Research on World Agricultural Economy
https://journals.nasspublishing.com/index.php/rwae

RESEARCH ARTICLE

A Time Trend and Persistence Analysis of Sunflower Oil and Olive Oil Prices in the Context of the Russia-Ukraine War

Manuel Monge

Faculty of Law, Business and Government, Universidad Francisco de Vitoria, Madrid, 28223, Spain

Abstract: The imbalances between sunflower oil production (Ukraine) and olive oil production (Europe) due to the substitution effects caused by the Russian invasion of Ukraine on 24 February 2022 affected the prices. Given that Ukraine is the largest producer of global sunflower oil and Europe is the largest territory that produces olive oil, this scientific article tries to analyze the global prices of both vegetable oils and understand how the war between Russia and Ukraine has affected them. Advanced statistical and econometric methods to carry out this analysis have been used. It is found that the prices of both variables separately have similar behavior and that the shock caused by the war will be transitory, with the original price trend recovering in the long term using fractional integration methods. In a multivariate analysis, using a causality test in the frequency domain we observe that both variables are related to each other, and the effects of war will have an impact in the long term, with olive oil being the cause. A negative relationship between both variables measured with a wavelet analysis is also observed. Furthermore, if this trend continues, the price of olive oil would prevail over the price of sunflower in the war between Russia and Ukraine. Finally, a 12-month prediction is presented using artificial neural networks, where the price of olive oil will be high for at least 11 more months. The price of sunflower oil is predicted to last for only 5 more months.

Keywords: Global olive oil prices; Global sunflower oil prices; Fractional integration; ARFIMA (p,d,q) model; FCVAR model; Causality test; Wavelet analysis

1. Introduction

For market participants, prices are essential signals because they give information about the efficient allocation of physical, human, and financial resources. The prices are the balance point between supply and demand, and agricultural commodities are essential for understanding and analyzing their behavior.

After the 2000s, agricultural commodities began to

*Corresponding Author:
Manuel Monge,
Faculty of Law, Business and Government, Universidad Francisco de Vitoria, Madrid, 28223, Spain;
Email: manuel.monge@ufv.es

Received: 30 April 2024; **Received in revised form:** 26 May 2024; **Accepted:** 28 May 2024; **Published:** 26 August 2024

Citation: Monge, M., 2024. A Time Trend and Persistence Analysis of Sunflower Oil and Olive Oil Prices in the Context of the Russia-Ukraine War. *Research on World Agricultural Economy*. 5(3): 24–36. DOI: https://doi.org/10.36956/rwae.v5i3.1096

DOI: https://doi.org/10.36956/rwae.v5i3.1096

Copyright © 2024 by the author(s). Published by Nan Yang Academy of Sciences Pte. Ltd. This is an open access article under the Creative Commons Attribution-NonCommercial 4.0 International (CC BY-NC 4.0) License (https://creativecommons.org/licenses/by-nc/4.0/).

suffer progressive financialization, where speculation is integral to their price movements [1–3].

Oilseeds as part of the agri-food sector in the market of edible vegetable oils play a crucial role in the global economy since they are related to the livelihoods of almost 8 billion people [4].

There are a limited number of countries that produce sunflower oil on a large scale [5]. Two-thirds of sunflower production is concentrated in Europe, including Ukraine and Russia.

Ukraine and Russia are key players in the global supply of several agricultural commodities, among which is sunflower oil [6]. With 4.4 million tons produced, Ukraine leads the world market for sunflower oil, followed by Russia with 4.1 million tons. A significant amount of the world's production of sunflower oil is produced in these two nations. Ukraine is the largest exporter of sunflower oil, equating to 70% of the world's sunflower exports [7].

Analysis has shown that some events over time have caused the price of agricultural commodities to vary: (1) structural reforms in the economy in the former communist countries in 1990–1995; (2) inflation during the period of 1995–1996 due to the weather conditions and labor shortages in agricultural commodities; (3) global financial crisis of 2008/2009; (4) in 2011, the troubles with the Greek debt crisis; and (5) the COVID-19 pandemic in 2020.

On 24 February 2022, Russia launched a full-scale invasion of Ukraine that drastically affected human life, the economy, and the infrastructure. Due to this devastating event, the Russian Federation suffered sanctions from Western countries. Among the sanctions adopted was the blockade of the capital markets and limiting export capacity [8–11].

Due to the sanctions mentioned above along with Ukraine's inability to export due to Russia's invasion of its main ports, agricultural commodities were subjected to speculative elements. The world market experienced a shortage in vegetable oils, entering a panic buying mode resulting in the same trend in prices, of sunflower oil, as well as other vegetable oils such as canola oil (36% increase), soya bean oil (41% increase), and palm oil (33% increase) during the same period [7].

According to the World Food and Agriculture Organization (FAO) [12], Russia and Ukraine are considered the "breadbasket of the world" because they are leaders as suppliers of food commodities. Due to this military conflict between both countries, FAO recorded a rise in the Food Price Index (FPI) of over 17.1%. This fact has direct impacts on food insufficiency, poverty, and malnutrition, especially in low-income countries [13].

Furthermore, this conflict between both countries comes at a delicate time when the rest of the countries around the world are recovering from the effects of the COVID-19 pandemic [6,14,15]. In actuality, the prices of agricultural items increased as a result of the COVID-19 epidemic [16,17], and they further increased as a result of the Russia-Ukraine war [18,19].

The EU is the largest producer of olive oil at the global level, and therefore the main competitor of one of the most in-demand vegetable oils such as sunflower oil. The Mediterranean region has the highest concentration of olive oil production, as reported by Muñoz et al. [20] and supported by data from the International Olive Council (IOC). Several EU nations, including Spain (the top producer, accounting for about 45% of total production on average), Greece, Portugal, and Italy, together account for 65.47% of total olive oil production. Also, 26.3% of the overall production is accounted for by other southern Mediterranean nations like Algeria, Morocco, Tunisia, Syria, and Turkey.

From a demand perspective, the amount of olive oil consumed worldwide, and its trajectory are dictated by the level of demand in the European Union and the primary producing nations. According to Mili and Bouhaddane [21], the use of olive oil in EU member states over the years 1990–1991 and 2004–2005 accounted for 72% of global consumption. However, this percentage dropped to 58% between 2006–2007 and 2019–2020 as a result of decreased consumption in the three major EU consumer countries—Greece, Italy, and Spain—that were affected by the epidemic and financial crises. However, in the EU non-producing nations like Germany and the United Kingdom (UK), consumption increased from 11% in 1995–1996 to 26% in 2019–2020. This represents a different trajectory.

The United States is another nation where olive oil usage has increased significantly. Over the last two decades, the nation's consumption of olive oil has tripled, overtaking Greece, which in 2019–2020 ranked third in the world with 330,000 tons of consumption, after Spain and Italy.

Menapace et al. [22] state that consumer preferences and labels indicating the product's place of origin can influence how olive oil prices fluctuate globally.

According to experts like Kohls Richard et al. [23], Siskos et al. [24], Menozzi [25], and others, the following particulars of this market could affect how olive oil prices behave: the amount of harvested land, the weather, the condition of the soil, the climate crisis, value-adding activities, the sustainability of production, the characteristics of organic and place of origin, changes in supply and demand, government incentives, exchange rates, GDP, etc.

The World Health Organization's formal proclamation of the coronavirus pandemic was a very relevant event that altered the behavior of the global price of olive oil and raised serious questions about its magnitude and ramifications for the global economy.

The COVID-19 pandemic caused a sharp decline in the demand for and sales of olive fruit oil, which had an impact on world pricing. Trade disruptions and lockdowns in multiple nations contributed to the industry's sluggish expansion. In the specific instance of the United States, the U.S. Census Bureau reports that imports of olive oil fell by 13% in 2020 compared to 2019.

On the other side, Italy's output of olive oil was only able to cover around 300,000 tons of demand during the period of 2019–2020, falling short of national needs. The confinement and restricted consumption during this time, the pricing behavior brought on by supplies from the major bottling factories, and the behavior of the Spanish market were the causes of these findings [26].

According to Francesca [26], COVID-19 and its aftereffects will have an impact on the olive harvest, which will lead to a decline in global production in the Mediterranean basin. This will primarily be because of the limited agroeconomic processing that will affect crucial operations like the inability to prepare the olive trees for the upcoming harvest. Due to a lack of procedures, the consumer believes that prices have increased as a result of the product shortage and the rising global demand for olive oil.

Europe is one of the main importers of sunflower oil, with 2.1 million tons imported in 2022, according to AgFlow①. The top importers are France (0.1 million tons), Italy (0.15 million tons), Spain (0.4 million tons), and the Netherlands (0.2 million tons).

On the other hand, the European Union is the largest producer of olive oil at the global level, representing 65.47% of the total production of olive oil on average according to the International Olive Council.

In this instance, disparities in the amount produced by various food sources—like olive and sunflower oils—may be the cause of price fluctuations. Imbalances between sunflower oil (Ukraine) and olive oil (Europe) production due to substitution effects caused by the Russian invasion of Ukraine on 24 February 2022, have influenced prices. Since Ukraine is the world's largest sunflower oil producer and Europe the largest olive oil producing territory, this scientific article tries to analyze the world prices of both vegetable oils and understand how the Russia-Ukraine war has affected them.

Therefore, consumers, farmers, and the policies that must be implemented to stabilize product prices over time can all benefit greatly from understanding how olive and sunflower oil prices behave in a cyclical and/or seasonal context.

The limited literature on univariate and multivariate analysis in the behavior of olive oil prices and sunflower oil prices is supplemented in multiple ways by this research.

To the best of our knowledge, this study adds several things that are not included in the body of current literature. Using COVID-19 and the Russia-Ukraine war as a structural break, it first uses long memory techniques to offer evidence on the statistical features (more especially, mean reversion and persistence) of the worldwide prices of olive oil and sunflower oil. To rule out possible spurious relationships, we have calculated the VAR-based Granger causality test based on the time domain and the Breitung and Candelon causality test based on the frequency domain. Finally, to understand the long-term relationship of the time series and their behavior during the structural changes, we use continuous wavelet transform (CWT).

This paper is organized as follows. The data used is described in Section 2. The research approaches are expounded upon in Section 3. Section 4 discusses the findings. Lastly, Section 5 contains the conclusions.

2. Data

The Federal Reserve Bank of St. Louis② provided the database that was used in this study. We make use of the worldwide prices, expressed in US dollars per metric ton, for sunflower and olive oils.

The monthly frequency analysis spans from January 1990 to October 2023. The first figure in the dataset is displayed in Figure 1.

① https://www.agflow.com/agricultural-markets-news/spain-leads-sunflower-oil-imports-in-europe/

② https://fred.stlouisfed.org/series/POLVOILUSDM
https://fred.stlouisfed.org/series/PSUNOUSDM

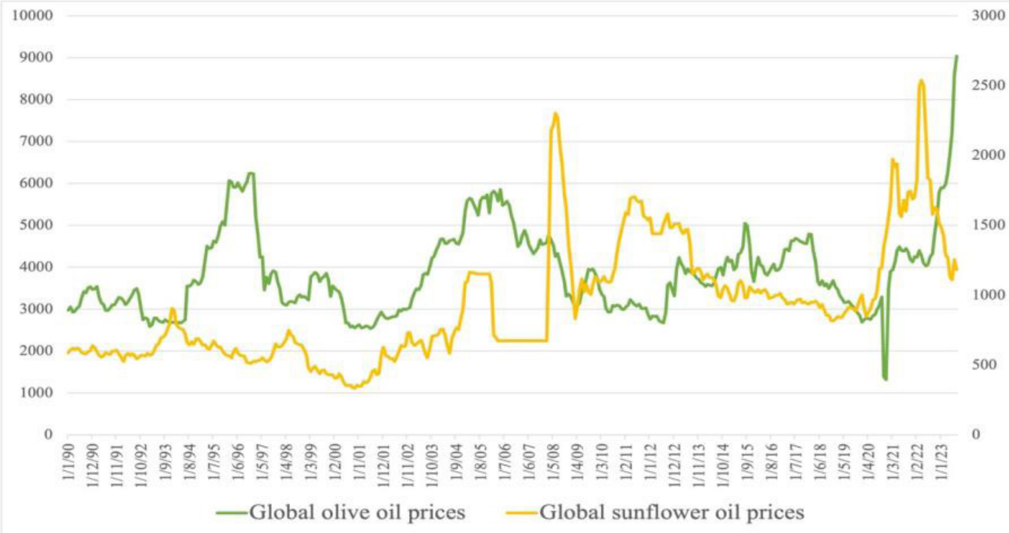


Figure 1. Global olive oil and sunflower oil price time series.

Some events over time have caused the price of the agricultural commodities here analyzed to vary: (1) structural reforms in the economy in the former communist countries in 1990–1995; (2) inflation during the period of 1995–1996 due to the weather conditions and labor shortages in agricultural commodities; (3) global financial crisis of 2008/2009; (4) in 2011, the troubles with the Greek debt crisis; and (5) the COVID-19 pandemic in 2019.

On 24 February 2022, Russia launched a full-scale invasion of Ukraine that drastically affected human life, the economy, and the infrastructure. According to Zolotnytska and Kowalczyk [27], this fact means a negative effect on the markets of vegetable oil prices, producing an increase not only in sunflower oil prices but in all others, as we can appreciate in Figure 1.

3. Methodology

3.1 Unit Roots

To model variables and comprehend interrelationships, statistics and econometrics, we employ single or multi-equation regression models of time series [28].

But it's crucial to comprehend how these time series behave before using these kinds of models. To deal with the series, one must first determine if the process is stationary I(0) when it does not have a unit root or non-stationary I(1) when it does [29].

Therefore, we utilize the conventional unit root test to ascertain each time series' integration order. The Dickey-Fuller test is the most popular and commonly used unit root test [30]. The augmented Dickey-Fuller test is created if a non-systematic component in the Dickey-Fuller models is autocorrelated [31]. Because of their higher power, several different tests have been taken into consideration. These include Phillips [32] and Phillips and Perron [33], which employed a non-parametric estimate of the spectral density u_t at the zero frequency. The methodology for analyzing the deterministic trend is based on Kwiatkowski et al [34].

3.2 ARFIMA (p, d, q) Model

We use a more sophisticated method after utilizing typical unit root tests to evaluate the integration sequence of each time series. The number of differences does not always need to be an integer value to achieve stationarity I(0); instead, it can be any point on the real line, which makes it fractional I(d) [35–39].

Therefore, we differentiate the time series using a fractional number to make the time series stationary I(0). Because of the lower power under fractional alternatives, this is a more sophisticated approach than unit root testing [40–42].

Determining and capturing the persistence of the data is another element of the I(d) models. This is the situation where observations are strongly linked yet separated in time.

The ARFIMA (p, d, q) model is the fractional integrated approach that we employ in this study article. The mathematical notation for this model is:

$$(1 - L)^d x_t = u_t,\ t = 1, 2, \tag{1}$$

The covariance stationary process I(0), which has a positive and finite spectral density function at zero frequency and a weak form of time dependence, is denoted by the symbol u_t in equation (1). The time series with an integrated process of order d is denoted by ($x_t \approx I(d)$), where d can be any real number and L is the lag-operator ($Lx_t = x_{t-1}$).

Consequently, we can say that x_t is $ARMA(p, d, q)$ if u_t is $ARMA(p, q)$.

Equation (1) yields the binomial expansion for the polynomial $(1 - L)^d$ where x_t for every real d depends on its entire history in addition to a finite number of previous observations. Accordingly, a larger value of d denotes a stronger degree of correlation between the series' observations.

The value of the parameter d determines which cases we can distinguish between. Table 1 presents a summary of the various outcomes of d.

Table 1. Interpretation of the Results of d for the ARFIMA Model.

Parameter	Explanation
$d = 0$	x_t process is short memory.
$d > 0$	x_t process is long memory.
$d < 0.5$	x_t is covariance stationary.
$d \geq 0.5$	x_t is nonstationary.
$d < 1$	x_t is mean reverting.
$d \geq 1$	x_t is not mean reverting.

Numerous techniques can be used to measure the degree of fractional integration and long-memory [43–49]. Nonetheless, we use the Bayesian information criterion (BIC) [50] and the Akaike information criterion (AIC) [51] to select the best ARFIMA model.

3.3 Breitung-Candelon Test

The causality test proposed by Breitung and Candelon [52] contributes to providing an idea about whether the relationship between both time series is temporary or permanent [53–55]. Because it interprets Granger causality across several frequency domains, this test has an advantage over other frequently used causality tests. To this end, two-time series—one based on coherence and the other on the bivariate spectral-density matrix—are categorized according to their spectral associations. An overall count of immediate forward and backward causality mechanisms is then obtained from the categorization.

According to Breitung and Candelon [52], the VAR(p) model below can be used to specify the interdependence between two variables, x and y:

$$x_t = \alpha_1 x_{t-1} + \alpha_p x_{t-p} + \beta_1 y_{t-1} + \ldots + \beta_p y_{t-p} + \beta_{1t} \tag{2}$$

The null hypothesis, H_0: $M_{y \to x}(W)$, as tested by Geweke [56], matches the null hypothesis of linear restriction given as:

$$R(W)\beta = 0 \tag{3}$$

where β denotes the coefficient vector of y. $R(W)$ is defined as:

$$R(W) = \begin{bmatrix} \cos(w)\cos(2w)\ldots\cos(pw) \\ \sin(w)\sin(2w)\ldots\sin(pw) \end{bmatrix} \tag{4}$$

The F-statistics for the null hypothesis in equation (3) has an approximated distribution of $F(2, T - 2P)$ for $Fw \overline{\in} (0, \pi)$. Furthermore, cointegration is frequently used as a framework for examining the frequency-based Granger causality test. Therefore, Breitung and Candelon [52] substitute x_t in equation (2) for Δx_t. As a result, the existence of cointegration between the series suggests that the primary long-term causation and zero-frequency causality share conceptual similarities. However, if there is no long-term link in the stationary case, the evidence of a causal association at a low frequency implies that the variable under consideration's frequency element can be predicted by a different variable.

3.4 Wavelet Analysis

Time series can be analyzed in the time-frequency domain using wavelet technology. Since stationarity is not required for this research paper, we will use two tools: wavelet coherency and wavelet phase difference. Examining the interaction between the time series in the frequency and time domains reveals indications of possible alterations, which we refer to as structural changes.

Moreover, the signal's frequency composition conceals the most crucial information. Thus, as far as we are aware, the time series can be described as an accumulation of elements that function at various frequencies.

In the end, we can conclude from reviewing the research done by Zhou [57], Podobnik and Stanley [58], Gu and Zhou [59], Jiang and Zhou [60], and others that analyzing the statistical relationships between two multifractal time series with a standard cross-correlation will yield misleading results.

The wavelet coherency graphic, which helps uncover information and/or hidden patterns in the time-frequency domain, illustrates the correlation between time series. The wavelet transform of a time series x_t obtained by projecting a mother wavelet ψ is defined as follows and is represented by $WT_x(a, \tau)$:

$$WT_x(a, \tau) = \int_{-\infty}^{+\infty} x(t) \frac{1}{\sqrt{a}} \psi^* \left(\frac{t-\tau}{a}\right) dt \tag{5}$$

where the wavelet coefficients of $x(t)$ translate the original time series into a function of τ and a to offer information on time and frequency. They are represented by $WT_x(a, \tau)$. Following Aguiar-Conraria and Soares [61], we choose the Morlet wavelet as the mother wavelet because it is a complex sine wave enclosed in a Gaussian envelope, which enables us to measure the synchronism across time series.

Understanding the relationship between two-time series is made easier by wavelet coherence. We can define this term as:

$$WCO_{xy} = \frac{SO(WT_x(a,\tau)WT_y(a,\tau)^*)}{\sqrt{SO(|WT_x(a,\tau)|^2)SO\left(|WT_y(a,\tau)|^2\right)}} \tag{6}$$

where the parameter SO is used to indicate the smoothing operator in terms of time and scale. The wavelet coherency is always one for all times and scales in the absence of this operator, which makes it crucial [62]. We may get the Matlab codes for the CWT resolution on the Aguiar-Conraria website③.

4. Empirical Results

The first analysis that we carry out in this research paper is the unit root/stationarity test to analyze the behavior of global olive and sunflower oil prices from January 1990 to August 2023 and the subsamples corresponding to before and after COVID-19. To do this analysis, the augmented Dickey-Fuller (ADF) test, the Phillips Perron (PP) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test are performed.

Table 2 displays the results obtained through the unit roots mentioned before. It is found that all original time series, as well as those studied before and following the COVID-19 periods, are nonstationary I(1). After analyzing the first differences, we find that all of the series are stationary I(0). Given that the aforementioned approaches only take into account integer degrees of differentiation—that is, 0 for stationary series and 1 for nonstationary ones—this is to be expected. Thus, in the following, we allow fractional differentiation throughout the previously mentioned ARFIMA technique, thereby providing additional flexibility in the dynamic definition of the model.

Fractionally integrated methods and ARFIMA (p, d, q) models are also used to analyze the persistence of the worldwide prices of olive and sunflower oil and their behavior before and after COVID-19, because the unit root methods under fractional alternatives have lower power.

The models' proper AR and MA orders are chosen using the Akaike information criterion (AIC) [51] and the Bayesian information criterion (BIC) [50]. Since the AIC and BIC might not be the ideal criteria for applications requiring fractional models, care should be taken in this case [39,63].

Using Sowell's maximum likelihood estimator [46] of different ARFIMA (p, d, q) specifications with all combinations of p, $q \leq 2$, Table 3 shows the estimates of the fractional differencing parameter d as well as the AR and MA terms for each time series.

③ https://sites.google.com/site/aguiarconraria/joanasoares-wavelets

Table 2. Unit Root Tests.

	ADF			PP		KPSS	
	(i)	(ii)	(iii)	(ii)	(iii)	(ii)	(iii)
Original Data							
Global Olive Oil Prices	0.635	−1.0902	−1.3535	−0.5412	−0.8234	0.4265*	0.1608
Global Sunflower Oil Prices	−1.1684	−3.2546*	−4.3702*	−2.8659	−3.7806*	3.5041	0.2313
Before the Russia-Ukraine War							
Global Olive Oil Prices	−0.4974	−3.1201	−3.1189	−2.8287	e−2.8247	0.236*	0.2082
Global Sunflower Oil Prices	−0.6962	−2.8256	−4.0346*	−2.4334	−3.5166*	3.2376	0.3034
After the Russia-Ukraine War							
Global Olive Oil Prices	−1.1541	−0.1588	−2.69	−0.7607	−1.7924	0.7205	0.1755
Global Sunflower Oil Prices	−3.0096*	−2.2938	−2.1683	−0.7904	−3.7659*	0.6876	0.1017*

Table 3. Results of Long Memory Tests.

Data Analyzed	Sample Size (days)	Model Selected	*d*	Std. Error	Interval	*I*(d)
			Original Time Series			
Global Olive Oil Prices	406	ARFIMA (2, *d*, 2)	1.07	0.087	[0.93, 1.21]	*I*(1)
Global Sunflower Oil Prices	406	ARFIMA (0, *d*, 0)	1.28	0.052	[1.20, 1.37]	*I*(1)
			Before the Russia-Ukraine War			
Global Olive Oil Prices	385	ARFIMA (0, *d*, 0)	1.07	0.047	[1.00, 1.15]	*I*(1)
Global Sunflower Oil Prices	385	ARFIMA (0, *d*, 0)	1.31	0.052	[1.22, 1.40]	*I*(1)
			After the Russia-Ukraine War			
Global Olive Oil Prices	21	ARFIMA (2, *d*, 1)	0.86	0.413	[0.18, 1.54]	*I*(1)
Global Sunflower Oil Prices	21	ARFIMA (0, *d*, 0)	0.90	0.513	[0.06, 1.75]	*I*(1)

It can be observed from Table 3 that the estimates obtained focusing on the original time series of global olive and sunflower oil prices are higher than 1 $d > 1$ in both cases. We observe a high degree of persistence with all values in the confidence bands in the interval and showing nonstationary I(1) behavior. Before the pandemic episode, both variables behaved similarly.

Focusing on "after the Russia-Ukraine war", we observe that the prices related to sunflower oil recovered before (d = 0.90) the olive oil prices (d = 0.86). So, the value of d of both time series is below 1. Therefore, the values support mean reversion behavior which implies transitory shocks and thus, in the event of an exogenous shock like the Russia and Ukraine war, the series will return to its original trend in the future.

Due to the lack of data since the Russia-Ukraine conflict began, and according to the confidence interval, the I(1) hypothesis cannot be rejected in both cases where the shock is expected to be permanent, causing a change in trend, which will need extraordinary measures to return to its original trend.

Once the statistical properties of each time series have been studied, frequency domain methods based on Breitung and Candelon [52] will be used to measure the causal effects of global olive oil and sunflower oil prices in the long, medium, and short term. The results are displayed in Table 4.

Table 4. Breitung and Candelon Frequency Domain Causality Test Results.

Hypothesis	Long Term ω = 0.05	Medium Term ω = 1.5	Short Term ω = 2.5
	Original Time Series		
d_Olive oil prices →d_Sunflower oil prices	1.10 (0.58)	5.91 (0.052)	6.67* (0.035)
	After the Russia-Ukraine War Period		
d_Olive oil prices →d_Sunflower oil prices	8.93* (0.0115)	2.07 (0.36)	0.29 (0.87)

Note: * shows that there is a significant causality relationship at the 5% significance level. The values in the brackets are the probability values of the F-statistics calculated for the relevant ω values.

We find different results using the frequency domain causality test for the full-time series and the period corresponding to the war between Russia and Ukraine.

The first result we found is that in both cases, the global olive oil prices cause effects on the global sunflower oil prices, and not the other way around. On the other hand, focusing on the results of the Wald test statistics and the p-values (in brackets) that are in Table 4, an interesting result will be observed if the focus is put on the war period. Corresponding to the period "after the Russia-Ukraine war", the frequency domain causality test reveals a long-term impact of the global olive oil prices on the global sunflower oil prices. As we know, two-thirds of the production of sunflower oil is concentrated in Europe, Ukraine, Russia, and the Trakya region of Turkey. Also, some European countries lead the global consumption of sunflower oil. The war in Ukraine has pushed prices to historically high levels. This commodity has been most directly affected with an increase of more than 40% since the day of the invasion due to the supply. Due to scarcity, the consumer has been forced to look for a substitute for this type of oil, such as olive oil. The global consumption of olive oil and its evolution is determined by demand levels in the European Union and their main producing countries [21]. If the adoption of olive oil at the expense of sunflower oil is imposed in the diet of consumers, given the geopolitical circumstances, this may have an impact on the price in the long term.

Finally, multivariate analysis based on the time-frequency domain is used to understand the correlation that exists between both variables, considering the Russia and Ukraine war period. Also, with this methodology, structural changes in the whole sample can be detected.

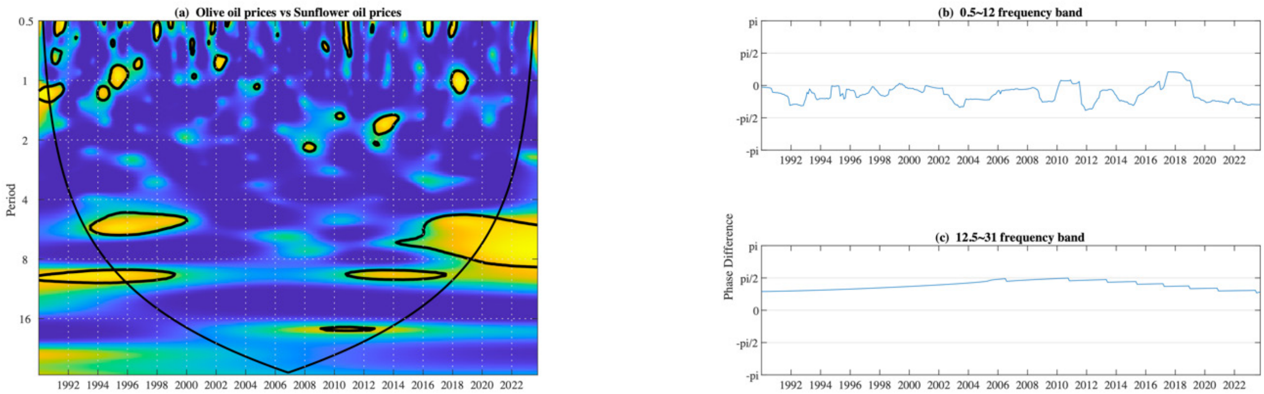


Figure 2. Wavelet coherency and phase difference analysis. (a) Olive oil prices vs Sunflower oil prices; (b) 0.5~12 frequency band; (c) 12.5~31 frequency band.

From Figure 2, we can get several results. Wavelet coherency is represented in Figure 2a and tells us when and at which frequencies the interrelations between time series occur and when they are the strongest, identifying the main regions with statistically significant coherency. Although we find a relationship in Figure 2a between both variables in the very short term corresponding to 0.5 to 3 months during the period analyzed, the regions of high coherence are the medium and low frequencies (in the frequency band from 4 to 31 business months) that correspond to the medium and long-term, respectively. The two main regions of high coherency (correlation) are (1) from late 1993 to the beginning of the 2000s; and (2) from the beginning of 2009 to 2019.

It is visible in Figure 2a that the period of high coherence that begins in 2009 at frequency 23, increases in frequency as time passes until reaching frequencies between 5 and 8 business months. It is also visible that this high correlation is maintained until the last data in the series. But, since 2019 periods of high coherence (relationship between variables) cannot be taken into account, as they are outside the cone of influence due to lack of data and are not statistically significant. Therefore, the behavior of both variables cannot be determined.

Once the regions that correspond to the high coherency (from late 1993 to the beginning of the 2000s and from the beginning of 2009 to 2019) have been identified, we note that the phase difference in Figure 2b shows that both series together have a negative relationship $[0, \frac{-\pi}{2}]$, that is, the increase in global olive oil prices causes global sunflower oil prices to decrease.

Although there is no statistical significance due to the lack of data, after 2019 a high relationship (high consistency) between the two variables is apparent. This highlights the price dependence between the two vegetable commodities. This behavior is in line with that published by the reference [64], which argues that in the case of vegetable oils, sunflower oil exports experienced the most immediate worldwide problems following the Russian invasion of Ukrainian territory. Roughly half of the sunflower oil that would have been exported was stopped from leaving the nation due to port closures. Vegetable oil costs increased as a result, typically by about 30%.

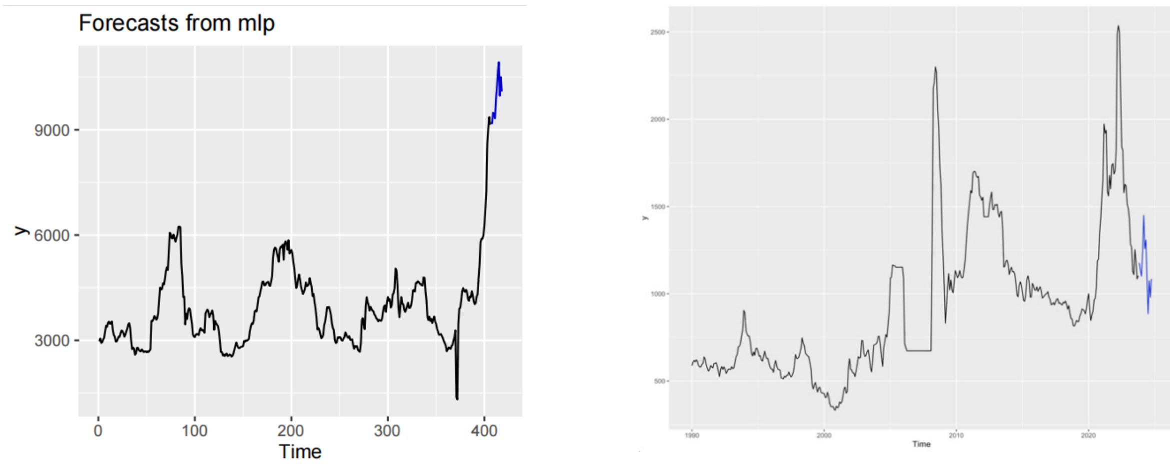
Finally, advanced machine learning-based computational intelligence techniques are used to understand the behavior and evolution of the global prices of olive and sunflower oil in the future, given the high persistence of the time series and the degree of integration determined by the fractional integration model.

We have predicted the time series using the multilayer perceptron (MLP) neural network for this purpose (see Figure 3). The reason is that to obtain the results, the underlying model—a non-parametric model—is necessary. It also has intriguing characteristics, such as non-linearity. The back-propagation rule, which underpins the MLP neural network technique, allows errors to spread across the network and enables the modification of the hidden processing components. Because of its extreme interconnectedness, every component in one layer feeds every other layer's component. Error corrective learning is used to train it [65–67].

Previously, given that each of the time series presented a non-stationary behavior, both have been differentiated for the prediction calculation. The forecasting accuracy using the ANN model is measured by mean square error (MSE) in both cases.

In the case of global olive oil prices, our 12-month prediction is expected to be $9,466.74 per metric ton. The maximum price will be reached after 11 months, with a predicted price of $11,130.30 per metric ton. This calculation presents an MSE of 0.3224.

For global sunflower oil prices, our 12-month forecast is expected to be $1084.74 per metric ton. The maximum price will be reached after 5 months, with a predicted price of $1449.29 per metric ton. Since then, it is expected that there will be a reversion of the price towards the mean. This calculation presents an MSE of 0.174.



(**a**) (**b**)

Figure 3. Forecast based on artificial neural networks. (**a**) Forecast of global olive oil in the next 12 months; (**b**) Forecast of global sunflower oil in the next 12 months.

5. Conclusions

On 24 February 2022, Russia launched a full-scale invasion of Ukraine. Due to this devastating event, the Russian Federation suffered sanctions from Western countries. Among these sanctions was limiting export capacity [9,10]. Due to the sanctions mentioned above along with Ukraine's inability to export due to Russia's invasion of its main ports, agricultural commodities were subjected to speculative elements. The world market experienced a shortage in vegetable oils as a result of entering the panic buying mode, causing the price of sunflower oil, as well as other vegetable oils such as canola oil (36% increase), soya bean oil (41% increase), and palm oil (33% increase), to follow the same trend in prices during the same period [7].

One of the main industries of Ukraine is sunflower oil production, with 56% of the total market share. On the other hand, Europe is one of its main markets since it is one of the largest importers of sunflower oil with 2.1 million tons in 2022. Also, the European Union is the largest producer of olive oil at the global level, representing 65.47% of the total production of olive oil on average. In this context, an imbalance in the production levels of these food sources, such as olive and sunflower oils, can produce differences in global prices. Therefore, understanding the behavior of olive oil and sunflower oil prices in a cyclical and/or seasonal context can be of great help to farmers and their incomes, consumers, and the policies that need to be implemented to stabilize product prices over the years.

There is scarce literature that analyzes the trends and persistence of global olive oil prices and global sunflower oil prices in the context of the Russia-Ukraine war. For this reason, this research paper is the first study that analyzes the statistical properties of these time series from January 1990 to October 2023, using several techniques based on fractional integration, causality tests in the frequency domain, wavelet analysis, and machine learning.

First, a univariate methodology based on fractional integration is used to analyze the trend and persistence of each time series. Putting the focus on the period after the Russia-Ukraine war, we observe that the prices related to sunflower oil recovered before the olive oil prices. The results of *d* support the hypothesis of mean reversion behavior which implies transitory shocks and thus, in the event of an exogenous shock, like the Russia and Ukraine war, the series will return to its original trend in the future.

Then, a methodology based on the frequency domain is used to measure the causal effects of global olive oil and sunflower oil prices in the long, medium, and short term. The first result we found is that in both cases, the global olive oil prices cause effects on the global sunflower oil prices, and not the other way around. The frequency domain causality test reveals a long-term impact of the global olive oil prices on the global sunflower oil prices in the period corresponding to "after the Russia-Ukraine war".

After that, a correlation analysis is carried out in the frequency domain based on wavelet continuous transform. We observe that the relationship between both variables is negative during the periods from late 1993 to the beginning of the 2000s and from the beginning of 2009 to 2019. Due to insufficient data, there is no statistical significance. However, after 2019, there is clear evidence of a strong correlation (high consistency) between the two variables. This demonstrates how the two vegetable commodities' prices are correlated. This conduct is consistent with the findings of the reference [64], which contends that, in the context of vegetable oils, exports of sunflower oil encountered the most acute global issues after Russia's invasion of Ukrainian territory. Port closures prevented around half of the sunflower oil that was scheduled for export from ever leaving the country. As a result, the price of vegetable oil rose, usually by around 30%.

Finally, to add further accuracy and rigor to this study, advanced computational intelligence techniques based on machine learning have also been used to forecast the price of each time series. A machine learning technique based on the multilayer perceptron (MLP) neural network has been used to verify the previous results. Our 12-month prediction suggests that the price of olive oil will be high for at least 11 more months.

Finally, a 12-month prediction is presented using artificial neural networks, where the price of olive oil will be high for at least 11 more months. On the other hand, the price of sunflower oil is predicted to be high for only 5 more months.

This research paper and the results presented here are intended to open new lines of research. By using data and methodologies based on time series analysis, some lines to be developed in the context of the Russia-Ukraine war would be to analyze the policy implications by analyzing agricultural policies, food security, international relations, and consumer welfare.

This study aims to have a broad and diverse audience, such as governments and international organizations, agricultural producers, consumers, researchers, financial and economic analysts, etc., with interests in agriculture, international trade, food security, and geopolitics.

Funding

This research received no external funding.

Data Availability

The data that support the findings of this study are available on request from the corresponding author.

Conflict of Interest

The authors declare no conflict of interest.

References

[1] Cheng, I.H., Xiong, W., 2014. Financialization of commodity markets. Annual Review of Financial Economics. 6(1), 419–441. DOI: https://doi.org/10.1146/annurev-financial-110613-034432

[2] Algieri, B., Kalkuhl, M., Koch, N., 2017. A tale of two tails: Explaining extreme events in financialized agricultural markets. Food Policy. 69, 256–269. DOI: https://doi.org/10.1016/j.foodpol.2017.05.004

[3] Algieri, B., Leccadito, A., 2019. Price volatility and speculative activities in futures commodity markets: A combination of combinations of p-values test. Journal of Commodity Markets. 13, 40–54. DOI: https://doi.org/10.1016/j.jcomm.2018.05.008

[4] Drejerska, N., Fiore, M., 2022. Digital and green trust in the agri-food business. In: Paliszkiewicz, J., Chen, K., Launer, M. (eds). Trust and Digital Business. Routledge: NY. pp. 148–157. DOI: https://doi.org/10.4324/9781003266525-14

[5] Pilorgé, E., 2020. Sunflower in the global vegetable oil system: situation, specificities and perspectives. OCL. 27(34). DOI: https://doi.org/10.1051/ocl/2020028

[6] Ben Hassen, T., El Bilali, H., 2022. Impacts of the Russia-Ukraine war on global food security: towards more sustainable and resilient food systems? Foods. 11(15), 2301.

DOI: https://doi.org/10.3390/foods11152301
[7] Muller, C.L., 2022. The effect of the Russia-Ukraine conflict on world edible oil prices. Oilseeds Focus. 8(2), 43–47.
[8] von Cramon-Taubadel, S., 2022. Russia's invasion of Ukraine—implications for grain markets and food security. German Journal of Agricultural Economics. 71(5), 1–13.
DOI: https://doi.org/10.30430/71.2022.5.apol
[9] Aliu, F., Kučera, J., Hašková, S., 2023. Agricultural commodities in the context of the Russia-Ukraine war: evidence from corn, wheat, barley, and sunflower oil. Forecasting. 5(1), 351–373.
DOI: https://doi.org/10.3390/forecast5010019
[10] Sun, M., Zhang, C., 2022. Comprehensive analysis of global stock market reactions to the Russia-Ukraine war. Applied Economics Letters. 30(18), 2673–2680.
DOI: https://doi.org/10.1080/13504851.2022.2103077
[11] Deininger, K., Ali, D.A., Fang, M., 2023. Impact of the Russian Invasion on Ukrainian Farmers' Productivity, Rural Welfare, and Food Security.
[12] FAO, 2022. The Importance of Ukraine and the Russian Federation for Global Agricultural Markets and the Risks Associated with the Current Conflict. Available online: https://www.fao.org/3/cb9013en/cb9013en.pdf (cited on 24 December 2023).
[13] FAO, 2022. Impact of the Ukraine-Russia Coflict on Global Food Security and Related Matters under the Mandate of the Food and Agriculture Organization of the United Nations (FAO). Available online: https://www.fao.org/3/ni734en/ni734en.pdf (cited on 11 May 2022).
[14] Kinateder, H., Campbell, R., Choudhury, T., 2021. Safe haven in GFC versus COVID-19: 100 turbulent days in the financial markets. Finance Research Letters. 43, 101951.
DOI: https://doi.org/10.1016/j.frl.2021.101951
[15] Batten, J.A., Choudhury, T., Kinateder, H., et al., 2022. Volatility impacts on the European banking sector: GFC and COVID-19. Annals of Operations Research. 330(1–2), 335–360.
DOI: https://doi.org/10.1007/s10479-022-04523-8
[16] Bajra, U.Q., Aliu, F., Aver, B., et al., 2022. COVID-19 pandemic-related policy stringency and economic decline: was it really inevitable? Economic Research-Ekonomska Istraživanja. 36(1), 499–515.
DOI: https://doi.org/10.1080/1331677x.2022.2077792
[17] Peersman, G., 2022. International food commodity prices and missing (dis)inflation in the euro area. Review of Economics and Statistics. 104(1), 85–100.
DOI: https://doi.org/10.1162/rest_a_00939
[18] Astrov, V., Ghodsi, M., Grieveson, R., et al., 2022. Russia's invasion of Ukraine: assessment of the humanitarian, economic, and financial impact in the short and medium term. International Economics and Economic Policy. 19(2), 331–381.
DOI: https://doi.org/10.1007/s10368-022-00546-5
[19] Jagtap, S., Trollman, H., Trollman, F., et al., 2022. The Russia-Ukraine conflict: Its implications for the global food supply chains. Foods. 11(14), 2098.
DOI: https://doi.org/10.3390/foods11142098
[20] Romo Muñoz, R., Lagos Moya, M., Gil, J.M., 2015. Market values for olive oil attributes in Chile: a hedonic price function. British Food Journal. 117(1), 358–370.
DOI: https://doi.org/10.1108/bfj-01-2014-0009
[21] Mili, S., Bouhaddane, M., 2021. Forecasting global developments and challenges in olive oil supply and demand: A delphi survey from Spain. Agriculture. 11(3), 191.
DOI: https://doi.org/10.3390/agriculture11030191
[22] Menapace, L., Colson, G., Grebitus, C., et al., 2011. Consumers' preferences for geographical origin labels: evidence from the Canadian olive oil market. European Review of Agricultural Economics. 38(2), 193–212.
DOI: https://doi.org/10.1093/erae/jbq051
[23] Kohls, R.L., Uhl J.N., 1990. Marketing of agricultural products, 7th ed. Macmillan: USA.
[24] Siskos, Y., Matsatsinis, N.F., Baourakis, G., 2001. Multicriteria analysis in agricultural marketing: The case of French olive oil market. European Journal of Operational Research. 130(2), 315–331.
DOI: https://doi.org/10.1016/S0377-2217(00)00043-6
[25] Menozzi, D., 2014. Extra-virgin olive oil production sustainability in northern Italy: a preliminary study. British Food Journal. 116(12), 1942–1959.
DOI: https://doi.org/10.1108/bfj-06-2013-0141
[26] Francesca, N., Planeta, D., Todaro, A., 2022. The impact of COVID-19 in the Italian wine and olive oil sector. In: Campisi, G., Mocciaro Li Destri, A., Amenta, C. (eds). COVID-19 and Communities.

Springer: Cham. pp. 177–179.
DOI: https://doi.org/10.1007/978-3-030-88622-6_21

[27] Zolotnytska, Y., Kowalczyk, S., 2022. Ukraina na światowym rynku rolnym. Kwartalnik Nauk o Przedsiębiorstwie. 65(3), 5–25.
DOI: https://doi.org/10.33119/knop.2022.65.3.1

[28] Box, G.E.P., Jenkins, G.M., 1970. Time Series Analysis Forecasting and Control, 1st ed. Holden-Day: USA.

[29] Nelson, C.R., Plosser, C.R., 1982. Trends and random walks in macroeconmic time series: some evidence and implications. Journal of Monetary Economics. 10(2), 139–162.
DOI: https://doi.org/10.1016/0304-3932(82)90012-5

[30] Dickey, D.A., Fuller, W.A., 1979. Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association. 74(366a), 427–431.
DOI: https://doi.org/10.2307/2286348

[31] Dickey, D.A., Fuller, W.A., 1981. Likelihood ratio statistics for autoregressive time series with a unit root. Econometrica. 49(4), 1057–1072.
DOI: https://doi.org/10.2307/1912517

[32] Phillips, P.C.B., 1987. Time series regression with a unit root. Econometrica. 55(2), 277–301.
DOI: https://doi.org/10.2307/1913237

[33] Phillips, P.C.B., Perron, P., 1988. Testing for a unit root in time series regression. Biometrika. 75(2), 335–346.
DOI: https://doi.org/10.1093/biomet/75.2.335

[34] Kwiatkowski, D., Phillips, P.C., Schmidt, P., et al., 1992. Testing the null hypothesis of stationarity against the alternative of a unit root. Journal of Econometrics. 54(1–3), 159–178.
DOI: https://doi.org/10.1016/0304-4076(92)90104-Y

[35] Adenstedt, R.K., 1974. On large-sample estimation for the mean of a stationary random sequence. The Annals of Statistics. 2(6), 1095–1107.
DOI: https://doi.org/10.1214/aos/1176342867

[36] Granger, C.W.J., Joyeux, R., 1980. An introduction to long-memory time series models and fractional differencing. Journal of Time Series Analysis. 1(1), 15–29.
DOI: https://doi.org/10.1111/j.1467-9892.1980.tb00297.x

[37] Granger, C.W., 1980. Long memory relationships and the aggregation of dynamic models. Journal of Econometrics. 14(2), 227–238.
DOI: https://doi.org/10.1016/0304-4076(80)90092-5

[38] Granger, C.W.J., 1981. Some properties of time series data and their use in econometric model specification. Journal of Econometrics. 16(1), 121–130.
DOI: https://doi.org/10.1016/0304-4076(81)90079-8

[39] Hosking, J.R.M., 1984. Modeling persistence in hydrological time series using fractional differencing. Water Resources Research. 20(12), 1898–1908.
DOI: https://doi.org/10.1029/wr020i012p01898

[40] Diebold, F.X., Rudebush, G.D., 1991. On the power of Dickey-Fuller tests against fractional alternatives. Economics Letters, 35(2), 155–160.
DOI: https://doi.org/10.1016/0165-1765(91)90163-F

[41] Hassler, U., Wolters, J., 1994. On the power of unit root tests against fractional alternatives. Economics Letters. 45(1), 1–5.
DOI: https://doi.org/10.1016/0165-1765(94)90049-3

[42] Lee, D., Schmidt, P., 1996. On the power of the KPSS test of stationarity against fractionally integrated alternatives. Journal of Econometrics. 73(1), 285–302.
DOI: https://doi.org/10.1016/0304-4076(95)01741-0

[43] Geweke, J., Porter-Hudak, S., 1983. The estimation and application of long memory time series models. Journal of Time Series Analysis. 4(4), 221–238.
DOI: https://doi.org/10.1111/j.1467-9892.1983.tb00371.x

[44] Phillips, P.C.B., 1999. Discrete Fourier transforms of fractional processes. Available online: https://researchspace.auckland.ac.nz/bitstream/handle/2292/149/193.pdf?sequence=1

[45] Phillips, P.C.B., 2007. Unit root log periodogram regression. Journal of Econometrics. 138(1), 104–124.
DOI: https://doi.org/10.1016/j.jeconom.2006.05.017

[46] Sowell, F., 1992. Maximum likelihood estimation of stationary univariate fractionally integrated time series models. Journal of Econometrics. 53(1–3), 165–188.
DOI: https://doi.org/10.1016/0304-4076(92)90084-5

[47] Robinson, P.M., 1994. Efficient tests of

nonstationary hypotheses. Journal of the American Statistical Association. 89(428), 1420–1437. DOI: https://doi.org/10.1080/01621459.1994.10476881

[48] Robinson, P.M., 1995. Gaussian semiparametric estimation of long range dependence. The Annals of Statistics. 23(5), 1630–1661. DOI: https://doi.org/10.1214/aos/1176324317

[49] Robinson, P.M., 1995. Log-periodogram regression of time series with long range dependence. The Annals of Statistics. 23(3), 1048–1072. DOI: https://doi.org/10.1214/aos/1176324636

[50] Akaike, H., 1979. A Bayesian extension of the minimum AIC procedure of autoregressive model fitting. Biometrika. 66(2), 237–242. DOI: https://doi.org/10.1093/biomet/66.2.237

[51] Akaike, H., 1973. Maximum likelihood identification of Gaussian autoregressive moving average models. Biometrika. 60(2), 255–265. DOI: https://doi.org/10.1093/biomet/60.2.255

[52] Breitung, J., Candelon, B., 2006. Testing for short-and long-run causality: A frequency-domain approach. Journal of Econometrics. 132(2), 363–378. DOI: https://doi.org/10.1016/j.jeconom.2005.02.004

[53] Tastan, H., 2015. Testing for spectral Granger causality. The Stata Journal. 15(4), 1157–1166. DOI: https://doi.org/10.1177/1536867x1501500411

[54] Ciner, C., 2011. Eurocurrency interest rate linkages: A frequency domain analysis. International Review of Economics & Finance. 20(4), 498–505. DOI: https://doi.org/10.1016/j.iref.2010.09.006

[55] Kırca, M., Canbay, Ş., Pirali, K., 2020. Is the relationship between oil-gas prices index and economic growth in Turkey permanent? Resources Policy. 69, 101838. DOI: https://doi.org/10.1016/j.resourpol.2020.101838

[56] Geweke, J., 1982. Measurement of linear dependence and feedback between multiple time series. Journal of the American Statistical Association. 77(378), 304–313. DOI: https://doi.org/10.1080/01621459.1982.10477803

[57] Zhou, W.X., 2008. Multifractal detrended cross-correlation analysis for two nonstationary signals. Physical Review E—Statistical, Nonlinear, and Soft Matter Physics. 77(6), 066211. DOI: https://doi.org/10.1103/physreve.77.066211

[58] Podobnik, B., Stanley, H.E., 2008. Detrended cross-correlation analysis: A new method for analyzing two nonstationary time series. Physical Review Letters. 100(8), 084102. DOI: https://doi.org/10.1103/physrevlett.100.084102

[59] Gu, G.F., Zhou, W.X., 2010. Detrending moving average algorithm for multifractals. Physical Review E—Statistical, Nonlinear, and Soft Matter Physics. 82(1), 011136. DOI: https://doi.org/10.1103/physreve.82.011136

[60] Jiang, Z.Q., Zhou, W.X., 2011. Multifractal detrending moving-average cross-correlation analysis. Physical Review E—Statistical, Nonlinear, and Soft Matter Physics. 84(1), 016106. DOI: https://doi.org/10.1103/physreve.84.016106

[61] Aguiar-Conraria, L., Soares, M.J., 2013. The continuous wavelet transform: Moving beyond uni-and bivariate analysis. Journal of Economic Surveys. 28(2), 344–375. DOI: https://doi.org/10.1111/joes.12012

[62] Aguiar-Conraria, L., Azevedo, N., Soares, M.J., 2008. Using wavelets to decompose the time—frequency effects of monetary policy. Physica A: Statistical Mechanics and Its Applications. 387(12), 2863–2878. DOI: https://doi.org/10.1016/j.physa.2008.01.063

[63] Beran, J., 1998. On unified model selection for stationary and nonstationary short- and long-memory autoregressive processes. Biometrika. 85(4), 921–934. DOI: https://doi.org/10.1093/biomet/85.4.921

[64] Glauber, J., Laborde D., 2023. The Russia-Ukraine Conflict and Global Food Security. International Food Policy Research Institute: USA.

[65] Guler, I., Ubeyli, E.D., 2005. An expert system for detection of electrocardiographic changes in patients with partial epilepsy using wavelet-based neural networks. Expert Systems. 22(2), 62–71. DOI: https://doi.org/10.1111/j.1468-0394.2005.00295.x

[66] Martínez, F., Frías, M., Charte, F., et al., 2019. Time Series Forecasting with KNN in R: the tsfknn Package. The R Journal. 11(2), 229–242. DOI: https://doi.org/10.32614/rj-2019-004

[67] Mapuwei, T.W., Bodhlyera, O., Mwambi, H., 2020. Univariate time series analysis of short-term forecasting horizons using artificial neural networks: The case of public ambulance emergency preparedness. Journal of Applied Mathematics. 1–11. DOI: https://doi.org/10.1155/2020/2408698