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Oil prices and agricultural commodity markets: Evidence from pre and during COVID-19 outbreak

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A B S T R A C T

This paper represents an analysis of the spillover effects and time-frequency connectedness between crude oil prices and agricultural commodity markets using both the spillover index of Diebold and Yilmaz (2012) and the wavelet coherence model to evaluate whether the time-varying return spillover index exhibited the intensity and direction of transmission during the Covid-19 outbreak. Overall, the current results shed light on that in comparison with the pre-Covid-19 period, and the return spillover is more apparent during the Covid-19 crisis. However, levels of the intensity of this relationship vary through the period of research, with several intervals witnessing both negative and positive interactions. Further, our findings indicate significant heterogeneity among agriculture commodity markets in the degree of spillover to crude oil prices over time, amplifying our understanding of the economic channels through which the agriculture commodity markets are correlated. More importantly, there exist significant dependent patterns about the information spillovers across the crude oil and agriculture commodity markets might provide prominent implications for portfolio managers, investors, and government agencies.

1. Introduction

The Covid-19 outbreak pandemics is a human tragedy, and the global economy faced unprecedented shock caused by the rapid spread of the deadly Covid-19. It has a growing influence on high scale disruption to businesses and the lives of millions of people. Covid-19 has created remarkable uncertainty, which has impacted tourism, travel, hospitality, supply chains, consumption, production, operations financial stress and product prices (Chang et al., 2020). The financial markets stand out as one of the more apparent channels reacting the effects of the pandemic on the economy (Sharif et al., 2020). The community of finance and economics scholars instantly reacted to the urgent need for research on the impacts of the Covid-19 outbreak (Goodell, 2020). Furthermore, the novel coronavirus has started to impact the real economy already, creating a crash on financial and commodity markets. It is challenging to forecast the scale of the economic consequences of the Covid-19 crisis, and we believe that existing literature already consists of several answers and methodologies that are able to employ to capture the economic effects of the current crisis (Goodell, 2020). In this article, we attempt to analyze the dynamic spillovers and time-frequency nexus between crude oil prices and agricultural commodity markets in the pre-and during the Covid-19 outbreak periods. The results of the paper may help us rethink the contagion phenomenon and establish novel approaches for evaluating this complex and unprecedented event.

Agricultural commodity markets and crude oil prices are fundamental determinants of the global economic performance (Su et al., 2019). More importantly, crude oil prices, as a crucial commodity in the world, have a considerable impact on a wide range of economic sectors in terms of direct and indirect transmissions (Vo et al., 2019; Shiferaw, 2019). For individual economies, agricultural commodity prices have remarkable welfare and policy implications (Melichar and Atems, 2019). More precisely, variations in rates of agricultural commodities involve an adjustment in crude oil prices, and crude oil prices is a significant input for transportation and processing in the agricultural sectors (Su et al., 2019). The increased agricultural commodity prices during the Covid-19 outbreak may expose manufacturers and consumers to additional risk, giving rise to significant stress, especially in food-insecure, developing countries. Therefore, policymakers must understand the connectedness between the two sectors better to take on a practical set of policy instruments to maintain the prices stable.

The current Covid-19 crisis, crude oil price plummeted dramatically to $1.15 per barrel in March 2020. As a result, the complicated behavior of crude oil prices has brought significant influence to agricultural

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commodity prices due to the restrictions of production and transportation. In addition, the prices of primary agricultural commodities increased in the pre-Covid-19 period and then witnessed a significant downward trend during the Covid-19 outbreak (see Fig. 2). The fluctuations of agricultural commodity prices have put pressure on the household sector, exacerbated global hunger problems, and posing a severe policy challenge (Su et al., 2019). Taking into consideration the structural changes induced by the Covid-19 outbreak, it is crucial to examine the time-frequency and dynamic connectedness between crude oil prices and agricultural commodity markets, which may provide important implications for policy adjustment based on time-varying market conditions.

The core focus of the current study is to employ both the spillover index of Diebold and Yilmaz (2012) and the wavelet coherence approaches to investigate the association across crude oil prices and agricultural commodity markets in the pre and during the Covid-19 pandemic era. Financial commodity markets are known to have fluctuations not only frequencies but also at different time horizons, especially in the Covid-19 crisis period. Using wavelets allows estimating coherence and connectedness in both short and long run horizons, which is crucial for policymakers and investors that seek for series degree of dependence (Madaleno and Pinho, 2014; Dahir et al., 2018; Hung, 2020c). Besides, we apply the spillover index of Diebold and Yilmaz (2012) to measure the direction of spillovers across crude oil prices and agricultural commodity markets. The main advantage of this method is that the spillover index captures the dynamic magnitude of return spillovers through time, exploring the direction of spillovers (Kang et al., 2019; Hung, 2020b). Therefore, the methodologies we use can support to exhume economic dynamic and time-frequency interactions across variables under investigation that have not been apprehended so far.

Overall, we can evaluate the nexus for various short-, medium-, and long-term cycles by using the combination of these techniques. Put it another way, if the short-term risk spillovers are higher than the medium- and long-term horizons, it suggests that most of the investors behave similarly at short-frequencies whilst they behave more heterogeneously in the medium- and long-term horizons when investing in risky assets (Kang et al., 2019a). The spectral representation of variance decompositions is useful in the current study because price volatilities on oil prices may generate interdependence with the agricultural market, with different degrees of persistence. Specifically, these frameworks allow us to determine in what particular periods and investment horizons the oil-agriculture causal associations are stronger because of investor's heterogeneity towards multiple economic and financial events. More accurately, investors take part in the markets at various time horizons that are signified by frequencies that span from seconds to many years since they have different expectations, investment objectives, institutional constraints, risk profiles, and different levels of information integration (Tiwari et al., 2018). As a result, economic and financial innovations can disseminate through markets leading to heterogeneous frequency responses. In the same vein, market participants who believe in short-run investment are worried about the market's short-term performance and make their decisions based on psychological behavior. This means that their reaction to shocks happens in the short term. At the same time, other market participants concentrate their attention on the long-term market performance, so their reactions to external shocks are mostly materialized in the long run. In this regard, it seems reasonable to assume that the causal associations in price and volatility between agricultural commodity markets and global oil prices can depend on the time scale.

Moreover, empirical examinations of dynamic linkage between crude oil prices and agricultural commodity markets have already been extended. Nevertheless, to the best of our knowledge, only a very limited body of work is devoted to the recent situation created by the COVID-19 crisis (Sharif et al., 2020; Goodell, 2020; Akhtaruzzaman et al., 2020). Our study fills this void in the literature by examining how the oil-agricultural commodity linkage changes in the pre and during the Covid-19 pandemic era. Furthermore, there is very little empirical research that looks into directional spillovers and time-frequency interdependence between crude oil prices and agricultural commodity markets when oil prices vary through the period of the Covid-19 outbreak. More explicitly, our main research questions are: What is the contribution of oil price changes in connection with international economic activity to agricultural commodity price changes? Do agricultural commodity prices respond to oil market activities in the pre and during the Covid-19 pandemic era? These problems have not been tackled in the literature.

The remainder of this paper is organized as follows. Section 2 provides the literature review on the oil-agricultural commodity linkage. Section 3 represents the data and methodologies. Section 4 provides the empirical findings, and Section 5 concludes and advises the policy implications.

2. Literature review

Numerous articles have investigated the contagion effect in international commodity markets. In recent years, there have been a large number of studies concentrating on the interrelatedness between crude oil and agricultural commodity markets. In general, most of the previous studies focused on two strands: price-level connectedness (Vo et al., 2019; Taghizadeh-Hesary et al., 2019; Shiferaw, 2019; Su et al., 2019; Pal and Mitra, 2019; Melichar and Atems, 2019; Cheng and Cao, 2019;Živkov et al. 2019a; Živkov et al., 2019b; Tiwari et al., 2021; Kumar et al., 2020; Mensi et al., 2017; Kumar et al., 2021) and volatility spillover effects across the markets under examination (Lu et al., 2019; Fasanya and Akinbowale, 2019; Guhathakurta et al., 2020; Kang et al., 2019; Chen et al., 2019; Tiwari et al., 2018; Albulescu et al., 2020; Kang et al. 2019, 2019). The present study examines the price of the related markets in terms of connectedness and spillovers, and we will, therefore, review several articles with respect to this topic in this section.

The causal relationship between crude oil prices and agricultural commodity markets has become a much-debated issue among academics (Su et al., 2019). There are mixed results in the prior papers. For example, Vo et al. (2019) examine the causal associations between agricultural products and oil markets. The study finds that the crude oil prices play a prominent role in explaining variations in the prices and volatility of agricultural commodities. At the same time, Taghizadeh-Hesary et al. (2019) confirm that agricultural food prices respond positively to any innovations from the crude oil market. Shiferaw (2019) supports the findings of Vo et al. (2019), but the author notices that the relationship between the agricultural commodity and energy prices is time-varying, which means that the prices of agricultural commodities and crude oil prices experience strong co-movement. In a similar fashion, Su et al. (2019) uncover that the dynamic, positive bidirectional causality exists between crude oil and agricultural prices and provide evidence that price spillover between two variables happens to agricultural commodities. Pal and Mitra (2019) find a strong relationship between returns of crude oil and agricultural commodity markets.

Melichar and Atems (2019) unveil asymmetric responses in agricultural commodity prices to crude oil markets, and provide evidence of heterogeneity after changes in US energy policy in 2016, with a strong correlation between crude oil and agricultural commodities prices. Cheng and Cao (2019) confirm the fact that there is a nonlinear causal association between crude oil and agricultural commodity markets. Živkov et al. (2019a) reveal strong spillover effect from crude oil to barley, corn and soybean in the longer time horizons. Moreover, the authors also indicate that agricultural commodities are impacted by crude oil in the periods of increased market turbulence. In a similar fashion, Živkov et al. (2019b) shed light on the low coherency in the short-run and high coherency in the long run between crude oil and agricultural commodity markets.

Existing literature has confirmed that there exist the price spillover mechanisms between crude oil prices and agricultural commodity markets. Lu et al. (2019) investigate the nature and dynamics of volatility spillovers between crude oil prices and agricultural commodity markets during the global financial crisis, and the results show that there is a bidirectional volatility spillover between crude oil and agriculture commodity markets in the crisis period. Specifically, the results indicate that crude oil and agricultural commodity markets become less integrated after the global financial crisis, the results in line with Peersman et al. (2019). Fasanya and Akinbowale (2019) demonstrate evidence of cross-market spillovers between the crude oil price and the main agricultural commodity markets in Nigeria, which implies that agricultural commodities render significant volatility spillovers. More importantly, the directional spillover between oil prices and agricultural commodities is weak in comparison with the directional spillover that happens across agricultural commodity markets. Similarly, Guhathakurta et al. (2020) examine the influence of crude oil price on the commodity markets, and the results show the significance of connectivity between oil and commodity markets demonstrating the nature and extent of such interrelations. Kang et al. (2019) indicate a bidirectional and asymmetric relationship between crude oil and agricultural commodity markets at all various frequency bands. In the same vein, the co-movement and asymmetric associations between crude oil and agriculture commodity prices have been examined by Chen et al. (2019). They present his work that there is a positive interconnectedness between the crude oil price and corn price, and this relationship is long-run equilibrium.

In this study, we revisit the issue of the impacts of crude oil price changes on agricultural commodity markets using both the spillover index of Diebold and Yilmaz (2012) and the wavelet coherence approaches. However, none of the studies mentioned above centres on the current situation created by the Covid-19 crisis. Therefore, we fill in the gap and give fresh insight into the impact of the Covid-19 crisis on the interdependence between crude oil prices and agricultural commodity markets.

3. Methodology

In this article, the spillover index of Diebold and Yilmaz (2012) and the wavelet coherence approaches have been employed. We briefly introduce the empirical methods used throughout the article in this section. Spillover index approach developed by Diebold and Yilmaz (2012) is also employed to capture the dynamic net directional spillover effects across these series. T**he wavelet time-frequency domain framework allows for different forms of localization, especially addressing the non-stationary time series** (Baruník et al., 2016). In this way, we can examine the co-movements and lead-lag interplay between assets using pairwise plots of wavelet coherence.

Diebold and Yilmaz (2012) spillover index and the wavelet coherence approach are employed to understand the relationships between time series. Compared with the existing literature, the most remarkable advantage of these methods is that time-varying and directional. We may assess the extent of information spillover across assets under examination at any particular date (Maghyereh et al., 2016; Hung, 2020b). In constant to the standard time-series frameworks that estimate the time-series in the time domain or frequency domain, the wavelet coherence technique explores the time and frequency elements of the time-series together at the same time (Tiwari et al., 2020; Hung, 2020c). This technique captures slow and existent interdependence among markets than standard methods that only consider the time domain perspective (Bouri et al., 2020; Al-Yahyaee et al., 2020). In addition, the wavelet coherence provides a more intuitive understanding of the nexus between the examined variables signifying short, medium, and long-run reactions, whether the relationships are positive or negative, and which variables are leading or lagging (Arain et al., 2020). As a result, it disentangles the short-run holding period from the long-run holding period in the investment period and uncovers the real connectedness across the assets.

3.1. Spillover index approach

Taking into consideration a covariance stationary Vector AutoRegression (VAR) model of order p and N variables, $x_i = \sum_{i=1}^{p}\varphi_i x_{t-i} + \varepsilon_i$, where $\varepsilon \sim (0, \sum)$ is a vector of independent and identically distributed distances. We can turn the VAR into a moving average (MA) representation, that is,$x_t = \sum_{i=0}^{\infty} A_i\varepsilon_{t-i}$ where $N \times N$ coefficient matrix A_i is obtained by the recursive substitution, $A_i = \varphi_1 A_{i-1} + \varphi_2 A_{i-2} + \cdots + \varphi_p A_{i-p}$, with $A_0 = I_n$, which is an identity matrix of order n, and $A_i = 0$ for $i < 0$. The MA presentation can be employed to forecast the future with the H-step-ahead.

The H-step-ahead generalized forecast-error variance decomposition can be written as:

$$\varphi_{ij}^{g}(H) = \frac{\sigma_{ij}\sum_{h=0}^{H-1}\left(e_i' A_h \sum e_i\right)^2}{\sum_{h=0}^{H-1}\left(e_i' A_h \sum A_h' e_i\right)} \tag{1}$$

where $\sum$is the variance matrix of the error vector, σ_{ii} is the standard deviation of the error term for the ith equation, and e_i is the selection vector with 1 as the ith elements, and 0 otherwise.

According to the properties of generalized VAR, we have $\sum_{j=1}^{N}\varphi_{ij}^{g}(H) \neq 1$. Each entry of the variance decomposition matrix is normalized by the row sum as

$$\widetilde{\theta}_{ij}^{g} = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N}\theta_{ij}^{g}(H)} \tag{2}$$

where $\sum_{j=1}^{N}\widetilde{\theta}_{ij}^{g}(H) = 1$ and. $\sum_{i,j=1}^{N}\widetilde{\theta}_{ij}^{g}(H) = N$

Total volatility spillover index proposed by Diebold and Yilmaz (2012) is defined as

$$S^{g}(H) = \frac{\sum_{i,j=1, j\neq i}^{N}\widetilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\widetilde{\theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{i,j=1,i\neq j}^{N}\widetilde{\theta}_{ij}^{g}(H)}{N} \times 100 \tag{3}$$

We can measure the directional volatility spillovers received by market i from all other markets j as:

$$S_{i.}^{g}(H) = \frac{\sum_{j=1,i\neq j}^{N}\widetilde{\theta}_{ij}^{g}(H)}{\sum_{j=1}^{N}\widetilde{\theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{i,j=1,i\neq j}^{N}\widetilde{\theta}_{ij}^{g}(H)}{N} \times 100 \tag{4}$$

Similarly, we can calculate the directional spillovers transmitted by market i to all other markets j as:

$$S_{i.}^{g}(H) = \frac{\sum_{j=1,i\neq j}^{N}\widetilde{\theta}_{ji}^{g}(H)}{\sum_{j=1}^{N}\widetilde{\theta}_{ji}^{g}(H)} \times 100 = \frac{\sum_{i,j=1,i\neq j}^{N}\widetilde{\theta}_{ji}^{g}(H)}{N} \times 100 \tag{5}$$

We can also obtain the net volatility spillover for each market by calculating the difference between (5) and (4) as:

$$S_{i}^{g}(H) = S_{.i}^{g}(H) - S_{i.}^{g}(H) \tag{6}$$

The net volatility spillover is simply the difference between the gross volatility shocks transmitted to and those received from all other markets (Diebold and Yilmaz, 2012).

3.2. Wavelet coherence

A brief note on wavelet coherence is defined as follows:

$$R_n^2\left(S\right) = \frac{\left|S\left(s^{-1}W_n^{XY}(s)\right)\right|^2}{S\left(s^{-1}\left|W_n^X(s)\right|^2\right).S\left(s^{-1}\left|W_n^Y(s)\right|^2\right.} \tag{7}$$

where S is a smoothing operator. Smoothing is achieved by convolution in time and scale.

$$S(W) = S_{scale}(S_{time}(W_n(s))) \tag{8}$$

Where S_{scale} and S_{time} illustrate smoothing on the wavelet scale axis and in time, respectively. Smoothing operator we use in this study is the Morlet wavelet, so the more suitable definition is given by Torrence and Webster (1999):

$$S_{time}\left(W\right) = \left(W_n\left(s\right)*c_1^{\frac{-t^2}{2s^2}}\right)\Big|_s \quad and \quad S_{time}(W)_s = (W_n(s)*c_2\Pi(0.6s))_s|_n \tag{9}$$

where c_1 and c_2 are normalization constants and Π is the rectangle function, the scale decorrelation length for the Morlet wavelet is 0.6.

The wavelet coherence coefficient measures the local linear correlation between two stationary time series at each scale and ranges $R_n^2(s) \in [0,1]$.

$W_n^{XY}(s)$ is the cross-wavelet power. It can be seen as the local covariance between the two-time series at each scale. Given time series $x(t)$ and $y(t)$, the cross-wavelet power can be written as

$$W_n^{XY}(s) = W_n^X(s)W_n^{*Y}(s) \tag{10}$$

where $W_n^X(s)$ and $W_n^{*Y}(s)$ are continuous wavelet transforms of two time series $x(t)$ and $y(t)$. The symbol * represents a complex conjugate.

The wavelet coherence phase is defined as

$$\varphi_n^{XY}(s) = \tan^{-1}\left(\frac{I\left\{S\left(s^{-1}W_n^{XY}(s)\right)\right\}}{R\left\{S\left(s^{-1}W_n^{XY}(s)\right)\right\}}\right) \tag{11}$$

where I and R are the imaginary and real parts of smooth power spectrum.

3.3. Data

In this study, the daily data of crude oil price (WTI) and six agriculture grain commodities: corn (CORN), copper (COPPER), Soybean (SOYBEAN), oats (OATS), wheat (WHEAT) and sugar (SUGAR) is employed to examine the impacts of oil price shocks on agricultural commodity prices before and after WHO announces Covid-19 outbreak 30 January 2020 (Covid-19). Goodell (2020) indicates that Covid-19 has significant influences on financial markets and institution both directly and indirectly. Motivated by his work, we divide the whole sample into two subsamples in order to shed light on the difference of the connectedness between crude oil and commodity prices in the pre and during Covid-19 periods. The first subsample spans the period from 2 February 2018 to 30 January 2020 (pre-Covid-19 period) and the second one is for the period from 31 January 2020 to 14 May 2020 (Covid-19 period). The crude oil and agricultural commodity prices are obtained from Thomson Reuters. We take into account the behaviours of the continuously compounded returns by taking the difference in the logarithm of two consecutive prices.

Table 1 represents the statistical properties of the crude oil and agricultural commodity real prices. Overall, the average returns of the six commodities during the pre-Covid-19 period are higher than those during the Covid-19 outbreak. WTI oil prices are more volatile than prices of agriculture commodities over the sample period shown. Skewness and kurtosis coefficients.

suggest that price changes of oil and all commodities are far from normally distributed, also formally confirmed by the Jarque-Bera test statistics.

Fig. 1 illustrates the correlation of examined variables based on the Pearson methodology, while Fig. 2 displays daily crude oil and agriculture commodity prices under investigation. We observe that all the six agriculture commodity prices follow similar movements over the research period, while the WTI oil prices exhibit a downward trend.

4. Empirical results

In this section, we describe the empirical methodologies throughout the study. It starts with the novel spillover index developed by Diebold and Yilmaz (2012) that allows for identification of time-varying net directional spillover effects between crude oil and agriculture commodity markets (Hung, 2020a). We also select wavelet coherence analysis, which provides dynamic connectedness between crude oil and

Table 1
Descriptive statistics of daily returns.

	Mean	Max	Min	Std. Dev	Skew.	Kurt.	JB	Obs.
Panel A. Pre-Covid-19 outbreak								
COPPER	−0.049979	.198920	−4.655553	1.162873	0.024272	4.199522	31.40637***	520
CORN	0.013705	4.499474	−6.287426	1.304732	−0.214445	5.548453	145.5369***	520
OATS	0.044158	7.384538	−5.406722	1.658070	−0.035837	3.967673	20.51748***	520
SOYBEAN	−0.018397	4.456832	−4.846827	1.057752	0.197552	4.757077	70.67966***	520
SUGAR	−0.009722	5.860098	−5.142304	1.601134	−0.006388	4.072442	25.06685***	520
WHEAT	0.049128	6.174801	−5.715841	1.70630	0.255039	3.355629	8.425791*	520
WTI	−0.028023	13.69440	−8.233565	2.051979	−0.005485	8.402906	636.1318***	520
Panel B. Covid-19 outbreak								
COPPER	−0.107787	3.714947	−7.282868	1.691326	−0.989413	6.467106	49.13778***	77
CORN	−0.233622	3.011612	−3.077166	1.282783	0.030072	3.072132	27.00196**	77
OATS	0.028451	3.071437	−3.436764	1.635761	0.046265	2.239903	18.07789**	77
SOYBEAN	−0.059509	2.462191	−3.232847	1.017817	−0.288136	4.417752	7.221513*	77
SUGAR	−0.464746	5.624725	−5.361418	2.439432	0.038068	2.826165	11.1047*	77
WHEAT	−0.153677	5.129329	−3.772275	1.604214	0.842099	4.694621	17.60048*	77
WTI	−0.684653	22.39400	−62.22046	12.18367	−1.736547	11.07388	238.1872***	77
Panel C. Full sample								
COPPER	−0.057144	4.198920	−7.282868	1.238996	−0.303481	5.624361	180.4848***	597
CORN	−0.016952	4.499474	−6.287426	1.303521	−0.182627	5.227854	14.73538***	597
OATS	0.042211	7.384538	−5.406722	1.653968	−0.026050	3.767895	14.73538***	597
SOYBEAN	−0.023493	4.456832	−4.846827	1.052138	0.145115	4.732020	76.71769***	597
SUGAR	−0.066124	5.860098	−5.361418	1.731105	−0.087809	4.028646	27.08773***	597
WHEAT	0.023989	6.174801	−5.715841	1.694012	0.320182	3.466947	15.62409***	597
WTI	−0.109338	22.39401	−62.22046	4.681595	−4.024551	63.66050	93144.03***	597

Note: *, **,*** represents the null hypothesis of normality is rejected at the 10%, 5% and 1% level, respectively.

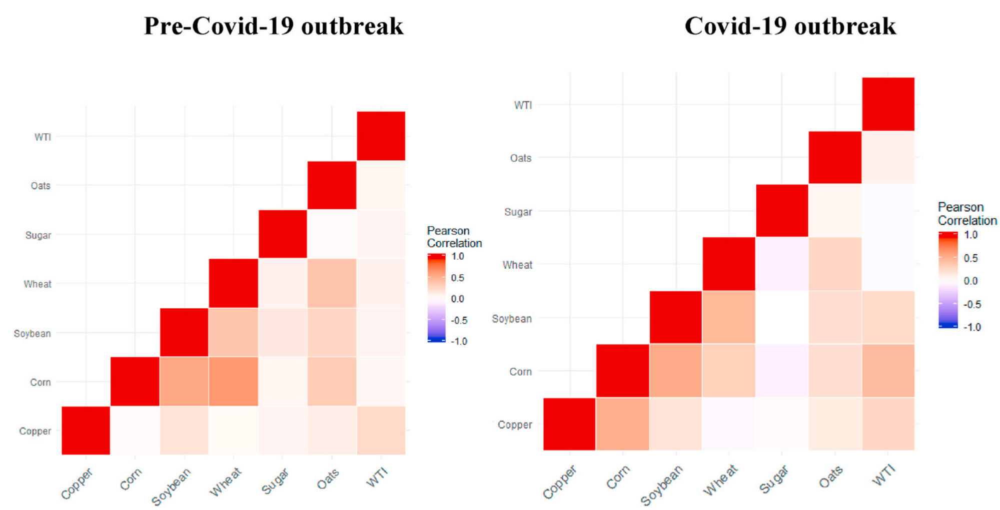

Fig. 1. Heat map of pairwise correlations before and after the WHO announcement.

agriculture commodity prices for different investment horizons (Dahir et al., 2018; Hung, 2020c).

4.1. Time-domain return spillover

Table 2 reports the description of the static spillover index for returns of the six agriculture commodity markets and WTI crude oil prices. Moreover, we also calculate the average directional spillovers and net spillovers in the pre and during the Covid-10 periods. This may provide some straightforward insights into spillover effect transmission trend across the market under investigation.

The analysis for the spillover table for returns of crude oil and agriculture commodity markets is done based on a daily vector autoregressive model of order 4 with using generalized variance decompositions of the 10-step-ahead forecast. The off-diagonal column sums present the "contribution to others" while the off-diagonal row sums give the "contribution to others". Put it another way, directional spillovers to is illustrated by "contribution to others" while directional spillover from is represented by "contribution from others" in the table. The main diagonal components capture own-variable spillovers of returns within and between markets. In a similar fashion, each component in each row, the off-diagonal opponents demonstrate the number of contributions of other markets to the forecast error variance of a specific examined market. The net return spillovers are obtained by subtracting the contribution from others from contributions to others or vice versa, which offers the difference between the contribution a market gives to and receives from others. The total spillover index is presented in the lower right corner of the table and approximately equal to the grand off-diagonal column sum (or row sum) with respect to the grand column sum including diagonals, expressed in percentage points. Briefly, the spillover table illustrates how innovations are received and transmitted within the system under examination.

We observe the total static spillover index among markets, decomposed by transmitters and recipients of return spillovers in both periods under consideration. The critical substantive figure is the total spillover index which indicates an average of 16.1% in the pre-Covid-19 period and 52.8% during the Covid-19 period for return forecast error variance results. It is obvious that the bidirectional return spillovers between crude oil and agriculture commodity markets are remarkably higher in the Covid-19 outbreak than in the pre-Covid-19 period. The important outcome was connected with increasing the magnitude and frequency of price overreactions of agricultural commodities during the Covid-19 pandemic in early 2020. This scenario started to change in March 2020 since agricultural commodities seem to witness the most price overreactions (Borgards et al., 2021). Perhaps this period roughly matches: 1) Spreading Covid-19 worldwide (a global threat outside of China), 2) The beginning of large-scale enforced social distancing in many Western countries (the confirmed cases in Italy, Spain, France and other European countries continued to increase), 3) the full global manifestation of Covid-19 (Goodell and Goutte, 2021).

More specifically, the corn market is the largest contributors to other markets, contributing 80.4%, followed by copper (13.9%) and oats (5.8%) in the pre-Covid-19 period. In the Covid-19 outbreak, the results from the return spillover index are similar to those of the pre-Covid-19 period. In the same vein, wheat, soybean, oats, sugar, crude oil are the recipient of return spillovers with the net values of −39.8, −33, −9.3, −1.1, and −6.3, respectively in the pre-Covid-19 period. More importantly, WTI crude oil price is the largest recipient of volatility spillover, with the net value of −34.2%, followed by wheat (−26.6) during Covid-19 outbreak pandemics. In general, various factors and measures have significantly contributed to the increased spillover effects coming from the Covid-19 outbreak. Furthermore, the total spillover index is more significant and increases profoundly during the Covid-19 outbreak, this means that the intensification of crisis effect transmission across markets under investigations. This segment of results falls in line with the findings of Guhathakurta et al. (2020), where the authors found the total spillover index among crude oil and commodity markets attained high values during the oil price boom of the global financial crisis 2008, and crash of 2015.

We further examine the dynamic behavior of total return spillovers during the Covid-19 outbreak because it is crucial to take into consideration cyclical movements and bursts in spillovers that could not be found out by the results shown in Table 2. Fig. 3 plots the time-varying return spillover index across examined markets, using 200-day rolling samples and 10-day-ahead forecast errors. The line graph was relatively uneventful, beginning with a burst of 23% in 2018, the return spillover trend decreased until the beginning of 2019 (19%). Following this, it slightly increased in the middle of 2019, which corresponds to the European debt crisis. However, the cyclical movements and bursts in spillovers were associated with the Covid-19 crisis episode, the spike of spillover index was trigged after the WHO announcement about the Covid-19 outbreak 20 January 2020, indicating the strong effects of the Covid-19 epidemic on return spillovers across oil-agriculture commodity markets. As a result, we can conclude that the Covid-19 outbreak crisis strengthens return spillovers across crude oil and six agriculture commodity markets. More specifically, the return spillover index was declining after February 2020 owing to the fall in the oil prices because of low demand in the Covid-19 outbreak period.

The time-varying net return spillovers are estimated based on 200-day rolling windows to determine which markets are net recipients

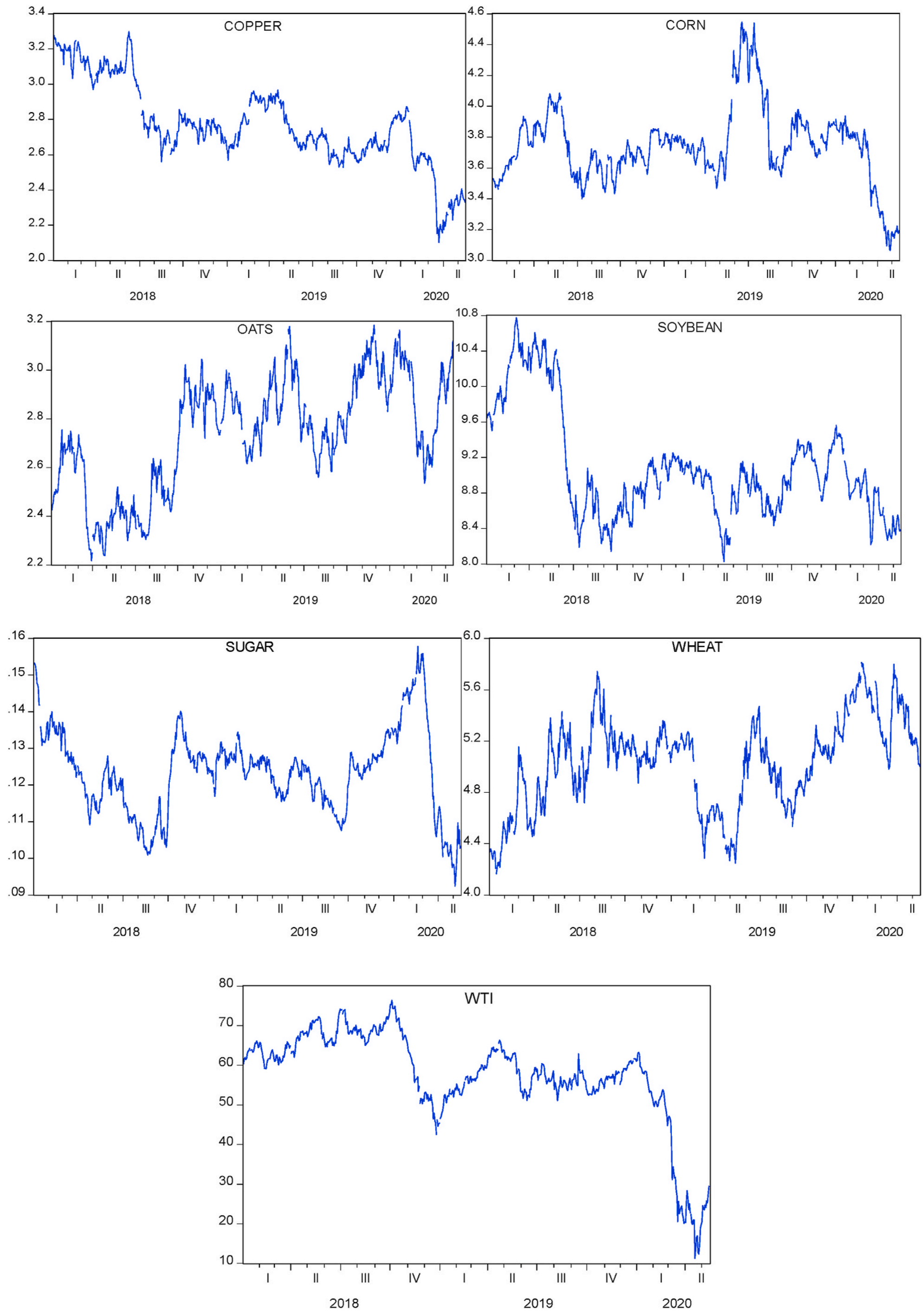

Fig. 2. Daily WTI and agriculture commodity prices.

and net transmitters of spillovers. The dynamic net return spillover is calculated by subtracting directional "to" spillover from directional "from" spillover. Therefore, we observe the various magnitude of return spillover according to positive or negative shocks, namely positive (negative) values show a source (recipient) of volatility to (from) other markets.

Fig. 4 reports the sign of the net spillovers that allows us to distinguish proportion in which good and bad volatilities from individual assets propagate among markets and result in negative and positive spillovers that materialize in the volatilities of the assets under investigation.

In contrast to the results presented in Table 2, the copper was the largest net recipient of return spillover, reaching a maximum level of 12.5% in the middle of 2019. The second-largest recipient of return spillovers was sugar and oats, with the high level of net return spillovers during the Covid-19 outbreak. It is valid for the case of WTI crude oil prices, which is consistent with the results of Table 2. On the other hand, corn, soybean and wheat are net transmitters of return spillovers. Its net contribution in market return is approximately 10% in the pre-Covid-19 period, reaching a peak of 18% in the Covid-19 period. Overall, the net return spillovers fluctuated with high spikes during the Covid-19 outbreak. The bar graph in each market reveals positive (net transmitter) value and negative (net recipient) values in the pre and during the Covid-19 outbreak. Our result gives further empirical evidence to the

Table 2
Total directional return spillovers.

	COPPER	CORN	OATS	SOYBEAN	SUGAR	WHEAT	WTI	From others
Panel A: Pre-Covid-19 period								
COPPER	97.4	0.2	0.6	1.1	0.0	0.3	0.4	2.6
CORN	0.3	97.6	0.0	0.0	0.2	0.6	1.3	2.4
OATS	1.2	11.6	84.9	0.5	1.3	0.2	0.3	15.1
SOYBEAN	4.4	30.4	0.5	63.3	0.0	1.0	0.4	36.7
SUGAR	0.7	0.3	0.8	1.4	96.6	0.1	0.1	3.4
WHEAT	0.1	37.4	3.4	0.2	0.5	57.4	0.9	42.6
WTI	7.2	0.4	0.5	0.3	0.4	0.7	90.4	9.6
Contribution to others	13.9	80.4	5.8	3.6	2.4	2.8	3.3	112.4
Contribution including own	111.3	178.1	90.7	67.0	98.9	60.2	93.7	16.1%
Net spillovers	11.3	78.1	−9.3	−33	−1.1	−39.8	−6.3	
Panel B: Covid-19 period								
COPPER	45.7	7.6	10.4	19.0	7.0	2.9	7.3	54.3
CORN	16.5	48.8	3.7	11.4	7.0	7.9	4.6	51.2
OATS	5.3	16.8	58.7	5.7	6.2	4.0	3.3	41.3
SOYBEAN	14.9	27.0	7.3	36.9	5.3	6.3	2.3	63.1
SUGAR	13.5	6.5	3.0	5.8	64.7	1.7	4.8	35.3
WHEAT	14.1	17.5	11.9	8.0	9.1	35.8	3.6	64.2
WTI	8.9	14.1	5.9	8.2	8.3	14.8	39.8	60.2
Contribution to others	73.2	89.5	42.3	58.1	42.8	37.6	26.0	369.6
Contribution including own	118.9	138.4	101.0	95.0	107.5	73.4	65.8	52.8%
Net spillovers	18.9	38.4	1.0	−5	7.5	−26.6	−34.2	

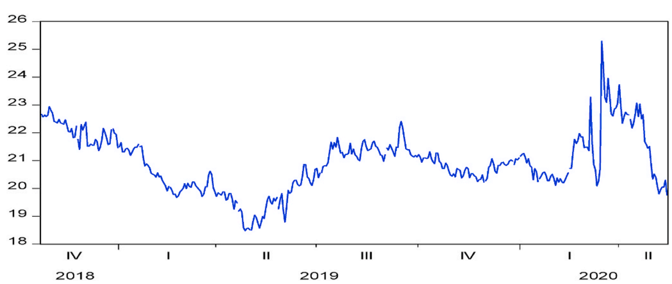

Fig. 3. Dynamic return spillover indices across WTI and six agriculture commodity markets.

propositions of Lu et al. (2019) and Peersman et al. (2019) in time domain space.

4.2. *The wavelet coherence*

Using the wavelet coherence, we analyze the time-varying associations between the WTI crude oil prices and agriculture commodity indices. The current Covid-19 crisis provides a unique opportunity to examine the dynamic co-movements between the variables under investigation. Moreover, wavelet coherence analysis can offer fresh insight into how such the agriculture commodity markets and crude oil prices have evolved over time and across frequency because bivariate wavelet coherence frameworks allow us to capture the co-movements and lead-lag correlation structures between the selected variables quickly (Hung, 2020a). Fig. 5 shows the wavelet coherence plots for each couple of indicators corresponding to pre and during the Covid-19 periods.

The horizon axis illustrates the time elements and frequency elements are denoted on the vertical axis. The horizontal axis spans the pre-Covid-19 period from February 2018 to January 2020, and the Covid-19 outbreak from February 2020 to May 2020. On the other hand, the frequency bands on the vertical axis are based on daily units covering from 4-to 128-day scales for the pre-Covid-19 period, and from 4-to 16-day scales for the Covid-19 outbreak. Besides, we rely on the color degradation to interpret the degree of local coherency between crude oil and agriculture commodity markets. The colors go from blue to yellow. More precisely, regions with significant intercorrelations are exhibited by warmer colors (yellow), while cooler colors (blue) islands demonstrate the two variables are less dependent. Cool islands outside of the significant areas suggest frequencies and time with no connectedness in the variables. As a result, the wavelet coherence tool tends to show the nexus between crude oil prices and agricultural commodity markets,

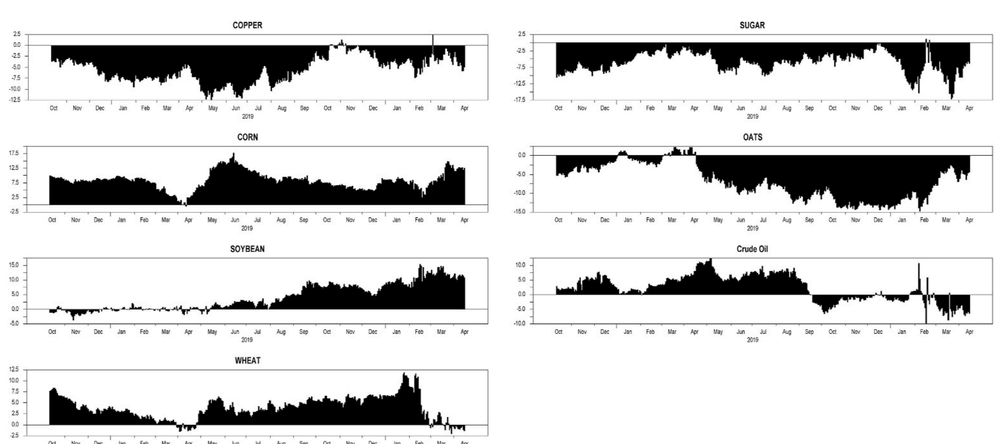

Fig. 4. Net return spillovers, six asset classes.

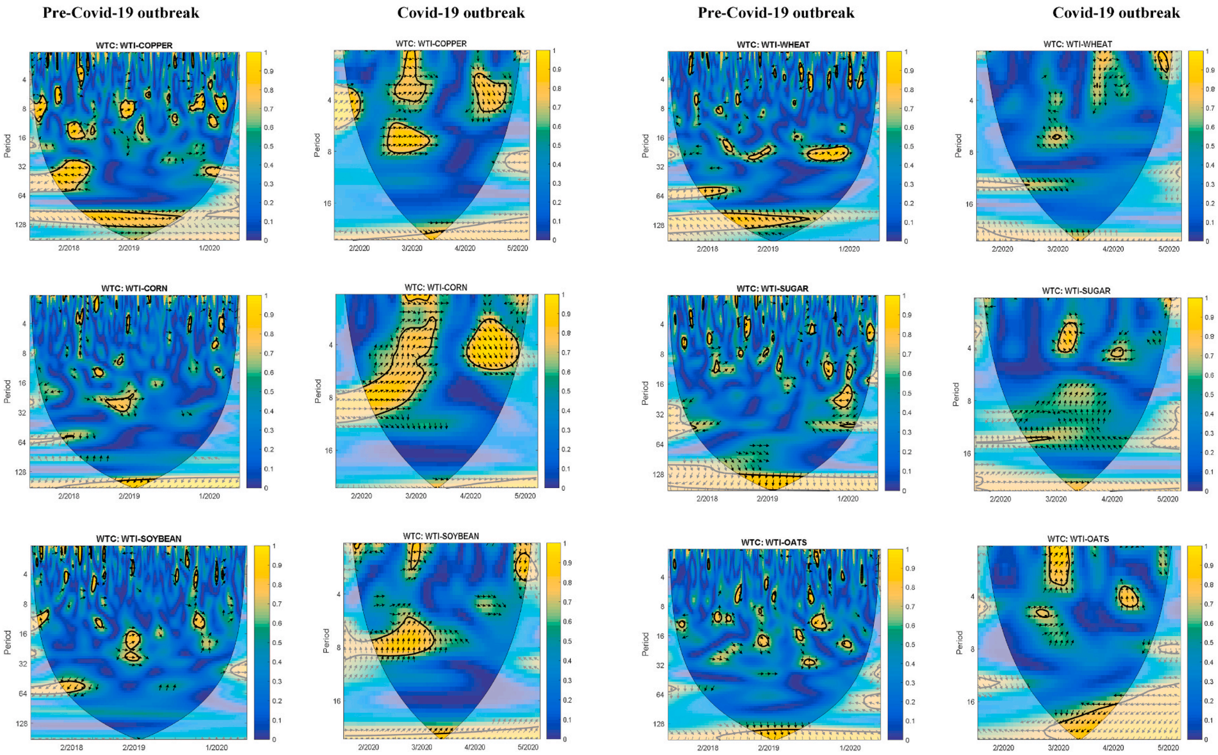

Fig. 5. Wavelet Coherence plots, pairwise estimates.

whilst the time-varying connectedness of time series are determined by observing lead-lag structure through different investment horizons. Arrows depict the direction of interrelatedness and causal effect connection between crude oil prices and agricultural commodity markets. For example, → and ← suggest that both crude oil prices and agricultural commodity markets are in phase and out of phase, respectively. An in-phase indicates that the return series move in the same direction (positive correlation), while they move in the opposite direction when two variables are in out of phase (negative correlation).

In addition, ↗ and ↙ reveal that crude oil prices are leading agriculture commodity markets, while ↘ and ↖ show that agriculture commodity markets are lagging those of crude oil prices.

By taking a close look at Fig. 5, we find several graphical evidence of low co-movements between crude oil prices and agriculture commodity indexes across frequencies and overtime in the pre-Covid-19 period. This is particularly true in the case of the wavelet coherency between WTI-SOYBEAN, WTI-CORN and WTI-OATS as shown by big islands of blue color localized in the pre-Covid-19 period in low, medium and high frequencies band. However, the coherency between WTI-SUGAR, WTI-WHEAT and WTI-COPPER experiences some significant regions of yellow color localized in high and medium frequencies band, corresponding to the periods December 2019 and January 2020 when Chinese authorities announced the novel coronavirus incurred in Wuhan.

The contagion during the Covid-19 outbreak, all markets under consideration seem to react to bad news coming from Wuhan city, Chinese authorities declared the new coronavirus on 21 December 2019. From the inspection of Covid-19 outbreak figure, some vital explanations emerge. In contrast to pre-Covid-19 period, the wavelet coherence analysis between the crude oil and agriculture commodity markets indicates a strong co-movement at all time scales and different frequency bands, suggesting a strong connectedness between both markets during the Covid-19 outbreak. More specifically, this tendency is more pronounced during the onset of the Covid-19 outbreak pandemics.

The associations between crude oil and agriculture commodity markets seem to react to bad news coming from the Covid-19 crisis. On 27 March 2020, the number of confirmed cases surpassed 500000, and it continues to increase. At the same time, the US has the most confirmed cases, and over 170 countries are now affected. Looking at the case of WTI-COPPER, WTI-CORN, WTI-OATS, WTI-SUGAR, and WTI-SOYBEAN, wavelet coherence plot exhibits the existence of substantial coherence islands between the onset of the novel coronavirus and in the middle of May, and at medium frequencies which show a medium-term co-movement between WTI crude oil and agriculture commodity markets corresponding to a constant increase of the infected counts across the world and the free fall of oil prices. This finding suggests that a high level of WTI and agriculture commodity markets co-movements is seen during the Covid-19 crisis, supporting the contagion hypothesis. We can identify causality and phase differences between WTI crude oil prices and agricultural commodity markets. We observe that the primary and most significant period of coherence and co-movements in both 4-8-day and 8-16-day bands since 1 February 2020, that arrows predominantly pointed up and to the right signifying an in-phase connectedness and a positive relationship between WTI crude oil prices and agricultural commodity markets. Besides, these arrows also reveal that WTI crude oil led agriculture commodity returns in the short and medium terms, over the full world containment. Apparently, several episodes of the Covid-19 outbreak influence these results.

Interestingly, in line with the findings displayed in time-domain return spillover and wavelet coherence, we find significant return spillovers from crude oil prices to the agricultural commodities and from each of the agricultural commodities to WTI markets. Specifically, there exists a significant co-movement of WTI crude oil prices and agriculture commodity markets during the Covid-19 outbreak period. A global price war in crude oil and several global restrictions on travel and immigration, has profoundly influenced the global economy's level of economic activity as a whole (Gray, 2020; Goodell and Goutte, 2021). Furthermore, the Commodity Markets Outlook published by the World Bank in 2020 reveals that the increasing commodity return spillover is because of profound changes in each type of commodity's supply and demand. It implies that the demand for agricultural commodities increased enormously during the Covid-19 outbreak. These results are consistent with recent studies on the influence of the Covid-19 pandemic on agricultural commodities. For instance, Borgards et al. (2021) consider the overreaction behavior of 20 commodities futures, focusing on the effect of the Covid-19 pandemic, and find that both the number and the amplitude of overreactions are higher during the Covid-19 pandemic. Adekoya and Oliyide (2020) investigate the impact of the pandemic on the connectedness between commodity and financial markets and unveil that the commodity price spillovers increase dramatically during the first wave of the Covid-19 pandemic in early 2020. In a similar fashion, Hung (2020d) also uses both the spillover index and wavelet coherence approaches to examine the influences of time-varying interlinks between crude oil prices and five developed stock markets in Europe. He reports that the price spillovers between these variables increase strongly during the Covid-19 pandemic.

Overall, we find a strong co-movement of WTI crude oil prices and agriculture commodity markets predominantly during the Covid-19 outbreak compared to pre-Covid-19 period. However, levels of the intensity of this relationship vary through the period of research, with several intervals witnessing both negative and positive interaction. The results of Živkov et al. (2019b), Melichar and Atems (2019), Su et al. (2019), Kang et al. (2019), Chen et al. (2019) and Živkov et al. (2019b) can be extended in this segment of the findings, where they found a strong connectedness between crude oil prices and agricultural commodity markets in the periods of increased market turbulence. Besides, our results also extend the findings of Kumar et al. (2019), Albulescu et al. (2020), Mensi et al. (2017), Kumar et al. (2020), Kang et al. (2019), Tiwari et al. (2018) and Tiwari et al. (2021) with the estimates of reaction of the relationship of crude oil prices to agricultural commodity markets. They argue a significant nexus between the agriculture and crude oil markets in terms of price and volatility spillovers.

5. Conclusion and policy implications

The Covid-19 outbreak has been spread rapidly all over the world already. Along with causing death worldwide, the Covid-19 outbreak has had a remarkable impact on the global economic cycle, financial and commodity markets. Of course, the outbreak also generated structural changes in the pricing dynamics for a wide range of different markets, with an emphasis on commodity markets owning to their interrelatedness with the real economy. The present empirical study investigates the spillover effects, and time-frequency connectedness between the crude oil prices and the agriculture commodity markets using both the spillover index of Diebold and Yilmaz (2012) and the wavelet coherence approaches in the pre and during Covid-19 periods. The whole sample period is from February 2018 to May 2020. The first period covers the pre-Covid-19 period from 2 February 2018 to 30 January 2020. The second period is the Covid-19 period from 31 January 2020 to 14 May 2020, which was characterized by widespread Covid-19.

Our empirical results may be summarized as follows. First, we investigate trends in the bidirectional net return spillover index across crude oil and agriculture commodity markets. The directional association from the crude oil market to agriculture commodity returns was lower than that in the opposite direction. Furthermore, the return spillovers exhibit an increasing pattern during the Covid-19 outbreak pandemics, confirming spillovers' intensity during periods of turmoil. Specifically, the crude oil market was a net recipient of return spillovers during the Covid-19 outbreak crisis, while it was a net transmitter of return spillovers in the pre-Covid-19 periods. Corn, soybean, and wheat markets were net transmitters of return spillover, while the copper, sugar, and oats were net recipients of return spillover over the period shown. Second, we find a strong co-movement of WTI crude oil prices and agriculture commodity markets predominantly during the Covid-19 outbreak compared to the pre-Covid-19 period. However, levels of the intensity of this relationship vary through the period of research, with several intervals witnessing both negative and positive interactions. Finally, our findings indicate significant heterogeneity among agriculture commodity markets in the degree of spillover to crude oil prices over time, amplifying our understanding of the economic channels through which the agriculture commodity markets are correlated.

Overall, the current results cast light on that in comparison with the pre-Covid-19 period, and the return spillovers are more apparent during the Covid-19 crisis. More importantly, there exist significant dependent patterns about the information spillovers across the crude oil and agriculture commodity markets might provide prominent implications for portfolio managers, investors, and government agencies. Apparently, the commodity boom and the later sharp drop in prices during the Covid-19 outbreak were gone with an unprecedented rise in activity across international investors in the commodity markets. Investors should unroll their positions in one commodity market if other markets drop prices suddenly lead them to reduce risk. At the same time, the Covid-19 pandemic is still ongoing, it can further impact oil prices because of the travel restrictions around the world. Hence, to prevent higher inflation due to the variations in agriculture commodity prices, policymakers should take into consideration oil prices when making policies to maintain relatively stable prices of agricultural commodities. We attribute the bidirectional return spillovers between crude oil prices and agriculture commodities, which provides a practical approach for policymakers to monitor and regulate oil and agriculture prices.

However, we acknowledge that our results should be taken with caution, given the small sample size and statistical inference from the used methods. We take into account that our paper makes a significant contribution to the fast-growing body of work on the financial influences of Covid-19, and to an ongoing concentration in the literature in connection with the oil-agriculture commodities relationship.

Availability of supporting data

Please contact author for data and program codes requests. Data is obtained from Bloomberg and Matlab is used to organize data.

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Ngo Thai Hung: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft.

Declaration of Competing interest

I hereby confirm that no conflict of interest has arisen in undertaking this research. I also hereby confirm that this piece of work is original and the manuscript has not been previously published or submitted anywhere else.

Nagayev et al., 2016, Rasoulinezhad and Yoshino, 2019, Zhang et al., 2020, Zivkov et al., 2019a

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References

Adekoya, O.B., Oliyide, J.A., 2020. How COVID-19 drives connectedness among commodity and financial markets: evidence from TVP-VAR and causality-in-quantiles techniques. Resour. Pol. 101898.

Akhtaruzzaman, M., Boubaker, S., Sensoy, A., 2020. Financial contagion during COVID–19 crisis. Finance Res. Lett. 101604.

Al-Yahyaee, K.H., Rehman, M.U., Al-Jarrah, I.M.W., Mensi, W., Vo, X.V., 2020. Co-movements and spillovers between prices of precious metals and non-ferrous metals: a multiscale analysis. Resour. Pol. 67, 101680.

Albulescu, C.T., Tiwari, A.K., Ji, Q., 2020. Copula-based local dependence among energy, agriculture and metal commodities markets. Energy 202, 117762.

Arain, H., Sharif, A., Akbar, B., Younis, M.Y., 2020. Dynamic connection between inward foreign direct investment, renewable energy, economic growth and carbon emission in China: evidence from partial and multiple wavelet coherence. Environ. Sci. Pollut. Control Ser. 27 (32), 40456–40474.

Baruník, J., Kočenda, E., Vácha, L., 2016. Gold, oil, and stocks: dynamic correlations. Int. Rev. Econ. Finance 42, 186–201.

Borgards, O., Czudaj, R.L., Van Hoang, T.H., 2021. Price overreactions in the commodity futures market: an intraday analysis of the Covid-19 pandemic impact. Resour. Pol. 71, 101966.

Bouri, E., Shahzad, S.J.H., Roubaud, D., Kristoufek, L., Lucey, B., 2020. Bitcoin, gold, and commodities as safe havens for stocks: new insight through wavelet analysis. Q. Rev. Econ. Finance 77, 156–164.

Chang, C.L., McAleer, M., Wong, W.K., 2020. Risk and financial management of COVID-19 in business, economics and finance. J. Risk Financ. Manag. 13, 102.

Chen, Z.M., Wang, L., Zhang, X.B., Zheng, X., 2019. The co-movement and asymmetry between energy and grain prices: evidence from the crude oil and corn markets. Energies 12 (7), 1373.

Cheng, S., Cao, Y., 2019. On the relation between global food and crude oil prices: an empirical investigation in a nonlinear framework. Energy Econ. 81, 422–432.

Dahir, A.M., Mahat, F., Ab Razak, N.H., Bany-Ariffin, A.N., 2018. Revisiting the dynamic relationship between exchange rates and stock prices in BRICS countries: a wavelet analysis. Borsa Istanbul Review 18 (2), 101–113.

Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: predictive directional measurement of volatility spillovers. Int. J. Forecast. 28 (1), 57–66.

Fasanya, I., Akinbowale, S., 2019. Modelling the return and volatility spillovers of crude oil and food prices in Nigeria. Energy 169, 186–205.

Goodell, J.W., 2020. COVID-19 and finance: agendas for future research. Finance Res. Lett. 101512.

Goodell, J.W., Goutte, S., 2021. Co-movement of COVID-19 and Bitcoin: evidence from wavelet coherence analysis. Finance Res. Lett. 38, 101625.

Gray, R.S., 2020. Agriculture, transportation, and the COVID-19 crisis. Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie 68 (2), 239–243.

Guhathakurta, K., Dash, S.R., Maitra, D., 2020. Period specific volatility spillover based connectedness between oil and other commodity prices and their portfolio implications. Energy Econ. 85, 104566.

Hung, N.T., 2020a. Volatility spillovers and time-frequency correlations between Chinese and African stock markets. Regional Statistics 10 (2), 63–82.

Hung, N.T., 2020b. Market integration among foreign exchange rate movements in central and eastern European countries. Soc. Econ. 42 (1), 1–20.

Hung, N.T., 2020c. Time-frequency nexus between bitcoin and developed stock markets in the asia-pacific. Singapore Econ. Rev. 1–26.

Kang, S.H., Uddin, G.S., Troster, V., Yoon, S.M., 2019. Directional spillover effects between ASEAN and world stock markets. J. Multinatl. Financ. Manag. 52, 100592.

Kang, S.H., Tiwari, A.K., Albulescu, C.T., Yoon, S.M., 2019a. Exploring the time-frequency connectedness and network among crude oil and agriculture commodities V1. Energy Econ. 84, 104543.

Kumar, S., Tiwari, A.K., Raheem, I.D., Ji, Q., 2020. Dependence risk analysis in energy, agricultural and precious metals commodities: a pair vine copula approach. Appl. Econ. 52 (28), 3055–3072.

Kumar, S., Tiwari, A.K., Raheem, I.D., Hille, E., 2021. Time-varying dependence structure between oil and agricultural commodity markets: a dependence-switching CoVaR copula approach. Resour. Pol. 72, 102049.

Lu, Y., Yang, L., Liu, L., 2019. Volatility spillovers between crude oil and agricultural commodity markets since the financial crisis. Sustainability 11 (2), 396.

Madaleno, M., Pinho, C., 2014. Wavelet dynamics for oil-stock world interactions. Energy Econ. 45, 120–133.

Maghyereh, A.I., Awartani, B., Bouri, E., 2016. The directional volatility connectedness between crude oil and equity markets: new evidence from implied volatility indexes. Energy Econ. 57, 78–93.

Melichar, M., Atems, B., 2019. Global crude oil market shocks and global commodity prices. OPEC Energy Review 43 (1), 92–105.

Mensi, W., Tiwari, A., Bouri, E., Roubaud, D., Al-Yahyaee, K.H., 2017. The dependence structure across oil, wheat, and corn: a wavelet-based copula approach using implied volatility indexes. Energy Econ. 66, 122–139.

Nagayev, R., Disli, M., Inghelbrecht, K., Ng, A., 2016. On the dynamic links between commodities and Islamic equity. Energy Econ. 58, 125–140.

Pal, D., Mitra, S.K., 2019. Correlation dynamics of crude oil with agricultural commodities: a comparison between energy and food crops. Econ. Modell. 82, 453–466.

Peersman, G., Rüth, S., Van der Veken, W., 2019. The interplay between oil and food commodity prices: has it changed over time? (No. 7826. CESifo Working Paper.

Rasoulinezhad, E., Yoshino, N., 2019. Energy and food security: linkages through price volatility. Energy Pol. 128, 796–806.

Sharif, A., Aloui, C., Yarovaya, L., 2020. COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: fresh evidence from the wavelet-based approach. Int. Rev. Financ. Anal. 101496.

Shiferaw, Y.A., 2019. Time-varying correlation between agricultural commodity and energy price dynamics with Bayesian multivariate DCC-GARCH models. Phys. Stat. Mech. Appl. 526, 120807.

Su, C.W., Wang, X.Q., Tao, R., Oana-Ramona, L., 2019. Do oil prices drive agricultural commodity prices? Further evidence in a global bio-energy context. Energy 172, 691–701.

Taghizadeh-Hesary, F., Rasoulinezhad, E., Yoshino, N., 2019. Energy and food security: linkages through price volatility. Energy Pol. 128, 796–806.

Tiwari, A.K., Khalfaoui, R., Solarin, S.A., Shahbaz, M., 2018. Analyzing the time-frequency lead–lag relationship between oil and agricultural commodities. Energy Econ. 76, 470–494.

Tiwari, A.K., Nasreen, S., Shahbaz, M., Hammoudeh, S., 2020. Time-frequency causality and connectedness between international prices of energy, food, industry, agriculture and metals. Energy Econ. 85, 104529.

Tiwari, A.K., Boachie, M.K., Suleman, M.T., Gupta, R., 2021. Structure dependence between oil and agricultural commodities returns: the role of geopolitical risks. Energy 219, 119584.

Torrence, C., Webster, P.J., 1999. Interdecadal changes in the ENSO–monsoon system. J. Clim. 12 (8), 2679–2690.

Vo, D.H., Vu, T.N., McAleer, M., 2019. Modeling the relationship between crude oil and agricultural commodity prices. Energies 12 (7), 1344.

Zhang, D., Hu, M., Ji, Q., 2020. Financial markets under the global pandemic of COVID-19. Finance Research Letters, p. 101528.

Zivkov, I.D., Kuzman, B., Subić, J., 2019a. How do oil price changes impact the major agricultural commodities in different market conditions and in different time-horizons? Econ. Comput. Econ. Cybern. Stud. Res. 53 (4).

Živkov, D., Njegić, J., Pećanac, M., 2019b. Multiscale interdependence between the major agricultural commodities. Agric. Econ. 65 (2), 82–92.