ZC) and crude oil (CL) also exhibit notable variability, while soybean oil (ZL) seems to have comparatively lower variability based on its smaller range and standard deviation.

The selection of subperiods is important to understanding the dynamics of the market during different global events. Therefore, we divided the period under consideration (i.e., March 4, 2002–August 1, 2023) into five subperiods based on specific economic and geopolitical markers that significantly influenced global markets. These subperiods are the first tranquil period (January

Table 1. Descriptive Statistics of the Time-Series Data Used in the Study

Variable	CL ($/barrel)	KE ($/bushel)	ZC ($/bushel)	ZL ($/bushel)
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
Minimum	10.010	271.250	186.250	15.850
Maximum	145.290	1367.750	831.250	90.600
First tranquil period (January 2002–December 2006)				
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
Minimum	22.500	271.250	186.250	15.850
Maximum	77.030	546.000	390.250	34.850
Financial crisis and commodity price increase (January 2007–December 2009)				
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
Minimum	33.870	442.250	293.500	27.700
Maximum	145.290	1337.000	754.750	70.400
Second tranquil period (January 2010–January 2020)				
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
Minimum	26.210	362.000	301.500	26.050
Maximum	113.930	988.000	831.250	59.770
COVID-19 period (February 2020–February 2022)				
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
Minimum	10.010	414.000	302.750	24.990
Maximum	95.720	963.000	772.750	72.890
War in Ukraine (March 2022–August 1, 2023)				
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
Minimum	66.740	771.250	497.000	46.200
Maximum	123.700	1, 367.750	818.250	90.600

Notes: CL represents crude oil futures prices, KE is Kansas City hard red wheat, ZC is corn, and ZL is soybean oil.
Source: Yahoo! Finance.

2002–December 2006), the period of financial crisis and commodity price increase (January 2007–December 2009), the second tranquil period (January 2010–January 2020), the COVID-19 pandemic period (February 2020–February 2022), and the war in Ukraine period (March 2022–August 1, 2023). The rationale for selecting February 2020 as the starting point for the COVID-19 pandemic period is derived from early market disruptions in anticipation of the pandemic's global spread, and

Table 2. Estimation of Hurst Exponents for Long-Term Memory of Time Series

Period	Corn and Crude Oil	Soybean Oil and Crude Oil	Wheat Crude Oil
First tranquil period	1.3557	1.4065	1.2221
Financial crisis and commodity price increase	1.3617	1.4256	1.4348
Second tranquil period	1.6026	1.6131	1.5150
COVID-19 period	1.8089	1.8717	1.8338
War in Ukraine period	1.6403	1.5503	1.6814
Whole period	1.1800	1.0996	1.0847

we choose February 2022 as the end of the COVID-19 period to focus on the distinct economic phase before the war in Ukraine, another major case-effect in global markets. The Ukraine war period, starting in March 2022, was 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

Exploring Long-Run Relationships

Table 2 presents the Hurst exponents 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: the COVID-19 pandemic, Ukraine war, second tranquil period, financial crisis, first tranquil period, and overall. These findings stress the importance of scrutinizing subperiods to understand long-term relationships, emphasizing the novelty of our approach. The prevalence of long-term relationships during the COVID-19 pandemic highlights its profound impact on the global market, particularly on crude oil. The pandemic induced a demand shock, drastically reducing international oil prices (Bourghelle, Jawadi, and Rozin, 2021), leading to a price collapse with severe market repercussions. This underscores crude oil's pivotal role as a significant global commodity and major influence on agriculture (Ezeaku, Asongu, and Nnanna, 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 (Ben 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, Chevallier, and Guesmi, 2017). Financialization intensifies linkages, particularly in crude oil, as commodities integrate with financial products like futures, options, and exchange-traded funds (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. In support of previous literature, 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, Shao, and Kim (2020), who emphasize a dynamic relationship between agricultural and energy markets. Our contribution lies in examining tranquil and crisis periods to assess the effect of each crisis on long-term relationships. Additionally, we employ multifractal analysis, complementing econometric models prevalent in the literature, thereby providing robust results.

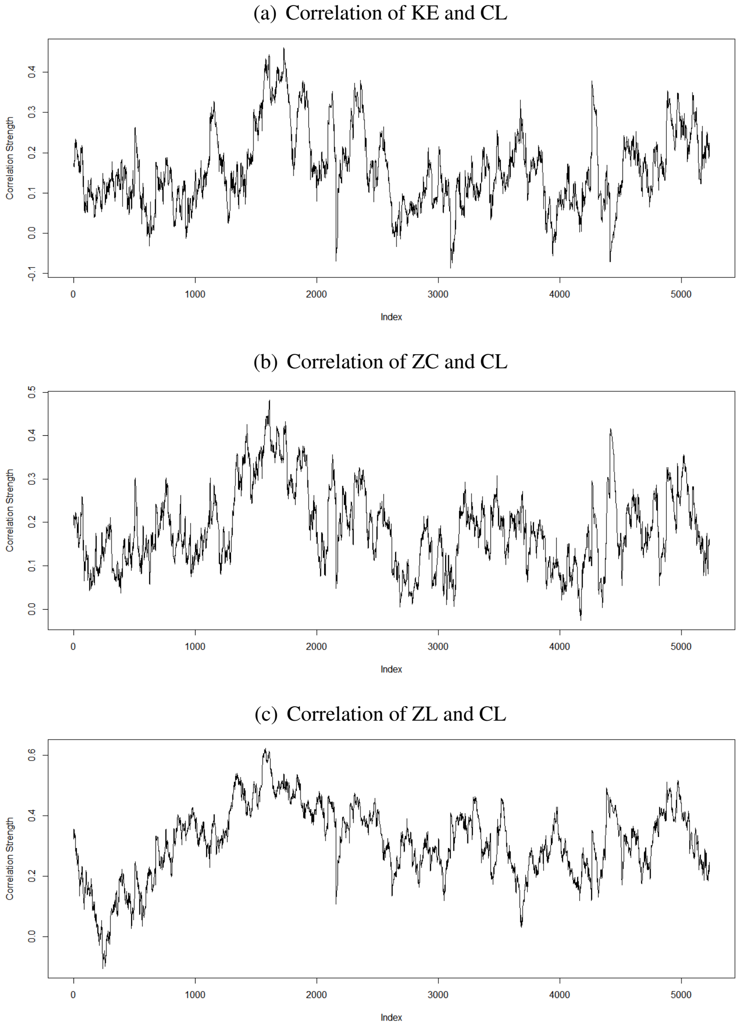

Figure 1. Dynamic Cross-Correlation Plots of Agricultural Commodities and Crude Oil

Notes: Dotted lines indicate the change in the subperiods examined.

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 of the agricultural commodities and 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; the maximum values are 0.460 for wheat, 0.481 for corn, and 0.623 for soybean oil. The plots in Figure 1 also show that corn and wheat demonstrate heightened volatility in their correlation with crude oil during the initial tranquil period. In contrast, soybean oil exhibits an upward trend. All commodities reach their peak correlation with crude oil during the financial crisis and the period of price increases, particularly on June 5, 2009, when wheat showed its maximum correlation of 0.460

with crude oil; on December 12, 2008, when corn indicated its maximum correlation of 0.481, and on October 30, 2008, when soybean oil showed its maximum correlation of 0.623.

In the subsequent tranquil period, the correlation of all commodities with crude oil exhibit elevated volatility. During 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 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 (i.e., 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 subperiods 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 comovements. 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 subperiods 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. Finally, the peaks in corn and wheat are more alike than those in soybean oil, which indicates that soybean oil—a significant biofuel and substitute energy source—is an essential commodity in its relationship with crude oil.

Causal Investigation

Table 3 presents the VL-Granger causality analysis. 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 Appendix 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 and 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, Salim, and Bloch, 2009; Wen et al., 2019), with economic and financial implications (Huntington, 2005; Lang and Auer, 2020). However, we extend these results by showing how these relationships change over subperiods of economic, financial, and political importance, including the COVID-19 pandemic 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 Miljkovic, 2022). 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 subperiods, consistent with prior studies (Wei Su et al., 2019), which also emphasize the impact of crises on this linkage (Umar, Jareño, and Escribano, 2021). 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.

Table 3. Variable-Lag Causality Results

Period	*X* Variable	*Y* Variable	*F*-Test	*p*-Value
First tranquil period	Corn	Crude oil	1.562	0.058
Financial crisis and commodity price increase	Crude oil	Wheat	6.477	0.011
	Crude oil	Corn	3.747	0.053
	Crude oil	Soybean oil	6.712	0.010
Second tranquil 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
	Soybean oil	Crude oil	6.585	0.011
	Crude oil	Soybean oil	3.377	0.067
Whole period	Crude oil	Wheat	7.493	0.006
	Soybean oil	Crude oil	3.788	0.052
	Crude oil	Soybean oil	3.794	0.052

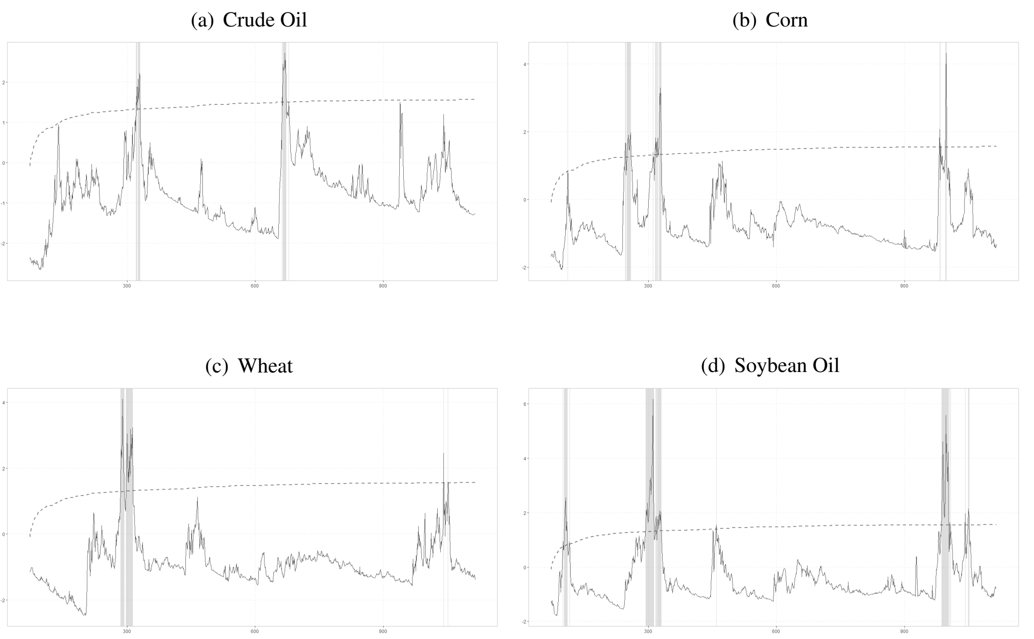

Figure 2. Bubble Detection for Crude Oil, Corn, Wheat, and Soybean Oil

Price Bubble Detection

Figure 2 presents the results of the price bubble detection. Appendix Table A3 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. Corn showed more price bubbles of shorter duration during 2004, during the financial crisis, and during the COVID-19 pandemic (specifically, in 2021); these 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, amid the COVID-19 pandemic (notably in 2021), and, most recently, with the onset of the war in Ukraine. Wheat demonstrated price bubbles during the financial crisis and the war in Ukraine. Evidence of price bubbles in crude oil and agricultural commodities remains contentious. While Gilbert (2010b) find weaker indications of bubble behavior in crude oil markets, Ajmi, Hammoudeh, and Mokni (2021) and Mao, Ren, and Loy (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, Torero, and von Braun (2009) suggest that speculative activity has contributed significantly to excess price surges and volatility in wheat, maize, soybeans, and rice markets during 2007–2008. However, Sanders and Irwin (2011b,a) challenge the hypothesis, finding no substantial evidence to link commodity index speculation to the 2007–2008 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 current price increase in crude oil is due not to speculation but rather to political events and the market's performance.

Hedging Strategies

Turning to the financial risk management context, we provide the optimal hedge ratios and optimal weights in Table 4. The optimal hedge ratios are relatively low during the first tranquil 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 tranquil period. At the same time, the weights show a strong preference for crude oil (CL) toward soybean oil (ZL), indicating that a more robust hedge between commodities might be better to mitigate risk during turbulent times. Moreover, during the second tranquil period, the optimal hedge ratios and weights are similar to those in the first quiet period, with some variation. In 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; Chunhachinda, De Boyrie, and Pavlova, 2019; Živkov, Manić, and Đurašković, 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. (2020) argue that the results for hedging strategies vary; 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

Table 4. Hedging Optimal Portfolio Ratios and Weights by Period and Commodities

		Porfolio Ratios		Weights	
Period	**Case**	**Average**	**Std. Dev.**	**Average**	**Std. Dev.**
First tranquil period	CL_KE	0.098	0.040	0.371	0.047
	KE_CL	0.060	0.022	0.629	0.047
	CL_ZC	0.150	0.049	0.362	0.103
	ZC_CL	0.088	0.029	0.638	0.103
	CL_ZL	0.155	0.064	0.335	0.094
	ZL_CL	0.086	0.039	0.665	0.094
Financial crisis and commodity price increase	CL_KE	0.417	0.281	0.419	0.238
	KE_CL	0.277	0.091	0.581	0.238
	CL_ZC	0.472	0.245	0.420	0.233
	ZC_CL	0.346	0.094	0.580	0.233
	CL_ZL	0.860	0.301	0.173	0.229
	ZL_CL	0.413	0.110	0.827	0.229
Second tranquil period	CL_KE	0.137	0.112	0.468	0.159
	KE_CL	0.118	0.089	0.532	0.159
	CL_ZC	0.163	0.112	0.443	0.183
	ZC_CL	0.121	0.078	0.557	0.183
	CL_ZL	0.502	0.228	0.227	0.145
	ZL_CL	0.194	0.073	0.773	0.145
COVID-19 period	CL_KE	0.233	0.324	0.361	0.196
	KE_CL	0.106	0.057	0.639	0.196
	CL_ZC	0.512	0.630	0.315	0.254
	ZC_CL	0.175	0.114	0.685	0.254
	CL_ZL	0.760	0.871	0.291	0.238
	ZL_CL	0.277	0.136	0.709	0.238
War in Ukraine period	CL_KE	0.343	0.059	0.422	0.098
	KE_CL	0.274	0.043	0.578	0.098
	CL_ZC	0.406	0.143	0.264	0.217
	ZC_CL	0.179	0.131	0.736	0.217
	CL_ZL	0.370	0.092	0.414	0.121
	ZL_CL	0.285	0.046	0.586	0.121
Whole period	CL_KE	0.195	0.165	0.421	0.163
	KE_CL	0.141	0.090	0.579	0.163
	CL_ZC	0.272	0.316	0.393	0.195
	ZC_CL	0.158	0.092	0.607	0.195
	CL_ZL	0.512	0.410	0.259	0.169
	ZL_CL	0.219	0.105	0.741	0.169

Notes: CL represents crude oil futures prices, KE is Kansas City hard red wheat, ZC is corn, and ZL is soybean oil.

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, this article aimed to answer these questions and to do so, we have employed a multifaceted approach.

Conclusion and Policy Implications

This article focuses on four commodities: crude oil (CL), wheat (KE), corn (ZC), and soybean oil (ZL). We divide the study period into different subperiods 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 are influenced by supply chain disruptions, economic shifts, or changes in demand. The case study of the war in Ukraine unveiled that the commodities examined behave differently, not only before and during the war but also 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 subperiods. 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, which played a part in their price increase.

During the war in Ukraine, geopolitical events significantly influenced 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; 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 that the subperiods chosen since the COVID-19 pandemic and the war in Ukraine overlapped. This did not affect the importance of our results, but future directions could look for a double effect, using machine learning or other techniques.

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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

Notes: Notably, "mu" represents the conditional mean for a variable or asset in the model, and "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. Many of the parameters are statistically significant, including 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.

Table A2. 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

Notes: CL represents crude oil futures prices, KE is Kansas City hard red wheat, ZC is corn, and ZL is soybean oil.

Table A3. Estimates of Variable-Lag Causality by Commodities and Period

Period	*X* Variable	*Y* Variable	*F*-Test	*p*-Value
First tranquil period	wheat	crude oil	0.377	0.539
	crude oil	wheat	1.114	0.189
	corn	crude oil	1.562	0.058
	crude oil	corn	0.023	0.878
	soybean oil	crude oil	0.046	0.830
	crude oil	soybean oil	0.030	0.863
Financial crisis & commodity price increase	wheat	crude oil	0.142	0.706
	crude oil	wheat	6.477	0.011
	corn	crude oil	0.270	0.603
	crude oil	corn	3.747	0.053
	soybean oil	crude oil	0.392	0.532
	crude oil	soybean oil	6.712	0.010
Second tranquil period	wheat	crude oil	0.095	0.758
	crude oil	wheat	9.583	0.002
	corn	crude oil	0.214	0.644
	crude oil	corn	1.601	0.206
	soybean oil	crude oil	0.565	0.452
	crude oil	soybean oil	0.013	0.908
Second tranquil period (1st part)	wheat	crude oil	0.008	0.930
	crude oil	wheat	7.584	0.006
	corn	crude oil	0.001	0.982
	crude oil	corn	0.306	0.581
	soybean oil	crude oil	0.043	0.837
	crude oil	soybean oil	0.209	0.648
Second tranquil period (2nd part)	wheat	crude oil	0.194	0.660
	crude oil	wheat	1.868	0.172
	corn	crude oil	1.470	0.002
	crude oil	corn	3.689	0.055
	soybean oil	crude oil	4.124	0.043
	crude oil	soybean oil	1.490	0.223
COVID-19 period	wheat	crude oil	0.227	0.634
	crude oil	wheat	1.870	0.041
	corn	crude oil	0.198	0.657
	crude oil	corn	0.212	0.646
	soybean oil	crude oil	0.123	0.726
	crude oil	soybean oil	0.012	0.912
War in Ukraine period	wheat	crude oil	0.462	0.497
	crude oil	wheat	7.301	0.007
	corn	crude oil	2.178	0.141
	crude oil	corn	2.710	0.101
	soybean oil	crude oil	6.585	0.011
	crude oil	soybean oil	3.377	0.067
Whole period	wheat	crude oil	0.001	0.977
	crude oil	wheat	7.493	0.006
	corn	crude oil	0.690	0.406
	crude oil	corn	1.506	0.220
	soybean oil	crude oil	3.788	0.052
	crude oil	soybean oil	3.794	0.052