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The impact of geopolitical risk on agricultural commodity prices

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Abstract: The escalation of the conflict between Russia and Ukraine had a detrimental effect on the global agricultural and food market and the price movements of essential commodities. In this study, we aim to investigate the effects of geopolitical risk on the prices of selected agricultural and food commodities using the linear and nonlinear ARDL (autoregressive distributed lag) model. Our results show evidence of the asymmetric impact of geopolitical risk on the prices of rapeseed, sugar, sunflower oil, and wheat. The findings also show no long-term link between geopolitical risk and corn, cotton, lumber, milk, oats, rough rice, and soybean prices.

Keywords: economic policy uncertainty; financial volatility; Russia-Ukraine war; time series analysis

The war between Russia and Ukraine is one of the most critical geopolitical events of the 21st century. On February 24, 2022, Russia commenced military activities in Ukraine and began an all-out assault. Since then, the prices of crucial commodities such as energy, minerals and agriculture have skyrocketed (Fang and Shao 2022). The deepening of the Russia-Ukraine disputes contributed to an enormous rise in geopolitical risk, which sent the global economy and markets reeling. Geopolitical risks result from international hostilities, war threats, armed conflicts, and terrorist activities (Lee and Lee 2020). They can also be considered a gauge of political unrest in the economy since they have a significant role in asset market valuations (Snowberg et al. 2007). Hence, geopolitical risks belong to the driving factors that affect the development of commodity prices. Furthermore, due to risk transmission and spillover effects, the interdependence of markets is particularly increased during times of high uncertainty and turbulence (Hassouneh et al. 2017; Ji et al. 2020; Xiao et al. 2020). According to Gardebroek et al. (2016), the markets for agricultural commodities are inextricably linked since they usually compete for limited natural resources, have similar input costs, and are regularly perceived as substitutes. Geopolitical risk also highly impacts commodity market links (Gong and Xu 2022). Just and Echaust (2022) claim that agricultural commodity markets became more integrated when markets recovered following the COVID-19 pandemic and after the start of the war conflict between Russia and Ukraine. Babar et al. (2023) state that particularly corn and sugar are the most and least effective transmitters of spillover, while soybeans are the most and least effective receivers during the Russia-Ukraine conflict. In contrast, Wang et al. (2022)

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provide evidence that spillover indices are brought on by geopolitical risk, and wheat and soybeans are net return spillover recipients during Russia-Ukraine tensions. Focusing on the global agricultural and food markets concerning geopolitical risk is crucial in the context of the latest events because Russia and Ukraine are significant world producers and exporters of arable crops and agricultural commodities. The main objective of this study is to examine how geopolitical risk influences the world prices of the leading agricultural commodities. Indeed, we analyse geopolitical risk's effects on futures commodity prices by applying the standard and nonlinear ARDL (autoregressive distributed lag) model from January 2, 2020, until July 29, 2022. Moreover, our study sheds light on which agricultural commodities are vulnerable to price disruptions and shifts in geopolitical risk caused by Russia-Ukraine tensions. We contribute to the existing literature in three ways. First, when studying geopolitical events concerning commodity markets, studies often focus on individual markets. Thus, in light of the latest occurrences, we aim to extend the existing literature by analysing interconnections between geopolitics and the agricultural and food market from a global perspective. Next, our analysis incorporates both linear and nonlinear methodologies to study interactions between commodity prices and changes in geopolitical risk. Our sample covers the period of the global outbreak of COVID-19 in addition to the war in Ukraine. Therefore, our approach allows us to investigate the effect of geopolitical risk on different asset classes under unpredictable market circumstances. Finally, except for the geopolitical risk index (GPR), we adopt two other uncertainty indicators: economic policy uncertainty (EPU) and the financial volatility index (VIX).

MATERIAL AND METHODS

Econometric techniques. We apply the autoregressive distributed lag (ARDL) technique to examine the geopolitical risk index (GPR), economic policy uncertainty (EPU), and the financial volatility index (VIX) implications on commodity prices. The first analysis phase involves detecting a long-term relationship between the time series using the ARDL bounds test introduced by Pesaran et al. (2001). The ARDL model allows for the effective estimation of long-term and short-term parameters and has several desirable properties over regular cointegration techniques. The endogeneity problem and serial correlation can simultaneously be fixed with an appropriate specification of ARDL (Pesaran and Shin 1999). The ARDL approach also can allow various lags for multiple regressors. Notably, the ARDL technique, contrary to previous methods, can be implemented either for stationary time series $I(0)$, stationary in first differences $I(1)$ or cointegrated with one another (Pesaran et al. 2001).

Nevertheless, the estimated F-statistics are deemed invalid if $I(2)$ variables are included in the model. Therefore, we assess the stationarity of the time series and their first differences using the Augmented Dickey-Fuller test (ADF) and the Phillips-Perron test (PP) to ensure that neither of the variables is integrated of order $I(2)$ or higher. Then, using the ARDL bounds testing approach, the presence of a long-run relationship is checked. The general form of the ARDL (p, q) model is as follows [Equation (1)]:

$$y_t = c_0 + \sum_{i=1}^{p} \phi y_{t-1} + \sum_{i=0}^{q} \beta_i x_{t-1} + u_t \tag{1}$$

where: y – dependent variable (the price of the agricultural commodity); c_0 – constant; ϕ, β – unknown parameters to be estimated; x – independent variable (GPR, EPU, VIX); p – number of optimal lags of the dependent variable; q – number of optimal lags of each explanatory variable; u_t – white noise error.

After reparameterisation in the form of conditional error correction, we get the following form [Equation (2)]:

$$\Delta y_t = c_0 + \sum_{i=1}^{p} \psi_i \Delta y_{t-1} + \sum_{i=0}^{q} \psi_i \Delta x_{t-1} + a e_{t-1} + u_t \tag{2}$$

where: α – dependent variable's adjustment speed to a short-run deviation from the equilibrium; ψ – short-term coefficients.

Following Pesaran et al. (2001), the e_{t-1} in Equation (2) can be replaced by the linear combination of lagged level variables of the model, and we can rewrite Equation (2) into the form [Equation (3)]:

$$\Delta y_t = c_0 + \sum_{i=1}^{p} \psi_i \Delta y_{t-1} + \sum_{i=0}^{q} \psi_i \Delta x_{t-1} + \gamma_i y_{t-1} + \\ + \gamma_i x_{t-1} + u_t \tag{3}$$

where: ψ – short-term effects; γ – long-run effects.

Pesaran et al. (2001) identified two different forms of critical values to test whether there is a long-term relationship between the two-time series. The first version presupposes that all model variables are $I(1)$, whereas the second type presumes that all included variables

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are $I(0)$. If both the estimated F-statistic and t-statistic are greater than the upper bound, the null hypothesis of no cointegration should be dismissed. The null hypothesis of no long-run association cannot be rejected if the derived F-statistic and t-statistic fall below the lower bound. Hence the ARDL model should be estimated in the first differences without the error correction factor. In the final scenario, the test is inconclusive if either the F-statistic or the t-statistic remains within the crucial ranges for the upper and lower bounds.

However, the findings may imply that a change in the independent variable will have an asymmetric or nonlinear impact on the response variable in either direction. Therefore, this paper also evaluates the possible asymmetry related to commodity prices and GPR, EPU, and VIX indices. Specifically, we employ Shin et al. (2014) nonlinear ARDL model (NARDL). By using positive and negative shocks of independent variables, this methodology enables the asymmetry to be tested. The '+' and '–' notations denote the partial sum of positive and negative changes of the independent variables [Equations (4, 5)].

$$x_t^+ = \sum_{i=1}^{t} \Delta x_i^+ = \sum_{i=1}^{t} \max(\Delta x_i, 0) \tag{4}$$

$$x_t^- = \sum_{i=1}^{t} \Delta x_i^- = \sum_{i=1}^{t} \max(\Delta x_i, 0) \tag{5}$$

The symmetric long-run specification of Equation (3) can be reformulated into the asymmetric specification as [Equation (6)]:

$$\Delta y_t = c_0 + \sum_{i=1}^{p} \psi_i \Delta y_{t-1} + \sum_{i=1}^{q} \psi_i \Delta x_{t-1}^+ + \sum_{i=1}^{q} \psi_i \Delta x_{t-1}^- + \\ + \gamma_i \Delta y_{t-1} + \gamma_i \Delta x_{t-1}^+ + \gamma_i \Delta x_{t-1}^- + u_t \tag{6}$$

It is possible to distinguish between the magnitude of a positive or negative change brought on by an increase in the independent variable and the size of a change brought on by a reduction in the independent variable using the NARDL model.

To check the robustness of our results, we used a set of different combinations of parameters to analyse how changes in regressors influence the regression coefficients. Besides, post-estimation diagnostic tests are performed to assess the normality (Jarque-Bera test), presence of serial correlation (Portmanteau test), heteroscedasticity (Breusch-Pagan test) and functional form (Ramsey RESET test).

Data. We study the impact of the GPR on agricultural commodity prices from January 2, 2020, to July 29, 2022. The sample period encompasses two distinct crisis periods: the COVID-19 pandemic and the Russia-Ukraine war. These two significant events caused a shock and disruptions in global agricultural commodity markets. Consequently, the selection of agricultural commodities was based on the agricultural trade of Ukraine and Russia with other countries. These shocks and supply disruptions are transmitted and reflected in global agricultural markets.

Table 1 provides the descriptive statistics for all studied variables. The GPR index counts press terms track-

Table 1. Descriptive statistics (observations = 648)

Variables	Mean	SD	Min.	Max.
ln*Corn*	6.224	0.297	5.713	6.707
ln*Cotton*	4.448	0.281	3.889	5.042
ln*Lumber*	6.537	0.427	5.560	7.430
ln*Milk*	2.919	0.178	2.419	3.254
ln*Oats*	6.037	0.355	5.535	6.693
ln*Rapeseed*	6.262	0.304	5.816	6.986
ln*Roughrice*	2.635	0.113	2.432	3.094
ln*Sugar*	2.762	0.201	2.220	3.017
ln*Sunflower*	7.081	0.351	6.461	7.783
ln*Soybeans*	7.110	0.234	6.711	7.478
ln*Wheat*	6.525	0.234	6.176	7.262
ln*EPU*	5.096	0.574	3.102	6.694
ln*GPR*	4.592	0.543	3.151	6.291
ln*VIX*	3.158	0.313	2.493	4.415

EPU – economic policy uncertainty index; *GPR* – geopolitical risk index; *VIX* – financial volatility index
Source: Authors' calculation

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ing significant geopolitical events, dangers, and conflicts. EPU is a measure of economic policy ambiguity derived from the ratio of the number of times the words 'economy', 'policy', and 'uncertainty' appear in newspapers across countries. VIX is a real-time market indicator that predicts stock market volatility over the next 30 days. The daily data for GPR, EPU, and VIX were obtained from MatteoIacoviello (https://www.matteoiacoviello.com/gpr.htm), FRED Economic Data (https://fred.stlouisfed.org/tags/series?t=daily%3Bepu), and Yahoo Finance (https://finance.yahoo.com/quote/%5EVIX/history/). Moreover, everyday futures prices of corn, cotton, lumber, milk, oats, rapeseed, rough rice, soybeans, sugar, sunflower oil, and wheat were obtained from Investing.com (https://www.investing.com/commodities/), Trading Economics (https://tradingeconomics.com/commodity/sunflower-oil), and Markets Insider (https://markets.businessinsider.com/commodities). Futures values are influenced by internal factors, including interest rates, the base price, interest (dividend) income, storing costs, the risk-free rate, and convenience yield. All commodities were given at current prices, stated in US dollars, and transformed into natural logarithm form.

RESULTS AND DISCUSSION

The development of agricultural commodity prices shows significant volatility during the period of higher uncertainty and rising trend over time (Figure 1; Figures 1A–1K represent the development of agricultural

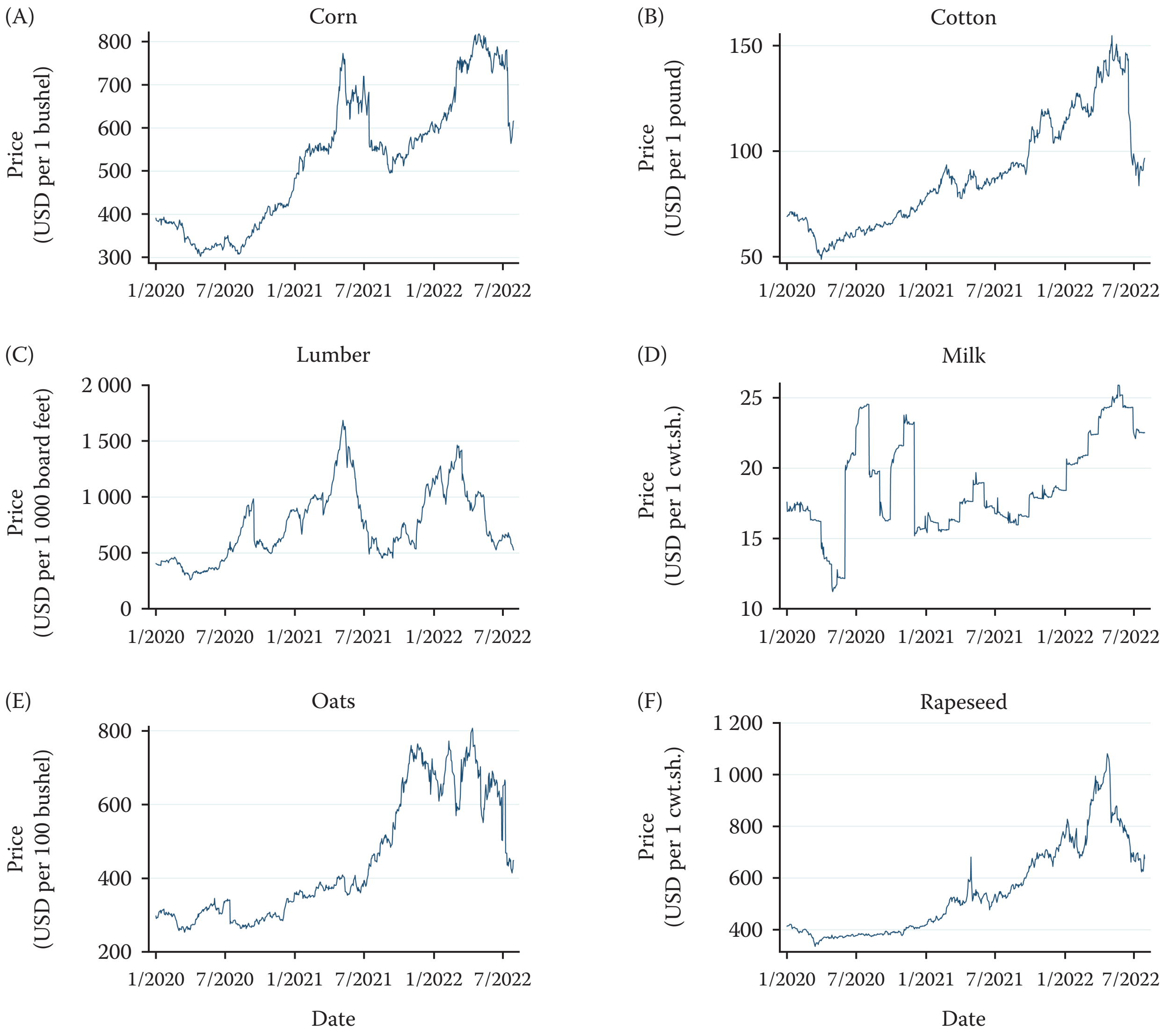

Figure 1. Development of agricultural futures prices and uncertainty indicators: (A) corn, (B) cotton, (C) lumber, (D) milk, (E) oats, (F) rapeseed, (G) rough rice, (H) soybeans, (I) sugar, (J) sunflower oil, (K) wheat, (L) economic policy uncertainty index (*EPU*), (M) geopolitical risk index (*GPR*), and (N) financial volatility index (*VIX*)

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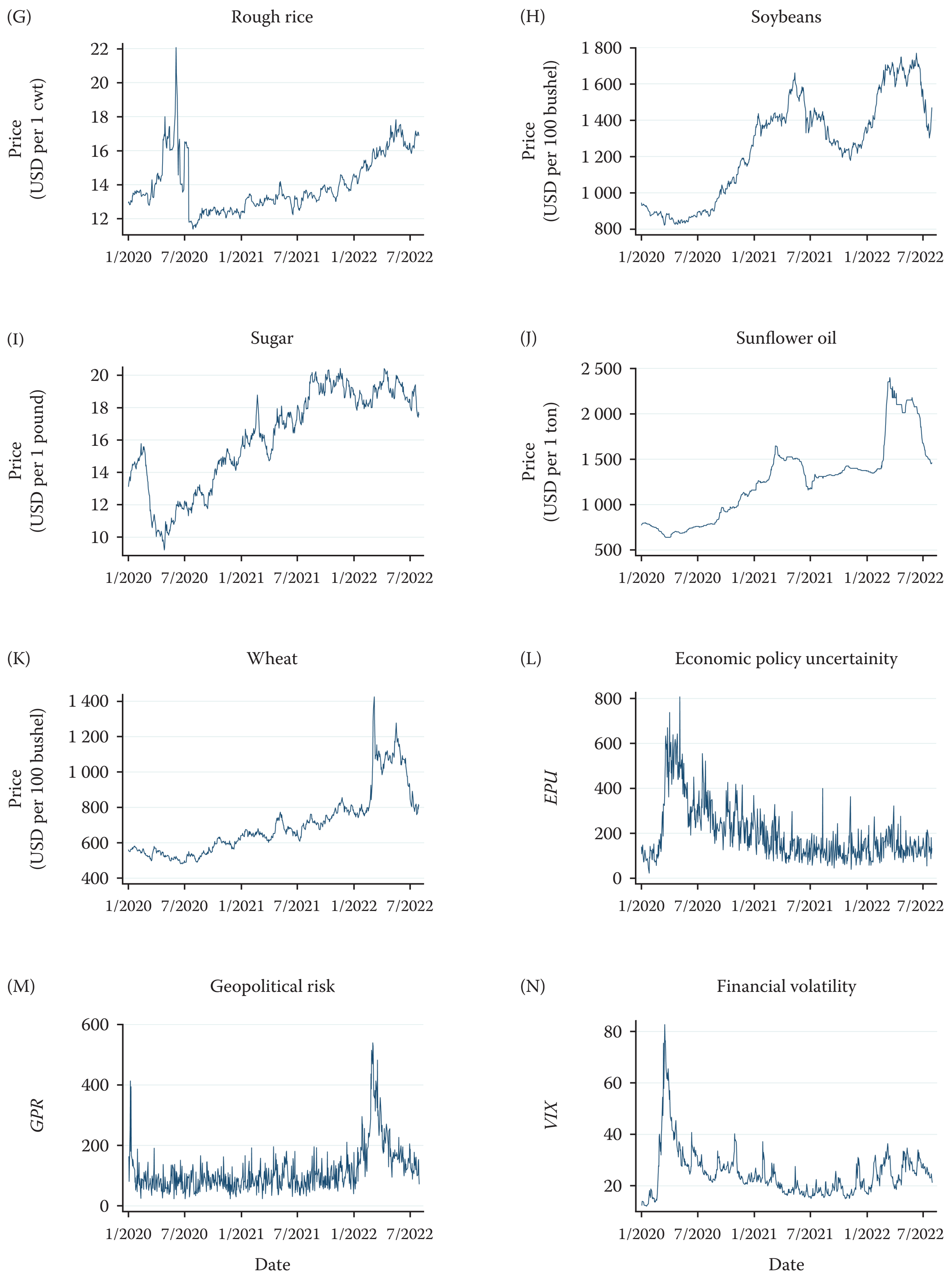

Figure 1. To be continued

Source: Authors' calculation

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commodity futures prices, Figures 1L–N display the development of EPU, GPR, and VIX indices, respectively.). Moreover, with the shock caused by the global pandemic, the EPU and the VIX skyrocketed. On the other hand, the escalation of tensions between Russia and Ukraine led to an enormous jump in the GPR. To estimate the impact of these events on the evolution of agricultural commodity prices, we commence our analysis with the application of the ADF test and PP test and verify the stationary properties of the analysed time series. Based on the results of the unit root tests, we made sure that neither of our variables is integrated of the second order $I(2)$ or higher, and we can advance to the ARDL bounds test to examine the cointegration between time series. The results of the unit root tests are available upon request from the authors.

As shown in Table 2, the t-statistics for all the price series are closer to zero than critical values for $I(0)$ variables at a 10% significance level. Therefore, the null hypothesis of no cointegration between commodity prices and uncertainty indicators cannot be rejected. However, this may be due to the nonlinear properties of the long-run relationship between the time series. In the next step, we thus estimated the NARDL model to account for the potential asymmetric reaction of the response variable to an increase or reduction in the explanatory variables. The findings prove a long-term association with rapeseed, rough rice, sugar, sunflower oil, and wheat prices. Using the F-test, we verified the existence of long-run and short-run asymmetry in the models (Table 3). The long-run F-test is significant in most cases. Hence the NARDL model is suitable for estimating the response of rapeseed, rough rice, sugar, sunflower and wheat prices. As no long-run relationship is found in the case of corn, cotton, lumber, milk, oats, and soybean prices, ARDL without error correction term, capturing only short-run effects, will be used to model these price series.

The results of the ARDL models for corn, cotton, lumber, milk, oats, and soybeans are shown in Table 4. Statistically significant coefficients of VIX in the case of cotton, lumber, oats, and soybeans indicate that increased VIX leads to a decrease in the prices of these commodities in the short term. Conversely, GPR and EPU do not influence agricultural commodity prices, and the commodity price reactions are insignificant in the short run.

Because rapeseed, rough rice, sugar, sunflower oil, and wheat prices respond asymmetrically to changed uncertainty indices, we employed a NARDL to model these prices (Table 5). The error correction terms in all of the estimated models are negative and statistically significant at a 1% significance level, which is preferable since it indicates the presence of cointegration and the speed at which the long-run equilibrium is being adjusted. The adjustment rate is 4.8% for rapeseed, 6.2% for rough rice, 5.3% for sugar, 1.5% for sunflower, and 4.5% for wheat prices, which displays the daily adjusting process. Thus, the long-run equilibrium is fully recovered in 21, 17, 19, 67, and 23 days, respectively.

The outcomes of the NARDL models show statistically significant VIX's negative (VIX–) and positive shocks

Table 2. The result of bounds tests for cointegration

Variables	ARDL		NARDL	
	F	t	F	t
ln*Corn*	1.414	–1.992	2.520	–2.260
ln*Cotton*	6.104***	–1.352	2.492	–2.770
ln*Lumber*	1.352	–1.992	1.236	–2.123
ln*Milk*	2.526	–2.914	2.384	–3.727*
ln*Oats*	1.563	–1.194	3.263	–3.599*
ln*Rapeseed*	2.635	–2.209	5.143**	–4.414***
ln*Roughrice*	2.747	–3.292	4.729**	–5.296***
ln*Sugar*	10.339***	–3.207	4.510**	–4.275**
ln*Sunfloweroil*	1.136	–1.483	3.966*	–4.011**
ln*Soybeans*	0.628	–1.074	2.313	–2.379
ln*Wheat*	3.061	–2.962	4.069*	–3.917**

*, **, *** 10, 5, and 1% significance levels, respectively; ARDL – autoregressive distributed lag; NARDL – nonlinear autoregressive distributed lag

Source: Authors' calculation

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Table 3. Asymmetry results

Variables		F-test	
		long-run asymmetry	short-run asymmetry
ln*Rapeseed*	ln*VIX*	6.564***	0.139
	ln*EPU*	4.751**	0.139
	ln*GPR*	7.115***	0.590
ln*Roughrice*	ln*VIX*	0.5181	0.304
	ln*EPU*	12.390***	1.156
	ln*GPR*	6.573***	2.490
ln*Sugar*	ln*VIX*	0.730	5.701**
	ln*EPU*	0.159	0.156
	ln*GPR*	7.688***	1.130
ln*Sunfloweroil*	ln*VIX*	0.044	0.117
	ln*EPU*	5.381**	0.928
	ln*GPR*	5.840**	0.007
ln*Wheat*	ln*VIX*	3.257*	5.947**
	ln*EPU*	1.192	0.023
	ln*GPR*	4.610**	0.079

*, **, *** 10, 5, and 1% significance levels, respectively; *VIX* – financial volatility index; *EPU* – economic policy uncertainty index; *GPR* – geopolitical risk index
Source: Authors' calculation

(VIX+) on rapeseed and sugar over the long term. The negative shock in financial volatility does not impact rapeseed prices, although the positive adjustment decreases the cost of rapeseed by 0.188%. Both positive and negative analogues of VIX(±) have a statistically significant impact on sugar prices. Reduced financial volatility by 1% raises the sugar prices by 0.211%, while a rise in financial volatility by 1% lowers the sugar prices by 0.249%. The VIX does not have asymmetric effects on rough rice, sunflower oil, and wheat prices, as these coefficients are statistically insignificant.

Besides, based on the findings of the NARDL model, we found that only rapeseed and rough rice are affected by long-run EPU's negative (EPU–) and positive (EPU+) shocks. A 1% decrease in economic policy uncertainty reduces the price of rapeseed and rough rice by 0.132% and 0.087%, respectively. In comparison, a 1% increase in economic policy uncertainty raises the price of rapeseed and rough rice by 0.149% and 0.108%. No asymmetry effects were confirmed for EPU and prices of sugar, sunflower oil and wheat because both changes are statistically insignificant.

Moreover, the results of NARDL indicate that GPR's negative (GPR–) and positive (GPR+) changes have a statistically significant effect on the evolution of rapeseed, sugar, sunflower and wheat in the

Table 4. Autoregressive distributed lag (ARDL) estimations of short-run effects

SR coefficients	ln*Corn*	ln*Cotton*	ln*Lumber*	ln*Milk*	ln*Oats*	ln*Soybeans*
*L*1	0.021	0.077	0.193***	–0.019	–0.066*	0.036
*L*2	–	–	–	–	0.079**	–
*L*3	–	–	–	–	–0.066*	–
*L*4	–	–	–	–	–0.177***	–
Dln*EPU*	–0.003	0.000	–0.003	0.004	0.000	–0.002
Dln*VIX*	–0.011	–0.035***	–0.083***	0.008	–0.028*	–0.017***
Dln*GPR*	–0.001	0.002	0.004	0.002	–0.002	–0.001

*, **, *** 10, 5, and 1% significance levels, respectively; ARDL – autoregressive distributed lag; SR – short run; *L*1–*L*4 – lagged variables; *VIX* – financial volatility index; *EPU* – economic policy uncertainty index; *GPR* – geopolitical risk index
Source: Authors' calculation

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Table 5. Nonlinear autoregressive distributed lag (NARDL) estimations

Variables	NARDL long and short run form				
	ln*Rapeseed*	ln*Rice*	ln*Sugar*	ln*Sunflower*	ln*Wheat*
Long-run coefficients					
VIX–	0.032	–0.013	0.211**	–0.119	–0.274
VIX+	–0.188*	–0.020	–0.249***	0.143	0.128
EPU–	–0.132*	–0.087*	0.050	0.032	–0.012
EPU+	0.149**	0.108*	–0.052	–0.065	0.022
GPR–	–0.253***	0.012	–0.076*	–0.409***	–0.272***
GPR+	0.269***	–0.023	0.087**	0.439***	0.289***
ECT	–0.048***	–0.062***	–0.053***	–0.015***	–0.045***
C	0.291***	0.161***	0.148***	0.096***	0.287***
Short-run coefficients					
d*VIX*–	–0.018	–0.015	–0.046***	–0.006	–0.038**
*L*1	0.003	0.031*	–0.011	–0.008	–0.006
*L*2	–0.005	–	–	–0.012	–0.004
*L*3	–	–	–	0.007	0.015
d*VIX*+	–0.015	0.022	0.010	–0.016	0.066**
*L*1	–0.021	–0.029	0.020	0.000	–0.002
*L*2	–0.003	–	–	0.011	0.058**
*L*3	–	–	–	–0.003	0.004
d*EPU*–	0.002	–0.001	0.001	0.000	–0.001
*L*1	–0.005	–0.007	0.000	0.002	–0.005
*L*2	–0.001	–	–	0.003	0.001
*L*3	–	–	–	0.001	0.006
d*EPU*+	–0.003	0.001	0.003	–0.001	–0.002
*L*1	–0.003	0.001	0.001	–0.002	0.004
*L*2	–0.001	–	–	0.001	0.003
*L*3	–	–	–	0.002	–0.006
d*GPR*–	0.003	0.005	0.001	0.001	0.007
*L*1	0.000	0.004	–0.001	–0.004*	–0.008*
*L*2	–0.001	–	–	–0.005**	–0.002
*L*3	–	–	–	–0.001	0.000
d*GPR*+	0.003	–0.003	0.007**	0.001	0.003
*L*1	–0.007*	0.000	0.000	–0.007***	–0.001
*L*2	–0.001	–	–	–0.001	–0.003
*L*3	–	–	–	–0.001	–0.004

*, **, *** 10, 5, and 1% significance levels, respectively; *VIX* – financial volatility index; *EPU* – economic policy uncertainty index; *GPR* – geopolitical risk index; *ECT* – error correction term; *L*1–*L*3 – lagged variables
Source: Authors' calculation

long term. A 1% reduction in GPR lowers the prices of rapeseed, sugar, sunflower and wheat by 0.253, 0.076, 0.409, and 0.272%, whereas a 1% increase in GPR raises the prices by 0.269, 0.087, 0.439, and 0.289% respectively.

Table 5 also shows the NARDL short-run effects. A negative shock in the VIX causes a fall in the prices of sugar and wheat, while a positive change affects only the price of wheat and leads to an increase in wheat prices. Neither of the changes in EPU,

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whether positive or negative, does have a statistically significant impact. In the case of GPR, positive change in GPR increases only sugar prices, whereas negative shock has a statistically insignificant impact.

Yang et al. (2022) observe that agricultural markets typically react to geopolitical threats. Based on our findings, we can conclude that while some commodities reacted to the GPR changes after the Russian invasion of Ukraine, others were immune to such shocks. The ongoing war between Russia and Ukraine has long-term implications for several agricultural markets. Indeed, corn, rapeseed, sunflower oil and wheat are the main exports of Russia and Ukraine, and our results prove that the global rapeseed, sunflower oil, and wheat markets have been directly affected by the growing GPR due to the intensification of Russia-Ukraine tensions. These findings align with Saâdaoui et al. (2022) and Umar et al. (2022). The interruption of wheat, sunflower oil, and rapeseed supplies as a result of the conflict in Ukraine has far-reaching effects on the global agrarian and food market (Berkhout et al. 2022). Indeed, rapeseed, wheat and sunflower oil are fundamental commodities used in several industries as production inputs. For instance, rapeseed has many practical applications, including those of edible oil, biodiesel, lubricant, and fodder. Likewise, sunflower oil is among the most commonly utilised oils, widely used in foods as a consumable oil or an emollient in cosmetics. Besides, wheat is usually processed into flour, used to create a variety of foods (e.g. bread, crumpets, buns, pasta, noodles, biscuits, and cakes). Consequently, the rising GPR has also affected these sectors, where rapeseed, sunflower oil, and wheat are used as inputs.

Moreover, we also find that the recent increase in GPR positively affects sugar prices in the long term. Findings are consistent with those of Mitsas et al. (2022) and Tiwari et al. (2021). On the other hand, an interesting finding is that increasing GPR has no direct impact on corn prices, as corn is one of the leading agricultural exports of both countries. Our results are consistent with those of Mitsas et al. (2022) but contradict Saâdaoui et al. (2022) and Tiwari et al. (2021). In other words, our findings suggest that factors other than GPR can explain the price development of a corn. For instance, Cao and Cheng (2021) and Hung (2021) argue that the corn market is the primary producer and receiver of spillovers in the agricultural market. Thus, spillovers among markets can be considered one of the reasons behind corn price volatility. Besides, based on our findings, the increased GPR has not affected the world's agricultural markets with cotton, lumber, milk, oats, soybeans, and rough rice. Consequently, other external or internal factors or spillover effects may explain these price rises. Our findings also suggest the impact of changes in EPU and VIX on the agricultural commodity futures prices, which is in line with several authors (Choi and Hong 2020; Zhu et al. 2020; Kisswani 2021; Wen et al. 2021; Feng et al. 2022; Lu and Zeng 2022).

CONCLUSION

The main objective of this paper was to investigate geopolitical risk's effects on the prices of agricultural and food commodities. First, we employed a linear ARDL model. Our results did not prove the existence of cointegration between geopolitical risk and corn, cotton, lumber, milk, oats, and soybean prices. Therefore, in the short and long-term, their price developments are influenced by other factors rather than geopolitical risk. Second, we assessed asymmetric links between geopolitical risk and commodity prices using a NARDL model. Long-run asymmetric effects were confirmed for rapeseed, sugar, sunflower oil, and wheat prices. The negative change in geopolitical risk decreases rapeseed, sugar, sunflower oil and wheat prices, while positive movements increase them. Interestingly, only sugar prices rise due to geopolitical occurrences in the short term. Besides, we found that rough rice prices are immune to geopolitical shocks. Thus, the latest geopolitical events can be considered important factors affecting the development of rapeseed, sugar, sunflower oil, and wheat prices.

Our empirical findings have substantial implications for academics, investors, portfolio managers, policymakers, and other market participants. The results of our study help to understand the vulnerability of primary agricultural and food commodity prices to geopolitical threats, their interlinkages and evolution over time. The tensions between Russia and Ukraine negatively impact particularly low- and middle-income countries that rely on agricultural imports from these regions and have not fully recovered from the global outbreak of COVID-19, with severe consequences for food insecurity. Besides, high levels of commodity and food prices push up inflationary pressures worldwide. Increasing inflation lowers purchasing power, consumption, and economic output. Governments and policymakers must adopt different measures to support households with increasing commodity and food prices. Besides, Russia is also an es-

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sential supplier of fertilisers and energy. Consequently, the prices of fertilisers and energy commodities also soared. Therefore, governments and policymakers should provide also support measures for farmers and food-processing businesses with increasing production costs. Our findings may be used to conclude how conflicts may affect future price developments, price volatility, market stability, security of essential food commodities, inflation, consumer spending and overall economic output. Therefore, the status of geopolitical risk must be kept in mind while making policy decisions and implementing strategies.

Further research may replicate and expand upon these results using alternative methodologies, up-to-date data, or additional regressors to fill the study gaps.

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