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Multifractal cross-correlation analysis between crude oil and agricultural futures markets: evidence from Russia–Ukraine conflict

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Abstract

Purpose – This study investigates the impacts of the Russia–Ukraine conflict on the cross-correlation between agricultural commodity prices and crude oil prices.

Design/methodology/approach – The authors used MultiFractal Detrended Fluctuation Cross-Correlation Analysis (MF-X-DFA) to explore the correlation behavior before and during conflict. The authors analyzed the price connections between future prices for crude oil and agricultural commodities. Data consists of daily futures price returns for agricultural commodities (Corn, Soybean and Wheat) and Crude Oil (Brent) traded on the Chicago Mercantile Exchange from Aug 3, 2020, to July 29, 2022.

Findings – The results suggest that cross-correlation behavior changed after the conflict. The multifractal behavior was observed in the cross correlations. The Russia–Ukraine conflict caused an increase in the series' fractal strength. The study findings showed that the correlations involving the wheat market were higher and anti-persistent behavior was observed.

Research limitations/implications – The study was limited by the number of observations after the Russia–Ukraine conflict.

Originality/value – This study contributes to the literature that investigates the impact of the Russia–Ukraine conflict on the financial market. As this is a recent event, as far as we know, we did not find another study that investigated cross-correlation in agricultural commodities using multifractal analysis.

Keywords Commodity markets, Agricultural, Russian–Ukraine conflict, Cross-correlation, Volatility

Paper type Research paper

1. Introduction

Agricultural commodities price volatilities increased substantially after the period 2006–2008, where prices hit their historical record (Wright, 2011; Trujillo-Barrera *et al.*, 2012; Jeong and Gopinath, 2022). Food-energy and food-stock market linkages carry major reasons to explain rising prices (Serra, 2011; Lahiani *et al.*, 2013). Energy prices influence feedstock markets, particularly crude oil prices (Tyner, 2010; Zhang *et al.*, 2010; Serra, 2011; Vacha *et al.*, 2013; Kristoufek *et al.*, 2014; Saghaian *et al.*, 2018; Janda and Kristoufek, 2019).

More recently, the global economic impacts of the Covid-19 pandemic have changed commodity price behavior (Sharma *et al.*, 2020; Borgdards *et al.*, 2021; Farid *et al.*, 2022; Hung, 2021; Wang and Shimokawa, 2021). The Covid-19 outbreak pointed to significant levels of volatility spillovers across crude oil and agricultural markets, changing the pattern of net transmission (World Bank, 2020; Rajput *et al.*, 2020; Beckman and Countryman, 2021; Borgdards *et al.*, 2021; Dmytrów *et al.*, 2021; Farid *et al.*, 2022; Hung, 2021).

The high volatility scenario was also intensified with the beginning of military conflict between the Russian Federation and Ukraine, from February 24, 2022, increasing the instability in financial and commodities markets. Specifically, grain prices exhibit positive

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breakpoints, once the positions of both countries in the wheat and corn international markets (Fang and Shao, 2022; Hassen and El Bilali, 2022; Just and Echaust, 2022; Wang *et al.*, 2022).

Further, crude oil has been a determinant in explaining volatility increase after the beginning of the conflict, becoming a net transmitter of return spillover, while wheat and soybeans become net volatility receivers (Fang and Shao, 2022; Hassen and El Bilali, 2022; Wang *et al.*, 2022). In addition, agricultural costs are affected by the disruption of Russian fertilizer exports (Adekoya *et al.*, 2022; Bongou and Yatié, 2022; Umar *et al.*, 2022).

Cross-correlation is a measure employed to evaluate the relationship between two time series. As Derrick and Thomas (2004) argue, cross-correlation quantifies the similarity between two series by examining how one series is correlated with the other at different points in time. In financial time-series analysis, cross-correlation analysis has become a widely utilized measure in several empirical investigations (Cao *et al.*, 2018).

Considering the uncertainties in the commodities price relationship, we examined the cross-correlation among international grain markets (wheat, corn and soybean CME futures) and crude oil markets (Brent) before and after the beginning of the military conflict. The analysis was conducted using the use of MF-X-DFA (Multifractal Detrended Fluctuation Cross-Correlation Analysis) method.

This study contributes to the empirical literature that evaluates price and volatility connections in agricultural commodities markets during crisis periods. Further, the analysis considering the Russia–Ukraine conflict can contribute new elements to the current (and sparse) literature, especially with the adoption of a methodology that allows the analysis on various timescales (Kristoufek, 2015; Quintino *et al.*, 2021).

The remainder of this paper is organized as follows. Section 2 discusses the existing literature on this topic. Section 3 presents the data used in this study. Section 4 presents a step-by-step description of multifractal methodology (MultiFractal Detrended Fluctuation cross-correlation analysis). Section 5 presents the results of the empirical investigation. Section 6 outlines the conclusions, implications, limitations and future research agendas.

2. Volatility dynamics in agricultural markets over crisis periods

Concerns over agricultural commodities price volatilities increased from period to 2006–2008, where prices reached the highest level in history (Wright, 2011; Trujillo-Barrera *et al.*, 2012; Jeong and Gopinath, 2022). Recently, after the Covid-19 pandemic crisis, this subject was treated by several studies (Rajput *et al.*, 2020; Sharma *et al.*, 2020; Beckman and Countryman, 2021; Dmytrów *et al.*, 2021; Borgdards *et al.*, 2021; Farid *et al.*, 2022; Hung, 2021; Wang and Shimokawa, 2021).

From 2006 to 2008 period, the major reasons for the substantial price increase were demand growth from developing countries, production shortfalls, U.S. monetary policy (led U.S. dollar devaluated) and an increase in biofuel production (Zhang *et al.*, 2010; Serra, 2011; Vacha *et al.*, 2013; Kristoufek *et al.*, 2014; Cabrera and Schulz, 2016; Saghaian *et al.*, 2018). Considering these different directions in the explanation of food prices, Serra and Zilberman (2013) highlighted the challenges to point to causality effects in commodity prices, which can result from speculations in financial futures and stock markets, as well as from weather conditions, policy regulations, macroeconomic policies and conditions, such as exchange rates and interest rates.

Most studies that focused on volatility analysis for the 2006–2008 period show evidence that energy prices have a significant influence on feedstock markets, especially under the relationship between crude oil prices and grain markets (Zhang *et al.*, 2010; Serra, 2011; Kristoufek *et al.*, 2014; Trujillo-Barrera *et al.*, 2012; Vacha *et al.*, 2013; Saghaian *et al.*, 2018). Thus, the increased price correlation between agricultural and energy markets results in stronger volatility spillovers and raises concerns among consumers, producers, financial markets and policymakers (Tyner, 2010; Saghaian *et al.*, 2018).

Recent studies have also focused on the linkages between energy and agricultural markets to evaluate the impacts of the Covid-19 pandemic on price volatilities. Commodities prices first declined, stimulated by oil and metal prices, once manufacturing and transportation were directly affected. Thus, the first (negative) impact on demand as well as on the energy markets partially affects agricultural commodities (World Bank, 2020; Rajput *et al.*, 2020; Dmytrów *et al.*, 2021). Later, the gradual recovery of economies, a decrease in global grain stocks, and an increase in crude oil prices led to a significant increase in agricultural commodity prices from mid-2020 to 2021 (Beckman and Countryman, 2021).

Agricultural commodities markets exhibit strong overreactions after the coronavirus crisis, where higher volatility was observed among grain markets (Rajput *et al.*, 2020; Beckman and Countryman, 2021; Hung, 2021). The Covid-19 outbreak pointed to significant levels of volatility spillovers across crude oil and agricultural markets, whereas corn, wheat and soybean increased their patterns as net transmitters of volatility to other markets, such as livestock, sugar and oats (Borgdards *et al.*, 2021; Farid *et al.*, 2022; Hung, 2021).

Recently, the conflict between Russia and Ukraine impacted commodity price dynamics, especially wheat and crude oil (Umar *et al.*, 2022; Wang *et al.*, 2022). Notwithstanding, indirect impacts on agricultural markets were noted as a consequence of the disruption of Russian fertilizer exports and the increase in agricultural production costs. Additionally, the dynamics of financial markets and global economic indicators, such as price indices and exchange rates, affect uncertainties over commodity futures prices (Adekoya *et al.*, 2022; Bongou and Yatié, 2022; Umar *et al.*, 2022).

Focusing on the volatility transmission in agricultural commodities prices, preliminary studies have pointed out that some of the grain markets (wheat, corn, barley and soybeans) exhibited greater volatility after the beginning of the Russia–Ukraine conflict, even in comparison to previous crisis periods, as the 2006–2008 and Covid-19 pandemic (Wang *et al.*, 2022; Just and Echaust, 2022; Hassen and El Bilali, 2022; Fang and Shao, 2022). Overall, it seems that crude oil has been a determinant in explaining the volatility increase after the start of the conflict, becoming a net transmitter of return spillovers, while wheat and soybeans are net volatility receivers (Wang *et al.*, 2022; Fang and Shao, 2022). However, Just and Echaust (2022) show that short-term volatility spillover increases among grain markets.

Prices connections in these preliminary studies used derivations of autoregressive traditional models. Just and Echaust (2022) apply Diebold and Yilmaz's (2014) spillover index to explore the role of each commodity in spillover transmission. Wang *et al.* (2022) used a time-varying approach of spillovers (TVP-VAR), an extension of the spillover approach of Diebold and Yilmaz (2014). Fang and Shao (2022) also used the spillover approach of Diebold and Yilmaz (2014), after measured the risk intensity of the conflict based on the Geopolitical Risk Index (GPR), estimating the relationship between GPR indices for Russia and Ukraine and then constructing a dynamic volatility model using the GJR-GARCH model.

Fractal and multifractal analyses have recently been used to understand price dynamics in agricultural commodities markets (He and Chen, 2010, 2011; Kim *et al.*, 2011; Li and Lu, 2012; Liu, 2014; Wang and Hu, 2015; Delbianco *et al.*, 2016; Lu *et al.*, 2017; Ruan *et al.*, 2020; Stosic *et al.*, 2020; Wang and Feng, 2020; Wang *et al.*, 2020; Gao *et al.*, 2022; Memon *et al.*, 2022). A few of these studies focused on the analysis of crisis cycles (Stosic *et al.*, 2020; Wang *et al.*, 2020; Gao *et al.*, 2022; Memon *et al.*, 2022) and the linkages between energy and agricultural prices (Liu, 2014; Delbianco *et al.*, 2016; Memon *et al.*, 2022). Furthermore, no studies have used these methods to investigate price dynamics after the beginning of the Russia–Ukraine conflict.

Most previous studies have focused on the Chinese market. He and Chen (2010) and Li and Lu (2012) investigated the price relationships in agricultural futures markets in China and the

US adopting a Multifractal Detrended Cross-Correlation Analysis (MF-DCCA). He and Chen (2011) applied a similar analysis between the Chinese and US markets, but their focus was on the dependency of price volume in agricultural futures markets. Lu *et al.* (2017) employed a MF-DFA and a MF-DCCA to examine cross-correlation behavior between Chinese exchange rate and four international commodities price indexes, including agricultural markets. Ruan *et al.* (2020) focused their analysis on the connections at the domestic level of the Chinese soybean, soybean meal and soybean oil markets, conducting an analysis using the MF-DFA and MF-DCCA methods.

Kim *et al.* (2011) and Stosic *et al.* (2020) also considered local markets price dynamics. Kim *et al.* (2011) examined agricultural prices return correlation in the Korean market and related their findings with the financial assets behavior in the same market. Stosic *et al.* (2020) investigated the multifractal properties of 12 agricultural markets in Brazil from 2000 to 2020, using daily and monthly prices. One of their goals was to understand the impacts of the 2007–08 commodities boom on the dynamics of Brazilian agricultural cash prices. Both these studies applied MF-DFA.

Other studies have examined commodity prices and volatilities at the international level. Liu (2014) investigated the cross-correlation between US spot grains and WTI crude oil markets, using a MF-DCCA. Delbianco *et al.* (2016) applied the MF-DFA to a long-run analysis considering the World Bank commodities price indexes for soybean, energy and non-fuel, and the Down Jones commodities price indexes for energy, Brent crude oil and petroleum. Their study used two different time series periods and daily and monthly data. International price indexes were also used by Gao *et al.* (2022), given special attention to crisis periods, as 2007–2008 and Covid-19. Gao *et al.* (2022) performed multifractal detrending moving average (MF-DMA).

Memon *et al.* (2022) also investigated the 2007–2008 crisis and Covid-19 impacts in the agricultural prices. The authors considered the daily international prices of several energy, metals and agricultural commodities, and employed a MF-DFA. Wang *et al.* (2020) examined the Covid-19 consequences over Brent crude oil and global sugar, wheat, orange juice and cotton markets performing a MF-DCCA.

Additionally, Wang and Hu (2015) examined the cross-correlation between the US interest rate and the CBOT soybean, corn wheat and rice futures markets by applying a multifractal detrended cross-correlation analysis (MF-DXA) for daily time series between 2000 and 2014. Wang and Feng (2020) also investigated the CBOT futures markets by performing two new fractal statistical methods to study the autocorrelation, cross-correlation and coupling correlation of the 12 US agricultural futures and spot markets.

3. Data

The data consist of daily returns of futures prices of agricultural commodities (corn, soybean and wheat) and crude oil (Brent) traded on the Chicago Mercantile Exchange from August 3, 2020, to July 29, 2022. Futures prices represent closing quotes for nearby contracts. Considering the Russia–Ukraine conflict, we consider two groups in the data sample: before (pre) and during (post) the conflict. The pre-conflict sample comprises the period from August 3, 2020, to February 23, 2022. The post-conflict sample was from February 24, 2022, to July 29, 2022.

This sample period comprises two entire years, as well as the Northern Hemisphere 2020/21 and 2021/22 crop seasons, pre-season and off-season. Therefore, the use of this period minimizes the possible effects of seasonality on agricultural prices, allowing for a better capture of potential conflict effects over these markets.

Data were collected from Refinitiv Eikon database and daily returns were calculated as follows:

$$R_t = \ln(P_t - P_{t-1}) \tag{1}$$

where R_t corresponds to the daily return and P_t is the price (index value) in the day t.

4. Methodology

4.1 MF-X-DFA methodology

We employed the MultiFractal Detrended Fluctuation cross-correlation analysis (MF-X-DFA or MF-DCCA) methodology developed by Zhou (2008) to evaluate the cross-correlation between two time series. This technique is particularly useful when dealing with data with different sampling frequencies and noise levels. Prior studies have demonstrated the effectiveness of this method (Zhang *et al.*, 2021; Cao and Xu, 2016; Xi *et al.*, 2016), including studies on the Russia–Ukraine conflict (Adekoya *et al.*, 2023). Therefore, we selected this method to effectively analyze the relationship between the time series under investigation and explain their cross-correlation.

This method examines the multifractal behavior of the cross-correlation between two series, $y(i)$ and $x(i)$, with size N, $i = 1,2, \ldots, N$. The MF-X-DFA method is described in five steps, as follows:

Step 1. Determine the profile of the two series:

$$X(i) = \sum_{n=1}^{i}\left(x(n) - \bar{x}\right), Y(i) = \sum_{n=1}^{i}\left(y(n) - \bar{y}\right), i = 1, 2, \ldots N, \tag{2}$$

where $\bar{x} = (1/N)\sum_{i=1}^{N} x(i), \bar{y} = (1/N)\sum_{i=1}^{N} y(i)$.

Step 2. Divide the two series $\{X(i)$ and $Y(i)\}$ into $Ns = \text{int}(N/s)$ non-overlapping segments of equal length s. When N is not an integer multiple of s, the process is repeated from the tail of the series. Thus, $2Ns$ can be obtained together.

Step 3. The local trends $X^v(i)$ and $Y^v(i)$ for each segment v ($v = 1,2,3, \ldots, 2Ns$) are evaluated by least-squares fitting with a polynomial of order m. In this study, we used $m = 1$, which is commonly used in MultiFractal Detrended Fluctuation cross-correlation analysis (MFX-DFA) to remove trends in the data while retaining the original fluctuations. The parameter "m" represents the order of the polynomial used for detrending the time series, and its choice depends on the properties of the data being analyzed. However, in some cases, other values of "m" may be more appropriate depending on the specific properties of the data being analyzed (see Cao *et al.*, 2018). The local covariance function is:

$$F^2(s,v) = \frac{1}{s}\sum_{i=1}^{s}|X((v-1)s+i) - X^v(i)| \cdot |Y((v-1)s+i) - Y^v(i)| \tag{3}$$

and for each segment v, $v = Ns + 1, \ldots, 2Ns$ follows:

$$F^2(s,v) = \frac{1}{s}\sum_{i=1}^{s}|X(N-(v-N_s)s+i) - X^v(i)| \cdot |Y(N-(v-N_s)s+i) - Y^v(i)| \tag{4}$$

Step 4. The q-order fluctuation function is obtained by averaging all segments, as follows:

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

for $q = 0$ the function is obtained as follows:

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

Step 5. The scaling behavior of the fluctuations is obtained by analyzing the log-log plot of $F_q(s)$ vs s. If series $y(i)$ and $x(i)$ are long-term cross-correlated, $F_q(s)$ will increase for large values of s.

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

The log of $F_q(s)$ is presented as follows:

$$logF_q(s) = H_{xy}(q)\log(s) + logA \tag{8}$$

where $H_{xy}(q)$ is the generalized cross-correlation exponent. If $H_{xy}(q)$ is dependent on q, the cross-correlation is multifractal; otherwise, it is monofractal (Ghazani and Khosravi, 2020). The behavior scale of the segment with a large fluctuation is obtained for positive q. On the contrary, ($q < 0$) will have small fluctuations. For $q = 2$, the $H_{xy}(q)$ has the same interpretation as the univariate Hurst exponent (Cao *et al.*, 2018). Thus, the cross-correlation is long-range persistent for $H_{xy}(2) > 0.5$. For $H_{xy}(2) < 0.5$, the correlation is anti-persistent, which means that a rising price is likely to follow another falling price. However, if $H_{xy}(2) = 0.5$, there is no cross-correlation, or there is a very short range. ΔH can be used to measure the degree of time-varying multifractality as follows:

$$\Delta H = H_{max}(q) - H_{min}(q) \tag{9}$$

Greater Δh values indicate a strong degree of multifractality. Another measure for quantifying the degree of multifractality is the efficiency measure (MDM) (Wang *et al.*, 2009; Kakinaka and Umeno, 2022). The MDM can be obtained as follows:

$$D = \frac{1}{2}(|H(-10) - 0.5| + |H(10) - 0.5|) \tag{10}$$

The value of $D = 0$ indicates that there is no change in H, and converges to 0.5. The series exhibit a monofractal structure. $D > 0$ indicates that the series is persistent, and $D < 0$ indicates anti-persistence.

It is also possible to estimate a multifractal-scale exponent. According to Kantelhardt *et al.*, 2002, this exponent is $\tau(q)$, as follows:

$$\tau_{xy}(q) = qH_{xy}(q) - 1 \tag{11}$$

The multifractality of the series is obtained by the spectrum f(α), which is related to $\tau(q)$ by a Legendre transformation as follows:

$$\alpha = H_{xy}(q) + qH'_{xy}(q) \tag{12}$$

$$f(\alpha) = q(\alpha - H_{xy}(q)) + 1 \tag{13}$$

where α is the first derivative of $\tau(q)$, called the singularity force or Hölder exponent, and $f(\alpha)$ is the singularity or multifractal spectrum.

In the monofractal series, the spectral parameters tend to be $\alpha = h(2)$ and $f(\alpha) = 1$. The relationship between the two measures shows the complexity of each part of the time series. If the graph $f(\alpha)$ and α presents an inverse parabolic shape of the spectra, it confirms the existence of multifractality for the series (see Cao *et al.*, 2018).

The width of the multifractal spectrum $\Delta\alpha$ is expressed as follows:

$$\Delta\alpha = \max(\alpha) - \min(\alpha) \tag{14}$$

Choi (2021) also suggests the calculation of the spectral asymmetry parameter, estimated as follows:

$$\theta = \frac{(\alpha_0 - \alpha_{min}) - (\alpha_{max} - \alpha_0)}{(\alpha_0 - \alpha_{min}) + (\alpha_{max} - \alpha_0)} \tag{15}$$

where α_0 is the value of α for the maximum value of $f(\alpha)$.

The asymmetry parameter θ determines the dominance of fluctuations in the multifractal spectrum. If $\theta = 0$, large or small fluctuations contribute to the multifractality. Parameter $\theta > 0$ implies that large fluctuations contribute substantially to the multifractal spectrum. The spectrum exhibits asymmetry on the left side. For $\theta < 0$, smaller fluctuations constitute the dominant multifractality source. The spectrum exhibits asymmetry on the right side. The R package "MFDFA" was used for MF-X-DFA analysis.

Finally, it is important to emphasize that the cross-correlation analysis performed in our empirical research using the MFXDFA method is an ex-post analysis based on past data and not an *ex ante* analysis that makes predictions about future outcomes. It is crucial to note that our study aims to investigate the relationships between variables using historical data, rather than making forecasts or projections for future prices.

5. Results and discussion

Figure 1 shows the series graphs of returns and futures market prices for crude oil and agricultural commodities in the period before and during the Russian-Ukraine conflict, where the rise in the price return volatility of crude oil and wheat is more evident as the conflict begins.

Table 1 shows the descriptive statistics of the series of returns for the crude oil and agricultural commodities futures markets. We can observe (Figure 1) that volatility clusters are present on the day of the Ukraine invasion by Russia (February 24th, 2022). Volatilities were more persistent in the crude oil and wheat markets because the standard deviation of returns was higher in the post-conflict period.

Russia is an important supplier of crude oil and wheat. Ukraine is an important supplier of corn. The conflict between countries affected world markets. The results are in line with the findings of Fang and Shao (2022), who show that the Russia–Ukraine conflict significantly increased agricultural, metallurgical and energy market volatility.

Figure 2 plots the log-log of the fluctuation functions $F_q(s)$ for $q = 2$ vs the time scale (s) for the series pairs of crude oil and agricultural commodities returns before and during the Russia–Ukraine conflict.

For both periods, each curve is linear, suggesting a cross-correlation between the crude oil and agricultural commodities futures markets. This evidence confirms the findings of Feng and Cao (2022) that there is a cross-correlation between crude oil and agricultural

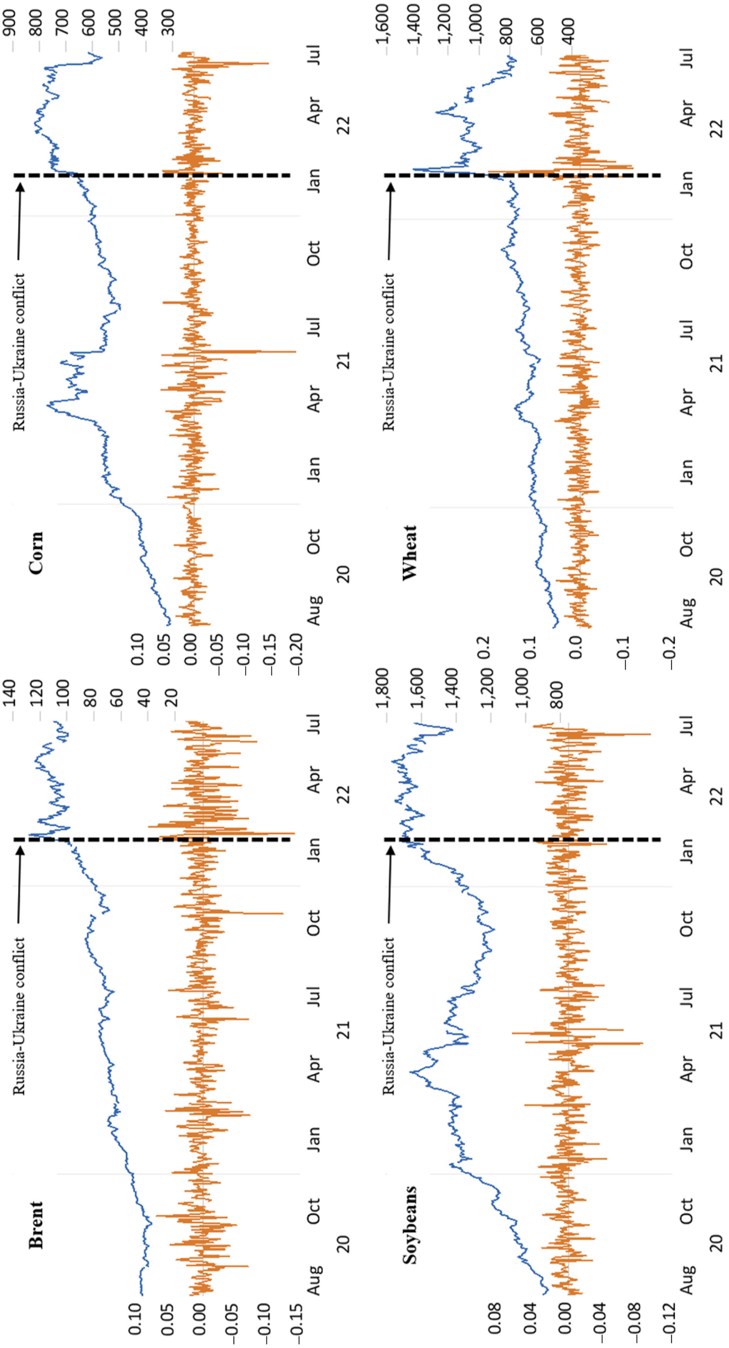

Figure 1.
Daily prices and returns of commodities markets

	Mean	Max	Min	Std. Dev	Skew	Kurt	J.B.
Brent							
pre-Conflict	0.0020	0.0721	−0.1231	0.0205	−0.8630	7.2612	0.0000
post-Conflict	0.0012	0.0843	−0.1411	0.0358	−0.6921	4.5289	0.0001
Wheat							
pre-Conflict	0.0013	0.0576	−0.0427	0.0182	0.3040	2.9854	0.0480
post-Conflict	−0.0008	0.1970	−0.1130	0.0420	0.7119	6.9423	0.0000
Soybean							
pre-Conflict	0.0016	0.0643	−0.0855	0.0147	−0.6339	7.4891	0.0000
post-Conflict	−0.0002	0.0398	−0.0937	0.0196	−1.0515	6.5374	0.0000
Corn							
pre-Conflict	0.0020	0.0621	−0.1910	0.0202	−2.2456	24.3102	0.0000
post-Conflict	−0.0010	0.0588	−0.1399	0.0255	−1.6516	10.3221	0.0000

Note(s): J.B. denotes the *p*-value of the Jarque–Bera normality test

Table 1.
Descriptive statistics of the return series before and during the Russia–Ukraine conflict

commodities futures prices, suggesting that crude oil futures price returns are affected by fluctuations in agricultural commodity futures price returns and vice versa.

However, the differences in the slopes between the lines of the graphs (Figure 2) before and during the conflict indicate that the Hurst exponents of the two periods are different. Evidence shows that the behavior of the cross-correlation between pairs differed after the beginning of the conflict. This evidence was more significant for Brent-soybean and Corn-soybean. According to Yao *et al.* (2021), distinct asymmetry on small timescales (s < 100) suggests that long-term investors should pay more attention to short-term asymmetric correlations.

Figure 3 shows the generalized Hurst exponent for different values of q in the range −10 to 10. We adopted a q range of −10 to 10, as suggested by Feng *et al.* (2022). To ensure the reliability of our results, we performed a robustness analysis by defining the scale from 10 to N/5; however, this has not been reported in the manuscript. The decreasing curvature of Hurst exponents indicates that cross-correlations between futures markets have multifractal properties. The results of $\Delta H>0$ (Table 1) confirm the multifractal characteristics of the series. The difference between the values before and during the Russia–Ukraine conflict is greater for pairs with wheat and soybean futures markets. The ΔH values were higher during the conflict. The differences were even greater for large fluctuations ($q > 0$), indicating that the asymmetric feature was more evident after the beginning of the Russia–Ukraine conflict and for large fluctuations. Such findings are more evident among Brent-Wheat, Corn-Soybean, Corn-Wheat and Soybean-Wheat. These results were different from the findings of Yao *et al.* (2021), who showed that the asymmetric characteristic is more evident when small-scale fluctuations occur.

The Hurst Exponent values indicate the persistence level of the cross-correlations. Figure 3 shows that the cross-correlations between futures markets were anti-persistent ($H < 0.5$) during the Russian conflict. The H values were lower after the conflict beginning for large fluctuations ($q > 0$). However, the values of H were higher than 0.5 for small fluctuations ($q < 0$) in the conflict. Except for the cross-correlation between Brent and Soybean. The results of $H(q = 2)$, H_{max}, H_{min} and *MDM* are listed in Table 2 and confirm these findings. $H(q = 2)$ values less than 0.5 and negative *MDM* (see Table 2) during conflict confirm anti-persistence. Feng and Cao (2022) argue that anti-persistence indicates that a positive (negative) change in futures prices is statistically more likely to be followed by a negative (positive) change in futures prices and vice versa. A possible explanation is that the shock of the Russia–Ukraine conflict affected the fluctuations in oil prices and agricultural commodities at the time of the event. The dissemination of information after the beginning of the event calmed the investors. After the event, the persistence of the shock dissipated in the series, and prices returned to the standard fluctuation. Shen and Chen (2022) state that the reduction in persistence can be explained by government interference in markets after an event, when they analyzed the effect of the Covid-19 outbreak on the stock market. These results corroborate Feng and Cao (2022) findings.

Multifractal spectrum analysis best describes nonlinear dependence. According to Cao *et al.* (2018), Feng *et al.* (2022) and Yao *et al.* (2021), the monofractal behavior is represented by a line on the graph of $f(\alpha)$ (multifractal spectrum), which occurs in series with a single characteristic scale of variation On the other hand, simple multifractal behavior is represented by a smooth curve, indicating variations on different scales, but not

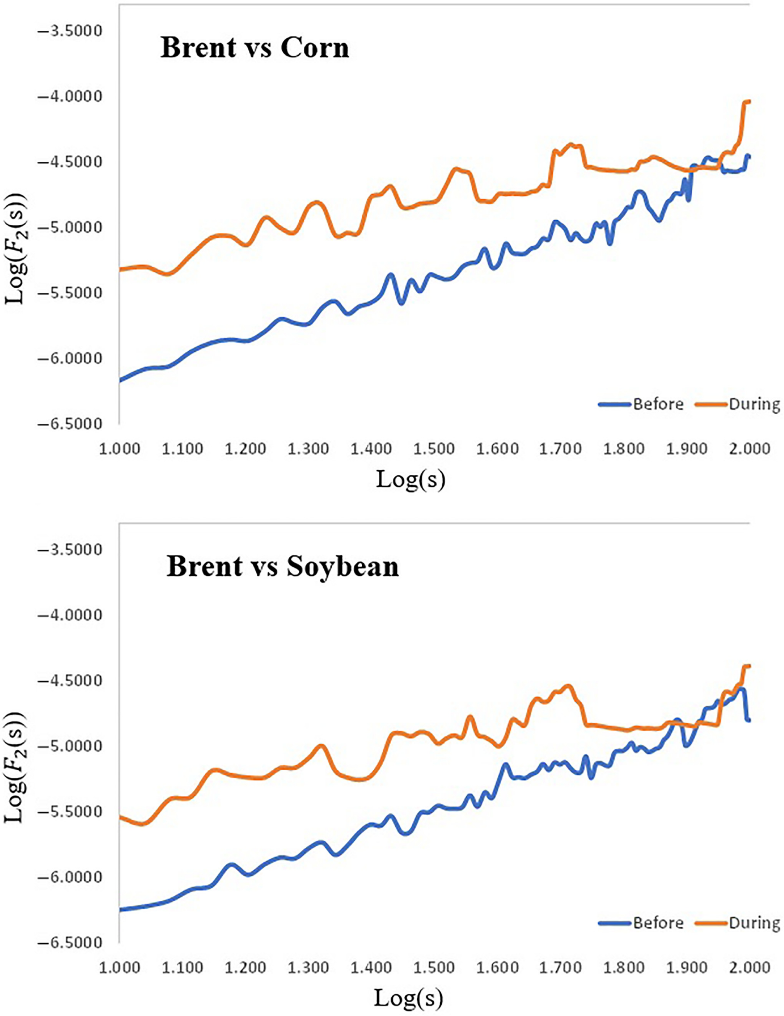

Figure 2.
Log-log plots of the fluctuation functions ($q = 2$) vs s for cross-correlations before and during the Russia–Ukraine conflict

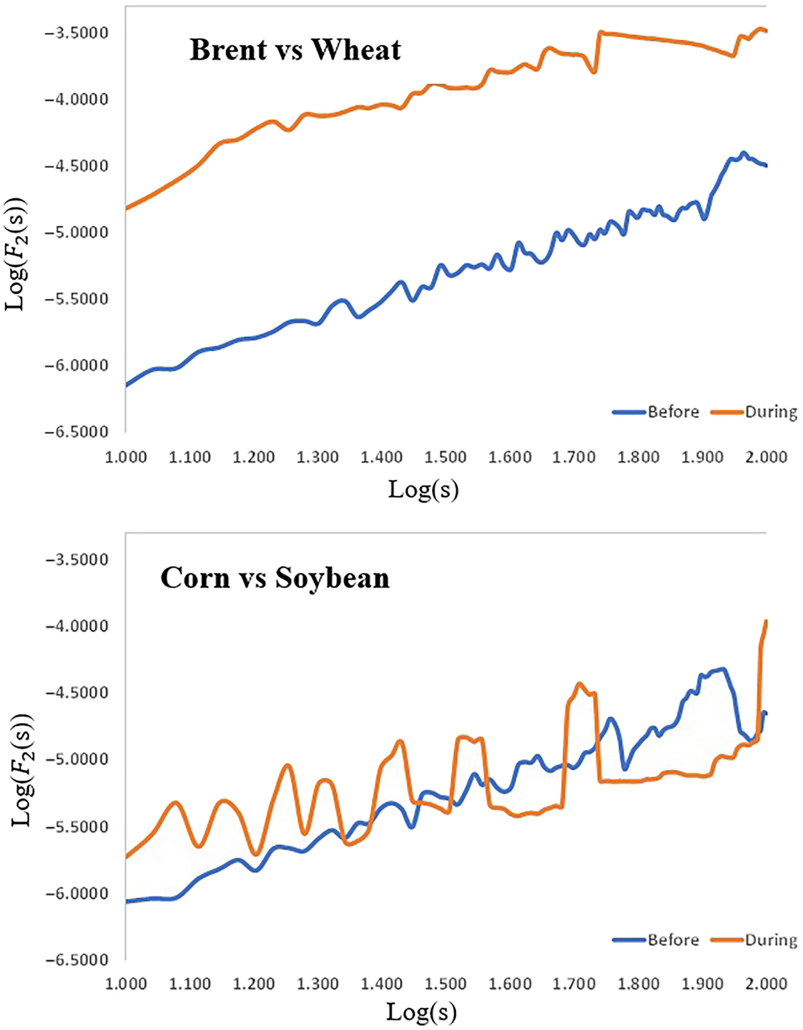
Brent vs Wheat
Log(F_2(s))
−3.5000
−4.0000
−4.5000
−5.0000
−5.5000
−6.0000
−6.5000
1.000
1.100
1.200
1.300
1.400
1.500
1.600
1.700
1.800
1.900
2.000
Log(s)
Before
During
Corn vs Soybean
Log(F_2(s))
Log(s)

Figure 2.

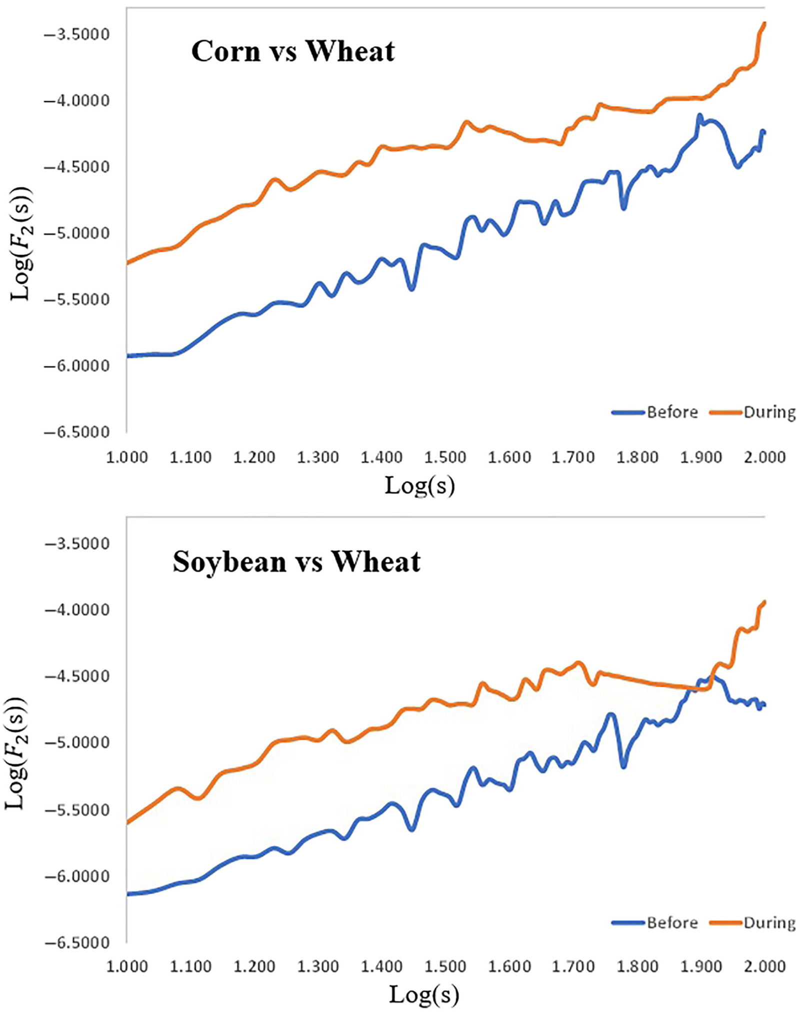
Corn vs Wheat
Log(F_2(s))
−3.5000
−4.0000
−4.5000
−5.0000
−5.5000
−6.0000
−6.5000
1.000
1.100
1.200
1.300
1.400
1.500
1.600
1.700
1.800
1.900
2.000
Log(s)
Before
During
Soybean vs Wheat
Log(F_2(s))
−3.5000
−4.0000
−4.5000
−5.0000
−5.5000
−6.0000
−6.5000
1.000
1.100
1.200
1.300
1.400
1.500
1.600
1.700
1.800
1.900
2.000
Log(s)
Before
During

Figure 2.

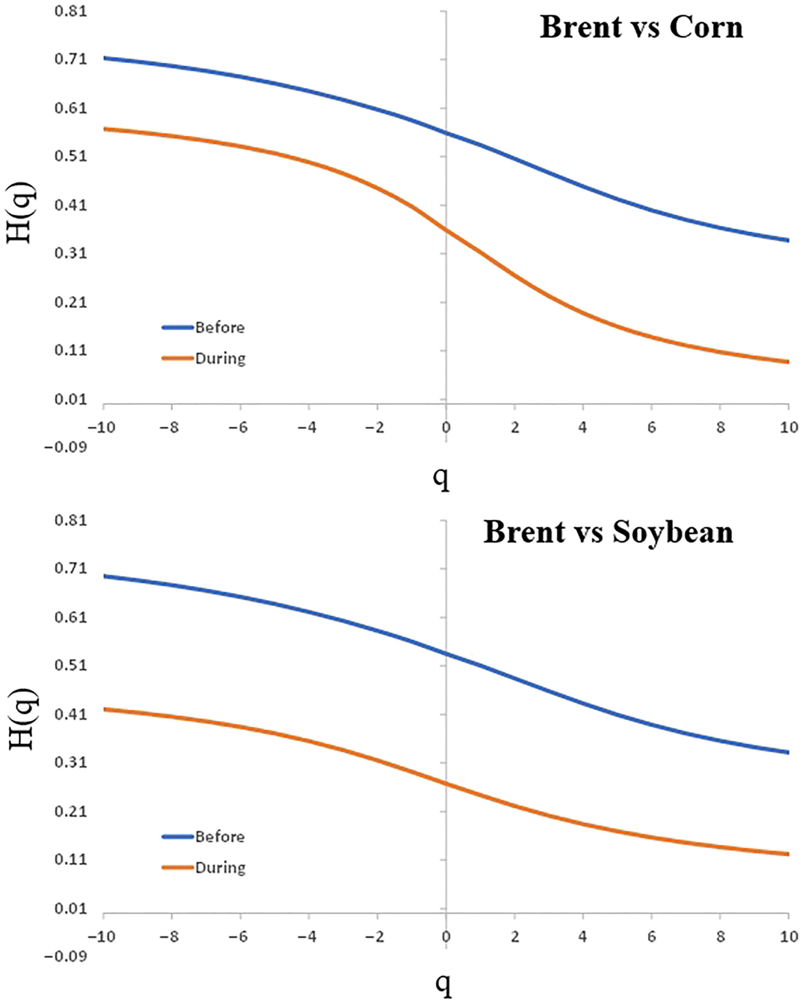

Figure 3.
Cross-correlation Hurst exponent before and during the Russia–Ukraine conflict

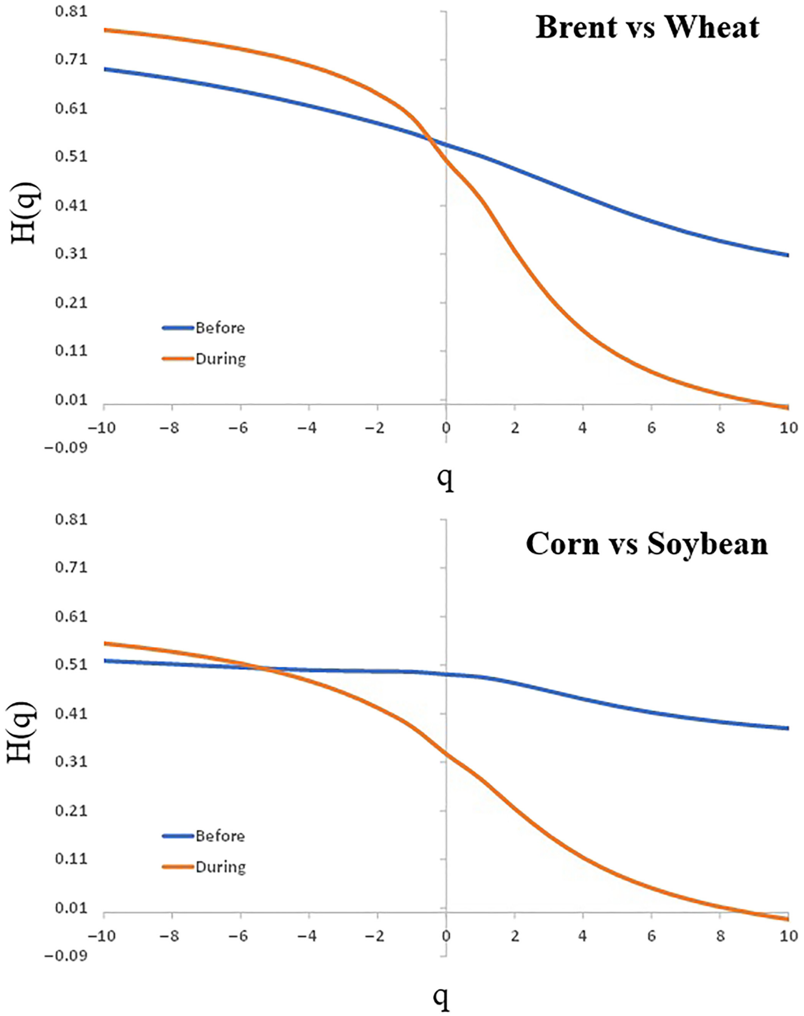
Brent vs Wheat
H(q)
0.81
0.71
0.61
0.51
0.41
0.31
0.21
0.11
0.01
−0.09
−10
−8
−6
−4
−2
0
2
4
6
8
10
q
Before
During
Corn vs Soybean
H(q)
0.81
0.71
0.61
0.51
0.41
0.31
0.21
0.11
0.01
−0.09
−10
−8
−6
−4
−2
0
2
4
6
8
10
q
Before
During

Figure 3.

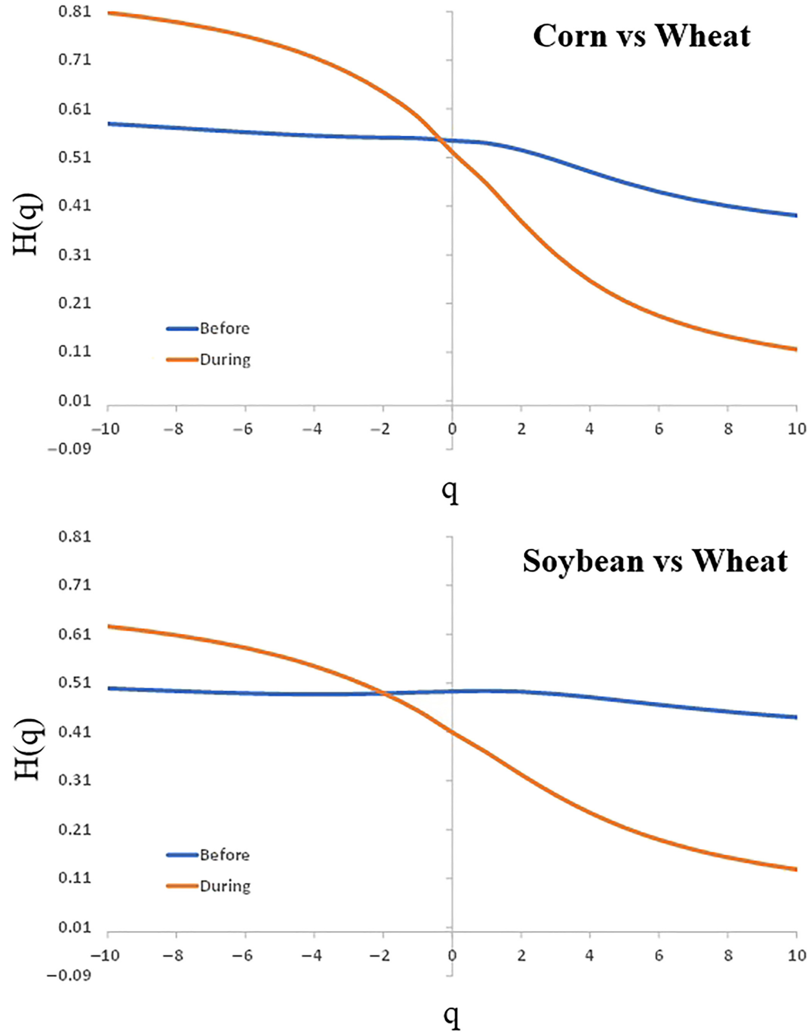
Corn vs Wheat
H(q)
0.81
0.71
0.61
0.51
0.41
0.31
0.21
0.11
0.01
−0.09
−10
−8
−6
−4
−2
0
2
4
6
8
10
q
Before
During
Soybean vs Wheat
H(q)
0.81
0.71
0.61
0.51
0.41
0.31
0.21
0.11
0.01
−0.09
−10
−8
−6
−4
−2
0
2
4
6
8
10
q
Before
During

Figure 3.

Table 2.
Multifractal parameters of cross-correlations

	α_{max}	α_{min}	$\Delta\alpha$	$H(q = 2)$	H_{max}	H_{min}	ΔH	θ	MDM
Brent vs Corn									
pre-Conflict	−0.2192	−0.7679	0.5487	0.5057	0.7133	0.3374	0.3759	0.1004	0.0254
post-Conflict	−0.3715	−0.9961	0.6246	0.2650	0.5673	0.0867	0.4806	−0.0106	−0.1730
Brent vs Soybean									
pre-Conflict	−0.2263	−0.7675	0.5412	0.4844	0.6954	0.3315	0.3639	0.0288	0.0135
post-Conflict	−0.5152	−0.9383	0.4231	0.2213	0.4209	0.1220	0.2989	−0.1397	−0.2286
Brent vs Wheat									
pre-Conflict	−0.2250	−0.8139	0.5889	0.4857	0.6913	0.3076	0.3837	0.1082	−0.0005
post-Conflict	−0.1604	−1.1195	0.9591	0.3166	0.7721	−0.0070	0.7791	0.1342	−0.1175
Corn vs Soybean									
pre-Conflict	−0.4512	−0.6753	0.2241	0.4729	0.5191	0.3796	0.1395	0.4378	−0.0507
post-Conflict	−0.3741	−1.1173	0.7432	0.2143	0.5548	−0.0138	0.5686	0.0581	−0.2295
Corn vs Wheat									
pre-Conflict	−0.3827	−0.6883	0.3056	0.5255	0.5795	0.3909	0.1886	0.4934	−0.0148
post-Conflict	−0.1111	−0.9924	0.8813	0.379	0.8079	0.1156	0.6923	0.0174	−0.0382
Soybean vs Wheat									
pre-Conflict	−0.4755	−0.6085	0.1330	0.4925	0.4993	0.4401	0.0592	0.5444	−0.0303
post-Conflict	−0.2979	−0.9727	0.6748	0.3227	0.6265	0.1281	0.4984	0.0092	−0.1227

extremely irregular. In addition, complex multifractal behavior is characterized by multiple curves and peaks in the graph of $f(\alpha)$, indicating extremely irregular variations at different scales, resulting in a highly heterogeneous distribution of singularities along the series, to be considered as an estimate of the multifractal force. Figure 4 plots the multifractal spectra of cross-correlations in the period before and during the Russia–Ukraine conflict for futures price returns of crude oil and agricultural commodities.

Table 2 reports α_{max}, α_{min}, $\Delta\alpha$ and θ values. The spectral curvature was greatest during the Russia–Ukraine conflict. Such evidence suggests that the dependencies are nonlinear between cross-correlations in both periods. Cao *et al.* (2018) state that one cannot simply conclude which variable is the cause of another volatility, as they interact with each other. The fact that the spectrum width during the Russia–Ukraine conflict was significantly greater than that before the conflict (see $\Delta\alpha$ in Table 2) suggests that the impact of fluctuations in returns is more persistent in bear markets than in bull markets.

Overall, we can observe that cross-correlations between markets occur regardless of the Russia–Ukraine conflict. However, the behavior of the correlations differed after the beginning of the conflict, which caused greater asymmetries of correlations and anti-persistent behavior ($H < 0.5$). Evidence suggests that the correlations between pre-conflict markets follow a random walk. However, this conflict has changed investors' decision-making behavior. The anti-persistent effect indicates that the cross-correlations are mean-reversing. In practice, this means that a high cross-correlation value after an extreme event is followed by a low value and vice versa.

Multifractal behavior was observed in the cross correlations. The Russia–Ukraine conflict caused an increase in the fractal strength of the series. According to Shen and Chen (2022), there are two sources of multifractality: the effect of fat tails and long-term correlations. Evidence suggests the effects of fat tail.

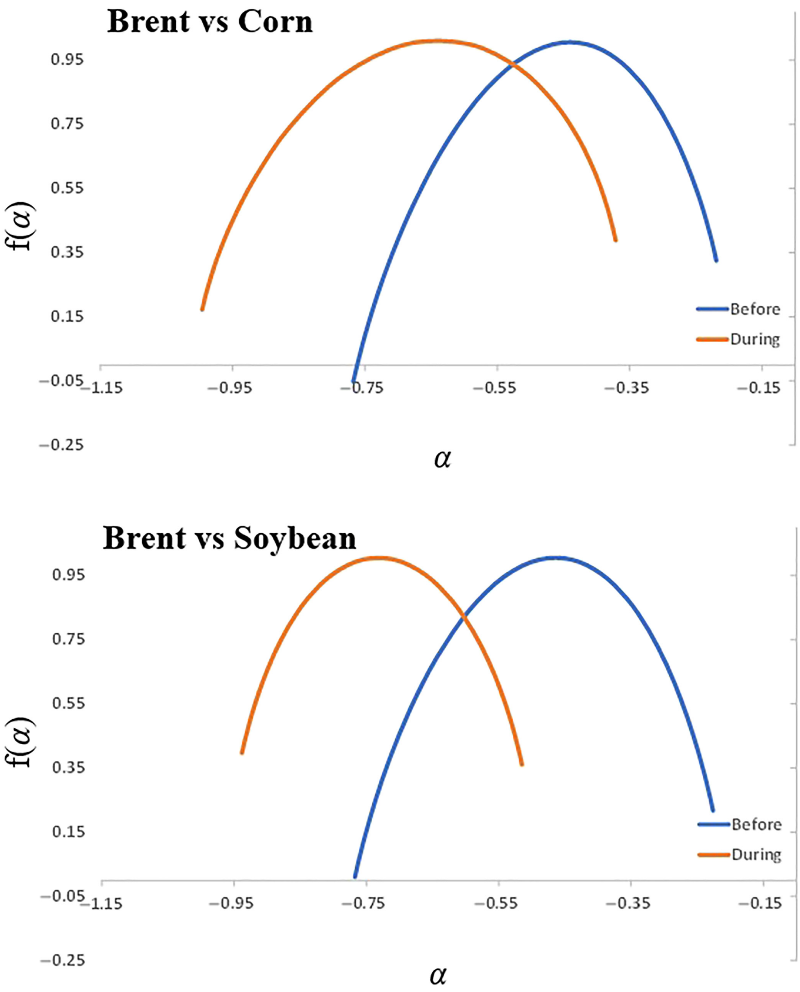

Figure 4.
Multifractal spectrum of cross-correlations before and during the Russia–Ukraine conflict

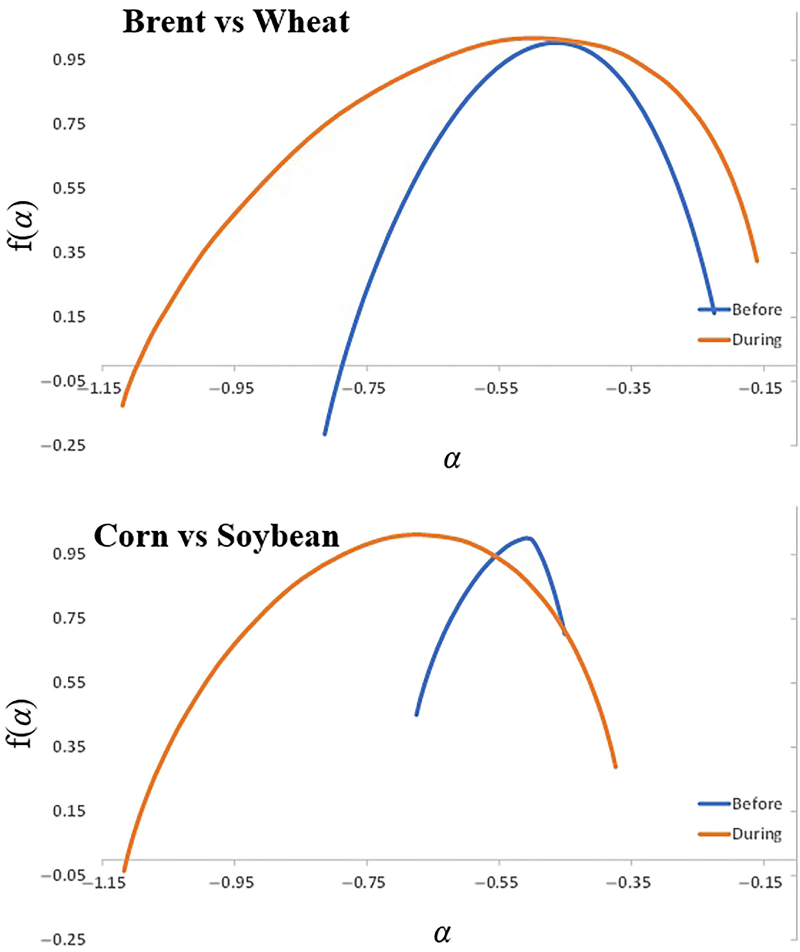
Brent vs Wheat
f(α)
0.95
0.75
0.55
0.35
0.15
−0.05
−0.25
−1.15
−0.95
−0.75
−0.55
−0.35
−0.15
α
Before
During
Corn vs Soybean
f(α)
0.95
0.75
0.55
0.35
0.15
−0.05
−0.25
−1.15
−0.95
−0.75
−0.55
−0.35
−0.15
α
Before
During

Figure 4.

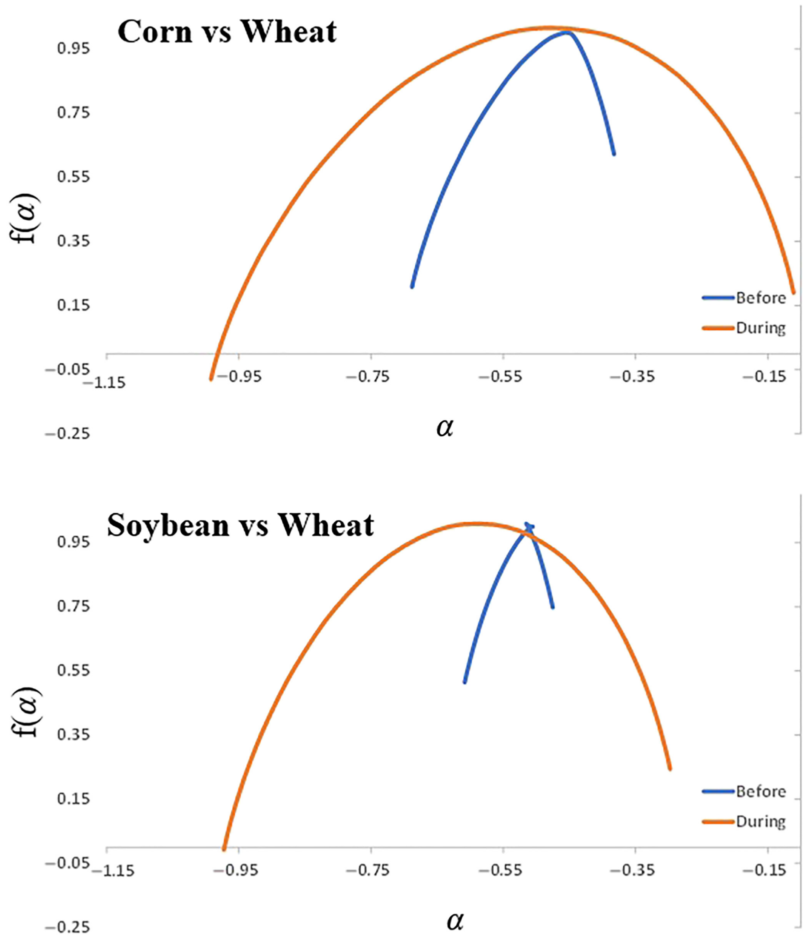

Figure 4.

Evidence shows that agricultural commodity futures markets were most affected by the Russia–Ukraine conflict. Correlations involving the wheat market had a greater impact. Just and Echaust (2022), Wang *et al.* (2022) and Fang and Shao (2022) corroborate the findings. Just and Echaust (2022) identified record return spillover transmissions among agricultural commodities during a period of conflict and the strongest transmitters are wheat, maize and barley. Wang *et al.* (2022) pointed out that volatility spillover in commodities markets exceed the level observed during the Covid-19 pandemic period. Fang and Shao (2022) showed that the intensification of the Russia–Ukraine conflict significantly increases the volatility of agricultural markets. On the other hand, the crude oil market has a lower impact. The findings confirm those of Huang *et al.* (2022), who suggest that investors in the crude oil market can hedge risk during extreme ups and downs.

6. Conclusion

This study analyzed the multifractality of cross-correlations of agricultural futures and crude oil markets during the Russia–Ukraine conflict. Corn, soybean, wheat and Brent markets traded on the CME from August 3, 2020 to July 29, 2022 were investigated. The main idea was to analyze whether the Russian–Ukraine conflict significantly changed the behavior of the grain and crude oil markets. Our findings reveal that conflict changes market behavior. The fractal strength increased after the beginning of the military conflict, and the anti-persistent behavior of the correlations was noted.

This study has several practical implications for investors, market analysts and risk managers. Cross-correlations between markets were observed to occur independently of extreme events, such as the Russia–Ukraine conflict. However, such events can affect the behavior of the correlations, leading to asymmetry and anti-persistent behavior. Investors must be mindful of such changes in cross-correlation behavior, as they can affect investment decision-making and risk management.

For investors in agricultural commodities, particularly in the wheat market, it is crucial to understand the transmission of recorded return spillovers during conflict periods. Doing so can assist with risk management and decision-making. The intensification of the Russia–Ukraine conflict could significantly increase the volatility of agricultural markets; therefore, investors must be ready to manage additional risks. One strategy to minimize risks could be to diversify their investment portfolios.

Moreover, cross-correlation analysis between oil and agricultural commodity prices suggests that investors should consider other commodity prices when assessing the risk and return of investments in oil and agricultural commodities. This is particularly important for investors who are significantly exposed to such markets. For instance, investors in the crude oil market can hedge risks during extreme booms and busts, which can assist in managing portfolios and minimizing losses.

These results are also important for market analysts who must factor political risk in their investment decisions. Increased price volatility during political conflicts can affect the profitability of commodity investment. Thus, it is essential to assess the political environment and market conditions carefully before making commodity investment decisions.

This study contributes to the literature on the impact of the Russia–Ukraine conflict on the financial market. No studies have investigated the impact of conflict on agricultural commodity returns using fractal analysis, especially when this analysis is based on cross-correlation between markets. The contribution of this study is also evident in the analysis of cross-correlations in commodities. The literature is still recent on this topic and there are few studies that investigate (He and Chen, 2010; Li and Lu, 2012; Lu *et al.*, 2017; Ruan *et al.*, 2020; Fernandes *et al.*, 2022).

The study was limited by the number of observations after the beginning of the Russia–Ukraine conflict. We used daily data, which limited our sample size. Cao *et al.* (2018) suggest a window with more than 200 observations. From the perspective of future studies, we suggest analyzing cross-correlation with intraday data. Another suggestion for a future agenda is to analyze the relationship between price and volume after the conflict. The literature is limited to price returns. No studies have analyzed the cross-correlation between prices and trading volumes.

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