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Research on World Agricultural Economy
https://journals.nasspublishing.com/index.php/rwae

RESEARCH ARTICLE

The Painful Double-Knock on Food Prices: 2008 Financial Crises and COVID-19 Pandemic

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ABSTRACT

Food supply and demand chains are susceptible to global shocks. Unstable and sudden food price hikes cause serious malnutrition problems and increase the number of food-insecure people, especially in developing countries. Using the FAO Food Price Index (FFPI), this study makes one of the first attempts to utilize monthly observations of the FFPI in dynamic time series ARDL and ARX settings to identify the effects of food prices on COVID-19 infection rates and the 2008 global financial crisis. Our empirical findings confirm that the financial crisis significantly increased the FFPI, although its effects decreased as markets equilibrated between 2007 and 2009. The pandemic has had a mild impact on food prices in the short run compared to the 2008 crisis, but in the long run, the COVID-19 outbreak has a larger impact, with 1 million new COVID-19 infections associated with an increase of between 0.0464 and 0.0509 points in the FFPI. Food price volatility and hikes, even if short-term, increase poverty, malnutrition, and food insecurity, foster social unrest, and lower people's living standards. This research implies that food prices are globally sensitive to both pandemics and financial crises, and the severity of the pandemic can drive

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ARTICLE INFO
Received: 18 July 2024 | Revised: 14 August 2024 | Accepted: 21 August 2024 | Published Online: 29 September 2024
DOI: https://doi.org/10.36956/rwae.v5i4.1179

CITATION
Riveros, J.M., Oduniyi, O.S., Hassan, S.M., 2024. The Painful Double-Knock on Food Prices: 2008 Financial Crises and COVID-19 Pandemic. Research on World Agricultural Economy. 5(4): 81–93. DOI: https://doi.org/10.36956/rwae.v5i4.1179

global food prices higher, depending on the number of infections. Over the long run, the impact of the outbreak surpasses that of the financial crisis. The latter tends to have a major impact on food prices in the short run but subsequently declines as markets begin to equilibrate, reflecting asymmetries between the two phenomena in their effects on food prices. Overall, the results indicate that the financial crisis and the COVID-19 pandemic had a short-run, immediate, augmenting impact on food prices. However, while the 2008 crisis affected the supply side only, COVID-19 had impacts on both the demand and supply sides.

Keywords: COVID-19; Food Price Index; ARDL; Global Shocks; Global Financial Crises

1. Introduction

While live counts of COVID-19-related human losses are published as real numbers across many sources and can be easily traced, the damage toll of the pandemic on the global economy and social systems is, by contrast, unclear, pervasive, and hard to quantify. Since the Coronavirus (SARS-CoV-2) outbreak in January 2020, every country has aspired to curb the uncontrolled spread of the deadly disease and mitigate its adverse socio-economic effects and the ensuing hardship on people's livelihoods [1–4].

Demand shocks and supply chain disruptions arising from global trade restrictions, travel limitations and drastic changes in consumption patterns have all increased volatility in import, export, producer and consumer prices. While most businesses were completely shut down following government prevention policies, food suppliers and retailers remained operational [5]. The COVID-19 pandemic has had long-lasting effects on the food supply chain as it adapted to supply chain disruptions, met increased market demand, applied protective measures for its workforce, and maintained quality and safety standards to protect people's lives [6–13].

The FAO Food Price Index (FFPI) measures the monthly change in international prices of a basket of five food commodities. The average export share of each group weighs the average prices. The FFPI hit a three-year high in 2020, driven by additional gains in December 2019. In general, commodity food prices have unexpectedly increased over the last 20 years, particularly between late 2006 and mid-2008, after several decades of relative stability and low levels [14]. Starting in 2006, there has been a global surge in food prices, rising by 27% in 2007 as the financial crisis loomed. This rise in 2006 is attributed to low investment and fund activities, adverse weather conditions, and a set of fiscal conditions across the world [15, 16]. This is also associated with a shift in investor preferences toward energy commodities, which dominated food commodity prices. The phenomenon of "financialization" is evident, as noted by Baffes and Wu [15], as well as Manogna et al. [17], where the agricultural sector's supply chain suffered from the "boom" in energy-related commodities. As investment decreased in the primary sector, production costs increased, and restrictive government policies further reduced the supply side. The supply chain became vulnerable as international investors' preferences shifted away from developing economies [15], creating a supply shock that increased costs due to the financialization of commodities [17], and also reduced the availability of credit and loans. The agricultural sector's supply chain became vulnerable to the financial crisis.

The deteriorating financial positions and global macroeconomic pressures have strained the world economy, amplifying the adverse impact of volatile and above-average food prices, especially on developing and poor nations [16, 18]. Between 2008 and 2010, the number of food-insecure people increased by 13% in Asia [19].

It is widely perceived that the COVID-19 pandemic has caused a global increase in the FFPI. According to Zurayk [20], there has been a global price increase in the food basket of 20% to 50%, caused by COVID-19, resulting from disruptions, temporary shortages, hoarding, and profiteering along the retail value chain. Concurrently, the farmers' inability to sell food produced during the pandemic lockdown also contributed to FFPI hikes. Similar to the 2007–2008 food price shock, the increase in commodity food prices on international markets was transmitted to the domestic market.

The impact has led to instability in domestic producer prices, particularly in the food sector. For example, to limit the spread of the virus, many countries instituted lockdown restrictions. During these restrictions, restaurants were not permitted to open, or if they were, only for limited hours before curfews began. Consequently, shelter-in-place orders led to food rushes and hoarding universally. Accordingly, demand for food from restaurants decreased relative to takeout and deliveries. Many food suppliers and factories were forced to close due to the severe impact of the pandemic [9].

Farmers were compelled to sell their harvests at lower prices to avoid dumping their products, even as input costs increased due to trade restrictions and labor shortages [10]. The effects of the lockdown disrupted the entire food supply chain, pushing up and destabilizing food prices [21, 22]; global food prices have risen for three consecutive months since August 2020, primarily influenced by firm demand, weak currencies, and trade-restrictive measures implemented by several countries to build up food reserves. Fan et al. [23] reported that the impact of COVID-19 on food prices is heterogeneous across different regions and products, with only a minor impact seen overall. The largest disruptions in food production and pricing have occurred in less-developed areas and regions where food is highly dependent on imports [24]. Coluccia et al. [9] showed that Italian agri-food exports have decreased as a direct consequence of the pandemic. While some countries still have adequate food reserves for the short term, prolonged pandemic conditions could lead to rising food insecurity [11, 25].

According to the the World Bank [26], the food price index increased by 13% between April and October 2020 due to the pandemic, and it is expected to rise an additional 1.5% in 2021. Mead et al. [27] showed that the Producer Price Index (PPI) decreased by 0.1% between March and June 2020. Zhang et al. [28] reported that agricultural output falls by 0.016% when the incidence rate of epidemics rises by 1%. It is projected that COVID-19 will reduce China's agricultural growth rate by 0.4% to 2.0% in 2020 under different scenarios.

It should be noted here that the impact of the COVID-19 pandemic on food prices lacks robust empirical evidence in the economic literature, creating a gap for further investigation. This study makes one of the first attempts to utilize monthly observations of the FFPI in a dynamic time-series approach, based on the Auto-Regressive Distributed Lag (ARDL) and Auto-Regressive with Exogenous variables (ARX) models, to identify the impact of COVID-19 incidence rates compared with the 2008 global financial crisis on the FFPI. Against this backdrop, it is worthwhile to engage in a comparative study of the impact of the 2008 global financial crisis and COVID-19. This study is relevant because it provides empirical evidence of the relationship between the COVID-19 outbreak and global food prices, and also compares the severity of this impact with that of the 2008 financial crisis.

The novelty of this research lies in providing a comparative study within the empirical literature that measures the impact on food crises from both phenomena, offering insights to policymakers about the reactions and asymmetries of food prices in response to financial crises and potential uncontrolled pandemic outbreaks. This differentiates the research from other studies that focus on countries [10] by examining their local commodity prices using interrupted time series analysis, or environmentally focused studies [11, 12, 29] that analyze specific geographic locations using descriptive statistics and focus on supply changes by manufacturers or industrial characteristics. More importantly, our study relies on dynamic time series modelling primarily for its econometric tractability and focus on non-spurious multivariate regressions.

The next section of the study presents the methodology used for the empirical estimations, followed by a discussion of the stylized facts about the behavior of the FFPI, COVID-19, and the financial crisis period within the analysis sample. The results are then presented, followed by a section on discussion and policy recommendations. The final section concludes the research.

2. Methodology

Our methodology is based on the specification of ARX and ARDL models to perform empirical analysis on the FFPI, which is a world average available monthly. The ARX and ARDL models were chosen over other econometric techniques because of their practical application in analyzing time-series dynamics [30] and their ability to avoid spurious relationships through the analysis of cointegration [31], which is interpreted as long-run dynamics. These models are also flexible, allowing for the inclusion of different multivariate frameworks, such as dummy variables representing shocks, and structural time series breaks with linear trends [32]. This is advantageous considering that panel data approaches are restricted to specific countries with data available before and after COVID-19, which is not easily accessible and often exists in different periods. Finally, given the primary focus on establishing global responses to COVID-19 and comparing these with the 2008 financial crisis's impact on the FFPI, time-series models enhance the ability to easily comprehend their dynamics.

The empirical specification follows a dynamic time series model (using dynamic specifications with focus on the long-run properties of econometrical models in comparison with the error correction models) with exogenous variables defined as an ARX model of the following linear form:

$$y_t = \alpha + \sum_{t=1}^{p} \beta_p y_{t-p} + \gamma_1 x_t + \gamma_2 D_i + \gamma_3 (D_i * T) + \delta T + e_t \quad (1)$$

where: y_t is the real FAO Food Price Index (FFPI); t is a month, y_{t-p} is the set of lagged dependent variables configuring the autoregressive signal structure from the previous values of the FFPI; x_t is the exogenous variable of COVID-19 world total cases of infections; D_i is dummy variable capturing the duration of the financial crisis of 2008–09 in months with a linear time trend T, with α as the autonomous coefficient of the model, with β, γ, and δ parameters to be estimated. By performing the hypothesis testing over the parameters, the influence and the relationship over the FFFPI can be tested empirically. (The financial crisis dummy variable takes in account the negative returns of the stock market of the Dow Jones as a measure/proxy of the crisis of 2008–09 in the following form:

$$D_i = \{ \begin{matrix} D = 1 \ \ for \quad r_t < 0 \\ D = 0 \ \ for \quad r_t > 0 \end{matrix} \quad (2)$$

where: for t restricted to 2007 < t < 2010, returns are defined by the performance of the stock market:

$$r_t = \frac{s_t - s_{t-1}}{s_{t-1}} \quad (3)$$

Where: s_t is the closing price of the Dow Jones Stock Market, and for values of t < 2007 and t > 2010, the dummy variable is equal to 0.)

The specification of the model in Equation (1) determines special importance in the observed signals overtime of the dependent y_t, where these signals also includes unobserved factors of the past which influence the present behavior of the variable, this concept leads to the use of autoregressive processes. These autoregressive signals are treated as explanatory variables capturing the influence of the time series history of the variable itself to explain the present state of the variable at time t. The rest of the variables defined in x and D are treated as independent exogenous factors in comparison to the endogenous signals.

In essence, the above model is an autoregressive distributed lag (ARDL) model expressed as follows:

$$y_t = \alpha + \delta T + \sum_{t=1}^{p} \beta_p y_{t-p} + \sum_{t=0}^{q} \gamma_q x_{t-q} + e_t \quad (4)$$

where: the exogenous regressors $\gamma_2 D_i + \gamma_3 (D_i * T)$ can be included in the specification of the ARDL to estimate long-run relationships (or cointegration) for the variables integrated of first order I(1) [33]. (To provide an empirical example of the long-run properties for variables, Pesaran, Shin and Smith [33] included several dummy variables in the specification of the determinants of wages for the UK in their study. The inclusion of the interaction term should be considered as a time-varying factor where the sole point is to delete a possible spurious unit-root behavior in the regressions. It is important to highlight that first-order integration implies a process which contains unit-roots in levels but at first differences become stationary. The intuition behind this according to Engle and Granger [34] is that a linear combination with non-stationary variables $y_t, x_t \ I(1)$ will produce stationary residuals $e_t \ I(0)$ if they are cointegrated over the long run (or in other words, variables will have a long-run relationship), so the linear combination will produce consistent, non-spurious results.

As a robustness check for the exogenous regressors in the estimates of Equation (1) and in comparison with the traditional ordinary least squares (OLS) estimator, a proposed alternative estimator is the robust regression approach. Authors like Berk[35], Nurunnabi et al.[36] and Mays et al.[37] identified several advantages to account for the bias and well-known inadequacies of the traditional OLS estimator in the context where the residuals u are not normally independently and identically distributed (normal *i.i.d.*). Robust regression outperforms the traditional OLS regression by weighting the residuals to overcome potential problems of outliers (atypical values) and abnormal observations. Tofallis[38] used percentages to the errors (a weighted conversion of the residuals) to overcome heteroskedasticity which is considered a robust regression approach. Rousseeuw and Leroy[39] discussed the importance of robust estimators derived from the robust regression approach as an alternative to the least squares method. Robust estimators in contrast can reduce bias and provide more accurate statistical inference.

The process to estimate the robust regression requires that we define the individual time period residual (or error) as:

$$e_t = y_t - \alpha + \sum_{t=1}^{p} \beta_p y_{t-p} + \gamma_1 x_1 + \gamma_2 D_i + \gamma_3 (D_i * T) + \delta T \tag{5}$$

The estimates of the parameters are determined by minimizing the residuals with a particular objective function of the form of:

$$\begin{aligned} \sum_{t=1}^{T} \rho\left(e_t\right) = \sum_{t=1}^{T} \rho\big[y_t - \alpha + \sum_{t=1}^{p} \beta_p y_{t-p} \\ + \gamma_1 x_1 + \gamma_2 D_i + \gamma_3 (D_i * T) + \delta T\big] \end{aligned} \tag{6}$$

where: ρ is the function which establishes the contribution for each residual at each time to the objective function, according to Fox and Weisberg[40], the contribution is positive, implying $\rho\left(e_t\right) \geq 0$, $\rho(0) = 0$, and $\rho\left(e_t\right) = \rho\left(-e_t\right)$. By defining the set of contributions as the influence curve $\phi = \rho$' calculated as the derivative of ρ, we can solve a model with a robust solution to the problem with a weighting function:

$$w\left(e_i\right) = \frac{\phi\left(e_i\right)}{e_i} \tag{7}$$

The weights at each time period residual are determined by $w_i = w\left(e_i\right)$. This is a process where the contribution of a weighted residual allows for the correction of potential biases from the original residuals improving the estimates. From this point, we selected the estimator proposed by Huber[41] and the bi-weight estimator described by Beaton and Tukey[42] as robust measures in comparison to OLS. We performed diagnostics tests of the residuals by checking the linear assumptions of correct specification withspecification test from Ramsey[43]. The omitted variables bias and absence of serial correlation were confirmed with tests outlined by Breusch[44] and Godfrey[45], respectively. We also tested for the stability of the parameters (time-invariant parameters) for the linear regression coefficients using the based cumulative sum of the residuals[46]. Homoscedasticity and stationarity were tested using tests of Breusch[47] and Engle and Granger[34]. Finally, the bound test of cointegration (test of long-run dynamics and non-spurious regressions) from Pesaran, Shin and Smith[33] is applied to the ARDL estimates. The assumptions mentioned were satisfied in the estimations, and they provide evidence of a non-spurious relationship that emerges between COVID-19 and the financial crisis indicators over the FFPI.

3. Stylized Facts

The variables' descriptive statistics are reported in **Table 1**. FFPI monthly observations from January 1990 to November 2020 are sourced from FAO[18]. World total cases of COVID-19 are obtained from ECDC[48].

The behavior of the financial crisis of 2008–2009 can only be followed by shocks in the financial market indices (**Figure 1**). Although imperfectly, as a measure of this crisis, we use the Dow Jones industrial average returns. It is sensitive to worldwide financial shocks and can be used to trace durations of severe hits of stock market returns. This index also imperfectly captures the "financialization" of commodities as a result of the ruptures in the stock markets. Until November 2019, there was no influence of COVID-19, and **Figure 1** only reflects the changes in the index during the period of the financial crisis.

The FFPI shows an increasing trend in the period associated with the financial crisis (**Figure 2**). The association marks a new pattern in the prices from 2008, which remained unstable over time in particular for de-

Table 1. Descriptive statistics: Food Price Index and Covid-19 world total cases.

Stats	Food Price Index	Δ Food Price Index	Covid-19 World Total Cases	Δ Covid-19 World Total Cases
N	371	370	371	370
Min	64.39435	−14.7627	0	0
Max	129.3471	7.793537	5.77e+07	1.20e+07
Mean	88.3028	0.07788	539798	155962.1
P50	84.6699	0.0901895	0	0
Sum	32760.34	28.81559	2.00e+08	5.77e+07
Coef. Variation	0.1781714	31.04671	8.367651	7.42327
Standard Dev.	15.73303	2.417917	4516841	1157749
Variance	247.5283	5.846322	2.04e+13	1.34e+12

Source: Own calculations.

veloping economies[17]. From 2006 it is visible that prices were already increasing, potentially due to the change in the preferences of the investors towards energy commodities, joined with policy restrictions, export bans with protective taxes[15], and the beginning of the "financialization" of the food commodities[17].

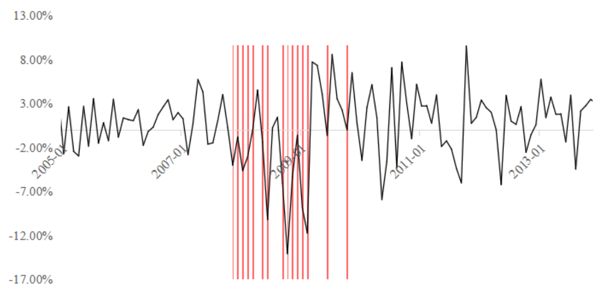

Figure 1. Financial crisis of 2008–2009 proxied by the Dow Jones industrial average returns.

Note: The vertical lines represent the financial crisis proxied by the dummy variable to represent the negative returns of the Dow Jones stock market between 2007 and 2010. Using this approach, a total of 15 months has been identified where the financial crisis has significantly decreased the returns of the stock market.

Source: Investing (2020).

Figure 2. Food Price Index time series.

Note: The red vertical lines represent the financial crisis proxy by the dummy variable. The blue square represents the COVID-19 influence.

Source: FAO (2020).

It is important to witness that in the second half of 2008, the FFPI decreased, potentially implying a reversion to the equilibrium once the financial crisis emerged. It is also important to remark that the Dow Jones index decreased in 2008 to its lowest value in 2002, −28.56 %. The returns show the process through which the index tried to recover during the crisis (for example in 2009, the return was 18.52%), but the volatility indicated ongoing decreases in the returns value of the stock market during the crisis.

Figure 3 shows the positive and exponential increasing trend in total COVID-19 incidences. As of November 2021, and only after 1 year of the pandemic outbreak, more than 57 million cases were globally reported.

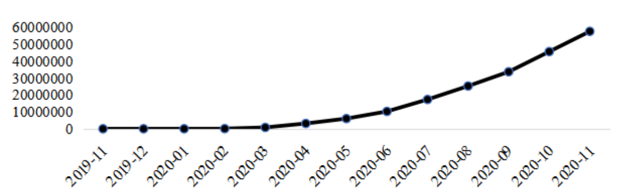

Figure 3. Covid-19 world total cases.

Source: ECDC (2020).

4. Results

The unit-root analysis in **Appendix A** (see **Table A1**) confirms the non-stationarity of real FFPI and the world total cases of COVID-19 in levels (see **Table A2**) but the series are integrated of first-order I(1). By performing the regressions of the model in Equation (1) and also the ARDL transformation, we have found evidence of cointegration according to the traditional Engle and Granger residual-based test with a 5% level of significance and the bound testing procedure [29] with a 10% level of significance (see **Table B2**). Engle and Granger's residual-based approach (see **Table B1**) indicates a stronger and more statistically significant long-run relationship between the variables in comparison to the bound testing procedure of Pesaran, Shin and Smith.

The results of the ARX model (see **Table C1**) and the ARDL (see **Table C2**) in short and long-run forms are presented in Appendix C. The OLS estimates (see **Table C1**) do not differ significantly from the robust regression with the bi-weight estimator of Beaton and Tukey. According to the ARX model and the short-run ARDL (see **Table C2**), COVID-19 has a positive and significant impact on the real FFPI. An increase of one million cases pushes FFPI up with 0.0464 points at the 95% confidence level. Following the same logic, one hundred million new infections cause an overall increase in FFPI by 4.64 units. The results remain the same as we shift to the robust regression methodology. Yet the numbers change slightly: an increase of one million new COVID-19 infections causes an increase of 0.0509 points to FFPI.

In comparison, the financial crisis of 2007-09 proxied by the dummy variable, Dow Jones monthly returns, shows a stronger impact on FFPI by 110.7 points at the 95% confidence level. The results consider 15 inconsecutive months from October 2007 (when the Dow Jones started to react to the financial crises) and November 2009. According to the estimations, FFPI recorded a monthly average reduction of 0.189 units. The robust regression results indicate a higher impact of the financial crisis variable on FFPI, wherein an initial increase of 128.2 units was associated with peak months of crises, followed by a gradual monthly decrease of 0.219, both significant at 99% confidence level.

The results of the short-run ARDL about the impact of the exogenous variables model are not different in comparison to the ARX model. Therefore, it is concluded that the FFPI effects of the COVID-19 and financial crises are nearly the same in the short-run. The inclusion of the error correction term to capture long-run dynamics does not change the impact of the variables on FFPI. The correction term is negative and significant with a value between zero and one, indicating a stable relationship over the long run. The adjustment speed towards long-run equilibrium is around 3.6% each month; this strongly indicates a significant long-term higher impact of the financial crisis on FFPI relative to COVID-19. This result might be erroneous due to: 1) possible misspecification in the cointegration form of the static long-run equations [49], and 2) the FFPI long-run effects of COVID-19 need to be treated cautiously, as the pandemic started at the beginning of 2020, and it is still early to claim conclusive evidence about its long-term effects.

5. Discussion and Policy Recommendations

Based on our primary results, it is evident that both the COVID-19 pandemic and the 2008–09 financial crisis led to significant increases in world average food prices, as measured by the monthly FFPI indicator. The effects were asymmetrical in both time and magnitude. In the short term, the financial crisis had a more substantial impact on the FFPI, raising it by about 110.7 to 128.2 units when the financial crisis started (proxied by the negative returns of the Dow Jones starting in 2007). However, this major shock began to gradually reverse each month by an average of 0.189 to 0.219 units on the FFPI, suggesting a return to market equilibrium. This pattern contrasts sharply with the impact of COVID-19 on the FFPI, where price increases were closely tied to the continually rising total number of confirmed infections worldwide.

Considering the information available up to October of 2023 of the Coronavirus Resource Center [50] the infections reached a total count of 676.6 million people, which according to our estimations implies a positive shock over the FFPI between 127.88 and 148.18 according to the econometrical models. Over the short-run, the effect is greater from the financial crisis, but over the long-run the COVID-19 pandemic surpasses it.

There are several reasons which can explain this behaviour. COVID-19 has been reported to affect the first sector of the economies across the world [10]. This situation led to a rupture in the entire agricultural supply chain. First, a shortage of labor started to emerge as COVID-19 was propagated by direct contact, and then the producers had to face an increase in the costs of inputs of the sector. The lockdowns and social distance policies restricted the production and trade of the agricultural chain. The food industry inside the primary sector (like the rest of the sectors) began to shrink, increasing the overall prices; whereas the demand during the outbreak was likely increased due to rational expectations and survival [51, 52]. This coincides with the arguments of Kawakatsu et al. [10] for Ghana, where the mass quarantines, prevention measures and transportation problems derived from exacerbating food insecurity are reflected in significant increases in prices. These results also align with the findings of Lufkin [21], where the output of the agricultural sector decreased. More importantly, the situation presented by Maqbool, Farhan and Qamar [11] is confirmed, and this relates to the increase in prices and negative impact on the agricultural output. In this scenario, COVID-19 can be interpreted as an exogenous shock influencing both the costs of production and the lack of technologies to overcome productivity shutdowns.

Turning the discussion to the financial crisis, it is clear that over the short-run the impact on the food prices is quite significant, this is explained by the shocks which deviate the market equilibrium in the financial markets and affect the real market economy. This result coincides with the findings of Manogna et al. [17], where in the BRICS countries, increased price volatility threatened the food security. The phenomena of "financialization of agricultural commodities" started to emerge, affecting the average price of food worldwide due to the financial crisis.

Our policy recommendation related to the outbreak of pandemics is to promote subsidies from the public sector to the agriculture sector in the short run. The studies from subsidies in Uganda [53] reflected that financial support for the producers of the agricultural sector can alleviate the effects of the COVID-19 outbreak. In particular, this result holds for the farm producers who managed to have positive production and increases in their income from agricultural activities compared to those farmers who did not get any subsidy or support from the government. Local government intervention is crucial to maintain the equilibrium in the supply side of agriculture. This is proven to reduce the time of recovery from the economic consequences of COVID-19. Over the long run, as shown in the econometrical estimations, the pandemic can contain greater consequences in food prices. Therefore, investment in health research and development must be a common goal across nations [54]. When the research for health, and development has a fixed or increasing budget from the government, the likelihood to respond adequately towards biological outbreaks increases.

Regarding the recommendations for the impact of the financial crises on food prices, markets must contain a form of regulatory scheme when food security is vulnerable. In particular, Manogna et al. [17] highlighted that developing economies tend to suffer from the "financialization" of the commodities, subject to the rules of financial markets including speculation. The volatility that emerges in the financial markets affects the stability of the real market production, which is a motive to promote strict and clear rules about the prices in agricultural markets, particularly for those that can threaten food security.

6. Conclusions

This research contributes to the existing literature strand on COVID-19 socioeconomic effects. As the pandemic is far from over, the damage toll is growing, in particular for poor and vulnerable people and nations. Health crises are getting more frequent, and assessing their ensued effects on global supply chains and demand patterns is inevitable. Understanding how the pandemic, in comparison with the 2008 Financial crisis, has affected global food prices is required to unfold and solve some of the current pandemic, as well as possible future crises and expected adverse effects. Veritably, food inflation constitutes a major component in general rates of inflation in developing and developed countries. Food price volatility and hikes, even if short-term, increase poverty, malnutrition and food insecurity, foster social unrest and dampen people's living standards. Our empirical results show that, over the short run, the current pandemic has lifted food prices, wherein 1 million new infection cases are associated with an increase of 0.0509 points in FFPI. However, it should be noted that COVID-19 resulted from both the demand and supply side; while the 2008 crisis resulted from the supply side only. The overall results indicate that both the financial crisis and the COVID-19 pandemic have had a short-run immediate augmenting impact on food prices. Over the long run, COVID-19 represented a major shock in comparison to the financial crisis of 2008, as 676.6 million infections took place up to October of 2023 considering the data of Brown et al.[46] drastically increasing the FFPI. The asymmetries from our empirical results imply that the shocks from the financial crisis are larger only in the short-run compared to the COVID-19 outbreak, but over the long run these change dramatically given the number of infections, harming the supply and demand sides of the food production, elevating the price over the long-run, yielding in more damage to the welfare. In contrast, the financial crisis has a pattern of recovery towards the equilibria which reduces and normalizes the impact on the FFPI over time.

This research can be extended by using other econometrical approaches, including vector-auto regressions with potential cointegration, the development of structural vector autoregression models, and if data availability allows, the use of panel data frameworks with common periodicities. In particular, if stable data of the food prices index can be acquired worldwide, along with other econometrical controls, it is possible to perform panel vector autoregressions. Similarly, if panel data is available, a dynamic stochastic general equilibrium model can be formulated, which can shed light on the dynamics of the response of the agents and the damages in the output of the economy.

Author Contributions

Oduniyi and Riveros did the conceptualization. All authors did the write-up. Riveros explored the data. Riveros and Oduniyi did the data analysis. Hassan did the conclusion part. All authors did the editing. All authors read through and agreed on the submission.

Funding

The authors received no funding for this study.

Data Availability

All data and materials are available on request.

Acknowledgements

The authors acknowledge the efforts of the reviewers and editor for their valuable suggestions to improve this manuscript.

Conflicts of Interest

All authors declared that there is no conflict of interests.

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Appendix A. Unit Root Tests

Table A1. Ideal lag selection for Food Price Index and Covid-19 world total cases.

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	−1532.76				249.751	8.35834	8.36257	8.36898
1	−844.391	1376.7	1	0.000	5.89796	4.61248	4.62094	4.63377
2	−824.564	39.654	1	0.000	5.32285	4.50989	4.52257	4.54181*
3	−822.048	5.032*	1	0.025	5.27906*	4.50162*	4.51854*	4.54419
4	−821.864	0.36848	1	0.544	5.30258	4.50607	4.52721	4.55928

Note: Selection-order criteria, Sample: 1990m5–2020m11, Number of obs = 367.

Table A2. Augmented Dickey-Fuller Test of unit-roots.

Variable	Z-Statistic	5% Critical Value	P-Value	Decision
Food Price Index	−2.166	−2.875	0.2189	Unit-root
Δ FoodPriceIndex	−8.619	−2.875	0.0000	Stationary
Covid Total Cases	4.648	−2.875	1.0000	Unit-root
Δ Covid Total Cases	−24.004	−2.875	0.0000	Stationary

Note: The symbol Δ represents the first difference operator. The tests are presented with the normal ADF specification, the specifications with trend, no constant, drift have as a result the same decision. The test is evaluated at ideal lag = 3 for the variables in levels and lag = 2 in first differences.
Source: Own authors.

Appendix B. Cointegration Tests

Table B1. Engle and Granger Residual-based test of cointegration (stationarity of the residuals).

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	−19.201	−5.858	−5.297	−5.005

Note: Engle-Granger test for cointegration has as a null hypothesis the statement of H0: No cointegration (Residuals are not stationary), against H1: Cointegration (Stationary Residuals), critical values from MacKinnon. In this case we strongly reject the null hypothesis of no cointegration, thus we accept the alternative hypothesis that the series are cointegrated given the stationary behavior of the residuals with a 1% level of significance.
Source: Own calculations using Stata 16.

Table B2. Pesaran, Shin and Smith Bounds testing procedure.

Confidence Level of Critical Values	10%		5%		1%		p-Value	
Integration Order	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
F	3.177	4.127	3.813	4.843	5.208	6.387	0.005	0.019
t	– 2.565	– 3.215	– 2.863	– 3.534	– 3.441	– 4.140	0.016	0.087

Note: H0: no level relationship, Selected Case 5: Unrestricted Intercept, Unrestricted time trend, assumed to be exogenous the interaction term with the linear time trend in the ARDL model, the above table presents the Kripfganz and Schneider critical values and approximate p-values.
Source: Own calculations using the Stata package of Kripfganz and Schneider.

Appendix C. Regression Outputs

Table C1. OLS and robust regression of the ARX model.

Variables	OLS FoodPriceIndex	Robust reg FoodPriceIndex
L.FoodPriceIndex	1.245***	1.249***
	(0.0521)	(0.0439)
L2.FoodPriceIndex	−0.163*	−0.142**
	(0.0834)	(0.0703)
L3.FoodPriceIndex	−0.118**	−0.131***
	(0.0531)	(0.0447)
Covid_total_cases	4.64e−08*	5.09e−08**
	(2.68e−08)	(2.26e−08)
D	110.7**	128.2***
	(53.11)	(44.73)
Trend	0.00338**	0.00192
	(0.00157)	(0.00132)
D*Trend	−0.189**	−0.219***
	(0.0910)	(0.0766)
Constant	1.338*	1.123*
	(0.729)	(0.614)
Observations	368	368
R-squared	0.980	0.986
Prob > F	0.0000	0.0000

Notes: OLS regression and robust regression of Equation (1) are done without the ARDL short and long-run forms, which is equivalent to a short-run model. Slightly different results can be seen in most of the parameteres, where the R-squared of the robust regression is higher.
Source: Own calculations.

Table C2. ARDL model regression.

Form of the Model:	ARDL: SR		ARDL: LR
Variables	**D.FoodPriceIndex**	**Variables**	**FoodPriceIndex**
ECT	−0.0359281***		
	(0.010948)		
LD.FoodPriceIndex	0.2809903***		
	(0.051802)		
LD2.FoodPriceIndex	−0.1176096**		
	(0.0530858)		
D.Covid_Total_Cases	4.64e−08*	L.Covid_Total_Cases	1.29e−06*
	(2.68e−08)		(7.43e−07)
D	110.7**	L. D	3080.814**
	(53.11)		(1611.944)
Trend	0.00338**		
	(0.00157)		
D*Trend	−0.189**		
	(0.0910)		
Constant	1.338*		
	(0.729)		
Observations	368	Observations	368
R-squared	0.980	R-squared	0.986
Prob > F	0.0000	Prob > F	0.0000

Notes: The table presents the short-run and long-run coefficients by an ARDL (3,0,0) model. Only contemporaneous values were allocated in the ARDL structure for exogenous variables. The cointegration test of the model is presented in **Appendix B**, in the section of the Pesaran, Shin and Smith Bounds testing procedure. The error correction term is presented in the short-run model, where it satisfies the condition to be negative, between 0 and 1 and statistically significant.
Source: Own calculations.