Original scientific paper

INVESTIGATING DYNAMIC SPILLOVER EFFECT OF WORLD PRICES TO MACEDONIAN FOOD PRICES

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Abstract
Internationally traded commodities often experience sudden and significant price fluctuations driven by a broad range of forces and factors. While thedeterminants of price volatility varyacross commodities, such sudden price developmentsgenerally arise from low short-term elasticities of demand and supply. This study examines the dynamic spillover relationship between global and Macedonian food prices by employing Markov Switching Regression (MSR) and Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroscedasticity (DCC-GARCH) models.We identifya structural shift in the dynamics of the international-domestic food price relationship, which differs betweenlow- and high-volatility regimes. Additionally, we find that the MKD/USD exchange rate drives the growingdifference between Macedonian and international food prices- reflecting, in fact, EUR/USD fluctuations given the fixed exchange rate of the Denarvis-à-vis the euro, as well as the fact that key global commodities, including food, oil, and fertilizers, are priced in US dollars. Conversely, oil prices tend to narrow this price difference.

Keywords: Foodprice volatility, Domestic food price inflation,Global food price transmission, Markov Switching Regression,DCC-GARCH model

JEL classification: C32, E31, F42

INTRODUCTION

Fluctuations in food prices can have pivotal economic and social consequences. When food prices increase, particularly in countries with a high share of low-income households, government intervention, whether through price controls or supply-side measures becomes essential. Additionally, taking into account that all sectors are having a reciprocal relationship with the food sector, it is easier to observe how sizable the impact of volatility in this sector is. Therefore, implementing policies that could affect the level and volatility of food prices is one of the issues that have been discussedrecently by many policymakers.

The prices of globally traded commodities often experience abruptand significant fluctuations as a consequence of a broad range of underlying factors. The determinants of price volatility differ between commodities, but in general, sudden price developments are the consequence of low elasticities of demand and supply in the short

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term. Moreover, market fundamentals are not the only sources of price changes, adding to supply and demand shocks a large variety of forces,such as: the impacts of changing climate regimes, key markets cycle stages, currency fluctuations, geopolitics, trade policies, investments, and so on.

Agricultural prices in particular vary because production and consumption are variable. To this end, there is predictable and unpredictable variability, the latter being characterized in terms of shocks. Shocks to production and consumption transmit into price volatility. Production variationscan reflect planted area oscillationsor crop yield variations, usually owing to atmospheric conditions (Gilbert and Morgan, 2010). Consumption varies because of changes in incomes, changes in prices of substitutes and shifts in tastes. However, the most important single factor influencing the price variability in agriculture, in general, is climatic shocks to crop yields.

The extent to which given production and consumption shocks lead to price volatility depends on supply and demand elasticities. Furthermore, stockholding causes volatility to amplify. When stocks are low, relatively small production or consumption shocks can have large price impacts, but when they are high, the reverse is the case. Stockholding will reduce volatility as long as stocks are accumulated in periods of excess supply and released in times of excess demand.

Against this backdrop, how erosive will be the food commodity price shock to the domestic economy, depends on how long the commodity market disruptions endure, and to what extent macroeconomic policiescan effectivelymanage the economic fallout.In this regard, while macroeconomic policies can mitigate the effects of food commodity price shocks to some extent, their impact is often constrained by external factors and structural challenges. To this end, addressing the root causes may require more targeted, sector-specific interventions beyond the scope of traditional macroeconomic measures.

Higher and more persistent inflation could in turn prompt a monetary policy response that lowers growth. The appropriate monetary policy response depends on the type of shock. Supply shocks are a far greater challenge for monetary policy as the output and inflation move in the opposite direction than demand shocks, which are characterized by inflation and output moving in the same direction. This implies that, in case of demand shock, an appropriate monetary policy response can reduce economic fluctuations and to stabilize the inflation. However, the policy response to supply shocks may require a more gradual response in order to avoid unnecessary volatility in real activity, which is only warranted as long as inflation expectations remain well anchored. The duration of the shock is also very important for monetary policy reaction. Short-lived shocks or other one-off changes in the level of commodity prices may not necessarily require for a policy response, as medium and long-term inflation expectations may remain well-anchored, especially in the case of strong central bank credibility. On the other hand, more prolonged supply shocks may have a systematic impact on inflation and could affect inflation expectations, meaning that monetary policy should respond to them (ECB, 2013).

This study aims at investigating the dynamic spillover relationship between world and domestic food prices, by employing monthly data from January 2004 until May 2022. We find that the relationship varies across the high and low volatility regimes. Markov switching regression model (MSR) is applied to validate the regime shifts. As a subsequent step, the DCC-GARCH model is used to analyze the time-varying correlation between the variables as robustness check. Additionally, the factors that cause a price difference between Macedonian and international food markets are exploredwithin MSR framework. To this end, we investigate the impacts of the MKD/USD exchange rate, oil prices, and relative growth of domestic and world food production on the food price relationships.

The results point out that the international/domestic food price relationship vary across thelow and high volatility regimes, indicating that the adjustment process does not behaveuniformly to shocks to equilibrium in different regimes. Also, two structural shiftsin the dynamic correlation between international and domestic food priceshave beendetected. Namely, the firstregime-switching is observed in 2014 (the post-European debt crisis period), while the second one occurred in 2021 (the post-pandemic recovery period).

In addition, the MSR model indicatesthat the MKD/USD exchange rate[2] is an important factor influencing pricedifferences between Macedonian and international food markets. It shows a positive relationship, meaning that a stronger depreciation of the domestic currency makes imports more expensive, thereby amplifying the impact of imported price shocks on domestic prices.Inclusion of the MKD/USD exchange rate explicitly in the model allows us to disentangle the role of global USD dynamics, which drive commodity pricing and cost shocks, from other factors. The USD is central to the price discovery process for food, oil, and fertilizers, since these commodities are globally priced and traded in dollars. Even if imports are invoiced in euros, their prices ultimately reflect USD benchmarks converted via the EUR/USD exchange rate.To this end, whenever the dollar strengthens, the euro price of these commodities rises, and the effect is passed through to denar prices despite the peg. During global crises, this mechanism becomes especially pronounced: USD appreciation often coincides with sharp increases in commodity prices, amplifying the cost pressures faced by small, import-dependent economies. Including MKD/USD in the model therefore improves accuracy by explicitly capturing how exchange-rate-amplified commodity shocks translate into domestic food price dynamics.

On the other hand, we find that the pricedifference between Macedonian and international food markets decreases as oil price(in USDollars)increase.Namely, a sharp rise in oil prices tends to lift food prices globally. The effect is stronger for raw food commodities, as shown in the FAO index, while domestic food inflation usually increases less. This is because domestic food baskets contain more processed products, where value-added stages absorb part of the cost shock. Higher oil prices raise costs for transport and packaging, but these inputs respond less than raw food materials. Domestic markets also adapt through substitution and supply chain adjustments, which helps contain consumer price pressures and narrows the gap between global and domestic food inflation.

The rest of this study is organized as follows. Section 1is reserved for literature review.Section 2covers theeconometric methodology, while the short explanation of data and the main empirical results arepresentedin the thirdsection. Concluding remarks are givenat thelast section.

[2] In reality, the Macedonian Denaris effectively fixed to the Euro, so changes in the MKD/USD exchange rate mirror the fluctuations of the Euro against the US Dollar.

1. LITERATURE REVIEW AND EMPIRICAL EVIDENCE

There is a growing literature focused on understanding the process of volatility spillover from international to domestic food prices.

To this end, Gelos and Ustyugova (2012) are exploring broad range of structural characteristics in order to explain commodity price shocks transmission across countries (31 advanced and 61 emerging and developing economies), over the period 2001–2010, using several approaches. They found that commodity price shocks have a stronger effect on domestic inflation in developing countries than in advanced economies. They conclude that economies with higher food shares in CPI baskets, fuel intensities, and pre-existing inflation levels were more prone to experience sustained inflationary effects from commodity price shocks, while more independent central banks, adoption of IT regime and higher governance scores are factors that help to ease the impact of these shocks.

Furceri et al. (2016) are estimating the impact of global food price shocks on domestic inflation in large group of countries, using two data sets. The estimations based on a country-by-country regression with monthly data for the period 2000-2012 suggested that global food price shocks had a much bigger impact on domestic food inflation in emerging and developing economies than in advanced economies.They also find evidence that inflation expectations are more anchored in advanced than in emerging economies, which could also explain the smaller impact on headline inflation from global food price shocks, additionally to the smaller weight of food in CPI basket and consumption of higher level of processed food.

Peersman (2019) examined the causal effects of fluctuations in international food commodity prices on inflation dynamics and the transmission mechanism to consumer prices in the euro area (EA)using a structural VAR model, identified with the global harvest shocks as an external instrument. The results show that exogenous food commodity price shocks have a strong impact on EA inflation, explaining on average 25%-30% of inflation volatility.An analysis of the transmissionmechanism shows that international food price shocks have an impact on food retail prices through the food production chain, but also trigger indirect effects via rising inflation expectations and nominal wages (second – round effect) and a depreciation of the euro, which augments import prices of non-food items in the HICP.

Igan et al. (2022) use structural vector autoregression (SVAR) model, with quarterly data for the period from 1972 to 2019, to estimate the responses of economic growth and inflation across a panel of 19 countries to a three commodity shocks:a supply-driven oil price shock, a “pure” oil price shock that is independent of changes in oil supply or global aggregate demand, and an agricultural commodity price shock that is independent of global aggregate demand. Overall, the results suggest that recent commodity price gains could raise inflation in a typical advanced economy by over 1 p.p. in 2022. Additionally, the authors conclude that the spillovers are typically larger for commodity importers.

In the analysis of IMF’s World Economic Outlook (IMF, 2022), using panel data and local-projections methods, the impact of food commodity prices on domestic food price inflation, including several control variables such as oil prices, the Baltic Dry Index, headline consumer price inflation and exchange rates was estimated. They found that food consumer price inflation increases about 0.3 percentage point in response to a

1 percentage point change in international food prices after about 10–12 months, leading to conclusion that the pass-through is about 30% for the average country.They found that the pass-through is larger for emerging market economies than for advanced economies, in part because food commodities have a higher cost share in the former group, but also for countries that score higher on trade openness, as greater cross-border arbitrage opportunities raise domestic prices' responsiveness to global food price shocks. This study captures the most recent increase in world food prices (2020-2022).

Pop, Rovinaru and Rovinaru(2013) were working on comparison of the volatility experienced at the international level and on the Romanian food market, concentrating the analysis during the years of the global financial crisis and immediately after its appeasement. The estimation is based on monthly data between January 2006 and November 2011 of the price indices evolution for the Romanian food market and corresponding ones at the international level from the International Monetary Fund (IMF) Primary Commodity Prices database and using ARIMA-EGARCH with a GED distribution as estimation method. The results showed an increase of volatility between 2008 and 2011 on both food markets, with conclusion that after 2007–2008, the Romanian market appears to be more synchronized, following the "peaks" in world prices one step behind, which is explained by the fact that Romania became more receptive to international shocks by joining the EU in 2007 and opening its markets. Comparing the evolutions of volatility for the two food markets, they found that in the midst of the GFC the food prices volatility was more pronounced on the international market than on the Romanian one, but in later period the volatility on the Romanian market become more acute than on the internationalone.

Ertugrul and Seven (2021) analyzed a dynamic spillover relationship between international food prices (FAO Food Price Index) and Turkish CPI food price index by employing Markov Switching Regression (MSR) and Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroscedasticity (DCC-GARCH) models to monthly data from 2003 to 2019. They found that structural shifts in the dynamics of the international/domestic food price relationship are present, and the relationship varies across the low and high volatility regimes. They also investigate the factors that cause the price difference between Turkish and international food markets by employing several econometric models, including ARDL, FMOLS, DOLS, and MSR. All models have shown that the exchange rate growth is the most important factor that significantly affects the growing difference between Turkish and international food prices; oil prices reduce that difference, while per capita food production growth difference (relative growth) variable has positive impact, but is statistically significant only for FMOLS model.

2. METHODOLOGY

To analyze the dynamic spillover relationship between world and domestic food prices, we employ Markov Switching regression (MSR) model, followingErtugrul and Seven (2021). The MSR model is an extended version of the simple exogenous probability models by employing a first-order Markov process for the regime probabilities. We define two regimes: low and high volatility regimes, differentiated by the regime-specific variances. To this end, the model is represented below, by Equations1 and 2.

$$DFPI_t = \alpha_{10} + \alpha_{11}DFPI_{t-1} + \alpha_{12}WFPI_t + \varepsilon_t^1 \quad (1)$$

$$DFPI_t = \alpha_{20} + \alpha_{21}DFPI_{t-1} + \alpha_{22}WFPI_t + \varepsilon_t^2 \quad (2)$$

where$DFPI_MK_t$ is the natural logarithm of the CPI-food price index that denotes the Macedonian food prices and $WFPI_t$ is the natural logarithm of the world raw price index that denotes the international food prices at time. $\alpha_{10}$and $\alpha_{20}$are the regime-dependent constants, $\alpha_{11}$and $\alpha_{21}$are the autoregressive (AR) coefficients, $_{12}$and $\alpha_{22}$are coefficients in front of world food price index, while $\varepsilon^1{}_t$and $\varepsilon^2{}_t$are the white-noise error terms with the regime-dependent variances $\sigma_{12}$and σ_{22}, respectively.

This regime-switching model has advantages over single regime modelsas there are lower volatility persistence and better forecasting performance (Cai, 1994; Dueker, 1997; Lamoureux and Lastrapes, 1990, cited in Ertugrul and Seven, 2021). The transition from Regime 1 to Regime 2 (or from Regime 2 to Regime 1) is determined according to the unobserved state variable s_t , which follows a first-order Markov process that could be shown as $Pr(s_t = j|s_{t-1} = i) = p_{ij}$ (Ertuğrul and Öztürk, 2013, cited in Ertugrul and Seven, 2021). The term p_{ij} denotes the probability of state i followed by state j (Bautista, 2003, cited in Ertugrul and Seven, 2021). Equation 3 shows the simplest version of the transition probability matrix with two states.

$$p = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}, \qquad where \sum\nolimits_{j=1}^{2} p_{ij} \;\; for\ every\ row\ i \quad (3)$$

In addition,for purposes of robustness checka Multivariate Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model was employed in order to examine the time-varying correlation between the time series of interest. The GARCH model is taking into account both the predictable and unpredictable components in the price process, while considering time-varying conditional variances, and consequently, only the stochastic or unpredictable components when modeling volatility (Jordaan et al. 2007, cited in Pop, Rovinaru and Rovinaru, 2013).

The general form of a GARCH (p,q) model (Bollerslev, 1986) includes two equations, one for the conditional mean and another for the conditional variance. The general model specificationis represented in Equations4 and 5:

$$y_t = c + \varepsilon_t\sigma_t, \qquad where\ u = \varepsilon_t\sigma_t \quad (4)$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i u_{t-i}^2 + \sum_{j=1}^{q} \beta_j\, \sigma_{t-j}^2 \quad (5)$$

whereε_{tt}~$iid(0,1)$, ω>0, α_i≥0 and β_j≥0. $\sigma_t^2$is known as the conditional variance since it is a one-period ahead estimate for the variance calculated based on any past information thought relevant. The α_i and β_j are ARCH and GARCH parameters, respectively. The parameter ωrepresents an average volatility, while the coefficients of ARCH-terms (α_i)reveal the volatility of previous periods of time and this volatility is measured with the aid of squared residuals from the equation of mean. The coefficients of GARCH-terms (β_j) show the persistence of past shocks on volatility.

Multivariate GARCH models are in spirit very similar to their univariate counterparts, except that the former also specify equations for how the covariances move over time. Several different multivariate GARCH formulations have been proposed in the literature. To this end, one specific type of models is focused on conditional correlations. These models, in fact,decompose a covariance matrix in terms of its corresponding standard deviations and correlation matrix. Bollerslev (1990) proposes the Constant Conditional Correlation (CCC) model which allows each series to follow a separate GARCH model while restricting the conditional correlations to be constant. The DCC model, developed by Engle (2002), is the generalization of Bollerslev's model that allows the conditional correlations to change over time and therefore it is possible to investigate the dynamic correlation between the variables of interest. Engle (2002) considered a dynamic matrix process, given in Equation 6:

$$Q_t = (1 - \alpha - \beta)S + \alpha\varepsilon_{t-1}\varepsilon'_{t-1} + \beta Q_{t-1} \tag{6}$$

where α is a positive and β a non-negative scalar parameter such that $\alpha + \beta < 1$, ensuring that model is mean reverting, S is the unconditional correlation matrix of the standardized errors ε_t, and covariance matrix Q_t is a weighted of average of positive definite and a positive semidefinite matrix. However, Capolin and McAleer (2013, quoted in Ertugruland Seven, 2021) expressed that the DCC model may be useful as a filter or a diagnostic check, but not the primary model.

3. DATA AND RESULTS
3.1. Data

To analyze the spillover relationship between international and Macedonianfood prices, as first step in this study, we employ monthly world food price index and Macedonian food price index data,covering the January 2004 - May 2022 period. FAO food price index (WFPI), expressedin terms of US dollars, is used as the world food price, and it is compiled from the FAO website. To measure theMacedonian food prices, we use the food subcomponent of a consumer price index, and thedata is obtained from the SSO's (State Statistical Office) website. All variables are expressed as natural logarithms in order to obtainelasticity coefficients in line with the existing literature.

For the second part of this analysis, we use the difference in Macedonian and international food price indexesas a dependent variable to analyze the factors that cause a price difference between Macedonian andinternational food prices. The price difference is calculated by subtracting world food price annual growth rate from Macedonian food price growth rate on a monthly basis.

As independent variables, both demand and supply-side variables are included: oil price,MKD/USD exchange rate, and per capita food production index, which corroborates with the field literature. To take into account the impact of energy prices on the price difference, Brent Crude oil price data from World Bank's Pink sheet database, expressed in US dollars, is used. We employthe MKD/USD exchange rate for controlling whether the difference between thefood price indexes was due to the renewed strength of the US dollar against the Euro from 2015 onwards, given the fixed exchange rate parity of the Denar against the Euro. The exchange rate data is obtained from the NBRNM's statistics. In orderto capture the supply-side effects, the difference in production growth rates, similar to the food price indexes, was employed. We use percapita food production indexes for North Macedonia and the world by taking the difference in growthrates,whichare obtained from the FAO'sdatabase[3]. All independent variables are used as year on year growth rates. Table 1 in the Appendix 1, displays thedescriptive statistics of the data.

Regarding world food and commodity prices in general, it can be observed that the volatility of prices has increased over time. Actually, starting from 2002, the international prices of all major commodity groups rose gradually, including food prices. The momentum of prices accelerated in 2007, with food prices growing by above 60% in February – March 2008 compared with the same period previous year and reaching the peak in June 2008. The rise in food price have mostly been affected by higher energy and fertilizer prices, low levels of inventories, shortfalls in certain crops and strong increases in the demand for crops (there was greater demand for the non-food use of agricultural commodities in the feeding of livestock and for the production of biofuels) (ECB, 2007). However, in September 2008, the global outlook had already dramatically deteriorated, as the financial crisis had started to spread, causing sharp commodity price declines. Accordingly, the boom experienced in the previous years, was followed by a sudden and intensive collapse, but very soon there was a consequent rises and falls in prices. Thus, commodity prices stopped their fall by the end of 2009 and started to rise again, with rebound during 2010 as the global economy started to overcome the crisis. Increased demand from China, significant production cuts for metals and oil, and some weather related factors in agricultural markets also contributed to higher prices. In spite of the recovery, even in 2011 prices continued to oscillate, as the world economies continued to struggle with other turbulences, such as the sovereign debt crises in Europe (Pop, Rovinaru and Rovinaru, 2013). Although the reasons for this instability were numerous, as it was stated in Pop, Rovinaru and Rovinaru (2013), the global economic crisis had a major impact on commodity price volatility during 2007-2011. The commodity prices went down gradually after that, with a stronger downward trend in 2015, when food prices, in terms of falling oil prices, were under the impact of abundant harvests (IMF, 2015). The period after 2016 was a period with relatively low and stable food prices. However, the Covid-19 pandemic's hit in early 2020 started new cycle of instability and the food prices reached even higher levels than the ones experienced during 2008 and 2011 shocks. This surge in international food prices (between April 2020 and May 2022) is a combination of supply-side factors (the 2020–22 La Niña episode and food trade restrictions), cereal-specific demand (China's 2021 restocking), low interest rates, and more recently, the war in Ukraine and the Russian blockade of wheat exports from Ukraine (IMF, 2022).

Figure 1 however points out toonly partial transmission from global food prices to domestic ones. Namely, the world food price developments might not be fully translatedinto domestic food inflation, as the share of countries' food production that is effectively exported is relatively small and most food production is consumed domestically (Arezki et al., 2016). Moreover, domestic food prices are usually

[3] Gross per capita food production indices have annual frequency. Last available reading in the moment of writing of this study was 2020. An extrapolation from annual to monthly data was implemented such that the average of the monthly indices in one calendar year corresponds to the value of the index in that particular year.

moderated by subsidies and local costs of food processing and distribution. The latter partly depend on the quality of logistic infrastructure and might show different price dynamics than agricultural raw materials. In fact, inflation of crops affects only a part of overall food expendituresand the impact on overall consumer price inflation is more limited. Still, in developing countries where people spend a larger share of their income on food and rely less on processed and packaged foods, the impact of crop inflation is higher (Woertz et al., 2014).

a) b)

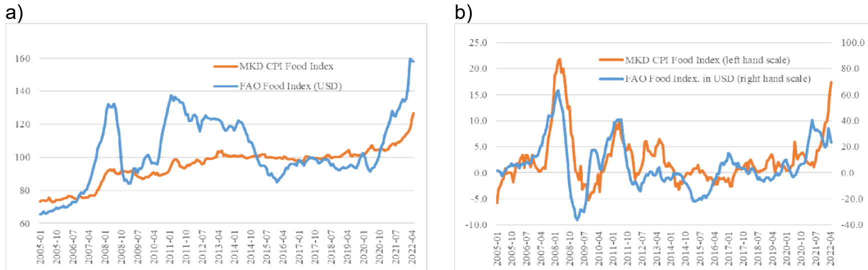

Figure 1. Domestic and World food price
a) Index, 2014-2016=100; b) Annual changes, in%
Source: FAO, State Statistical Office of Republic of N. Macedonia, author's calculations

3.2. Empirical Results

In order to explore the dynamic spillover relationship between world and domestic food prices, a Markov Switching regression (MSR) was applied. For the sake of robustness check, we further estimate a DCC_GARCH model. As it was already stated in thesection 3.1, the series are expressed as year on year changes, as both series are nonstationary in levels, but stationary in difference. The results of the unit root test is given in Appendix 1, Table 2. In what follows, the factors that determine the price differences between domestic and world food prices are investigated.

3.2.1. Spillover Relationship between World and Macedonian Food Prices

Before proceeding with the Markov Switching Regression, apreexamination of possible regimes was conducted. For this purpose, the sample standard deviation of annual changes of domestic and world food prices was analyzed, where each period represents a 12 months moving average standard deviation (Figure 2).

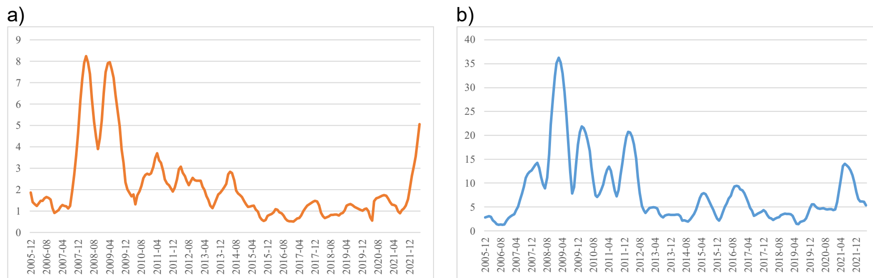

Figure 2. Standard deviations (12 months moving average)
a) Domestic food inflation; b) FAO Food index inflation
Source: State Statistical Office of Republic of N. Macedonia, FAO, author's calculations.

Figure 2 in fact, considers historical volatility and is based on dispersion metrics, such as the standard deviation.It essentially identifies two regimes representing high- and low-volatility periods. Periods of excessive volatility to largest extent mark the 2006-2008 global food price crises when a great number of trade policy measures provoked counterproductive effects. Namely, in this period, several countries implemented export restrictions of food commodities in order to protect domestic markets (Woertz et all, 2014), but it represented in many cases a significant reduction in the international supplies and consequently an increasing in the international food prices.Since the beginning of 2022, Russia's invasion of Ukraine has resurged as a cause of a renewed disruptive period for global food prices.

Markov Switching regression model was specifiedfollowing the Equations1 and 2 in Section 2. Table 1 summarizes the results.

Table 1. Markov Switching regression (MSR) results

Dependent Variable: DL12FPI_MK		
Regime 1		
Variable	Coefficient	Probability
Constant	0.02	0.26
DL12FPI_FAO	0.08	0.00
Log(σ)	-4.05	0.00
Regime 2		
Variable	Coefficient	Probability
Constant	0.02	0.14
DL12FPI_FAO	0.01	0.75
Log(σ)	-5.00	0.00
Common		
AR(1)	0.93	0.00
Transition Matrix Probabilities		
Low to High	0.88	
High to Low	0.87	
Statistics:		
Inverted AR Roots	0.93	
Durbin-Watson stat	1.73	
Jarque-Bera normality test	17.50	0.00

Table 1 shows that the specified model can correctly discriminate between the high (Regime1) and low (Regime 2) volatility regimes, where Regime 1 has a higher variance than Regime2. The elasticity coefficient between the world and Macedonian food pricesis positive in both regimes, 0.08 for Regime 1 and 0.01 for Regime 2. However, the corresponding coefficient in Regime 2 is statistically indistinguishable from zero. The interpretation of elasticity coefficients is as follows: a 1 p.p. increase in the annual growth rate of world food prices speeds up by 0.08 p.p.and 0.01 p.p. Macedonianannual food inflation rate for Regime 1and Regime 2, respectively[4].

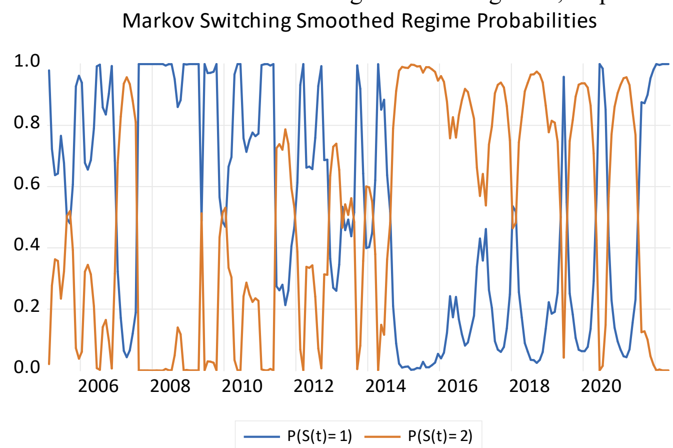

Figure 3. Regime Probability Graph
Source: Author's calculations.

Regime probability graphthat shows which regime is valid for each period is presented as Figure 3. It indicates a regime shift in August 2014, but also at the end of the sample, i.e. in July 2021 reflecting the post-pandemic recovery. According to Figure 3, Regime 1 is valid for the period 02.2005-08.2014, as well as for the end of analyzed data span i.e. 07.2021-05.2022, while Regime 2 is valid for the rest of the period (09.2014-06.2021).

Moreover, the probability of being in a high volatility regime is only marginally higher than the probability of being in the low volatility regime. This is evidence that both regimes have similar levels of persistency. The average duration of the high volatility regime is 8.6 months. In contrast, the average duration of the low volatility regime is 7.5 months.

3.2.2. Robustness check

After the dynamic regression analysis, DCC-GARCH model of Engle (2002) was applied to capture the dynamiccorrelation (the correlation over periods) between the

[4]Equations with lagged values of world food prices were also estimated. However, the lagged values turned out to be statistically insignificant and were associated with smaller coefficients compared to the current values.

world and Macedonian food pricevariables as a robustness check. Theresults are presented in Figure 4.

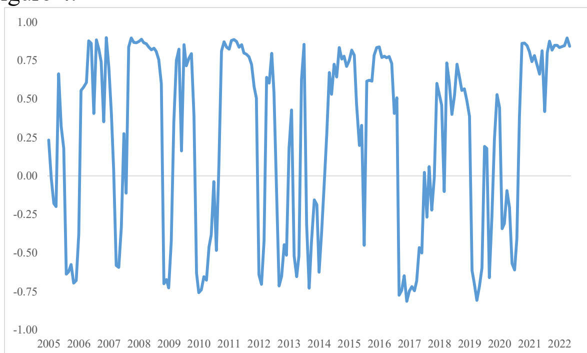

Figure 4. Results on Dynamic Conditional Correlation
Source: Author's calculations.

The DCC results show that the dynamic correlations between international and Macedonian food prices turn to be negative mainly in crisis times, for instance, in 2010 - the aftermath of the Global financial crisis, in 2017 - domestic political crisis, as well as prior and during the acute phase of the pandemic, i.e. in 2020.

3.2.3. Determinants of Price Differences between Domestic and World Food Markets

This sub-section aims at determining the factors that cause differences between domestic and international food price growths. To this end, our preferred modeling choice isMSR.The basic regression model is shown in Equation 8, following the model setting as in Equations 1 and 2 in Section 2:

$$FPIGD_t = \beta_0 + \beta_1 OILG_t + \beta_2 EXCG_t + \beta_1 FPIG_t + \varepsilon_t \tag{8}$$

where $FPIGD_t$ is the growth difference (relative growth) of food price indexes that is obtained by subtracting the year on year world food price change from the domestic food price growth at time *t*, $OILG_t$ is the oil pricein US dollars y-o-y growth, $EXCG$ is the MKD/US dollar exchange rate y-o-y growth, and $FPIGt$ is the per capita production index growth difference between North Macedonia and World.

Data availability in this particular case limits the estimation sample to 01.2005-12.2020.

The estimation output is given in Table 2.

Figure 5 plots the volatility of the growth differential of food price indices (relative growth). The trajectory clearly points out to two distinct regimes, i.e. high and low volatility regime.

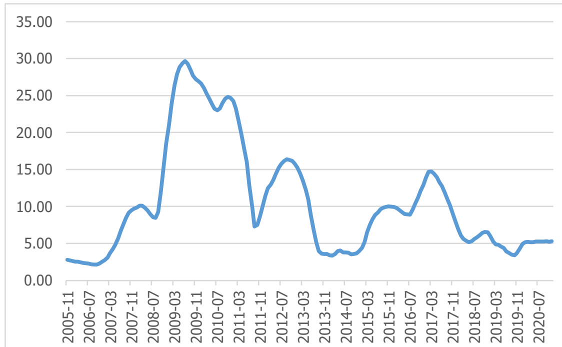

Figure 5. Standard deviation of food annual inflation differential (24 months moving average)
Source: FAO, State Statistical Office of Republic of N. Macedonia, author's calculations.

This corroborates with the regime probability chart (Figure 6) showing two distinct regimes.

Table 2. Estimated MSR model

Dependent Variable: FPIGD		
Regime 1		
Variable	Coefficient	Probability
Constant	0.08	0.17
OILG	-0.27	0.00
EXCG	0.33	0.01
FPPC_D	0.48	0.50
Log(σ)	-3.46	0.00
Regime 2		
Variable	Coefficient	Probability
Constant	-0.03	0.50
OILG	-0.04	0.01
EXCG	0.29	0.00
FPPC_D	0.17	0.13
Log(σ)	-3.73	0.00
Common		
AR(1)	1.20	0.00
AR(2)	-0.24	0.00
Transition Matrix Probabilities		
Low to High	0.97	
High to Low	0.99	
Statistics:		
Inverted AR Roots	0.95	
Inverted AR Roots	0.25	
Durbin-Watson stat	2.02	
Jarque-Bera normality test	0.85	0.65

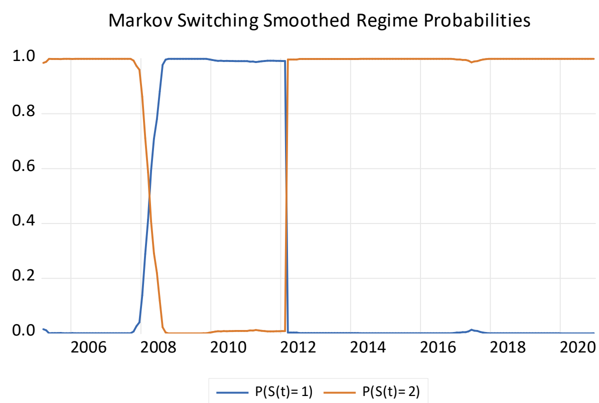

Figure 6. Regime Probability
Source: Author's calculation

According to Table 2,the exchange rate growth variableis positively and statistically significantly associated with the price growth differential between North Macedonia and the world in both regimes.When the domestic currency depreciates relative to the US Dollar (which, in practical terms, occurs when the Euro depreciates against the US Dollar, given the fixed exchange rate of the Denar to the Euro), i.e., when the exchange rate grows positively, the cost of imported goods rises because more of the domestic currency is needed to purchase the same amount of foreign goods. Food products, especially those that are not produced locally or are dependent on imported raw materials, will see a direct increase in price due to this depreciation, which then gets passed on to consumers in the form of higher food prices. The coefficients are similar in both regimes, around 0.3, which means that for every 1p.p. increase in exchange rate y-o-y growth, the food price growth differential between North Macedonia (measured in denars) and global food prices (measured in US dollars) increases by about 0.3 percentage points.These results corroborate with Ertugrul and Seven (2021).

The estimated coefficient of the oil price growth variable is negative and statistically significant in both regimes. Namely, when oil prices experience a strong increase, it tends to affect countries worldwide in a similar manner. This is because oil is a key input in many industries—especially in food production, transportation, and processing. Rising oil prices increase the cost of production and transportation for food, which typically leads to higher food prices globally. However, the negative coefficient suggests that when oil prices rise, the gap between domestic food inflation and world food inflation narrows. At its core, the impact of oil price shocks on food inflation is more nuanced in domestic markets due to the role of value-added stages and supply chain adjustments, which help cushion the rise in prices and narrow the gap between domestic and global food inflation. More precisely, processed foods which enter the domestic food price index typically go through multiple value-added stages, such as preparation, packaging, distribution, and retail. Each of these stages adds layers of cost that may be less directly affected by raw material price increases, especially when compared to unprocessed food commodities. These steps introduce opportunities for cost absorption, substitution, or more flexible pricing strategies that can mitigate the immediate effects of raw material price rises. The coefficients vary between -0.27 in Regime 1 (high volatility) and -0.04 in Regime 2 (low volatility), indicating that a 1 p.p. speed up in world oil price growth causes a reduction of 0.27 p.p. and 0.04 p.p., respectively, in the food price growth differential.

The estimated coefficient of the per capita food production growth difference variable is positive in both regimes and statistically insignificant for Regime 1 but has border significance for Regime 2. One would expect a negative relationship between supply-side effects and growth difference of food prices in both regimes, as a higher growth rate in domestic production compared to world production growth (resulting in a positive production growth differential) should lead to a more significant decrease in domestic food prices than in global food prices, thereby creating a larger negative food inflation differential. However, most likely the dynamics between these two variables is dominated by some country-specific characteristics.In essence, stronger growth in domestic food production alone might not be sufficient to reduce inflation if the country remains heavily reliant on imports and if the structure of domestic production doesn't align with the overall needs of the population. This suggests that a more holistic approach, addressing issues like diversification of production and import dependencymay be needed to better understand and influence inflation dynamics.

CONCLUSIONS

In this study, first the dynamic spillover relationship between international andMacedonian food prices by employing the MSR and DCC-GARCH models was analyzed, to monthly data between January 2003 and May 2022. We find structural shifts in the dynamics of the international/domestic food price relationship, and the relationship varies across the low and high volatility regimes. The MSR model suggests two structural shifts in the dynamic correlation of international and domestic food prices. The first one occurred in the aftermath of GFC and European debt crisis and is characterized by higherprice volatility as well as by stronger transmission from international to domestic food prices. The second shift is associated with mid-2021 – May 2022 as end of analyzed period. This sub-sample covers two simultaneous shocks, i.e. the post-pandemic recovery and the war in Ukraine, when uncertainty and volatility increased and food and energy prices experienced strong shocks all around the world.

The DCC results show that the dynamic correlations between international and Macedonian food prices turn to be negative mainly in crisis times, for instance, in 2010 - the aftermath of the Global financial crisis, in 2017 - domestic political crisis, as well as prior and during the acute phase of the pandemic, i.e. in 2020.

This study summarizes as well the factors that cause a difference between domestic and international food price growths. The exchange rate proves to be an important factor, with positive sign. In simple terms, if the exchange rate Denar/US Dollar depreciates by 1 percent over a year (which, in fact, occurs when the Euro depreciates by 1 percent against the US Dollar, given the fixed exchange rate of the Denar to the Euro), food price growth in North Macedonia (measured in denars)is expected to exceed global food price growth (measured in US dollars) by about 0.3 percentage points, all else being equal. This relationship remains relatively stable across both economic regimes analysed, highlighting the consistent impact of exchange rate movements on food inflation.

Oil price growth is also found as relevant determinant. In the analysed period, its coefficient is negative and statistically significant in both regimes. This suggests that the effect of oil price shocks on food inflation is more complex in domestic markets because of the influence of value-added stages and supply chain adjustments, which help mitigate price increases and reduce the difference between domestic and global food inflation. The FAO Food Price Index primarily tracks raw food prices, which are more directly impacted by oil price increases. In contrast, domestic food inflation includes both raw and processed foods. This distinction helps explain why domestic food inflation may rise less sharply than global food inflation during oil price surges.

The estimated coefficient of the per capita production growth difference variable is positive in both regimes and statistically insignificant for Regime 1, but has border significance for Regime 2, although negative relationship between supply-side effects and growth difference of food prices is expected. Against this background, most probably the dynamics between these two variables is dominated by some country-specific characteristics.Put differently, simply boosting domestic food production may not lower inflation if the country remains reliant on imports and if production doesn't meet domestic needs.

Overall, the results suggest that domestic food prices have an increased responsiveness to external shocks in terms of high and volatile world food prices.

Given the critical importance of food prices, both their level and volatility have become central issues for policymakers at both global and domestic levels. In this context, a broader strategy, focusing on diversifying production, reducing import dependence is needed to tackle inflation effectively. Policymakers, especially those handling agricultural policies, should focus on increasing domestic food production in the medium to long term, ensuring sustainable production practices, addressing structural issues in the food supply chain, and managing short-term risks related to unprocessed food inflation.

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APPENDIX 1

Table 1. Variable descriptive statistics

	DL12FPI_FAO	DL12FPI_MK	FPIGD	OILG	EXCG	FPPC_D	FPPC_D1
Mean	0.04	0.02	-0.02	0.05	0.01	0.00	0.00
Median	0.03	0.01	-0.02	0.06	0.00	0.01	0.01
Maximum	0.49	0.20	0.45	1.02	0.24	0.26	0.19
Minimum	-0.45	-0.06	-0.32	-1.12	-0.16	-0.29	-0.23
Std. Dev.	0.17	0.05	0.15	0.39	0.09	0.09	0.09
Skewness	0.03	1.70	0.39	-0.53	0.31	-0.52	-0.57
Kurtosis	3.35	6.40	3.24	2.86	2.59	6.12	5.40
Jarque-Bera	1.09	200.98	5.90	9.80	4.75	86.39	56.47
Probability	0.58	0.00	0.05	0.01	0.09	0.00	0.00
Sum	8.93	4.99	-3.94	9.81	1.10	0.54	0.54
Sum Sq. Dev.	6.27	0.44	4.88	31.31	1.60	1.57	1.40
Observations	209	209	209	209	209	192	192

Note: The table reports the summary statistics for the used variables. LFPI_FAO, LFPI_MK, FPIGD, OILG, EXCG, FPPC_D and FPPC_D1 represent the natural logarithm of the World food price index, the natural logarithm of the Macedonian food price index, growth difference of the food price indexes of N.Macedonia and the world, oil price growth, exchange rate growth and growth difference of the food production of N.Macedonia and world, respectively. Growth rates refer to annual growth.

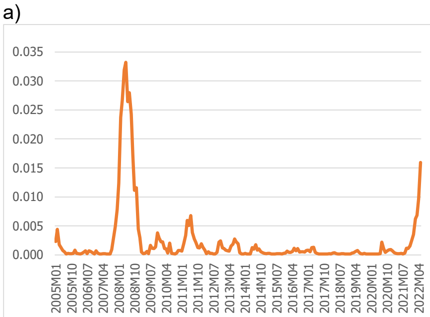
Table 2. ADF test for stationarity

ADF test*	t-stat	prob.	variable	t-stat	prob.
LFPI_FAO	-1.985139	0.6058	DL12FPI_FAO	-3.389689	0.0008
LFPI_MK	-1.536002	0.8143	DL12FPI_MK	-0.788566	0.3734
Phillips-Perron test*	adj. t-stat	prob.	variable	adj. t-stat	prob.
LFPI_FAO	-1.889301	0.6567	DL12FPI_FAO	-2.915626	0.0037
LFPI_MK	-1.634658	0.7762	DL12FPI_MK	-2.208122	0.0266

*Tests on series expressed as log level is performed with option 'Constant and Trend' and in case of 12 months log difference is performed with option 'None'. In case of ADF test, Schwarz criterion was used, while in Phillips-peron test, Newey-West Bandwidth was applied.

APPENDIX 2

a)



b)

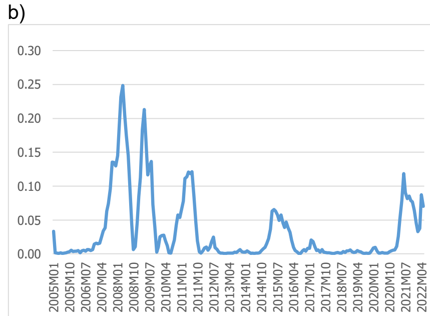


Figure 1. Estimated Individual Conditional Variances
a) Domestic food inflation; b) FAO Food index inflation
Source: State Statistical Office of Republic of N. Macedonia, FAO, author's calculations.