COVID-19 and the Russia-Ukraine War: Implications for Agricultural Commodity Prices and Food Security

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Introduction

The invasion of Ukraine resulting from Russia's expansionist aim began on February 24, 2022, and not only caused a humanitarian catastrophe in Ukraine by bringing about loss of life, property, and infrastructure but also significantly disrupted all production processes, including agriculture. supplier and Ukraine account for about a quarter of global wheat exports (Cohen & Ewing, 2022). The Russian invasion of Ukraine has deeply affected the world through commodity and energy markets, trade, financial markets (Umar et al., 2022), food prices (Nicas, 2022), population displacement (Jagtap et al., 2022), and market confidence weakening (Adekoya OB et al., 2022; Boubaker et al., 2022; Boungou & Yatié, 2022; Saâdaoui et al., 2022). While countries across the world have yet to fully recover from the disastrous economic consequences of the COVID-19 pandemic, the invasion of Ukraine exacerbates economic woes, especially in the global food supply chain, and significantly impacts food security (Behnassi & El Haiba, 2022; Jagtap et al., 2022). The unexpected COVID-19-induced regional, national, and international lockdowns negatively affect the supply of inputs, transport of agricultural products, and labor availability in the agricultural food and marketing sector, significantly worsening food availability, access, and prices on a global scale (Barrett, 2020; FAO, 2020a; Laborde et al., 2020). For example, in many African countries and India, food price increases exceeded 15% compared to the pre-COVID-19 period (Hernandez et al., 2020).

The price increases continue since the commencement of the Russia-Ukraine war (Byjoel, 2022; Mbah & Wasum, 2022; Nicas, 2022). For example, since the beginning of the conflict, wheat prices increased by nearly 40% (World Bank, 2022). Additionally, rising energy prices and the collapse of much of Europe's logistics systems drive up the prices of staples (Saâdaoui et al., 2022). The Russian invasion of Ukraine opened a new period of turmoil in the European as well as the global economy (Qureshi et al., 2022). The Russia-Ukraine war is thus compounding all cited problems, and the sharp increases in food prices jeopardize food security worldwide, especially for the most vulnerable individuals (Berlinger, 2022; Jagtap et al., 2022).

The Russia-Ukraine war has also negatively affected Turkey, a country sharing access to the Black Sea with Ukraine and Russia, among others. The effects have been disheartening as illustrated by Turkey's economic confidence index dropping from 100.8 points to 98.2 points between January and February 2022. Also, the Purchasing Managers' Index (PMI) fell from 50.5 points in January 2022 to 50.4 points in February 2022.

Previous empirical results generally point to a possible positive relationship between the COVID-19 pandemic and food prices in both developed and developing economies with very few exceptions (Agyei et al., 2021). For example, the COVID-19 pandemic has had a significant spillover effect on the prices of staple products such as eggs and fodder wheat (Küçük et al., 2022) and caused a food price increase in sub-Saharan African countries (Agyei et al., 2021). Mahajan and Tomar (2021) examined online prices during the COVID-19 pandemic, whereas Yan et al. (2021) emphasized the impact of trade bans on the prices of agricultural products following cross-country restrictions. Saâdaoui et al. (2022) studied the multiscale cross-correlation of the Russian-Ukrainian conflict between geopolitical risk and food prices. The literature review conducted within the scope of the current study revealed the absence of considering the effects of both the COVID-19 pandemic and the Russia-Ukraine war on wheat, sunflower oil, and corn prices. Russia and Ukraine export large volumes of the three commodities to a number of less developed or emerging economies, including Turkey.

With the unprecedented disruptions in the global economy and the supply chain, it is essential to uncover the negative impacts of both the COVID-19 pandemic and Russia's war on Ukraine on the basic nutritional needs of society and threats to food security. Food security is affected directly by the possible disruption of exports from Russia and Ukraine, while the resulting price increases, e.g., energy, affect farmer production decisions resulting in lower domestic supplies. Given the profound impacts of both phenomena on global food security, understanding the effects of both the COVID-19 pandemic and the war on the long-term risk of contagion between them and agricultural commodity markets is critical for both policy design and agricultural production decisions. This study determines the effects of the Russia-Ukraine war, COVID-19 pandemic, and exchange rate on the mean return, transmission, and spread of long-term risks of wheat, sunflower oil, and corn in Turkey. Geopolitically, Turkey occupies a key position in the Russia-Ukraine war and the Turkish government negotiated to secure the grain corridor for safe grain exports from Ukraine during the war. The contribution of this study to the literature is, therefore, to clarify the effects of COVID-19, the Russia-Ukraine conflict, and the exchange rate return on the actors of the main food supply chain in Turkey, and to offer knowledge to develop solutions and strategies for national food security. Another contribution of the current study is to elicit the role and contagion of COVID-19, the Russia-Ukraine war, and the exchange rate return variables, most of which are in the form of structural change, in communicating the uncertainty transmission in the price formation of selected agricultural products. Also, the relevance of the current study's results extends to countries with characteristics similar to Turkey by providing insights into their policy formulation.

Data and Methods

Data

Data used in the current study originated from several sources. Wheat, corn, and sunflower oil prices were obtained from the daily values of the Adana Commodity exchange market database.

The real dollar exchange rate series was obtained from the Electronic Data Delivery System (EVDS) of the Central Bank of the Republic of Turkey (CBRT). Wheat, corn, and sunflower oil prices have been deflated using the producer price index (PPI). Daily data covering the period 2010:01-2022:07 are used to examine the volatility between the markets under consideration. A total of 1,133 observations were used in the analysis[1]. In addition, the effects of the COVID-19 pandemic and the Russia-Ukraine war on the commodity markets were compared to the pre-and post-pandemic and the pre-and post-war periods[2].

Econometric approach

This study examines the relationship between wheat, sunflower, and corn prices under the uncertainty created by both the COVID-19 pandemic and the Russian-Ukrainian war. Baba, Engle, Kraft, and Kroner (BEKK) multivariate Generalized Autoregressive Conditional Heteroscedasticity (MGARCH) model proposed by Engle and Kroner (1995) (hereafter BEKK-MGARCH) is applied to the variance equation to elicit the price uncertainty pass-through between the three staples. For the mean equation, the Vector Error Correction Model (VECM) was preferred, considering the fact that the differences in the natural logarithms of agricultural products turn into returns when there is a co-integration between staple prices. Furthermore, this study adds asymmetric effects to the conditional variance equation of agricultural commodities, assuming that negative and positive shocks will have different effects on the long-term risks of crop prices (Rahman & Serletis, 2012; Salisu & Oloko, 2015). The VECH model, known as the vector stacking covariance matrix, is not attractive because the covariance matrix defined as H does not meet the semi-definite positive condition and suffers from convergence problems with the parameters being

[1] RATS 10 was used in estimation. Also, there was a loss of match-related observations as three agricultural products had to be traded on the stock exchange on the same day to be used in the analysis.

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over-stacked. Alternatively, the constant conditional correlation model (CCC), although it satisfies the semi-definite positive condition of the variance-covariance matrix, loses its appeal due to the overload of parameters and the time-independent nature of the conditional correlation. Although the time-varying conditional correlation (DCC) model provides the semi-definite positive condition in the variance-covariance matrix due to less parameter load, we preferred to use the BEKK model, which allows asymmetric information flow from more information sources (Engle and Kroner, 1995; Rahman and Serlitis, 2012; Salisu and Oloko, 2015; Urak et al., 2022; Urak and Bilgic, 2023).

Following Grier et al. (2004) and Rahman and Sertelis (2012), the square roots of the conditional variances were added to the mean equations of each staple to measure the direct effect of the conditional risks on each commodity price change. The conditional mean and conditional variance equations are presented in Equation (1) and Equation (2), respectively,

$$\Delta \mathrm{LnPr}_{i,t} = \mu_i + \sum_{j=1}^{p} \Phi_{ij} \Delta \mathrm{LnPr}_{i,t-j} + \theta_i \mathrm{R}_{exr,t-1} + \vartheta_i \mathrm{COVID\text{-}19}_{t-1} + \tau_i \mathrm{War}_{t-1} + \sum_{i=1}^{3} \Psi_{ii} \sqrt{\mathrm{h}_{i,t-1}} + \sum_{k=1}^{K} \alpha_{ik} \mathrm{z}_{k,t-1} + \varepsilon_{i,t-1},$$

where $i = w, s, c,$ j=1,...,p, and k=1,...,K

$$\begin{pmatrix} \Delta \mathrm{LnPr}_{w,t} \\ \Delta \mathrm{LnPr}_{s,t} \\ \Delta \mathrm{LnPr}_{c,t} \end{pmatrix} = \begin{pmatrix} u_w \\ u_s \\ u_c \end{pmatrix} + \begin{pmatrix} a_w \\ a_s \\ a_c \end{pmatrix} z_{t-1} + \sum\nolimits_{j=1}^{p} \begin{pmatrix} \Phi_{ww,j} & \Phi_{ws,j} & \Phi_{wc,j} \\ \Phi_{sw,j} & \Phi_{ss,j} & \Phi_{sc,j} \\ \Phi_{cw,j} & \Phi_{cs,j} & \Phi_{cc,j} \end{pmatrix} \begin{pmatrix} \Delta \mathrm{LnPr}_{w,t-1} \\ \Delta \mathrm{LnPr}_{s,t-1} \\ \Delta \mathrm{LnPr}_{c,t-1} \end{pmatrix} \tag{1}$$

where $\varepsilon_t \sim (0, H_t)$ and $\varepsilon_{i,t-1} = H_{i,t-1}^{1/2} \eta_{i,t-1},$

Equation (1) expresses the conditional mean equation, and the symbol Δ denotes the first difference operator, whereas j denotes the lag parameter. $\mathrm{LnPr}_{i,t}$ stands for the natural logarithm of wheat (w), sunflower oil (s), and corn (c) prices. The mean equation also measures the unitary effect of fluctuations in real exchange rate returns ($\mathrm{R}_{exr,t-1}$) and the shifting effects of both the pandemic ($\mathrm{COVID\text{-}19}_{t-1}$) (assuming 0 for observations before 1 December 2020, and 1 after) and the ongoing war between Russia and Ukraine (War_{t-1}) (assuming 0 and 1 for observations before

23 February 2022) on logarithmic changes in three agricultural commodity prices in Turkey. The effects of the square of the conditional variances ($\sqrt{h_{i,t-1}}$) are also captured on the logarithmic changes in commodity prices. The purpose of using such variables here is to empirically elicit whether they overlap with the theory suggesting that increased risk in commodity markets reduces market returns. Moreover, the study also determines the equivalents to returns or the effects of error correction factors (e.g., $z_{k,t-1}$) on the market log-price differences of the respective products. The Bayesian Information Criterion (BIC) was used to determine the lag length.

The conditional variance employed to identify risk spreads among the three staples is:

$$H_t = \Upsilon\Upsilon' + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B + D'\xi_{t-1}\xi'_{t-1}D \,. \quad (2)$$

In Equation (2), H_t is a 3x3 matrix that represents the time-dependent conditional variance. The variance of a commodity defines the risk. In this study, the H matrix determines the impact of both short- and long-term contagion in the commodity prices, as well as short- and long-term directionless fluctuations in cross-market prices, on the market's long-run conditional return variance. The H matrix consists of two parts, where the first part covers the constant including pure constant parameters and parameters stemming from the exchange rate return, COVID-19, and the Russia-Ukraine war (Zhen et al., 2018; Urak et al., 2022; Urak and Bilgic, 2023), whilst the second part covers market-induced short-term shocks, long-term risks, and asymmetric effects. All such effects reflect the market-driven supply-demand dynamics. Therefore, the constant part is $\Upsilon\Upsilon'$ in the time-varying conditional variance equation (H_t), where $\Upsilon = (C + \Gamma Exr_{t-1} + \Omega \text{COVID-19}_{t-1} + \Pi \text{War}_{t-1})$. The constant term, Υ, is incorporated to reflect the effects of the exchange rate (Exr), the COVID-19 pandemic, and the war between Russia and Ukraine on the time-dependent conditional variance-covariance of considered agricultural commodities in Turkey. The corresponding parameters C, Γ, **Ω**, and Π appear as a 3x3 upper triangular matrix. The COVID-19 and war period are binary variables used in time-varying conditional variance equations to empirically reveal how the risk levels of the three agricultural commodities shifted during the respective COVID-19 and wartime periods.

By using the exchange rate return in each mean equation, we measure the response of the change in commodity prices to the change in the exchange rate return, while using the exchange rate variable itself in the conditional variance equations, we determine how the commodity risk levels (for example, the conditional variance) responds to changes in the value of the exchange rate series. The second part of the H matrix consists of the additive components of short-term shocks ($\varepsilon_{t-1}\varepsilon'_{t-1}$), long-term uncertainty (H_{t-1}), and short-term asymmetric effects ($\xi_{t-1}\xi'_{t-1}$). Parameter matrices, A(3x3), B(3x3), and D(3x3), correspond to each listed effect. While the short-term shocks and asymmetric information series are derived from the above mean equation, the time-varying conditional variance series is also composed of those two information variables and updates itself until the parameter value reaches the log-likelihood function at convergence value within the framework of the looping.

Results

Examining the data series

Table 1 shows descriptive statistics, correlation coefficients, and the Autoregressive Conditional Heteroscedasticity (ARCH) effects. The sunflower oil market is subject to uncertainty because the difference between previous and current prices (expressed in logs) defines the price change. The notion is confirmed by the large variance of log prices of sunflower oil among the considered commodities. The real exchange rate has a high mean and shows volatility. The skewness and kurtosis coefficients show that some series are not normally distributed (Table 1), confirmed by the Jarque-Bera test results. Also, the Ljung-Box Q statistic indicates the log series are autocorrelated.

Antecedent statistics on the use of series

The ARCH-Lagrangian Multiplier (hereafter, LM) test result (Engle, 1982) revealed strong evidence of the ARCH effect in the log price series. Under the circumstances, the volatility pass-through between the log series should be handled using the multivariate GARCH models. The Augmented Dickey–Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) unit root tests support converting the series into the first differences (I(1)) to assure stationarity. The integration at I(1) may indicate the co-integrated relationship between the series and was tested using the Johansen (1995) test. Because of the test sensitivity to the lag length, the use of BIC determined the optimal lag length as three. The three-lag Johansen co-integration test indicates the existence of two co-integrating vectors. Lastly, high correlation coefficients[3] between the log series provided a priori evidence that there may have been a high degree of pass-through between the conditional variances of the considered series.

The co-movements of the log series show the effects of market-related factors and non-market problems on price formations over time. Wheat, sunflower oil, and corn prices, which were fairly stable between 2010 and 2020, increased rapidly after February 2020, when the COVID-19 pandemic started affecting the world economy. The key factor according to IFPRI (2020) and Baffes and Wu (2020) was the supply chain disruption and labor shortages that created a supply-demand imbalance, which caused an upward price movement. During the COVID-19 pandemic, household demand for large quantities of cereals substantially increased further exerting upward pressure on prices. However, the COVID-19 pandemic created significant demand uncertainty

[3] Since the series were not normally distributed, the Spearman method was used to elicit the correlation relationship between the series.

(Vijlder, 2020; Hunter et al., 2020) affecting commodity prices (Vijlder, 2020). Such outcomes have exacerbated food insecurity in countries experiencing prior food access problems. Response to the COVID-19 pandemic significantly disrupted food supply chains affecting agriculture and food retailing.

The compatibility of the data with the t-distribution was verified. The Wald (W) statistic value ($W = 361.515$ and $p < 0.000$) shows that the parameters derived under the t-distribution are superior in explaining the mean and time-variant conditional heteroscedasticity. The existence of a leptokurtic non-normal distribution of conditional residuals was elicited under such a distribution. The robust standard errors are also used to calculate the parameter statistics. The following discussion refers to the t-distribution of the maximum likelihood function and the statistically significant parameters.

Results and discussion

The log price difference between two consecutive periods ($\Delta LnPr$) defines the return on a commodity. The return analysis shows two co-integrating vectors (Table 2). The mean equations are equivalent to the VECM. Both co-integration equations show that a 1% ascent or descent in sunflower oil and corn prices changed wheat prices by 0.157% and 0.680%, respectively. The effects of 0.82% and 0.39% increase in sunflower prices occurred due to the 1% change in wheat and corn prices, respectively. An earlier study reported a significant pass-through between the prices of agricultural products (Urak et al., 2018; Urak & Bilgic, 2023). The plausible reasons why the effects of sunflower oil and corn returns on wheat differ in the long-term equation are that more corn than sunflower oil is produced in Turkey, and that corn and wheat compete in many uses, including animal feed. Turkey produced 6.7 million tons of corn and 2.7 million tons of sunflower in 2021 (TSI, 2022).

Next, the VEC model (in the form of mean equations) analyzed the effects of the three-period lag values of log prices of each considered commodity, the exchange rate, the COVID-19 pandemic, and the Russia-Ukraine war, the square roots of the conditional variances, and error correction factors on the log price difference of three commodities. The direction and magnitude of the effects on the commodities in question differ as the lag length varies (Table 2). While the one-time feedback variable COVID-19 (i.e., ϑ) has a positive effect on returns in the wheat and sunflower markets in Turkey, the Russia-Ukraine war only increases corn returns (τ), showing that the pandemic and war caused an upward shift in the returns of the selected agricultural commodities in the country. The one-period lagged exchange rate (θ) has a significant effect on wheat market returns, which is a crucial staple in Turkey's food sector and is most affected by the pandemic. The pandemic and war immediately negatively affected the energy sector and, then, gradually spread to other sectors in Turkey, causing inflation, especially in food prices. While low-income families were most affected, farmers could earn higher revenues from selling their crops.

The increase in uncertainty in the corn market negatively affects the returns in the wheat market (Ψ_{cc}=-0.070), while the long-term risks from the sunflower oil market positively affect own returns (Ψ_{ss}=0.180). The spread of uncertainty from the corn market lowers the market return of sunflower oil (Ψ_{cc}=-0.156). Similarly, the uncertainty in sunflower oil dampens returns in the corn market (Ψ_{ss}=-0.038). The varying effects of uncertainty across the markets suggest that increases in uncertainty in one market are offset to some extent by decreases in uncertainty in another market Additionally, the two error corrections (α_j, j=1,2) derived from the co-integration analysis have varied effects regarding returns to the three staples. There is a return to the long-term relationships in the wheat market, but the sunflower oil market departs from the long-term equilibrium, while the long-term equilibrium in the return of the corn market recurs.

Table 3 shows the parameter values of the variance equation of the VECM - BEKK MGARCH model. Short-term uncertainties arising from the wheat market (i.e., the ARCH effect) are statistically insignificant. Good or bad news in the wheat market increases the uncertainty of wheat returns in Turkey. The increase in uncertainty can be considered a negative, especially for those who engage in commodity trading. Simultaneously, the short-term risk pass-through from the wheat market to the long-term risks of the other two commodities (a_{12}=-0.084 and a_{13}=-0.118) were also statistically insignificant. The results imply that while the short-term uncertainties originating from the wheat market prolong the long-term uncertainties in its market, the short-term uncertainty offsets the uncertainty in corn and sunflower oil markets. On the other hand, short-term market-related events dominating the sunflower oil market increase the long-term risks both in own market (a_{22}=0.444) and, to a much lesser degree, in the corn market (a_{23}=0.054). Similarly, the market-driven short-term economic and non-economic processes in the corn market increase long-term risks both in own (a_{33}=0.537) and the sunflower oil market (a_{32}=0.074). It appears that the effects of the short-term shocks have a higher effect on corn's long-term risks because the market has a higher specific gravity than sunflower oil. Interestingly, the short-term shocks originating from markets of both staples cause widespread long-term uncertainty in their markets and the other considered markets. Such results indicate that overflows resulting from short-term uncertainty (i.e., ARCH effects) pose a threat both to their internal dynamics and to uncertainties in competing markets. Hamadi et al. (2017), McKnight et al. (2021), McKnight et al. (2022), and Tiwari et al. (2022) reported similar results.

Long-term uncertainty spillovers from the commodity market further reinforced the uncertainties in their respective markets (b_{11}=0.970 for wheat, b_{22}=0.640 for sunflower oil, and b_{33}=0.746 for corn markets). The finding suggests that past volatility is important in determining future volatility. Corn and sunflower oil markets are most affected by their short-term shocks and long-term risks, while wheat is most (more than the other two staples) affected by its long-term fluctuations. The findings correspond to the relative importance of the three markets in Turkey. For example, there was a statistically significant positive uncertainty spreading from the wheat market to the sunflower oil market (b_{12}=0.054), a negative risk spillover from the sunflower oil market to the wheat market (b_{21}=-0.022), but positive to the corn market (b_{23}=0.076). Also, there was a transmission from the corn market, which curbed the risk of long-term uncertainty in the sunflower oil market (b_{32}=-0.088). Among the long-term cross-effects, the relationship between sunflower oil and corn is further pronounced. Interestingly, the uncertainty pass-through stems positively from the sunflower oil market onto the corn market, while there is a bearish effect from corn onto the sunflower oil market. Unlike short-term shock effects, there is strong evidence that long-term market uncertainty exacerbates price formation uncertainty in own market, although it mitigates price formation uncertainty in other markets.

When analyzing the short-term asymmetric information spillover in the long-term uncertainties, the short-term negative news originating only from the sunflower oil market (d_{22}=0.499) diverges from the positive news, causing a more permanent risk in its market. The negative news in particular contributes to the price formation in the sunflower oil market making the risk in the market more permanent. While the asymmetric information had no significant insignificant effect on the own market, it tamed the long-term volatility spread in the wheat market (d_{31}=-0.071).

Examining the effect of the exchange rate, the COVID-19 pandemic, and the Russia-Ukraine war in the variance equation on the conditional variances, the exchange rate enhances wheat and sunflower oil return volatility (Γ_{11}=-0.002 and Γ_{22}=-0.006). The results imply that an increase in the exchange rate (weakening of the Turkish lira against the US dollar), due to commodity own supply and demand, reestablishes the volatility of wheat and sunflower oil prices in Turkey. The increasing exchange rate attracts producers and brokers to commodity markets because of hedging against a possible risk by selling their products and switching from Turkish Lira to foreign currency. Askan et al. (2022) and Urak et al. (2022a) found that the exchange rate was an important factor in determining the volatility of agricultural commodities. The main reason for such a situation is Turkey's high dependence on agricultural imports. Although the country's self-sufficiency in wheat prevents the market from exchange rate increases, the large imports of sunflower oil and corn directly affect the consumer while generating high margins along the supply chain from the producer to the importer. The volatility of agricultural commodities imported in large volumes is particularly sensitive to the exchange rate.

Results in Table 3 show that the COVID-19 pandemic and the Russia-Ukraine war have different effects on the time-varying conditional variances of wheat, sunflower oil, and corn prices. The pandemic effects on the conditional variances of both wheat and sunflower oil markets (Ω_{11}=-0.006 and Ω_{22}=-0.022) are statistically insignificant. Turkey imported sunflower oil mainly from Russia. In the early stages of the pandemic, wheat and sunflower oil imports were disrupted and the conditional variance of both products decreased. The efforts of producers, traders, or brokers to mitigate the impact of the pandemic by supplying their products support the findings. During the pandemic, many countries, including Turkey, restricted agricultural commodity exports by imposing quotas or export bans to stabilize domestic prices and encourage production. These actions may have increased the country's tax revenues but also caused the prices of exported commodities to increase in international markets.

The effect of the Russian-Ukraine war on wheat (Π_{11}=0.010) and sunflower oil (Π_{22}=0.039) conditional variances is positive and statistically significant. Also, the war affects the mutual relationship between the two markets positively, and therefore, the negative developments in one market are also valid in the other market (Π_{21}=0.060). Overall, the results show that the war between Russia and Ukraine has shifted the conditional volatility of agricultural commodity prices upwards. The extreme volatility in the commodity returns in 2019 exposed low-and middle-income families to food insecurity. Since the outbreak of the conflict, prices of staple food products have risen sharply in parallel with energy prices. In Turkey, the sunflower oil price in particular increased by 34%. Protecting Turkish farmers from price volatility led to increased grain purchase subsidies by more than 50%[4] and mitigated the negative impacts of the war. Moreover, on March 4, 2022 (after the Russian invasion of Ukraine), the Ministry of Trade imposed export restrictions on sunflower seed and oil as well as corn oil and its derivatives (Official Newspaper of TR, 2022). Additionally, the government restricted sales on the quantity of sunflower oil, sugar, and selected other staples and limited the time of sales in retail, including in Agricultural Credit Cooperative outlets. In this context, we can infer that the measures taken by the government to reduce volatility, especially in the wheat and sunflower oil markets, failed to reduce tensions.

Effects of pandemic and war on post-model time-dependent conditional variances and correlations

The examination of the distributional relationship around the median between the variances and correlations of the post-estimations of agricultural commodities, the COVID-19 pandemic, and the war, yields remarkable findings. For example, while the wheat market was not affected by the pandemic, the Russia-Ukraine war, whose escalation overlapped with the pandemic, almost doubled the volatility by shifting the spillover transmission in the Turkish wheat market upwards. However, both the sunflower oil and corn markets' volatilities were affected in Turkey. While there was an incredible increase in the uncertainty in the corn market during the pandemic, the war

[4] Soil Products Office (SPO) increased the 2022 wheat purchase premiums from 600 ₺ to 1000 ₺ per ton (SPO, 2022).

(overlapping with the pandemic) almost tripled the swings in the corn market. While the primary victims of the price swings are low-income families, it also reduces farmer expectations causing a pessimistic outlook. It appears that the efforts to open corridors in the Black Sea for grain shipments from Ukraine to ease market tension were appropriate. The possible post-war developments could involve export quotas imposed on grain from Ukraine and Russia or export tariffs suggesting that Turkey and other importing countries could face high prices of imported agricultural commodities. Other possible supply constraints in exporting countries, for example, an imposition of export limits to protect their domestic markets, could lead to even higher international prices.

The bilateral distributional correlations between commodities before and after the pandemic and prior to and after Russia's invasion of Ukraine (including the overlap with the pandemic) show different structural cases. While the bilateral relationship between wheat and sunflower oil markets was as expected before the pandemic, the relationship tightened during the pandemic and became rivetted once the war started. On the other hand, while the uncertainty correlation between the wheat and corn markets remained stable, the correlation between the sunflower oil and the corn markets changed. The relationship between the two commodity markets was positive before the pandemic but turned negative during the pandemic, with almost a double contagion effect, and the negative relationship deepened with the onset of war. This means that price fluctuations in one commodity market are restricted by the developments in the other market, and the aforementioned process continues validating our maximum likelihood estimates.

With the strengthening of the relationship between commodities at the onset of the pandemic and, later, the war, decision-makers require information about the cases of positive and negative relationships for policy planning. Specifically, the negative relationship between the wheat and the sunflower oil markets was -0.08, on average before the pandemic and nearly doubled to -0.15 after the pandemic outbreak. In turn, the positive correlation mean was 0.13 for wheat and sunflower oil before the pandemic, but increased to 0.22 after the pandemic erupted. In the case of wheat and corn markets, the negative uncertainty relationship between wheat and corn was -0.10 before the COVID-19 pandemic, but -0.05 after the pandemic started, or cut in half. However, the positive relationship of 0.08 before the pandemic increased somewhat to 0.11 after the pandemic. Additionally, the negative uncertainty relationship between the sunflower oil and corn market increased once the pandemic began and reached -0.20. Finally, the positive correlation between those commodities increased from 0.17 to 0.20 after the pandemic.

Wheat and sunflower oil showed a negative correlation in the uncertainty of their before-the-war relationship that increased 2.5 times once the war started, reaching -0.20. The positive uncertainty relationship between those commodities increased much less, from 0.15 to 0.22. The findings show the strengthening of the relationship between commodity markets once the war began and one can deduce that negative relationships trigger negative relationships and positive relationships trigger positive relationships as a result of the ongoing war. There is no evidence of negative and positive relationships between the wheat and corn markets before the war or after the war started. The observed relationship between sunflower oil and the corn markets was similar.

Conclusion and recommendations

This study examined the impact of two unforeseen events of international importance, the COVID-19 pandemic and the Russian-Ukrainian war, on conditional volatilities of three important agricultural commodities, i.e., wheat, sunflower oil, and corn. Furthermore, the study analyzed the commodity price volatility pass-through in the atmosphere of uncertainty following the COVID-19 pandemic and the war. The volatility pass-through among agricultural commodities was estimated using the VECM-BEKK MGARCH model. The model analyzed the long-term relationship between commodities and the impact of short-term shocks on long-term equilibrium, the impact of conditional variances on returns, the impact of short-term shocks on conditional variance, and the asymmetric effect of (good and bad) news on conditional variance. A series of tests confirmed the compatibility of the model with the data.

The series were found to be co-integrated in the long run following the Johansen test. Further, it is determined that short-term deviations are directed toward long-term equilibrium. At the same time, the existence of reciprocal causality among commodities indicates that commodity prices affect each other. The conditional variance of wheat lacked a statistically significant effect on the returns of sunflower oil and own return, but the conditional variance of corn had a statistically significant effect on other commodities. The COVID-19 pandemic effect, measured by a binary variable, significantly increased the returns of wheat and sunflower oil. The Russian-Ukrainian war had a significant effect on wheat returns imported to Turkey in large amounts from Ukraine and Russia. That particular supply channel was blocked after the commencement of the war and constrained the wheat supply within Turkey, increasing wheat returns both in Turkey and in global markets. The instituted ban on exports by the Turkish government maintained a stable supply of sunflower oil and corn, which reduced the possible effects of the war and was likely responsible for the statistically insignificant effect of the war.

Finally, an analysis of the volatility pass-through between wheat, sunflower oil, and corn reveals that there is a volatility pass-through between the returns of all three commodities. At the same time, the asymmetric nature of this pass-through causes positive and negative news between markets to have different effects on return volatility. While long-term uncertainties in each market are affected by both short-term (ARCH effect) and long-term (GARCH effect) uncertainties stemming from their markets' internal dynamics, the short-term shocks in opposite markets aggravate such risk. However, long-term uncertainty stemming from opposite markets mitigates risk transmission to the market in question and could correct long-term distortions in the relevant market, returning the price to its long-term equilibrium.

The exchange rate, the COVID-19 pandemic, and the Russian-Ukrainian war significantly affect the volatility of returns. The findings regarding the COVID-19 pandemic confirmed its negative effect on the prices of staples but also the mitigation of risks in selected agricultural markets. The results show that the Russian-Ukrainian war has vastly worsened the entrenched risks in the commodity markets. High costs combined with an energy crisis led to substantial food inflation in Turkey and burdened consumers. The disruptions in the supply chain forced the government to take a series of measures to curb the war's impact on food prices. To alleviate consumer difficulty in purchasing staples, the state-supported Agricultural Credit Cooperatives opened their outlets throughout the country and offered less expensive food products than in the chain supermarkets. However, due to the lack of regulatory enforcement and the collusion between chain supermarkets and the leading food suppliers, consumer access to staples continues to be compromised, risking food insecurity. To improve long-term food security, Turkey can expand arable land with new technologies to boost crop production, especially sunflower. Considering additional countries as suppliers to overcome bottlenecks in the supply chain of staple food products and stabilizing prices can include Turkic countries of Central Asia, which can offer agricultural commodities exported by Russia or Ukraine in the country.

A source of uncertainty in commodity markets is the search for alternative assets to diversify investments. While the financialization of commodity markets affects agricultural commodities and staple food prices, monitoring and understanding price formations is greatly needed. Ensuring the continuity of global and national food supply chains is critical to secure food supplies and failure to act means exposing vulnerable population groups to food insecurity. Therefore, policymakers have to undertake a practical set of policy instruments to maintain stable prices. For example, monitoring price collusion between large food suppliers could limit sudden price changes. Implementation of a digital label system, in the long run, will facilitate monitoring price volatility through an online self-control system managed by a government agency. Expansion of cold storage facilities will facilitate the logistics and transportation of perishable goods. Separately, the international community can create additional staple food depots to counter food insecurity caused by armed conflicts or localized epidemics. Such proactive management simplifies responses to circumvent the human impact of food supply disruptions, thus promoting social stability and peace. For example, the recent opening of the grain corridor across the Black Sea initiated by Turkey and backed by the United Nations has restored the continuity of grain shipments from Ukraine and lowered prices. Agricultural areas, water sources, farms, crops, livestock, and fisheries, crucial for ensuring food security, could be explicitly designated as protected non-military targets and new rules could be incorporated into international humanitarian laws safeguarded by international sanctions. How the sanctions against Russia and Belarus, following the Russian invasion of Ukraine, and the measures to secure national food supplies affected international markets and sensitive populations also need to be considered.

The lack of mechanisms (such as a stock market) to reflect instantaneous energy-induced price changes in Turkey can be considered a limitation of this study. Energy prices are changed by the Energy Market Regulatory Board with varying frequency, for example weekly, biweekly, or even twice a week. The omission of energy prices from the current study, for example, oil prices, was due to the inconsistent length of periods between price changes that did not match our other data.

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Table 1. Descriptive statistics of three staples and the exchange rate series, in logs.

Statistics	Wheat	Sunflower oil	Corn	Exchange Rate
Mean	1.193	1.867	1.020	2.434
Standard deviation	0.197	0.277	0.219	0.222
Skewness	1.777	1.647	1.949	0.294
Kurtosis	2.522	2.362	3.162	-1.015
Jarque-Bera	832.631	720.588	1104.435	60.458
	(0.000)	(0.000)	(0.000)	(0.000)
Q(6)	6063.622	5918.571	5689.152	6191.363
	(0.000)	(0.000)	(0.000)	(0.000)
LM-ARCH(6)	10917.731	5865.763	2675.717	19865.696
	(0.000)	(0.000)	(0.000)	(0.000)
ADF	-0.056	-1.690	-2.175	-1.135
KPSS	8.771***	7.459***	9.073***	1.226***
Correlation coefficient				
Wheat	1.000	-	-	-
Sunflower oil	0.598	1.000	-	-
Corn	0.514	0.442	1.000	-
Exchange Rate	0.441	0.632	0.346	1.000

Note: Q is statistics of Ljung-Box for the null hypothesis of the absence of autocorrelation for a series. The LM-statistic tests all series for the multivariate ARCH effects.

*, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Table 2. Parameters of conditional mean equations.

Estimate	Wheat	Sunflower oil	Corn
Cointegration Equations			
$P_t^w - 0.157P_t^s - 0.680P_t^c - 0.195$ and $P_t^s - 0.823P_t^w - 0.389P_t^c - 0.483$			
Constant (μ)	0.003	0.006**	0.002
	(0.004)	(0.003)	(0.002)
$\Phi_{ww,1}$	-0.407***	-0.006	0.014
	(0.034)	(0.028)	(0.035)
$\Phi_{ws,2}$	-0.163***	0.013	0.042
	(0.037)	(0.029)	(0.036)
$\Phi_{wc,3}$	-0.002	0.018	0.048
	(0.027)	(0.028)	(0.033)
$\Phi_{sw,1}$	0.010	-0.358***	-0.048***
	(0.019)	(0.027)	(0.015)
$\Phi_{ss,2}$	0.028	-0.049*	0.020
	(0.017)	(0.027)	(0.016)
$\Phi_{sc,3}$	0.053***	0.015	0.010
	(0.013)	(0.022)	(0.017)
$\Phi_{cw,1}$	-0.007	-0.029*	-0.621***
	(0.009)	(0.016)	(0.023)
$\Phi_{cs,2}$	-0.017	-0.043**	-0.334***
	(0.011)	(0.019)	(0.022)
$\Phi_{cc,3}$	-0.001	-0.040***	-0.151***
	(0.011)	(0.015)	(0.021)
θ	0.001**	0.001	-0.001
	(0.001)	(0.001)	(0.001)
ϑ	0.006***	0.011***	0.003
	(0.001)	(0.003)	(0.003)
τ	0.003	-0.009	0.018*
	(0.007)	(0.013)	(0.010)
Ψ_{ww}	-0.003	-0.143	-0.042
	(0.183)	(0.100)	(0.098)
Ψ_{ss}	-0.022	0.180***	-0.038*
	(0.016)	(0.057)	(0.022)
Ψ_{cc}	-0.070**	-0.156***	-0.002
	(0.075)	(0.053)	(0.050)
α_{1i}	-0.002**	0.001	0.001
	(0.001)	(0.001)	(0.001)
α_{2i}	-0.001	0.003***	-0.002**
	(0.001)	(0.001)	(0.001)

*, ** and ***, indicate statistical significance at 10%, 5%, and 1%, respectively.

Table 3. Parameters of conditional variance equations.

Parameters	Wheat (i = 1)	Sunflower oil (i = 2)	Corn (i = 3)
Constants in $\Upsilon\Upsilon'$***:***			
Pure constant parameters(C):			
c_{1i}	0.003***	-	-
	(0.001)		
c_{2i}	-0.009***	0.011***	-
	(0.003)	(0.002)	
c_{3i}	-0.004	-0.001	0.014***
	(0.002)	(0.003)	(0.003)
Parameters associated with exchange rate (Exr_{t-1}***):***			
Γ_{1i}	-0.002***	-	-
	(0.000)		
Γ_{2i}	-0.006***	-0.006***	-
	(0.001)	(0.002)	
Γ_{3i}	-0.002*	-0.002	0.001
	(0.001)	(0.001)	(0.001)
Parameters associated with selected agricultural commodities price return in the COVID-19 period (COVID-19_{T-1}***):***			
Ω_{1i}	-0.006***	-	-
	(0.002)		
Ω_{2i}	-0.001	-0.022***	-
	(0.005)	(0.004)	
Ω_{3i}	0.023*	-0.023	0.004
	(0.014)	(0.017)	(0.038)
Parameters associated with selected agricultural commodities price return in the war period (War_{t-1}***):***			
Π_{1i}	0.010**	-	-
	(0.005)		
Π_{2i}	0.060***	0.039*	-
	(0.020)	(0.020)	
Π_{3i}	-0.051*	0.069**	-0.007
	(0.029)	(0.034)	(0.081)
ARCH parameters:			
a_{1i}	0.097	-0.084	-0.118
	(0.209)	(0.070)	(0.116)
a_{2i}	-0.002	0.444***	0.054**
	(0.010)	(0.094)	(0.027)
a_{3i}	-0.014	0.074*	0.537***
	(0.018)	(0.039)	(0.051)
GARCH parameters:			
b_{1i}	0.970***	0.054**	0.041
	(0.008)	(0.027)	(0.026)
b_{2i}	-0.022*	0.640***	0.076**
	(0.012)	(0.042)	(0.039)
b_{3i}	0.010	-0.088**	0.746***
	(0.014)	(0.038)	(0.053)
GARCH asymmetric parameters:			
d_{1i}	0.259	0.191	-0.216
	(0.207)	(0.270)	(0.223)
d_{2i}	0.009	0.499***	-0.041
	(0.014)	(0.074)	(0.036)
d_{3i}	-0.071***	0.090	-0.170
	(0.015)	(0.061)	(0.128)
Shape(t degrees)		3.670***	
		(0.193)	

*, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Table 4. Some diagnostic and hypothesis tests.

Parameters	Wheat (i = 1)	Sunflower oil (i = 2)	Corn (i = 3)
Panel A: Residual Diagnostic Tests			
Serial Correlation in residuals:			
LB-Q(20)	22.723 (0.416)	16.826 (0.664)	21.149 (0.388)
McLeod-Li(20)	20.972 (0.399)	0.818 (1.000)	12.478 (0.899)
HM-Q(20)		162.248(0.825)	
ARCH Effects in residual squares:			
ARCH-LM(20)	0.973 (0.493)	0.150 (1.000)	0.804 (0.710)
HM-Q^2 (20)		82.403 (1.000)	
Additional Statistics:			
z	0.002 (0.940)	0.006 (0.833)	0.004 (0.890)
z^2	1.015 (0.493)	0.963 (0.514)	0.956 (0.517)
AIC		-13107.795	
SBC		-12582.200	
HQC		-12908.524	
Log FPE		-13319.795	
Log-Likelihood Value		-6659.898	

Panel B: Model Specification Tests		
Granger Causality Tests		
H_0: No effects of all other variables in the mean wheat equation, except for the constant and lagged wheat parameters		595.547 (0.000)
H_0: No effects of all other variables in the mean sunflower oil equation, except for the constant and lagged sunflower oil parameters		80.205 (0.000)
H_0: No effects of all other variables in the mean corn equation, except for the constant and lagged corn parameters		63.771 (0.000)
No GARCH	H_0: $a_{ij} = b_{ij} = d_{ij} = 0$ for all i, j =1,2,3	86651.530 (0.000)
Diagonal GARCH	H_0: All off-diagonal elements of A, B, and D are jointly zero	109.633 (0.000)
No Asymmetry	H_0: $d_{ij} = 0$ for all i, j =1,2,3	124.260 (0.000)
H_0 : Off-diagonal exchange rates in the conditional variance equations are jointly zero		23.778 (0.000)
H_0 : Off-diagonal of COVID-19 in the conditional variance equations are jointly zero		3.339 (0.342)
H_0 : Off-diagonal of war in the conditional variance equations are jointly zero		26.706 (0.000)

Notes: Q and Q^2 are Ljung-Box statistics for the null hypothesis of autocorrelation absence in a series in question on standardized and standardized squared residuals, respectively. HM Q and HM Q^2 statistics are Hosking's multivariate portmanteau Q-statistics on the standardized and standardized squared residuals, respectively, in diagnosing the null hypothesis of no autocorrelation in all series for lag one through the specified number of lags. The LM-statistic tests are a set of series for the multivariate ARCH effects under the null hypothesis that the series means are zero and are not serially correlated with a fixed covariance matrix.