The Impact of the Covid-19 Pandemic Determinants on Selected Agricultural Commodity Prices

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DOI: https://doi.org/10.15414/isd2022.s4.06

Abstract
The global Covid-19 pandemic is the most notable event that has been affecting our lives since the end of 2019. The ongoing pandemic influenced many sectors, including agriculture and commodity markets. The evolution of selected agricultural commodity prices during the global pandemic of Covid-19 is investigated in this paper. The major goal is to determine if the Covid-19 indicators affect the price movements of cocoa, corn, sugar, and wheat. Using the ARDL model, we examined the daily prices of chosen commodities from January 23, 2020, to November 30, 2021. Our results show that the price of corn and wheat was not statistically significantly affected by the Covid-19 pandemic determinants. On the other hand, in the case of cocoa, we observed a negative indirect effect of financial volatility in the long run. Furthermore, in the short-run cocoa prices were negatively influenced by the financial volatility index as well as new daily Covid-19 cases. Besides, sugar prices were affected by the increase in the new confirmed Covid-19 cases and death in the long run. We also found an indirect negative impact of the financial volatility on the sugar prices in the short and long run. Moreover, sugar prices were in the short-run heavily affected by its previous developments as well as by the Covid-19 media coverage index.

Keywords: Cocoa, Corn, Covid-19, Sugar, Wheat

JEL Classification: C32, G19, Q 02

1. Introduction
While in the past commodities were traded for their importance as inputs to production, today commodities are also of interest to investors as a financial asset. Thus, investors in general, as well as portfolio managers, brokers, and traders, became participants in the commodity market. According to Balcilar and Sertoglu (2020) in uncertain times, these market actors try to prevent each other from acting, making the market turbulent and loud. At the same time, commodity markets are well-developed, with characteristics such as risk transfer and volatility mitigation. As a result, during the past decade, the financial markets have become more intertwined with commodity markets.

Endogenous variables, macroeconomic factors, and exogenous uncertainties all influence agricultural commodity price changes (Liu, Liu, Ye, Tang & Wang, 2022). The emergence of the novel coronavirus Covid-19 was perhaps the most momentous event in our lives in 2020 - 2021. The coronavirus pandemic negatively affected the world economy, international markets and global society. The pandemic’s negative impacts have created economic and financial instability throughout the world, culminating in a global recession. Border closures, lockdowns, travel restrictions, as well as social distancing, were used by countries all around the world to manage the outbreak. Numerous industries, including services, industry, and agriculture, have been badly impacted (Chang, McAleer, & Wong, 2020). Besides, a
significant worldwide decline in commodity markets was also reported at the same time, in addition to the severe impact of these measures on economic activity, supply routes, and international trade (Aslam, Aziz, Nguyen, Mughal, & Khan, 2020). Agricultural commodity market swings have well-established ramifications for the whole economy, and Covid-19 has impacted both sides of the market, demand and supply of agricultural products. Thus, all types of commodities have suffered a considerable drop in demand and supply as a result of the latest coronavirus pandemic (Ji, Zhang, & Zhao, 2020; Borgards, Czudaj & Van Hoang, 2020). For instance, Elleby, Dominguez, Adenauer, and Genovese (2020) in their study examine the effects of the demand shock induced by the Covid-19 pandemic on global agricultural markets, as well as the initial wave of lockdown measures implemented by countries in the first half of 2020 to control it. Besides, the global pandemic reduced also investments into commodities (Shaikh, 2021). Thus, all these events had an impact on commodity pricing.

Salisu, Akanni, and Raheem (2020) proved that the relationship between stock markets and agricultural commodity markets is critical during times of crisis. Significant volatility, commodity price flips, and financial market uncertainty are only a few of the impacts of the crisis (Antonakakis, Chatziantoniou, & Filis, 2017). It is widely acknowledged that the global pandemic-19 has also raised global uncertainty, volatility, and risk. Bakas and Triantafyllou (2020) estimated the influence of the Covid-19 pandemic’s uncertainty on commodity market volatility. Their results show a strong impact on the volatility caused by the pandemic. On the other hand, using the TPV-VAR model, Adekoya and Oliyide (2021) investigated the influence of the Covid-19 epidemic on linkages across commodity and financial markets. Likewise, Kotyza, Czech, Wielechowski, Smutka, and Procházka, (2021) examined possible structural changes in the link between sugar prices and financial market instability in times of coronavirus crisis. Gharib, Mefteh-Wali, and Jabeur (2021) showed that the linkages between oil and other commodity prices have shifted dramatically throughout the outbreak and that they are meant for investment strategies such as cross-hedging and speculating. On the other hand, using multifractal detrended cross-correlation analysis, Wang, Shao and Kim (2020) investigated the cross-correlation between agricultural futures markets and crude oil. The findings show that there is a high cross-correlation between London Sugar futures and Brent Crude Oil and that this cross-correlation rises as the Covid-19 contagion spreads. The study by Le, Do, Nguyen, and Sensoy (2021) offered evidence on the frequency-based dependence networks of various financial assets in the tails of return distributions given significant price swings during the Covid-19 outbreak. The results demonstrate that cross-asset tail-dependency of equities, currency, and commodities grows significantly, particularly in the left-tail, indicating a greater degree of tail contagion effects.

In contrast, Musa, Rabiu, Nafisa and Muktari (2020) indicated that the number of new coronavirus infections has a negative influence on oil prices, but a long-term favourable impact on the food price index. Oil prices, as well as the food price index, were severely impacted in the short term. Moreover, according to Adekoya, Oliyide and Oduyemi (2021), the pandemic was significant in spreading risk across commodity and financial markets. Similarly, the study of Ge and Tang (2020), showed that the uncertainty shock has a significant impact on commodity prices. On the other hand, Salisu et al. (2020) discovered a positive correlation between commodity yields and the Global Pandemic Fear Index, with commodity yields increasing as the fear of a new coronavirus grew. The study of Balcilar and Sertoglu (2020) used daily data to investigate the impact of the Covid-19 sentiment on key agricultural commodity prices more specifically on cattle, cocoa, coffee, corn, cotton, hog, rice, soya oil, soybeans, soybean meal, sugar, and wheat. In a cross-section of revenue from commodity futures, Bannigidamath and Narayan (2021) investigated whether investors appreciate the risk
component of pessimism from economic news. In contrast, the effect of the Covid-19 pandemic panic on commodity price volatility was investigated by Umar, Gubareva, Naeem, and Akhter (2021). According to Sadefo Kamdem, Bandolo Essomba, and Njong Berinyuy (2020), the number of verified coronavirus infections and deaths influences commodity price volatility. Sifat, Ghafoor, and Ah Mand, (2021) studied the Covid-19 pandemic as well as commodity speculation, such as oil, precious metals, and agricultural futures. In contrast, Ji et al. (2020) assessed the secure function of assets during the pandemic. Gold and soybean futures, according to the findings, have played a significant "safe haven" function during the downturn. Likewise, Maghyereh and Abdoh (2020) discovered that commodity prices are influenced by investors’ attitudes. Moreover, according to Ezeaku, Asongu and Nnanna (2020) commodity investments may become less liquid and volatile as Covid-19 continues to destabilize the global economy.

In this paper, we aim to contribute to the study of the Covid-19 effects and their impact on the agricultural commodity markets and fill the gap in the literature with analysis focusing on agricultural commodities. Our study is structured as follows. Section 2 describes the data and provides an overview of the methodology used. Section 3 discusses the findings and conclusions are summarized in chapter 4.

2. Data and Methods

To analyse the impact of the Covid-19 pandemic on the price development of agricultural commodities we employ an ARDL model. The ARDL model is an ordinary least square-based model that may be used to represent both non-stationary and mixed order of integration time series. In a general-to-specific modelling framework, this model uses a suitable number of lags to reflect the data generation process. A simple linear transformation may be used to generate a dynamic error correction model (ECM) using ARDL. According to Pesaran and Shin (1999), a suitable ARDL model definition is enough to solve both the serial correlation and endogeneity problems. Another advantage of the ARDL technique is that each regressor can have a different number of delays. The ARDL approach, unlike other methods, may be employed both in the case of stationary times series I(0) or stationary in first differences I(1).

To test for the presence of a long-term relationship between prices of corn, cocoa, sugar and wheat and chosen Covid-19 indicators, we use the ARDL bounds test devised by Pesaran, Shin, and Smith (2001).

We tested the stationarity of time series using the Augmented Dickey-Fuller (ADF) test to ensure that none of the variables is integrated of order I(2) or higher. Akaike information criterion (AIC) was used to decide on the number of lags. After stationarity testing, the ARDL bounds testing approach was used to determine whether or not there is a long-term link. The general form of the ARDL model \((p, q, ..., q)\) is as follows:

\[
y_t = c_0 + c_1 t + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{i=0}^{q} \beta_i x_{t-i} + u_t
\]

(1)

where \(y\) is the dependent variable, \(x\) is the independent variable, \(p\) is the number of optimal lags of the dependent variable and \(q\) represents the number of optimal lags of each explanatory variable. The constant is \(c_0\) and the trend \(c_1t\). After reparameterization in the form of an error correction model we get:

\[
\Delta y_t = c_0 + c_1 t - \alpha (y_{t-1} - \theta x_t) + \sum_{i=1}^{p-1} \psi_{yi} \Delta y_{t-i} + \sum_{i=0}^{q-1} \psi_{xi} \Delta x_{t-i} + u_t
\]

(2)
where $\alpha$ expresses the rate of adjustment of the dependent variable to the short-term shock, $\theta$ represents the long-term and $\psi$ short-term coefficients. For a particular degree of significance, there are two types of critical values. The first type assumes that all of the variables in the model are I(1), whereas the second type assumes that all of the variables are I(0). If the estimated F-statistic exceeds the upper limit, the null hypothesis of no cointegration is rejected. The null hypothesis of no long-term link cannot be rejected if the computed F statistic is less than the lower limit, and the ARDL model should be estimated in the first differences without the error correction term. The conclusion is inconclusive if the F statistic is between these two thresholds (Pesaran et al., 2001).

We used the natural logarithms of all variables. The inclusion of natural logarithms in the model, according to Musa et al. (2020), enhances the linearity assumption, decreases the challenges of multicollinearity and heteroscedasticity, and makes the coefficients in terms of elasticity simpler to grasp. Finally, we used the Breusch-Godfrey LM test to check for residual serial correlation, the Engle ARCH-LM test to check for ARCH effects, and the Jarque-Bera test to check for normality at the end of our estimation.

The descriptive characteristics of the time series employed are shown in Table 1. Daily prices of corn, cocoa, sugar, and wheat were derived from investing.com\(^6\). Furthermore, we employed Covid-19 indicators to test for the influence of the Covid-19 pandemic on commodity prices: daily cases of newly infected patients, daily fatalities, panic index, media hype index, false news index, infodemic index, and media coverage index. The worldwide daily cases and new daily fatalities were gathered from ourworldindata.org\(^7\). The panic index, media hype index, false news index, infodemic index, and media coverage index data were gathered from ravenpack.com\(^8\). In addition, we included the economic policy uncertainty index (epu), and the financial volatility index (vix) in our models to control for the influence of financial and equity volatility and economic and policy uncertainty. Fred.stlouisfed.org\(^9\) provided information regarding daily epu. Finance.yahoo.com\(^{10}\) provided us with vix information. Moreover, we created a set of models for each of the four commodities to assess the impact of the Covid-19 pandemic. The variables considered for each model are listed in Table 2.

Table 8: Descriptive statistics of commodity prices and Covid-19 determinants

| Variable             | Obs | Mean      | Std. dev. | Min  | Max  |
|----------------------|-----|-----------|-----------|------|------|
| Sugar                | 462 | 15.24103  | 2.953629  | 9.21 | 20.7 |
| Corn                 | 462 | 467.9832  | 122.1897  | 302.75 | 772.75 |
| Wheat                | 462 | 618.1456  | 85.476    | 473.62 | 856  |
| Cocoa                | 462 | 2502.268  | 177.5869  | 2160 | 3054 |
| new cases            | 462 | 377687.9  | 230352.3  | 98  | 905842 |
| new deaths           | 462 | 7616.764  | 3903.593  | 1  | 18062 |
| panic index          | 462 | 2.41367   | 1.139167  | 0.61 | 7.1  |
| media hype index     | 462 | 30.00381  | 11.40348  | 6.21 | 60.11 |
| fake news index      | 462 | 0.6167532 | 0.3268111 | 0.08 | 1.9  |

\(^6\) https://www.investing.com/commodities/
\(^7\) https://ourworldindata.org/coronavirus
\(^8\) https://coronavirus.ravenpack.com/
\(^9\) https://fred.stlouisfed.org/series/USEPUINDXD
\(^{10}\) https://finance.yahoo.com/quote/%5EVIX/
3. Results and Discussion

Because the ARDL model required all variables to be stationary at their levels or the first differences, we used a unit root test\(^{11}\) to check the stationarity of time series in the first phase of our estimation. The results show that all the variables are stationary at their first differences at the 1\% significance level. According to the cointegration testing using the ARDL bounds test\(^{12}\), the findings for certain commodities significantly varied in different versions of the estimated models. T-stat and F-stat were employed to check if there was a cointegration between the variables. None of the commodity models for corn and wheat verified the cointegration link between Covid-19 determinants. In the case of cocoa, we found four models which verify the existence of the long-term relationship (Table 3). On the other hand, cointegration was verified in all models of sugar (Table 4).

3.1 Covid-19 determinants and cocoa prices

As seen from Table 3 the error correction terms are negative and highly statistically significant as desired. None of the Covid-19 factors had a long-term influence on the cocoa price in these models. Although, the coefficients of financial volatility are highly statistically significant and influence negatively cocoa prices in long run. Besides, financial volatility harms cocoa prices also in the short run. As a result, a rise in financial volatility leads to a drop in cocoa prices in the short and long term. Furthermore, the increase in newly infected patients causes a price drop in the short term.

\(^{11}\) The results of the unit root ADF test are available upon request from authors

\(^{12}\) The results of the ARDL bounds test are available upon request from authors
Table 3: ARDL estimates for cocoa

| Var.          | 1.1          | 1.2          | 1.5          | 1.6          |
|---------------|--------------|--------------|--------------|--------------|
| ECT           | -0.0450***   | -0.0454***   | -0.0438***   | -0.0425***   |
| new cases     | -0.0231      |              |              |              |
| new deaths    |              | -0.0258      |              |              |
| infodemic index| -0.1733      |              |              |              |
| media coverage index |              |              | -0.2396      |              |
| LR            |              |              |              |              |
| Vix           | -0.1919***   | -0.2139***   | -0.1815***   | -0.1737***   |
| LD.cocoa      | 0.00267      | 0.0214       | 0.0156       | 0.0151       |
| L2D.cocoa     | 0.09889***   | 0.1077***    | 0.1049***    | 0.1014***    |
| L3D.cocoa     | 0.0656584    | 0.0735       | 0.0750       | 0.0749       |
| D1.new cases  | -0.0082***   |              |              |              |
| LD.new cases  |              | -0.0017      |              |              |
| L2D.new cases |              | -0.0014      |              |              |
| L3D.new cases |              | -0.0037      |              |              |
| D1.new deaths |              | -0.0033      |              |              |
| LD.new deaths |              | 0.6000       |              |              |
| L2D.new deaths|              | 0.0012       |              |              |
| L3D.new deaths|              | 0.0001       |              |              |
| D1.infodemic index |              |              | -0.0163  |              |
| LD.infodemic index |              |              | 0.0095  |              |
| LD.media coverage index |              |              | -0.0169    |              |
| D1. media coverage index |              |              | 0.0044     |              |
| D1.vix        | -0.0245***   | -0.0224***   | -0.0222***   | -0.0226***   |
| LD.vix        | -0.0133      | -0.0124      | -0.0151      | -0.0151      |
| D1.epu        | -0.0023      | -0.0028      | -0.0041      | -0.0033      |
| LD.epu        | -0.0003      | -0.0011      | -0.0018      | -0.0013      |
| L2D.epu       | -0.0019      | -0.0018      | -0.0029      | -0.0023      |
| L3D.epu       | -0.0035      | -0.0037      | -0.0035      | -0.0033      |
| Constant      | 0.4688***    | 0.4684***    | 0.4620***    | 0.4730***    |

Source: Authors calculations in Stata

3.2 Covid-19 determinants and sugar prices

Cointegration was verified in all models with sugar (see Table 4). The error correction terms in all of these models are negative and highly statistically significant. The coefficients of new
daily cases and new daily fatalities are similarly statistically significant, implying that they have a long-term impact on sugar prices. Sugar prices rise in lockstep with the number of newly infected Covid-19 patients. A similar impact on sugar prices has also increased in deaths caused by the coronavirus. Furthermore, a rise in financial volatility leads to a long-term fall in sugar prices. Similarly, a surge in financial volatility leads sugar prices to decline in the short term. Similar results were obtained also by Kotyza et al. (2021). Additionally, sugar prices are largely impacted by previous developments in the short term. The Covid-19 media coverage index, on the other hand, has a short-term impact on sugar prices. When the amount of publicity in the media grows, so does the price.

Table 4: ARDL estimates for sugar

| Var.            | 1.1   | 1.2   | 1.3   | 1.4   | 1.5   | 1.6   | 1.7   |
|-----------------|-------|-------|-------|-------|-------|-------|-------|
| ECT             | -0.0480 | -0.0308 | -0.0498 | -0.0435 | -0.0446 | -0.0492 | -0.0427 |
| ***             |       |       |       |       |       |       |       |
| new cases       | 0.0446*** |       |       |       |       |       |       |
| new deaths      | 0.0494 |       |       |       |       |       |       |
| panic index     |       | 0.1802 |       |       |       |       |       |
| media hype index|       |       | 0.1661 |       |       |       |       |
| infodemic index |       |       |       | 0.3496 |       |       |       |
| media coverage index |       |       |       |       | 0.4819 |       |       |
| fake news index |       |       |       |       |       |       | 0.2244 |
| Epu             | -0.0954 | -0.0829 | -0.0191 | -0.0830 | -0.0769 | -0.0571 | -0.0936 |
| Vix             | -0.4515 | -0.5297 | -0.9360 | -0.7586 | -0.8000 | -0.7608 | -0.7492 |
| ***             |       |       |       |       |       |       |       |
| SR              |       |       |       |       |       |       |       |
| LD.sugar        | -0.4911 | -0.5013 | -0.5155 | -0.5105 | -0.5120 | -0.5013 | -0.5080 |
| ***             |       |       |       |       |       |       |       |
| L2D.sugar       | -0.2950 | -0.2996 | -0.3086 | -0.3038 | -0.2987 | -0.2954 | -0.3048* |
| ***             |       |       |       |       |       |       |       |
| L3D.sugar       | -0.1334 | -0.1380 | -0.1425 | -0.1401 | -0.1417 | -0.1394 | -0.1422 |
| ***             |       |       |       |       |       |       |       |
| D1.new cases    | 0.0076 |       |       |       |       |       |       |
| L.D.new cases   | -0.0051 |       |       |       |       |       |       |
| L2D.new cases   | 0.0014 |       |       |       |       |       |       |
| L3D.new cases   | -0.0005 |       |       |       |       |       |       |
| D1.new deaths   | 0.0023 |       |       |       |       |       |       |
| Variable                  | Value         |
|--------------------------|---------------|
| LD.new deaths            | 0.0008        |
| L2D.new deaths           | 0.0014        |
| L3D.new deaths           | 0.0028        |
| D1.panic index           | -0.0107       |
| LD.panic index           | -0.0095       |
| L2D.panic index          | 0.0033        |
| L3D.panic index          | 0.0014        |
| D1.media hype index      | -0.0314       |
| LD.media hype index      | -0.0024       |
| L2D.media hype index     | 0.0156        |
| L3D.media hype index     | -0.0294       |
| D1.infodemic index       | 0.0817        |
| LD.infodemic index       | 0.0136        |
| LD.media coverage index  | 0.2328        |
|                         | ***           |
| D1.media coverage index  | -0.0889       |
| LD.fake news index       | -0.0107       |
| L2D.fake news index      | -0.0117       |
| L3D.fake news index      | -0.0043       |
| D1.vix                   | -0.0634       |
|                         | ***           |
|                         | ***           |
|                         | ***           |
|                         | ***           |
|                         | ***           |
|                         | ***           |
| LD.vix                   | -0.0520       |
|                         | ***           |
|                         | ***           |
|                         | ***           |
|                         | ***           |
|                         | ***           |
|                         | ***           |
| D1.epu                   | 0.0079        |
|                         | 0.0066        |
|                         | 0.0022        |
|                         | 0.0051        |
|                         | 0.0052        |
|                         | 0.0054        |
|                         | 0.0062        |
| LD.epu                   | 0.0104        |
|                         | 0.0094        |
|                         | 0.0055        |
|                         | 0.0086        |
|                         | 0.0075        |
|                         | 0.0071        |
|                         | 0.0090        |
4. Conclusion

The purpose of this study is to add to the discussion on the influence of Covid-19 on the development of commodity prices. We focused on agricultural commodity prices as there is a gap in the literature that focuses on agricultural commodity markets. Daily observations of corn, cocoa, sugar, and wheat prices, as well as several Covid-19 indicators, including new daily cases of covid positive patients, daily fatalities, panic index, media hype index, false news index, infodemic index, and media coverage index, were used. Economic policy and financial market uncertainty were also taken into account.

In the case of corn and wheat, we found out that there is no cointegration link between the price and pandemic determinants. In the case of cocoa, only financial volatility has an impact on cocoa prices in the long and short run. When the financial volatility increases the sugar prices fall in both periods. Besides, the increase in newly infected patients causes a price drop of cocoa in the short term as well. In contrast, the cointegration relationship was verified in all models of sugar. Sugar prices climb in lockstep with the number of Covid-19 patients that are newly infected as well as deaths due to coronavirus. Furthermore, an increase in financial volatility causes sugar prices to fall over time. Sugar prices are heavily influenced by recent developments in the short term. The Covid-19 media coverage index has also a short-term influence on sugar prices. As the degree of media attention rises, so does the sugar price.

Given that the Covid-19 pandemic is still ongoing, there is room for additional study based on more up-to-date data as time progresses. Besides, commodity prices react to shifting economic conditions produced by the pandemic scenario. Thus, this makes commodity price data analysis during Covid-19 more difficult and necessitates more attention from academics and policymakers for further research.

Acknowledgements

This publication was supported by the Operational Program Integrated Infrastructure within the project: Demand-driven research for the sustainable and innovative food, Drive4SIFood 313011V336, co-financed by the European Regional Development Fund and by the Slovak Research and Development Agency under contract No. APVV-18-0512.

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