Agrekon

Agricultural Economics Research, Policy and Practice in Southern Africa

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/ragr20

The COVID-19 effects on agricultural commodity markets

Mehmet Balcilar, Kamil Sertoglu & Busra Agan

AGREKON
2022, VOL. 61, NO. 3, 239–265
https://doi.org/10.1080/03031853.2022.2078381

The COVID-19 effects on agricultural commodity markets

Mehmet Balcilar [a,b], Kamil Sertoglu [a] and Busra Agan [a]

[a]Eastern Mediterranean University, North Cyprus, Turkey; [b]OSTIM Technical University, Ankara, Turkey

ABSTRACT
This study examines the effect of the COVID-19 pandemic on major agricultural commodity prices (cattle, cocoa, coffee, corn, cotton, hog, rice, soya oil, soybeans, soybean meal, sugar and wheat) using daily data from 1 January 2016 to 25 February 2022. We measured COVID-19 effect using a news-based sentiment index. A robust nonparametric Granger causality-in-quantiles test is used to test the effect of the COVID-19 sentiment on agricultural commodity prices and price volatility. We find significant Granger causality from the news-based COVID-19 sentiment to mean of the agricultural commodity prices in the lower and upper ranges of the quantiles. Moreover, findings show that the COVID-19 sentiment is also causal for variance of agricultural commodity prices, but only above the quantile ranges above the first quarter. Thus, COVID-19 is causal for large volatility changes in agricultural commodity prices. Accordingly, the extremely negative sentiment associated with COVID-19 has not only caused a price crash in agricultural markets, but also significantly increased market risk. Policymakers should be wary of the risks and vulnerabilities of agricultural commodities to extreme events, as well as the ramifications for producers and consumers throughout the economy.

ARTICLE HISTORY
Received 1 November 2021
Accepted 2 May 2022

KEYWORDS
COVID-19; agricultural commodity markets; quantile Granger causality; news-based sentiment index; Granger causality

JEL CODES
Q02; E32; C32

1. Introduction

The commodity market is characterised as a rapidly changing environment where all concerned stakeholders are ready for unexpected events all the time. Trades in the commodity market take place in the primary economic sector and not in manufactured products. The players that are involved in the commodity market include, but are not limited to, investors in general and portfolio managers, brokers, and traders. In an uncertain time, these actors forestall the actions of each other, which makes the market volatile and noisy (Moews and Ibikunle 2020). Commodity markets are also well-developed, with the possession of volatility reduction and risk transfer features. For instance, access to financial derivatives[1] is possible with the globalisation of commodity markets, while risk related to commodity exports can be transferred to investors seeking speculative opportunities.

Within no time, the global economy was taken aback by the world-wide outbreak of the COVID-19 (coronavirus) pandemic. The COVID-19 pandemic brought tremendous uncertainty about the future, leaving consumers and firms reluctant to make new decisions on spending and investment. It also caused severe interruptions in daily life and economic activity. Consequently, a global recession arose, triggered by both adverse demand and supply factors. Countries around the globe restricted their borders to contain the pandemic through border shutdowns, lockdowns, and travel restrictions, along with social distancing. As Kirsten (2022) points out, the COVID-19 pandemic is a classic “Black Swan” occurrence, with unparalleled scope, features, effects, and government responses around the

CONTACT Mehmet Balcilar mehmet@mbalcilar.net Department of Economics, Eastern Mediterranean University Famagusta, North Cyprus, via Mersin 10, Turkey

globe. The global economy has been profoundly disrupted by the legislative restrictions imposed by governments in most nations on the movement of people, products, and services. Agricultural and food production were not immune to the pandemic's disruption of the global economy, which had significant effects on agricultural commodity prices. Besides the severe impact of these measures on economic activities, supply channels, and international trade, a considerable global downturn in the commodity markets was also noted at the same time (Aslam et al. 2020). An extreme shock in the commodity market could be observed both from the demand side and the supply side. The worst affected was the oil market, where a steep price reduction was observed in March 2020, and a declining trend in metal prices. Since the agricultural sector is indirectly associated with other economic activities, it is therefore the least affected sector by the pandemic to date. However, according to the Food and Agriculture Organization (FAO 2020), there has been downward pressure on agriculture commodity prices since the onset of the pandemic. Moreover, it is argued that staple crops such as wheat and rice will be less affected than animal-based products and vegetable oil. Based on FAO and OCED 10-year projections of the agricultural outlook, though in the short-term some commodity prices have recovered, it is too early to be complacent as the projections anticipate that agricultural prices will be slightly lower in real terms over 2020–2029. The negative concern about the COVID-19 pandemic could last for a longer time on commodity markets. The unspecified impact could weaken the global growth prospect and, as a result, cause a deep recession and containment of demand for commodities.

The significant slowdown in economic growth caused by the COVID-19 pandemic is through the inter-linked channels of labour supply constraints, increased production costs, temporary higher prices of consumer goods, and reduced consumption. The global powers, i.e., the group of seven (G7) nations, are highly impacted by the COVID-19 shock, which constitutes 41 percent of global manufacturing exports, 65 percent of world manufacturing, and 60 percent of the world GDP (Baldwin and di Mauro 2020). The negative consequences of the contagion are also transmitted to other poor economies. The concept of "macroeconomic flu" presented by di Mauro (2020) does not seem to fit with the COVID-19 shock as it might disrupt the global economic prospect on a large scale. North Africa and the Middle East are particularly affected by the disturbances in oil prices and tourism. The travel restrictions and border closures jolt the economic activities in the European Union (Arezki and Nguyen 2020; Meninno and Wolf 2020). Since all the markets are inter-related (the commodity market, financial market, global economy, as well as changes in public sentiment), policy responses to the pandemic shock are highly challenging (Mann 2020).

The fluctuations in agricultural commodity markets have well-established implications for the whole economy, and COVID-19 has affected both the demand and supply of agricultural products, which could cause a crisis in the global food system. However, the literature on the issue is scant. The available literature is limited to the impact of COVID-19 on commodity markets and commodity price returns (Salisu, Akanni, and Raheem 2020; Shruthi and Ramani 2020), the impact of COVID-19 on stock markets (He et al. 2020), the correlation between commodity futures and COVID-19 (Wang, Shao, and Kim 2020), concerns over agricultural production due to COVID-19 (Pu and Zhong 2020), impact of COVID-19 on global food security and food supply network, among others (Bakalis et al. 2020; Nchanji et al. 2021; Perdana et al. 2020; Shirsath et al. 2020; Singh et al. 2020; Udmale et al. 2020).

The extant literature indicates diverse findings regarding COVID-19 and agricultural commodity markets (see e.g., among others, Bakalis et al. 2020; Elleby et al. 2020; Pu and Zhong 2020; Salisu, Akanni, and Raheem 2020; Shruthi and Ramani 2020; Singh et al. 2020; Udmale et al. 2020; Wang, Shao, and Kim 2020). Section 2 presents a review of the relevant studies. These disparate conclusions can be attributed in part to the time span of data, estimating methodology, and data type, which may be panel, cross-sectional, or time-series. The occurrence of abrupt changes, structural breaks, frequent outliers, and nonlinear dynamic effects are all concerns when investigating time series data such as commodity prices. When methods that are inadequate to account for such characteristics are utilised, erroneous statistical inferences may be obtained. To our knowledge, no study has examined the dynamic relationships between COVID-19 and agricultural commodity prices using rich and robust econometric methods. The COVID-19 pandemic has caused extreme changes in most economic variables, such as asset prices, foreign exchange rates, interest rates, unemployment, trade flows, and commodity prices. Consequently, both the level and volatility of commodity prices are affected. A measure of the COVID-19 pandemic that can be used to study how it affects markets is not directly observable. However, price and volatility changes occur as a response to information flow through news.

With this backdrop, the objective of this study is to examine the effect of the COVID-19 pandemic on the agricultural commodity markets in terms of its effects on price levels and volatility of prices. Moreover, we also aim to measure the COVID-19 pandemic through a news-based sentiment index and then utilise a robust nonparametric Granger causality-in-quantiles test to investigate the effect of the turbulent economic state due to COVID-19 on agricultural commodity prices. As a result, we assess both the impact of the COVID-19 pandemic on agricultural markets and whether a news-based sentiment index is useful for predicting agricultural commodity prices and volatility. The non-parametric Granger causality-in-quantiles is well suited to studying the effects of the COVID-19 pandemic since the pandemic creates extreme changes both in sentiment index and commodity prices. Mean-based estimation methods, such as the linear vector autoregressive (VAR) models and the linear Granger causality test based on VAR models, capture relationships at the centre of the relevant distribution, but they usually fail to find relationships that may hold onto the tails of the distribution. Quantile vector auto-regression and quantile Granger causality in general are widely-used in the literature, ranging from the use of measuring asset price booms (Cecchetti and Li 2008) to the asymmetric impact of oil price shocks on the stock market (Zhu et al. 2016), the casual nexus between oil and metal prices (Balcilar, Hammoudeh, and Asuba 2015; Shafiullah et al. 2021) and the credit risk spillover effect (Ando, Greenwood-Nimmo, and Shin 2017), among others. The quantile-based inference can be used to study relationships at any point in support of the distribution. Thus, the robust nonparametric approach adopted in this study is well-suited to studying the effects of the COVID-19 pandemic, which caused historically extreme changes both in the sentiment index and the agricultural commodity prices we study.

Our study contributes to the literature on several fronts. Firstly, we study a broad number of individual agricultural commodities, which include cattle, cocoa, coffee, corn, cotton, hogs, rice, soya oil, soybeans, soybean meal, sugar, and wheat, not an aggregate commodity index. Thus, our findings are free of aggregation bias and cover a large agricultural commodity range. Therefore, we also uncover which commodities are more prone to COVID-19 effects and whether effects are homogenous across commodities. Secondly, we use the news-based sentiment index of Buckman et al. (2020) to measure the COVID-19 pandemic effect, which is one of the best approaches for investigating the effect of the pandemic on market prices and volatility as the pandemic effect is transmitted to market outcomes through the news. Thirdly, the nonparametric causality-in-quantiles approach based on Jeong, Härdle, and Song (2012) and further extended by Balcilar et al. (2016, 2018) to higher order moments – using the approach of Nishiyama et al. (2011)–is a robust approach against misspecifications. The approach is also quite rich and allows us to discover causality from COVID-19 to agricultural prices, not only at the centre (mean) of the distribution but also over the entire distribution. This is particularly important since the COVID-19 pandemic created extreme movements both in the news-based sentiment index we use and also in agricultural commodity prices. The mean-based estimation approaches fail to detect dynamic interactions on tails, which is particularly true in our case, as we are examining a period with extreme changes. Fourthly, we do not only test for causality in the mean from the COVID-19 sentiment index to agricultural commodity prices, but also for causality in variance using the approach developed by Balcilar et al. (2016). Thus, the nonparametric causality-in-quantiles in the conditional variance test we use allows us to investigate how the COVID-19 sentiment affects market volatility.

Our findings show that the news-based COVID-19 sentiment index has a significant effect on both the mean and variance of agricultural commodity prices. However, the effect of COVID-19 on agricultural commodity prices is only significant in the extreme tails. The news-based sentiment index Granger causes agricultural commodity prices generally below the quantile of 0.20 and above the quantile of 0.70. We do not find any significant causality in the centre quantiles. However, significant heterogeneity exists across commodities in quantile ranges where significant causality is not observed. We also find significant causality in the variance from the COVID-19 sentiment to all the agricultural commodity price series we consider. However, significant causality in variance occurs generally in quantile ranges above the 0.20-th or 0.50-th quantile. Thus, the COVID-19 sentiment only causes high marked volatility. The low volatility values or periods are not related to COVID-19. Analogous to the causality in the mean, there exists significant heterogeneity across the commodities in the quantile ranges where significant causality is observed.

The rest of the study is organised as follows. In Section 2, we present a review of the existing literature. Section 3 describes the data and outlines the details of the methodology used in the paper. Section 4 presents empirical results. Section 5 is about the discussions, while Section 6 concludes the study and provides some policy implications.

2. Literature review

This section reviews the relevant literature on the effect of the COVID-19 pandemic on major agricultural commodity prices. The existing literature contains various explanations and findings regarding the COVID-19 and agricultural commodity market relationship. For example, Shruthi and Ramani (2020) utilised a variance causality test to examine the effect of the food cost crises during the pre-COVID period and post-COVID period. The findings suggest that there is zero risk transmission among agricultural commodities, while volatility in the oil market is causing volatility in the agricultural product markets. A predictive panel data model was used by Salisu, Akanni, and Raheem (2020) to examine the role of the global fear index (GFI) in predicting commodity price returns. Findings suggest that an increase in COVID-19-related fear leads to an increase in commodity price returns. Wang, Shao, and Kim (2020) explored the cross-correlation between agricultural futures markets and crude oil by using multifractal detrended cross-correlation analysis. The results confirm that there is a strong cross-correlation between the London sugar future market and Brent crude oil, where this cross-correlation has increased with the emergence of the COVID-19 pandemic.

COVID-19's effect on agricultural commodity prices could be a consequence of indirect effects on demand and supply conditions. A few studies document supply effects experienced in various countries. Based on interviews with key stakeholders in South Africa, Meyer et al. (2022) examine the consequences of agricultural production from a macro and sector-wide viewpoint. They look at the agricultural value chain's many constraints and how they affect major agricultural sectors. Their findings point to distributional issues that influenced vulnerable groups' access to services, which was reinforced by the initial exclusion of informal traders from critical services. They also point to negative consequences for non-food businesses like wine, where trade was restricted. Agricultural production could be negatively affected in China due to unreasonable restrictions, such as the restriction of labour and supplies, food-related logistics and services caused by COVID-19 (Bakalis et al. 2020; Pu and Zhong 2020). In order to assess the impact of labour unavailability due to COVID-19 and its impact on agricultural production and food security in India, Sing et al. (2020) utilised a spatial ex-ante modelling framework. Findings from the study suggest that under the delay scenario, wheat productivity loss is higher than rice productivity loss, whereas the total system productivity loss is estimated to range from 9 percent to 21 percent. Udmale et al. (2020) investigate the potential effects of the COVID-19 pandemic on the global food supply and zero hunger (SDG-2). Based on the findings, it was identified that countries in Africa (15 countries), Latin America (10 countries) and Asia (4 countries) are the most vulnerable to transitory food insecurity due to COVID-19. With the objective of determining the location and capacity of regional food hubs, the food supply network, and minimum logistics cost, Perdana et al. (2020) utilised the multi-objective many-to-many location-routing problem model. Results indicate that a scenario involving health and food safety protocols for food delivery in the new era is the best scenario for the optimal food supply network. Elleby et al. (2020) employ a multi-country commodity agriculture model and perform a scenario-based analysis of the International Monetary Fund (IMF) economic growth forecasts to examine the demand side effects of the COVID-19 pandemic and lockdowns. They find that international meat prices will fall by 7–18% while dairy prices will fall by about 4–7% in 2020 following the decline in global economic growth. Considering another effect, Beckman and Countryman (2021) examine changes in agricultural production and trade shocks during the COVID-19 pandemic, estimating the effect of these shocks on GDP by using a simulation model. Their findings imply that changes in agriculture during the COVID-19 pandemic have had a higher impact on the US economy than on agriculture's share of the economy before the pandemic period. Therefore, COVID-19 has seemed to have a substantial impact on the economy.

Regarding regional studies, Pu and Zhong (2020) investigate the impact of COVID-19 on agricultural production in China. They find that arbitrary restrictions hinder agricultural product export channels and essential production inputs, interrupt production cycles, and eventually impair production capacity. Another study by Zhang et al. (2020) examine the effects of the COVID-19 pandemic on agricultural products in China using a dynamic panel model over the 2002–2018 period. Based on the findings, the COVID-19 pandemic process has a negative effect on agricultural production productivity. Meyer et al. (2022) use a primary data set from a study of medium and large enterprises and farms in the beef, citrus, and maize value chains in South Africa to find that lockdowns harmed these three vertical value chains because lateral limitations strangled important segments of the verticals. Likewise, Udmale et al. (2020) examine the impact of the COVID-19 pandemic on the global food supply by focusing on developing countries in Africa, Latin America, Oceania, and Asia. Their study provides evidence that the current pandemic is likely to produce transitory food insecurity in such susceptible countries. Khan et al. (2021) also focus on the impacts of the COVID-19 pandemic on the agricultural sectors in Bangladesh, finding that agricultural products and costs are much higher in the food chain than before the pandemic period. Later, Boughton et al. (2021) assess the effects of the COVID-19 pandemic on Myanmar's agri-food sector using panel phone surveys in the second quarter of 2020, finding that the agri-food system demonstrates resilience, but supply disruptions occur due to movement restrictions and liquidity constraints. Based on in-depth interviews with 40 market-oriented small- and medium-scale farmers in South Africa, according to Wegerif (2022), COVID-19-related impacts include decreased output and income, as well as job losses.

Several studies directly model the influence of COVID-19 on agricultural markets. For instance, Ramakumar (2020) examines the effects of COVID-19 on agricultural products on a worldwide scale, particularly in India, employing 16 crops from April through May 2020. Their findings show that foreign trade in agricultural products dropped during the lockdown. Using a partial equilibrium simulation model, Davids, Vink, and Cloete (2022) conclude that intermittent bans on alcoholic beverage sales in South Africa, which have had a significant impact on the wine business, have had an indirect impact on GDP growth, consumer spending, and exports. According to the simulation results, the ensuing stock building leads to a lengthy period of lower pricing. Agriculture has been badly harmed since supply has decreased and shortages have begun. On the other hand, Varshney, Roy, and Meenakshi (2020) examine the impact of the spread of COVID-19 and the resulting lockdown on wholesale prices and volumes traded in agricultural commodities during a three-month period in over 1000 markets. Their results indicate that agriculture markets provide substantial resilience in the face of the COVID-19 shock. Agricultural sustainability during the COVID-19 outbreak is affected by lockdown policies in society. Rad et al. (2021) investigate the dynamic consequences of the COVID-19 pandemic on food security in Iran. They find that the pandemic process has a negative influence on agricultural and food security because of the lockdown policies. Their findings are in line with the results of Höhler and Lansink (2021), who find increased volatility in stock prices and downward swings in returns in the food supply chain under the impact of the pandemic.

In response to market shocks, agricultural products may act differently than other commodity classes. For instance, they adjust to the long-run equilibrium faster than other commodities, such as metals and energy. In one of the pioneering studies, Pindyck and Rotemberg (1990) observe a similar pattern of commodity price behaviour and co-movement. This finding is furthered by investigating the relationship among commodity classes using a variety of models and methodologies. Daglis, Konstantakis, and Michaelides (2020) study the effects of the COVID-19 outbreak on agricultural commodities, particularly the pricing of oats and wheat, from January to June 2020. Their study implies that there are statistically significant and positive effects of the COVID-19 pandemic on the prices of oats and wheat. Bouri et al. (2021) examine the connectedness between agricultural commodities, energy, and metals from September to May 2020. Their findings indicate that there are both strong and moderate levels of volatility connectedness between energy and metals, as well as moderate degrees of connectedness within the group of agricultural commodities. On the other hand, Hung (2021) studies the spillover effects and connectedness between crude oil prices and agricultural commodities markets during the COVID-19 epidemic using the spillover index and wavelet coherence model. The empirical findings indicate that there is a high correlation between WTI crude oil prices and agricultural commodities markets, particularly during the COVID-19 outbreak, and that both markets exhibit positive and negative interactions as well as significant heterogeneity. Another study by Umar, Gubareva, and Teplova (2021) also uses the wavelet approach to analyze the effects of the COVID-19 outbreak on the volatility of commodity prices. The results confirm that there is high, medium, and low coherence among various commodities and also that the low confidence intervals reflect the diversification benefits of commodities in the event of the COVID-19 pandemic. Another study by Umar et al. (2021) analyzes the relationships between agricultural commodities and oil prices using the Granger causality test, static and dynamic rolling connectedness, and daily data from 2002 through 2020, spanning the global financial crisis, the European sovereign debt issue, and the COVID-19 pandemic crisis. Their findings show a statistically significant causal relationship between oil shocks and agricultural commodities like grains, live cattle, and wheat. Later, Umar, Riaz, and Zaremba (2021) analyze the links among nine commodity markets, covering monthly data over the period of 1780–2020 using network connectedness and granger causality. They find that grains, soft foods, and precious metals are the primary net transmitters of spillover, and their connectedness increases during economic crises and high uncertainty. In addition, the paper by Y. Sun et al. (2021) examines the long-term link and causality between crude oil and agricultural commodity prices using monthly data from 2001 to 2020 under the impact of the COVID-19 outbreak. Their empirical findings demonstrate a bidirectional causal relationship between oil and agricultural commodity prices. Lastly, Umar et al. (2021) investigate the return and volatility interactions between oil prices and a variety of agricultural commodities using spillover indices from 2000 to 2020. They find that the interactions were increased during the COVID-19 pandemic crisis and times of high uncertainty. Wang, Shao, and Kim (2020) use multifractal detrended cross-correlation analysis (MF-DCCA) between agricultural and crude oil commodities from 2017 to 2020. They demonstrate a strong and persistent relationship between sugar and crude oil commodities during the period of COVID-19. Shruthi and Ramani (2020) investigate volatility transmission during the financial crisis, employing impulse response functions and variance causality tests to account for the impact of the food price crisis in the post-COVID and pre-COVID periods. The results of the variance causality test suggest that there is no risk transmission among agricultural commodities, although oil market volatility has had a spillover effect on agricultural commodity prices, except sugar, in the post-crisis period. So, this study shows that statistical volatility transmission changes after the food price crisis.

A more recent study by Cao and Cheng (2021) investigates the spillover connectedness between food and crude oil markets during the COVID-19 pandemic period. They find that the food-oil market system has the highest short-term spillover effect, and the spillovers during the pandemic are substantially smaller than during the financial crisis. Chen, Rehman, and Vo (2021) employ a multivariate generalised autoregressive conditional heteroscedasticity (MGARCH) model to forecast the prices of precious metals, base metals, energy, and agricultural commodities from September to July 2020. They conclude that volatility-based clustering is aligned with the traditional level during the COVID-19 pandemic.

There is also a growing literature on the implications of economic uncertainty on agricultural commodity markets during the COVID-19 crisis. Moreover, another study by T. T. Sun et al. (2021) uses Granger causality analysis to examine the effects of trade policy uncertainty on prices of agricultural commodities from 2005 to 2020, including the period of COVID-19. They conclude that agricultural commodity prices have a positive causal relationship with trade policy uncertainty. Recently, Ben Haddad, Mezghani, and Gouider (2021) utilise the time-varying vector-autoregressive (TVP-VAR) method to analyze the uncertainty of connectedness among commodities over the period from 1960 to 2020. Their empirical findings show that uncertainty has persistent spillover effects on commodity prices during the COVID-19 outbreak period. Even more, Umar, Jareño, and Escribano (2022) utilise the time-varying parameter vector autoregressive model (TVP-VAR) model to examine the dynamic return and volatility connectedness among the agricultural commodities and the coronavirus media coverage index (MCI) from January to July 2020. The results show that the commodity market has a negative net dynamic connectedness from grain to livestock during the start of the COVID-19 pandemic. Lastly, Liu et al. (2022) also use the TVP-VAR approach to investigate the adverse effect of public sentiment on agricultural products during the COVID-19 pandemic in China. Their findings indicate that online negative sentiment has a significant effect on agricultural commodity prices.

While prior studies have examined COVID-19's various effects on agricultural commodities, they have not specifically examined the influence on prices. Additionally, their data is either low frequency or only covers a short period during the COVID-19 pandemic. Additionally, the nonlinear properties of the data from the crisis era may have an adverse effect on the methods used in these studies. Our study addresses a gap in the current literature by analyzing the effect of the news-based sentiment index developed by Buckman et al. (2020) on the prices of a broad range of individual agricultural commodities utilising high frequency data and longer COVID-19 period coverage. Additionally, we use a nonparametric estimation method that is robust to nonlinear dynamic effects.

3. Econometric methodology and data

3.1 Methodology

A generalisation of the Jeong, Härdle, and Song (2012) test using the framework of Nishiyama et al. (2011), which is an extension of the nonparametric causality-in-quantile test to higher moments, is offered by Balcilar et al. (2016, 2018). The extension in Balcilar et al. (2016, 2018) is bivariate and limited to one lag. An analytical framework of this generalised nonparametric causality-in-quantile test for multivariate cases with higher order lags is provided in this section. Granger causality tests with more than two variables, or a lag order greater than two even in a bivariate case, require the use of a multivariate generalised version of a nonparametric causality-in-quantiles test. Agricultural commodity markets are believed to behave asymmetrically or nonlinearly. Hence, testing predictability in agricultural commodity markets and its volatility over the entire conditional distribution by using the nonparametric quantile estimation approach seems reasonable. The approach, besides being robust to miss-specification errors, also has the capability to test for causality in higher moments of data, i.e., variance, rather than causality in the first movement of data, i.e., mean only.

Suppose agricultural commodity prices are denoted by y_t, whereas the sentiment index is denoted by x_t with m as additional covariate variables $w_{i,t}$, $i = 1, 2, \ldots, m$. The predictors that are used as a control variable in the model are specified as $W_t \equiv (w_{1,t}, w_{2,t} \ldots, w_{2,m})'$. In order to define the multivariate quantile causality test, the following definitions are used:

$Y_{t-1} \equiv (y_{t-1}, \ldots, y_{t-p})'$, $X_{t-1} \equiv (x_{t-1}, \ldots, x_{t-p})$, $W_{t-1} \equiv (w_{1,t-1}, \ldots, w_{1,t-p}, \ldots, w_{m,t-1}, \ldots, w_{m,t-p})'$. Let $Z_t \equiv (Y'_t, X'_t, W'_t)'$ also represent the full information set and $Z_t \backslash X_t \equiv V_t \equiv (Y'_t, W'_t)'$ be the full information set excluding X_t. The conditional distribution of y_t given Z_{t-1} and $Z_{t-1} \backslash X_{t-1}$ is algebraically expressed as $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ and $F_{y_t|Z_{t-1}\backslash X_{t-1}}(y_t|Z_{t-1}\backslash X_{t-1})$, respectively.

Let the conditional θ-th quantile of y_t be given by $Q_\theta(y_t|\cdot)$ where is the information set. In the framework of Nishiyama et al. (2011) and Jeong, Härdle, and Song (2012), Granger non-causality is defined in quantiles as: x_t does not Granger cause y_t in the θ-th quantile, if

$$Q_\theta(y_t|Z_{t-1}) = Q_\theta(y_t|Z_{t-1}\backslash X_{t-1}) \tag{1}$$

On the other hand, Granger causality in quantiles suggest that x_t Granger causes y_t in the θ-th quantile, if

$$Q_\theta(y_t|Z_{t-1}) \neq Q_\theta(y_t|Z_{t-1}\backslash X_{t-1}) \tag{2}$$

The equivalent representations of Equations (1) and (2) are as follows:

$$H_0: \quad P\{F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1}\backslash X_{t-1})|Z_{t-1}\} = \theta\} = 1 \tag{3}$$

$$H_1: \quad P\{F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1}\backslash X_{t-1})|Z_{t-1}\} = \theta\} < 1 \tag{4}$$

where $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Z_{t-1}\backslash X_{t-1}) \equiv Q_\theta(y_t|Z_{t-1}\backslash X_{t-1}))$ are the θ-th quantiles satisfying that the probability of $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$ is one.

For the construction of the test, consider the metric $J = \{\epsilon_t E(\epsilon_t|Z_{t-1}) f_Z(Z_{t-1})\}$, where $f_Z(Z_{t-1})$ is the marginal of Z_{t-1}. The emergence of the error term ϵ_t is because of the null in Equation (3) which can only hold if $E[1\{y_t \leq Q_\theta(Z_{t-1}\backslash X_{t-1})|Z_{t-1}\}] = \theta$, which implies $1\{y_t \leq Q_\theta(Z_{t-1}\backslash X_{t-1})\} = \theta + \epsilon_t$, where $1\{\cdot\}$ is the indicator function. The metric J can be re-specified as:

$$J = E[\{F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1}\backslash X_{t-1})|Z_{t-1}\} - \theta\}^2 f_Z(Z_{t-1})] \tag{5}$$

The empirical form of Equation (5) based on Jeong, Härdle, and Song (2012) is given by:

$$\hat{J}_T = \frac{1}{T(T-1)h^{(k+2)p}} \sum_{t=p+1}^{T} \sum_{s=p+1,\, s\neq t}^{T} K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \hat{\epsilon}_t \hat{\epsilon}_s \tag{6}$$

where the kernel function $K(\cdot)$ is defined with bandwidth h, sample size T, and lag order is p. The unknown regression error $\hat{\epsilon}_t$ for a given quantile θ can be estimated empirically as:

$$\hat{\epsilon}_t = 1\{y_t \leq \hat{Q}_\theta(Z_{t-1}\backslash X_{t-1})\} - \theta \tag{7}$$

where the estimate of the θ-th conditional quantile is denoted by $\hat{Q}_\theta(Z_{t-1})$. Jeong, Härdle, and Song (2012) argue that causality in conditional mean (1-st moment) implies causality in higher order moments, but not vice versa, which necessitates the adoption of a k-th moment sequential testing approach for causality:

$$H_0: \quad P\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Z_{t-1}\backslash X_{t-1})|Z_{t-1}\} = \theta\} = 1, \quad k = 1, 2, \ldots, K \tag{8}$$

$$H_1: \quad P\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Z_{t-1}\backslash X_{t-1})|Z_{t-1}\} = \theta\} < 1, \quad k = 1, 2, \ldots, K \tag{9}$$

In order to formulate the test statistic, we replace y_t by y_t^k in Equation (6). The equality in Equation (8) and inequality in Equation (9) holds if and only if $J \geq 0$ and $J > 0$. respectively. Therefore, the rescaled of version of the test statistic can be expressed as:

$$t = \frac{\hat{J}_T}{T^{-1} h^{-(m+2)p/2} \sigma_0} \xrightarrow{d} N(0, 1)$$

where

$$\hat{\sigma}_0 = \sqrt{2}\theta(1-\theta)\sqrt{\frac{1}{T(T-1)h^{(m+2)p}}}\sqrt{\sum_{t=p+1,t\neq s}^{T} K^2\left(\frac{Z_{t-1}-Z_{t-1}}{h}\right)}$$

The expression for the θ-th quantile of y_t is given by:

$$\hat{Q}_0(Z_{t-1}\backslash X_{t-1}) = \inf\{y_t: \hat{F}_{y_t|Z_{t-1}\backslash X_{t-1}}(y_t|Z_{t-1}\backslash X_{t-1}) \geq \theta\},$$

where

$$\hat{F}_{y_t|Z_{t-1}\backslash X_{t-1}}(y_t|Z_{t-1}\backslash X_{t-1}) = \frac{\sum_{s=p+1,s\neq t}^{T} K((V_{t-1}-V_{s-1})/h)1\{y_s \leq y_t\}}{\sum_{s=p+1,s\neq t}^{T} K((V_{t-1}-V_{s-1})/h)}$$

The empirical implementation of the nonparametric causality-in-quantiles test can be framed based on the following model specification:

$$(s_{i,t}^{cmp})^{(m)} = m(Z_{t-1}) + \epsilon_t$$

where $(s_{i,t}^{cmp})$ is agricultural commodity price. For causality in mean, we have $m = 1$ while for causality in variance we have $m = 2$.

Three main choices are involved in the empirical implementation of the test: lag order (p), bandwidth (h), and the kernel types for $K(\cdot)$ and $L(\cdot)$. In order to avoid the over-parametrization problem, which is a higher concern in nonparametric models due to curse dimensionality problems, we use the Schwarz Information Criterion (SIC) to select the lag order (p). The bandwidth h is determined by the leave-one-out least-squares cross-validation. We use Gaussian kernels for $K(\cdot)$ and $L(\cdot)$.

3.2 Data

The data used in the study is at the daily frequency covering the period from 1 January 2016 to 25 February 2022. The data for the commodity price series are sourced from the Datastream database. Buckman et al. (2020) The news-based sentiment index, which is constructed by Buckman et al. (2020) using the approach of Shapiro, Sudhof, and Wilson (2020), can be found on the Federal Reserve Bank of San Francisco's website.[2] Information on commodity prices and news-based sentiment index data is given in Table 1. There are 1,343 observations in the analysis period, 814 in the pre-COVID period (1 January 2016–14 February 2020) and 529 in the post-COVID period (15 February 2020–25 February 2022). We analyze the pre- and post-COVID-19 periods separately and also perform time-varying analysis for robustness. We include 12 major agricultural commodity prices in the dataset. Namely, these include cattle (Live Cattle CME 1st Fut. Usc/Bu), cocoa (Cocoa-ICCO Daily Price US$/MT), coffee (Coffee-ICO Composite Daily ICA c/lb), corn (Corn No. 2 Yellow U $/Bushel), cotton (Cotton, 1 1/16Str Low-Midl, Memph $/Lb), hogs (HOG 51–52% US 3 AREA Ntnl MR U$/Cwt), rice (Processed, U$/50KG), soya oil (Crude Decatur US $/lb), soybeans (No.1 Yellow $/Bushel), soybean meal (48% FOB K. City $/MT), sugar (Raw Sugar-ISA Daily Price c/lb), and wheat (No. 2, Soft Red U$/Bu).

The news-based sentiment index is used as a measure of market participants' reactions to the COVID-19 pandemic. Assessing the timing and magnitude of the COVID-19 pandemic on various aspects of the economy requires high frequency data as the situation is rapidly changing. Economic consequences are usually assessed based on so-called hard data such as payroll employment, personal income, consumer spending, and business investment. Unfortunately, these data come with delays and do not help to assess the effects of the pandemic on agricultural commodity prices. There are further issues with using such data since they are the consequence, not the cause, and only indirectly capture the markets' reactions to the pandemic. Sentiment analysis quantifies the emotional content of any set of texts based on a predefined list of words. The sentiment context

Table 1. Data information.

Code	Description	Commodity type	Currency	Unit	Source	Description
Commodity price data						
CATTLE	Live Cattle CME 1st Fut. Usc/Bu	Livestock	United States Cent	Pound	Chicago Mercantile Exchange (CME)	Live Cattle Chicago Mercantile Exchange(CME) First Positional Futures United States Cents Per Pound
COCOA	Cocoa-ICCO Daily Price US$/MT	Softs	United States Dollar	Metric Tonne	International Cocoa Organization (ICCO)	Cocoa-International Cocoa Organization(ICCO) Daily Price USA United States Dollar Per Metric Tonne
COFFEE	Coffee-ICO Composite Daily ICA c/lb	Softs	United States Cent	Pound	International Coffee Organization (ICO)	Coffee-International Coffee Organization(ICO) Composite Daily International Coffee Agreement (ICA) UC/Pound
CORN	Corn No.2 Yellow U$/Bushel	Grains	United States Dollar	Bushel	U.S. Department of Agriculture	Corn Number 2 Yellow Central Illinois USD / Bushel
COTTON	Cotton, 1 1/16Str Low -Midl,Memph $/Lb	Fibres	United States Dollar	Pound	U.S. Department of Agriculture	Cotton, 1 1/16STR Low – Middling, Memphis USD / Pound
HOG	HOG 51–52% US 3 AREA Ntnl MR U $/Cwt	Livestock	United States Dollar	Hundred Weight	Refinitiv	Hog 51–52% USA 3 Area NTNL MR U$ / Hundredweight
RICE	Rice, Processed, U$/50KG	Grains	United States Dollar	50 Kilograms	Refinitiv	Rice, Processed, U$ / 50KG
SOYAOIL	Soya Oil, Crude Decatur US $/lb	Agricultural Oils	United States Dollar	Pound	U.S. Department of Agriculture	Soya Oil, Crude Decatur USD / Pound
SOYBEAN	Soybeans, No.1 Yellow $/Bushel	Oil Seeds	United States Dollar	Bushel	U.S. Department of Agriculture	Soybeans, Number 1 Yellow USD / Bushel
SOYMEAL	Soymeal 48% FOB K.City $/MT	Oil Seeds	United States Cent	Metric Tonne	Refinitiv	Soymeal 48% Free on Board Kansas City United States Dollar Per Metric Tonne
SUGAR	Raw Sugar-ISA Daily Price c/lb	Softs	United States Cent	Pound	International Sugar Organization (ISO)	Raw Sugar-International Sugar Agreement (ISA) Daily Price UC/Pound
WHEAT	Wheat No.2,Soft Red U$/Bu	Grains	United States Dollar	Bushel	U.S. Department of Agriculture	Wheat Number 2, Soft Red USD / Bushel
News sentiment data						
NEWSSENT	News sentiment	–	–	Index	Federal Reserve Bank of San Francisco	The Daily News Sentiment Index, High frequency measure of economic sentiment based on lexical analysis

Note: The commodity price series are sourced from the Datastream database. The news sentiment index of Buckman et al. (2020) is obtained from the Federal Reserve Bank of San Francisco website at https://www.frbsf.org/economic-research/indicators-data/daily-news-sentiment-index/.

is constructed using the rapidly developing field of natural language processing. Shapiro, Sudhof, and Wilson (2020) use a lexical approach to construct sentiment scores for economics-related news articles from 16 major US newspapers.[3] The newspaper articles used for the index construction are compiled by the news aggregator service LexisNexis and contain at least 200 words.

4. Empirical results

In order to have an idea of the overall tendency of the commodity prices and the COVID-19 sentiment index, we present their time series plot in Figure 1. The sentiment index displayed in Figure 1 is constructed using the classification of the contents of the news as negative, neutral, or positive. Therefore, positive values in Figure 1 represent positive sentiment, while negative values represent negative sentiment, and neutrality corresponds to zero. As the figure shows, the sentiment index has a value around 0.12 in the mid-January 2020, indicating quite a positive market sentiment. In a month's time, the index drops significantly–more than 100%–and becomes negative by mid-February 2020. The drop in sentiment continues until mid-May 2020, reaching a minimum of −0.48, implying a 300% decline compared to the beginning of January 2020. Then, the index starts to rise in the first week of June 2020, but still indicates negative sentiment until February 2021.

Figure 1 also presents the time series plots of the agricultural commodity price series for the period considered in the study. As revealed by the figure, all agricultural commodity prices display a sharp and significant drop, continuing from early February 2020 to August 2020. All commodity prices reach their single minimum or one of the two in April 2020, except cocoa and coffee, for which the minimum is reached at the end of June 2020. Cocoa, coffee, and hogs have two or more local minimums. These four commodities do also show larger fluctuations during the period considered. The decline from the end of January 2020 to April 2020 ranges from 10% to 25%, with the majority having a decline of about 25%. However, we observe a reversal of the negative trends in all agricultural commodity prices around mid-2020. Indeed, most agricultural commodities, excluding cocoa, showed record growth in the second half of 2020. For cattle, coffee, cotton, sugar, and wheat, the positive price growth still continues in 2022. The growth in agricultural commodity prices from mid-2020 to mid-2021 ranges from 150% to 500%. Thus, the strong positive trend in economic sentiment is linked to strong increases in the prices of agricultural commodities. Thus, all agricultural commodity prices show high sensitivity to negative COVID-19 pandemic sentiment during the period when the pandemic was severe and affected millions of people every day, with about 200,000 positive new daily cases. Although all agricultural commodity prices look highly sensitive to the COVID-19 pandemic, they also possess some heterogeneity in terms of speed of decline and fluctuation pattern.

Key features of the series can be seen from the descriptive statistics given for the log growth rates in Table 2. In Table 2, we report the mean, standard deviation, kurtosis, skewness, Jarque-Bera normality test (JB), Ljung-Box first- [Q(1)] and fifth-order [Q(5)] autocorrelation tests, and first- [ARCH(1)] and fifth-order [ARCH(5)] Lagrange multiplier tests for autoregressive conditional heteroscedasticity (ARCH) for all series. Panel A of Table 2 displays the descriptive statistics for the pre-COVID-19 pandemic period, while Panel B displays them for the post-COVID-19 pandemic period. In both subsamples, most commodity price series have a positive average growth over the period, except for cattle, cocoa, coffee, soya oil, soybeans, and sugar, which have negative average growth in the pre-COVID-19 period, and cocoa in the post-COVID-19 period. The sentiment index has a positive average growth rate in the pre-COVID-19 period, while it has a negative average growth rate in the post-COVID-19 period. The average growth rates in general are several times higher in the post-COVID-19 period than in the pre-COVID-19 period. In the post-COVID-19 period, the most volatile commodity price series were corn, cotton, soya oil, and soymeal, while the least volatile series were cattle, cocoa, and soybeans. All agricultural price series do have a small asymmetry, as indicated by estimates of the skewness coefficient, but not all of them are uniformly positively or negatively skewed. The excess kurtosis coefficient estimates show that all series display fat tails in both

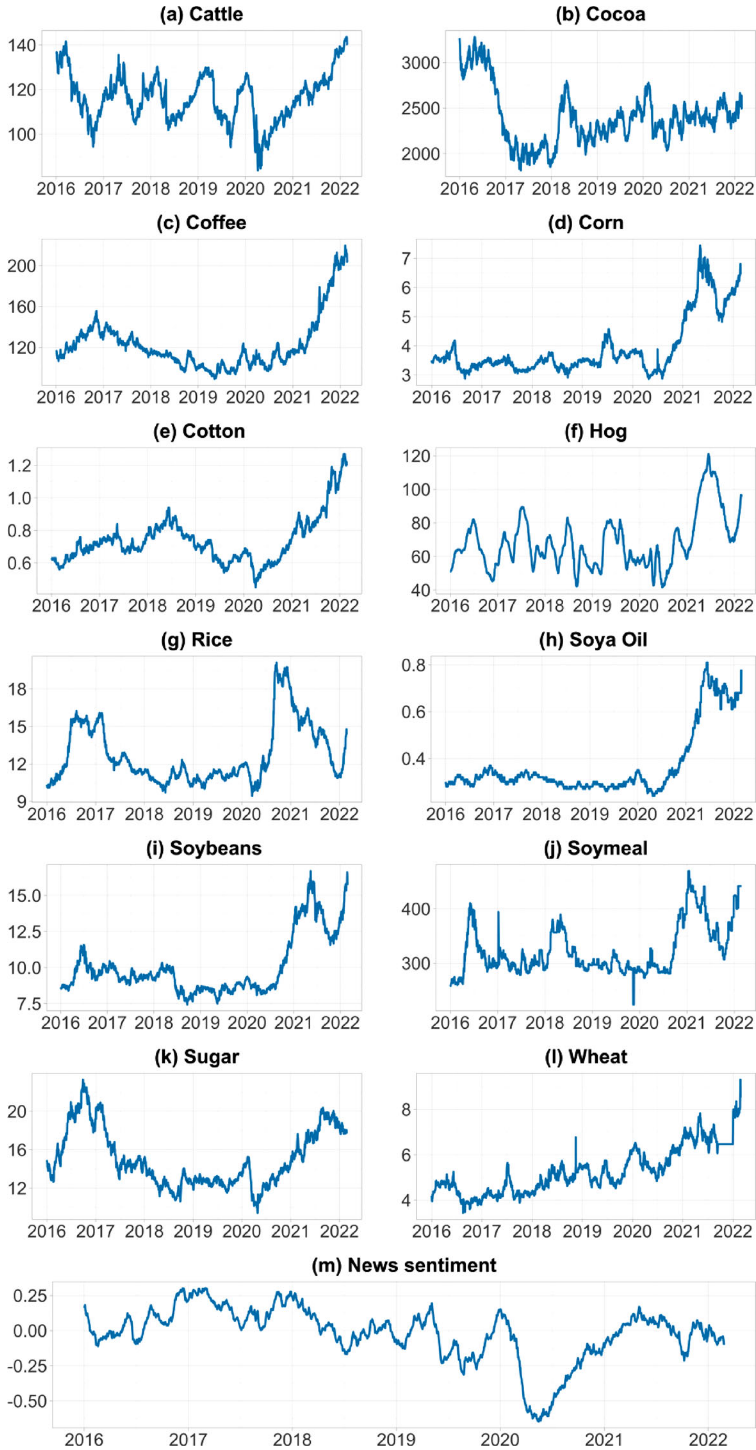

Figure 1. Agricultural commodity price and news sentiment series.

Note The figure displays the price of agricultural commodities and the news sentiment index over the period from 1 January 2016 to 25 February 2022. The positive values the news sentiment index represent positive sentiment while negative values represent negative sentiment.

Table 2. Descriptive statistics.

Series	*N*	Mean	S.D.	Min	Max	Skewness	Kurtosis	JB	Q(1)	Q(5)	ARCH(1)	ARCH(5)
Panel A: Pre-COVID-19 pandemic period												
CATTLE	814	−0.010	1.335	−15.952	4.938	−2.955	29.448	30761.236***	0.530	4.346	0.032	0.099
COCOA	814	−0.046	1.582	−5.815	5.959	−0.028	0.561	11.132***	0.264	2.340	0.002	11.388**
COFFEE	814	−0.020	1.140	−3.687	3.666	−0.057	0.472	8.293**	1.532	2.909	3.312*	10.730*
CORN	814	0.000	1.391	−8.528	5.145	−0.412	3.267	388.590***	2.724*	7.017	4.073**	10.167*
COTTON	814	0.008	1.413	−4.879	4.879	0.256	1.073	48.712***	0.645	1.545	12.134***	14.297**
HOG	814	0.004	1.155	−9.187	4.944	−0.299	6.542	1474.214***	320.074***	1446.408***	20.580***	69.585***
RICE	814	0.004	1.086	−8.258	4.820	−0.365	5.190	938.820***	1.793	10.634*	12.419***	14.117**
SOYAOIL	814	−0.004	1.701	−3.637	6.454	0.083	1.026	37.334***	38.774***	51.159***	2.390	4.005
SOYBEAN	814	−0.002	1.247	−5.580	5.699	0.003	2.862	280.544***	0.874	10.457*	0.639	33.742***
SOYMEAL	814	0.021	2.001	−28.372	26.934	−0.359	89.595	273660.917***	50.094***	56.391***	188.679***	299.655***
SUGAR	814	−0.021	1.674	−4.861	8.721	0.294	1.519	91.255***	4.980**	9.767*	0.504	3.983
WHEAT	814	0.031	2.390	−24.668	23.915	0.213	31.653	34171.408***	35.584***	52.016***	170.687***	227.318***
NEWSSENT	814	0.075	0.118	−0.167	0.302	0.158	−0.968	34.818***	803.842***	3849.874***	774.443***	772.050***
Panel B: Post-COVID-19 pandemic period												
CATTLE	529	0.028	1.348	−5.229	5.456	0.123	4.004	359.499***	7.992***	14.237**	157.467***	205.724***
COCOA	529	−0.019	1.383	−5.727	4.630	−0.111	1.000	23.784***	1.688	8.650	5.820**	7.616
COFFEE	529	0.128	1.617	−7.250	8.035	0.197	2.454	138.440***	0.465	7.300	7.622***	49.036***
CORN	529	0.103	2.048	−16.191	16.799	−0.211	16.177	5824.361***	1.812	9.486*	105.098***	128.619***
COTTON	529	0.116	1.719	−5.129	5.827	−0.248	0.481	10.817***	1.086	15.252***	0.144	13.174**
HOG	529	0.113	1.487	−6.201	7.576	0.268	3.944	353.837***	58.948***	390.834***	48.834***	118.646***
RICE	529	0.040	1.423	−3.942	7.353	0.983	3.354	337.206***	3.590*	32.131***	0.281	69.520***
SOYAOIL	529	0.174	2.281	−10.863	13.720	0.500	8.424	1602.664***	1.201	7.388	2.998*	60.931***
SOYBEAN	529	0.110	1.353	−8.852	6.578	−0.457	5.130	605.615***	0.130	2.904	7.394***	10.241*
SOYMEAL	529	0.087	1.762	−9.426	11.249	1.137	15.026	5136.220***	0.003	0.899	1.795	14.219**
SUGAR	529	0.035	1.618	−5.249	8.166	0.213	1.557	58.681***	0.044	5.104	40.211***	58.302***
WHEAT	529	0.064	1.903	−8.867	19.715	2.172	21.834	11017.234***	0.438	1.262	0.025	0.271
NEWSSENT	529	−0.151	0.223	−0.646	0.169	−0.850	−0.519	69.790***	528.661***	2613.264***	520.986***	517.091***

Note: The table reports statistics for the log growth rates of each series in percent. The data covers the period from 1 January 2016 to 25 February 2022 with pre-COVID-19 period of 1 January 2016–24 February 2020 and post-COVID-19 period of 15 February 2020–25 February 2022. In addition to mean, standard deviation (S.D.), minimum, maximum, skewness, and kurtosis, the table also reports Jarque-Bera normality test (JB), first [Q(1)] and fifth [Q(5)] order Ljung-Box portmanteau test for serial correlation, and first [ARCH(1)] and fifth [ARCH(5)] order autoregressive conditional heteroskedasticity tests. *N* denotes the number of observations. *, **, and *** denote rejection at 10%, 5%, and 1% level, respectively.

subsamples. Normal distribution is rejected for all series in both subsamples. Moreover, the majority of the series show significant serial correlation and conditional heteroskedasticity. The estimates of the distribution shape (skewness, kurtosis, and more generally, the JB statistic) indicate that these series are likely to display nonlinear dynamics. This last observation further motivates the study to consider a nonparametric approach.

It is necessary for the variables to be stationary before we estimate the tests. The augmented Dickey-Fuller (ADF), Elliot-Rothenberg-Stock (ERS), Kwiatkowski-Phillips-Schmidt-Shin (KPSS), and Phillips-Perron (PP) unit root tests are reported in Table 3 to assess the stationarity of the variables. All the test results in Table 3 reveal that all series are nonstationary in log levels but stationary in log first differences both in the pre- and post-COVID-19 periods as they all have a unit root in log levels but not in log first differences. As a result, our analyses are based on the daily log growth rates in percent (%), which is written as $\log(y_t/y_{t-1}) \times 100$ where y_t is the level variable and y_{t-1} is the first-lag value of the variable.

Before testing for nonparametric causality in quantiles, we first consider linear Granger causality. These tests are performed on a bivariate VAR model estimated for each of the commodity price series and the sentiment index. Both the commodity price and news sentiment series in the VAR model are in the first log difference forms. The linear Granger causality tests given in Table 4 show that the COVID-19 sentiment does not Granger cause 11 of the 12 agricultural commodity prices in the pre-COVID-19 period and 10 out of 12 in the post-COVID-19 period. The test values tend to be higher in the post-COVID-19 period, indicating some higher predictive power of the sentiment

Table 3. Unit root tests.

Variable	ADF	ERS	KPSS	PP	ADF	ERS	KPSS	PP
	Model A: Tests with a constant deterministic term				Model B: Tests with constant and trend deterministic terms			
Panel A: Pre-COVID-19 pandemic period								
CATTLE	−2.850*	5.435	0.410*	−2.825*	−2.846	11.335	0.403***	−2.806
COCOA	−2.702*	17.253	0.674**	−3.060**	−2.625	19.934	0.650***	−2.940
COFFEE	−0.124	12.749	1.284***	−0.073	−0.431	28.802	1.191***	−0.430
CORN	−0.466	13.199	3.339***	−0.531	−1.726	18.810	0.850***	−1.786
COTTON	−0.524	15.877	1.176***	−0.558	−0.961	20.232	0.745***	−1.016
HOG	−1.797	11.005	0.989***	−2.041	−1.972	11.964	0.411***	−2.224
RICE	−1.870	17.397	0.897***	−1.471	−1.876	26.721	0.633***	−1.459
SOYAOIL	0.307	27.449	2.992***	0.252	−0.755	35.971	1.218***	−0.912
SOYBEAN	−0.219	20.316	2.368***	−0.253	−0.958	23.695	1.144***	−0.966
SOYMEAL	−2.283	9.727	1.587***	−2.542	−2.704	6.896	0.484***	−2.951
SUGAR	−1.608	4.496	1.241***	−1.575	−1.577	15.967	1.128***	−1.528
WHEAT	−1.305	13.425	5.338***	−1.460	−1.460	6.380	0.312***	−2.167
Panel B: Post-COVID-19 pandemic period								
CATTLE	−27.054***	0.026***	0.167	−37.231***	−27.069***	0.091***	0.035	−37.248***
COCOA	−27.281***	0.149***	0.150	−39.667***	−27.286***	0.219***	0.043	−39.679***
COFFEE	−27.639***	0.053***	0.405*	−39.419***	−27.681***	0.128***	0.109	−39.468***
CORN	−30.099***	0.086***	0.179	−41.897***	−30.131***	0.237***	0.037	−41.917***
COTTON	−29.692***	0.029***	0.222	−41.851***	−29.712***	0.107***	0.117	−41.867***
HOG	−10.009***	0.088***	0.031	−28.414***	−10.008***	0.286***	0.028	−28.410***
RICE	−14.394***	0.395***	0.071	−39.651***	−14.391***	0.667***	0.073	−39.641***
SOYAOIL	−31.107***	0.434***	0.460*	−45.785***	−31.161***	0.444***	0.091	−45.833***
SOYBEAN	−26.892***	0.088***	0.226	−40.221***	−26.920***	0.259***	0.079	−40.240***
SOYMEAL	−23.054***	0.013***	0.060	−45.354***	−23.051***	0.046***	0.050	−45.341***
SUGAR	−27.276***	0.069***	0.110	−38.442***	−27.272***	0.170***	0.068	−38.435***
WHEAT	−29.126***	0.225***	0.069	−46.213***	−29.130***	0.456***	0.022	−46.207***
NEWSSENT	−23.899***	0.328***	0.038	−34.799***	−23.892***	0.451***	0.034	−34.790***
NEWSSENT	−27.054***	0.026***	0.167	−37.231***	−27.069***	0.091***	0.035	−37.248***

Note: The augmented Dickey-Fuller (ADF), Elliot-Rothenberg-Stock (ERS), Kwiatkowski-Phillips-Schmidt-Shin (KPSS), and Phillips-Perron (PP) unit root tests are displayed in table. In the test regression, Model A only includes a constant as a deterministic component, whereas Model B includes both a constant and a linear time trend. For the DF, ERS, and PP tests, the null hypothesis is that the series is nonstationary, whereas for the KPSS test, it is stationary. The superscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 4. Granger causality tests in a linear VAR model.

Dependent variable	F-statistic	*p*-value	Lag (*p*)
Panel A: Pre-COVID-19 pandemic period			
CATTLE	0.1140	0.8922	2
COCOA	0.1316	0.8767	2
COFFEE	0.4828	0.6171	2
CORN	1.1316	0.3228	2
COTTON	0.7580	0.4688	2
HOG	0.9265	0.4747	6
RICE	4.6104**	0.0101	2
SOYAOIL	0.2249	0.7986	2
SOYBEAN	1.0913	0.3360	2
SOYMEAL	0.0620	0.9399	2
SUGAR	1.0430	0.3526	2
WHEAT	0.4138	0.6612	2
Panel B: Post-COVID-19 pandemic period			
CATTLE	0.1291	0.8789	2
COCOA	1.1340	0.3222	2
COFFEE	1.0113	0.3641	2
CORN	1.5560	0.2115	2
COTTON	0.1680	0.8454	2
HOG	0.6765	0.6687	6
RICE	3.0753**	0.0466	2
SOYAOIL	0.0052	0.9948	2
SOYBEAN	0.0152	0.9849	2
SOYMEAL	4.4828**	0.0115	2
SUGAR	0.5014	0.6058	2
WHEAT	0.2286	0.7957	2

Note: The table reports the *F*-statistic for testing Granger causality from news sentiment to commodity price series in a linear VAR model. The lag order (*p*) is selected by the Schwarz's Bayesian information criterion using the full-sample data coving the period 1 January 2016–25 February 2022.

index. The Granger causality test based on a linear VAR model has two weaknesses. First, nonrejection of the null of no Granger causality implies nonexistence of a linear causality, however, there may still be nonlinear causality. Second, the linear VAR model is a mean-based model, so it has the ability to detect dynamic links at the centre of the conditional distribution of the dependent variable. That is, it can estimate average dynamic links, but it does not have the ability to estimate dynamic links in the tails of the distribution. In order to assess the existence of nonlinearities, we estimate the Brock, Dechert, and Scheinkman (BDS, Broock et al. 1996) independence tests for the residuals of the VAR models. The BDS test results given in Table 5 show that the linear VAR model results might be unreliable since the series shows nonlinearity. The BDS test rejects linearity for 10 of the 12 commodity prices, with the exceptions of cocoa and soybeans. Given the nonlinear behaviour of agricultural commodity price series, we consider the nonparametric causality-in-quantiles test since this test is robust against nonlinearity and can successfully estimate a dynamic relationship at any point of the support distribution.

We estimate the rolling Pearson correlation coefficients between the sentiment index and the growth rate of agricultural commodity prices to further demonstrate that the linear Granger causality test results may be unreliable because the relationship between the sentiment and commodity price series may be time-varying. These correlations are estimated using 250 daily observations in each window in a rolling fashion. To prevent missing 250 observations from the start, the sample period is extended to 16 January 2015. Figure 2 shows the rolling Pearson correlation estimates for the period from January 2016 to 25 February 2022. Just before the COVID-19 pandemic, the correlation estimates for practically all agricultural commodity price growth were around zero. In all rolling correlation estimates, we see an upward trend around the time of the COVID-19 pandemic. After February 2020, all correlations become positive. Thus, the significant worsening in the sentiment index associated with large commodity price drops in the early months of the pandemic, and the subsequent recovery both in the sentiment index and agricultural commodity prices,

Table 5. Broock et al. (1996, BDS) tests for nonlinearity.

Equation	$m=2$	$m=3$	$m=4$	$m=5$	$m=6$
Panel A: Pre-COVID-19 pandemic period					
CATTLE	1.557	2.601***	3.218***	3.786***	4.165***
COCOA	0.846	1.099	0.890	1.199	2.155**
COFFEE	1.167	1.083	1.977**	2.625***	3.124***
CORN	1.357	1.611	1.922*	2.315**	2.782***
COTTON	1.060	0.850	1.336	1.491	1.823*
HOG	8.770***	11.495***	14.228***	18.928***	24.892***
RICE	1.396	1.536	1.394	1.185	1.125
SOYAOIL	10.075***	9.391***	9.025***	8.250***	7.971***
SOYBEAN	1.136	1.313	2.101**	2.254**	3.024***
SOYMEAL	6.439***	5.975***	5.532***	5.056***	6.400***
SUGAR	1.319	0.858	−0.004	−0.129	0.100
WHEAT	2.408**	2.514**	3.708***	4.307***	5.029***
Panel B: Post-COVID-19 pandemic period					
CATTLE	7.152***	7.601***	8.037***	9.072***	9.843***
COCOA	−0.379	−0.310	−0.227	−0.321	−1.096
COFFEE	1.207	1.705*	1.807*	2.241**	2.231**
CORN	0.319	0.942	1.881*	2.466**	3.410***
COTTON	2.346**	2.528**	2.828***	2.706***	1.516
HOG	6.326***	9.007***	11.213***	14.718***	19.127***
RICE	1.312	2.812***	3.390***	4.621***	6.463***
SOYAOIL	−1.353	−2.195**	−2.748***	−3.161***	−2.110**
SOYBEAN	−0.034	−1.046	−0.855	−0.827	−0.998
SOYMEAL	−4.074***	−5.773***	−6.977***	−7.452***	−5.222***
SUGAR	2.189**	1.752*	1.351	2.578***	3.443***
WHEAT	3.491***	7.748***	13.717***	27.342***	54.586***

Note: The table reports the *z*-statistic of the BDS test which has the null of i.i.d. residuals for the commodity price equation of the estimated VAR model. *m* denotes the embedding dimension. *, **, and *** denote rejection at 10%, 5%, and 1% level, respectively.

indicates a strong co-movement of these series. This co-movement is the main reason for the predictive ability of the economic sentiment index for agricultural commodity prices. From January to December 2020, the correlation coefficients for all commodities increased by 3–6 times. The considerable rise in correlations after the COVID-19 pandemic suggests time-varying nonlinear dynamic linkages between the sentiment index and agricultural commodity prices that a linear model cannot detect.

The nonparametric causality-in-quantiles test results for the conditional mean in the post-COVID-19 period are given in Figure 3. We observe from Figure 3 that the COVID-19 sentiment Granger causes all agricultural commodity prices in quantile ranges below 0.35–0.50 and quantile ranges above 0.50–0.75 at all traditional significance levels, with the exception of cattle, for which causality exists at all quantiles. However, the Granger causality from the sentiment index to commodity price is significant below 0.40-th for cocoa, coffee, corn, hog, rice, soybeans, and sugar while significant causality is found above 0.60-th quantile for cocoa, coffee, corn, cotton, hog, rice, soya, oil, soybeans, sugar, and wheat. Thus, the null hypothesis of no causality is not rejected for the quantile range of 0.40–0.60 for most of the agricultural commodity prices. In sum, we do not find Granger causality from the sentiment index to agricultural commodity prices in the mid quantiles in the post-COVID-19 period. The sentiment index–when the sample period particularly covers the COVID-19 pandemic–causes extreme price movements in all agricultural commodity price series, with the exception of cattle, where causality also exists in mid-quantiles. Rejections also occur with very high test values, notably in the quantile ranges below 0.20, with values of roughly 300–400. This happens because severe negative sentiment, as in the case of COVID-19, causes a significant drop in prices, while improvements in the sentiment index, particularly in the positive value range, cause agricultural commodity prices to rise. Our results show that sentiments represent the overall state of an economy and therefore have rich content to explain extreme movements in major economic variables. According to Buckman et al. (2020), the COVID-19 pandemic caused

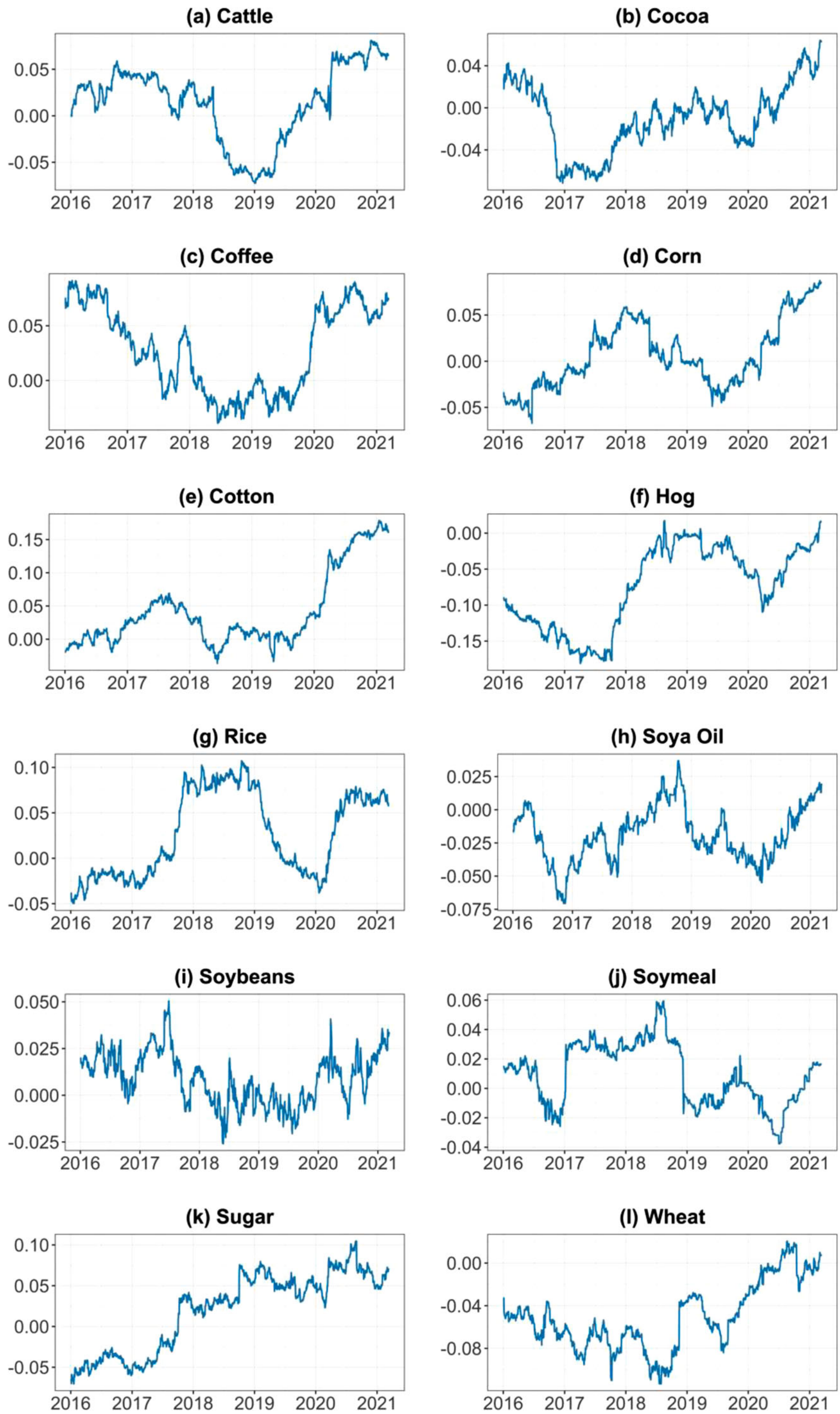

Figure 2. Rolling correlation coefficient estimates.

Note: The figure plots the rolling Pearson correlation coefficient estimates over the period 1 January 2016–25 February 2022. A fixed window size of 250 days is used in the rolling estimation.

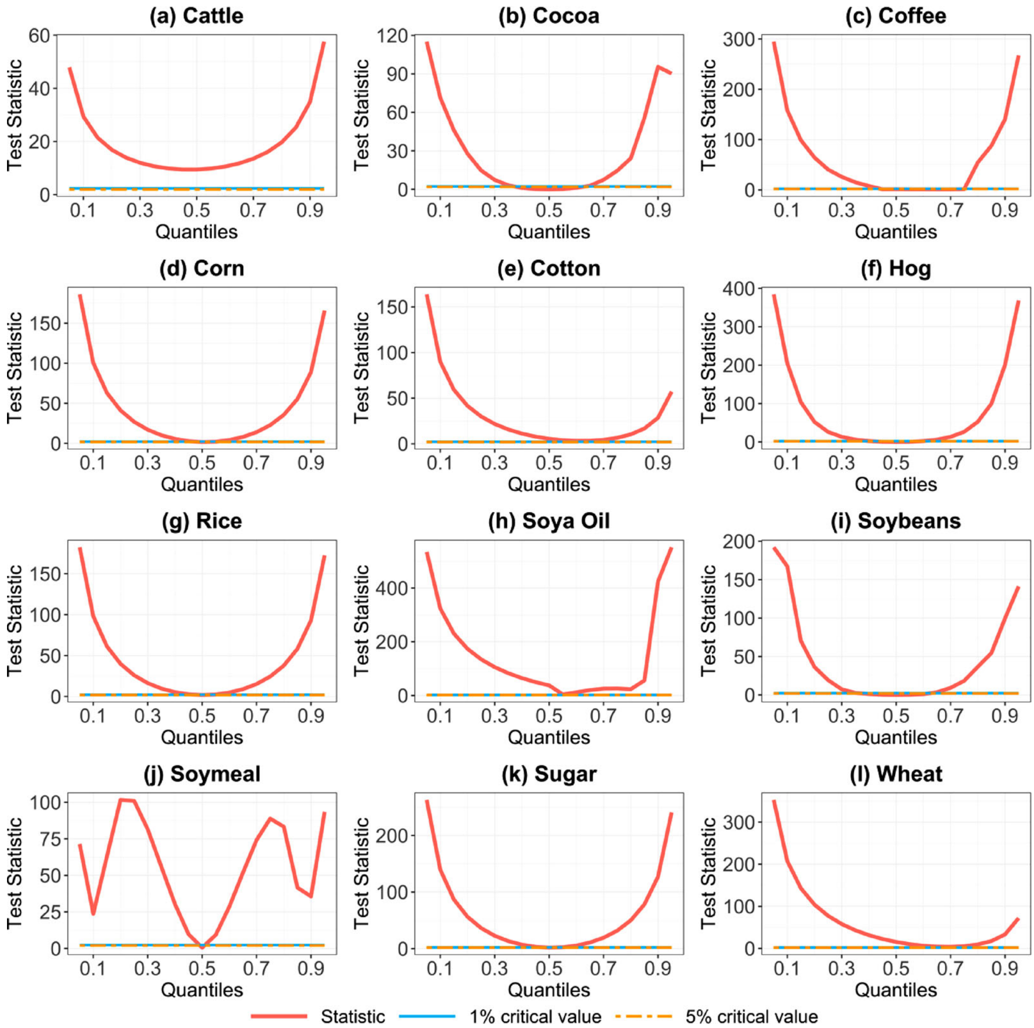

Figure 3. Nonparametric Granger causality-in-quantiles for conditional mean during the post-COVID-19 pandemic period.

Note: The nonparametric Granger causality-in-quantiles for the mean tests estimated for the post-COVID-19 period from 15 February 2020 to 25 February 2022 are plotted in the figure. The tests are estimated with a step size of 0.05 for quantile ranges of 0.05 to 0.95.

the extreme negative economic sentiment in the first half of 2020, implying that the huge drops in agricultural commodity prices in the first half of 2020 were primarily due to the pandemic.

Although causality in the first moment (mean) generally implies causality in higher order moments, the opposite is not necessarily true. Moreover, lack of causality in mean in certain quantiles does not necessarily imply non-causality in higher order moments. Therefore, it is of interest to test for causality in second order or higher moments. Moreover, the second moment represents volatility, and Granger causality in the second moment implies that the COVID-19 also effects commodity price risk, not only the price level, which is relevant information for all decision makers. The causality in variance (second moment) is particularly of interest to investors, portfolio managers, and policymakers. When the volatility of agricultural commodity prices is considered, the nonparametric causality-in-quantiles tests for the variance given in Figure 4 show that the news-based COVID-19 sentiment Granger causes agricultural commodity prices in quantile ranges above the 0.25-th quantile for coffee, corn, cotton, rice, soya oil, soybeans, and sugar; above the 0.40-th quantile for soymeal; and all for cattle, hogs, and wheat. Indeed, causality-in-variance is very strong in quantiles above the

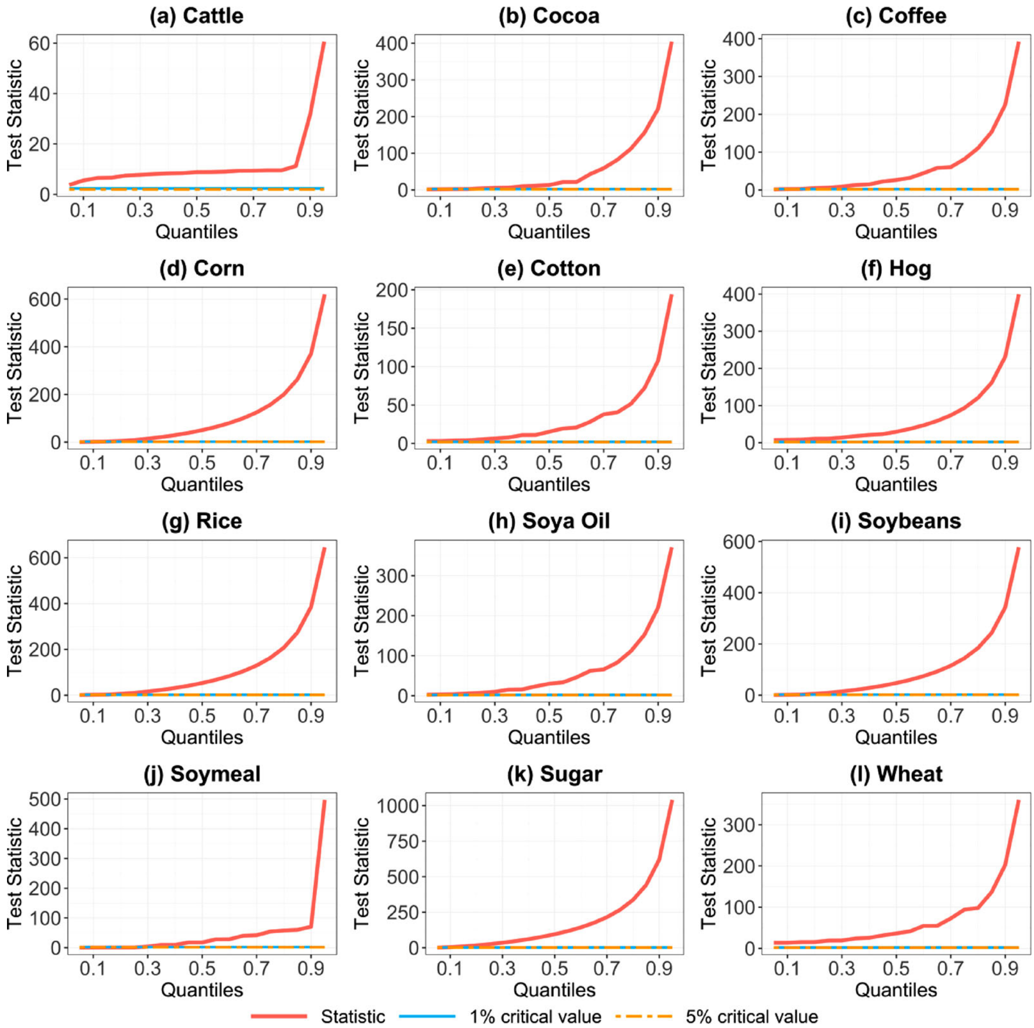

Figure 4. Nonparametric Granger causality-in-quantiles for conditional variance during the post-COVID-19 pandemic period.

Note: The nonparametric Granger causality-in-quantiles for the variance tests estimated for the post-COVID-19 period from 15 February 2020 to 25 February 2022 are plotted in the figure. The tests are estimated with a step size of 0.05 for quantile ranges of 0.05 to 0.95.

median volatility (0.50-th quantile.) with test statistic estimates above 50 or 100. This indicates the strong volatility effect of the COVID-19 pandemic on agricultural commodity prices. Thus, extreme sentiments (negative or positive) cause higher market volatility, which complements the results for causality in the mean. Therefore, COVID-19 not only caused large falls in agricultural commodity prices, but it also caused a higher market risk.

In order to see whether the predictive ability of the sentiment index has increased during the pandemic period and whether the changes in agricultural commodity prices are related to the effects of the pandemic, we also perform the nonparametric causality-in-quantiles test results for the conditional mean and variance in the pre-COVID-19 period, which covers the period between January 2016 and 14 February 2020. These results are given in Figure 5 for the causality in the mean and Figure 6 for the causality in variance. For the causality in mean, Figure 5 indicates that the sentiment index does not Granger cause agricultural commodity prices at all quantiles for cocoa, coffee, and sugar at the 5% significance level, while some weak causality is found only below 0.10-th and above 0.90-th quantiles for cattle, rice, and soybeans. Granger causality outside the 0.40–0.60 quantile ranges is found for

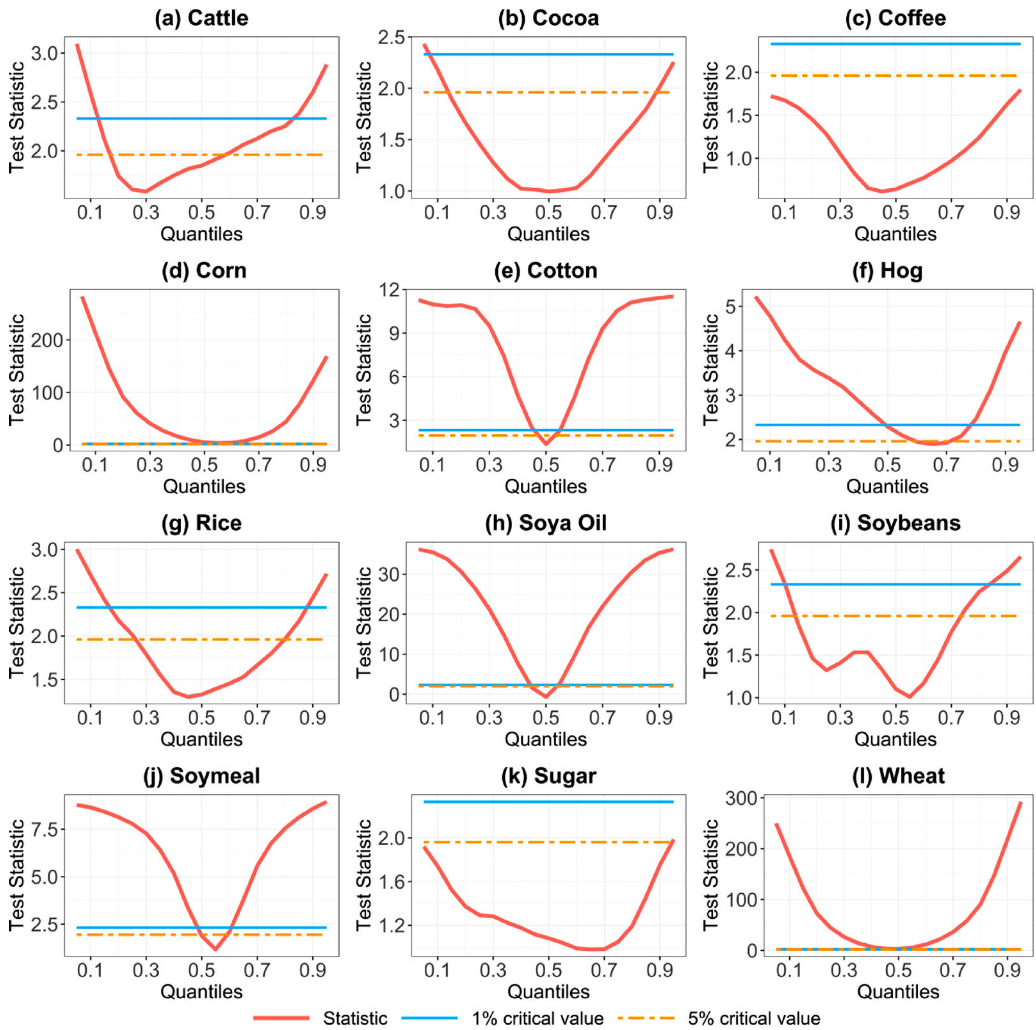

Figure 5. Nonparametric Granger causality-in-quantiles for conditional mean in the pre-COVID-19 pandemic period.

Note: The nonparametric Granger causality-in-quantiles for the mean tests estimated for the pre-COVID-19 period from 1 January 2016 to 14 February 2020 are plotted in the figure. The tests are estimated with a step size of 0.05 for quantile ranges of 0.05 to 0.95.

cotton, hog, soya oil and soymeal. However, for these commodities, the causality-in-quantiles test values are about 10–20 times smaller than the test values obtained for the post-COVID-19 period. Only for corn and wheat, comparable test statistics to the post-COVID-19 period are obtained. For the causality in variance in the pre-COVID-19 period, Figure 6 indicates test results comparable to those of the post-COVID-19 period for cocoa, coffee, corn, cotton, rice, soybeans, and wheat. For other commodities, causality in variance is not found in low quantiles (cattle, soymeal, and sugar), and test values are 10–20 times smaller than the corresponding test value in the post-COVID-19 period. Thus, the causality in variance results also indicates some weaker causality in the pre-pandemic period compared to the post-pandemic period. These findings reveal that the sentiment index's predictive ability in the pre-COVID-19 period was not as great as it was in the post-COVID-19 period. This result is quite strong for the causality in the mean, indicating that the effect of the COVID-19 pandemic was stronger on the level of agricultural commodity prices than its volatility.

To ensure robustness of our results, we also run bivariate rolling bootstrap Granger causality tests proposed by Balcilar, Ozdemir, and Arslanturk (2010) and Balcilar and Ozdemir (2013) and later

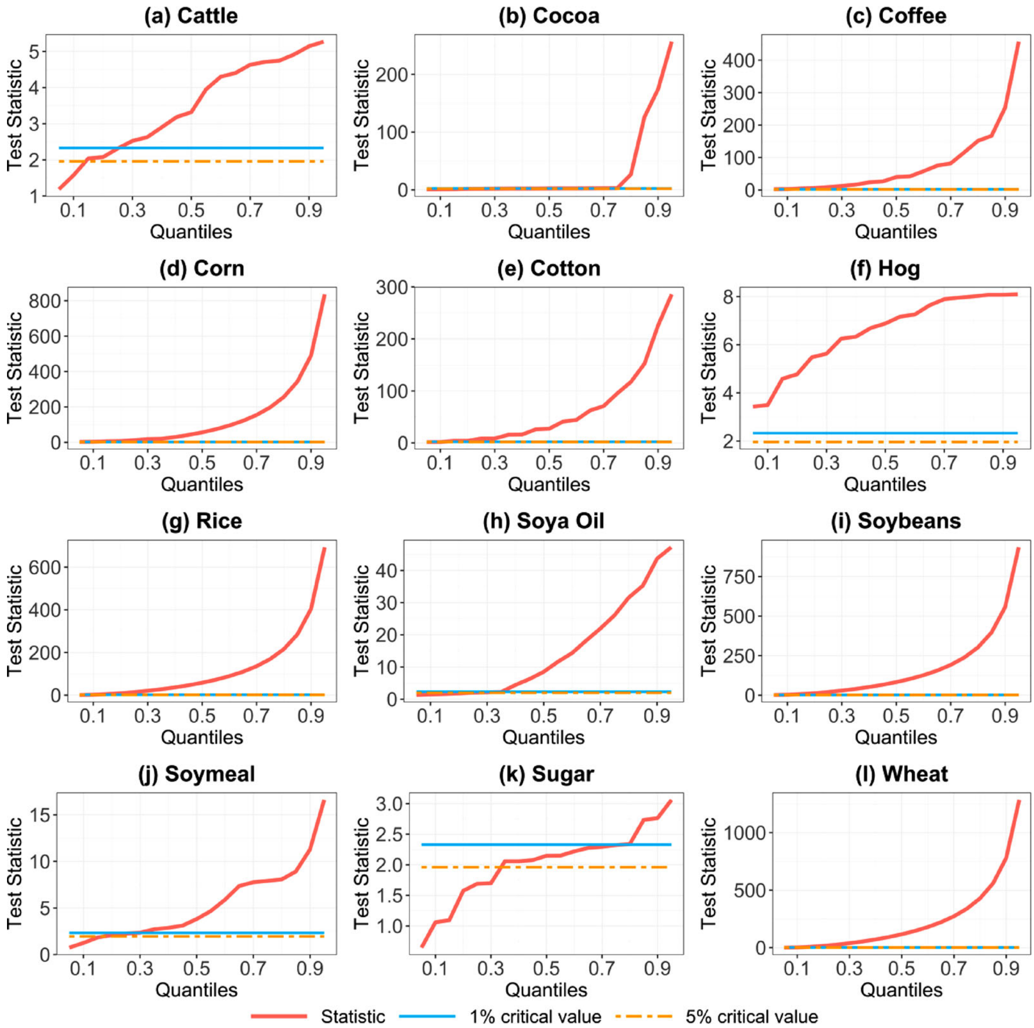

Figure 6. Nonparametric Granger causality-in-quantiles for conditional variance in the pre-COVID-19 pandemic period.

Note: The nonparametric Granger causality-in-quantiles for the variance tests estimated for the pre-COVID-19 period from 1 January 2016 to 14 February 2020 are plotted in the figure. The tests are estimated with a step size of 0.05 for quantile ranges of 0.05 to 0.95.

extend by Shi, Phillips, and Hurn (2018) and Shi, Hurn, and Phillips (2020). Although the rolling Granger causality tests are linear, they are time-varying and, thus, can adopt to structural breaks in causality relationships, although they may not be as robust as the nonparametric quantile causality test. An advantage of the rolling Granger causality test is its ability to identify the periods where the sentiment index Granger causes commodity prices. We estimate the rolling Granger causality tests for the period from 1 January 2016 to 25 February 2022 using a rolling linear VAR model with a fixed window size of 250 days. The sample starting period of the data is extended 16 January 2015, so that the rolling tests are available from 1 January 2016. The lag order is fixed and selected by the Schwarz's Bayesian information criterion using the full sample data. The 5% and 10% critical values are obtained using the parametric bootstrap method with 2,000 replications. The rolling Granger causality tests are plotted in Figure 7. The rolling tests in Figure 7 were all insignificant right before the COVID-19 pandemic started. Although there were periods before February 2020 where the rolling tests are significant for some commodities, which usually occur around 2017–2018, they do not extend to 2020. In particular, for cocoa, coffee, corn, cotton, rice, soya oil,

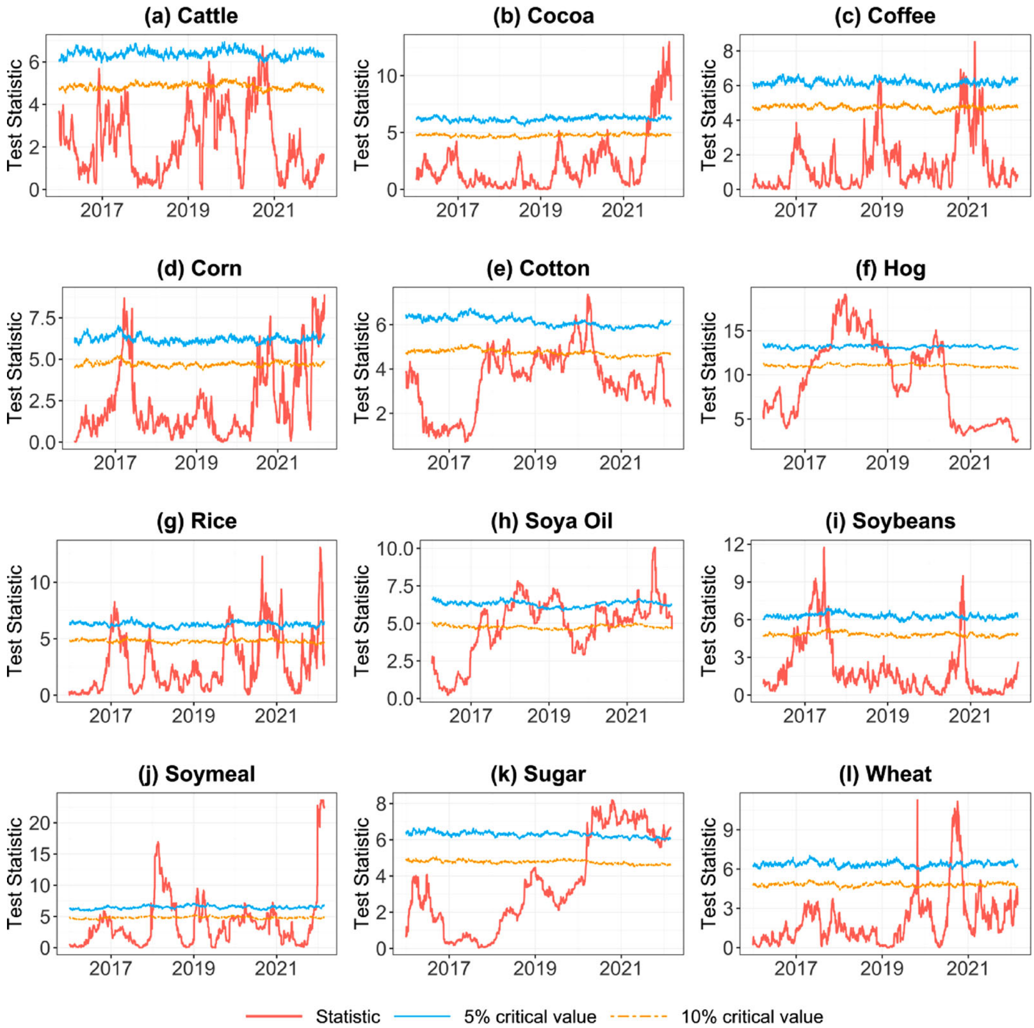

Figure 7. Rolling Granger causality tests.

Note: The rolling Granger causality tests for the period from 1 January 2016 to 25 February 2022 are plotted in the figure. The tests are estimated using a rolling linear VAR model with a fixed window size of 250 days. The lag order is fixed and selected by the Schwarz's Bayesian information criterion using the full sample data. The 5% and 10% critical values are obtained using parametric bootstrap method with 2,000 replications.

soymeal, sugar, and wheat, rolling tests reach their peak values with statistical significance at the 5% level. For most of these commodities, rolling tests only become significant in the post-COVID-19 period. According to the results given in Figure 7, the rolling Granger causality tests are not as significant in the pre-COVID-19 period as they are in the post-COVID-19 period. As a result, the COVID-19 pandemic had a considerable impact on agricultural prices, even when other factors were taken into account. These results show that the quantile causality we find in the post-COVID-19 is robust and not a result of effects arising from other factors in the sample period we study.

5. Discussion

Our findings link to the previous literature in several ways. Our findings indicate that COVID-19 related economic sentiment significantly influences agricultural commodity prices. A number of studies have complementary findings to our study by showing how the pandemic effects work. A few studies show that these effects work through the lockdowns and mobility restrictions that affect demand and supply. Varshney, Roy, and Meenakshi (2020), Höhler and Lansink (2021) and Daglis, Konstantakis, and Michaelides (2020) show that such pandemic related effects influence agricultural commodity prices. Restrictions of labour supply, food-related logistics, and difficulties in accessing services caused by the COVID-19 pandemic are other channels causing effects on agricultural commodities (Bakalis et al. 2020; Pu and Zhong 2020; Singh et al. 2020). Beckman and Countryman (2021) and Zhang et al. (2020) show that the pandemic affects the agricultural commodity market through its impact on productivity. The COVID-19 pandemic also had an enormous effect on trade due to the closing of ports and airports. Some countries have also imposed export restrictions on agricultural products. Ramakumar (2020) shows that foreign trade in agricultural products has dropped, while Pu and Zhong (2020) find that arbitrary restrictions hinder agricultural product export channels and essential production inputs, interrupt production cycles, and eventually impair production capacity. Countryman (2021) also finds that trade shocks affect agricultural commodity prices. The findings of these studies also complement our findings as reductions in trade affect both the supply and price of agricultural commodities.

Several studies help to understand how the economic sentiment state translates into commodity price changes by showing significant price transmission effects among agricultural commodities and also spillover from oil and other assets such as precious and industrial metals (Bouri et al. 2021; Cao and Cheng 2021; Hung 2021; Y. Sun et al. 2021; Umar, Jareño, and Escribano 2021; Umar, Riaz, and Zaremba 2021; Umar, Jareño, and Escribano 2022; Wang, Shao, and Kim 2020). Shruthi and Ramani (2020), Chen, Rehman, and Vo (2021), Umar, Gubareva, and Teplova (2021), Umar et al. (2021) and Umar, Jareño, and Escribano (2022) show that the pandemic also affects agricultural commodity prices through volatility spillover from other commodities.

Negative economic sentiment caused by the COVID-19 pandemic generates uncertainties for producers, traders, investors, and consumers. Thus, uncertainty is an important channel that may translate the effect of the COVID-19 sentiment on agricultural markets. A few studies confirm our results by showing that uncertainty affects agricultural commodity prices. T. T. Sun et al. (2021) find that trade policy uncertainty has a persistent spillover effect on agricultural commodity prices, while Ben Haddad, Mezghani, and Gouider (2021) show that uncertainty has persistent spillover effects on commodity prices. Even more related, Umar, Jareño, and Escribano (2022) examine the coronavirus media coverage index and show a significant effect on price and volatility spillovers. Liu et al. (2022) find that negative public sentiment during the COVID-19 pandemic in China has a significant effect on agricultural commodity prices.

6. Conclusion and policy implications

COVID-19, declared as a pandemic on March 11, 2020, caused a sudden stop in economic activity globally. Beyond its catastrophic worldwide health effects, COVID-19 is also seen as the greatest economic shock since World War II. The COVID-19 pandemic has driven most commodity prices down. Its initial impact on agricultural commodity prices has also been negative. However, COVID-19 represents a catastrophic situation and its impact on agricultural markets cannot be guided by prior experience. With food production maintained during the pandemic and the knock on the consumption of food in a global recession, agricultural commodity prices tumbled. Although most current assessments imply a contraction of both supply and demand for agricultural products, the situation still remains uncertain. Moreover, the effects are not uniform across various agricultural commodities in terms of length and magnitude. Against this backdrop, this paper examines whether the COVID-19 pandemic has had a significant effect on agricultural commodity markets.

Our results show that the news-based COVID-19 sentiment index Granger causes both the mean and variance of the agricultural commodities. However, causality in the mean is mostly significant in the lower (below 0.40-th quantile) and upper (above 0.60-th quantile) quantile ranges, implying extreme price movements are caused by severe negative and positive sentiments. We further find that COVID-19 did not only cause a significant decline in agricultural commodity prices but it is also causal for market volatility above the quantile ranges 0.55. Thus, extreme sentiments cause high price volatility in agricultural markets. We find no significant causality in the mean around the median quantile, implying that COVID-19 sentiment is primarily responsible for extreme changes in agricultural commodity prices. In this study, we found that the COVID-19 pandemic had a big impact on the volatility of agricultural commodity prices. This is because the extreme low and high quantiles in the mean correspond to the volatility at high quantiles. Our results show that the news-based sentiment index is helpful for predicting agricultural prices, particularly when the economies are in a turbulent state. In addition, the rolling Granger causality tests using a linear VAR model show that the effect of the COVID-19 on agricultural commodities corresponds to the post-COVID-19 period, which is in line with the nonparametric causality-in-quantiles tests. Policymakers should be aware that agricultural markets are highly prone to events like pandemics. News-based sentiment indexes can be informative about the future developments in agricultural markets.

Our findings imply that a large number of producers will be affected by large price falls, and that, moreover, increased market risk has significant implications for investors and managers. Policymakers should consider the effects of large price falls or increases on consumers and producers. Periods of events such as the pandemic may cause significant interruptions in agricultural production, which has significant implications for both consumers and producers. Because agricultural commodity markets are critical markets, significant governmental initiatives are required to ensure price stability during times of economic instability. Although the COVID-19 pandemic is unlikely to impair food security in many countries in the short term, insufficient supply could lead to price changes in some countries as agricultural commodity imports decline. As a result, policymakers must ensure that agricultural commodities are supplied in adequate quantities to maintain food security. Given that the COVID-19 epidemic resulted in considerable price drops for a few months before large price increases, authorities should consider the agricultural commodity market as a useful tool for monitoring trade circumstances more accurately. Furthermore, policymakers may be able to forecast uncertain occurrences based on public sentiment, allowing them to take steps to mitigate the impact of economic uncertainty. Our findings are also of relevance to portfolio managers and investors looking for investment possibilities in commodity markets or attempting to diversify the risk of their portfolios through different hedging measures. Investors can forecast price changes based on the sentiment index and then decide whether to invest in the agricultural commodity market and alter their investment decisions to prevent risks, as economic sentiment has an impact on agricultural commodity prices. The relevance of alternative assets for hedging is highlighted by the substantial Granger causality from economic sentiment to agriculture prices in the tails. There are, however, no-cause intervals around the median quantiles. The non-causality intervals reveal that different agricultural commodities have appealing characteristics during normal times, offering diversification benefits. During a period of extreme events, however, the diversity benefits vanish.

For future research, one can consider the transmission channels of the COVID-19 pandemic's effect on agricultural commodity prices. There are various channels through which the pandemic may affect the agricultural markets, including effects on supply, demand, cost, and trade effects. Furthermore, one could look into the indirect effects of the COVID-19 pandemic on agricultural commodity prices via spillover from other commodity markets.

Notes

1. Such as futures, forwards, and options.
2. The sentiment index data is available at the website https://www.frbsf.org/economic-research/indicators-data/daily-news-sentiment-index/.

3. The lexical approach used by Buckman et al. (2020) and Shapiro, Sudhof, and Wilson (2020) relies on a pre-defined list of words associated with the emotion of the domain of the event studied, which is "economics related" in our case.

Disclosure statement

No potential conflict of interest was reported by the author(s).

ORCID

Mehmet Balcilar http://orcid.org/0000-0001-9694-5196
Kamil Sertoglu http://orcid.org/0000-0002-3731-0171
Busra Agan http://orcid.org/0000-0003-1485-9142

References

Ando, T., M. Greenwood-Nimmo, and Y. Shin. 2017. *Quantile connectedness: Modelling tail behavior in the topology of financial networks*. Available at SSRN 3164772. doi:10.2139/ssrn.3164772.

Arezki, R., and H. Nguyen. 2020. Novel coronavirus hurts the Middle East and North Africa through many channels. *Economics in the Time of COVID-19*, 53.

Aslam, F., S. Aziz, D.K. Nguyen, K.S. Mughal, and M. Khan. 2020. On the efficiency of foreign exchange markets in times of the COVID-19 pandemic. *Technological Forecasting and Social Change* 161: 120261.

Bakalis, Serafim, Vasilis P. Valdramidis, Dimitrios Argyropoulos, Lilia Ahrne, Jianshe Chen, P.J. Cullen, Enda Cummins, et al. 2020. Perspectives from CO+RE: How COVID-19 changed our food systems and food security paradigms. *Current Research in Food Science* 3: 166–72.

Balcilar, M., R. Gupta, C. Kyei, and M.E. Wohar. 2016. Does economic policy uncertainty predict exchange rate returns and volatility? Evidence from a nonparametric causality-in-quantiles test. *Open Economies Review* 27, no. 2: 229–50.

Balcilar, M., R. Gupta, D.K. Nguyen, and M.E. Wohar. 2018. Causal effects of the United States and Japan on Pacific-Rim stock markets: Nonparametric quantile causality approach. *Applied Economics* 50, no. 53: 5712–27.

Balcilar, M., S. Hammoudeh, and N.F. Asuba. 2015. A regime-dependent assessment of the information transmission dynamics between oil prices, precious metal prices and exchange rates. *International Review of Economics & Finance* 40: 72–89.

Balcilar, M., and Z.A. Ozdemir. 2013. The Export-Output growth nexus in Japan: A bootstrap rolling window approach. *Empirical Economics* 44, no. 2: 639–660. doi:10.1007/s00181-012-0562-8.

Balcilar, M., Z.A. Ozdemir, and Y. Arslanturk. 2010. Economic growth and energy consumption causal nexus viewed through a bootstrap rolling window. *Energy Economics* 32, no. 6: 1398–410.

Baldwin, R., and B.W. di Mauro. 2020. Economics in the time of COVID-19: A new eBook. *VOX CEPR Policy Portal*, 2–3.

Beckman, J., and A.M. Countryman. 2021. The importance of agriculture in the economy: Impacts from COVID-19. *American Journal of Agricultural Economics* 103, no. 5: 1595–1611. doi:10.1111/ajae.12212.

Ben Haddad, H., I. Mezghani, and A. Gouider. 2021. The dynamic spillover effects of macroeconomic and financial uncertainty on commodity markets uncertainties. *Economies* 9, no. 2 (June): 91. doi:10.3390/economies9020091.

Boughton, D., J. Goeb, I. Lambrecht, D. Headey, H. Takeshima, K. Mahrt, I. Masias, et al. 2021. Impacts of COVID-19 on agricultural production and food systems in late transforming Southeast Asia: The case of Myanmar. *Agricultural Systems* 188: 103026. doi:10.1016/j.agsy.2020.103026.

Bouri, E., B. Lucey, T. Saeed, and X.V. Vo. 2021. The realized volatility of commodity futures: Interconnectedness and determinants. *International Review of Economics & Finance* 73, February 2020: 139–51. doi:10.1016/j.iref.2021.01.006.

Broock, W.A., J.A. Scheinkman, W.D. Dechert, and B. LeBaron. 1996. A test for independence based on the correlation dimension. *Econometric Reviews* 15, no. 3: 197–235.

Buckman, S.R., A.H. Shapiro, M. Sudhof, and D.J. Wilson. 2020. News sentiment in the time of COVID-19. *FRBSF Economic Letter* 08: 1–5.

Cao, Y., and S. Cheng. 2021. Impact of COVID-19 outbreak on multi-scale asymmetric spillovers between food and oil prices. *Resources Policy* 74: 102364.

Cecchetti, S.G., and H. Li. 2008. *Measuring the impact of asset price booms using quantile vector autoregressions*. Waltham, MA: Brandeis University.

Chen, J.M., M.U. Rehman, and X.V. Vo. 2021. Clustering commodity markets in space and time: Clarifying returns, volatility, and trading regimes through unsupervised machine learning. *Resources Policy* 73, no. February: 102162. doi:10.1016/j.resourpol.2021.102162.

Daglis, T., K.N. Konstantakis, and P.G. Michaelides. 2020. The impact of COVID-19 on agriculture: Evidence from oats and wheat markets. *Studies in Agricultural Economics* 122, no. 3: 132–9.

Davids, T., N. Vink, and K. Cloete. 2022. COVID-19 and the South African wine industry. *Agrekon* 61, no. 1: 42–51. doi:10.1080/03031853.2021.1975550.

di Mauro, B.W. 2020. Macroeconomics of the flu. In *Economics in the time of COVID-19*, ed. R. Baldwin, and B. W. di Mauro, 31–35. London: CEPR Press.

Elleby, C., I.P. Domínguez, M. Adenauer, and G. Genovese. 2020. Impacts of the COVID-19 pandemic on the global agricultural markets. *Environmental and Resource Economics* 76, no. 4: 1067–1079. doi:10.1007/s10640-020-00473-6.

FAO. 2020. Food commodities still at risk of coronavirus 'market shock' – FAO/OECD.

He, Q., J. Liu, S. Wang, and J. Yu. 2020. The impact of COVID-19 on stock markets. *Economic and Political Studies* 8, no. 3: 275–288. doi:10.1080/20954816.2020.1757570.

Höhler, J., and A.O. Lansink. 2021. Measuring the impact of COVID-19 on stock prices and profits in the food supply chain. *Agribusiness* 37, no. 1: 171–86.

Hung, N.T. 2021. Oil prices and agricultural commodity markets: Evidence from Pre and during COVID-19 outbreak. *Resources Policy* 73: 02236. doi:10.1016/j.resourpol.2021.102236.

Jeong, K., W.K. Härdle, and S. Song. 2012. A consistent nonparametric test for causality in quantile. *Econometric Theory* 28, no. 4: 861–87.

Khan, A.U., I.J. Ema, A.S. Afsana, A.U. Khan, A. Zannaty, R. Faruk, and S. Rahman. 2021. Effects of coronavirus disease (COVID-19) on agricultural sectors in Bangladesh: A review. *International Journal for Asian Contemporary Research* 1, no. 1: 89–97.

Kirsten, J. 2022. Special collection of articles on the impact of the COVID-19 pandemic on South African agriculture. *Agrekon* 61, no. 1: 1–2. doi:10.1080/03031853.2022.2034791.

Liu, Y., S. Liu, D. Ye, H. Tang, and F. Wang. 2022. Dynamic impact of negative public sentiment on agricultural product prices during COVID-19. *Journal of Retailing and Consumer Services* 64, no. September 2021: 102790. doi:10.1016/j.jretconser.2021.102790.

Mann, C.L. 2020. Real and financial lenses to assess the economic consequences of COVID-19. In *Economics in the time of COVID-19*, ed. R. Baldwin, and B. W. di Mauro, 81–85. London: CEPR Press.

Meninno, R., and G. Wolf. 2020. As coronavirus spreads, can the EU afford to close its borders? In *Economics in the time of COVID-19*, ed. R. Baldwin, and B. W. di Mauro, 87–91. London: CEPR Press.

Meyer, F., J. Kirsten, T. Davids, M. Delport, H. Vermeulen, W. Sihlobo, and L. Anelich. 2022. A sector-wide review of the COVID-19 impact on the South African agricultural sector during 2020–21. *Agrekon* 61, no. 1: 3–20. doi:10.1080/03031853.2022.2030241.

Meyer, F., T. Reardon, T. Davids, M. van der Merwe, D. Jordaan, M. Delport, and G. Van Den Burgh. 2022. Hotspots of vulnerability and disruption in food value chains during COVID-19 in South Africa: Industry- and firm-level "pivoting" in response. *Agrekon* 61, no. 1: 21–41. doi:10.1080/03031853.2021.2007779.

Moews, B., and G. Ibikunle. 2020. Predictive intraday correlations in stable and volatile market environments: Evidence from deep learning. *Physica A: Statistical Mechanics and its Applications* 547: 124392.

Nchanji, E.B., C.K. Lutomia, R. Chirwa, N. Templer, J.C. Rubyogo, and P. Onyango. 2021. Immediate impacts of COVID-19 pandemic on bean value chain in selected countries in sub-Saharan Africa. *Agricultural Systems* 188: 103034.

Nishiyama, Y., K. Hitomi, Y. Kawasaki, and K. Jeong. 2011. A consistent nonparametric test for nonlinear causality—specification in time series regression. *Journal of Econometrics* 165: 112–27.

Perdana, T., D. Chaerani, A.L.H. Achmad, and F.R. Hermiatin. 2020. Scenarios for handling the impact of COVID-19 based on food supply network through regional food hubs under uncertainty. *Heliyon* 6, no. 10: e05128.

Pindyck, R.S., and J.J. Rotemberg. 1990. The excess co-movement of commodity prices. *The Economic Journal* 100, no. 403: 1173–89.

Pu, M., and Y. Zhong. 2020. Rising concerns over agricultural production as COVID-19 spreads: Lessons from China. *Global Food Security* 26, no. July: 100409. doi:10.1016/j.gfs.2020.100409.

Rad, A.K., R.R. Shamshiri, H. Azarm, S.K. Balasundram, and M. Sultan. 2021. Effects of the COVID-19 pandemic on food security and agriculture in Iran: A survey. *Sustainability (Switzerland)* 13: 18.

Ramakumar, R. 2020. Agriculture and the COVID-19 pandemic: An analysis with special reference to India. *Review of Agrarian Studies* 10: 1.

Salisu, A.A., L. Akanni, and I. Raheem. 2020. The COVID-19 global fear index and the predictability of commodity price returns. *Journal of Behavioral and Experimental Finance* 27: 100383.

Shafiullah, M., S.M. Chaudhry, M. Shahbaz, and J. Reboredo. 2021. Quantile causality and dependence between crude oil and precious metal prices. *International Journal of Finance & Economics* 26, no. 4: 6264–80.

Shapiro, A.H., M. Sudhof, and D.J. Wilson. 2020. Measuring news sentiment. *Journal of Econometrics*. https://www.sciencedirect.com/science/article/pii/S0304407620303535

Shi, S., S. Hurn, and P.C.B. Phillips. 2020. Causal change detection in possibly integrated systems: Revisiting the money–income relationship*. *Journal of Financial Econometrics* 18, no. 1: 158–80.

Shi, S., P.C.B. Phillips, and S. Hurn. 2018. Change detection and the causal impact of the yield curve. *Journal of Time Series Analysis* 39, no. 6: 966–87.

Shirsath, P.B., M.L. Jat, A.J. McDonald, A.K. Srivastava, P. Craufurd, D.S. Rana, et al. 2020. Agricultural labor, COVID-19, and potential implications for food security and air quality in the breadbasket of India. *Agricultural Systems* 185: 102954.

Shruthi, M.S., and D. Ramani. 2020. *Statistical analysis of impact of COVID 19 on India commodity markets*. Materials today: proceedings.

Singh, B., R. Dhall, S. Narang, and S. Rawat. 2020. The outbreak of COVID-19 and stock market responses: An event study and panel data analysis for G-20 countries. *Global Business Review*, In press. doi:10.1177/0972150920957274.

Sun, Y., N. Mirza, A. Qadeer, and H.P. Hsueh. 2021. Connectedness between oil and agricultural commodity prices during tranquil and volatile period. Is crude oil a victim indeed? *Resources Policy* 72, no. April: 102131. doi:10.1016/j.resourpol.2021.102131.

Sun, T.T., C.W. Su, N. Mirza, and M. Umar. 2021. How does trade policy uncertainty affect agriculture commodity prices? *Pacific-Basin Finance Journal* 66, no. January: 101514. doi:10.1016/j.pacfin.2021.101514.

Udmale, P., I. Pal, S. Szabo, M. Pramanik, and A. Large. 2020. Global food security in the context of COVID-19: A scenario-based exploratory analysis. *Progress in Disaster Science* 7: 100120. doi:10.1016/j.pdisas.2020.100120.

Umar, Z., M. Gubareva, and T. Teplova. 2021. The impact of COVID-19 on commodity markets volatility: Analyzing time-frequency relations between commodity prices and coronavirus panic levels. *Resources Policy* 73, no. June: 102164. doi:10.1016/j.resourpol.2021.102164.

Umar, Z., M. Gubareva, M. Naeem, and A. Akhter. 2021. Return and Volatility Transmission between Oil Price Shocks and Agricultural Commodities. *PloS One* 16, no. 2: e0246886. doi: 10.1371/journal.pone.0246886.

Umar, Z., F. Jareño, and A. Escribano. 2022. Dynamic return and volatility connectedness for dominant agricultural commodity markets during the COVID-19 pandemic era. *Applied Economics* 54, no. 9: 1030–54.

Umar, Z., Y. Riaz, and A. Zaremba. 2021. Patterns of spillover in energy, agricultural, and metal markets: A connectedness analysis for years 1780-2020. *Finance Research Letters* 43, no. March: 101999. doi:10.1016/j.frl.2021.101999.

Varshney, D., D. Roy, and J.V. Meenakshi. 2020. Impact of COVID-19 on agricultural markets: Assessing the roles of commodity characteristics, disease caseload and market reforms. *Indian Economic Review* 55, no. 0123456789: 83–103. doi:10.1007/s41775-020-00095-1.

Wang, J., W. Shao, and J. Kim. 2020. Analysis of the impact of COVID-19 on the correlations between crude oil and agricultural futures*, Chaos, Solitons & Fractals* 136: 109896.

Wegerif, M. 2022. The impact of COVID-19 on black farmers in South Africa. *Agrekon* 61, no. 1: 52–66. doi:10.1080/03031853.2021.1971097.

Zhang, S., S. Wang, L. Yuan, X. Liu, and B. Gong. 2020. The impact of epidemics on agricultural production and forecast of COVID-19. *China Agricultural Economic Review* 12, no. 3: 409–25.

Zhu, H., X. Su, Y. Guo, and Y. Ren. 2016. The asymmetric effects of oil price shocks on the Chinese stock market: Evidence from a quantile impulse response perspective. *Sustainability* 8, no. 8: 766.