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2008 Financial Crises V.s. COVID 19: The Painful Double-Knock of Food Prices.

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Abstract

Food supply and demand chains are highly sensitive 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 FAO Food Price Index (FFPI), this study makes one of the first attempts to utilize monthly observations of FFPI in a dynamic time series ARDL and ARX settings for identifying food price effects of the COVDI 19 infection rates V.s. 2008 global financial crises. Our empirical findings confirm that the pandemic has a mild impact on food prices relative to the 2008 crisis, wherein 1 million new COVID 19 infection cases are associated with an increase of only 0.0509 points in FFPI.

Keywords: COVID 19, Food Price Index, ARDL

JEL Classification: I1, E31

Introduction

While the real-time counters of COVID 19's infection and death cases are interpretable and traceable, on contrary, its damage toll on the global economy and social systems is still unclear, pervasive, and hard to quantify. Since the Coronavirus (SAR-Cov-2) outbreak in January 2020, every country aspired to curb the hysterical spread of the deadly disease and to mitigate its adverse socio-economic effects and the ensued hardship on people's livelihood (World Tourism Organization, and World Health Organization, 2020).

Demand shocks and supply chain problems arising from global trade boundaries travel restrictions as well as drastic changes in consumption patterns, all have increased volatility in import, export, producer, and consumer prices. Where most businesses were completely shut following the government's prevention policies, the food suppliers and retailers remained operational (Cyber Security and Infrastructure Security Agency [CISA], 2020). While adapting to supply chain disruptions, meeting big market demand, applying protective measures for its workforce, and maintaining quality and safety standards to protect people lives, the COVID-19 pandemic has stemmed long-lasting effects on the food sector chain (Galanakis, 2020; Hailu, 2020; Coluccia, et al. 2020).

The stimuli impact of the COVID 19 pandemic on food prices lacks convulsive empirical evidence. This study makes one of the first attempts to utilize monthly observations of FFPI in a dynamic time series ARDL and ARX settings for identifying the impact of COVDI 19 incidence rates, V.s. 2008 global financial crises, on FFPI. 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.

The FAO food price index (FFPI) is a measure of the monthly change in international prices of a basket of five food commodities. The average prices are weighted by the average export share of each of the groups. The FFPI hits a three-year high in 2020 pushed by additional gains in December. In general, commodity food prices have increased unexpectedly in recent years, that is between late 2006 and mid-2008, after several decades of relative stability and low levels (Rezitis and Sassi, 2013).

Starting in 2006, there has been a global surge in food prices, continue rising to 27% in 2007 with the financial crises on the horizon. The deteriorating financial positions and the global macroeconomic pressures have strained the world economy leading to amplifying the adverse impact of the volatile and above-average food prices, especially of developing and poor nations (FAO, 2009). Between 2008 and 2010, the number of food-insecure people has increased by 13% in Asia (Shapouri et al. 2010). Throughout the 2008 financial crisis surge years, Cudjoe, et al. (2010) state that the rising oil prices, US dollar ($) depreciation, biofuel policies, market speculation, and temporarily imposed trade restrictions all have contributed to the rapid surge in financial crises-induced food prices.

It is generally perceived that the COVID 19 pandemic has caused a global increase in FFPI. According to Zurayk (2020), there is 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 inability of farmers to sell food that was produced during the pandemic lockdown attributed as well to the FFPI hikes. Similar to the 2007-2008 food prices shock, the increase in commodity food prices on international markets was transmitted into the domestic market. Changes in international food prices do not translate into domestic prices on a one-to-one basis. The transmission is influenced by several factors, including the share of imported food and the governments' ability to charge taxes and/or subsidies (Brinkman, et al. 2010). Concurrently, the impact has led to instability in domestic producer prices, especially in the food sector. For example, in an attempt to limit the spread of the virus, many countries instituted lockdown restrictions. During the restrictions, restaurants were not permitted to open, and if open, only for a certain time before the curfew starts, thus, shelter-in-home order, food rush, and hoarding occurred universally. Accordingly, the demand for food from restaurants was reduced relative to takeaway and deliveries. Many food suppliers and factories were closed down due to the hard-hit impact of the pandemic (Coluccia, et al. 2020).

Farmers were forced to sell their harvest at a lower price to avoid dumping their products. The effect of the lockdown cut across the food supply chain, pushing up and destabilizing food prices (Lufkin, 2020). According to FAO (2020), global food prices have been on the rise for three consecutive months since August 2020, which was mainly influenced by firm demand, weak dollars, and trade-restrictive measures applied by several countries to build up food reserves. Yu et al (2020) reported that the impact of COVID-19 on food prices is heterogeneous in different regions for different products, with a minor impact seen on the overall. The largest disruptions of food production and pricing appear especially in less-developed areas, as well as in regions where food is highly dependent on imports (Fan et al., 2017). Coluccia, et al. (2020) showed that Italian Agri-food exports have decreased as a direct consequence of the pandemic. Some countries still have adequate food reserves for the short term, but as the pandemic resumes over the long term, food insecurity will rise as an alarming issue (Deaton and Deaton, 2020).

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

Methodology

The empirical specification follows a dynamic time series model[1] with exogenous variables defined as an ARX model of the following linear form:

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[1] Following Wickens and Breusch (1988) in using dynamic specifications with a focus on the long-run properties of econometrical models in comparison with the error correction models.

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

Where y_t is the real FAO Food Price Index -FFPI- at month t, y_{t-p} is the set of lagged dependent variables configuring the autoregressive signal structure, x_t is the exogenous variable of COVID 19 world total cases, D_i is dummy variable capturing the duration of the financial crisis of 2008-09 in months[2] with a linear time trend T. With α as the autonomous coefficient of the model with $\beta, \gamma,$ and δ parameters.

The specification of the model in equation (1) determines special importance in the observed signals overtime of the dependent y_t, where these signals includes also unobserved factors of the past which influence the present behavior of the variable. 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 model expressed as follows:

$$y_t = \alpha + \delta T + \sum_{t=1}^{p} \beta_p y_{t-p} + \sum_{t=0}^{q} \gamma_q x_{t-q} + e_t \qquad (2)$$

Where the exogenous components $\gamma_2 D_i + \gamma_3 (D_i * T)$ can be included[3] in the specification of the ARDL to estimate long-run relationships for variables integrated of the first order I(1) (Pesaran, Shin, and Smith, 2001). The intuition behind this and according to Engle and Granger (1987) is that a linear combination with non-stationary variables $y_t, x_t \sim I(1)$ will produce stationary residuals $e_t \sim I(0)$ if they're cointegrated over the long-run, 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 comparison with the traditional ordinary least squares -OLS- estimator, the proposed

[2] The financial crisis dummy variable takes into 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:

$$D_i = \begin{cases} D = 1 \; for \;\; r_t < 0 \\ D = 0 \; for \;\; r_t > 0 \end{cases}$$

For t restricted to 2007<t<2010. And returns defined by the performance of the stock market:

$$r_t = \frac{s_t - s_{t-1}}{s_{t-1}}$$

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.

[3] To provide an empirical example of the long-run properties for variables Pesaran, Shin and Smith (2001) 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 deleted a possible spurious unit-root behaviour in the regressions (Beyer, Haug and Dewald, 2009).

alternative estimation is the robust regression approach. Authors like Berk (1990), Hamilton (1991), Nurunnabi, Nasser, Rahmatullah Imon (2007), and Mays, Birch, and Einsporn (2000) appointed 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 and abnormal observations. Tofallis (2008) used percentage to the errors to overcome heteroskedasticity which is considered as a robust regression approach. Rousseeuw and Leroy (1987) discussed the importance of robust estimators derived from the robust regression approach i as an alternative to the simply least squares method.

The process for robust regression involves that we define the individual period residual as:

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

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

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

Where ρ is the function which gives the contribution for each residual at each period to the objective function, according to Fox and Weisberg (2013) $\rho(e_t) \geq 0$, $\rho(0) = 0$, $\rho(e_t) = \rho(-e_t)$. By defining the influence curve $\varphi = \rho'$ as the derivative of ρ we can solve a model with a robust solution to the problem with a weight function:

$$w(e) = \frac{\varphi(e)}{e}$$

With $w_i = w(e_i)$ for the weights at each period residual basis. From this point, we selected Hubert (1964) estimator and the Beaton and Tukey (1974), bi-weight estimator, as robust measures in comparison to OLS. Diagnostics of the residuals implied checking the linear assumptions of correct specification with Ramsey (1969) specification test. Omitted-variables bias and absence of serial correlation was confirmed with Breusch (1978) and Godfrey (1978) tests. The stability of the parameters (time-invariant parameters) for the linear regression coefficients was tested using the based cumulative sum of the residuals (Brown, Durbin and Evans, 1975). Homoscedasticity and stationarity were tested using the Breusch and Pagan (1979) and Engle and Granger (1987) test. Finally, the bound test of cointegration from Pesaran, Shin and Smith (2001) is applied to the ARDL estimates.

Stylized Facts

The variables' descriptive statistics are reported in Table 1. FFPI monthly observations from January 1990 to November 2020 are sourced from FAO (2020). World total cases of COVID 19 are obtained from the European Centre for Disease Prevention and Control - ECDC- (2020).

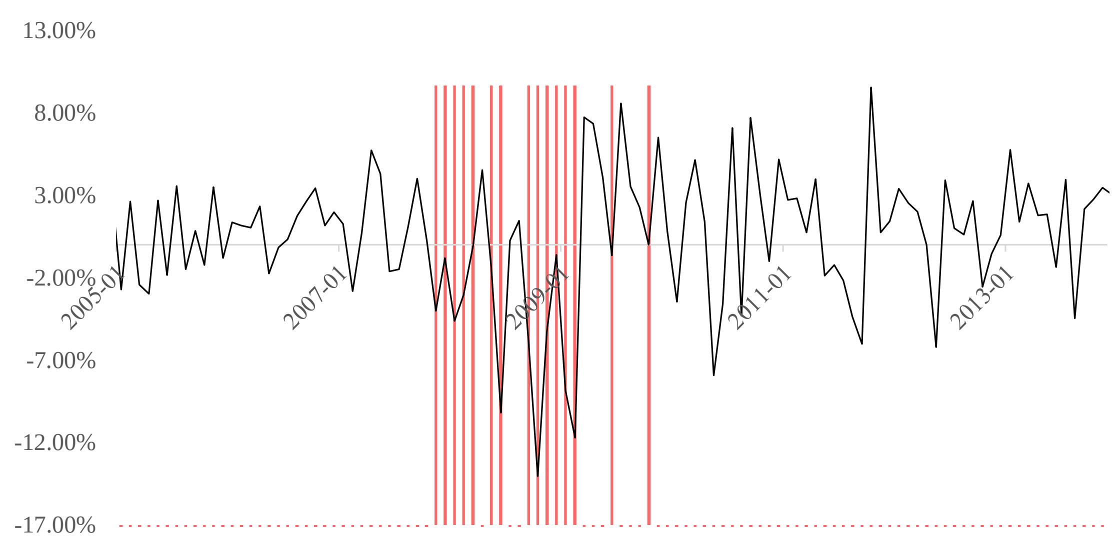
Table 1 Descriptive Statistics Food Price Index and Covid-19 World Total Cases

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	.07788	539798	155962.1
P50	84.6699	.0901895	0	0
Sum	32760.34	28.81559	2.00e+08	5.77e+07
Coef. Variation	.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.

The behavior of the financial crisis of 08-09 can only be followed by shocks in the financial market indices (Graph 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.

Graph 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)

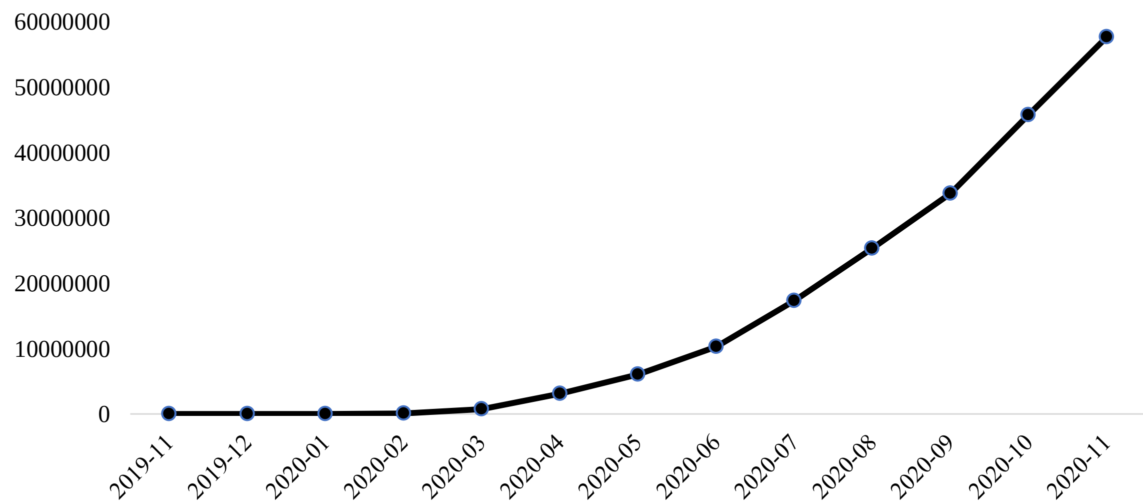
The FFPI shows an increasing trend in the period associated with the financial crisis (Graph 2). The association marks a new pattern in the prices from 2008, which remained unstable over time.

Graph 2 Food Price Index Time Series

Note: The vertical lines represent the financial crisis proxy by the dummy variable. Source: FAO (2020)

Graph 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.

Graph 3 Covid-19 World Total Cases



Source: ECDC (2020)

Results

The unit-root analysis in Appendix A confirms the non-stationarity of real FFPI and the world total cases of Covid-19 in levels 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've found evidence of cointegration by the traditional Engle and Granger residual-based test with a 5% level of significance and the Pesaran, Shin, and Smith (2001) bound testing procedure with a 10% level of significance (appendix B). Engle and Granger's residual-based approach 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 and the ARDL in short and long-run forms are presented in Appendix C. The OLS estimates 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, the COVID 19 has a positive and significant weak 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 number 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 the FFPI with an initial shock of increase associated to 110.7 points at the 95% confidence level, after this initial shock the effect of the financial crisis started to decline. The results consider 15 consecutive months from October 2007 (when the Dow Jones started to react to the financial crises) and November 2009. According to the estimations, after the initial shock originated in the financial crisis, the FFPI recorded a monthly average reduction of 0.189 units in time, as a result of a stabilization process of the financial markets. 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 %[4].

Before and throughout the 2008 crisis years, the consequent rise in oil prices and the extensive production of Biofuels can correlate with the associated food prices increase. Oil and food prices are tightly linked because producing and transporting food requires a large quantity of energy (Berthelot 2008). Biofuel production requires a large number of crops, a large share of the World cereal reserves, and nearly a third of the US Maize production, the leading exporter of this crop on the world market, and went to biofuels in 2007. Biofuels accounted for 70-75% of the rise in food prices from 2002 to 2008 (Berthelot 2008; Mitchell 2008; Van Braun 2008). These distinctive market anomalies that marked the crisis leading and surge years explain the oversized food price impact of the 2008 crises relative to the COVID 19 pandemic.

The results of the short-run ARDL about the impact of the exogenous variables model are not different in comparison to the ARX model. The inclusion of the error correction term to capture long-run dynamics doesn't 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 the COVID 19. The mild food price effect of the COVID 19 is reported by other studies such as Yu et al. (2020). This result might be erroneous due to 1) possible misspecification in the cointegration form of the static long-run equations (Wickens and Breusch, 1988), 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.

Conclusion

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/nations. Health crises are getting more frequent, 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 the global food prices is required to unfold and solve some of the current pandemic, as well possible future crises, expected adverse effects. Veritably, food inflation constitutes a major component in general rates of inflation in developing as well as developed countries. Food prices volatility and hikes, even if short-termed, increase poverty, malnutrition, food insecurity, foster social unrest, and dampen people living standards. 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.

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Appendix A – Unit root tests.

Table 2 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	.36848	1	0.544	5.30258	4.50607	4.52721	4.55928

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

Table 3 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 the 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 4 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 (1990, 2010). 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 behaviour of the residuals with a 1% level of significance. Source: Own's Calculations using Stata 16.

Table 5 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 (2018) critical values and approximate p-values. Source: Own Calculations using the Stata package of Kripfganz and Schneider (2016)

Appendix C – Regression outputs

Table 6 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, this is equivalent to a short-run model. Slightly different results can be seen in most of the parameters, where the R-squared of the robust regression is higher. Source. Own Calculations.

Table 7 ARDL Model Regression.

FORM OF THE MODEL:	ARDL: SR		ARDL: LR
Variables	D.FoodPriceIndex	VARIABLES	FoodPriceIndex
ECT	-.0359281***		
	(.010948)		
LD.FoodPriceIndex	.2809903***		
	(.051802)		
LD2.FoodPriceIndex	- .1176096**		
	(.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.