Letters in Spatial and Resource Sciences (2024) 17:29
https://doi.org/10.1007/s12076-024-00393-9

ORIGINAL PAPER

# Unveiling an asymmetric relationship between global crude oil and local food prices in an oil-importing economy

**Sergei Kharin**[1] · **Zuzana Kapustova**[2] · **Ivan Lichner**[1]

Received: 19 June 2024 / Accepted: 14 October 2024


**Abstract**

Recent swift comovements of local food and global crude oil prices have attracted the attention of policymakers and researchers. To evaluate this relationship, many studies have used time series models to explore global crude oil and local food prices. However, robust research based on advanced nonlinear time series models that incorporate control variables for their formation is lacking. In this paper, nonlinear techniques are applied to assess the asymmetric nexus between Brent oil prices and local retail food prices in Slovakia. To estimate this value, we extend the single-threshold NARDL approach to the MTNARDL model. The nominal exchange rate and industrial production index are used as the control variables. Compared with conventional NARDL models, the MTNARDL model provides a more detailed representation of global oil–local food price linkages and detects the asymmetric effect of global oil prices on food prices from both long- and short-term perspectives. Interestingly, with respect to long- and short-term food price volatility, changes in response to oil price fluctuations are greatest under a regime with rather a small number of positive and moderate changes.

**Keywords** Price transmission · ARDL · NARDL · MTNARDL · Food prices · Energy prices · Asymmetric effects

**JEL Classification** Q410 · C510

✉ Sergei Kharin
sergei.kharin@savba.sk

Zuzana Kapustova
zuzana.kapustova@uniag.sk

Ivan Lichner
ivan.lichner@savba.sk

[1] Institute of Economic Research, Slovak Academy of Sciences, Bratislava, Slovakia

[2] Slovak University of Agriculture in Nitra, Nitra, Slovakia

Published online: 11 November 2024

## 1 Introduction

In recent years, due to the high rate of inflation and concerns about food security, research concerning food price volatility has gained significant popularity (e.g., Mohajan 2013; Guan et al. 2023). As mentioned by Köse and Ünal (2022), food price volatility is associated with food supply, food shortages, people´s welfare, social instability and economic growth. According to Abdlaziz et al. (2016), even if there is a complex set of interrelated factors inducing escalations in food commodity prices and worldwide shifts in the production and consumption of agricultural commodities, devaluation of the dollar and oil/food interdependence are fundamental factors that can lead to fluctuations in food prices worldwide. Demirtaş et al. (2023) considered oil to be an essential element of industrial and agricultural production; therefore, a shift in oil prices in this context is associated with price volatility in general and (retail) food price hikes more specifically.

Notably, there have been many studies on time series models of global crude oil and local food price relationships; however, there is still a lack of studies related to price transmission between crude oil prices and domestic food prices in oil-dependent economies based on advanced nonlinear time series models incorporating significant control variables. Additionally, studies employing econometric models do not provide consistent evidence on the relationship between oil and food prices at the global level. Thus, evidence from country-level studies sheds some light on this issue considering regional specifics.

To this end, this paper aims to provide empirical evidence on the asymmetric relationship between oil and food price dynamics in high-income oil-importing countries. The contribution of this paper is an improved understanding of the price dynamics in the energy–retail food price nexus for oil-importing countries with relatively low levels of food security compared to other EU countries (Abdullaieva et al. 2022) by applying the multithreshold NARDL (MTNARDL) model introduced by Verheyen (2013) and Pal and Mitra (2015). The relationships between energy and retail food prices are captured by multiple-threshold models to provide robust evidence. To obtain relevant knowledge on the pass-through effect of global crude oil prices on local food prices in Slovakia, three versions of the ARDL specification are employed, and their performance is evaluated. Differentiation of the price change thresholds provides the most accurate estimates. Interestingly, the results suggest that local food prices are more responsive in times of moderate and low positive oil price changes, as evidenced by the greater profit margins of local companies. This finding adds valuable insights to the results of single threshold studies that focused only on periods of positive and negative oil price fluctuations (e.g., Moralista and Martir 2023; Masih et al. 2011).

To our knowledge, this study is the first to consider such a technique jointly with simulation-based impulse response analysis to examine the asymmetry in the oil−food price relationship from an oil-importing country perspective. However, to date, the MTNARDL method has been used to explore asymmetric pass-throughs from oil prices to inflation (Pal and Mitra 2019; Raheem et al. 2020; Li and Guo 2021) or in other contexts.

Finally, our findings have key implications for policy-makers and other stakeholders in terms of improving subsidy distribution and regulatory mechanisms to control the asymmetric effects of crude oil price fluctuations. The results of our study could serve as a basis for more effective social support policies in periods of high oil price volatility.

The remainder of the paper is organized as follows. Findings from recent literature in the area of the oil-food price nexus and developments in the methodologies used to study this phenomenon are provided in the next section. The Methodology and Data section describes the data sources and estimation methods used, the Empirical findings section presents the results of alternative estimates, and the conclusions and policy recommendations are provided in the final section.

## 2 Literature review

In addition to the factors influencing the food price changes mentioned in the introductory section, energy prices are among the key forces that have driven these changes since 2007. The food price decreased when the oil price fell dramatically in 2008, and an upwards trend was observed in food commodity prices after the crude oil price increased in 2009 (Chen et al. 2020). Oil shocks influence food prices through (1) the shift in energy prices, which affects the market for agricultural commodities, and (2) the demand for biofuel feedstock, which is linked to food availability and subsequently food prices (Gilbert 2010; Konandreas 2012; Darwez et al. 2023). Mitchell (2008) provided evidence that high energy prices have contributed to approximately 15–20% greater U.S. food commodity production and transport costs and have boosted the production of biofuels. As stated by Janda and Krištoufek (2019), post-2005 biofuel growth created a significant economic and policy dilemma related to the pricing relationship between fuel and agricultural products. Mokni and Youssef (2020) considered the exchange rate as another possible factor influencing the indirect existence of the oil-agricultural commodity relationship. Furthermore, Ibrahim (2015) mentioned that food import bills are usually higher in periods of high oil prices for countries that import food, which subsequently drives up the cost of food in the country, compared to those in periods of low oil prices.

Matthews (2023) claimed that food prices in the EU increased significantly in 2022 and 2023; however, food price inflation was greater in Central European countries than in the remaining EU because the populations in these countries spend more on food than do those in Western European countries as a percentage of overall household expenditure. For example, the median Slovak household spent approximately 26% of its income, almost 10 p.p. more than the EU average, to buy food (Casalis 2023). Matthews (2023) noted that there are numerous reasons contributing to the sharp increase in food prices, such as rising energy costs, drought, and animal disease outbreaks, as well as the COVID-19 pandemic (the impact was quite short lived and largely overturned itself), and the energy crisis after Russia invaded Ukraine in 2022 resulted in a sharp spike in the price of crude oil and food items. Tass et al. (2024) also noted that the world has been facing an extraordinary rise in food and energy prices, especially in Europe, as a result of the Russia-Ukraine war because of Europe's considerable dependence on Russian energy imports (approximately 29% of crude oil imports into the EU in 2020). Oravcova (2023) added that the Russia–Ukraine conflict, which began in February 2022, revealed the weakness of the Central European region in the energy sector, while a problem of dependence on third countries in energy has been exposed; this was also the case for Slovakia. Slovakia, a country with a small open economy in Central Europe, imports almost all of its crude oil. On the other hand, Slovakia's agri-food trade balance is shaped by the exports of agricultural commodities and imports of processed food, which points to insufficient vertical integration of agri-commodity production and food production (Škamlová 2022). According to Bartóková and Ďurčová (2022), Slovak agriculture has experienced structural changes in the last two decades, which have seriously affected Slovak agricultural output and food prices. This empirical study, determining the sector's position and role in the economy, confirmed a growing international openness, as well as a dependence on foreign inputs and production. Due to the limited market space, the Slovak Republic is an economy whose agrarian sector is significantly influenced by international markets (Matošková et al. 2017). Kašťáková et al. (2022) added that Slovakia has remained a net importer of agri-food products, even if its position in the European Common Agricultural Market strengthened after its accession to the EU in 2004. For example, Škamlová (2022) provided evidence that certain agrocommodities (such as milk and beef) are strongly dependent on imports. On the other hand, Slovakia is a pro-export-oriented country in terms of essential commodities with lower value added (e.g., seed oils). Hlavackova (2021) described the Slovak retail food market as being concentrated, price sensitive, and competitive. The Ministry of Finance of the Slovak Republic (2023) also confirms that there is extremely strong competition in the food retail sector in Slovakia that guarantees market pressure on the price level, especially for goods for daily consumption. In addition, the Slovak food sector is more energy intensive in comparison to countries in western Europe; thus, after the recorded peak of food prices in March 2023, the growth rate of food prices in Slovakia stabilized in 2023, benefiting from the reduction in energy prices. Hence, the development of input prices created more favourable conditions for stabilizing retail food price dynamics.

Olofin and Salisu (2016) explained the oil price−inflation nexus from a policy perspective and noted that monetary policy authorities are responsible for keeping prices stable and that inflation represents a measure of macroeconomic stability; notably, foreign investors usually take this factor into account when choosing investments. Moreover, Alnour et al. (2023) reported that the effects of pandemics worldwide (e.g., COVID-19), together with escalating threats from geopolitical instability and other territorial disputes (e.g., the Ukraine-Russia war), have made it even more crucial to review energy and food pricing issues. Hence, analysing the oil-food linkage is necessary for adopting policy decisions to support consumers and industries under inflation pressure.

The food-energy nexus has gained considerable attention globally, and experts have continued to debate the nature and direction of oil and food price dynamics over the past few years. Chowdhury et al. (2021) concluded that the methodology applied in the majority of studies is linear and that the linkage between energy and food prices is examined via standard time series techniques. Vector autoregression

(VAR), structural VAR, cointegration, Granger causality, standard ARDL, and vector error correction methods were employed in studies by Nazlioglu and Soytas (2012), Irz et al. (2013), Wang et al. (2014), Lucotte (2016), Roman et al. (2020), Olayungbo (2021) and Mokni (2023). However, as nonlinearity[1] has generally been reported for asset price and volatility relations, it is more suitable for exploring the links between the oil and agricultural commodity markets in a nonlinear framework (Liu 2014). The possible nonsymmetric adjustment of food prices to oil price changes is commonly linked to variables such as pricing power and the influence of government initiatives, including price floors as well as ceilings. (Siagian 2023). Furthermore, Adesoun et al. (2023) stressed the importance of structural shifts and seasonal variations in the oil-food nexus because both markets contain macroeconomic variables that are sensitive to exogenous factors and policy uncertainty. Thus, nonlinear approaches have been used to study the asymmetry in oil-food price links because applying linear models may lead to incorrect conclusions.

As an extension of the general modelling approaches described above, many studies have employed the NARDL approach of Shin et al. (2014). Studies by Abdlaziz et al. (2016), Zmami and Ben-Salha (2019), Chowdhury et al. (2021) and Karakotsios et al. (2021) provided clear evidence of asymmetry between oil and food prices. The findings obtained by applying the NARDL model revealed that oil prices had an asymmetrical impact on food inflation in Pakistan (Sarwar et al. 2020; Kashif et al. 2022) and Saudi Arabia (Darwez et al. 2023). Additionally, based on the NARDL method, Cherif et al. (2021) observed long-term asymmetrical effects in food price responses to oil prices in the majority of countries in the Middle East and North Africa region. However, the absence of asymmetrical behaviour has been confirmed for some crude oil exporters (Kuwait and Saudi Arabia), as well as Tunisia from the oil-importing group.

In addition to the abovementioned studies, further studies performed a nonlinear Granger causality test to explore the price dynamics in the energy-food nexus. For instance, the nonlinear Granger causality approach, applied by Adeosun et al. (2023), confirmed the bidirectional link between Brent oil and global food commodity prices from January 1990 to February 2021.

Aside from the foregoing nonlinear techniques, other methods that capture the threshold effect, e.g., nonlinear structural TVAR and TVECM models, were employed by Cheng and Yan (2019), who confirmed that price indices of crude oil and food interacted bidirectionally with each other from January 1990 to June 2017 on the global scale. Furthermore, these findings demonstrated that the food price indices generally reached equilibrium and increased more quickly than did the oil price indices when a threshold was reached. Our research on the asymmetric relationships between global oil prices and local retail food prices builds on the nonlinear ARDL methodology briefly described in the introductory section and elaborated in more detail in the following section.

[1] The rise and fall of energy prices do not have similar effects on food prices.

## 3 Methodology and data

### 3.1 Empirical strategy

To analyse the relationships between domestic food prices and global oil prices, we adopt ARDL family models with nonlinear transformation, including single and multiple threshold alternatives. The single-threshold NARDL model was introduced by Shin et al. (2014). Several researchers have extended the NARDL model to multiple thresholds (MTNARDL) (Verheyen 2013; Pal and Mitra 2015). The techniques result from the regression models developed by Shin and Pesaran (1999) and Pesaran et al. (2001). The NARDL and MTNARDL models are extensions of the linear ARDL model that can consider the asymmetric effects of fluctuations in time series. The advantages of nonlinear models compared to widely used regression techniques are demonstrated in the following aspects. First, the ordinary least squares approach can be applied, and inference is drawn through bounds testing irrespective of the variable integration order. However, NARDL models are not applicable if the regressors are I(2) or higher because the presence of such variables leads to invalid F-statistics for testing cointegration (Meyer et al. 2018). Second, NARDL techniques allow modelling of asymmetries and cointegration dynamics jointly. Third, NARDL models perform better than other cointegration techniques in cases with small sample sizes (Sek 2019).

We start our research with preliminary tests to identify time series properties. First, we perform sieve bootstrap-augmented Dickey-Fuller (ADF) tests for each of the logarithmic variables (Smeekes 2013). The ADF test by Dickey and Fuller (1981) suffers from potential distortion issues related to dataset size. As a result, bootstrap unit root tests are widely used as alternatives to asymptotic inference methods (Smeekes and Wilms 2024). The R package bootUR of version 1.0.3, written by Smeekes and Wilms (2024), was used. For the purpose of determining the maximum lag, the ad hoc rule suggested by Schwert (1989) is applied. To determine the optimal lag order, the Bayesian information criterion (BIC) is used.

First, the baseline ARDL model (Pesaran et al. 2001) is specified as follows:

$$\Delta Food_t = \beta_0 + \beta_1 Food_{t-1} + \beta_2 Oil_{t-1} + \beta_3 ER_{t-1} + \beta_4 IProd_{t-1} + \\ + \sum_{q=1}^{k} \varphi_{1q} \Delta Food_{t-q} + \sum_{q=0}^{m} \varphi_{2q} \Delta ER_{t-q} + \sum_{q=0}^{n} \varphi_{3q} \Delta IProd_{t-q} + \sum_{q=0}^{p} \varphi_{4q} \Delta Oil_{t-q} + \upsilon_t \tag{1}$$

where $Food_t$ is the logarithmic representation of the food price index at the consumer level (proxy for food prices); $\beta_0$ is an intercept; $Oil_t$ is the logarithmic representation of the spot oil price; $ER_t$ is the natural logarithm of the nominal exchange rate (NER); $IProd_t$ denotes the logarithmic representation of the industrial production index; $\Delta$ is the difference operator; $k$, $m$, $n$, and $p$ are lag orders; $\beta_1$, $\beta_2$, $\beta_3$ and $\beta_4$ are long-term parameters; $\sum \varphi_1, \sum \varphi_2, \sum \varphi_3$ and $\sum \varphi_4$ are short-run parameters; and $\upsilon_t$ is a vector of i.i.d. random errors.

To assess the cointegration between variables, a bounds test with the null hypothesis ($\beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$) is used. To fit the regression model (see *Eq.* 1), we use the OLS estimator. For the purpose of obtaining the final model specifications, we adopt a general-to-specific technique by removing lags if higher lags are found to be insignificant at the 5% level. In other words, a backwards elimination algorithm is used. The final lag length in our model is determined based on the BIC, and the maximum is determined to be 12 lags. The application of the general-to-specific technique at least partially eliminates potential problems with overfitting of the models estimated.

Next, following Shin et al. (2014), we split the exogenous variable (oil price) into partial sums of negative and positive fluctuations, which can be defined as follows:

$$Oil_t^- = \sum_{q=1}^{t} \Delta Oil_q^- = \sum_{q=1}^{t} \min\left(\Delta Oil_q, 0\right) \tag{2a}$$

$$Oil_t^+ = \sum_{q=1}^{t} \Delta Oil_q^+ = \sum_{q=1}^{t} \max\left(\Delta Oil_q, 0\right) \tag{2b}$$

where $Oil_t^-$ and $Oil_t^+$ are the partial sums of negative and positive changes in Brent prices ($Oil_t$), respectively.

Based on Eqs. 2a and b, the conventional ARDL model of Pesaran et al. (2001) can be developed to analyse existing asymmetries and is written in error correction form (Shin et al. 2014):

$$\begin{aligned}\Delta Food_t =& \beta_0 + \beta_1 Food_{t-1} + \beta_2 Oil_{t-1}^+ + \beta_3 Oil_{t-1}^- + \beta_4 ER_{t-1} + \beta_5 IProd_{t-1} + \\ &+ \sum_{q=1}^{k} \beta_{6q} \Delta Food_{t-q} + \sum_{q=0}^{m} \beta_{7q} \Delta ER_{t-q} + \sum_{q=0}^{n} \beta_{8q} \Delta IProd_{t-q} + \sum_{q=0}^{p} (\varphi_q^+ \Delta Oil_{t-q}^+ + \varphi_q^- \Delta Oil_{t-q}^-) + \upsilon_t\end{aligned} \tag{3}$$

where most variables are defined as in Eq. 1; $\beta_1$,$\beta_2$,$\beta_3$, $\beta_4$ and $\beta_5$ are long-term parameters; and $\xi_t = Food_t - (\alpha_1 Oil_t^+ + \alpha_2 Oil_t^- + \alpha_3 ER_t + \alpha_4 IProd_t)$ represents the nonlinear error correction term, where $\alpha_1 = -\frac{\beta_2}{\beta_1}$, $\alpha_2 = -\frac{\beta_3}{\beta_1}$, $\alpha_3 = -\frac{\beta_4}{\beta_1}$ and $\alpha_4 = -\frac{\beta_5}{\beta_1}$. Additionally, $\beta_6$, $\beta_7$, $\beta_8$, and $\varphi^+$, $\varphi^-$ are short-term parameters; $\sum_{q=0}^{p} \varphi_q^+$ reflects the short-term impact of Brent oil price positive changes on food prices; and $\sum_{q=0}^{p} \varphi_q^-$ reflects the short-term effect of an oil price reduction on food prices.

NARDL model fitting is implemented in the same manner as described above for the ARDL specification (*Eq.* 1). The null of cointegration absence ($H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$) among the variables of interest is tested via the procedure of Pesaran et al. (2001). After cointegration assessment, the Wald test is applied to analyse the long-term ($H_0 : \beta_2 = \beta_3$) and short-term $\left(\sum_{q=0}^{p} \varphi_q^+ = \sum_{q=0}^{p} \varphi_q^-\right)$ asymmetries between the pair of prices. Equation 3 reveals a symmetric (asymmetric) long-term Brent price transmission to the food price (in the event of oil price increases, it leads to large (small) fluctuations in the food price in comparison with the food price effect of Brent price reductions of the same magnitude; i.e., $\beta_2 > \beta_3$ or $\beta_2 < \beta_3$).

Unlike the NARDL model, the MTNARDL model allows us to capture different effects of regressor changes on the dependent variable based on the fluctuation magnitude in the explanatory variable. To overcome the data adequacy problem and to assess the asymmetric effects precisely, we split the logarithmic Brent series ($Oil_t$) into partial sum series as follows:

$$Oil_t = Oil^0 + Oil_t^1 + Oil_t^2 + Oil_t^3 + Oil_t^4 + Oil_t^5 \tag{4}$$

where $Oil_t^1$, $Oil_t^2$, $Oil_t^3$, $Oil_t^4$, and $Oil_t^5$ are partial sum series limited with thresholds at the 20th, 40th, 60th and 80th quintiles of Brent price fluctuations, respectively, and are defined as follows:

$$Oil_t^1 = \sum_{q=1}^{t} \Delta Oil_q I\{\Delta O_q \leq \tau_{20}\} \tag{5a}$$

$$Oil_t^2 = \sum_{q=1}^{t} \Delta Oil_q I\{\tau_{20} < \Delta Oil_q \leq \tau_{40}\} \tag{5b}$$

$$Oil_t^3 = \sum_{q=1}^{t} \Delta Oil_q I\{\tau_{40} < \Delta Oil_q \leq \tau_{60}\} \tag{5c}$$

$$Oil_t^4 = \sum_{q=1}^{t} \Delta Oil_q I\{\tau_{60} < \Delta Oil_q \leq \tau_{80}\} \tag{5d}$$

$$Oil_t^5 = \sum_{q=1}^{t} \Delta Oil_q I\{\Delta Oil_q > \tau_{80}\} \tag{5e}$$

where $\boldsymbol{I}\{\cdot\}$ is a function that yields the following values: "1" if the condition within $\{\}$ is satisfied and "0" otherwise; $\tau_{20}$, $\tau_{40}$, $\tau_{60}$, and $\tau_{80}$ are thresholds for the 20th, 40th, 60th and 80th quintiles of Brent price fluctuations, respectively.

Given the splitting method for explanatory variables described above, the MTNARDL model can be defined as follows:

$$\begin{aligned}\Delta Food_t = &\beta_0 + \beta_1 Food_{t-1} + \beta_2 ER_{t-1} + \beta_3 IProd_{t-1} + \sum_{q=1}^{5} \beta_4^q Oil_{t-1}^q + \\ &+ \sum_{q=1}^{k} \varphi_{1q} \Delta Food_{t-q} + \sum_{q=0}^{m} \varphi_{2q} \Delta ER_{t-q} + \sum_{q=0}^{n} \varphi_{3q} \Delta IProd_{t-q} + \sum_{q=1}^{5} \sum_{j=0}^{p} \varphi_{4j}^q \Delta Oil_{t-j}^q + v_t\end{aligned} \tag{6}$$

where the variables are as previously defined.

MTNARDL model fitting is performed in the same manner as described for the models above with a backwards elimination algorithm. The null hypothesis of the absence of cointegration among variables of interest is tested via the technique described above. We apply the Wald test to analyse long-term ($H_0 : \beta_4^1 = \beta_4^2 = \beta_4^3 = \beta_4^4 = \beta_4^5$) and short-term ($\sum_{j=0}^{p} \varphi_{4j}^1 = \sum_{j=0}^{p} \varphi_{4j}^2 = \sum_{j=0}^{p} \varphi_{4j}^3 = \sum_{j=0}^{p} \varphi_{4j}^4 = \sum_{j=0}^{p} \varphi_{4j}^5$) asymmetric pass-through relations from Brent to food prices.

We use the decomposition of Brent price changes into quintile partial sums to accommodate nonlinearity and asymmetry as well as to ascertain whether the effect of oil price changes varies across different levels of increase and decline. Such levels ($Oil_t^1, Oil_t^2, Oil_t^3, Oil_t^4$ and $Oil_t^5$) are related to extreme negative, rather negative, moderate (low negative or low positive), rather positive and extremely positive changes in Brent prices, respectively. Pal and Mitra (2019) argued that the purpose of decomposing price changes into five partial sums is to discover any plausible asymmetric linkage between oil price changes and the dependent variable. Moreover, such splitting allows the nonlinearities to be captured better and rather volatile changes to be distinguished from less severe changes.

Although the analysis of short- and long-term relationships is possible, interpreting the effects on food price changes, given the fluctuations in the oil price variable with a multitude of lags and lagged first differences, can often be difficult. To solve this problem, following Jordan and Philips (2019), we adopt stochastic simulations (using the R package "dynamac" from Jordan and Philips 2022). To describe the asymmetric responses of the variable of interest to an impulse of another variable, plots of the simulation results are presented, namely, period-over-period changes in the food price variable due to the shock in the oil price variable and the cumulative sum of the period-over-period changes in the variable of interest. The response in the food price variable is created by changing the Brent price variable. In our study, in the 5th period, the oil price variable is "shocked" by 0.2 (20%). This shock is distributed appropriately, as defined by the model specification with single or multiple thresholds. We can determine the central effect of the Brent price fluctuation on the consumer food price change across the simulations within the time range (equal to 24 months in our study). The inferences are made based on 5000 simulations.

### 3.2 Data

To analyse the effect of Brent prices on local food prices, we employ a database with monthly frequency observations. The time span is from January 2010 to December 2023. Retail food prices are approximated by the consumer price index for commodity groups of COICOP 1 – Food and nonalcoholic beverages. The data are sourced from the Slovak Statistical Office (DATAcube database 2024). Crude oil prices are the U.S. dollar prices per Brent Crude barrel obtained from the Federal Reserve Bank of St. Louis (Federal Reserve Economic Data (FRED) 2024). Moreover, we incorporate the nominal exchange rates (NERs) of USD/EUR and the industrial production index, which are presented as control variables. The data are obtained from the Slovak National Bank (Macroeconomic indicators 2024) and the Slovak Statistical Office (DATAcube database 2024). The use of the nominal exchange rate has proven to be a partial oil and food shock absorber in consumer price formation (Belke and Dreger 2015). As a proxy

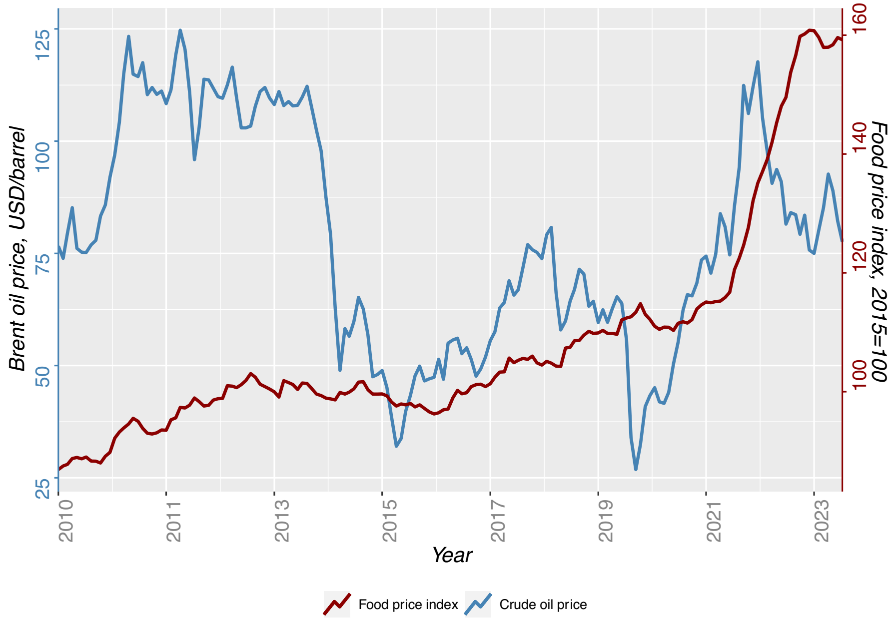


**Fig. 1** Series of Brent prices and consumer price indices for food commodity groups in Slovakia from January 2010 to December 2023 *Source* Federal Reserve Bank of St. Louis (Federal Reserve Economic Data 2024); Statistical Office of the Slovak Republic (DATAcube database 2024).

**Table 1** Statistics for the variables, January 2010-December 2023. *Source* Statistical Office of the Slovak Republic (DATAcube database 2024), Federal Reserve Bank of St. Louis (Federal Reserve Economic Data (FRED) 2024), National Bank of Slovakia (Macroeconomic indicators 2024)

| Variable | N | Mean | SD | Min | Max | Median | CV | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|---|---|
| Food price index | 168 | 108.14 | 18.01 | 86.91 | 160.82 | 101.37 | 0.17 | 1.74 | 2.28 |
| Oil price | 168 | 78.28 | 25.02 | 26.85 | 124.70 | 75.78 | 0.32 | 0.07 | − 1.17 |
| NER | 168 | 1.20 | 0.11 | 0.98 | 1.44 | 1.17 | 0.10 | 0.43 | − 0.99 |
| Industrial production index | 168 | 101.45 | 14.36 | 66.50 | 131.60 | 102.15 | 0.14 | − 0.06 | − 0.90 |

of economic activity, we employ industrial production data. All the variables are log-transformed to mitigate time series fluctuations and achieve robust and consistent results.

The fluctuations in oil and retail food prices can be observed in Fig. 1. As shown, some patterns of transmission between oil and retail food prices are visually apparent. Hence, cointegration relationships are possible, and the application of the proposed approach to capture potential long- and short-term asymmetries seems appropriate. Additionally, visual analysis confirmed the probable nonstationarity of the time series.

The descriptive statistics summarize the main features of the economic variables used to reveal the relationships between the price series under evaluation (Table 1).

Based on an analysis of the data, we infer that global crude oil prices are mostly spread around the mean value; however, the coefficients of variation for the consumer food price and industrial production indices are significantly lower. The distributions, except for the industrial production index, which has a negative skewness coefficient, have a tail on the right side. Moreover, in cases with a negative coefficient of kurtosis, the oil price and industrial production index values are concentrated near the centre of the curve, with few time series values in the tail region.

## 4 Empirical findings

According to the empirical strategy described above, we assess the logarithmic time series for the order of integration. Given the price developments in Fig. 1, we incorporate an intercept and a temporal trend into the model used to test the unit root presence. The diagnostic results are summarized in Table 2.

The output summarized in Table 2 reveals that the null of nonstationarity is accepted for all the variables in levels because the p value exceeds 0.05. In contrast, testing based on log-transformed time series with first differences shows that the test statistics are significant at the 1% critical level. Hence, all the logged variables are integrated of the first order, i.e., I(1). These findings suggest that nonlinear cointegration techniques can be applied to examine the relationships between variables and capture potential asymmetries in price linkages.

Taking the results of the bootstrap test into account, we test for cointegration. Table 3 reports that the bounds test F values are greater than the critical value of the upper bound at the 5% significance level. This result reveals the existence of nonlinear cointegration. We can conclude that the variables covary in the long-term period. Thus, applying the methodological approaches described above to analyse price relationships is reasonable.

To define the food-crude oil price nexus, we fit a linear model. The results of standard ARDL estimation within the backwards elimination procedure are presented in Table 4. From the long-term coefficients in Table 4, we find that Brent price fluctuations have a positive (although very limited) effect on Slovak food prices. Similarly, changes in industrial production affect food price formation

**Table 2** Bootstrap Dickey-Fuller test results. *Source* Authors' own calculations

| Time series* | Levels | | | 1st differences | | |
|---|---|---|---|---|---|---|
| | Largest root | Test statistic | *p* value ** | Largest root | Test statistic | *p* value** |
| Food price index | 0.9723 | −2.509 | 0.226 | 0.3452 | −8.973 | 0.000 |
| Oil price | 0.9490 | −2.567 | 0.301 | 0.1953 | −9.137 | 0.000 |
| NER | 0.9327 | −2.787 | 0.185 | 0.2571 | −10.03 | 0.000 |
| Industrial production index | 0.7249 | −2.470 | 0.428 | 0.1750 | −9.868 | 0.000 |

*—Logarithmic variables; **—Based on 1000 bootstrap replications of size n = $1.75T^{1/3}$, values are calculated

**Table 3** Bounds test of cointegration. *Source* Authors' own calculations

| Model | F-statistic | Critical values | | Conclusion |
|---|---|---|---|---|
| | | I (0) | I (1) | |
| ARDL | 6.054*** | 3.23 | 4.35 | Cointegration |
| NARDL | 12.543*** | 3.23 | 4.35 | Cointegration |
| MTNARDL | 15.592*** | 3.23 | 4.35 | Cointegration |

The asymptotic critical values are obtained from Pesaran et al. (2001) for an unrestricted intercept and no trend (long term regressors number equals 3). *** denotes rejection of the null of cointegration absence at the 1% significance level

directly but have a negligible effect on food prices. The appreciation of the nominal exchange rate pushed food prices lower and had the most substantial effect in the long term. However, in the short term, an increase (decrease) in the Brent price results in a decrease (increase) in the consumer food price index.

However, the ARDL model cannot capture the effect of fluctuations in Brent prices or the magnitude of these changes. Therefore, considering the limitations of typical linear ARDL models, models with thresholds are used to analyse the asymmetric effect of Brent price fluctuations on local retail food prices. The results of NARDL estimation and diagnostic tests are summarized in Table 5. The NARDL model was applied with the ordinary least squares algorithm described above.

Before conclusions are drawn, we check the adequacy of the model specification by means of several diagnostic tests. Additionally, we analyse the cumulative sums of recursive residual plots to assess model stability. All the tests reveal that the errors are normally distributed, autocorrelation and ARCH effects are not present, and the model parameters are stable throughout the period under consideration. For example, the SW test statistic is 0.993, with a p value of 0.650. Consequently, we accept the null hypothesis of residual normality. Therefore, the NARDL model should be considered adequately specified.

The long-term coefficients reveal asymmetry in the transmission of global crude oil prices to consumer food prices (Table 5). In other words, increases in Brent prices affect local food prices to a greater degree as they decrease. Furthermore, a decrease in oil prices does not lead to a decrease in food prices. Hence, there is evidence of the presence of strong market power (Meyer et al. 2018; Sarwar et al. 2020).

Market conditions in Slovakia limit options for the government to effectively shape the setting of prices of food products. As mentioned above, the Slovak food trade balance is shaped by the exports of agricultural commodities and imports of processed food, which points to the insufficient vertical integration of food production. Accordingly, Slovak retailers are more dependent on food import prices than on a decrease in the Brent price. In addition, a 10% increase in the oil price results in

**Table 4** ARDL model results. *Source* Authors' own calculations

Dependent variable $\Delta Food_t$

| Regressor | Long-term coefficient | s.e. | Regressor | Short-term coefficient | s.e. | Regressor | Short-term coefficient | s.e. |
|---|---|---|---|---|---|---|---|---|
| Intercept | −0.024 | 0.0371 | $\Delta Food_{t-1}$ | 0.299*** | 0.0741 | $\Delta IProd_{t-2}$ | 0.023*** | 0.0079 |
| $Food_{t-1}$ | −0.008 | 0.0153 | $\Delta Food_{t-4}$ | 0.206*** | 0.0697 | $\Delta IProd_{t-6}$ | −0.031*** | 0.0061 |
| $Oil_{t-1}$ | 0.012*** | 0.0028 | $\Delta Food_{t-6}$ | −0.283*** | 0.0819 | $\Delta IProd_{t-7}$ | −0.016** | 0.007 |
| $IProd_{t-1}$ | 0.004 | 0.0071 | $\Delta Oil_t$ | 0.015** | 0.0067 | $\Delta IProd_{t-9}$ | −0.039*** | 0.0067 |
| $ER_{t-1}$ | −0.050** | 0.0129 | $\Delta Oil_{t-5}$ | 0.015** | 0.0069 | $\Delta IProd_{t-11}$ | −0.016** | 0.0063 |
| | | | $\Delta IProd_{t-1}$ | −0.023*** | 0.0076 | | | |

| | Test value | *p* value |
|---|---|---|
| Adj. $R^2$ | 0.51 | |
| SW | 0.99 | 0.353 |
| BG | 14.02 | 0.3 |
| DW | 2.02 | 0.399 |
| BP | 8.06 | 0.922 |
| CUSUM | Stable | |
| CUSUM of squares | Stable | |

s.e.—standard error, SW—Shapiro−Wilk test for normality of errors, BG—Breusch-Godfrey test for serial correlation, CUSUM—visual cumulative sum test for stability (plots are not presented here but are available from the authors upon request), DW—Durbin-Watson test, BP—Breusch−Pagan test for conditional heteroscedasticity. ***/**/* denote 1, 5 and 10% significance levels, respectively

**Table 5** NARDL model estimates. *Source* Authors' own calculations

Dependent variable $\Delta Food_t$

| Regressor | Long-term coefficient | s.e. | Regressor | Short-term coefficient | s.e. | Regressor | Short-term coefficient | s.e. |
|---|---|---|---|---|---|---|---|---|
| Intercept | 0.424*** | 0.0697 | $\Delta Food_{t-1}$ | 0.319*** | 0.0701 | $\Delta IProd_{t-3}$ | 0.020*** | 0.0066 |
| $Food_{t-1}$ | −0.062*** | 0.0117 | $\Delta Food_{t-4}$ | 0.193** | 0.0763 | $\Delta IProd_{t-4}$ | 0.033*** | 0.0067 |
| $Oil^{+}_{t-1}$ | 0.018*** | 0.0032 | $\Delta Food_{t-6}$ | −0.240*** | 0.0778 | $\Delta IProd_{t-5}$ | 0.024*** | 0.0072 |
| $Oil^{-}_{t-1}$ | 0.012*** | 0.0025 | $\Delta Food_{t-10}$ | 0.249*** | 0.0725 | $\Delta IPord_{t-7}$ | 0.022*** | 0.0073 |
| $IProd_{t-1}$ | −0.030*** | 0.0070 | $\Delta Oil^{+}_{t-3}$ | −0.028*** | 0.0134 | $\Delta IPord_{t-8}$ | 0.036*** | 0.0064 |
| $ER_{t-1}$ | −0.051*** | 0.0118 | $\Delta Oil^{-}_{t-11}$ | 0.021*** | 0.0091 | $\Delta IProd_{t-10}$ | 0.014** | 0.0066 |
| | | | $\Delta IProd_{t-2}$ | 0.041*** | 0.0076 | | | |

Diagnostic tests

| | Test value | *p* value | | | Test value | *p* value |
|---|---|---|---|---|---|---|
| Adj. $R^2$ | 0.56 | | | | | |
| SW | 0.993 | 0.650 | Long-term asymmetry | | | |
| BG | 4.86 | 0.051 | Wald test | F-statistic | 28.449 | 0.000 |
| DW | 2.16 | 0.716 | | | | |
| BP | 18.17 | 0.444 | Short-term asymmetry | | | |
| CUSUM | Stable | | Wald test | F-statistic | 8.616 | 0.004 |
| CUSUM of squares | Stable | | | | | |

s.e.—standard error, SW—Shapiro–Wilk test for normality of errors, BG—Breusch–Godfrey test for serial correlation, CUSUM—visual cumulative sum test for stability (plots are not presented here but are available from the authors upon request), DW—Durbin–Watson test, BP—Breusch–Pagan test for conditional heteroscedasticity. ***/**/* denote 1, 5 and 10% significance levels, respectively an "annualized"[2] 2.16% increase in the consumer food price index in the long term. This outcome suggests a limited pass-through of global oil prices to local retail food prices.

The results of this research also indicate that changes in the NER and industrial production cushion impact domestic food prices in the long term. For example, an increase in the NER of 10% results in an "annualized" decrease in the domestic food price index of 6.12%. However, in the short run, these results are consistent only with a positive correlation between industrial production ($\Delta IProd_{t-2}$, $\Delta IProd_{t-3}$, $\Delta IProd_{t-4}$, $\Delta IProd_{t-5}$, $\Delta IProd_{t-8}$, $\Delta IProd_{t-10}$) and consumer food prices.

Considering our findings regarding the short-term variations owing to long-term development, it is worth mentioning the presence of asymmetry in price transmission. The Wald test is used to detect asymmetric effects between global oil and local consumer food prices. The null hypothesis of symmetry is not accepted. Indeed, a positive change in the oil price ($\Delta Oil^{+}_{t-3}$) contributes to a decrease in the local retail food price. Unlike those for positive oil price changes, the short-term coefficient for oil price decreases ($\Delta Oil^{-}_{t-11}$) has a positive sign.

The impulse response plots also confirm asymmetric relationships between consumer food and oil price fluctuations. The simulation results reveal that positive changes in oil prices have greater aggregate effects on food prices than do negative changes. This finding is confirmed by the fact that the cumulative effect of the shock in $Oil^{+}_{t}$ is an approximately 5.8% (Fig. 2, panel b) increase in the retail food price, whereas the shock in $Oil^{-}_{t}$ leads to a food price index change of approximately 4 percentage points (Fig. 2, panel d). Moreover, a 20-percentage-point shock to $Oil^{+}_{t}$ causes an immediate increase in the food price index of approximately 0.5%, whereas a shock to $Oil^{-}_{t}$ during the same period results in a food price index change of only 0.3%. In addition, fluctuations in $Oil^{+}_{t}$ cause food price changes to peak in the 5th month after the shock. Then, food price changes start decreasing until the effect fully decays over 23–24 months. However, the food price change reaches a maximum in the 10th month after $Oil^{-}_{t}$ shocks, followed by a gradual decrease until the effect fades over 20 months.

As mentioned above, the single-threshold NARDL technique distinguishes only the effects of bidirectional changes (positive or negative) in Brent prices. To improve the depth and robustness of our results, we also fit the MTNARDL model alternative, which enables us to refine the fluctuations according to direction and size.

Table 6 represents the estimates obtained from the MTNARDL model with Brent price series volatility decomposed into quintiles.

Assuming that long-term asymmetry is revealed in the single-threshold model, the Wald test in the MTNARDL model also significantly supports asymmetric effects. Additionally, in the short term, the null of symmetry is not accepted at the 5% significance level. Indeed, the long-term coefficients vary substantially across each quintile subseries. The sign of the long-run coefficients of the MTNARDL estimations is in line with that of the NARDL estimations. Additionally, the effect of

[2] The models are based on the monthly data and coefficients estimated represent average monthly change in long-term. The annualized values refer to coefficients multiplied by 12 months.

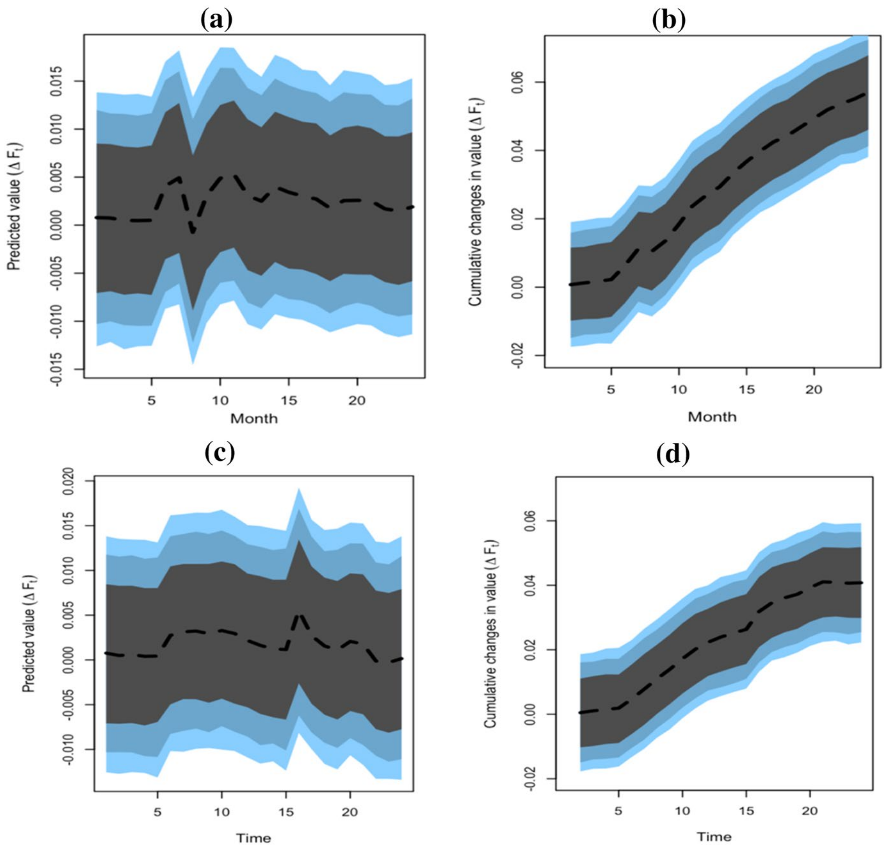


**Fig. 2** NARDL model simulation effects of a 20-percentage-point shock in $Oil_t^+$ (**a**, **b**) and in $Oil_t^-$ (**c**, **d**) on food price changes ($\Delta Food_t$). *Note* The predicted value is denoted by the black dotted line, whereas the 75th, 90th, and 95th percentiles of the predictions from the simulations are marked with coloured areas (from darkest to lightest). *Source* Authors' calculations

extreme and rather positive changes in oil prices ($Oil_{t-1}^5$ and $Oil_{t-1}^4$) is greater than the impact of their negative counterparts ($Oil_{t-1}^1$ and $Oil_{t-1}^2$) at the corresponding levels. In other words, the main factor driving the observed asymmetries in the retail sector is dependence to a greater degree on food imports and the insufficient vertical integration of local food production rather than global oil price changes. Moreover, only the coefficient for the moderate threshold ($Oil_{t-1}^3$) is not statistically reliable at the 1% level. A negative response to consumer food price changes is not observed. The impacts of changes in industrial production and the NER on retail food prices are the same as those observed for the NARDL model specification.

In the short-term part of the model, the coefficients vary across Brent price subseries. Statistically significant effects of Brent price changes are detected across almost all quintiles ($\Delta Oil_{t-1}^1$, $Oil_{t-2}^1$, $\Delta Oil_{t-3}^1$, $\Delta Oil_{t-4}^1$, $\Delta Oil_{t-10}^1$, $\Delta Oil_{t-11}^1$, $\Delta Oil_{t-10}^2$, $\Delta Oil_{t-4}^3$, $\Delta Oil_{t-5}^3$ and $\Delta Oil_{t-9}^4$). However, the immediate response of consumer

**Table 6** MTNARDL model estimation results. *Source* Authors' own calculations

Dependent variable $\Delta Food_t$

| Regressor | Long-term coefficient | s.e. | Regressor | Short-term coefficient | s.e. | Regressor | Short-term coefficient | s.e. |
|---|---|---|---|---|---|---|---|---|
| Intercept | 0.531*** | 0.0932 | $\Delta Food_{t-4}$ | 0.216*** | 0.0784 | $\Delta Oil^3_{t-5}$ | 0.221** | 0.0879 |
| $Food_{t-1}$ | −0.102*** | 0.0189 | $\Delta Food_{t-6}$ | −0.330*** | 0.069 | $\Delta Oil^3_{t-6}$ | 0.311*** | 0.0854 |
| $Oil^1_{t-1}$ | 0.030*** | 0.0046 | $\Delta Food_{t-10}$ | 0.236*** | 0.0718 | $\Delta Oil^4_{t-9}$ | −0.064** | 0.0302 |
| $Oil^2_{t-1}$ | 0.042*** | 0.016 | $\Delta Oil^1_{t-1}$ | −0.030*** | 0.0101 | $\Delta IProd_{t-2}$ | 0.038*** | 0.007 |
| $Oil^3_{t-1}$ | 0.014 | 0.0289 | $\Delta Oil^1_{t-2}$ | −0.033*** | 0.0119 | $\Delta IProd_{t-3}$ | 0.028*** | 0.0071 |
| $Oil^4_{t-1}$ | 0.055*** | 0.0145 | $\Delta Oil^1_{t-3}$ | −0.031*** | 0.0118 | $\Delta IProd_{t-4}$ | 0.037*** | 0.0069 |
| $Oil^5_{t-1}$ | 0.038*** | 0.005 | $\Delta Oil^1_{t-4}$ | −0.025** | 0.0115 | $\Delta IProd_{t-5}$ | 0.023*** | 0.0067 |
| $IProd_{t-1}$ | −0.012* | 0.0095 | $\Delta Oil^1_{t-10}$ | −0.019** | 0.0095 | $\Delta IProd_{t-8}$ | 0.027*** | 0.0059 |
| $ER_{t-1}$ | −0.100*** | 0.016 | $\Delta Oil^1_{t-11}$ | 0.022** | 0.0092 | $\Delta ER_{t-2}$ | 0.100*** | 0.0365 |
| | | | $\Delta Oil^2_{t-10}$ | −0.095** | 0.0424 | $\Delta ER_{t-3}$ | 0.068** | 0.0337 |
| | | | $\Delta Oil^3_{t-4}$ | 0.191** | 0.0913 | $\Delta ER_{t-4}$ | 0.093*** | 0.0332 |

Diagnostic tests

| | Test value | p value | | | Test value | p value |
|---|---|---|---|---|---|---|
| Adj. $R^2$ | 0.600 | | | | | |
| SW | 0.989 | 0.228 | Long-term asymmetry | | | |
| BG | 1.65 | 0.201 | Wald test | F-statistic | 12.754 | 0.000 |
| DW | 1.78 | 0.022 | | | | |
| BP | 27.77 | 0.583 | Short-term asymmetry | | | |
| CUSUM | Stable | | Wald test | F-statistic | 5.363 | 0.002 |
| CUSUM of squares | Stable | | | | | |

s.e.—standard error, SW—Shapiro–Wilk test for normality of errors, BG—Breusch–Godfrey test for serial correlation, CUSUM – visual cumulative sum test for stability (plots are not presented here but are available from the authors upon request), DW—Durbin–Watson test, BP—Breusch–Pagan test for conditional heteroscedasticity. ***/**/* denote 1, 5 and 10% significance levels, respectively. $\tau_{20} = -0.062(-6.2\%)$, $\tau_{40} = -0.008(-0.8\%)$, $\tau_{60} = 0.027$ (2.7%), and $\tau_{80} = 0.067(6.7\ \%)$

food price changes to Brent price fluctuations is greatest when the oil price fluctuates moderately—Brent price changes within the range of the 40th–60th quintiles ($\Delta Oil^3_{t-4}$, $\Delta Oil^3_{t-5}$, $\Delta Oil^3_{t-6}$). These results indicate that during periods of relative oil price stability, local retailers gain from higher profit margins. However, interpreting the cumulative asymmetric effects on food price changes, given the fluctuations in the oil price variable with a multitude of lags, can often be difficult. Under such circumstances, we employ the simulation-based impulse response for visual analysis to complement the MTNARDL estimation results. Visual analysis allows us to identify the immediate and cumulative food price responses to oil price shocks over a set period across different levels of Brent price fluctuations.

The simulation results from the MTNARDL reveal asymmetric dynamics in the food and oil price nexus. From the impulse response plots (Fig. 3), we show that the rather positive fluctuations in oil price ($Oil^4_t$, Fig. 3, panels g and h) have the greatest aggregate effect on consumer food price change; more precisely, the magnitude of this change is approximately 10%. This finding corresponds with the highest coefficient under the same regime in the long run ($Oil^4_{t-1}$). Interestingly, in terms of the cumulative effect, a shock to the oil price variable under a regime with moderate changes ($Oil^3_t$) causes an approximately 15-percentage-point change in the food price in the 6th month after the shock, followed by a sharp decrease in the food price by approximately half. As far as the period-over-period changes are concerned (left panels of Fig. 3), food price changes vary significantly across shocks in oil prices under different regimes with unequal fluctuations. Owing to the shock in $Oil^3_t$, the immediate effect of food price changes reaches a maximum magnitude (approximately 4%) in the 4th month after the shock (Fig. 3, panel e). Indeed, as a result of shocks in oil price variables under regimes with rather negative and rather positive changes ($Oil^2_t$ and $Oil^4_t$, respectively), retail food price volatility is almost identical. Moreover, food price responses to the extreme negative shock in $Oil^1_t$ are relatively more volatile than are food price reactions to the positive shock of similar magnitude in $Oil^5_t$.

All the diagnostic tests revealed a normal distribution of errors, autocorrelation and no ARCH effect, and the model parameters were stable throughout the period under consideration. Hence, the MTNARDL model should be considered adequately specified. Considering the goodness of fit of each model, we can conclude that the adjusted $R^2$ value of the MTNARDL model is greater than that of the other models.

In summary, the use of the MTNARDL approach allowed us to unveil asymmetries in the pass-through between Brent and local food prices. Furthermore, the effect of Brent price changes on food prices varies considerably across regimes of price fluctuations.

## 5 Conclusions

This study analyses the asymmetric nexus between global energy and local food prices for an oil-importing country considering the parameters of industrial production and the nominal exchange rate. Nonlinear ARDL models are suitable tools for estimating asymmetric price relationships under a cointegration

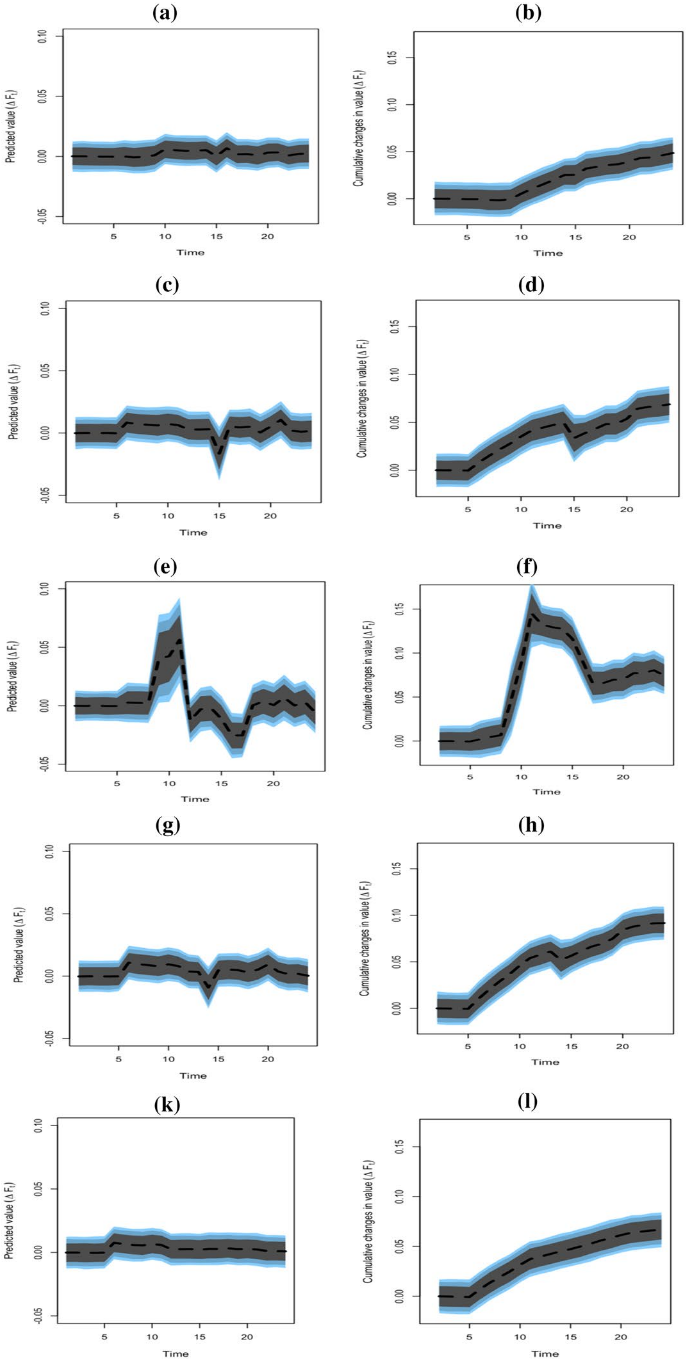


**Fig. 3** MTNARDL model simulation effects of a 20% point shock in $Oil_t^1$ (**a**, **b**), $Oil_t^2$ (**c**, **d**), $Oil_t^3$ (**e**, **f**), $Oil_t^4$ (**g**, **h**) and $Oil_t^5$ (**k**, **l**) on food price changes ($\Delta Food_t$). *Source* Authors' calculations

framework (Shin et al. 2014). Their specifications allow for the incorporation of the possible asymmetric effects of negative and positive changes in oil prices on the food price variable, whereas the impact of oil price fluctuations in the standard linear ARDL model remains the same. More importantly, unlike typical linear approaches, nonlinear ARDL models are applied to I(0) and I(1) time series (or a combination of the two), connecting long- and short-term dynamic processes. Accordingly, unbiased results can be obtained.

The NARDL technique captures only positive and negative oil price changes. We extend the single-threshold NARDL approach to an MTNARDL framework by decomposing oil price changes into quintile partial sums. This allows us to analyse price links in detail. The MTNARDL technique differs from other methods in that its ability to estimate the effects of extremely high or very low changes in oil prices on food prices differs. This situation implies that policy makers have various options for addressing economic imbalances. Compared to linear and single-threshold regressions, the MTNARDL model is more stable and better represents global oil-local retail food price linkages.

For cases with conventional positive and negative crude oil price changes, asymmetry is found in the short term and long term. When we decomposed series into five quintile partial sums, the impact of crude oil prices on consumer food prices was also determined to be asymmetric in both the long and short terms. Additionally, some important findings were obtained. First, cointegration among the prices and incomplete pass-through of Brent prices to local food prices was detected, and this finding was consistent with those of large-scale studies on global oil-local food price transmission (Ibrahim 2015; Abdlaziz et al. 2016; Sarwar et al. 2020). Second, only the coefficient for moderate changes ($Oil^3_{t-1}$) was not statistically significant in the long term. However, in the short run, food price changes in response to oil price changes were greatest when the Brent price fluctuated moderately ($Oil^3_{t-4}$). In contrast, large negative shifts in oil prices ($\Delta Oil^1_{t-1}$, $\Delta Oil^1_{t-2}$, $\Delta Oil^1_{t-3}$, $\Delta Oil^1_{t-4}$, $\Delta Oil^1_{t-10}$) resulted in food price decreases. This finding indicates that during periods of relative oil price stability, local companies gain from higher profit margins. The lack of significance of high oil price increases resonates with the findings of Ghassan and AlHajhoj (2016), who argue that the return of high oil prices to long-run equilibrium might shape market expectations and subsequently the price formation process.

This research seeks to fill the gap in the knowledge on the asymmetric nexus between global oil and local food prices by applying the MTNARDL model. The asymmetric transmission of Brent prices to local consumer food prices, especially in the long term, should cause concern in the Slovak government in terms of support for low-income households. These individuals spend most of their budgets on food products. Given that Slovakia depends on the import of crude oil, when those prices start to gradually increase, we recommend that the government adopt support mechanisms targeted at food prices (especially basic food items) for low-income households. However, in the fight against price inflation, food producers and retailers must also be involved in the process and create a supportive framework in periods of crude oil volatility. Furthermore, Slovak policy-makers should focus on improving the subsidy distribution and regulatory mechanisms, taxing crude oil products and developing monetary policy to control asymmetric effects on crude oil price fluctuations.

This study can be followed up in several ways by introducing real exchange rate regimes and adding greater flexibility to the model specifications by incorporating spline effects with a more intuitive visualization of the asymmetric food price responses to oil price shocks. These extensions have the potential to provide additional insights into the relationships between the variables of interest and more nuanced policy tools. The research presented in this paper has some important limitations involving data series length and the assessment of other possible control variables, including wholesale and producer food commodity prices, fertilizer costs and diesel fuel prices. These limitations provide additional possible pathways for further research on this topic.

**Acknowledgements** We are thankful to Sergei Kharin for support from the EU project *"Next Generation EU through the Recovery and Resilience Plan for Slovakia"* *No. 09I03-03-V01-00054*. Ivan Lichner appreciates the support from the project *VEGA-2/0158/24*.

**Author contributions** SK: conceptualization, methodology, software, formal analysis, investigation, writing—original draft, writing—review and editing, visualization, supervision. ZK: writing—original draft, writing—review and editing. IL: conceptualization, writing—original draft, writing—review and editing, project administration.

**Funding** Open access funding provided by The Ministry of Education, Science, Research and Sport of the Slovak Republic in cooperation with Centre for Scientific and Technical Information of the Slovak Republic.

## Declarations

**Conflict of interest** The authors declare that they have no conflict of interest.



## References

Abdlaziz, R.A., Rahim, K.A., Adamu, P.: Oil and food prices co-integration nexus for Indonesia: a non-linear autoregressive distributed lag analysis. Int. J. Energy Econ. Policy **6**(1), 82–87 (2016)

Abdullaieva, A., Andrusenko, N., Hromová, O., Martynova, L., Prutska, O., Yurchyk, I.: The impact of the Russian-Ukrainian war on EU food security. Econ. Aff. **67**(4), 859–867 (2022). https://doi.org/10.46852/0424-2513.4s.2022.19

Adeosun, O.A., Olayeni, R.O., Tabash, M.I., Anagreh, S.: Revisiting the oil and food prices dynamics: a time varying approach. J Bus. Cycle Res. (2023). https://doi.org/10.1007/s41549-023-00083-3

Alnour, M., Altıntaş, H., Rahman, M.N.: Unveiling the asymmetric response of global food prices to the energy prices shocks and economic policy uncertainty. World Develop. Sustain. **3**, 100083 (2023). https://doi.org/10.1016/j.wds.2023.100083

Bartóková, Ľ, Ďurčová, J.: Agricultural sector and its importance for the Slovak economy: structural analysis. Ekonomický Časopis/journal of Economics **70**(3), 237–263 (2022). https://doi.org/10.31577/ekoncas.2022.03.02

Belke, A., Dreger, C.: The transmission of oil and food prices to consumer prices: evidence for the MENA countries. Int. Econ. Econ. Policy **12**(1), 143–161 (2015). https://doi.org/10.1007/s10368-014-0283-x

Casalis A.: When food bites back. What quarterly firm-level data reveal about food Inflation. *Policy Brief*, No. 2. National Bank of Slovakia. (2023). Available at https://nbs.sk/dokument/24aa1832-d652-4812-a1c4-63d4caa7802d/stiahnut?force=false (accessed Mar 18, 2024)

Chen, D., Gummi, U.M., Lu, S., Mu'azu, A.: Modelling the impact of oil price fluctuations on food price in high and low-income oil exporting countries. Agric. Econ. Czech. **66**(10), 458–468 (2020). https://doi.org/10.17221/197/2020-AGRICECON

Cheng, S., Yan, C.: On the relation between global food and crude oil prices: an empirical investigation in a nonlinear framework. Energy Econ. **81**, 422–432 (2019). https://doi.org/10.1016/j.eneco.2019.04.007

Cherif, H.H., Chen, Z., Ni, G.: Modelling the symmetrical and asymmetrical effects of global oil prices on local food prices: a MENA region application. Environ. Sci. Pollut. Res.pollut. Res. **28**(46), 65499–65512 (2021). https://doi.org/10.1007/s11356-021-14842-1

Chowdhury, M.A.F., Meo, M.S., Uddin, A., Haque, M.M.: Asymmetric effect of energy price on commodity price: New evidence from NARDL and time frequency wavelet approaches. Energy **231**, 120934 (2021). https://doi.org/10.1016/j.energy.2021.120934

Darwez, F., Alharbi, F., Ifa, A., Bayomei, S., Mostfa, E., Lutfi, A., Haya, M.A., Alrawad, M.: Assessing the impact of oil price volatility on food prices in Saudi Arabia: insights from nonlinear autoregressive distributed lags (NARDL) analysis. Econ. Innov. Econ. Res. J. **11**(2), 5–23 (2023). https://doi.org/10.2478/eoik-2023-0056

DATAcube database: Multidimensional tables (cubes) for indicators of economic and socio-economic development provided by the Statistical Office of the Slovak Republic. (2024) Available at https://datacube.statistics.sk/#!/lang/en (accessed Jan 31, 2024)

Demirtaş, C., Soyu Yıldırım, E., Dur, D.T.: Do oil prices have an effects on food prices? Fresh Evid. Türkiye **15**(1), 79–91 (2023)

Dickey, D.A., Fuller, W.A.: Likelihood ratio statistics for autoregressive time series with a unit root. Econometrica **49**(4), 1057–1072 (1981)

Federal Reserve Economic Data (FRED): Crude oil prices: Brent—Europe, federal reserve bank of St. Louis. (2024) Available at https://fred.stlouisfed.org/series/MCOILBRENTEU (accessed Jan 31, 2024)

Ghassan, H.B., AlHajhoj, H.R.: Long run dynamic volatilities between OPEC and non-OPEC crude oil prices. Appl. Energy **169**, 384–394 (2016). https://doi.org/10.1016/j.apenergy.2016.02.057

Gilbert, C.L.: How to understand high food prices. J. Agric. Econ. **61**(2), 398–425 (2010). https://doi.org/10.1111/j.1477-9552.2010.00248.x

Guan, Y., Yan, J., Shan, Y., Zhou, Y., Hang, Y., Li, R., Liu, Y., Liu, B., Nie, Q., Bruckner, B., Feng, R., Hubacek, K.: Burden of the global energy price crisis on households. Nat. Energy **8**(3), 304–316 (2023). https://doi.org/10.1038/s41560-023-01209-8

Hlavackova, M.: Retail food. United States Department of Agriculture. Foreign Agricultural Services. LO2021–0001. (2021) Available at: https://apps.fas.usda.gov/newgainapi/api/Report/DownloadReportByFileName?fileName=Retail%20Foods_Berlin_Slovakia_07-11-2021.pdf

Ibrahim, M.H.: Oil and food prices in Malaysia: a nonlinear ARDL analysis. Agric. Food Econ. (2015). https://doi.org/10.1186/s40100-014-0020-3

Irz, X., Niemi, J., Liu, X.: Determinants of food price inflation in Finland—The role of energy. Energy Policy **63**, 656–663 (2013). https://doi.org/10.1016/j.enpol.2013.09.023

Janda, K., Kristoufek, L.: The relationship between fuel and food prices: methods, outcomes, and lessons for commodity price risk management. SSRN Electron. J. (2019). https://doi.org/10.2139/ssrn.3336355

Jordan S., and Philips, A.Q.: Dynamac: Dynamic Simulation and Testing for Single-Equation ARDL Models [R package version 0.1.12]. (2022). Available at https://CRAN.R-project.org/package=dynamac (accessed June 10, 2024)

Jordan, S., Philips, A.Q.: Dynamic simulation and testing for single-equation cointegrating and stationary autoregressive distributed lag models. R J. **10**(2), 469–488 (2019)
Karakotsios, A., Katrakilidis, C., Kroupis, N.: The dynamic linkages between food prices and oil prices. Does asymmetry matter? J. Econ. Asym. **23**, e00203 (2021). https://doi.org/10.1016/j.jeca.2021.e00203
Kashif, U., Hong, C., Naseem, S., Akram, M.W., Meo, M.S.: Impact of oil price fluctuations on food prices: fresh insight from asymmetric ARDL approach of co-integration. Int. J. Glob. Energy Issues **44**(2/3), 264 (2022). https://doi.org/10.1504/IJGEI.2022.121389
Kašťáková, E., Žatko, M., Jarossová, M.A.: The impact of the Russian embargo on the development and specialization of agri-food trade between Slovakia and Russia. Potravinarstvo/slovak Journal of Food Sciences **16**, 590–602 (2022). https://doi.org/10.5219/1779
Konandreas, P.: Trade Policy Responses to Food Price Volatility in Poor Net Food-Importing Countries. *Price Volatility and Beyond* 320203, International Centre for Trade and Sustainable Development (ICTSD). (2012). https://doi.org/10.22004/ag.econ.320203
Köse, N., Ünal, E.: The effects of the oil price and temperature on food inflation in Latin America. Environ. Develop. Sustain. **26**, 3269–3295 (2022). https://doi.org/10.1007/s10668-022-02817-2
Li, Y., Guo, J.: The asymmetric impacts of oil price and shocks on inflation in BRICS: a multiple threshold nonlinear ARDL model. Appl. Econ. **54**(12), 1377–1395 (2021). https://doi.org/10.1080/00036846.2021.1976386
Liu, L.: Cross-correlations between crude oil and agricultural commodity markets. Physica A A **395**, 293–302 (2014). https://doi.org/10.1016/j.physa.2013.10.021
Lucotte, Y.: Co-movements between crude oil and food prices: a post-commodity boom perspective. Econ. Lett.lett. **147**, 142–147 (2016). https://doi.org/10.1016/j.econlet.2016.08.032
Macroeconomic indicators: Nominal and real effective exchange rate indices (based on consumer prices, industrial producers prices, manufacturing prices and unit labour costs) compiled in National Bank of Slovakia for slovak economy. (2024). Available at https://nbs.sk/en/statistics/selected-macroeconomics-indicators/effective-exchange-rate/ (accessed Jan 31, 2024)
Masih, R., Peters, S., De Mello, L.: Oil price volatility and stock price fluctuations in an emerging market: evidence from South Korea. Energy Econ. **33**(5), 975–986 (2011). https://doi.org/10.1016/j.eneco.2011.03.015
Matošková, D., Gálik, J., Jamborová, M.: Fungovanie slovenského trhu s agropotravinárskymi produktami a špecifiká jeho ponuky (The functioning of the Slovak agri-food market and the specifics of its supply). NPPC-VÚEPP Bratislava. (2017). ISBN 978–80–8058–617–1
Matthews, A.: Food price situation in Europe. Stud. Agric. Econ. **125**, 60–68 (2023). https://doi.org/10.7896/j.2563
Meyer, D.F., Sanusi, K.A., Hassan, A.: Analysis of the asymmetric impacts of oil prices on food prices in oil-exporting, developing countries. J. Int. Stud. **11**(3), 82–94 (2018). https://doi.org/10.14254/2071-8330.2018/11-3/7
Ministry of Finance of the Slovak Republic (2023). Analysis of the price development of main food items 2/2023/Analýza cenového vývoja základných druhov potravín 2/2023. Available at: https://www.mfsr.sk/files/archiv/19/Analyza-vybranych-druhov-potravin-2-2023.pdf
Mitchell, D.: A Note on Rising Food Prices (2008). World Bank Policy Research Working Paper No. 4682, (2008). Available at https://ssrn.com/abstract=1233058 (accessed Feb 28, 2024)
Mohajan, H.K.: Global food price hike is a burden to the poor. Int. J. Inf. Technol. Bus. Manag. **19**(1), 1–15 (2013)
Mokni, K.: Detrended cross-correlations analysis between oil shocks and world food prices. Int. J. Energy Sect. Manage. **18**(1), 183–199 (2023). https://doi.org/10.1108/ijesm-10-2021-0019
Mokni, K., Youssef, M.: Empirical analysis of the cross-interdependence between crude oil and agricultural commodity markets. Rev. Financ. Econ. **38**(4), 635–654 (2020). https://doi.org/10.1002/rfe.1096
Moralista, R.B., Martir, E.M.: Oil price volatility and business profitability: evidence from the local market. J. Adv. Zool. **44**(S-5), 1602–1606 (2023). https://doi.org/10.17762/jaz.v44iS-5.1398
Nazlıoğlu, Ş, Soytaş, U.: Oil price, agricultural commodity prices, and the dollar: a panel cointegration and causality analysis. Energy Econ. **34**(4), 1098–1104 (2012). https://doi.org/10.1016/j.eneco.2011.09.008
Olayungbo, D.O.: Global oil price and food prices in food importing and oil exporting developing countries: A panel ARDL analysis. Heliyon **7**(3), e06357 (2021). https://doi.org/10.1016/j.heliyon.2021.e06357

Olofin, S. and Salisu, A.: Modelling oil price-inflation nexus: The role of asymmetries and structural breaks. CEAR 2016 Working Paper Series, (2016).https://doi.org/10.13140/RG.2.2.28665.26722
Oravcová, V.: Energy without Russia. The Consequences of the Ukraine war and the EU Sanctions on the Energy Sector in Europe. Friedrich-Ebert-Stiftung. (2023). Available at https://library.fes.de/pdf-files/bueros/budapest/20408.pdf (accessed Mar 17, 2024)
Pal, D., Mitra, S.K.: Asymmetric impact of crude price on oil product pricing in the United States: an application of multiple threshold nonlinear autoregressive distributed lag model. Econ. Model. **51**, 436–443 (2015). https://doi.org/10.1016/j.econmod.2015.08.026
Pal, D., Mitra, S.K.: Asymmetric oil price transmission to the purchasing power of the U.S. dollar: a multiple threshold NARDL modelling approach. Resourc. Policy **64**, 101508 (2019). https://doi.org/10.1016/j.resourpol.2019.101508
Pesaran, M.H., Shin, Y., Smith, R.J.: Bounds testing approaches to the analysis of level relationships. J. Appl. Economet.economet. **16**, 289–326 (2001). https://doi.org/10.1002/jae.616
Raheem, I.D., Ajide, K.B., Agboola, Y.H.: A new insight into oil price-inflation nexus. Resour. Policy. Policy **68**, 101804 (2020). https://doi.org/10.1016/j.resourpol.2020.101804
Roman, M., Górecka, A., Baran, J.: The linkages between crude oil and food prices. Energies **13**(24), 6545 (2020). https://doi.org/10.3390/en13246545
Sarwar, M.N., Hussain, H., Maqbool, M.B.: Pass through effects of oil price on food and non-food prices in Pakistan: A nonlinear ARDL approach. Resour. Policy. Policy **69**, 101876 (2020). https://doi.org/10.1016/j.resourpol.2020.101876
Schwert, G.W.: Tests for unit roots: a Monte Carlo investigation. J. Bus. Econ. Stat. **7**(2), 147–159 (1989)
Sek, S.K.: Effect of oil price pass-through on domestic price inflation: evidence from nonlinear ARDL models. Panoeconomicus **66**(1), 69–91 (2019). https://doi.org/10.2298/PAN160511021S
Shin, Y., Yu, B. and Greenwood-Nimmo, M.: Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. In R. C. Sickles & W. C. Horrace (Eds.), Festschrift in honor of Peter Schmidt: Econometric methods and applications. Springer, New York. (2014). https://doi.org/10.1007/978-1-4899-8008-3_9
Shin, Y., Pesaran, M.H.: An Autoregressive Distributed Lag Modelling Approach to Cointegration Analysis. In: Strom, S. (ed.) Econometrics and Economic Theory in the 20th century: The Ragnar Frish Centennial Symposium, pp. 371–413. Cambridge University Press (1999)
Siagian, P.: Determinants of banking operational efficiency and the relationship between the factors to market price: evidence from Indonesia. Economics (Bijeljina) **11**(2), 153–168 (2023). https://doi.org/10.2478/eoik-2023-0051
Škamlová, L.: Food self-sufficiency in Slovakia from the perspective of land use and production approach. Eur. Countrys. **14**(1), 121–139 (2022). https://doi.org/10.2478/euco-2022-0007
Smeekes, S.: Detrending bootstrap unit root tests. Economet. Rev.. Rev. **32**(8), 869–891 (2013). https://doi.org/10.1080/07474938.2012.690693
Smeekes, S. and Wilms, I.:*ootUR: An R package for bootstrap unit root tests*. (2024).https://doi.org/10.48550/ARXIV.2007.12249
Tass, M.A., Bhat, A.A., Riyaz, I., Hakim, I.A.: Russia-Ukraine war and its impact on global oil and food prices. J. Adv. Zool. (2024). https://doi.org/10.53555/jaz.v45iS1.3556
Verheyen, F.: Exchange rate nonlinearities in EMU exports to the US. Econ. Model. **32**, 66–76 (2013). https://doi.org/10.1016/j.econmod.2013.01.039
Wang, Y., Wu, C., Yang, L.: Oil price shocks and agricultural commodity prices. Energy Econ. **44**, 22–35 (2014). https://doi.org/10.1016/j.eneco.2014.03.016
Zmami, M., Ben-Salha, O.: Does oil price drive world food prices? Evidence from linear and nonlinear ARDL modeling. Economies **7**(1), 12 (2019). https://doi.org/10.3390/economies701001