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RESEARCH ARTICLE

Asymmetrical relationship between COVID-19 global fear index and agricultural commodity prices

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ABSTRACT

Grains and oilseed crops are widely used as key input elements for global food safety in food and livestock sub-sectors, as well as in other sectors such as energy, services and industry. In addition, they play an active role in the international agricultural markets. Therefore, price structure in the grain and oilseed market is important for agriculture and many other sectors. This study was designed to reveal how the fear of COVID-19 has globally affected grain prices. The study covered the one-year period from March 11, 2020, when COVID-19 was first recognized as a pandemic, to March 11, 2021. The Global Fear Index (GFI) and the price sub-indices created by the Grain Oil Council were used to determine the impact of the fear caused by COVID-19 on grain prices. Assuming an asymmetrical relationship between variables, the Nonlinear Autoregressive Distributed Lag model was used to determine this relationship. According to the model results, it was found that in the long term, agricultural commodity prices gave an increase (decrease) response to the positive (negative) effects in the GFI, and that the effect of an increase in the GFI on agricultural commodity prices was greater than the effect of a decrease. Accordingly, it is thought that the analysis and predictions which take into account the asymmetrical effect would give more realistic results and thus contribute considerably to the market regulations. It will also help policymakers make more rational decisions in their search for solutions to the problems in the cereal market.

Keywords: COVID-19; Agricultural Commodities Prices; NARDL model; Asymmetric Effects

INTRODUCTION

Corona virus was declared a pandemic by the World Health Organization on March 11, 2020, less than three months after its first report on December 31, 2019 in Wuhan town of Hubei province in China. During the one-year period, the total number of cases exceeded 130 million and there were nearly 3 million deaths (World Health Organization, 2021). Compared to the previous Severe Acute Respiratory Syndrome (SARS) and Middle East Respiratory Syndrome (MERS), new corona virus has a quite high rate of spread. In just a few months, it has become one of the world's greatest health problems, triggering global fear (Erokhin and Gao, 2020; Daglis et al., 2020).

The temporary policies developed by many countries around the world focusing on social distancing to slow the spread of the pandemic seem to be effective in reducing the spread of the disease while causing constrictions in the economies of the countries (Hart et al., 2020; Poudel et al., 2020). Also due to globalization, COVID-19 has led to major changes in the balance of unemployment, growth and supply and demand with restrictions on both national and international movement of people and goods (Beckman et al., 2021; Ceylan et al., 2020). Thus, the rapid spread of COVID-19 has brought a global economic problem along with a global health problem.

The transformation of COVID-19 into an economic crisis has had impact in many sectors (Bai et al., 2020). This has brought the focus of many researchers to COVID-19 impact assessments on a sectoral basis (Ozturk, 2020; Sharma and Nicolau, 2020; Fana et al., 2020; Eroglu, 2021; Milani, 2021). In the early stages of the pandemic, the agricultural sector did not receive as much attention as other sectors of the economy. However, the pressure on supply and demand and the concerns that food security may be at risk and that a global food crisis may occur in the future have taken the sector to a strategic position over time (Clapp and Moseley, 2020; Schmidhuber, 2020; Musa et al., 2020; Ramakumar, 2020; Poudel et al., 2020; Salisu et al., 2020; Elleby et al., 2020). On the other hand, due to

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the interrelationship of agriculture with many sectors, the possible effect of pandemic in the agricultural sector has led to a domino effect in sectors closely related to agriculture (Hart et al., 2020). The pandemic has directly and indirectly caused economic shocks and social costs in the agricultural sector through macroeconomic factors, energy and credit markets, and input and output prices in agricultural factor markets (Stephens et al., 2020; Schmidhuber, 2020). As a result of measures to control the spread of the disease, food demand has been reshaped, the workforce has experienced severe contractions, and agriculture and food systems experienced disruptions (Elleby et al., 2020; Laborde et al., 2021; Daglis et al., 2020).

International trade restrictions have led to a loss of revenue in exporter countries due to the disruption in global food supply chain while the countries whose food supply is largely based on imports had concerns about food security (Siche, 2020; Laborde et al., 2020; Vickers et al., 2020; Beckman and Countryman, 2021; Mouloudj et al., 2020; Daglis et al., 2020). On the other hand, the bottlenecks in the economy and the global health concerns created by COVID-19 are putting pressure on input and output prices in the agricultural sector (Borgards et al., 2021; Karagol et al., 2021).

In the early days of the pandemic, the prices of important crops such as barley, corn, wheat and rice tended to fall slightly. However, due to the increase in the rate of spread of the pandemic, quotas for trade and continued demand increase, prices have risen rapidly since the second half of 2020. Indeed, international prices for wheat, corn and barley increased by 22.8, 45.6 and 32.2%, respectively, over the one-year period starting from the date when the World Health Organization declared COVID-19 a pandemic. According to Ezeaku et al. (2021), although the grain market has shown a resilient structure to the epidemic and the price volatility has remained low, the COVID-19 pandemic continues to be a source of uncertainty in the market. As a matter of fact, it is predicted that the COVID-19 pandemic in the long term may lead to a major change in grain market due to a decrease in biofuel demand, increased concerns about food safety, changes in consumer behavior, increased investments in digital supply chains, a decrease in global feed demand, a return to the globalization trend in supply chains and an increase in government interventions (Skuratovic, 2021).

The focus of the present study was on the impact of COVID-19 on grain and oilseed markets. Grain and oilseed products are widely used as critical inputs in food and livestock sub-sectors which are of paramount importance in global food safety, as well as in energy services and industry sectors, and play an active role in the international agricultural products trade. Therefore, price structure in the grain market is important for many agricultural and non-agricultural sectors. The present study aimed to determine how the fear of COVID-19 globally affects grain prices asymmetrically. In the literature, the impact of the crisis on food prices and their volatility was investigated, but no study was found that addressed the asymmetrical relationship. In addition, the fact that evaluating the prices in grain sector, which is related to the food safety, livestock, nutrition and energy sectors, has a critical value in this period adds to the importance of the study. In the study, the global fear index (GFI) developed by Salisu and Akanni (2020) to measure the fear/panic associated with the COVID-19 outbreak was used. This allowed us to evaluate the impact of COVID-19 case and death numbers as a whole on agricultural commodity prices.

LITERATURE REVIEW

Reaching of COVID-19 to pandemic status has raised health concerns as well as global economic problems. This has caused stagnation and uncertainty in the markets on a national and global scale and, like many sectors, had considerable effect on the agricultural sector. Considering the fact that the structural changes in the markets have a direct effect on price changes especially in times of crisis, research on price structure in agricultural markets has also been of great interest during COVID-19. Research to assess the impact of COVID-19 on agricultural commodity prices basically focus on the correlation between energy and agricultural markets, price changes before and during COVID-19, and the impact of concern and panic brought on by COVID-19 on agricultural commodity prices.

In recent years, the increase in demand for energy plants and the fact that oil is one of the main inputs in agricultural production have further strengthened the relationship between energy prices and agricultural commodity prices. Therefore, it is inevitable that changes in energy prices will cause changes and fluctuations in agricultural commodity prices. This interaction becomes more pronounced especially in times of uncertainty and crisis. For this reason, studies examining the relationship between energy prices and agricultural commodity prices have been of great interest in the literature during the COVID-19 pandemic. Using the daily data in the period 2002-2020, Umar et al. (2021) stated that the change in oil prices led to changes and volatility in agricultural commodity prices during the Global Financial Crisis, the European sovereign debt crisis and the COVID-19 pandemic crisis. Wang et al. (2020), on the other hand, found a strong long-term positive correlation between crude oil prices and agricultural commodity prices. Ezeaku et al. (2021) stated that the impact of the shocks in the oil market during the COVID-19 process varied in different crops. They found that corn and wheat prices had a considerable and positive reaction to oil market shocks, but soybean and rice prices reacted negatively to the oil shock.

On the other hand, the effect of COVID-19 on agricultural commodity prices is evaluated independently from other sectors. In the literature, there are studies that examine the changes in agricultural commodity prices by taking into account the number of cases and deaths caused by COVID-19. There are also studies that considered COVID-19 as a period and observed the price changes by comparing it with other periods. Since the pandemic has led to the global economic crisis, the impact of this process on prices has been specifically investigated. The pandemic has led to reductions in the growth rates of the national economies, contractions in domestic demands and similar deteriorations in world trade. National and international measures to slow down the spread of the disease have also greatly affected the agricultural sector. Tough differed on regional, national and global scales, prices have changed markedly in the process. Singh et al. (2020) examined the changes in food prices in different regions of Nepal by addressing two separate periods before and during the COVID-19 period. They found that there was a significant increase in all food prices except animal products during COVID-19, but these price changes differed by region. Daglis et al. (2020) examined the impact of global COVID-19 case numbers on oat and wheat prices through multiple impact-response analysis. They concluded that there was a cointegration relationship between global case numbers and oat and wheat prices, and that the spread of COVID-19 increased wheat and oat prices. Salisu et al. (2020) aimed to demonstrate the predictive power of the Global Fear Index in the predictability of commodity prices by using a data set of commodity prices and global fear indices of 24 globally traded products, including agricultural products such as cocoa, coffee, oats, rice, wheat, sugar, soybean. The results confirmed that there was a positive relationship between commodity price returns and the global fear index, and that commodity returns increased along with the fear about COVID-19. Cariappa et al. (2020) examined the volatility in retail and wholesale wheat prices for five different regions of India during this period using the GARCH model. The findings suggested that wheat prices increased after the lockdown, but this increase was not immense overall. In other words, they argued that the effect of the lockdown was not large enough to cause a structural breakdown and volatility in the long-term wheat prices. In contrast, Kumar et al. (2020) statistically demonstrated that COVID-19 had an in-depth effect on the spot and future prices of wheat in the National Commodity and Derivatives Exchange [NCDEX], one of India's major stock exchanges, in the early stages of the pandemic (January-April 2020 period) and that volatility in the commodity market increased further during this period. Sun et al. (2021) examined the causality relationship between trade policy uncertainties and agricultural commodity markets to investigate whether agricultural trade policy uncertainty (TPU) was important for agricultural commodity prices (ACP) from a Chinese perspective in the period from 2005:M1 to 2020:M10. As a result of this study, which examined four different periods, they found a positive relationship at 10% level of significance from TPU to ACP in the periods of 2008: M7-2008: M12, 2020: M5-2020: M9, which also covered the COVID-19 process. In their study, they concluded that in general, the COVID-19 pandemic disrupted the trade flow of agricultural commodities, reduced Chinese imports and significantly increased ACP. Gutierrez and Pierre (2020) evaluated the global response of grain prices to oil prices, stock-use ratio and export shocks using the Global Vector Automatic Regression (GVAR) model, a multi-country time series model that is independently modeled on each market and linked to trade-based compound variables, based on leading countries in wheat, barley and corn exports. They stated that despite the concerns about disruption in the supply chain the oil market may have contributed to the stability of global grain prices in early 2020, that export restrictions in the first half of 2020 could significantly increase global prices, and that such restrictions could affect more than the target commodity through cross-commodity price links.

The change in agricultural commodity prices during the COVID-19 crisis has been studied on a linear scale in recent literature. However, there are no linear approaches to how positive and negative shocks related to COVID-19 would affect agricultural commodity prices. Examining the models which may involve asymmetrical relationship among variables using symmetrical methods can lead to misleading of policymakers. In this respect, it is considered important to take into account the asymmetrical relationship in determining policies to ensure stability. Assuming that the targeting the asymmetrical relationships may yield more effective results, how the positive and negative shocks in the global fear index (GFI) developed by Salisu and Akanni (2020) affect agricultural commodity prices was examined using the Nonlinear Autoregressive Distributed Lag (NARDL) model in the present study.

MATERIAL AND METHOD

Data

The data set consisted of the Global Fear Index and the Grain and Oilseed Sub-Index[1]. Daily series of each sub-index price of grain and oilseed index (GOI) developed by the International Grain Council (IGC) was taken from www.igc.int/en/default.aspx. The GFI series were obtained from Salisu and Akanni (2020). The starting period of the study was taken as the date on which COVID-19 was declared as a pandemic by the World Health Organization (WHO). Accordingly, daily data was collected between March 11, 2020 and March 11, 2021.

The Global Fear Index (GFI), which aims to measure daily concerns and feelings about the spread and severity of COVID-19, is a composite index of two factors based on reported cases and deaths. This index, which has a score range of 0-100, indicates the absence or existence of fear. GFI is composed of The Reported Cases Index (RCI) which measures how much the reported cases deviate from the expected ones over a 14-day period, and The Reported Death Index (RDI) which measures how much the reported deaths deviate from the expected ones over the same 14-day period. RCI is calculated as follows:

$$GFI_t = 0.5 * (RCI_t + RDI_t)$$

On the other hand, the sub-indices created on the basis of 1 January 2000 were revised based on the date of March 11, 2020, when COVID-19 was announced as a pandemic by the World Health Organization. All variables in the study were used in logarithmic form to facilitate interpretation of the results of the analysis.

Descriptive analysis

Understanding the characteristics of the variables examined is critical in determining the econometric technique. The mean, standard deviation, skewness, kurtosis and distribution normality of variables were tested under descriptive statistics (Table 1). It was observed that the means of price indices (lnbarley, lnmaize, lnrice, lnsoybean, lnwheat) had similar values, and lnmaize had the highest average. The skewness values of the price index series were determined as left skewed, and the kurtosis values were determined as platykurtic distribution. The mean global fear index (LNGFI) series was 3.975, the skewness value was close to 2, while the kurtosis value had leptokurtic distribution. According to Jargue-Bera test statistics, not all series were distributed normally.

1 IGC GOI Barley sub-index was calculated using Argentina Up River, Australia Port Adelaide, Black Sea Fob, EU (France) Rouen and EU (Germany) Hamburg. IGC GOI Maize sub-Index was calculated from Argentina Rosario (Up River), Black Sea, Brazil Paranagua, US Gulf. IGC GOI Wheat Sub-Index was calculated from Argentina Up River, Australia Port Adelaide, Black Sea, Canada St. Lawrence and Vancouver, EU (France) Rouen, US Gulf and PNW. All indices were calculated by IGC.

Table 1: Descriptive statistical analysis

	lnbarley	lnmaize	lnrice	lnsoy bean	lnwheat	lngfi
Mean	4.69	4.73	4.67	4.83	4.68	3.98
Median	4.63	4.66	4.67	4.79	4.65	3.94
Maximum	4.91	5.03	4.74	5.13	4.84	4.52
Minimum	4.54	4.47	4.61	4.55	4.54	3.68
Std. Dev.	0.11	0.19	0.03	0.19	0.09	0.16
Skewness	0.53	0.27	0.17	0.13	0.36	1.92
Kurtosis	1.87	1.47	2.25	1.46	1.74	6.95
Jarque-Bera	25.72	28.31	7.41	26.32	22.86	28.26
Probability	0.00	0.00	0.02	0.00	0.00	0.00

Unit root test

Many methods are applied for the estimation of asymmetric relationship in the time series, and these methods are preferred based on the stationary condition of the series. Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests were used to test the stationary ratings of the series. The stationary ratings of the series were examined depending on constant and constant and trend-containing. Accordingly, based on both unit root test result, it was observed that the variables other than the lngfi were stationary when the first-degree difference was taken (Table 2). lngfi variable was found to get stationary when the first-degree difference (I(1)) was received according to PP statistic but it was stationary at the level (I(0)) according to ADF statistic.

Unlike Engle-Granger cointegration (1987) and Johansen Cointegration (1988 and 1990) models, the Autoregressive Distributed Lag (ARDL) model allows both to study cointegration between series with varying degrees of stationary condition and to model long and short-term dynamics at the same time (Pesaran et al., 2001). In this context, taking into account the unit root test results, Nonlinear Autoregressive Distributed Lag (NARDL) boundary test, which is an extension of the linear ARDL model, was selected as the cointegration model (Shin et al., 2014).

Model estimation

Unlike the Autoregressive Distributed Lag model (ARDL), which assumes that all external data series have a symmetrical effect on the dependent variable, the NARDL model suggests that there may be an asymmetric effect. Therefore, in the present study, the NARDL model developed by Shin et al. (2014) was used to examine the short- and long-term asymmetrical effect of COVID-19 on major staple crops prices. NARDL model predictions:

lnY_t lvariable denotes lnbarley, lnmaize, lnrice, lnsoybean and lnwheat series (Equation 1).

Table 2: Unit root tests

	Level I (0)				First difference I (1)			
	ADF (C)	ADF (C/T)	PP (C)	PP (C/T)	ADF (C)	ADF (C/T)	PP (C)	PP (C/T)
lnbarley	0.57	-1.67	0.65	-1.92	-12.91	-13.02	-13.05	-13.14
lnmaize	0.08	-2.60	0.17	-2.66	-12.17	-12.21	-12.21	-12.17
lnrice	-2.52	-2.56	-2.45	-2.38	-6.46	-6.47	-13.93	-13.94
lnsoybean	-0.31	-2.18	-0.36	-2.39	-14.57	-14.54	-14.59	-14.56
lnwheat	-0.04	-1.64	-0.18	-1.77	-14.93	-14.92	-14.96	-14.95
lngfi	-4.76	-4.67	-3.42	-3.95	---	---	-30.19	-27.31

[a] At 1% significance level, when Augmented Dickey-Fuller (ADF) and Phillips-Perron unit root test statistics contained constant (C) and constant and trend (C/T), MacKinnon (1996) critical levels were -3.46 and -3.99, respectively.
[b] Lagging lengths were determined automatically using Akaike Information Criterion for ADF and using Bartlett Kernel for PP.

Table 3: Bound cointegration test

	F_{PPS}
lnbarley=f (lngfi$^+$, lngfi$^-$)	3.35*
lnmaize=f (lngfi$^+$, lngfi$^-$)	4.38***
lnrice=f (lngfi$^+$, lngfi$^-$)	3.32**
lnsoybean=f (lngfi$^+$, lngfi$^-$)	3.58**
lnwheat=f (lngfi$^+$, lngfi$^-$)	2.88***

a***, **, * denotes significance at 1, 5 and 10% level, respectively.
b For FPSS the critical upper (lower) values are 5.00 (4.13), 3.87 (3.1), 3.35 (2.63) for 1, 5, and 10%, respectively.

Model I: $$lnY_t = \beta^+ lngfi_t^+ + \beta^- lngfi_t^- + u_t \quad (1)$$

where β^+ and β^- are the asymmetric long-run parameters to be estimated, and u_t denotes the error process (i.e., deviations from the long run equilibrium relationship with a stationary zero-mean).

Asymmetrical error correction model, on the other hand, is given below (Equation 2):

Model I-a:

$$\Delta lnY_t = \delta + \rho lnY_{t-1} + \theta^+ lngfi_t^+ + \theta^- lngfi_t^- + \sum_{j=1}^{p-1} \alpha_j \Delta lnY_{t-j} + \sum_{j=0}^{q-1} \left(\mu_t^+ \Delta lngfi_{t-j}^+ + \mu_t^- \Delta lngfi_{t-j}^-\right) + \varepsilon_t \quad (2)$$

Where $\theta^+ = \rho\beta^+$ and $\theta^- = \rho\beta^-$, μ_t^+ and μ_t^- are the short-run adjustments towards positive and negative changes in $lnbarley_t, lnmaize_t, lnrice_t, lnsoybean_t, lnwheat_t$. The NARDL model follows the same pathway for testing the null hypothesis ($\rho = \theta^+ = \theta^- = 0$) of no cointegration against the alternative hypothesis

($\rho \neq \theta^+ \neq \theta^- \neq 0$) of cointegration. The next step utilizes the Wald test to examine the long-run asymmetry ($\theta^+ = \theta^-$) and short-run asymmetry ($\sum_{(j=0)}^{(q-1)} \mu_{(k,i)}^+ = \sum_{(j=0)}^{(q-1)} \mu_{(k,i)}^-$). Finally, we test the disequilibrium following a positive or negative shock in $lnbarley_t, lnmaize_t, lnrice_t, lnsoybean_t, lnwheat_t$ using the asymmetric dynamic multiplier effect on $lnbarley_t, lnmaize_t, lnrice_t, lnsoybean_t, lnwheat_t$ with a percentage change in $lngfi_t^+$ and $lngfi_t^-$ expressed as (Equation 3):

Model I-b:
$$m_h^+ = \sum_{(j=0)}^{h} \frac{\partial lnY_{(t+j)}}{(\partial lngfi_t^+)}, m_h^- = \sum_{j=0}^{h} \frac{\partial lnY_{t+j}}{\partial lngfi_t^-}, h = 0,1 \quad (3)$$

As $h \to \infty$, $m_h^+ \to \beta^+$ and $m_h^- \to \beta^-$, where β^+ and β^- represent the positive and negative long-run asymmetric coefficients.

RESULTS AND DISCUSSION

NARDL bound cointegration test results are given in Table 3. According to these results, the significance levels vary and there was a long-term relationship between each Crop Price Index and the Global Fear Index. After fulfilling the cointegration specification, we continued with the estimated short-run and long-run coefficients which are presented in Table 4. AIC (Akaike Information Criteria) was used to determine the optimal lagging length during the analysis phase.

When creating the NARDL model for each agricultural commodity price index, the maximum lagging length of 4 was used for dependent and dynamic regressors and optimal models were determined using the Akaike Information Criterion (AIC). After this stage, four diagnostic tests were used to verify the validity of the predicted models: Durbin-Watson for the first-degree autocorrelation detection, Breusch-Pagan-Godfrey for determining heterogeneity, Breusch-Godfrey LM for serial correlation detection and Ramsey RESET for determining the functionality of the model. The long-term relationship between variables was previously demonstrated by the bound test and supported by the negative and significant error correction coefficient (ECTt-1) given in Table 4. WLR test results showing the existence of a long-term asymmetrical relationship for each model were statistically significant. However, it was shown that the model established for lnsoybean had the problem

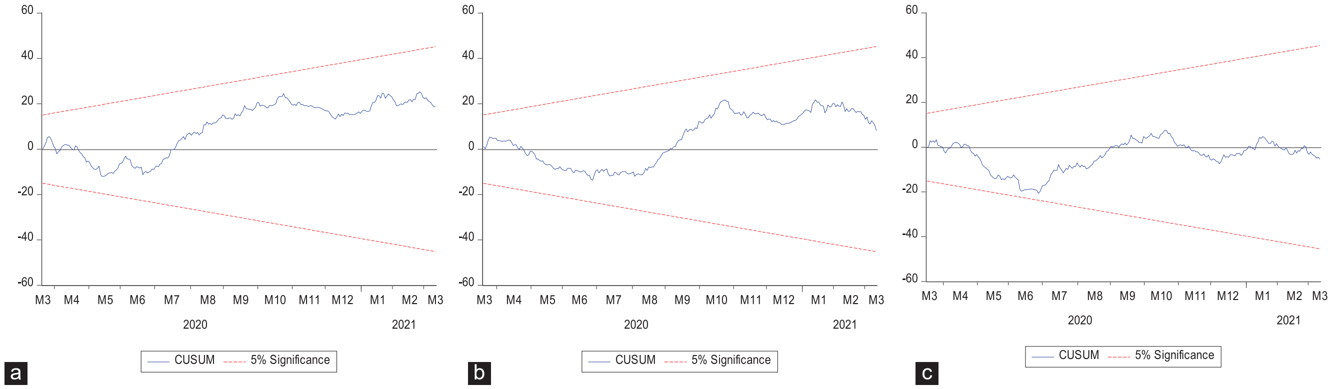

Fig 1. Rubber stem girth of rubber as affected by sweet corn-okra intercropping

Table 4: Dynamic asymmetric estimates of Global Fear index effects with NARDL

	Y (lnbarley)	Y (lnmaize)	Y (lnrice)	Y (lnsoybean)	Y (lnwheat)
lnY_{t-1}	-0.02**	-0.05***	-0.01	-0.05**	-0.025**
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
$lngfi^+$	0.01**	0.01**	0.01**	0.01	0.01**
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
$lngfi^-$		0.01**	0.01**	0.01	0.01*
		(0.01)	(0.002)	(0.01)	(0.00)
$lngfi^-_{t-1}$	0.01**				
	(0.00)				
ΔlnY_{t-1}	0.19***	0.24***	0.09	0.11*	0.12***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.01)
ΔlnY_{t-2}			0.15**		
			(0.06)		
ΔlnY_{t-3}			0.11*		
			(0.06)		
$\Delta lngfi^+$					
$\Delta lngfi^-$	-0.02*				
	(0.01)				
c	0.09**	0.20***		0.24**	0.12**
	(0.04)	(0.06)		(0.09)	(0.05)
Ect_{t-1}	-0.02***	-0.05 ***	-0.01***	-0.051***	-0.03***
	(0.01)	(0.01)	(0.00)	(0.01)	(-0.03)
Long-run Asymmetric Effects					
$lngfi^+$	0.38**	0.32***	0.47	0.17**	0.28*
	(0.16)	(0.09)	(0.53)	(0.08)	(0.15)
$lngfi^-$	0.30 **	0.21 **	0.45	0.07	0.23
	(0.15)	(0.09)	(0.52)	(0.08)	(0.14)
c	4.61***	4.53 ***	4.84***	4.60***	4.64***
	(0.05)	(0.04)	(0.22)	(0.03)	(0.06)
Error Metrics					
R^2	0.99	0.99	0.97	0.99	0.99
Adj. R^2	0.99	0.99	0.97	0.99	0.99
DW	2.04	1.94	1.99	1.98	1.84
AIC	-7.51	-6.60	-8.04	-6.38	-7.10
Diagnostic Tests					
χ^2_H *B-P-G*	0.98[0.43]	1.19[0.32]	6.45[0.00]	4.10[0.01]	1.25[0.29]
χ^2_{SC}*LM*	0.84[0.43]	0.67[0.51]	0.03[0.98]	1.99[0.14]	1.37[0.26]
χ^2_{FF}	0.38[0.70]	0.92[0.36]	0.11[0.91]	1.76[0.08]	1.26[0.21]
W_{LR}	3.24***	3.66***	1.70*	2.45**	2.69**

a***, **, * denotes significance at 1, 5 and 10%, respectively.

b ( ) is the standard error, χ^2_H *B-P-G* refers to Heteroskedasticity Test: Breusch-Pagan-Godfrey; χ^2_{SC}*LM* represents Breusch-Godfrey Serial Correlation LM Test; χ^2_{FF} means Ramsey RESET Test; and W_{LR} refers to Wald test of the additive Long-term symmetry condition. [ ] values represent probability values of diagnostic tests.

of heterogeneity, and the hypothesis that the functionality of the model is valid was rejected at 10% significance level. At the same time, in the model established for lnrice, due to the heterogeneity in the model, the hypothesis that there is no heterogeneity between the variables was rejected.

Considering the descriptive tests, the validity of the NARDL models established for lnrice and lnsoybean was found to be questionable and no evaluation was made. In addition, Figure 1(a), 1(b), 1(c) describes cumulative summary tests for NARDL models established for lnbarley, lnmaize and lnwheat, respectively. Accordingly, CUSUM plots show the stability of models estimated at the 95% confidence interval.

In the long-term asymmetric relationship between the global fear index and the barley price, it was found that a 1% increase in the fear index (lngfi+) could lead to a 0.38% increase in the barley price (lnbarley) and a 1% decrease could lead to a 0.30% decrease in the price of barley (lngfi-). In other words, barley prices reacted to the positive (negative) effects in the global fear index by increasing (decreasing), and it can be stated that the effect of an increase in the global fear index on prices was greater than the that of decrease (lngfi+ = 0.376 > lngfi- = 0.297). As Lock (2021) pointed out, global barley prices during this period were shaped largely by export controls imposed by the Russian Federation and Argentina and as a result of China›s high demand. Therefore, it could be stated that the price volatility in the barley market was a result of the uncertainty caused by COVID-19. Accordingly, the findings that similar price fluctuations could occur in global markets during periods of increased or decreased fear and panic were consistent with the literature.

It was shown that the global fear index affected corn prices asymmetrically in the long term. Accordingly, it was concluded that a 1% increase in the global fear index (lngfi+) represented by COVID-19 could increase corn prices by 0.32%, while a decrease of 1% (lngfi-) could reduce corn prices (lnmaize) by 0.21%. This indicated that corn prices reacted to the positive (negative) effects in the global fear index by increasing (decreasing). Similar to barley prices, the effect of an increase in the global fear index on corn prices was larger than the effect of a decrease effect. In recent years, approximately 90% of the world's corn exports have been made by Argentina, Brazil, the USA and Ukraine, and changes in the supply, demand and trade of these countries have significantly affected the world's corn prices. In the early stages of the pandemic, restriction measures taken in countries and around the world caused structural shocks in demand. The recession in the services sector due to restrictions such as quarantine led to contractions in the livestock and feed sectors, directly affecting corn prices in many countries (Neroba, 2020). As in barley, the fact that China is a major importer of corn is another issue that significantly affected market prices of corn (FAO, 2020). On the other hand, corn prices on a global scale varied depending on high production expectations and rapid stock increases in the U.S. and Brazil, and the quota and tax policies of exporting countries. The effect of oil prices on corn prices was also very clear during this period. Corn, which is widely used in ethanol production, reacts quickly to the change in energy prices arising from energy demand. During COVID-19 process, the contraction in ethanol demand, especially in the United States, continued to put pressure on corn prices (Elleby, 2020; Mizik et al., 2020; Neroba, 2021; Sun et al., 2021).

Unlike barley and corn prices, the effect of the decrease in the global fear index (lngfi-) on wheat prices (lnwheat) was not statistically significant. Therefore, it can only be stated that a 1% increase in the global fear index (lngfi+) had an increasing effect of 0.28% on wheat prices (lnwheat). Wheat export leader Russia appeared to have intervention power in the market, and its tax and quota policies and customs controls on exports resulted in price increases. But the growing demand for Australian and Argentine wheat increased the competition in the markets and balanced the rapid price increases. On the other hand, the increase in wheat demand in global markets, especially the high wheat demands of China and Pakistan in the last 15 years, has played an important role in the price increases. With the pandemic process, the increase in wheat demand has caused many countries to increase their wheat stocks under the current uncertainty and risk conditions. This has created the perception that prices will remain high in international markets (Anonymous, 2021). It can also be stated that strong price increases in corn has contributed to upward movement as wheat becomes more attractive economically for feed rations (Agricultural Market Information System (AMIS), 2021).

It is known that uncertainty in economies is a significant pressure on prices, which was clearly shown with global wheat, barley and corn prices in the present study. In fact, the results of the present study were in line with the predictions put forward by Daglis et al. (2020), Karagöl et al. (2021) Laborde et al. (2021) that the increasing spread rate of the pandemic may lead to an increase in agricultural commodity prices. In addition, the findings of the present study also lent support to the conclusion that export restrictions may affect more than targeted commodities through cross-commodity price links for wheat, barley and corn prices reached by Gutierrez and Pierre (2020) using the Global Vector Auto Regression (GVAR) model.

Generally, the number of leading exporter countries in wheat, barley and corn exports in world trade is small, but their total share in the market exceeds 80%. The findings of the present study clearly indicate that olypolistic structure has the power to determine world prices. The fact that COVID-19 uncertainty has led to asymmetrical effect on prices in the long term and that the effect of an increase in the fear index on prices is higher than the effect of a decrease could be explained by the fact that negative shocks are frequently more influential than positive shocks in oligopoly markets.

CONCLUSION

The COVID-19 pandemic has had a significant impact on agricultural markets on a global scale. In this process, decreased energy prices as a result of lower energy demand led to major changes in the grain sector through reasons such as increased concerns about food safety, changes in consumer behavior, increase in investments in digital supply chains, decrease in global feed demand, return to the globalization trend in supply chains and increase in government interventions, changes in quotas and tax policies in foreign trade. This puts pressure on cereal prices. Therefore, the change in prices and the direction of this change are closely related to the fear and panic brought about by the pandemic. It can be concluded that exporting countries in particular are very effective in guiding the world prices. As a matter of fact, the present study which evaluated the asymmetric relationship among barley, corn and wheat export prices and global fear indices (GFI) using the lower price indexes created by Grain Oil Council over a one-year period revealed that the oligopoly market shaped the world prices.

In its production forecasts report released in 2021, the International Grain Council stressed that not many problems appear in the supply side but that demand pressure will greatly affect the course of the prices. The trend of many countries to increase stocks due to uncertainty created by the pandemic indicated possible long-term volatility in the global wheat, corn and barley trade. The fact that importers increased their imports considerably through tax breaks while exporter countries made major changes in export quotas and taxation and the signal of a decrease in export amounts fueled the trend of price increases. This led to increased speculative activity in the stock markets and strengthened the commitment of the financial and agricultural markets.

The pressure of the COVID-19 process on cereal prices remains to be strong. It was found in the present study that the changes in COVID-19 related cases and deaths affected barley, corn and wheat prices asymmetrically in the long term. The effect of an increase in the Global fear index on prices was higher than that of a decrease.

The finding that the grain market, which has oligopoly power on a global scale, responded to negative shocks faster than positive ones was something expected. However, the sudden changes in the prices of these agricultural commodities, which are important for food security, can cause major problems in the economies of importing countries, especially the low-income ones. In this context, it is very important to ensure price stability in the market. Accordingly, the analysis and predictions taking into account the asymmetrical effect could help reduce the volatility in cereal prices. In addition, the uncertainty brought about by COVID-19 pandemic is thought to have a greater impact on prices than supply and demand shocks. Therefore, trade policies to be developed taking into account the asymmetrical effect revealed by this study which would guarantee the dynamic circulation of grains, financing methods to facilitate trade for developing countries, and the search for solutions to adapt climate and environmental risks to the grain supply chain are predicted to have considerable, stabilizing effects on the prices in global grain markets.

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