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IMPACTS OF THE COVID-19 PANDEMIC ON THE AGRICULTURAL PRICES: NEW INSIGHTS FROM CWT GRANGER CAUSALITY TEST

Covid-19 Pandemisinin Tarım Fiyatları Üzerindeki Etkisi: Sürekli Dalgacık Dönüşümü Bazlı Granger Nedensellik Testi

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Keywords:
COVID19, Agricultural Commodity Prices, Wavelets, Causality.

JEL Codes:
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Abstract

In this paper, the impacts of the Covid-19 mortality rates on the agricultural spot prices were investigated by using both standard techniques and wavelet-based cohesion and Granger causality tests. Our dataset consisted of daily observations of the mortality rates as well as corn, oats, rapeseed, rice, soybeans, and wheat prices during the period January 22 to September 18, 2020. The findings of the paper revealed that the mortality rate was cointegrated with the prices of corn, oats, rapeseed, and soybeans. Further, the VECM results showed that the mortality rate unidirectionally Granger-caused the corn and rapeseed prices in the long-run, and the oat prices in the short- and long-run. On the other hand, the wavelet cohesion results revealed that the dynamics of the interdependence of the underlying variables were time-varying and heterogeneous over time horizons. The wavelet-based Granger-causality test, however, indicated that the mortality rates negatively caused most of the agricultural prices. These findings yield some important implications for policymakers.

Anahtar Kelimeler:
COVID19, Tarım Emtia Fiyatları, Dalgacıklar, Nedensellik.

JEL Kodları:
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Özet

Bu çalışmada, korona virüsü pandemisinin spot tarım fiyatları üzerindeki etkisi, hem standart metod hem de dalgacık bazlı korelasyon ve Granger nedensellik testler kullanılarak, incelenmiştir. 22 Ocak – 18 Eylül 2020 dönemine ait günlük ölüm oranı ile mısır, yulaf, kolza, pirinç, soya fasulyesi ve buğday fiyatları ele alınmıştır. Elde edilen test sonuçlarına göre ölüm oranı ile mısır, yulaf, kolza ve soya fasulyesi fiyatları arasında uzun dönemli eşbütünleşme ilişkisinin varlığı tespit edilmiştir. Ayrıca, ölüm oranının mısır ve kolza fiyatlarının uzun dönemde, yulaf fiyatlarının ise hem kısa hem de uzun dönemde Granger nedeni olduğu bulgusuna rastlanmıştır. Diğer taraftan, dalgacık bazlı korelasyon analizi sonuçlarına göre değişkenler arasındaki ilişki zamana göre değişmekte, diğer bir ifadeyle heterojen özellikler sergilemektedir. Dalgacık bazlı nedensellik test bulgularına göre ise, ölüm oranındaki negatif gelişmelerin çoğu tarım fiyatlarındaki negatif gelişmeleri üzerinde istatistiksel olarak anlamlı nedensellik ilişkisine sebep olduğu ortaya çıkmıştır. Elde edilen bulgular, politika yapıcılar için önemli sonuçlar doğurmaktadır.

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1. Introduction

The unprecedented disease that witnessed in 2020 is the Covid-19 pandemic. The diseases like the Covid-19 always influence human life and activities, for instance, livestock, agriculture, tourism, transport, education, manufacturing (Siche, 2020). This virus, as it has spread fast, not only damaging human health and causing thousands of dead but also devastating economic activities around. According to an Organisation for Economic Co-operation and Development (OECD) report, in the second quarter of 2020, the real gross domestic product (GDP) of OECD countries is estimated to fall dramatically by about 9.8%. And the report also claims that this GDP contraction has never been seen in the history of OECD countries. The stock markets around the world fell extremely at a low level when the danger of the virus was realized. There has never been such a big fall in stock markets in previous infectious diseases (Baker et al., 2020). However, after the Covid-19 outbreak had been realized, the primary concern has been on the side of hiking unemployment due to lockdown processes as many producers stopped manufacturing goods or servicing. Service-based economies will be hit hard by the virus as the number of people working higher and their jobs will be at risk due to lockdowns (Fernandes, 2020). The second concern has been on the issue of a supply chain break. That is, the practice of quarantines and the spread of the virus, causing illness among the workforce, made the movement of goods and services problematic. Brewin (2020) pointed that increase in virus among truck drivers in Canada and the USA, will in effect deepen the problem of delivery of grain to market and lead to potential delays as an example of how the supply chain could be disrupted. To deal with these problems governments have taken action to lessen the degree of the complication of economic activities.

On general economic issues, major countries especially the USA, European Union, and Japan have taken monetary steps to deal with the disruption caused by the pandemic. For instance, the Federal Reserve has cut the benchmark interest rate by a total of 150 basis points and with a lending program to support households and capital markets. Similarly, the European Central Bank, with Pandemic Emergency Purchasing Program promised to market to use 750 Billion Euro funds. While these campaigns have an immediate effect on financial markets and stabilized the capital markets soon after the lockdowns, the response of the real economy has not known properly and the recovery of real sectors may take time as the evolution of the virus still mysterious.

As stated by Kara and Diken (2020) the harvest of agricultural commodities more prone to variation in climatic changes such as shortage of rainfall. These climatic changes and its consequences may be coupled with infectious disease like Covid-19 and hence, one of the biggest worries has been the supply of food and agricultural products. As the world has become more global, the supply chain expands beyond international borders (Kerr, 2020). And pandemic events like Covid-19 inevitably affect the distribution of agricultural products. Already this issue has created difficulty in supplying food at the beginning of the outbreak when the quarantine practices began. In some part of the world, for instance in India, when the lockdown was put in place abruptly, agricultural activities like harvesting, selling of agricultural products, and procuring goods that are used for production purpose come to a halt and the distribution of commodities like wheat, chickpea, mustard and tomato to consumption markets were falling sharply immediately upon the announcement of quarantine (Rawal, Kumar, Verma, and Pais, 2020). Another problem exacerbated the food supply as the governments announced quarantines on cities, the inhabitants soon panicked and rushed into markets to buy foods and urgent needs. This situation even worsened the availability of food and other major necessities. This creates complications not only for food price volatility but also a considerable effect on the population those who may have difficulty reaching foods (Siche, 2020).

To handle food security and appropriate food distribution system, governments stepped in and have taken action to stabilize any disrupted market. BSE Institution of Canada has set up a working group to arrange beef supply of the country between firms, industry, and regulators to prevent any shortfall of beef (Brewin, 2020). Alike, the Chinese National Emergency Food Supply System began to arrange transport and distribution of food which is defined as grain products for large and middle-size cities (Pu and Zhong, 2020).

Concerning the price level of food and agricultural products, there are two implications for price volatility. The first implication is that the price of food increased in retail markets. Because when the quarantine rules have been implemented, people have rushed into markets and purchased food more than they needed. As a result of this situation, retail prices increased at least at the beginning of lockdown until the panic was over. On the other hand, a similar price increase was not seen on the producer side. Moreover, the value of the main commodities had fallen once the outbreak spread around the world. Covid-19 was first seen in Wuhan, the city of China in December. And then, the World Health Organization had declared this disease as a pandemic in January. Soon it became realized as a dangerous virus, the world alarmed and lockdowns started to be implemented all over the world. While the disease spread, commodity markets frightened and started to fall dramatically as demand and supply depressed. Brent oil sank to the bottom in April as demand fall. Even, the oil futures were falling to negative territory in prices. Similarly, the price of agricultural products was affected too and started to fall in January. This weakening in the price of agricultural products and major commodities is expected because the economic lockdown will reduce the return of crop and livestock (Lawley, 2020), and as unemployment increases the disposable income fall (Rawal et al., 2020). The fall in prices of main agricultural products such as wheat, corn, soybean, oats, and rapeseed continued until May 2020. As mentioned above, measures taken to tackle the virus and reduce its huge impact on economies and social life had relieved the financial markets and society. In May, while social life slightly gets back to normal, economic activities had also begun to pick up. Accordingly, as the supply and demand side was relaxed, commodity prices started to rise after May in line with stock markets.

In retrospect of the literature, voluminous papers are studying the impacts of the Covid-19 pandemic on the financial markets through econometrical tools. Noteworthy papers examine the effects of the Covid-19 pandemic on the stock markets, such as Akhtaruzzaman, Boubaker, and Sensoy (2020), Gherghina, Armeanu, and Joldeș (2020), Lahmiri and Bekiros (2020), Öztürk, Şişman, Uslu, and Çıtak (2020), Şenol and Zeren (2020), Topcu and Gulal (2020), among others. In an earlier research, Şenol and Zeren (2020) drawn on Fourier based test to investigate the effects of the Covid cases and death figures on the MSCI World, MSCI Europe, MSCI G7, and MSCI emerging markets and pointed a long-run relationship between these variables. Akhtaruzzaman et al. (2020), on the other hand, provided evidence of financial contagion between financial and non-financial firms in China and G7 countries during the Covid-19 outbreak and revealed that the latter firms were found to be less prominent in transmitting contagion than the former firms. Some empirical research has been conducted on analyzing the relationship between the Covid-19 pandemic and currency markets. These include Narayan, Devpura, and Hua (2020), who compared the relationship between the Japanese Yen and stock market returns and highlighted that the association was stronger during the Covid-19 outbreak than the pre-crisis period; Aslam, Aziz, Nguyen, Mughal, and Khan (2020), who investigated currency market efficiency using high-frequency data through multifractal detrended fluctuation analysis and found (i) evidence of the presence of multifractality in forex markets and (ii) that the Swiss Franc and the Canadian dollar showed the highest efficiency among six major currencies during the Covid-19 pandemic. Several studies examined these impacts on the oil markets, including Ghazanfari (2020), Salisu, Ebuh, and Usman (2020), and Sari and Kartal (2020). Among these papers, Sari and Kartal (2020) investigated the effects of the Covid-19 daily case numbers on oil, gold, and VIX index with the Autoregressive-Distrubuted Lag (ARDL) limit test and presented significant results in terms of long-run linkage between the Covid-19 cases and two out of three variables, i.e. gold prices and VIX index. Similarly, a strand of research papers of the Covid-19 outbreak period examined the safe-haven property of investment assets. Of these studies, Conlon and McGee (2020) conducted empirical research on the cryptocurrency markets and revealed that the safe-haven role of Bitcoin was not evidenced. Besides, Ji, Zhang, and Zhao (2020) found that gold and soybean commodity futures were excellent safe-haven assets among cryptocurrency, foreign exchange, gold, and commodities during the Covid-19 outbreak. Goodell and Goutte (2020), employing the wavelet coherence approach, exhibited evidence of significant impacts from levels of Covid-19 death numbers on Bitcoin prices on the 3~7 days scale (at higher frequencies) between April 5 and April 29. The findings of Dutta, Das, Jana, and Vo (2020) regarding the DCC-GARCH model suggested that a portfolio including oil and gold should have been preferred to a portfolio including oil and Bitcoin because of its lower risk level. However, the results of Mensi, Sensoy, Vo, and Kang (2020) showed that oil and gold markets have been inefficient since these markets exhibited strong sensitivity to market trends and the Covid-19 pandemic as well as time scales, pointing to the investor sentiment effect. Putting the paper of Wang, Shao, and Kim (2020) aside in which the authors investigate the impact of the Covid-19 pandemic on the cross-correlation of oil-agricultural future markets, it is evident that the literature on the Covid-19 mortality rates and agricultural spot prices is scarce which motivate us to study this relationship. Our paper, to the best of our knowledge, is the first empirical research to examine the impacts of the Covid-19 daily mortality rates on global agricultural spot prices in terms of econometric analysis with standard techniques as well as wavelets in the existing literature.

In this paper, the wavelet-based causality test proposed by Olayeni (2016) as well as standard econometric analyzing tools were used to investigate the impact of the Covid-19 pandemic on the agricultural spot prices. The novelty of the wavelet approach is to enable us to study this effect within the frequency bands and time-scales simultaneously. Applications of this test have received a great deal of attention in the literature. Some of the most recent and notable papers include Alam, Shahzad, and Ferrer (2019) on the oil-foreign exchange futures contracts relationship; Jun, Mahmood, and Zakaria (2020) on the effect of trade openness on pollution in China; Kang, Tiwari, Albulescu, and Yoon (2019) on nonferrous metal futures co-movement in Shanghai and London; Tiwari, Olayeni, Olofin, and Chang (2019) on inflation-economic growth associated in India; and Torun and Demireli (2019) on the relationship among stock, gold, and currency markets in Turkey.

The remainder of the paper is structured as follows. In Section 2, a brief literature concerning the impacts of the Covid-19 pandemic on asset prices as well as the agricultural commodity markets are provided. Section 3 introduces wavelets, continuous wavelet transform (CWT), and the method of the CWT-based Granger causality. Section 4 defines the sample data and highlights its descriptive statistics. The empirical findings are discussed in Section 5. Finally, concluding remarks in Section 6 close the study.

2. Related Literature Review

Since the Covid-19 outbreak has started, researchers and academics have been studying to investigate the effect of this crisis. While many researchers focused on the health side of the virus, economists interested in the devastating effect of the virus on economic activities. On the economic side, the supply chain break and supply-demand shock have been on the spot and the negative effect of the virus on the value of agricultural products and food. It should be noted that there is one common point almost by all researchers shared is that as the virus causes uncertainty, the prediction of future outcomes seems vague. For instance, Atkeson (2020), Baker et al. (2020), Fernandes (2020), and Gupta et al. (2020) explored the effect of Covid-19 on the overall economy. Others, such as Brewin (2020), Kerr (2020), Lawley (2020), Pu and Zhong (2020), Rawal et al. (2020), and Siche (2020) studied the influence of the virus on agricultural products and food.

By using the SIR model for Covid-19, Atkeson (2020) provides some predictions for the United States for the period of the next 12 to 18 months. The author first used a simulation of transmission of disease and indicated under what circumstances the U.S. population will be infected. As the rate of transmission increases, the number of population increases too. For example when the rate is 1.6, then it takes a quite long time for the U.S. population to be infected, and accordingly, the economic consequences will be lower. However, the author does not know the exact consequences of the virus on economic activities as there is uncertainty on the virus for the future. In their paper, Gupta et al. (2020) claimed that if the disease spread for a long time, the economic effect of this will much bigger. This, in turn, will shake the financial system. The authors point several setbacks that occur after the outbreak. When the pandemic started people avoid traveling, the oil demand reduced, the industrial production fall which leads to stock markets collapse 20% in a short time. However, similar to Atkeson (2020), the authors also do not know the exact problems caused by the virus as the transmission rate and spread of the disease not known. In his study, Fernandes (2020) found several predictions regarding the virus for the world economy. The author estimates that the GDP growth of the world may be reduced by 3% to 6% depending on the country. When analyzing 30 countries' data, the median GDP fall constitutes for about 2.8%. Furthermore, in some scenarios, there may be a 10% or even 15% fall in GDP for some countries. The author points out that, the service-oriented countries where the tourism industry is at large will be hard by the disease.

When looking at one of the main indicators of the economic process, the stock market prices lead the way. Stock markets across the world are the most affected asset class by the outbreak of the virus. Baker et al. (2020) examined this effect. The author constructed a series with news that quote the virus daily. Data start from 24 February 2020 to 24 March 2020. On 22 trading days, there were 18 jumps in stock prices. The author believes that the volatility and fall in prices of stock markets during Covid-19 were never seen and comparable with the previous crisis times.

While the given previous literature has been dealing with the effect of the virus on overall economic activities, there is also a study that is dealt with the restriction of human mobility caused by the negative impact of Covid-19. Yang, Zhang, and Chen (2020) used the DSGE equilibrium model to see this effect. Besides this model, when using the impulse response function, the authors found that as the risk of virus increases the health problems start to arise and this influences the workforce productivity which in turn lowers the tourism revenue as a health risk and tourism demand is closely related. Their DSGE model suggests that as the tourism industry disturbed badly by this kind of pandemic event, the government should subsidize this sector to create wealth and to stimulate other economic agents to recover the economy.

There are also a handful of studies that reviewed the effect of Covid-19 on agricultural products. Of them, Brewin (2020) looked at the Canadian agricultural situation when the virus spread. The author state that, while the supply of food in Canada disrupt by the disease, the efficiency of products to be delivered to the Canadians is not short and seems to in enough amount. When looking at canola prices, the author sees no visible effect on prices during the virus. Similarly, Kerr (2020) spoke about the disruption caused by the virus. As the lockdown processes were in place, the problem of supply occurs and export decreases and as a result, the people lose income. In the short run, like other economic activities, agricultural products were also disrupted, especially their deliveries. Rawal et al. (2020) analyzed the impact of Covid-19 on Indian agricultural products. According to the authors' estimate, the price of seven main commodities including wheat, chickpea, mustard, potato, onion, tomato, and cauliflower have shown no clear indication of the effect of the virus is. Contrarily, due to lockdown and homestay and illness among the workers, there seem to be delays in delivering agricultural products in India. On the other hand, Wang et al. (2020) examined the relationship between crude oil and agricultural futures markets by using the multifractal detrended cross-correlation method. Agricultural products in question were London Sugar, London Wheat, USA Cotton #2, and USA Orange Juice futures. When estimating the DCCA coefficient, they found a correlation between these futures and oil prices. However, when using multifractal cross-correlation, the only robust correlation found to be between oil and sugar prices. The authors further argue that at the time of Covid-19, the relation between oil and agricultural futures markets were even stronger. Again, oil and sugar prices were found to have a strong linkage.

3. Methodology

This section provides a brief discussion of wavelets and so-called CWT before the discussion of the CWT based causality test introduced by Olayeni (2016). All the necessary details for the understanding of these approaches will be provided, however, the technical details of well-known tests, such as Lee and Strazicich (2003) unit root test with multiple structural breaks and Hatemi-J (2008) cointegration test with two unknown regime shifts are left to the readers.

3.1. Wavelet Transforms

With their ability to quantify events in both time and scale, wavelets have long been used by researchers as a novel nonparametric approach to overcome the drawbacks of Fourier analysis. As its term advocates, wavelets are short or small waves, i.e., they grow and decay in the short-time given that they have a finite length and oscillatory behavior. To capture features that localized both in times, through translations, and in frequency, through dilatations, a basic function (called mother wavelet and its scaled and translated versions) is utilized for the wavelet transform. In other words, this wavelet is squeezed and shifted to capture the frequency and time information, respectively, from the underlying data. Here, the outcome is defined as a CWT if the transform is computed for all data locations and is described as a discrete wavelet transform in the case of a process at discrete steps. Given that wavelets have good frequency and time localization properties, the resulting time-frequency partition by the discrete or continuous wavelet transform is long in frequency (time) when capturing high- (low) frequency events, therefore, they display good (poor) time resolution but poor (good) frequency resolution. Differently speaking, a wavelet with a small (large) scale has fine (coarse) time resolution but coarse (fine) frequency resolution. The wavelet transform, in fact, logically adjusts itself to capture frequency and time behaviors of the data across a wide range of frequencies (see Gençay, Selçuk, and Whitcher, 2001; Percival and Walden, 2000 for details).

3.2. Continuous Wavelet Transform

By projecting a time series, $x(t) \in L^2(\mathbb{R})$,onto the mother (original) wavelet function, $\psi_{s,\tau}(t) = \psi\big((t-a)/b\big)/\sqrt{b}$, one can obtain the wavelet coefficients of CWT through using the following convolution (Olayeni, 2016)

$$W_X(a,b) = x * \psi_{a,b}(t) = \int_{-\infty}^{+\infty} x(t)\frac{1}{\sqrt{b}}\tilde{\psi}\left(\frac{t-a}{b}\right)dt \tag{1}$$

where$\tilde{\psi}$ denotes the complex conjugate of function ψ. By varying the wavelet scale b and translating along with the localized time index a, as indicated in Torrence and Compo (1998), one can captures simultaneously and efficiently time and frequency components of $x(t)$.To capture the variability of $x(t)$ as a function of scale and time, on the other hand, one can calculate the power spectrum as $W_{XX}(a,b) = |W_X(a,b)|^2$, measuring the relative contribution at each time and scale to the time series' variance, from Eq. (1). According to Olayeni (2016), Eq. (1) could be discretized for time series as given below

$$W_X^z(a,b) = \frac{\delta t}{\sqrt{b}}\sum x_n \cdot \tilde{\psi}\left((z-n)\frac{\delta t}{\sqrt{b}}\right) \tag{2}$$

where$b$ and a, respectively, denote the scale and location parameter and δt signify a uniform step size with $x_n = 1,2,\ldots,N$ and $z = 1,2,\ldots,N-1$. Here, the wavelet power is represented as $|W_X^z(a,b)|^2$ and the cross-spectrum can be defined as $W_{XY}^z(a,b) = W_X^z(a,b)\widetilde{W}_Y^z(a,b)$, where the complex conjugate of $W_Y^z(a,b)$ is $\widetilde{W}_Y^z(a,b)$.

By using the Morlet wavelet function, one can attain a tradeoff balance between the resolution in time and frequency

$$\psi_0(\eta) = \frac{1}{\sqrt[4]{\pi}} e^{i\omega_0 \eta} \frac{1}{\sqrt{e^{\eta^2}}} \tag{3}$$

where η denotes dimensionless time and ω_0 is the nondimensional frequency. Here, it is convenient to choose ω_0 as equal to 6 so that it satisfies the admissibility condition (Grinsted, Moore, and Jevrejeva, 2004).

Given two time series $x_i(t)$ and $y_j(t)$, with wavelet transforms $W_{x_i}(a,b)$ and $W_{y_i}(a,b)$, one can define the cross-wavelet spectrum, measuring the local covariance, as $W_{x_i y_j}(a,b) = W_{x_i}(a,b)W^{*}_{y_j}(a,b)$. Then, one can attain the measure of wavelet correlation as given (Rua, 2010)

$$\rho_{XY}(a,b) = \frac{\Im\{b^{-1}|\Re(W^m_{XY}(a,b))|\}}{\Im\{b^{-1}\sqrt{|W^m_X(a,b)|^2}\} \cdot \Im\{b^{-1}\sqrt{|W^m_Y(a,b)|^2}\}} \tag{4}$$

where $\Im(Q) = \Im_{scale}(\Im_{time}(Q))$ with $\Im_{scale}$ as the smoothing operator along the scale axis while $\Im_{time}$ as the smoothing operator along the time axis. Besides, $\Re$ denotes the real part of the cross-wavelet spectrum. As a correlation measure, $\rho_{XY}(s,\tau)$ is limited between -1 and +1. The wavelet coherence, with a condition of $0 \leq R_{XY}(a,b) \leq 1$, can be simply written by the following expression

$$R_{XY}(a,b) = \frac{\Im\{b^{-1}|(W^m_{XY}(a,b))|\}}{\Im\{b^{-1}\sqrt{|W^m_X(a,b)|^2}\} \cdot \Im\{b^{-1}\sqrt{|W^m_Y(a,b)|^2}\}} \tag{5}$$

3.3. Olayeni (2016) Causality in Continuous Wavelet Transform

The first step for the causality in CWT is to define the concept of phase-difference between x and y as given

$$\phi_{XY}(a,b) = \phi_X(a,b) - \phi_Y(a,b) = tan^{-1}\left(\frac{\Im\{W^m_{XY}(a,b)\}}{\Re\{W^m_{XY}(a,b)\}}\right) \tag{6}$$

where the phase-difference is bounded between $-\pi$ and π, namely, $-\pi \leq \phi_{XY}(a,b) \leq \pi$. If the phase-difference, $\emptyset_{XY}(a,b)$, is in the range of $(0,\pi/2)$ and $(-\pi/2,0)$, then it is concluded that the underlying two variables are in-phase and move in the same direction. Conversely, they are out-of-phase if the phase-difference, $\emptyset_{XY}(a,b)$, is in the range of $(\pi/2,\pi)$ and $(-\pi,-\pi/2)$, suggesting that they move in the reverse direction. Further, the intervals $\emptyset_{XY}(a,b) \in (0,\pi/2)$ and $\emptyset_{XY}(a,b) \in (-\pi,-\pi/2)$ suggest that x (y) leads (lags) y (x). Other spaces of interest can be described in the same way.

By imposing the phase sub-intervals on Rua's (2010) wavelet correlation measure, Olayeni (2016) suggests using the following indicator functions for the case that whether y leads x

$$I_{Y\to X}(a,b) = \begin{cases} 1, & if\ \emptyset_{XY}(a,b) \in (0,\pi/2) \cup (-\pi,-\pi/2) \\ 0, & otherwise \end{cases} \tag{7}$$

$$I_{Y\to X}(a,b) = \begin{cases} 1, & if\ \emptyset_{XY}(a,b) \in (0,\pi/2) \\ 0, & otherwise \end{cases} \tag{8}$$

$$I_{Y\to X}(a,b) = \begin{cases} 1, & if\ \emptyset_{XY}(a,b) \in (-\pi,-\pi/2) \\ 0, & otherwise \end{cases} \tag{9}$$

where equation (7) refers to causality from Y to X; equation (8) shows a negative (out-of-phase) causality, i.e., $Y^{-} \rightarrow X^{-}$; and Eq. (9) purports a positive (in-phase) causality, i.e., $Y^{+} \rightarrow X^{+}$.

Olayeni (2016) proposed a modified Granger causality in CWT through augmenting the Rua (2010) wavelet correlation formula as given,

$$G_{CE}(a,b) = \frac{\Im\{b^{-1}|\Re(W_{XY}^{m}(a,b))I_{CE}(a,b)|\}}{\Im\{b^{-1}\sqrt{|W_{X}^{m}(a,b)|^{2}}\}\cdot\Im\{b^{-1}\sqrt{|W_{Y}^{m}(a,b)|^{2}}\}} \tag{10}$$

whereCE denotes causation effect from x to y ($X \rightarrow Y$) or in the reverse direction ($Y \rightarrow X$). If predictive information, for example, flows from $x$to y, then the indicator function is represented as $I_{X\rightarrow Y}(a,b)$ or $I_{Y\rightarrow X}(a,b)$ in the second case. On the other hand, if the indicator function $I_{X\rightarrow Y}(a,b)$ is true over $\emptyset_{XY} \in (0,\pi/2)$or $\emptyset_{XY} \in (-\pi/2,0)$, then $G_{X\rightarrow Y}(a,b)$ is a measure of in-phase causality. Besides, if the indicator function $I_{X\rightarrow Y}(a,b)$ is true over $\emptyset_{XY} \in (-\pi,-\pi/2)$or $\emptyset_{XY} \in (\pi/2,\pi)$, then $G_{X\rightarrow Y}(a,b)$ is a measure of out-of-phase causality.

4. Data and Preliminary Tests

To examine the effects of the Covid-19 pandemic on the global agricultural prices, this paper used a dataset included of 166 daily observations (in natural logarithm) for spot prices for corn, oats, rapeseed, rice, soybeans, and wheat from January 22, 2020, to September18, 2020. Further, the mortality rates of the Covid-19 pandemic are calculated as the cumulative total death divided by the cumulative total cases. Our data were collected from various online sources. Corn, oats, soybeans, and wheat spot prices, expressed in U.S. Dollars per bushel, were extracted from Macrotrends LLC (https://www.macrotrends.net) whereas rapeseed and rice spot prices, expressed in USD per cwt., are available from the Markets Insider website (https://markets.businessinsider.com/commodities). Besides, the mortality rates of the Covid-19 pandemic were retrieved from https://www.worldometers.info/on September 19, 2020. Summary statistics per the logarithmic prices are given in Table1. In this table, the data as well as the correlation coefficients between the agricultural markets with the mortality rates are analyzed.

Table 1. Descriptive Statistics for the Natural Logarithms of the Prices

	CORN	OATS	RAPESEED	RICE	SOYBEANS	WHEAT	COVID
Mean	1.2267	1.0577	5.9342	2.6395	2.1777	1.6632	4.4658
Maximum	1.3705	1.2398	6.0155	3.0942	2.3452	1.7587	7.2752
Minimum	1.1199	0.9302	5.8156	2.4327	2.1063	1.5575	1.9925
SD	0.0706	0.0677	0.0343	0.1387	0.0445	0.0469	1.5712
Skewness	0.4752	0.3586	-0.5129	0.6554	1.2103	-0.0193	0.4011
Kurtosis	1.8278	2.1627	4.2403	2.9478	5.0778	2.1771	1.9159
N	166	166	166	166	166	166	166
Correlation	-0.756***	0.427***	-0.393***	0.695***	-0.607***	-0.379***	

Note: *, **, or *** indicate rejection of the null hypothesis of normality at 10%, 5%, and 1% significance levels, respectively.

As shown in Table 1, the spot prices of rapeseed, rice, soybeans, wheat, corn, and oats reached their peak values in terms of daily closing prices of 6.016 (on January 22), 3.094 (on June 4), 2.345 (on September 18), 1.759 (on January 23), 1.371 (on January 23), and 1.240 (on June 4), respectively, during the global pandemic crisis. The prices, on the other hand, hit the lowest levels on March 16, July 29, March 16, June 26, April 28, and March 17, respectively, during the underlying period. As the coefficient of standard deviation indicates, the logarithm of rice prices showed the highest volatility (0.139)among the agricultural prices, followed in turn by corn (0.071) and oats (0.068)prices whereas the logarithm of rapeseed prices had the lowest volatility(0.034). Except for the corn and wheat prices, the other agricultural prices exhibited positive skewness. The skewness of the soybeans was the highest (1.21), followed by the rice (0.655) and then corn prices (0.475). The fourth moment showed that the distributions of all variables were leptokurtic, i.e., distributed with fatter and heavy tails than a normal distribution. Both the results of kurtosis and skewness are indicative of a rejection of normality assumption for all prices. The mortality rates of Covid-19, on the other hand, hit a record high of 7.3% and a low of 1.99% on April 29 and February 5, 2020, respectively. It posted the highest standard deviation of 1.5712% among the underlying variables and revealed positive skewness and kurtosis and deviation from normality at the 1% significance level. The mortality rates of Covid-19 were negatively and significantly correlated with the prices of corn, rapeseed, soybeans, and wheat and were positively and significantly correlated with the oats and rice spot prices. The time series of daily closing prices of six commodities with the daily Covid-19 mortality rates are depicted in Figure 1. It is evident that all prices, unsurprisingly, exhibit structural breaks, which is a frequently observed phenomenon in financial time series and, therefore, requires analyzing the relationship through econometrical tools allowing structural changes. Since the presence of structural breaks such as financial/economic crises, regime shifts, war, epidemics, etc. in the time series will cause the behavior mechanism to change, that is, the power of the conventional unit root and cointegration tests will be reduced substantially in the case of structural breaks existence, two novel tests, the Lee and Strazicich (2003) unit root test and the Hatemi-J (2008) cointegration test, taking multiple unknown structural breaks into account, are employed.

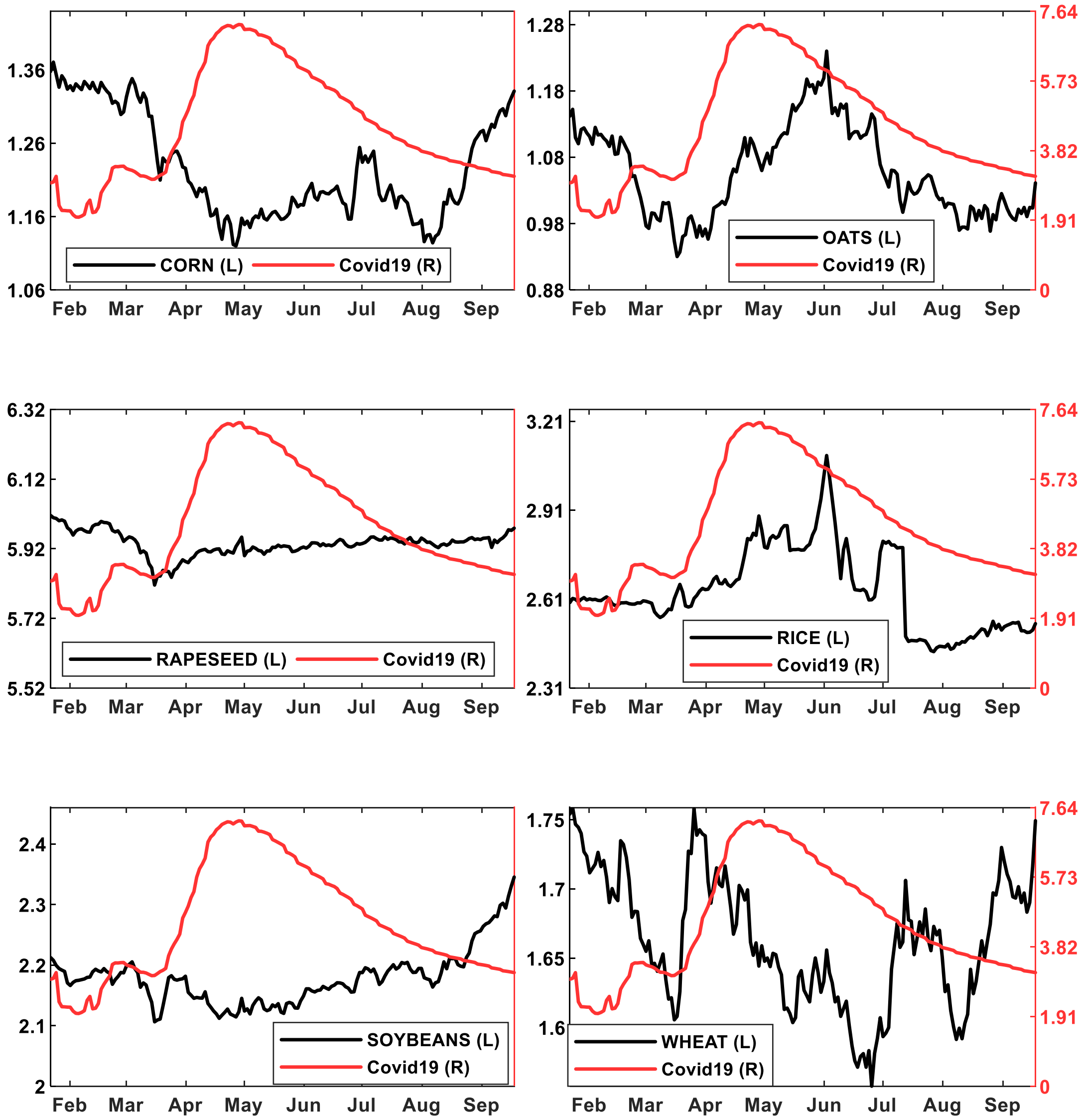

Figure 1. Time Series Trend Agricultural Spot Prices And Covid19 Mortality Rates (19-09-2020)

5. Empirical Findings and Discussions

In this section, the stationarity of variables is first tested employing the test of Lee and Strazizich (2003) unit root and report the findings in Table 2. Given the outcome of this approach with multiple structural breaks, the possibility of estimating a long-run association between the mortality rates and the spot prices are considered and the cointegration results based on the Hatemi-J (2008) cointegration test are provided in the next table. Since the presence of cointegration linkage precludes non-causality between the pair of cointegrated variables, the approach of Granger causality based on VECM is applied and the results are provided in Table 4. Lastly, the CWT based correlation estimations obtained by employing the test of Rua (2010) and causality test of Olayeni (2016) based on CWT is performed for the pairs of spot prices with the mortality rates, and the findings are visualized in Figure 2 and Figure 3 and 4, respectively. In this paper, the research and publication ethics are complied with and it should be remarked that this paper does not require permission from the ethics committee and/or legal/special permission.

Table 2. Lee and Strazizich (2003) Unit Root Test

Log(Prices)				Logarithmic First Difference (Prices)		
Model A	**LM**	**BP1**	**BP2**	**LM**	**BP1**	**BP2**
LN_CORN	-1.899	Mar-11	Mar-17	-11.11***	Apr-20	Jun-29
LN_OATS	-1.954	Apr-14	Apr-23	-12.407***	Apr-27	Jun-01
LN_RAPESEED	-2.674	Mar-06	Mar-13	-13.494***	Mar-10	Mar-18
LN_RICE	-3.627*	Jul-14	Aug-05	-10.485***	Jun-08	Jun-10
LN_SOYBEANS	-2.123	Mar-31	Apr-30	-10.591***	Mar-20	Aug-26
LN_WHEAT	-3.167	Mar-31	May-12	-11.615***	Mar-27	Jun-08
COVID19	-2.989	Feb-21	Apr-09	-7.533***	Mar-23	Mar-27
Model C	**LM**	**BP1**	**BP2**	**LM**	**BP1**	**BP2**
LN_CORN	-4.132	Apr-27	Jul-28	-11.449***	Jun-29	Jul-14
LN_OATS	-4.279	Mar-13	Jun-04	-13.345***	Mar-18	Jun-25
LN_RAPESEED	-4.789	Mar-10	Apr-06	-14.701***	Mar-06	Apr-07
LN_RICE	-5.057	Apr-17	Jul-16	-11.834***	Jul-13	Jul-16
LN_SOYBEANS	-5.269	Apr-30	Aug-03	-11.982***	Mar-11	Mar-23
LN_WHEAT	-4.828	Apr-08	Jun-03	-13.702***	Mar-17	Mar-24
COVID19	-4.893	Feb-19	Apr-21	-11.158***	Mar-20	May-27

Note: ***,**, or * show the rejection of the null hypothesis of unit root at 1%, 5%, or 10% level of significance, respectively. The abbreviation BP1 (BP2) stands for the first (second) structural breakpoint. Model A and Model C is a model with a break in intercept and a model with a break in intercept & trend, respectively.

As provided in Table 2, the null hypothesis of the Lee and Strazicich (2003) unit root test is strongly rejected at the 10% significance level for only one variable when Model A is used, i.e., LN_RICE is stationary around a broken trend with double structural breaks on July 14 and August 5. The null hypothesis, however, is strongly rejected for all log difference prices. Accordingly, the results indicate the presence of a cointegration relationship for five out of six pairs of variables in level.

Table 3. Hatemi-J (2008) Cointegration Test

Dependent		Independent	ADF	TB1	TB2	Phillips Za	TB1	TB2
LN_CORN	~	COVID19	-6.701***	Mar-11	Jun-23	-67.449*	Mar-12	Jun-23
LN_OATS	~	COVID19	-6.227**	Mar-10	Apr-09	-54.283*	Mar-10	Apr-08
LN_RAPESEED	~	COVID19	-7.059***	Mar-06	Apr-16	-73.834*	Mar-09	Mar-09
LN_SOYBEANS	~	COVID19	-5.998*	Jun-11	Jun-30	-47.112	Jun-05	Jun-29
LN_WHEAT	~	COVID19	-4.644	Apr-02	May-20	-28.81	Jun-12	Jun-23

Note: *, **, or *** indicate the rejection of the null hypothesis with no-cointegration linkage at the 10%, 5%, or 1% level of significance, respectively.

The findings of the cointegration test of Hatemi-J (2008) allowing for multiple structural breaks in Table 3 provide the evidence against the null hypothesis of no cointegration relationship for four out of five pairs of variables, that is, the mortality rates and the spot prices of corn, oats, rapeseed, and soybeans moved in the same direction. This test, however, fails to reject the null hypothesis for the wheat prices and shows that these spot prices are found to be completely independent, namely, the mortality rates of the Covid-19 pandemic is not the forcing variable of the wheat spot markets.

Table 4. Granger Causality Test Results based on VECM

Independent		**Dependent**	**Lag (k-1)**	χ^2 **-statistics**	$\mathbf{ect_{t-1}}$
COVID19+dummy	$\nRightarrow$	LN_CORN	1	0.89315	-0.05683**
COVID19+dummy	$\nRightarrow$	LN_OATS	4	9.01424*	-0.03677***
COVID19+dummy	$\nRightarrow$	LN_RAPESEED	1	0.35621	-0.05678**
COVID19+dummy	$\nRightarrow$	LN_SOYBEANS	2	0.42176	-0.00562

Note: *, **, or *** indicate the rejection of the null hypothesis with no causal relationship at the 10%, 5%, and 1% level of significance, respectively. The dummy variable is a variable that takes the value 1 or 0 to indicate the presence or absence of the structural breaks according to the Hatemi-J's (2008) cointegration results.

In the last step, the approach of Granger causality based on VECM is employed to unveil the direction of both short- and long-run causal linkages among the cointegrated prices and the results are provided in Table 4. As evident from the table, a dummy variable is included to show whether or not the structural breakpoints of the Hatemi-J (2008) cointegration test strengthen the predictability of mortality rates on the development of the agricultural prices. The findings provide significant evidence that lagged values of the Covid-19 mortality are found to be useful for prediction in future directions of the corn, oats, and rapeseed spot prices. Explicitly, the mortality rates Granger-cause the corn and rapeseed prices only in the long-run. Besides, there seems to be strong evidence of one-way short- and long-run causal effects from the mortality rates to the oats spot prices. LN_SOYBEANS co-moves with, however, doesn't Granger caused by COVID19 in neither the short-run nor long-run, that is, the test fails to find any causal effect from the mortality rates to the soybeans spot prices since both the test statistic and the error correction term are not different from zero at any reasonable significance level.

Two robustness methods are executed to check the validity of the above findings and depict the findings in Figure2 and Figures3 and 4, respectively. In the first stage, a wavelet-based tool introduced by Rua (2010) is performed for a robust check between the mortality rates and the natural logarithms of the agricultural spot prices. The findings of Rua (2010) approach, at a first glance, reveal that the dynamics of the interdependence between the mortality rates and the agricultural spot prices is time-varying and heterogeneous, namely, the correlation varies considerably over time and across frequencies. For example, the mortality rates and the corn prices have intensive positive cohesion over May–June, and July–August, at 4 and 8~16 days scale, respectively, as depicted by two islands of red color. On the other hand, a high negative correlation appears between June and August on the 4-days scale and between the mid-of August and the mid-of September, in the 4~8 days of the time scale, as highlighted by four islands of blue color. Similarly, a strong positive cohesion arises between the mortality rates and the rapeseed spot prices over April–June on the 16~32 days scale (at lower frequencies) and during May at higher frequencies (2~6 days scale).In contrast, the findings reveal significant evidence of strong negative cohesion, with several islands of blue color, between the mid-of May and July on the 3~6 days scale, at the beginning of July on the 4~6 days scale, and the intermediate frequency of 8~10 days scale during the mid-of August. These findings show that there seem to be significant causal relationships between the mortality rates with the corn and rapeseed prices, respectively, as visualized at the top panel of Figure 3 and the middle panel of Figure 4.

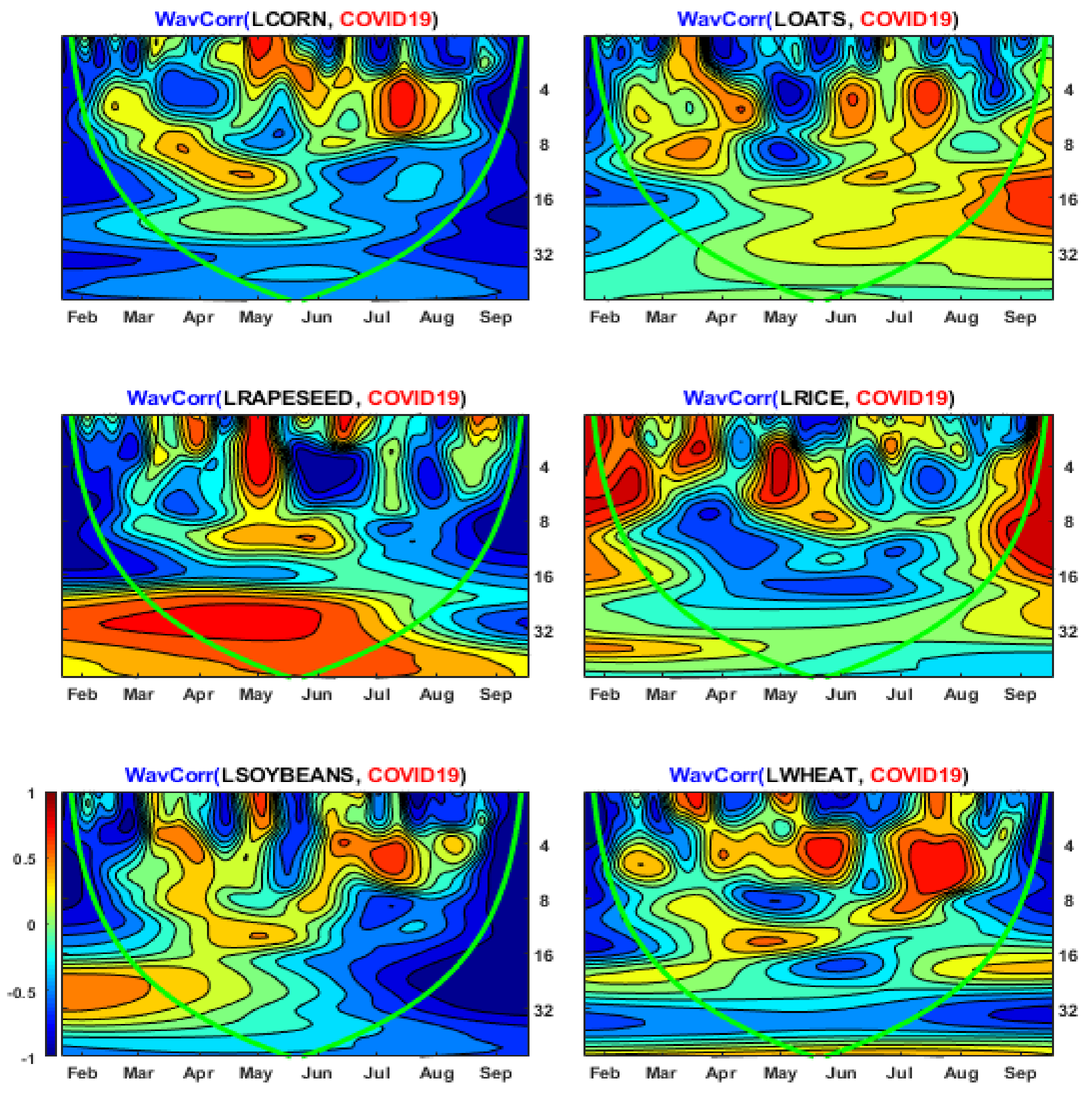

Figure 2. Rua (2010) Wavelet Correlation Estimations

Note: Each plot involves three dimensions: time, frequency, and color code. The horizontal x-axis indicates the time intervals, from the beginning to the end of the underlying sample period, while the vertical axis measures the scale, from scale 2 (4 days) to scale 5 (32 days). The color code value for wavelet cohesion (correlation) depicted on the left-hand side of the bottom panel ranges from dark blue (perfect negative correlation) to dark red (perfect positive correlation). Moreover, cross-hatched regions, as indicated by Torrence and Compo (1998), on either end show the cone of influence (COI) depicted by a thick green solid line isolating regions in which the wavelet cohesion is statistically significant at the 5% level against white noise. Since the wavelet is not completely localized in time, i.e. CWT suffers from border effects, the periods outside or overlapping the cone of influence must be ignored, and therefore, these periods should be interpreted carefully.

In Figures 3 and 4, the findings of causality in the CWT approach proposed by Olayeni (2016) are presented. The positive (in-phase) causality results are depicted on the left-hand side whereas the negative (out-of-phase) causality results are exhibited on the right-hand side of the figures. The graphs of the wavelet causality running from the mortality rates to the spot prices of corn, oats, and rapeseed are displayed in Figure 3. Evidently, the findings indicate the absence of in-phase causal effects from the mortality rates to the corn and oats prices during the sample period. Visual inspection allows detecting the presence of anti-phase (causal) effects from the mortality rates to the corn prices on the 3~6 and 4~8 days scale at the beginning of the Covid-19 pandemic and the end of the sample period, i.e. in September. In fact, there are significant red islands, implying negative causality running from the mortality rates, but they are negligible since they are located outside of the cone of influence. In a similar vein, the red island located on the 2~6 days scale, at the right-hand side, and in the middle panel, is also within the negligible area.

Figure 4 presents the findings of in-phase and out-of-phase causality running from the mortality rates to the spot prices of rice, soybeans, and wheat. Visual inspection indicates that the mortality rates positively Granger-causes the rice prices between March and April on the 4-days scale. The soybeans prices are, however, negatively Granger-caused by the mortality rates at the beginning of August on the 16~24 days scale and at the end of August on the 4~8 days scale. Similar but visually small negative causal effects run from the mortality rates to the wheat spot prices before February and after September on the 3~8 days scale. All these findings from the figures taken together reveal little empirical evidence of negative causal effects from the mortality rate to the agricultural spot prices when compared to the cointegration and VECM causality test results. That is, the results show significant but relatively small evidence that the lagged value of the mortality rates can be used to predict spot agricultural price changes at higher frequencies, i.e. in the short-run, contradicting the results of the aforementioned approaches.

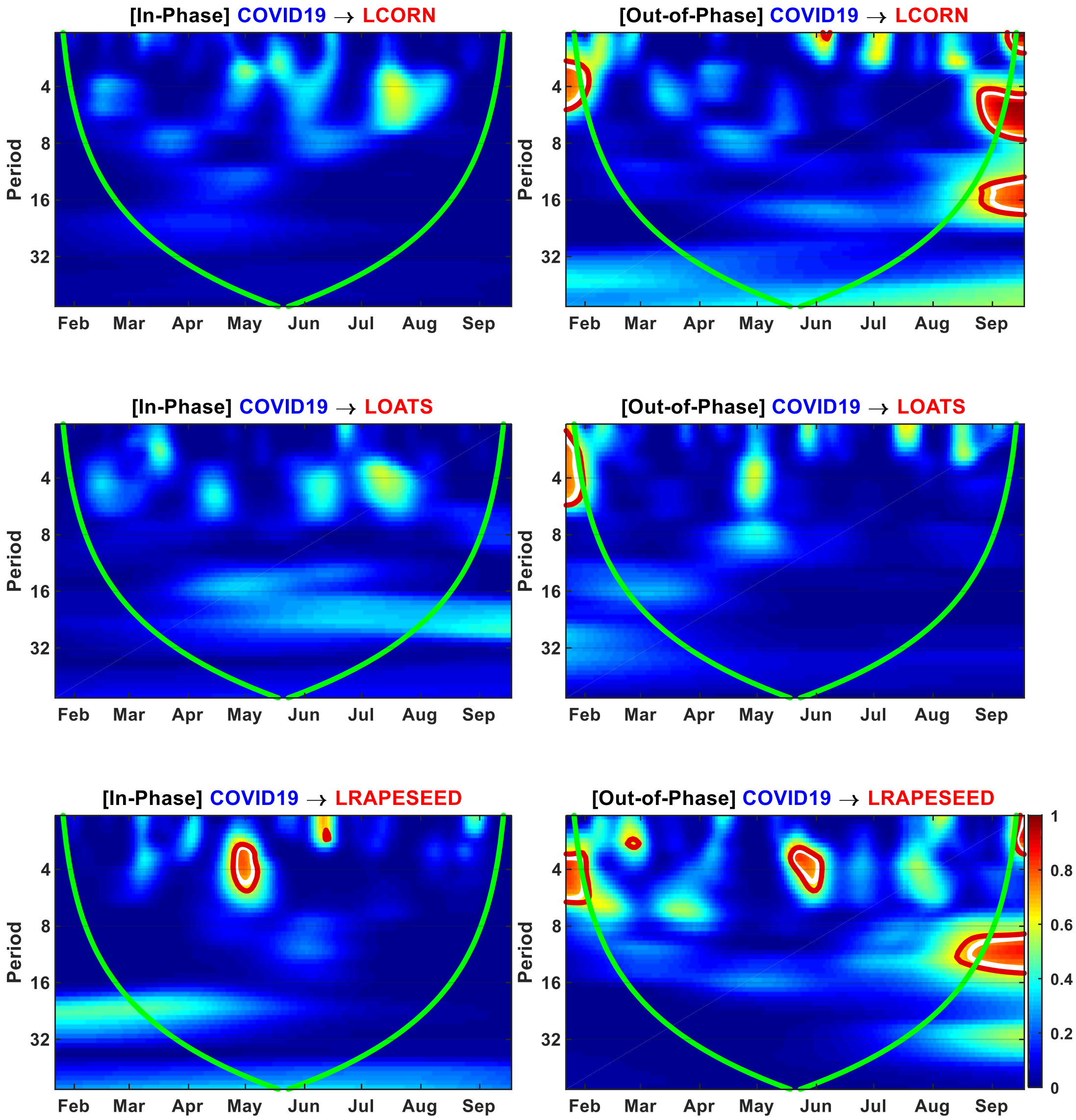

Figure 3. Olayeni (2016) CWT Causality Test Results

Note: Each plot involves three dimensions: time, frequency, and color code. The horizontal x-axis indicates the time intervals, from the beginning to the end of the underlying sample period, while the vertical axis measures the scale, from scale 2 (4 days) to scale 5 (32 days). The color code bar for wavelet causality depicted on the right-hand side of the bottom panel ranges from dark blue (no causality) to dark red (significant causality). The significance levels are obtained from Monte Carlo simulation with 10,000 replications estimated on an ARMA(1,1) process with null of no causality. The red (white) contour indicates rejection at the 10% (5%) significance level of the null hypothesis. Further, a thick green solid line is the cone of influence, namely, a surrounding wall that pulls apart the negligible areas affected by the edge effects from the significant areas. Accordingly, as stated before in Figure 2, the periods outside or overlapping the cone of influence are explicitly ignored.

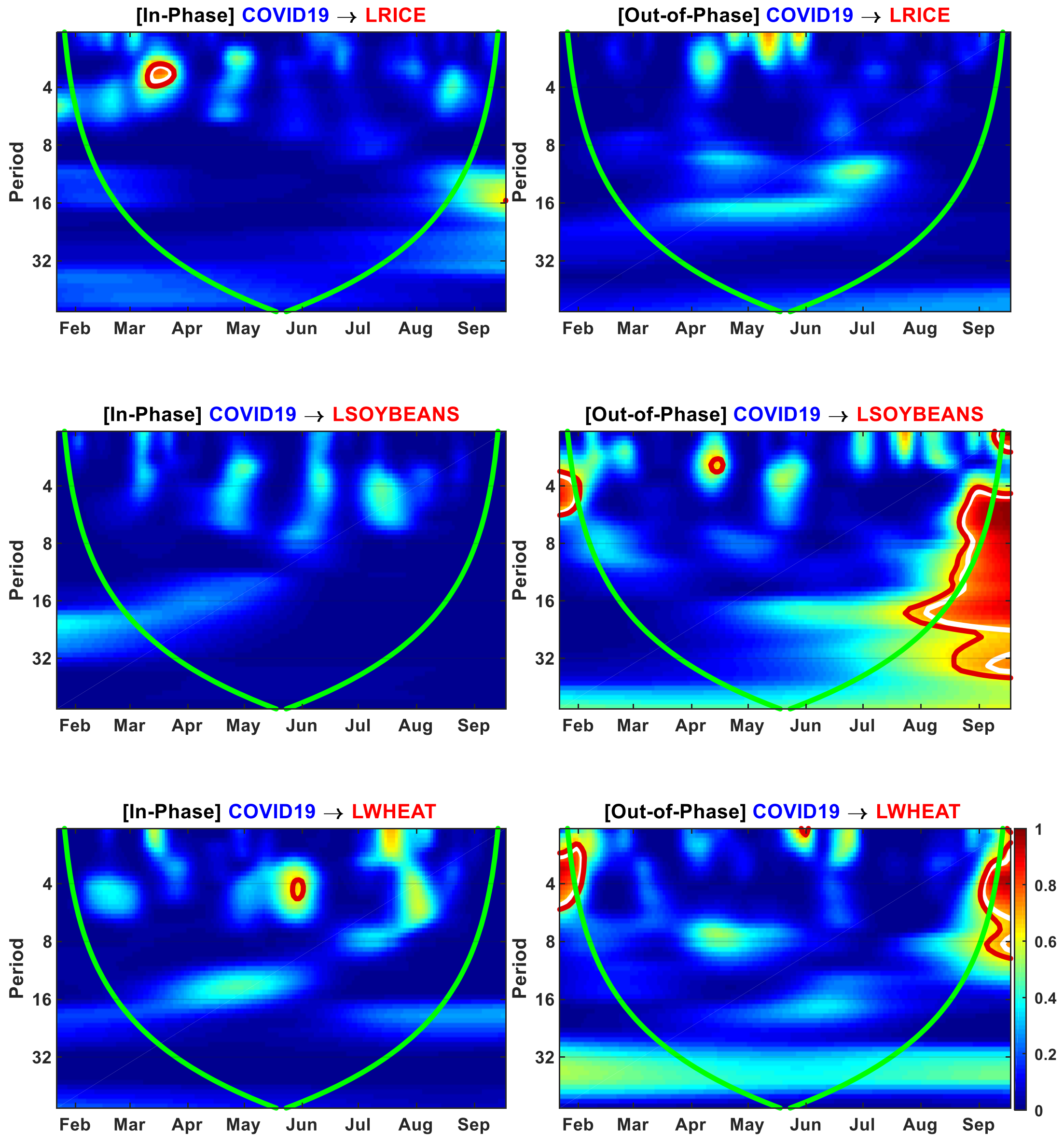

Figure 4. Olayeni (2016) CWT Causality Test Results

Note: Each plot involves three dimensions: time, frequency, and color code. The horizontal x-axis indicates the time intervals, from the beginning to the end of the underlying sample period, while the vertical axis measures the scale, from scale 2 (4 days) to scale 5 (32 days). The color code bar for wavelet causality depicted on the right-hand side of the bottom panel ranges from dark blue (no causality) to dark red (significant causality). The significance levels are obtained from Monte Carlo simulation with 10,000 replications estimated on an ARMA(1,1) process with null of no causality. The red (white) contour indicates rejection at the 10% (5%) significance level of the null hypothesis. Further, a thick green solid line is the cone of influence, namely, a surrounding wall that pulls apart the negligible areas affected by the edge effects from the significant areas. Accordingly, as stated before in Figure 2, the periods outside or overlapping the cone of influence are explicitly ignored.

6. Conclusion

The impact of the daily cumulative mortality rate of the Covid-19 pandemic on the spot prices of agricultural commodities has been investigated by applying both standard and wavelet approaches, covering the period of January 22, 1920, to September 18, 2020, with a total of 166 observations. Our findings show that six out of seven variables are integrated into the first order. The mortality rates exhibit a long-run relationship with the prices of corn, oats, rapeseed, and soybeans at different significant levels. The commodity prices of corn, oats, and rapeseed are found to be Granger-caused by the mortality rates whereas the soybeans prices could not be predicted by the movements in the mortality rate in neither the short-run nor long-run. On the other hand, the wavelet-based correlation approach proposed by Rua (2010) reveals that the relationship between the underlying time series is not homogenous across time scales. Moreover, the findings of the causality test of Olayeni (2016) provide significant evidence of out-of-phase causality over the higher frequencies at the beginning and mid of the Covid-19 outbreak and the end of the sample period for the spot prices of corn, rapeseed, soybeans, and wheat. Further, the mortality rates positively cause the rapeseed and rice prices on the 4 days scale in May and between March and April, respectively. Overall, the findings show that the mortality rates have significant impacts on the agricultural spot prices during the tested period.

Our results provide important implications for policymakers in constructing suitable policies. As the production of agricultural commodities more prone to variation in climatic changes such as shortage of rainfall (Kara and Diken, 2020), the disease like Covid-19 will even worsen the situation of the developing nations that depend more on agricultural commodities. Similar concerns were raised by the United States Agricultural Department which reported that there may be a food supply problem due to coronavirus which may further lead to a price increase of agricultural products. Hence, organizations like World Bank or IMF together with World Food Organization could help not only developing nations but also planning agricultural commodities in overcoming sustaining the production of agricultural products even at the time of infectious disease. As found above short and long-term relationship between the variables, these plans could be arranged accordingly. As for the developing nations which are said to be more prone to negative effects of disease like Covid-19, it could be best for them to maintain capital flow for their agricultural investments. Thus, these countries can be sufficiently effective in the storage, transport, and production of agricultural commodities.

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