IJEEP

INTERNATIONAL JOURNAL OF ENERGY ECONOMICS AND POLICY

EJ EconJournals

ISSN: 2146-4553

International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

EconJournals

International Journal of Energy Economics and Policy, 2024, 14(2), 27-36.

Revisiting the relationship between Oil Price and Food Prices in the US: Evidence from Threshold Cointegration with Asymmetric Adjustment

Abderrazek Ben Hamouda*

Faculty of Economics and Management of Tunis, University of Tunis El Manar, Tunisia. *Email: abderrazek.benhamouda@fsegt.utm.tn

Received: 08 September 2023 **Accepted:** 03 January 2024 **DOI:** https://doi.org/10.32479/ijeep.15103

ABSTRACT

The main objective of this paper is to investigate the interaction between oil and food prices using threshold cointegration analysis. The study uses monthly data from January 1997 to September 2020. Empirical results reveal evidence of asymmetry in the adjustment process toward equilibrium. Uni-directional causality is detected between the variables, with oil prices causing changes in food prices. Additionally, oil prices are found to be cointegrated with food prices, suggesting the presence of an asymmetric adjustment mechanism. Specifically, the speed of adjustment to equilibrium varies depending on the sign of the last equilibrium error. The study recommends that policymakers should consider adopting measures that promote energy diversification, sustainable agricultural practices, and price stabilization mechanisms to mitigate the impact of oil price fluctuations on food prices and to enhance overall economic stability.

Keywords: Oil price; Food Price; Nonlinear Cointegration, Asymmetric ECM
JEL Classifications: F22, Q56

1. INTRODUCTION

In recent years, fluctuations in oil and food prices have garnered increasing interest within the global economic community due to their substantial impact on the global economy and people's well-being. The correlation between these two pivotal markets has become an increasingly captivating area of research for scholars, economists, and policymakers. While the links between oil and food prices are often discussed, a profound understanding of the nature of this relationship remains crucial to shed light on economic policies and trade strategies.

The conjunction of the global Covid-19 pandemic and geopolitical tensions has had significant repercussions on the global oil and food markets. The pandemic led to widespread economic disruptions, with lockdowns, travel restrictions, and supply chain disruptions impacting the demand and supply of oil and food products. Concurrently, geopolitical tensions have created an atmosphere of uncertainty in the oil markets, with potential risks of supply disruptions, while food security may be compromised by geopolitical instability. In this intricate context, the fluctuations in oil and food prices are closely monitored, carrying crucial implications for the global economy and access to food for vulnerable populations.Haut du formulaire Understanding the dynamics between food and oil prices has garnered significant interest in recent economic studies. These inquiries have delved into the intricate relationship between these two variables, seeking to comprehend how fluctuations in oil prices might impact food costs. Recent studies have employed diverse methodologies to probe this connection, revealing divergent conclusions regarding the nature and strength of the association between these prices.

Several recent research works have furthered the exploration of the intricate relationship between food and oil prices, using a variety of empirical methodologies and diverse temporal periods (Mokni and Ben Salha, 2020; Taghizadeh-Hesary et al., 2019; Zmami and Ben-Salha, 2019; Mokni and Youssef, 2020; Lundberg et al., 2020; Roman et al., 2020; Sun et al., 2023; Yu et al., 2023; Mokni, 2023; Mastroeni et al., 2022; Naeem et al., 2022; Dadzie et al., 2023). The findings of these studies highlight diverse interactions between food and oil prices, varying based on contexts and methodologies used. For instance, some studies reveal significant links between oil price fluctuations and food commodity costs, demonstrating a direct influence of oil shocks on food expenses (Sun et al., 2023; Yu et al., 2023). Other studies underscore a robust and positive correlation between food and oil prices, whether it's a causal relationship between oil price variations and those of food commodities or an enduring asymmetric association (Mokni and Ben-Salha, 2020; Taghizadeh-Hesary et al., 2019; Mokni, 2023; Dadzie et al., 2023). These divergent conclusions call for an in-depth understanding of the dynamics between oil price fluctuations and food costs, emphasizing the importance of tailored policies to mitigate the adverse impacts of oil price variations on food expenses.

This paper makes a valuable contribution to the existing literature by shedding new light on the complex relationship between oil and food prices, offering insights in three ways. Firstly, our study provides compelling evidence of the existence of asymmetric threshold cointegration between these two markets. To achieve this objective, we employ a nonlinear cointegration approach, specifically focusing on the threshold effect through TAR (Threshold Autoregressive) models, including consistent TAR, momentum TAR, and consistent momentum TAR. Secondly, our investigation centers on the long-term relationship between oil prices and food prices within the context of the U.S. market, which is characterized by its size and diversity. Indeed, U.S. economic and energy policies have major implications for global oil and food markets, thus justifying our choice of this economy to understand the interactions between these two markets on a global scale. Thirdly, to analyze the long-run asymmetric equilibrium relationship between oil and food prices, we utilize the asymmetric cointegration model proposed by Enders and Siklos (2001), where the adjustment coefficient of the error correction term varies depending on the equilibrium error, whether it is positive or negative, thereby providing a more nuanced understanding of their relationship.

The remainder of the paper is structured as follows. An overview of the available oil and food literature is presented in Section 1. In Section 2, discusses the data and empirical methodology. Section 3 presents the preliminary analysis. Section 4 presents the empirical results and Section 5 concludes the paper.

2. LITERATURE REVIEW

Various empirical methodologies are employed to examine the relationship between oil and food prices. Prior researches by Hooker (2002), Lardic and Mignon (2008), and Rafailidi and Katrakilidis (2014) have shown the presence of a nonlinear relationship between economic variables and oil prices. Zhang et al. (2010) utilized the VECM (Vector Error Correction Model) to analyze the causality between fuel and agricultural commodity prices, such as corn, soybean, and wheat. The authors concluded that there is no direct long-run price relationship between fuel and agricultural commodity prices, with only limited direct short-run relationships observed. On the other hand, Ibrahim and Said (2012) employed a Co-integration model to study the impact of oil prices on consumer price inflation in Malaysia over the period from 1971 to 2009. The results indicated the presence of both short-term and long-term relationships between oil and food prices. Chen et al. (2010) investigate the relationships between crude oil prices and global grain prices, focusing on corn, soybean, and wheat. Their empirical findings indicate that changes in each grain price are notably influenced by fluctuations in both crude oil prices and other grain prices. This influence is observed during the period from the 3rd week of 2005 to the 20th week of 2008, highlighting the competition among grain commodities driven by the demand for biofuels, specifically through the use of soybean or corn for ethanol and bio-diesel production, particularly during times of heightened crude oil prices. Alghalith (2010) examined the relationship between oil prices and food commodities, indicating that an increase in oil prices leads to a rise in food prices, while an increase in oil supply has a reducing effect on food prices.

By considering the structural VAR, Cha and Bae (2011) find that a rise in crude oil price leads to a rise in corn prices in the short run. Additionally, Karimi et al. (2014) investigated the effect of oil prices on food price inflation in the United States during the period 1984-2014 using threshold autoregressive (TAR) and time threshold autoregressive models (MTAR). Their results revealed that the cointegration adjustment between food prices and oil prices is asymmetric. Moreover, when the price of oil decreases, the speed of adjustment of the price of foodstuffs is faster. Ibrahim (2015) employs the nonlinear ARDL model for analyzing commodity prices during the period 1971-2012. Empirical findings demonstrate a significant relationship between an increase in oil prices and food prices in both the short and long run. However, food prices do not react to the reduction of oil prices. Paris (2018) uses regime-switching models for the period 2001-2014 and finds evidence of long-run effects of oil prices on agricultural commodity prices. Additionally, he discovers that biofuel production amplifies the impact of oil prices on agricultural commodity prices.

Pal and Mitra (2017) examine the linkages between crude oil prices and world food price indices. They analyze monthly price data from January 1990 to February 2016, initially using cointegration tests to establish a significant relationship between crude oil prices and various food categories. Subsequently, they apply a wavelet method to integrate both temporal and frequency aspects of the data. The findings reveal that world food prices, including cereals, vegetable oils, and sugar, move in tandem with and are influenced by crude oil prices, highlighting implications for short-term policy considerations. The study conducted by Luo and Ji (2018) examines the volatility interconnections between US crude oil futures and five agricultural commodity futures in China. Using advanced models and high-frequency data, the researchers uncover time-varying characteristics of volatility spillover. The findings indicate a presence of volatility transmission from the

US crude oil market to China's agricultural commodity markets, albeit with a relatively weak impact. Additionally, the research reveals an asymmetric effect in volatility interconnections, with negative volatility demonstrating a more pronounced increase in market interdependence compared to positive volatility.

More recently, Mokni and Ben Salha (2020) study the relationship between the price of crude oil and the world food price during the period 1960-2019 using a nonlinear Co-integration model. The outcomes demonstrate the existence of Granger causation moving from positive and negative oil price variations in food prices. In contrast, positive and negative food price changes Granger influence oil prices only at the lowest and higher extremities of the oil price distribution. Taghizadeh-Hesary et al. (2019) examined the link between oil prices and food commodities in eight Asian countries, concluding a significant association where oil price variations account for 64.17% of food price variance. Zmami and Ben-Salha (2019) studied the nonlinear and linear association between food and oil prices using the ARDL technique, confirming an asymmetric association and concluding that positive oil shocks disturb food prices in the long term. Mokni and Youssef (2020) studied the cross-correlation between oil prices and commodity prices from 2003 to 2017, concluding a strong persistence between the variables. They also examined whether oil prices have an immediate or delayed impact on commodity prices, concluding a delayed impact less than the immediate effect.

Lundberg et al. (2020) used the mixed-domain wavelet approach, concluding an anticyclical and procyclical association between food and oil prices. Roman et al. (2020) explore the connections between crude oil prices and specific food price indexes (dairy, meat, oils, cereals, and sugar), aiming to ascertain the directional impact. By reviewing fuel-food price linkage models and incorporating insights from time series literature, the study employs diverse methods such as the Augmented Dickey-Fuller test, Granger causality test, cointegration test, vector autoregression model, and vector error correction model. The analysis spans from January 1990 to September 2020. Empirical findings reveal long-term relationships between crude oil and meat prices. Additionally, short-term linkages are observed between crude oil prices and food, cereal, and oil prices. Notably, the interconnections among these variables intensify during the period from 2006 to 2020.

Several recent studies have delved into the intricate relationship between food and oil prices using diverse methodologies and varying time frames. In a recent study by Sun et al. (2023), the relationship between oil and food prices was examined using advanced econometric techniques. They analyzed monthly data from 1993 to 2020, exploring how different quantiles of oil shocks affected various food price indices. The findings from Sun et al. (2023) revealed a positive association between food prices and these indices across various quantiles. Specifically, they observed stronger relationships between extremely high and low quantiles under an oil demand shock, particularly evident in dairy, meat, and overall food indexes. Corn, soybean, and wheat indicated a stronger relationship in lower quantiles. Yu et al. (2023) investigated the impact of oil price shocks on food prices in China from 2000 to 2021 using the Quantile on Quantile (QQ) estimation technique. The study confirmed nonlinear dependence between oil and food prices, revealing a strong positive correlation in higher quantiles, indicating that rising global oil prices directly affect food costs. However, lower and medium quantiles showed a poor negative effect of crude oil prices on food prices. The findings highlight significant disparities across quantiles, emphasizing the need for policy measures to address the adverse effects of oil price fluctuations on food prices in China. Mokni (2023) investigates the relationship between food and oil prices using SVAR analysis from 1974 to 2018, revealing a robust positive and significant correlation between food and oil prices. Similarly, Mastroeni et al. (2022), examining the period from 2000 to 2018 through wavelet analysis, highlighted a strong positive connection between these prices. In a different approach, Naeem et al. (2022) utilized a connectedness approach spanning from 2006M1 to 2020M10, indicating that while short and long-term spillovers between oil volatility and commodity prices are less pronounced, intracorrelations are notably stronger. Dadzie et al. (2023), in a study covering 2011 to 2021 using VECM, VAR, and ARDL, unveiled the enduring influence of oil prices on food costs, emphasizing a persistent positive and significant relationship in both the long and short run periods, affirming the complex but evident interdependence between food and oil prices.

3. DATA AND EMPIRICAL METHODOLOGY

In this paper, we use three variables, namely oil price (WTI) and food prices (vegetable oil (soybean oil) and other food (bananas)) from United States at monthly frequency. The main objective is to study the nonlinear cointegration between variables. The two food prices are extracted from the World Bank Commodity Price Data. We deflate them using the US consumer price index to obtain the real oil and food prices. The WTI is sourced from www. Eia.gov. The period span from January, 1997 to September, 2020.

In recent years, there has been an increasing utilization of threshold cointegration in studies on price transmission. Cointegration has commonly been employed to examine the interplay between price variables. The two main approaches of cointegration are the Johansen and Engle-Granger two-step methods. Both approaches assume a symmetric relationship among variables. Balke and Fomby (1997) adopted a two-step approach based on Engle and Granger's (1987) method to investigate threshold cointegration. Enders and Granger (1998) and Enders and Siklos (2001) extended the standard Dickey-Fuller test, allowing for the consideration of asymmetric movements in time-series data. This enables the testing of cointegration without assuming a symmetric adjustment to a long-term equilibrium. Subsequently, this method has been widely applied to analyze the asymmetric transmission of prices.

The conventional tests of cointegration such as Engle and Granger (1987) is a residual-based test that analyze the validity of long-run relationship among oil price and food prices by estimating the following model:

$$Y_t = \beta_0 + \beta_1 X_t + \varepsilon_t \quad (1)$$

Where Y_t is the food prices of United states at time t and X_t is the WTI oil price. ε_t is the residual in equation (1) and β_0 and β_1 are coefficients.

The implicit assumption of linear and symmetric adjustment (Engle and Granger, 1987) is problematic. Enders and Siklos (2001) proposed a two-regime threshold cointegration approach to entail asymmetric adjustment in cointegration analysis. They argued that the Engle-Granger cointegration test is likely to lead to misspecification errors when the adjustment of the error correction term is asymmetric.

To address this issue, they enhance the Engle-Granger two-step cointegration test by including an asymmetrical error correction term. In the subsequent stage, they assess the stationarity of the disturbance term ε_t by employing an asymmetric test approach known as the Threshold Autoregressive (TAR) cointegration model, which was proposed by Enders and Granger (1998) and Enders and Siklos (2001).

The equation of a TAR process is:

$$\Delta\varepsilon_t = I_t\rho_1(\varepsilon_t - 1 - \tau) + (1 - I_t)\,\rho_2(\varepsilon_t - 1 - \tau) + \mu_t \tag{2}$$

Where ρ_1, ρ_2 are coefficients, τ is the value of the threshold, μ_t is a white-noise disturbance and I_t is the Heaviside indicator such that:

$$I_t = \begin{cases} 1\, if\ \varepsilon_t - 1 \ge \tau \\ 0\, if\ \varepsilon_t - 1 < \tau \end{cases} \tag{3}$$

Under the null hypothesis of no cointegration between the variables, the -statistic for the null hypothesis $\rho_1=\rho_2=0$ has a nonstandard distribution. Rejecting this assumption means that Eq. (2) is an attractor such that the equilibrium value of the $\{\varepsilon_t\}$ is τ. When the lagged value of ε_t exceeds its long-run equilibrium value, the adjustment process is represented by $(\rho_1\varepsilon_{t-1}-\tau)$. On the other hand, if the lagged value of ε_t falls below its long-run equilibrium value, the adjustment is given by $\rho_2(\varepsilon_{t-1}-\tau)$. When $-1<|\rho_1|<|\rho_2|<0$, negative discrepancies tend to persist longer than positive discrepancies. Furthermore, Tong (1983) demonstrated that the Ordinary Least Squares (OLS) estimates of ρ_1 and ρ_2 follow an asymptotic multivariate normal distribution when the sequence $\{\varepsilon_t\}$ is stationary. Hence, if the null hypothesis $\rho_1=\rho_2=0$ is rejected, it is possible to test for symmetric adjustment (i.e., $\rho_1=\rho_2$) using a standard F-test. Rejecting both null hypotheses $\rho_1=\rho_2=0$ and $\rho_1=\rho_2$ indicates the presence of threshold cointegration and asymmetric adjustment.

Since the exact nature of the nonlinearity may not be known, Enders and Siklos (2001) consider another kind of asymmetric cointegration test methodology that allows the adjustment to be contingent on the change in ε_{t-1} (i.e., $\Delta\varepsilon_{t-1}$) instead of the level of ε_{t-1}. In this case, the Heaviside indicator of Eq. (3) becomes.

$$I_t = \begin{cases} 1\, if\ \Delta\varepsilon_t - 1 \ge \tau \\ 0\, if\ \Delta\varepsilon_t - 1 < \tau \end{cases} \tag{4}$$

This specification becomes particularly relevant when the adjustment of the series demonstrates a higher degree of "momentum" in one direction compared to the other (Thompson, 2006; Kuo and Enders, 2004; Enders and Siklos, 2001; Enders and Granger, 1998). In other words, the speed at which adjustment occurs depends on whether ε_t is increasing (i.e., widening) or decreasing (i.e., narrowing). According to Thompson (2006) and others, if $|\rho_1|<|\rho_2|$, an increase in ε_t tends to persist, while decreases quickly revert back to the threshold. This specific model is referred to as the momentum-threshold autoregressive (M-TAR) cointegration model. The TAR model captures asymmetrically profound movements, such as positive deviations being more prolonged than negative deviations. The M-TAR model allows the autoregressive decay to be influenced by $\Delta\varepsilon_{t-1}$. As a result, the M-TAR specification is capable of capturing asymmetrically "sharp" movements in the sequence of $\{\varepsilon_t\}$ (Caner and Hansen, 2001).

In both the TAR and M-TAR cointegration processes, the null assumption of $\rho_1=\rho_2=0$ could be tested, while the null hypothesis of symmetric adjustment may be tested by the restriction, $\rho_1=\rho_2$. Generally, there is no presumption to whether to use TAR or M-TAR specifications. Thus, it is recommended to select the adjustment mechanism by a model selection criterion such as AIC or BIC. Furthermore, if the errors in Eq. (2) are serially correlated, it is possible to use the augmented form of the test:

$$\Delta\varepsilon_t = I_t\rho_1\left(\varepsilon_t - 1 - \tau\right) + \left(1 - I_t\right)\rho_2\left(\varepsilon_t - 1 - \tau\right) + \sum\nolimits_{i=1}^{P}\varphi_i\Delta\varepsilon_{t-i} + v_t \tag{5}$$

To use the tests, we first regress ε_t on a constant and call the residuals, $\{\hat{\varepsilon}_t\}$ which are the estimates of $(\varepsilon_{t-1}-\tau)$. In a second step, we set the indicator according to Eq. (3) or Eq. (4) and estimate the following regression:

$$\Delta\widehat{\varepsilon_t} = I_t\rho_1\left(\widehat{\varepsilon_{t-1}} - \tau\right) + \left(1 - I_t\right)\rho_2\left(\widehat{\varepsilon_{t-1}} - \tau\right) + \sum\nolimits_{i=1}^{P}\varphi_i\Delta\widehat{\varepsilon_{t-1}} + v_t \tag{6}$$

The number of lags p is specified to account for serially correlated residuals and it can be selected using AIC, BIC, or Ljung-Box Q test. In several applications, there is no reason to expect the threshold to correspond with the attractor (i.e., τ=0). In such circumstances, it is necessary to estimate the value of along with the values of ρ_1 and ρ_2. A consistent estimate of the threshold t can be obtained by adopting the methodology of Chan (1993). A super consistent estimate of the threshold value can be attained with several steps. First, the process involves sorting in ascending order the threshold variable, i.e., $\widehat{\varepsilon_{t-1}}$ for the TAR model or the $\Delta\widehat{\varepsilon_{t-1}}$ for the M-TAR model. Second, the potential threshold values are determined. If the threshold value is to be meaningful, the threshold variable must actually cross the threshold value (Enders, 2004). Thus, the threshold value τ should lie between the maximum and minimum values of the threshold variable.

The Engle and Granger (1987) equilibrium correction specification (ECM) assumes a symmetric adjustment process to account for disequilibrium among variables. However, in order to address asymmetries, two modifications have been introduced to the ECM model. Firstly, Granger and Lee (1989) proposed decomposing the error correction terms and first differences of the variables into positive and negative values. Secondly, the Granger and Lee (1989) approach was further extended by incorporating the threshold cointegration mechanism. This results in an asymmetric error correction model with threshold cointegration, which can be represented as follows:

$$\Delta X_t = \theta_x + \delta_x^{+} Z_{t-1}^{+} + \delta_x^{-} Z_{t-1}^{-} + \sum_{j=1}^{J} \alpha_{xj}^{+} \Delta X_{t-j}^{+} + \sum_{j=1}^{J} \alpha_{xj}^{-} \Delta X_{t-j}^{-} + \sum_{j=1}^{J} \beta_{xj}^{+} \Delta Y_{t-j}^{+} + \sum_{j=1}^{J} \beta_{xj}^{-} \Delta Y_{t-j}^{-} + v_{x,t} \tag{7}$$

And

$$\Delta Y_t = \theta_y + \delta_y^{+} Z_{t-1}^{+} + \delta_y^{-} Z_{t-1}^{-} + \sum_{j=1}^{J} \alpha_{yj}^{+} \Delta X_{t-j}^{+} + \sum_{j=1}^{J} \alpha_{yj}^{-} \Delta X_{t-j}^{-} + \sum_{j=1}^{J} \beta_{yj}^{+} \Delta Y_{t-j}^{+} + \sum_{j=1}^{J} \beta_{yj}^{-} \Delta Y_{t-j}^{-} + v_{y,t} \tag{8}$$

Where k = {1, 2}, $Z_{t-1}^{+} = I_t \widehat{\varepsilon_{t-1}}$ and $Z_{(t-1)}^{-} = (1 - It)\widehat{\varepsilon_{t-1}}$

4. PRELIMINARY ANALYSIS

Table 1 reports summary statistics of WTI, soybean oil and bananas. The highest mean and standard deviation are observed for soybean oil during the period. In addition, soybean oil is characterized by the highest standard deviation. Asymmetry is measured by the values of skewness and kurtosis is a measurement for flatted distribution. We see that a banana has negative skewness. However, WTI and soybean oil have positive skewness. The Jarque-Bera test statistic which rejects the null hypothesis of normality.

Table 1: Descriptive statistics

Variables	WTI	Soybeans oil	Bananas
Mean	55.4860	764.0760	0.7743
Maximum	133.9271	1535.160	1.2952
Minimum	11.3100	286.8900	0.2859
SD	28.3258	280.3882	0.2672
Skewness	0.4152	0.5485	−0.1285
Kurtosis	2.2464	2.7994	1.8324
Jarque-Bera	14.9337***	14.7713***	16.9742***
	0.0005	0.0006	0.0002
Observations	285	285	285

*, ** and *** denote the significance at 10%, 5% and 1% levels

Figure 1 display the time series plots for the oil prices (WTI), soybean oil and bananas. We observe that WTI and soybean oil and WTI and bananas have an evident co-movement in general, which reveals a high possibility of cointegration between these series. In addition, the two pairs of series display divergent movement indicating possible nonlinear cointegration.

Figure 1: Dynamics of monthly WTI, soybean oil and bananas

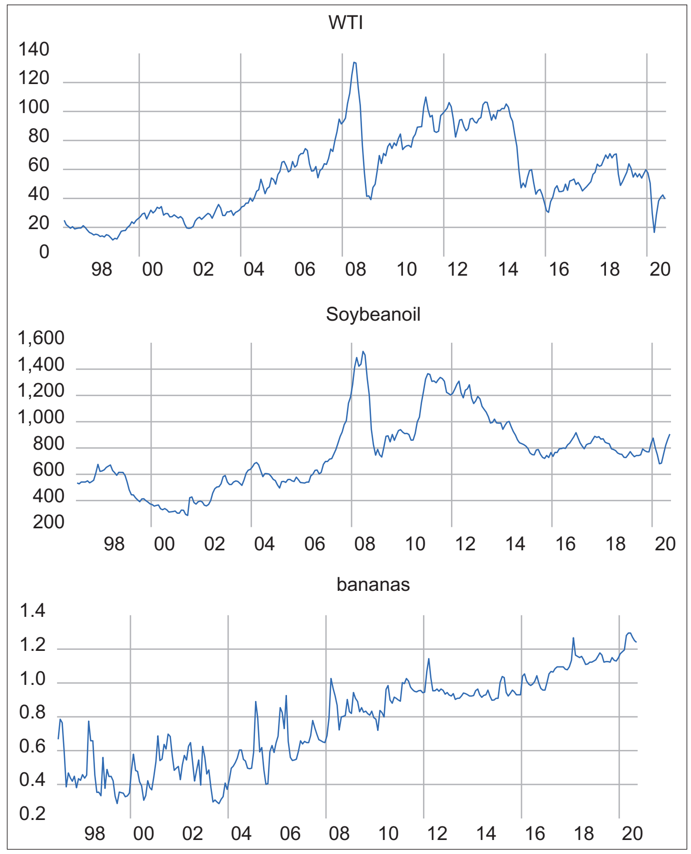

Table 2 shows the results of the stationarity tests, namely the ADF and PP. The observation of the results indicates that all the series are stationary in first difference. We conclude that WTI, soybean oil and bananas are integrated processes of order one, or unit root processes.

5. EMPIRICAL RESULTS

Results of the Engle and Granger (1987) cointegration tests are reported in Table 3. Results provide evidence for the alternative hypothesis of linear cointegration. Indeed, the parameters β_0 and β_1 are statistically significant. To study the possibility of asymmetric price transmission mechanism between oil price and food price, we conduct a nonlinear cointegration analysis by using the threshold auto-regression models. Four models are used in this paper such as the TAR with τ=0, consistent TAR with τ estimated, Momentum-TAR with τ=0 and consistent M-TAR with τ estimated.

To study the existence of a serial correlation in the residual series, we choose an optimal lag for each model. For the empirical diagnostic analysis, we focus on three information criterion namely AIC, SBIC and L-Jung Box statistics at different orders 4, 8 and 12. The value of the threshold τ is unknown and has to be estimated along the values of ρ_1 and ρ_2. We follow the Chan's (1993) method to estimate the threshold values for consistent TAR and M-TAR models.

Table 4 reports the empirical results of the threshold cointegration tests for the TAR, consistent-TAR, momentum TAR and consistent-MTAR. Through the four nonlinear models, the results indicate the rejection of the null hypothesis of threshold cointegration

Table 2: Unit root tests results

Variables	ADF-Level		ADF-difference		I (d)	PP-Level		PP-difference		I (d)
	t-statistic	P-value	t-statistic	P-value		t-statistic	P-value	t-statistic	P-value	
WTI	−2.4959		−11.2859***	0.0000	I (1)	−2.0266	0.5838	−10.6528***	0.0000	I (1)
Soybeans oil	−2.4684	0.3437	−10.1878***	0.0000	I (1)	−2.2653	0.4511	−10.1723***	0.0000	I (1)
Bananas	−2.3060	0.3100	−10.9796***	0.0000	I (1)	−2.2062	0.5122	−15.1677***	0.0000	I (1)

*, ** and *** denote the significance at 10%, 5% and 1% levels

Table 3: Linear cointegration results tests (Engle and Granger (1987))

Pairs of variables	β_0		β_1	
	coefficient	P-value	Coefficient	P-value
WTI-Soybeans oil	299.828***	0.0000	8.367***	0.0000
WTI-Bananas	0.501***	0.0000	0.005***	0.0000

*, ** and *** denote the significance at 10%, 5% and 1% levels.

(ρ_1=ρ_2=0) for the WTI-soybean oil pair. On the other hand, for the pair WTI-bananas, we note that the null hypothesis of threshold cointegration is rejected for the consistent-TAR. These results confirm the evidence of a cointegrating relationship between the oil price and food. In this case we can examine whether their adjustment coefficients are different across positive and negative errors. This procedure serves to verify the evidence of an asymmetric cointegration through the hypothesis H0: ρ_1=ρ_2. If the two previous tests reject the null assumption, so asymmetry test makes sense. Based on information criterion AIC and SBIC and L-Jung Box statistics, we observed that the C-TAR is the most applicable model for variables' adjustment to long-run equilibrium for the pair WTI-Bananas. However, the C-MTAR is the efficient model for variables' adjustment to long-run equilibrium for the pair WTI-soybean oil.

Figure 2 illustrates the variations of the SSE for the C-TAR model considering a lag of 8. By observing the WTI-bananas pair, we see that the lowest SSE for the consistent-MTAR model is -1.41 at the threshold value of 0.059. The best threshold value with the lowest SSE is estimated to be 0.176 for the consistent TAR model. It is the best model characterized by the lowest AIC statistic of −659.777 and BIC statistic of −619.952.

Figure 3 shows the variations of the SSE for the C-MTAR model considering a lag of 2. By observing the WTI-soybean oil pair, we see that the lowest SSE for the consistent-MTAR model is 520.000 at the threshold value of 4.889. The best threshold value with the lowest SSE is estimated to be 137.299 for the consistent-MTAR model. It is the best model characterized by the lowest AIC statistic of 2909.605 and BIC statistic of 2927.814.

As shown in Table 4, we found limited evidence of asymmetric price transmission between oil prices and food prices. Therefore, oil prices became cointegrated with the food, the adjustment mechanism is asymmetric and the speed of adjustment to the equilibrium is different when the last equilibrium error has different signs. This means that the change in the equilibrium error has a different impact on the adjustment speed to the new equilibrium.

By focusing on the WTI-bananas pair results, we reveal that the F test of the C-TAR model relating to the null hypothesis of absence of cointegration has a statistic of 2,305 and which is significant at the 10% level. This indicates that oil and bananas are cointegrated with an adjustment threshold. Likewise the F statistic for the null hypothesis of symmetric price transmission has a value of 4.487 and it is significant at the 5% level. Therefore, the adjustment process is asymmetric when WTI and bananas adjust to achieve the long-term equilibrium. Considering the WTI-soybean oil pair, we observe for the C-MTAR model that the F test relating to the null hypothesis of absence of cointegration admits a statistic of 5.617 which is significant at a level of 1%. This result indicates that WTI and soybean oil are cointegrated with an adjustment threshold. In addition, the F statistic for the null hypothesis of symmetric price transmission has a value of 3.987 and it is significant at the 5% level. Therefore, the adjustment process is asymmetric when WTI and soybean oil adjust to achieve the long-term equilibrium.

Figure 2: Threshold value for TAR

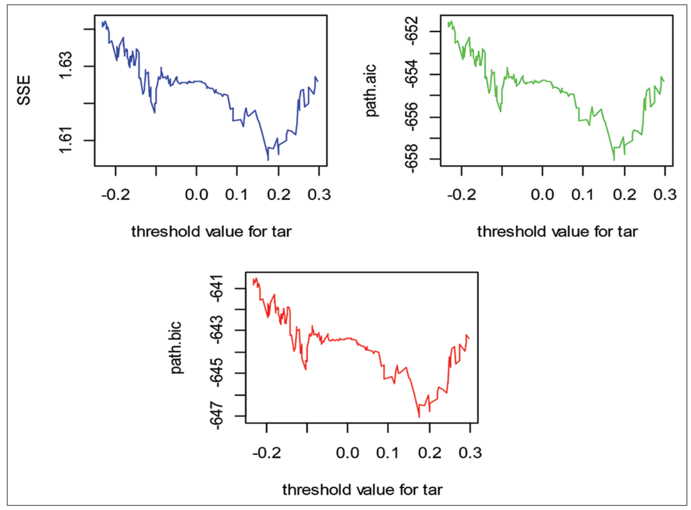

Figure 3: Threshold value for M-TAR

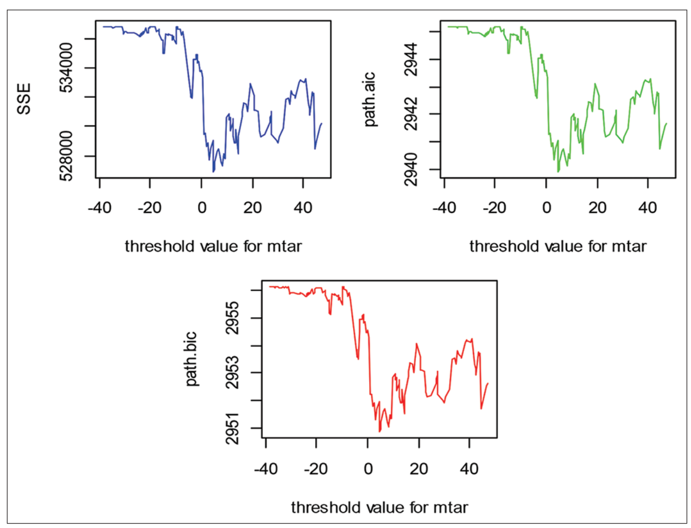

Table 4: Results of the nonlinear cointegration tests (threshold)

Pairs of variables	WTI-Bananas				WTI-Soybean oil			
	TAR	C-TAR	M-TAR	C-MTAR	TAR	C-TAR	M-TAR	C-MTAR
lags (p)	8	8	8	8	1	2	1	2
Threshold (τ)	0	0.176	0	0.059	0	137.299	0	4.889
ρ_1	0.022	0.023	−0.017	−0.051	−0.061**	−0.075***	−0.036	−0.01
t-Statistic	(0.84)	(0.87)	(−0.564)	(−0.942)	(−2.466)	(−2.658)	(−1.53)	(−0.408)
ρ_2	−0.056*	−0.061*	0.001	−0.002	−0.042*	−0.03	−0.067***	−0.077***
t-Statistic	(−1.718)	(−1.821)	(0.021)	(−0.076)	(−1.842)	(−1.418)	(−2.768)	(−3.337)
total obs	285	285	285	285	285	285	285	285
coint obs	276	276	276	276	283	282	283	282
AIC	−659.308	−659.777	−655.381	−655.963	2922.812	2911.926	2922.266	2909.605
BIC	−619.484	−619.952	−615.556	−616.139	2937.394	2930.135	2936.848	2927.814
Q_{LB} (4)	0.989	0.99	0.99	0.985	0.657	0.901	0.7	0.93
Q_{LB} (8)	0.994	0.996	0.996	0.994	0.761	0.906	0.805	0.945
Q_{LB} (12)	0.994	0.995	0.993	0.993	0.592	0.807	0.555	0.695
No CI: Ø	2.072	2.305*	0.163	0.445	4.683***	4.432**	4.962***	5.617***
H0: ρ_1=ρ_2=0	0.128	0.0921	0.8493	0.6414	0.0099	0.0127	0.0076	0.0040
No APT: F	4.028**	4.487**	0.213	0.775	0.328	1.675	0.869	3.987**
H0: ρ_1=ρ_2	0.046	0.035	0.645	0.379	0.567	0.197	0.352	0.047

Number in parentheses are the t-value. *, ** and *** denote the significance at 10%, 5% and 1% levels

Table 5: Results of asymmetric ECM with threshold cointegration

Variable	C-TAR (lag = 6)				C-MTAR (lag = 4)			
	WTI		Bananas		WTI		Soybean oil	
	Coefficients	t-statistic	Coefficients	t-statistic	Coefficients	t-statistic	Coefficients	t-statistic
θ	1.1505	1.407	0.0373***	3.430	1.1577*	2.014	0.5407	0.122
α_1^+	0.1576	1.192	−0.0001	−0.095	0.0553	0.434	0.5217	0.531
α_2^+	−0.0218	−0.169	−0.0020	−1.172	−0.0255	−0.203	0.0295	0.030
α_3^+	−0.0333	−0.257	−0.0001	−0.064	−0.0251	−0.200	−0.0702	−0.073
α_4^+	−0.2041	−1.552	0.0018	1.075	−0.2269	−1.826	−0.5896	−0.616
α_5^+	0.0317	0.240	−0.0015	−0.881	-	-	-	-
α_6^+	−0.1044	−0.765	−0.0009	−0.505	-	-	-	-
α_1^-	0.5392***	5.146	−0.0008	−0.618	0.4517***	3.966	−0.4352	−0.497
α_2^-	0.0106	0.096	−0.0003	−0.215	−0.0499	−0.412	1.3124	1.407
α_3^-	−0.1594	−1.430	−0.0014	−0.946	−0.1993	−1.646	−2.4299**	−2.606
α_4^-	0.1616	1.444	−0.0004	−0.271	0.0150	0.135	0.4849	0.566
α_5^-	−0.1115	−0.993	0.0010	0.679	-	-	-	-
α_6^-	−0.0490	−0.476	−0.0004	−0.349	-	-	-	-
β_1^+	4.1751	0.632	−0.2052*	−2.334	−0.0041	−0.296	0.3089**	2.850
β_2^+	6.4563	0.916	−0.3610***	−3.851	−0.0130	−0.905	−0.1422	0.2025
β_3^+	−3.9836	−0.541	−0.1475	−1.506	0.0228	1.550	0.2308*	2.031
β_4^+	10.2851	1.372	−0.2916**	−2.925	0.0284	1.930	0.1412	1.246
β_5^+	−0.0839	−0.011	−0.2084*	−2.090	-	-	-	-

(Contd...)

Table 5: ***(Continued)***

Variable	C-TAR (lag = 6)				C-MTAR (lag = 4)			
	WTI		Bananas		WTI		Soybean oil	
	Coefficients	t-statistic	Coefficients	t-statistic	Coefficients	t-statistic	Coefficients	t-statistic
β_6^+	4.0092	0.529	−0.2160*	−2.144	-	-	-	-
β_1^-	5.6086	0.580	−0.1174	−0.913	0.0304	1.947	0.6607***	5.494
β_2^-	−0.4966	−0.052	0.0622	0.492	0.0245	1.481	0.0297	0.233
β_3^-	15.8549	1.784	0.0889	0.753	−0.0159	−0.979	−0.1607	−1.282
β_4^-	0.0184	0.002	−0.0952	−0.832	0.0136	0.865	0.1588	1.306
β_5^-	8.7661	1.037	0.0874	0.778	-	-	-	-
β_6^-	−3.1052	−0.380	−0.0798	−0.733	-	-	-	-
δ^+	6.4875	1.681	−0.1041*	−2.027	0.0019	0.620	−0.0018	−0.076
δ^-	−0.9453	−0.539	−0.0635*	−2.719	0.0048	1.723	−0.0393	−1.800
Diagnostic								
R-squared	0.2332	-	0.2215	-	0.2517	-	0.2872	-
Adjusted R-squared	0.1538	-	0.1408	-	0.2001	-	0.2380	-
F-stat	2.936***	(0.0000)	2.747***	(0.0000)	4.876***	(0.0000)	5.8420***	(0.0000)
AIC	1703.016	-	−698.681	-	1690.151	-	2833.047	-
BIC	1804.590	-	−597.108	-	1762.847	-	2905.743	-
Q (4)	0.987	-	0.949	-	0.902	-	0.904	-
Q (8)	1.000	-	0.587	-	0.980	-	0.596	-
Q (12)	1.000	-	0.646	-	0.998	-	0.504	-
Granger Causality Test	**F-stat**	**P-value**	**F-stat**	**P-value**	**F-stat**	**P-value**	**F-stat**	**P-value**
$H_{01}:\alpha_{yj}^+ = \alpha_{yj}^-$	5.180***	0.000	0.607	0.836	3.929***	0.000	1.209	0.294
$H_{02}:\beta_{xj}^+ = \beta_{xj}^-$	0.549	0.881	4.418***	0.000	2.007**	0.046	7.980***	0.000

Q_{LB} (P) denote the significance level for the Ljung-Box Q statistic, The P-Value are in parentheses, *, ** and *** denote the significance at 10%, 5% and 1%. Levels

In order to investigate the movement of the oil price and food price series in a long-run equilibrium relationship, we analyze the asymmetric error correction model. The results of the C-TAR model for the WTI-bananas pair are reported in Table 5. Diagnostic analyses on the residuals with AIC, BIC and Ljung-Box Q statistics select a lag of six for the model. The consistent-TAR model is the best from the threshold cointegration analyses and the error correction terms are constructed using Equation (4) and Equation (6). Results indicate that WTI is cointegrated with bananas and it also exhibits asymmetric adjustments. In addition, the short-term equilibrium adjustment process mainly occurs with bananas since δ+ = δ−.

For regimes with positive shocks (WTI is higher than bananas), the adjustment coefficient for WTI is 6.4875 and −0.1041 for bananas. This means that, in the next period, WTI price will go down and bananas will go up, and thus, the price deviation will increase. Considering regimes with negative shocks (bananas is lower than WTI price), the adjustment coefficient for bananas is −0.0635 and −0.9453 for WTI. This denotes that, in the next period, WTI price will go down and bananas will go down as well, but WTI drops more and thus the price deviation will decrease. The adjusted R-squared value is 0.1538 for the WTI and 0.1408 for bananas. In addition, the AIC and BIC statistics for WTI are both larger than those for the bananas. This means that the model specification is better fitted on the WTI price. The Granger causality between this pair is analyzed by the F-tests. The F-statistic of 5.180 reveals that bananas does Granger cause WTI. Besides, the F-statistic of 4.418 indicates that WTI does Granger cause bananas. This indicates that, in the short-term, both variables affect each other.

The results of the C-MTAR model for the WTI-Soybean oil pair are reported in Table 5. Diagnostic analyses on the residuals with AIC, BIC and Ljung-Box Q statistics select a lag of four for the model. The consistent-MTAR model is the best from the threshold cointegration analyses. Results indicate that WTI is cointegrated with Soybean oil and it also exhibits asymmetric adjustments. In addition, the short-term equilibrium adjustment process mainly occurs with bananas since δ+ = δ−.

Considering regimes with positive shocks (WTI is higher than soybean oil), the adjustment coefficient for WTI is 0.0018 and

−0.0019 for soybean oil. This means that, in the next period, WTI price will go down and soybean oil will go up, and thus, the price deviation will increase. For regimes with negative shocks (soybean oil is lower than WTI price), the adjustment coefficient for soybean oil is −0.0393 and 0.0048 for WTI. This denotes that, in the next period, WTI price will go down and bananas will go up, but WTI drops more and thus the price deviation will decrease. The adjusted R-squared value is 0.2001 for the WTI and 0.2380 for soybean oil. Besides, the AIC and BIC statistics for soybean oil are both larger than those for the WTI. This indicates that the model specification is better fitted on the soybean oil. The Granger causality between WTI-soybean oil pair is analyzed by the F-tests. The F-statistic of 3.929 reveals that soybean oil does Granger cause WTI. Besides, the F-statistic of 7.980 indicates that WTI does Granger cause soybean oil. This indicates that, in the short-term, both variables affect each other.

6. CONCLUSION

In this paper, we study the dynamic relationship between oil and food prices. Specifically, we focused on the linkages between variables in both the short-run and long-run horizons under both the linear and nonlinear threshold cointegration framework. We employ the methodology developed by Enders and Siklos (2001), focused on a nonlinear (threshold) cointegration model allowing for nonlinear adjustment to long-run equilibrium. From the linear cointegration approaches, we can reject the null hypothesis of no cointegration. In addition, using the consistent TAR and consistent-MTAR specifications, we found evidence of asymmetry in the adjustment process to equilibrium.

Our findings confirm that increase in oil price possesses an inflationary threat to US food price level. Moreover, due to the asymmetric adjustment of the food price, the food prices tend to grow faster when oil prices increase. Indeed, there is no effect of immediate offsetting when the oil prices decrease and, therefore, the food prices tend to remain high. This study documents the possibility of asymmetric effect of oil price-shocks on food inflation, which is greater when oil price increases than when it decreases. The results are very useful for policy-makers in designing appropriate policies to curve the inflationary impact of oil prices. The increases and the changes in oil are specifically related on food price and indicate the evidence of market power in United States food markets.

Additionally, the non-linear cointegration between oil prices and food commodities underscores the importance of appropriate economic policies and risk management. Governments and policymakers need to consider these intricate relationships when formulating policies related to agriculture, energy, and international trade. They can consider measures such as diversifying energy sources, supporting local agriculture, and implementing risk management policies to mitigate the potential effects of oil price fluctuations on food prices.

In summary,the non-linear cointegration of oil prices and food commodities holds significant economic and political implications. Gaining a thorough understanding of this intricate relationship can facilitate the development of more effective policies to address price fluctuations and mitigate the associated economic and social risks. The study's findings could have substantial implications for national and international economic policies, particularly concerning food security, energy resource management, and the stabilization of essential commodity prices. Additionally, gaining a better understanding of the interactions between these pivotal markets could aid economic actors in making informed decisions regarding investments, risk management, and strategic planning in a complex and dynamic economic environment.

REFERENCES

Alghalith, M. (2010), The interaction between food prices and oil prices. Energy Economics, 32(6), 1520-1522.

Balke, N.S., Fomby, T.B. (1997), Threshold cointegration. International Economic Review, 38(3), 627-645.

Caner, M., Hansen, B. (2001), Threshold autoregression with a unit root. Econometrica, 69(6), 1555-1596.

Cha, K.S., Bae, J.H. (2011), Dynamic impacts of high oil prices on the bioethanol and feedstock markets. Energy Policy, 39(2), 753-760.

Chan, K.S. (1993), Consistency and limiting distribution of the least squares estimator of a threshold autoregressive model. Annals of Statistics, 21(1), 520-533.

Chen, S.T., Kuo, H.I., Chen, C.C. (2010), Modeling the relationship between the oil price and global food prices. Applied Energy, 87(8), 2517-2525.

Dadzie, P., Nambie, N.B, Obobi, B.A. (2023), Impact of petroleum energy price volatility on commodity prices in Ghana. International Journal of Economics and Financial Issues, 13(1), 73-82.

Enders, W. (2004), Applied Econometric Time Series. New York: John Wiley and Sons, Inc. p480.

Enders, W., Granger, C.W.F. (1998), Unit-root tests and asymmetric adjustment with an example using the term structure of interest rates. Journal of Business and Economic Statistics, 16(3), 304-311.

Enders, W., Siklos, P.L. (2001), Cointegration and threshold adjustment. Journal of Business and Economic Statistics, 19, 166-176.

Engle, R., Granger, C.W.J. (1987), Cointegration and error correction: Representation, estimation, and testing. Econometrica, 55(2), 251-276.

Granger, C.W.J., Lee, T.H. (1989), Investigation of production, sales, and inventory relationships using multicointegration and non-symmetric error correction models. Journal of Applied Econometrics, 4, 145-159.

Hooker, M.A. (2002), Are oil shocks inflationary? Asymmetric and nonlinear specifications versus changes in regime. Journal of Money, Credit and Banking, 34(2), 540-561.

Ibrahim, M.H. (2015), Oil and food prices in Malaysia: A nonlinear ARDL analysis. Agricultural and Food Economics, 3, 1-14.

Ibrahim, M.H., Said, R. (2012), Disaggregated consumer prices and oil price pass-through: Evidence from Malaysia. China Agricultural Economic Review, 4, 514-529.

Karimi, M., Kaliappan, S.R., Matemilola, B.T. (2014), World oil price and food prices in US: Evidence from the threshold cointegration models. The Empirical Economics Letters, 13(10), 1129-1136.

Kuo, S.H., Enders, W. (2004), The term structure of Japanese interest rates: The equilibrium spread with asymmetric dynamics. Journal of the Japanese and International Economies, 18(1), 84-98.

Lardic, S., Mignon, V. (2008), Oil prices and economic activity: An asymmetric cointegration approach. Energy Economics, 30(3), 847-855.

Lundberg, C., Skolrud, T., Adrangi, B., Chatrath, A. (2020), Oil price pass through to agricultural commodities. American Journal of

Agricultural Economics, 103, 721-742.

Luo, J., Ji, Q. (2018), High-frequency volatility connectedness between the US crude oil market and China's agricultural commodity markets. Energy Economics, 76, 424-438.

Mastroeni, L., Mazzoccoli, A., Quaresima, G., Vellucci, P. (2022), Wavelet analysis and energy-based measures for oil-food price relationship as a footprint of financialisation effect. Resources Policy, 77, 102692.

Mokni, K. (2023), Detrended cross-correlations analysis between oil shocks and world food prices. International Journal of Energy Sector Management, 18, 183-199.

Mokni, K., Ben-Salha, O. (2020), Asymmetric causality in quantiles analysis of the oil-food nexus since the 1960s. Resources Policy, 69, 101874.

Mokni, K., Youssef, M. (2020), Empirical analysis of the cross-interdependence between crude oil and agricultural commodity markets. Review of Financial Economics, 38(4), 635-654.

Naeem, M.A., Karim, S., Hasan, M., Lucey, B.M., Kang, S.H. (2022), Nexus between oil shocks and agriculture commodities: Evidence from time and frequency domain. Energy Economics, 112, 106148.

Pal, D., Mitra, S.K. (2017), Time-frequency contained co-movement of crude oil and world food prices: A wavelet-based analysis. Energy Economics, 62, 230-239.

Paris, A., (2018), On the link between oil and agricultural commodity prices: Do biofuels matter? International Economics, 155, 48-60.

Rafailidi, P., Katrakilidi, C. (2014), The relationship between oil prices and stock prices: A nonlinear asymmetric cointegration approach. Applied Financial Economics, 24(12), 793-800.

Roman, M., Górecka, A., Domagała, J. (2020), The linkages between crude oil and food prices. Energies, 13(24), 6545.

Sun, Y., Gao, P., Raza, S.A., Shah, N., Sharif, A. (2023), The asymmetric effects of oil price shocks on the world food prices: Fresh evidence from quantile-on-quantile regression approach. Energy, 270, 126812.

Taghizadeh-Hesary, F., Rasoulinezhad, E., Yoshino, N. (2019), Energy and food security: Linkages through price volatility. Energy Policy, 128, 796-806.

Thompson, M.A. (2006), Asymmetric adjustment in the prime lending-deposit rate spread. Review of Financial Economics, 15(4), 323-329.

Tong, H. (1983), Threshold Models in Non-Linear Time Series Analysis. New York: Springer-Verlag.

Yu, Y., Peng, C., Zakaria, M., Mahmood, H., Khalid, S. (2023), Nonlinear effects of crude oil dependency on food prices in China: Evidence from quantile-on-quantile approach. Journal of Business Economics and Management, 24(4), 696-711.

Zhang, Z., Lohr, L., Escalante, C., Wetzstein, M. (2010), Food versus fuel: What do prices tell us? Energy Policy, 38(1), 445-451.

Zmami, M., Ben-Salha, O. (2019), Does oil price drive world food prices? Evidence from linear and nonlinear ARDL modeling. Economies, 7(1), 12.