THE IMPACT OF MACROECONOMIC UNCERTAINTY AND OIL PRICES ON FOOD PRICES: EMPIRICAL EVIDENCE FROM SERBIA

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ABSTRACT

The purpose of the paper is to investigate the impact of crude oil prices and domestic macroeconomic uncertainty on food prices in Serbia over the period 2007-2022. The methodological framework is based on cointegration analysis and the structural vector autoregressive model. The empirical results indicate significant and positive long-term effects of uncertainty and oil prices on food prices. Over a one-year horizon, about one-third of the fluctuations in food prices can be attributed to the variability of shocks in uncertainty and oil prices, while their relative influence is slightly more than half after two years. The impact of uncertainty on food price variability peaks within six months, after which its influence diminishes. In contrast, the impact of oil prices gradually increases and becomes the dominant factor in the variability of food prices after a year and a half.

Introduction

In recent years, several events have caused significant changes in oil and food prices. At the beginning of 2020, the COVID-19 pandemic led to a large drop in global energy commodity prices. One of the main reasons of this negative impact is the drop-in demand for energy due to the slowdown in economic activity during the first wave of the pandemic. In 2021, there was a significant increase in energy prices as a result of both demand-side and supply-side factors. Russia's invasion of Ukraine in early 2022 caused increased uncertainty around energy supplies and drove energy prices even higher. A sharp rise in energy costs was the primary driver behind the surge in consumer food inflation during 2021 and 2022 (ECB Economic Bulletin, Issue 2/2024).

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Analyzing fluctuations in food prices and their key drivers is crucial for every country, both economically and socially. The economic aspects of these changes are reflected in their impact on the agriculture sector, inflation, purchasing power, and overall economic stability. For consumers, particularly in low-income countries, food accounts for a substantial share of household spending. Sharp increases in food prices can jeopardize food security, while also widening social inequality and deepening poverty (De Hoyos & Medvedev, 2011).

Numerous studies have explored the influence of oil prices on food prices (Serra et al., 2011; Nazlioglu et al., 2013; Nazlioglu & Soytas, 2011; Baumeister & Kilian, 2014; Fowowe, 2016; Zmami & Ben-Salha, 2019; Chen et al., 2020). The direct and indirect transmission mechanisms have been identified (Fowowe, 2016). An increase in oil prices influences agricultural commodity prices directly by rising both transportation costs and the costs of vital agricultural inputs. Additionally, some agricultural commodities are used for renewable fuel production like ethanol and biodiesel. The rise in oil prices may increase demand for these agricultural commodities due to the increasing use of biofuel as an alternative energy source. The indirect channel works through the exchange rate, where higher oil prices lead to a larger current account deficit, resulting in a depreciation of the local currency.

While there is extensive research on the link between oil prices and food prices, the impact of uncertainty has received less attention. One of the challenges in empirical research is measuring uncertainty. Since pioneering paper Bloom (2009), many studies have focused on constructing measure to capture its level (Bachmann et al., 2013; Jurado et al., 2015; Rossi & Sekhposyan, 2015; Baker et al., 2016). The Real Option Theory shows that levels of investment and consumption are reduced due to uncertainty (Bloom, 2014). The changes in investment in agricultural products have a direct impact on their supply, and consequently, their prices. However, it is more challenging to delay purchases of nondurables like food, so the impact of uncertainty on nondurable consumption through the real option channel will be lower (Bloom, 2014). Frimpong et al. (2021) point out that global economic policy uncertainty can affect commodity price fluctuations through domestic agricultural policy adjustments. Since not all countries are major producers of every commodity, global economic uncertainty affects terms of trade, resulting in commodity price co-movements as countries adjust their production and trade strategies. The impact of economic policy uncertainty on food prices has been investigated by several empirical studies (Frimpong et al.,2021; Wen et al.,2021; Long et al., 2023; Chen et al.,2024), using news-based index developed in Baker et al. (2016).

The purpose of this paper is to investigate the impact of crude oil prices and domestic macroeconomic uncertainty on food prices in Serbia. Monthly data are employed covering the period from December 2007 to December 2022. In Serbia, food and non-alcoholic beverages represent the largest category of individual household spending. Specifically, this category accounts for 36% of total consumption expenditure.[3] Given the high share of food expenditures, any significant rise in food prices could threaten

3 Household budget Survey, 2022, Statistical Office of the Republic of Serbia.

price stability and overall inflation level. After a long period of stable inflation in Serbia, inflation began to rise in mid-2021, reaching a 15.1% by the end of 2022. Around two-thirds of y-o-y inflation, measured in December 2022, originated from food and energy prices.[4] Serbia pursues the inflation targeting as a framework for monetary policy. The strong influence of food prices on inflation makes the implementation of monetary policy more challenging. The volatility of food prices disrupts inflation forecasts, can lead to distorted inflation expectations and undermines public confidence in the central bank, which is crucial for effective inflation targeting (Šoškić, 2015).

The following research questions are considered: Is there a long-run relationship between crude oil prices, macroeconomic uncertainty and food prices in Serbia? What are the dynamic impacts of domestic macroeconomic uncertainty and crude oil price shocks on food price fluctuations in Serbia? These questions are addressed in the context of cointegration analysis and the structural vector autoregressive model. The empirical results indicate significant and positive long-term effects of uncertainty and oil prices on food prices. Over a time horizon of one year, about one third of the fluctuations in food prices can be attributed to the variability of shocks in uncertainty and oil prices. The importance of these shocks increases with the time horizon, so that their relative influence is slightly more than half after two years.

This paper contributes to the existing literature in three ways. First, the existing studies have not examined the impact of macroeconomic uncertainty and crude oil prices on food prices in Serbia. The empirical findings from this study could be of interest to various economic agents. For instance, policymakers in Serbia can use this information to develop sustainable agricultural and trade policies aimed at reducing the economic and social effects of food price fluctuations. Second, previously conducted research about uncertainty and food prices mainly use EPU index (Baker et al., 2016) in the empirical analysis. Ozturk & Sheng (2018) point out that this uncertainty measure provides a high standard for the attention of reporters and editors, who may overlook uncertainty events if they do not cover the topic in their reporting. This study employs the econometric approach proposed by Jurado et al. (2015), that incorporates a wide range of macroeconomic indicators. Thirdly, two different econometric methods are used to improve the robustness of the results. Cointegration analysis aims to uncover the long-run determinants of food prices and to model the adjustment of food prices to the long-run equilibrium relationship. The structural vector autoregressive model provides a framework for assessing the dynamic response of food prices to shocks in uncertainty and oil prices after identifying structural short-run restrictions.

Literature review

The connection between oil and food prices has been explored in a large number of studies. Empirical results are inconclusive. On the one hand, numerous studies offer evidence that crude oil frequently acts as an exogenous factor, transmitting volatility

4 Inflation report, February 2023, National Bank of Serbia.

from the oil prices to food prices (Ciaian, 2011; Serra et al., 2011; Nazlioglu et al., 2013). On the other hand, various studies present different results indicating either no spillover from crude oil to food prices (Nazlioglu & Soytas, 2011; Baumeister & Kilian, 2014; Fowowe, 2016) or a bidirectional influence between them (Tiwari et al. 2018; Adeosun et al., 2023).

Ciaian (2011) examined the relationship between the energy, bioenergy and global prices for nine agricultural commodities. The analysis was carried out on weekly data from January 1993 to December 2010. To account for structural breaks, sample were divided into three equal periods: 1993-1998, 1999-2004, and 2005-2010. Cointegration between agricultural commodity and oil prices was observed only in the third period. Granger causality test revealed that changes in oil prices lead to changes in agricultural commodity prices, but not the other way around. Similar results were found in Nazlioglu et al. (2013). Serra et al. (2011) examined the transmission patterns between ethanol, corn, oil, and gasoline prices in the United States from January 1990 to December 2008. The results from smooth transition vector error correction model showed that energy price surges cause corn prices to rise.

In contrast, the empirical findings from some studies indicate that food prices are not influenced by fluctuations in oil prices. Nazlioglu & Soytas (2011) analyzed the interrelationship between global oil prices, the lira–dollar exchange rate, and the prices of five individual agricultural commodities in Turkey for the period: January 1994-March 2010. The long-run causality analysis showed that agricultural commodity prices were unaffected by changes in oil prices. Similar findings were obtained for South Africa (Fowowe, 2016). Baumeister & Kilian (2014) employed VAR models to examine the transmission of oil price shocks to food prices before and after shift in U.S. biofuel policy in May 2006. Data were divided into two parts: 1974:M01-2006:M04 and 2006M05:2013M05. The results indicated no connection between food and oil prices during any of the observed periods.

Common factors, including economic conditions, advancements in technology, and market trends, may lead to fluctuations in both food and oil prices. Due to their interconnectedness, changes in food prices could potentially serve as an indicator for future changes in oil prices (Adeosun et al., 2023). Tiwari et al. (2018) applied the continuous wavelet (CWT) to examine the time-frequency relationship between the oil price index and 21 international price indices of agricultural commodities for the period: January 1980 - May 2017. The results indicated a significant long-term association between variables considered. Adeosun et al. (2023) examined causal links in globally traded oil and eight international price indices from January 1990 to February 2021 using bootstrapped time-varying Granger causality method. The findings revealed that oil prices and six food commodity prices influence one another, and that wheat and soybean prices have a causal effect on oil prices.

Several empirical studies have examined the effect of uncertainty on food prices. Most of them focused on economic policy uncertainty (EPU), using the news-based indicator developed in Baker et al. (2016). Wen et al. (2021) investigated the symmetric and asymmetric impacts of EPU index on food prices in China based on monthly sample January 1998 - May 2020. The application of ARDL models suggested that higher food prices are driven by an increase in uncertainty over both the short and long term, while results from NARDL models indicated only short-term effect. Frimpong et al. (2021) investigated the effect of global EPU index on the co-movement of five major agricultural commodities using monthly data from January 1997 to December 2019. The wavelet analysis showed that removing the effect of uncertainty significantly reduced the coherence among agricultural commodities.

Long et al. (2023) used NARDL models to investigate the asymmetric impact of global EPU on international grain prices from January 1998 to May 2021. The results showed that EPU positively correlates with international grain prices, causing prices to rise with policy uncertainty increases and fall with its decreases. Chen et al. (2024) analyzed the effect of oil prices and global EPU on domestic food prices in 41 developing countries from January 2000 to March 2023. The cointegration analysis revealed a long-run relationship between uncertainty, oil and food prices in developing countries.

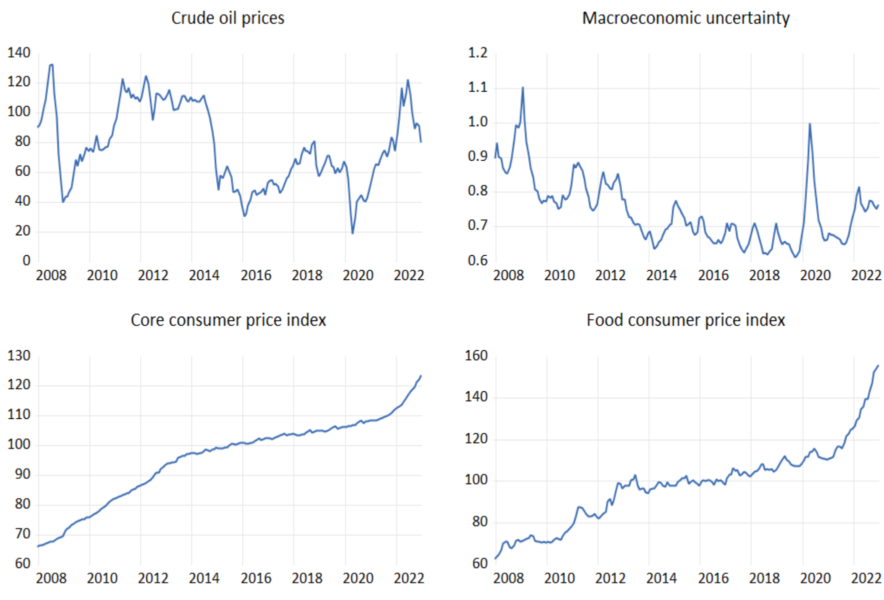
The effect of macroeconomic uncertainty on food prices has been the focus of only a few studies. Joëts et al. (2017) analyzed the impact of macroeconomic uncertainty on international commodity markets (energy, precious metals, agriculture, and industry) using a measure of macroeconomic uncertainty developed in Jurado et al. (2015). For agricultural markets, the analysis spanned from February 1980 to December 2011. The results from structural threshold VAR model showed that changes in the variability and level of macroeconomic uncertainty have a strong effect on the agricultural markets. Ben et al. (2021) estimated individual commodity price uncertainty for eight main categories of commodity markets for the period January 1960 - June 2020. The estimation of commodity price uncertainty was based on the approach of Jurado et al. (2015). The time-varying VAR models were applied to analyze the dynamic connectedness between commodity uncertainties and Jurado et al. (2015) macroeconomic uncertainty index. The findings indicated that commodity price uncertainty is significantly impacted by macroeconomic uncertainty.

Data description

The dataset for this analysis consists of food consumer price index in Serbia (FCPI), core consumer price index in Serbia (CCPI), indicator of macroeconomic uncertainty in Serbia (MU) and the crude oil prices (OILP). Core prices are based on consumer price index after excluding energy, food, alcohol and tobacco. Monthly observations from December 2007 to December 2022 are used. The data of food and core price indices are taken from Eurostat. The one-month ahead macroeconomic uncertainty measure based on econometric approach proposed by Jurado et al. (2015) is derived. The data of crude oil prices (Brent – Europe, dollars per barrel) are taken from FRED, Federal Reserve Bank of St. Louis. In the analysis, logarithm values of variables are used, and the food and core consumer price indices are seasonally adjusted using Census X-12 method.

The data on crude oil prices, the macroeconomic uncertainty indicator and the core and food price indices are shown in Figure 1. Oil prices do not appear to be stationary, with two sub-periods characterized by different price levels. From 2008 to 2014, crude oil prices were relatively high, with two sharp declines occurring in 2008 and 2014. The sharp decline in 2008 was triggered by the global financial crises, while the price drop in 2014 was due to an increasing oversupply of oil. In contrast, oil prices were significantly lower from 2015 to 2021. At the beginning of 2020, the COVID-19 pandemic caused a strong drop in oil prices. The years 2021–2022 saw a strong rebound, driven by the economic recovery and supply constraints, which are exacerbated by Russia's invasion of Ukraine. The indicator for macroeconomic uncertainty is characterized by stationary fluctuations, albeit with two significant spikes caused by the global financial crises in 2008 and the COVID-19 pandemic in 2020. Core and food consumer price indices show a strong upward trend, which is described by the presence of the unit root (stochastic trend). In addition, the price index for food has been rising significantly since mid-2021.

Figure 1. Crude oil prices, macroeconomic uncertainty, core and food consumer price indices



Source: Eurostat, FRED and author's calculations

Methodology review

Empirical methodology comprises three important steps. First, the stationarity of the time series is examined using several unit root tests. Second, the existence of the long-run relationship between the variables under consideration is examined within the autoregressive distributed lag (ARDL) model and bounds testing approach (Pesaran, Shin & Smith, 2001). Third, the short-term dynamic structure between the variables is derived from the impulse response analysis and the decomposition of the forecast error variances estimated from the SVAR. The ARDL modelling approach and SVAR modelling will be briefly discussed.

ARDL modelling

The ARDL model of order (p,q) is defined as follows (Cho, Greenwood-Nimmo & Shin, 2023):

$$y_t = \gamma_0 + \sum_{j=1}^{p} \phi_j y_{t-j} + \sum_{j=0}^{q} \boldsymbol{\theta}_j^{\prime} \boldsymbol{x}_{t-j} + error \tag{1}$$

where y_t denotes the variable to be modelled (in this study food consumer price index) and $\boldsymbol{x}_t^{\prime}$ refers to the vector of explanatory variables (in this study it contains the core consumer price index, macroeconomic uncertainty and crude oil prices).

Model (1) is often stated in the following form:

$$y_t = \gamma_0 + \boldsymbol{x}_t^{\prime}\boldsymbol{\gamma} + \sum_{j=1}^{p} \phi_j y_{t-j} + \sum_{j=0}^{q-1} \Delta\boldsymbol{x}_{t-j}^{\prime}\boldsymbol{\delta}_j + error \tag{2}$$

where $\boldsymbol{\gamma} = \sum_{j=0}^{q} \boldsymbol{\theta}_j$ and $\boldsymbol{\delta}_j = -\sum_{i=j+1}^{q} \boldsymbol{\theta}_i$.

The specification of the ARDL model enables the following unconditional error-correction model (Cho, Greenwood-Nimmo & Shin, 2023):

$$\Delta y_t = \gamma_0 + \rho y_{t-1} + \boldsymbol{\theta}^{\prime} \boldsymbol{x}_{t-1} + \sum_{j=1}^{p-1} \eta_j \Delta y_{t-j} + \sum_{j=0}^{q-1} \boldsymbol{\kappa}_j^{\prime} \Delta \boldsymbol{x}_{t-j} + error \tag{3}$$

under the following restrictions:

$\rho = \sum_{j=1}^{p} \phi_j - 1$, $\boldsymbol{\theta} = \sum_{j=0}^{q} \boldsymbol{\theta}_j$, $\boldsymbol{\kappa}_0 = \boldsymbol{\theta}_0$, $\eta_l = -\sum_{i=l+1}^{p} \phi_i$, $\boldsymbol{\kappa}_j = -\sum_{i=j+1}^{q} \boldsymbol{\theta}_i$, and $l = 1,2, \ldots, p-1,\ j = 1,2, \ldots, q-1$.

If cointegration is present, so that the linear combination $u_t = y_t - \boldsymbol{\beta}^{\prime} \boldsymbol{x}_t$ is stationary, then (3) takes the following form of the conditional error-correction model:

$$\Delta y_t = \gamma_0 + \rho u_{t-1} + \sum_{j=1}^{p-1} \eta_j \Delta y_{t-j} + \sum_{j=0}^{q-1} \boldsymbol{\kappa}_j^{\prime} \Delta \boldsymbol{x}_{t-j} + error \tag{4}$$

Vector of cointegration parameters $\boldsymbol{\beta}$ is equal to $-\boldsymbol{\theta}/\rho$. The corresponding cointegration estimators are derived from applying the OLS method to equations 1-3. Estimators of cointegration parameters are super-consistent with asymptotically normal mixed distribution, whereas estimators of short-run parameters are consistent and asymptotically normally distributed (Pesaran, Shin & Smith, 2001).

The test for the existence of a long-run relationship (cointegration) is based on the bounds testing approach of Pesaran, Shin & Smith. The null hypothesis that there is no long-run relationship, $\rho = 0$ and $\boldsymbol{\theta}^{\prime} = \boldsymbol{0}$, is tested using the formula of the F-statistic derived from equation (3). However, this statistic does not have a standard F- distribution.

The test approach allows various assumptions regarding the order of integration of the time series. The test can be conducted regardless of whether the time series are stationary, unit root processes or a combination of both. The test also includes various combinations of deterministic components (constant and trend).

The ARDL model has been used extensively in empirical literature. It has several modifications that are also frequently applied. For example, the non-linear ARDL model accounts for the possibility that positive and negative components in the subset of explanatory variables (e.g. oil prices) may have different long-run and short-run effects on the dependent variable (Shin, Yu & Greenwood-Nimmo, 2014).

SVAR modelling

Standard vector autoregressive (VAR) model of order *k* for the vector time series $\boldsymbol{X}_t$ (*mx1*) is defined as follows:

$$\boldsymbol{X}_t = \Phi_1 \boldsymbol{X}_{t-1} + \Phi_2 \boldsymbol{X}_{t-2} + \cdots + \Phi_k \boldsymbol{X}_{t-k} + \boldsymbol{\varepsilon}_t \tag{5}$$

$\Phi_1, \Phi_2, ..., \Phi_k$ are parameter matrices (*mxm*). The error component $\boldsymbol{\varepsilon}_t$ (*mx1*) contains zero mean individually uncorrelated time series with finite variance. It has multivariate normal distribution with the covariance matrix denoted by $\boldsymbol{\Sigma}$. In this study $\boldsymbol{X}_t$ contain the four variables introduced above.

In order to enable a structural interpretation within the framework of VAR models, additional identifying restrictions are often introduced for the model parameters. This leads to a structural VAR model (SVAR), which is suitable for several econometric investigations. Two of the most important of these are: 1. Impulse response function analysis and 2. Forecast error variance decomposition. The impulse response function analysis allows the estimation of the expected responses of the model variables to a one-time unexpected random shock. The forecast error variance decomposition measures the contribution of the variability of the unexpected random shock to the total variability of the model variables.

The SVAR model with short-run restrictions reads as follows:

$$\Lambda_0 \boldsymbol{X}_t = \Lambda_1 \boldsymbol{X}_{t-1} + \Lambda_2 \boldsymbol{X}_{t-2} + \cdots + \Lambda_k \boldsymbol{X}_{t-k} + \boldsymbol{u}_t \tag{6}$$

$\Lambda_0, \Lambda_1, \Lambda_2, ..., \Lambda_k$ are parameter matrices (*mxm*). Structural relations are introduced through the matrix Λ_0. The covariance matrix of vector error component $\boldsymbol{u}_t$ (*mx1*), $\boldsymbol{\Sigma}_u$ is a unit matrix: $E(\boldsymbol{u}_t \boldsymbol{u}_t^{'}) = \boldsymbol{\Sigma}_u = I_m$. The individual error components of $\boldsymbol{u}_t$ are referred to as structural shocks or structural innovations. They have zero mean and they are individually serially uncorrelated. Structural shocks are also mutually uncorrelated with individual variance equals to 1.

Given that equation (6) is in structural form, it needs to be transformed into its reduced form representation. Under reduced form $\boldsymbol{X}_t$ should only be a function of $\boldsymbol{X}_{t-1}, \boldsymbol{X}_{t-2}, \dots, \boldsymbol{X}_{t-k}$. This can be achieved by pre-multiplying both sides of equation (6) by Λ_0^{-1}:

$$\boldsymbol{X}_t = \Lambda_0^{-1}\Lambda_1\boldsymbol{X}_{t-1} + \Lambda_0^{-1}\Lambda_2\boldsymbol{X}_{t-2} + \cdots + \Lambda_0^{-1}\Lambda_k\boldsymbol{X}_{t-k} + \Lambda_0^{-1}\boldsymbol{u}_t \qquad (7)$$

which turns out to be standard VAR model in form (5) with following assumptions: $\Lambda_0^{-1}\Lambda_i = \boldsymbol{\Phi}_i, i = 1, \dots, k$, and $\boldsymbol{\varepsilon}_t = \Lambda_0^{-1}\boldsymbol{u}_t$.

The relation $\boldsymbol{\varepsilon}_t = \Lambda_0^{-1}\boldsymbol{u}_t$ is essential. It indicates out that the error-components in $\boldsymbol{\varepsilon}_t$ of the VAR model (5) are a function of the structural shocks in $\boldsymbol{u}$. Stated differently, as $\boldsymbol{u}_t = \Lambda_0\boldsymbol{\varepsilon}_t$, this suggests that structural shocks can be derived from shocks in reduced form, but via Λ_0, which captures structural relationships. To estimate elements of Λ_0 (or Λ_0^{-1}), one must start from the reduced-form model, which provides information about covariance matrix (Kilian, 2013):

$$\boldsymbol{\Sigma} = E(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t') = \Lambda_0^{-1}E(\boldsymbol{u}_t\boldsymbol{u}_t')\Lambda_0^{-1'} = \Lambda_0^{-1}\boldsymbol{\Sigma}_u\Lambda_0^{-1'}$$

$$\boldsymbol{\Sigma} = \Lambda_0^{-1}\Lambda_0^{-1'} \qquad (8)$$

Equation (8) associates the covariance matrix in the standard VAR model ($\boldsymbol{\Sigma}$) with parameters that design structural relations (Λ_0^{-1}). Elements of $\boldsymbol{\Sigma}$ can be estimated consistently and therefore taken as given. The question is how to determine and identify unknown parameters of Λ_0^{-1}. Normally, certain zero restrictions are imposed on some parameters of Λ_0^{-1}.

The covariance matrix $\boldsymbol{\Sigma}$ contains *m(m+1)/2* free parameters (as being symmetric matrix). This is therefore the maximum number of parameters in Λ_0^{-1} that can be uniquely identified. There is a number of different ways how identification can be achieved (Killian & Lutkepohl, 2017).

In an alternative representation of the SVAR restrictions (8) the diagonal elements of $\boldsymbol{\Sigma}_u$ are unrestricted, while the diagonal elements of Λ_0 are set to one. Both Λ_0 and Λ_0^{-1} are lower triangular. In this representation the variances of structural shocks are different from unity. This form will be used for reporting empirical results.

Empirical results

Unit root tests

Our empirical work begins with a unit root test. The model with constant and trend is employed for the food and core price indices, while the model with only a constant is used for their first differences. The models for the macroeconomic uncertainty indicator and crude oil prices contain only a constant as a deterministic component. The results of several unit root tests are shown in Table 1. All tests indicate that food, core and oil prices are integrated of order 1. The results of the ADF and ERS tests show that the indicator for macroeconomic uncertainty is a stationary variable.

Table 1. Results of unit root tests

Variable	Test for unit root in	ADF	Number of lags	Unit root	KPSS	Unit root	ERS	Unit root
FCPI	Level	-0.98	1	Yes	0.21	Yes	-1.14	Yes
	First difference	-9.97*	0	No	0.17*	No	-7.72*	No
CCPI	Level	-2.51	3	Yes	0.39	Yes	-1.40	Yes
	First difference	-2.58***	2	No	0.52*	No	-2.36**	No
MU	Level	-3.72*	1	No	0.98	Yes	-2.04**	No
	First difference	-	-	-	0.09***	No	-	-
OILP	Level	-2.62	2	Yes	1.21	Yes	-2.31	Yes
	First difference	-9.11*	1	No	0.05***	No	-9.1*	No
Note: The test-statistic values below the critical values for the 1%, 5%, and 10% significance levels are marked with *, ** and ***. The number of lags indicates how many correction elements are incorporated in the ADF and ERS tests. In the KPSS test, truncation parameter matches the number of corrections in the ADF test, or it is equal to 10.								

Source: Author's calculations

Cointegration analysis

In this study, cointegration analysis examines the existence of a long-run equilibrium relationship between food prices, core prices, uncertainty and oil prices. To achieve main objective of assessing the long-run importance of uncertainty and oil prices for food prices, this analysis also includes core prices, which control for the influence of general market conditions on food prices.

This existence is tested with the autoregressive distributed lag (ARDL) model, as this approach can be applied when the variables are a combination of stationary and unit root processes, which is the case for this sample.

The trend component is included as a deterministic part of the cointegration space. In many empirical analyses, such a trend accounts for the long-run effects of variables that are not explicitly included in the cointegration modelling. The number of lags in the

ARDL model is chosen according to the minimum value of the Schwarz information criterion starting with a maximum of twelve lags. The statistical properties of the models are evaluated by performing autocorrelation and normality tests.

The calculated value of the bound-F test is 5.07, while the corresponding set of critical values at the 5% significance level contains the following values: 3.38 for I(0) and 4.23 for I(1). Since 5.07 is larger than 4.23, the existence of a long-run relationship between food prices, core prices, uncertainty and oil prices is confirmed. The estimated long-run elasticities are shown in Table 2 and indicate that the combination denoted by COIN is stationary: COIN= FCPI-0.77*CCPI-0.36*MU-0.10*OILP-0.002*t. All estimated long-run elasticities are positive and significant. A 1% increase in uncertainty leads to an increase in food prices by 0.36%, while a 1% increase in oil prices yields an increase in food prices by 0.10%. These figures show that food prices react relatively strongly to changes in both uncertainty and oil prices.

The estimated equilibrium error correction model is shown in Table 3. The estimated adjustment coefficient, -0.096, is highly significant. Thus, each month about 10% of food inflation is corrected towards the estimated long-run relationship with core prices, uncertainty and oil prices. The short-term dynamics of food inflation are captured by its own lagged value (with an estimate of 0.22) and by current core inflation (with an estimate of 0.62).

Table 2. Estimated long-run elasticities normalized on food prices

FCPI	CCPI	MU	OILP	Trend
1	0.77 (0.00)	0.36 (0.00)	0.10 (0.00)	0.002 (0.00)
Note: p-values are reported in parentheses below cointegration estimates.				

Source: Author's calculations

Table 3. Estimated ECM for food inflation ($\Delta FCPI_t$)

Variable	**Estimate**	***p*-value**
$COIN_{t-1}$	**-0.096**	0.00
$\Delta FCPI_{t-1}$	0.223	0.00
$\Delta CCPI_t$	0.616	0.01
Constant	0.051	0.00
Diagnostic statistics		
R^2=0.45, SC=-6.2395, Q(6)=4.39(0.62), Q(12)=15.70(0.21), Q(24)=22.05(0.58), $Q^2(6)$=8.41(0.21), $Q^2(12)$=15.20(0.23), JB=0.21(0.90)		
Note: Model contains four impulse dummy variables that take non-zero values 1 for the following months: March, 2011; May, 2012; September, 2012, and October, 2022.		

Source: Author's calculations

The asymmetric response of food prices is then tested with respect to positive and negative changes in both uncertainty and oil prices. However, this type of non-linearity could not be confirmed as the corresponding values of the F-statistics were found to be non-significant (2.02 with a p-value of 0.15 for uncertainty and 0.48 with a p-value of 0.49 for oil prices).

An alternative version of cointegration model is estimated, which assumes that food prices are expressed as a deviation from core prices: FCPI-CCPI. It was then tested whether this deviation is associated with uncertainty and oil prices in the long run. Such a modification is indeed justified by previous cointegration estimate, which provides a relatively high estimate for the CCPI of 0.77. The calculated value of the F-test for the bound test is now 5.77, above the critical 5% values of 3.88 and 4.61. Therefore, the presence of a long-term relationship is confirmed.

The estimated cointegrated relation is given as follows: COIN1= (FCPI-CCPI)-0.38*MU-0.09*OILP-0.0016*t. Long-run elasticities of uncertainty and oil prices remained practically unchanged. This finding suggests that the stochastic trend in the difference between food prices and core prices is due to movements in uncertainty and oil prices. A new ECM based on COIN1 is reported in Table 4.

Table 4. Estimated ECM for difference between food and core inflation ($\Delta FCPI_t$- $\Delta CCPI_t$)

Variable	Estimate	*p*-value
$COIN1_{t-1}$	**-0.103**	0.00
$\Delta FCPI_{t-1}$	0.229	0.00
Constant	-0.041	0.00
Diagnostic statistics		
R^2=0.40, SC=-6.2525, Q(6)=5.16(0.52), Q(12)=16.65(0.16), Q(24)=21.99(0.58), $Q^2(6)$=8.62(0.20), $Q^2(12)$=16.63(0.16), JB=0.05(0.97)		
Note: The same dummies as in Table 3 are included.		

Source: Author's calculations

The deviation of food prices from core prices is significantly equilibrium-adjusted toward long-run relation with oil prices and uncertainty. The monthly adjustment is estimated at around 10%.

Analysis of the dynamic structure based on SVAR model

To determine the dynamic impact of oil price and uncertainty shocks on food prices, VAR model is employed. The model includes the following variables: oil prices (OILP), indicator of macroeconomic uncertainty (MU), core price index (CCPI) and food price index (FCPI). Specifically, VAR(8) model with constant, trend, and eight impulse dummy variables is estimated. Number of lags is chosen according to the sequential testing of lags significance. Model contains impulse dummy variables that are designed to account for several one-time outliers. They are defined as: D1={1, for January 2009; 0, otherwise}, D2={1, for March 2011; 0, otherwise}, D3={1, for May 2012; 0, otherwise}, D4={1, for February 2015; 0, otherwise}, D5={1, for August 2016; 0, otherwise}, D6={1, for March 2020; 0, otherwise}, D7={1, for April 2020; 0, otherwise} and D8={1, for May 2020; 0, otherwise}. Several multivariate tests confirm that the model performs statistically well (Tables 5).

Table 5. Multivariate test statistics

Test for	Value	p-value
Autocorrelation of order 1	22.87	0.12
Autocorrelation of order 2	13.12	0.66
Autocorrelation of order 6	14.41	0.57
Autocorrelation of order 12	9.15	0.91
Normality	12.28	0.14
Note: Autocorrelation and normality results are obtained using the multivariate LM and multivariate Doornik-Hansen tests, respectively.		

Source: Author's calculations

Structural shocks are identified by imposing short-run restrictions that form a recursive model. The ordering of the variables is as follows: oil prices (OILP), indicator of macroeconomic uncertainty (MU), core price index (CCPI) and food price index FCPI It is assumed that the following restrictions apply: 1) Domestic shocks do not have contemporaneous effects on oil prices, 2) Only oil price shocks have contemporaneous effects on macroeconomic uncertainty, 3) Shocks in food price index do not have contemporaneous effects on core price index. The SVAR model is estimated, and the results indicate that oil price shocks do not have a statistically significant contemporaneous impact on core and food prices. Also, uncertainty shocks do not affect core prices within the same month. Consequently, three more zero restrictions are imposed on matrix that governs the contemporaneous interaction between variables (Λ_0).

The structural parameters in matrix $\Lambda_0 = \begin{pmatrix} 1 & 0 & 0 & 0 \\ \lambda_0^{21} & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & \lambda_0^{42} & \lambda_0^{43} & 1 \end{pmatrix}$ are estimated by maximum likelihood method (Table 6). The results indicate that a positive shock in oil prices corresponds to a reduction in macroeconomic uncertainty within the same month (λ_0^{21}). However, such an outcome can be explained by the huge exogenous shocks in 2008 and 2020, to which oil prices and uncertainty reacted in opposite directions. The partial correlation coefficient between these two variables, that controls the influence of two exogenous shocks, is in fact positive (0.12). The empirical findings suggest that shocks in macroeconomic uncertainty (λ_0^{42}) and core price index (λ_0^{43}) have a statistically significant contemporaneous impact on food prices. Specifically, an increase in macroeconomic uncertainty leads to a rise in food prices within the same month. Also, a positive shock in core price index causes food prices to rise within the same month. Imposed restrictions are accepted as empirical valid, because the likelihood ratio test statistic for overidentifying restrictions is 2.42 with the p-value 0.49.

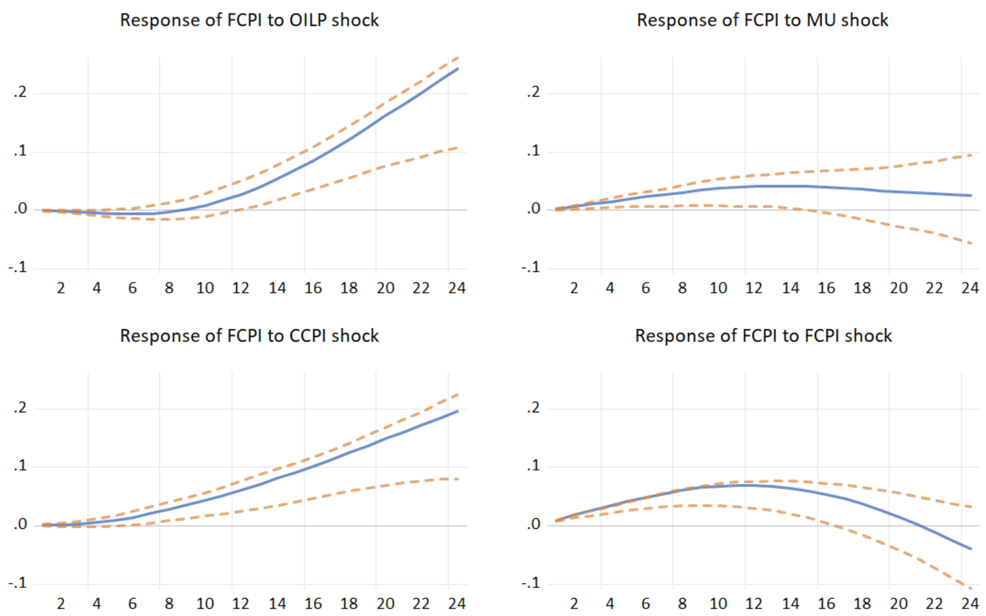
Table 6. Estimates of structural parameters

Structural parameters	Estimate	Std. error	z-statistic	p-value
λ_0^{21}	0.05	0.02	2.90	0.04
λ_0^{42}	-0.08	0.03	-2.73	0.01
λ_0^{43}	-0.74	0.38	-1.94	0.05

Source: Author's calculations

From the estimated SVAR, impulse response analysis and forecast error variance decomposition are performed. Figure 2 depicts accumulated impulse response functions for food price index. The results indicate that a positive shock in oil prices does not affect food prices in the first nine months. However, starting from the tenth month, a statistically significant positive effect is found. A positive shock in macroeconomic uncertainty has a statistically significant positive effect on food prices within the first year, whereas a positive shock in the core price index has a statistically significant positive impact on food prices even after two years.

Figure 2. Accumulated impulse response functions for food price index



Note: Orange lines represent 95% confidence intervals. They are calculated using standard percentile bootstrap with 1000 bootstrap repetitions.

Source: Author's calculations

Table 7 presents the results of the forecast error variance decomposition. The figures show the percentage of the forecast error variance of food price index that can be explained by individual shocks at different time horizons (1, 6, 9, 12, 18 and 24 months). The contribution of macroeconomic uncertainty is estimated at 17%, 16% and 12% for 6, 9 and 12 months respectively. For the 24 months horizon, however, the contribution of uncertainty drops to 3%. The results show that oil and core prices play a more important role as the time horizon increases. In particular, a 20% of fluctuations in food prices are explained by the oil price shock at a 12 months horizon, and 51% at a 24 months horizon. The contribution of the core price index is estimated at 23%, 31% and 24% for 9, 12 and 24 months respectively. Own shocks to food prices account for 56% of their own variability after 9 months and 22% after 24 months.

To summarize, the impact of uncertainty on the variability of food prices is greatest over a six-month period. After that its influence on the variability of food prices decreases. The influence of oil prices gradually increases and becomes the dominant factor in the variability of food prices after one and a half years.

Table 7. Forecast error variance decomposition of food price index (in %; values in each row sum to 100%)

Horizon (in months)	Shock in OILP	Shock in MU	Shock in CCPI	Shock in FCPI
1	0.1	4	2	93.9
6	2	17	10	71
9	5	16	23	56
12	20	12	31	37
18	47	5	29	19
24	51	3	24	22

Source: Author's calculations

Conclusions and discussions

The paper provides econometric results on multivariate time series modelling of food prices in Serbia over the period 2007-2022. The dynamics of food prices are examined using the dynamics of the following time series: core prices in Serbia, uncertainty about the macroeconomy in Serbia and world oil prices. Two different econometric aspects are considered. First, the long-run behavior of food prices in the context of cointegration is investigated. Second, the dynamic responses of food prices to exogenous shocks are discussed using SVAR.

The results indicate that food prices are determined in the long run by core prices, domestic uncertainty and world oil prices. While oil prices are the cost-driving factor, the indicator of macroeconomic uncertainty in Serbia provides a composite measure of macroeconomic instability that takes into account the effects of the various macroeconomic factors. An alternative interpretation of the cointegration result shows that the deviation of food prices from core prices is explained in the long run by macroeconomic uncertainty and oil prices. The recent rise in food prices above the core price level can therefore be attributed to the positive impact of both oil prices and domestic macroeconomic uncertainty.

The long-run elasticity of domestic uncertainty is estimated at 0.36% and the long-run elasticity of oil prices at 0.09%. These estimates differ from the estimates in Chen, Gummi, Lu and Hassan (2024) for a panel of higher income oil-importing countries that includes Serbia (0.57% and 0.33% for global uncertainty and oil prices, respectively). These values are not directly comparable due to differences in the data structure, the methodology applied and the uncertainty concept used, but they at least confirm a positive significant reaction of food prices to uncertainty and global oil prices.

Looking at the dynamic response of food prices to unexpected random shocks in the considered variables, derived from the SVAR specification, main results show that over a one-year horizon about one third of the fluctuations in food prices can be attributed to the variability of shocks in uncertainty and oil prices. The relevance of these shocks increases with the time horizon, so that their relative influence is slightly more than half after two years.

The impact of uncertainty is greatest over a period of six months, after which it decreases. On the other hand, the influence of oil prices gradually increases and becomes the dominant factor in the variability of food prices after a year and a half. In the short term, therefore, uncertainty shocks play a more important role, but in the long term, oil price shocks predominate.

In Mladenović, Arsić & Nojković (2024), it was found that world energy prices significantly determine Serbian inflation as measured by the consumer price index. It is further argued that Serbia, as a small country that has no influence on global energy prices, can neutralize the negative effects of sharp fluctuations in world energy prices by concluding long-term energy contracts, building energy storage facilities and introducing administrative price control, especially in the short term. The same measures can be advocated as a control mechanism for food prices in times of high macroeconomic instability and rising oil prices.

Conflict of interests

The authors declare no conflict of interest.

References

1. Adeosun, O. A., Olayeni, R. O., Tabash, M. I., & Anagreh, S. (2023). Revisiting the oil and food prices dynamics: A time varying approach. *Journal of Business Cycle Research*, *19*, 275-309.
2. Bachmann, R., Elstner, S., & Sims, E. R. (2013). Uncertainty and economic activity: Evidence from business survey data. *American Economic Journal: Macroeconomics*, *5*, 217-249.

3. Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The quarterly journal of economics*, *131*, 1593-1636.
4. Baumeister, C., & Kilian, L. (2014). Do oil price increases cause higher food prices?. *Economic Policy*, *29*, 691-747.
5. Ben Haddad, H., Mezghani, I., & Gouider, A. (2021). The dynamic spillover effects of macroeconomic and financial uncertainty on commodity markets Uncertainties. *Economies*, *9*, 91.
6. Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica*, *77*, 623-685.
7. Bloom, N. (2014). Fluctuations in uncertainty. *Journal of economic Perspectives*, *28*, 153-176.
8. Chen, D., Gummi, U. M., Lu, S., & Hassan, A. (2024). Oil price, economic policy uncertainty and food prices in oil-exporting and oil-importing developing economies. *Economic Change and Restructuring*, *57*, 151.
9. Chen, D., Gummi, U. M., Lu, S. B., & Mu'azu, A. (2020). Modelling the impact of oil price fluctuations on food price in high and low-income oil exporting countries. *Agricultural Economics/Zemedelska Ekonomika*, *66*. 458–468.
10. Cho, J.S., Greenwood-Nimmo, M., & Shin, Y. (2023). Recent developments of the autoregressive distributed lag modelling framework. *Journal of Economic Survey*, 37. 7-32.
11. Ciaian, P. (2011). Food, energy and environment: Is bioenergy the missing link?. *Food Policy*, *36*, 571-580.
12. De Hoyos, R. E., & Medvedev, D. (2011). Poverty effects of higher food prices: a global perspective. *Review of Development Economics*, *15*, 387-402.
13. European Central Bank (2024). Economic Bulletin, Issue 2/2024. European Central Bank. https://www.ecb.europa.eu/press/economic-bulletin/html/eb202402.en.html
14. Fowowe, B. (2016). Do oil prices drive agricultural commodity prices? Evidence from South Africa. *Energy*, *104*, 149-157.
15. Frimpong, S., Gyamfi, E. N., Ishaq, Z., Kwaku Agyei, S., Agyapong, D., & Adam, A. M. (2021). Can global economic policy uncertainty drive the interdependence of agricultural commodity prices? Evidence from partial wavelet coherence analysis. *Complexity*, *2021*, 8848424.
16. Joëts, M., Mignon, V., & Razafindrabe, T. (2017). Does the volatility of commodity prices reflect macroeconomic uncertainty?. *Energy Economics*, *68*, 313-326.
17. Jurado, K., Ludvigson, S. C., & Ng, S. (2015). Measuring uncertainty. *American Economic Review*, *105*, 1177-1216.
18. Kilian, L. (2013). Structural Vector Autoregressions. In N. Hashimzade and M.A. Thornton (Eds.), *Handbook of Research Methods and Applications in Empirical Macroeconomics* (pp. 515-554). Cheltenham, UK, Edward Elgar.

19. Kilian, L. & Lutkepohl, H. (2017). *Structural Vector Autoregressive Analysis*, Cambridge University Press, New York.
20. Long, S., Li, J., & Luo, T. (2023). The asymmetric impact of global economic policy uncertainty on international grain prices. *Journal of Commodity Markets*, *30*, 100273.
21. National Bank of Serbia (2023). Inflation report February. National Bank of Serbia. Belgrade. Serbia. https://www.nbs.rs/export/sites/NBS_site/documents-eng/publikacije/ioi/izvestaji/inflation_report_02_2023.pdf
22. Nazlioglu, S., Erdem, C., & Soytas, U. (2013). Volatility spillover between oil and agricultural commodity markets. *Energy Economics*, *36*, 658-665.
23. Nazlioglu, S., & Soytas, U. (2011). World oil prices and agricultural commodity prices: Evidence from an emerging market. *Energy Economics*, *33*, 488-496.
24. Ozturk, E. O., & Sheng, X. S. (2018). Measuring global and country-specific uncertainty. *Journal of international money and finance*, *88*, 276-295.
25. Pesaran, M.H., Shin, Y., & Smith, R. J. (2001). Bounds Testing Approaches to the Analysis of the Level Relationship*, Journal of Applied Econometrics, 16*, 289-326.
26. Rossi, B., & Sekhposyan, T. (2015). Macroeconomic uncertainty indices based on nowcast and forecast error distributions. *American Economic Review*, *105*, 650-655.
27. Serra, T., Zilberman, D., Gil, J. M., & Goodwin, B. K. (2011). Nonlinearities in the US corn-ethanol-oil-gasoline price system. *Agricultural Economics*, *42*, 35-45.
28. Shin, Y., Yu. B., & Greenwood-Nimmo, M. (2014). Modelling asymmetric cointegration and dynamic multipliers in nonlinear ARDL framework. In W. Horrace & R. Sicklers (Eds.). *Festschrift in Honor of Peter Schmidt: Econometric methods and applications* (pp. 281-314) New York, NY: Springer.
29. Statistical Office of the Republic of Serbia (2022). Household budget Survey. Statistical Office of the Republic of Serbia. Belgrade. Serbia. https://publikacije.stat.gov.rs/G2023/PdfE/G20235699.pdf
30. Šoškić, D. (2015). Inflation impact of food prices: Case of Serbia. *Economics of Agriculture*, *62*, 41-51.
31. Tiwari, A. K., Khalfaoui, R., Solarin, S. A., & Shahbaz, M. (2018). Analyzing the time-frequency lead lag relationship between oil and agricultural commodities. *Energy Economics, 76*, 470–494.
32. Wen, J., Khalid, S., Mahmood, H., & Zakaria, M. (2021). Symmetric and asymmetric impact of economic policy uncertainty on food prices in China: A new evidence. *Resources Policy*, *74*, 102247.
33. Zmami, M., & Ben-Salha, O. (2019). Does oil price drive world food prices? Evidence from linear and nonlinear ARDL modeling. *Economies*, *7*, 12.