Analysis of the impact of COVID-19 on the correlations between crude oil and agricultural futures

Jian Wang [a], Wei Shao [b], Junseok Kim [a],*

[a] Department of Mathematics, Korea University, Seoul 02841, Republic of Korea
[b] Department of Economics, Korea University, Seoul 02841, Republic of Korea

A R T I C L E   I N F O

A B S T R A C T

In this study, we explored the impact of COVID-19 on the cross-correlations between crude oil and agricultural futures markets. A multifractal detrended cross-correlation analysis (MF-DCCA) approach was utilized to analyze the cross-correlations between the Brent crude oil and agricultural futures such as London Sugar, London Wheat, USA Cotton #2, and USA Orange Juice futures. We initially confirmed their correlations by calculating the DCCA coefficient. Then, from the multifractal aspect, the cross-correlations were further explored, and the sources for forming the correlations were discussed. The results show that the Brent Crude Oil has the strongest cross-correlation with London Sugar Future market among other three agricultural future markets. Then we investigated the influence of COVID-19 on the cross-correlations of multifractality between crude oil and agricultural futures. The experimental results indicated that the persistence under the influence of COVID-19 became stronger, and the cross-correlations of multifractality between crude oil and sugar future market is the strongest. In addition, the cross-correlations of all the agricultural futures increased after the emergence of COVID-19 except the orange juice future market. In general, COVID-19 has a great impact on the cross-correlation of multifractal property between crude oil and most selected agricultural future markets.

1. Introduction

The changes in energy prices represented by crude oil in recent years are the main factors affecting the fluctuation of international agricultural product prices [1]. Crude oil and its downstream products are inextricably linked with the production, processing, transportation, and sales of most agricultural products. The large fluctuations in crude oil prices can always affect the supply and demand balance of agricultural products, and then shocked the fluctuation of agricultural product prices.

International crude oil prices have always been a key topic of global concern, and their influencing factors are also more complex, such as capital speculation, geopolitical conflicts, supply and demand relationships, and changes in the US dollar index. In addition, as the emergence of COVID-19 affects the commodity markets in China and other regions in the world, the proliferation of COVID-19 has caused impacts of global crude oil demand. Since January

2020, the new coronavirus has affected China's crude oil demand to a certain extent. At the end of February, it further expanded to South Korea, Iran, Italy and other countries and regions. In addition, in March, the United States, Britain, Spain and other countries spread rapidly, which affected the global demand for crude oil and caused panic about the economic outlook of the global market. We note that the international benchmark Brent crude oil fell to its lowest level since 2002.

With the rapid development of global financial markets, traders tend to follow global portfolio strategies to reduce market risk. Such an investment portfolio covers various financial commodities including stocks, options, futures, and bonds in different exchanges and in different countries. The futures market is also one of the important financial sectors for capital flows, which includes many agricultural futures markets.

Some research literatures have proved that the price of crude oil has a strong correlation with the futures prices of most agricultural products. The Johansen cointegration test was used to study the covariates between crude oil prices and corn, sorghum, sugar, soybean, soybean oil, and palm oil prices from 2003 to 2007 in [2]. The analysis showed no co-integration relationship over the entire sample period. However, analysis of the 2006-2007 sub-sample

showed that soybean and corn prices were cointegrated with crude oil. Besides, Natanelov et al. [3] studied the co-movements between crude oil and agricultural commodities by Johansen cointegration, Threshold cointegration, and vector error correction model. Their results indicated that the relationship is a dynamic concept, and some economic and policy development may change the relationship between crude oil and agricultural commodities. Du et al. [4] studied the fluctuation relationship between international crude oil futures and corn, wheat futures markets from 1998 to 2009 by using stochastic volatility models. The models were estimated by using Bayesian analysis, Markov chains, and Monte Carlo methods. They found that crude oil futures and corn, wheat futures markets have significant volatility spillover effects after the second half of 2006, which has a huge connection with the rise of bioethanol fuel.

Since the multifractal detrended fluctuation analysis (MF-DFA) was first introduced by [5], the method has been applied in various problems for investigating the nonlinear phenomena [6–8]. Empirical researches showed that multifractal theory can better describe the various complex phenomena and behaviors existing in financial markets compared with traditional efficient market hypothesis [9–14]. Afterwards, Zhou [15] extended this method to analyze the cross-correlation analysis for two nonstationary series, which is the MF-DCCA [10,16,17]. It is worth mentioning that the cross-correlations between crude oil and agricultural commodity markets were first investigated by Liu [18] from a multifractal perspective.

In this article, we first use MF-DCCA to check the cross-correlations between the Brent crude oil price series and agricultural futures such as London Surgar, London Wheat, USA Cotton #2, and USA Orange Juice future price series. In addition, we mainly study the impact of COVID-19 on the fluctuation of global crude oil prices and agricultural futures prices using MF-DFA, and use MF-DCCA to analyze the change of correlations between the crude oil price and agricultural futures prices caused by COVID-19.

The remainder of the paper is organized as follows. We introduce the procedure of MF-DCCA in Section 2. In Section 3, we give a description of data information. The empirical results are illustrated in Section 4. Section 5 provides a conclusion.

2. Multifractal detrended cross-correlation analysis

In this section, we first briefly introduce the MF-DCCA. The procedure of MF-DCCA is generally concluded by the following steps.

I. Let x_t and y_t, for $t = 1, 2, ..., N$ be the given two time series. Then, construct the profile series.

$$X(t) = \sum_{k=1}^{t}(x_k - \tilde{x}), \tag{1}$$

$$Y(t) = \sum_{k=1}^{t}(y_k - \tilde{y}), \tag{2}$$

where $\tilde{x}$ and $\tilde{y}$ denote the mean of two time series.

II. Divide two profiles X and Y into $N_s = int(\frac{N}{s})$ non-overlapping segments with time scale s. Since N is not always an integral multiple of s, some fractions of each profile may remain. To ensure all the information of the time series, the same procedure is repeated from the end to the start. Then, $2N_s$ non-overlapping segments are obtained.

III. For each subsegment v, we acquire the local trends with an kth-order polynomial fit.

$$\widetilde{x_v(i)} = \delta_1 i^k + \delta_2 i^{k-1} + \cdots + \delta_k i + \delta_{k+1}, \quad i = 1, 2, ..., s; \ k = 1, 2, ... \tag{3}$$

$$\widetilde{y_v(i)} = \gamma_1 i^k + \gamma_2 i^{k-1} + \cdots + \gamma_k i + \gamma_{k+1}, \quad \imath = 1, 2, ..., s; \ k = 1, 2, ... \tag{4}$$

IV. Compute the detrended covariance $F^2(s, v)$. For $v = 1, 2, ..., N_s$,

$$F^2(s, v) = \frac{1}{s} \sum_{i=1}^{s} \{|X[(v-1)s + i] - \widetilde{x_v(i)}||Y[(v-1)s + i] - \widetilde{y_v(i)}|\}. \tag{5}$$

For $v = N_s + 1, N_s + 2, ..., 2N_s$,

$$F^2(s, v) = \frac{1}{s} \sum_{i=1}^{s} \{|X[N - (v - N_s)s + i] - \widetilde{x_v(i)}||Y[N - (v - N_s)s + i] - \widetilde{y_v(i)}|\}. \tag{6}$$

V. Average the detrended covariances to obtain the qth-order fluctuation function as

$$F_q(s) = \left\{\frac{1}{2N_s} \sum_{v=1}^{2N_s}[F^2(s, v)]^{\frac{q}{2}}\right\}^{\frac{1}{q}}, \ for \ q \neq 0, \tag{7}$$

and

$$F_q(s) = \exp\left(\frac{1}{2N_s} \sum_{v=1}^{2N_s}\ln[F^2(s, v)]\right), \ for \ q = 0. \tag{8}$$

VI. Observe the log-log plots of $F_q(s)$ versus s, if $F_q(s)$ increase against s, then the scaling behavior exists, that is the two time series are long-range cross-correlated. Then the power-law expression $F_q(s) \propto s^{H_{xy}(q)}$ can be obtained, where $H_{xy}(q)$ is the generalized Hurst exponent versus q. Especially, when $x(t)$ and $y(t)$ are the same time series, then MF-DCCA becomes MF-DFA.

$H_{xy}(q)$ reveals the large fluctuations exist in the time series with $q > 0$, and if $q < 0$, the generalized Hurst exponent reveals the small fluctuations. If $H_{xy}(2) > 0.5$, then the cross-correlations of the time series pair are positive persistent, indicating one series are statistically to be followed by the other series. If $H_{xy}(2) < 0.5$, the cross-correlations of the time series pair are negative persistent, showing that the changing trends of two time series are opposite. If $H_{xy}(2) = 0.5$, there exists no correlations with each other. The extent of multifractality can be derived by calculating the range of $H_{xy}(q)$, a larger $\Delta H_{xy} = H_{xy}(q_{min}) - H_{xy}(q_{max})$ denotes a high level of multifractal nature.

VII. The Mass exponent $\tau_{xy}(q)$ has been proved that can describe the multifractal degree [19]. The $\tau_{xy}(q)$ is defined as

$$\tau_{xy}(q) = qH_{xy}(q) - 1, \tag{9}$$

The cross-correlation of two time series is multifractal when $\tau_{xy}(q)$ shows a nonlinear behavior versus q. By observing the curvature of the curve, we can acquire the multifractal extent. A stronger multifractality of cross-correlations will have a high curvature, vice versa.

VIII. The singularity strength α_{xy} and singularity spectrum $f_{xy}(\alpha)$ are obtained by Legendre transform as

$$\alpha_{xy} = H_{xy}(q) + qH'_{xy}(q), \tag{10}$$

$$f_{xy}(\alpha) = q[\alpha_{xy} - H_{xy}(q)] + 1, \tag{11}$$

where α_{xy} describes the cross-correlation of time series pair, and $f_{xy}(\alpha)$ denotes the fractal dimension of α_{xy}. $\Delta\alpha_{xy} = \alpha_{xy_{max}} - \alpha_{xy_{min}}$ describes the strength of multifractality, and a larger $\Delta\alpha_{xy}$ denotes a stronger multifractal property, suggesting there exists a stronger cross-correlations between two time series.

Table 1
Descriptive statistics for the total sample.

Commodity	Code	Exchange	Min	Max	Mean	σ	Skewness	Kurtosis
Brent Crude	LCO	ICE	22.74	86.29	63.10	10.25	-0.78	4.74
London Surgar	LSU	ICE	294.00	484.20	357.92	36.69	1.20	4.29
London Wheat	LWB	ICE	129.75	194.65	151.61	14.02	0.89	2.82
USA Cotton #2	CT	ICE	48.85	95.25	73.26	8.41	-0.01	2.67
USA Orange Juice	OJ	ICE	91.25	171.35	129.96	24.20	-0.08	1.63
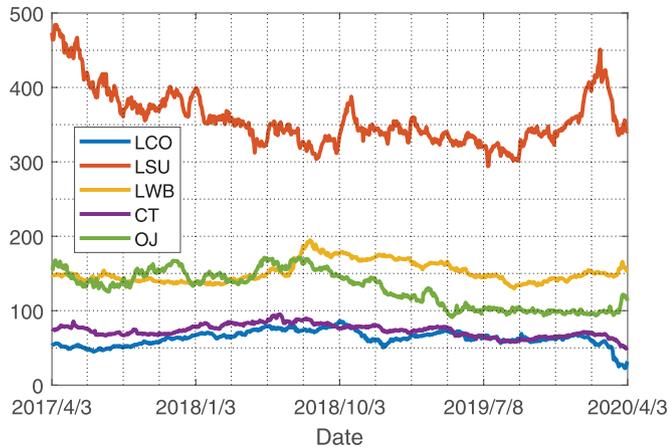
Fig. 1. Closing price time series of Brent Crude and agricultural futures. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 2. DCCA coefficients of Brent Crude and agricultural futures.
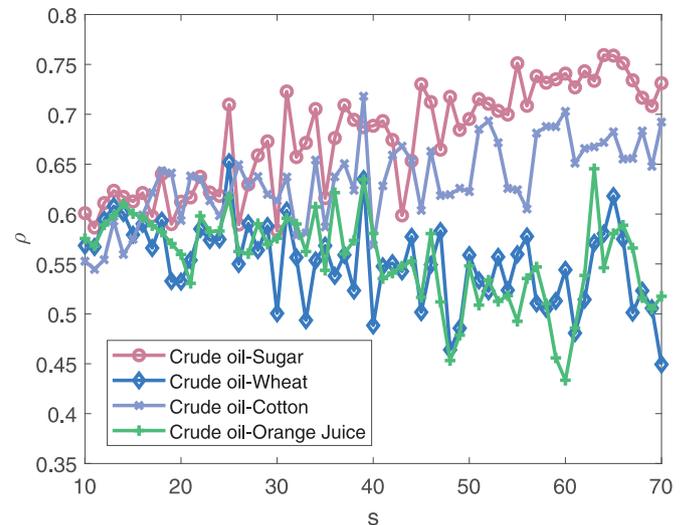
3. Data collection

In this section, we choose the daily closing prices of London Brent Oil and agricultural futures such as London Surgar, London Wheat, USA Cotton #2, and USA Orange Juice futures to analyze the cross-correlations between them. The reasons for our selection of these agricultural futures will be analyzed and explained in Section 4.2. Our sample data covers the period from 3 April, 2017 to 3, April, 2020. After eliminating the non-matching missing data, the time series of Brent Crude Oil consists of 776 observations, and the other time series length of four agricultural futures are 762, 761, 761, and 759, respectively. Based on the total data of Brent Crude, we interpolate the price time series of the other four agricultural futures, and the length of the series after interpolation are all equal to 776. The time series of daily closing prices of all the commodities are illustrated in Fig. 1, the codes and exchange information of these commodities and their statistics are introduced in Table 1. In addition, the sample for analyzing the impact of COVID-19 consist of two periods which are the period 1 before the emergence of COVID-19 and the period 2 after the emergence of COVID-19. The detailed sample information will be introduced in Section 4.3.

4. Experiment results

4.1. DCCA coefficient

We first test whether the time series of crude oil and agricultural futures have a cross-correlation by DCCA coefficient, and then use MF-DCCA to study the cross-correlation and multifractal relationship between them. The DCCA coefficient test method proposed by Zebende [20] can be summarized as follows.

$$\rho = \frac{F_{xy}^2(s)}{F_x(s)F_y(s)}. \tag{12}$$

In the above equation, $F_{xy}^2(s)$ denotes the detrended covariance's fluctuation function of two time series x and y, $F_x(s)$ and $F_y(s)$ represent each single detrended fluctuation function. ρ ranges from $-1 < \rho < 1$. When $\rho = 1$, there exists perfect cross-correlations between the two time series, and $\rho = -1$ means the two time series exist perfect anti cross-correlations, when $\rho = 0$, there exists no cross-correlations.

As shown in Fig. 2, all the DCCA coefficients $0 < \rho < 1$, suggesting the nonlinear cross-correlations existed between the time series. The DCCA coefficients between crude oil and different agricultural futures are plotted in Fig. 2 with different marks.

4.2. Preliminary test

In this section, we further adopt the MF-DCCA method to accurately quantify the multifractal cross-correlations between Brent crude oil and agricultural future markets. According to [8,10], we set the window scale s ranges from 50 to 200, the value of order q is $q = -10, -9, \ldots, 9, 10$.

As can be seen from Fig. 3, for different q, all the fluctuation function $F_q(s)$ and the window scale s show a good power law relationship, i.e., there exist cross-correlation between Brent Crude Oil and all agricultural future markets. This shows that changes in the volatility of the agricultural future markets are not only affected by their own volatility, but also by the volatility of the Brent Crude Oil market. By fitting the log-log plots of fluctuation function $ln(F_q(s)) - ln(s)$ of the closing price sequence of crude oil and agricultural futures using least square method, the slope $H_{xy}(q)$ can be obtained in Fig. 4.

It can be seen from Fig. 4 that $H_{xy}(q)$ decreases with the increasing of q, which shows not fixed constants, indicating the cross-correlations of multifractality exist between the crude oil market and all the agricultural future markets. When q varies from -10 to 0, the decreasing rate of the Hurst exponent values of all
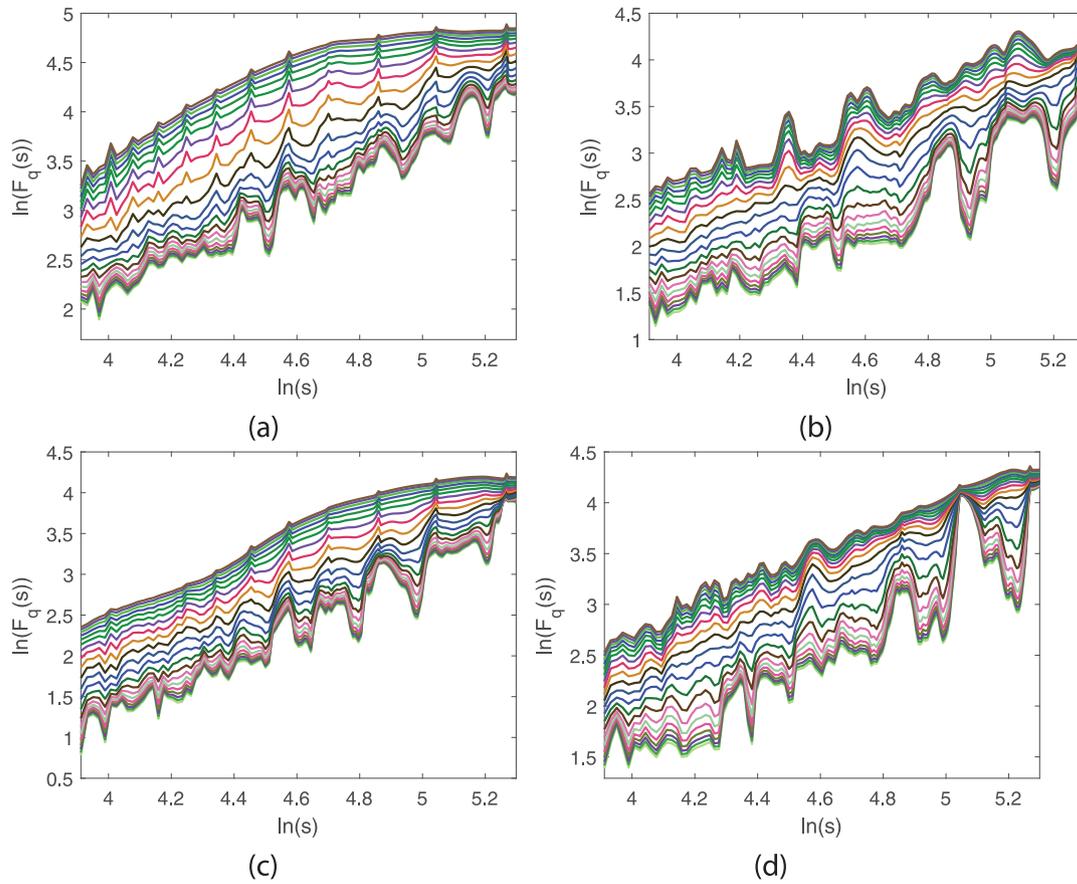
Fig. 3. The log-log plots of $F_q(s)$ versus s for Brent Crude and (a) LSU, (b) LWB, (c) CT, (d) OJ. In each subfigure, from bottom to top, the value of q are -10, -9,..., 9, 10.
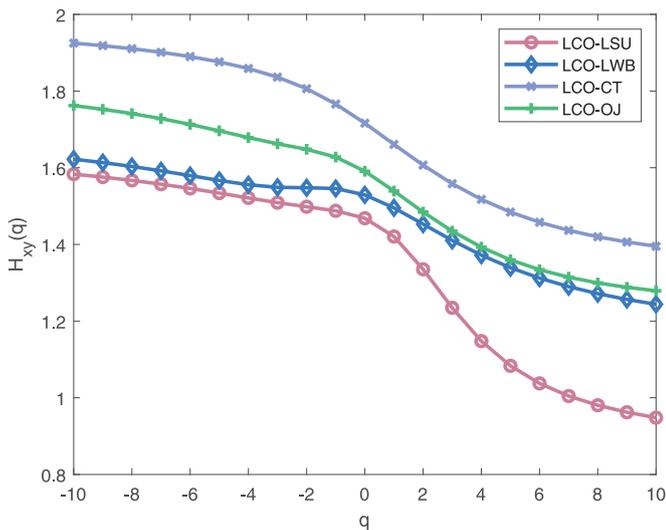

Fig. 4. Nonlinear relationship between $H_{xy}(q)$ and q for crude oil and agricultural futures.

Table 2
Cross-correlation exponents of multifractality for crude oil and agricultural futures.

Series Pair	$H_{xy}(2)$	$\Delta H_{xy}(q)$	$\Delta \alpha_{xy}$
LCO-LSU	1.3351	0.6351	0.8247
LCO-LWB	1.4531	0.3784	0.5678
LCO-CT	1.6068	0.5299	0.6860
LCO-OJ	1.4845	0.4829	0.6502

series pairs are accelerated, indicating the $H_{xy}(q)$ reveals the small fluctuations. Otherwise, when q varies from 0 to 10, the decreasing rate of the Hurst exponents gradually slow down, suggesting the large fluctuations exist in the series pair. In addition, in Fig. 4 and Table 2, we see that when $q = 2$, all $H_{xy}(q)$ are greater than 0.5, indicating that there is a long-range correlation between the time series of the Brent Crude market and all agricultural future markets,
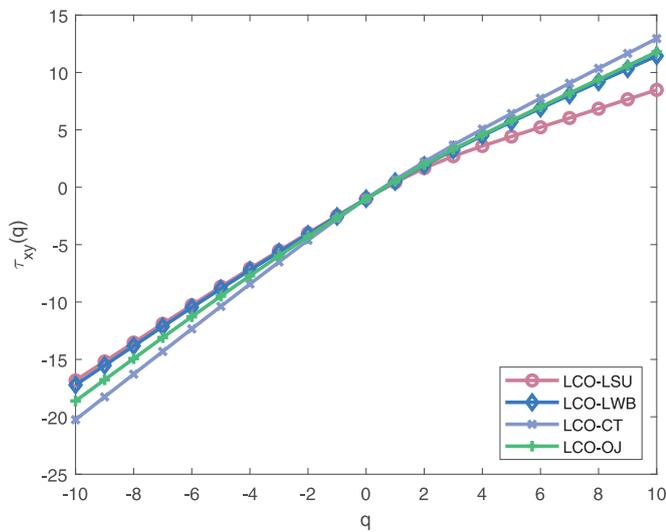
i.e., the fluctuations in the crude oil market will has an impact on the future returns of the selected agricultural future markets.

We envisage several reasons for the long-range correlation between crude oil and selected agricultural products. For sugar future, the medium between crude oil and the white sugar market is sugar-based ethanol, and a considerable portion of international sugar is used to produce ethanol. While ethanol is mainly used for fuel, the price of crude oil has a greater impact on the production and sales of fuel ethanol. When the price of crude oil is low, the market expects that the production and sales of fuel ethanol will decrease, companies will increase the sugar ratio, sugar supply tends to be loose, and the downward pressure on sugar prices will increase; when the price of crude oil is high, the market expected production and sales of fuel ethanol will increase, companies usually increase ethanol production, white sugar supply tends to be tight, and the upward momentum of sugar prices has increased. That is, crude oil regulates the supply and demand balance of sugar by affecting the production and sales of ethanol, therefore, crude oil has a cross-correlation on the sugar future market. Ethanol fuel is also a medium for wheat and crude oil. The new ethanol production line mainly uses wheat and barley. Ethanol can help peo-

Fig. 5. Relationship between $\tau(q)$ and q for crude oil and agricultural futures.
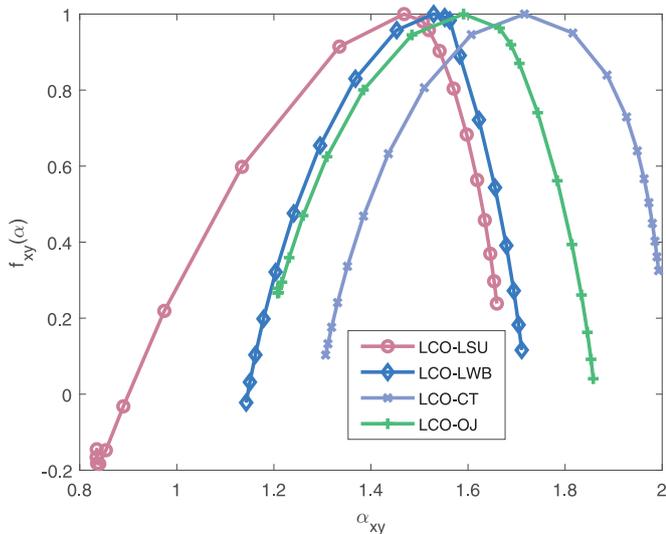

Fig. 6. The multifractal spectra for crude oil and agricultural futures.

ple reduce their dependence on petroleum and is a renewable bio-fuel. The main link between crude oil and the cotton market is the chemical fiber. The main raw materials for the production of chemical fiber are PTA and MEG, and the final upstream raw material of the PTA and MEG is crude oil. Chemical fiber and cotton are mainly used to produce textile and apparel products, and the two categories have a strong substitution relationship. At last, the correlation between crude oil and orange juice price is also strong. We assume that crude oil has a greater impact on the transportation cost of orange juice, and large fluctuation in crude oil prices often change the sentiment of the entire commodity market, it is highly likely that orange juice price is affected by the sentiment of the entire commodity market and show a strong correlation with crude oil price.

As shown in Figs. 4, 6, and Table 2, $\Delta H_{xy}(q)$ and $\Delta \alpha_{xy}$ between Brent Crude Oil and London Surgar is the highest, we then conclude that crude oil has the strongest cross-correlation with sugar future market among other three agricultural future markets. Besides, by comparing the curvatures of the curves in Fig. 5, the curve of LCD-LSU has the largest curvature, which corroborates the strongest cross-correlation exists between crude oil and sugar future market.
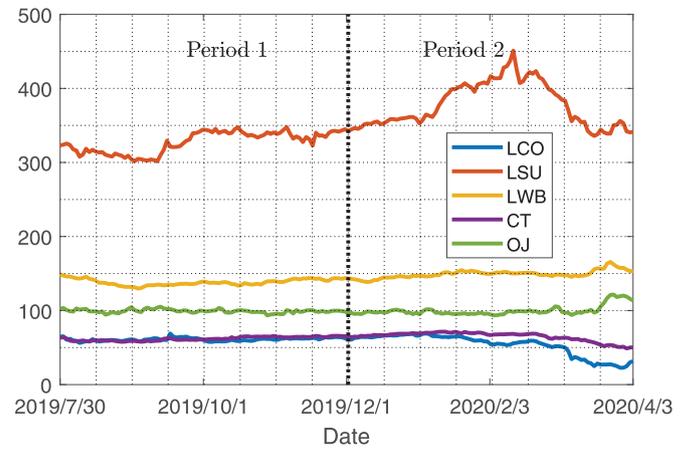

Fig. 7. Subsample of closing price time series of Brent Crude and agricultural futures. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

### 4.3. COVID-19 impact on cross-correlations

Due to the outbreak of COVID-19, which weakened the global crude oil demand, oil production giants have also reduced production to reduce global supply to prevent the decline of oil prices from continuing to spread. However, as COVID-19 erupts in more and more countries, it will further weaken the demand for crude oil. Even if the output is reduced on the basis of the existing production reduction, it may not be enough to keep up with the decline in demand.

In this section, we explore the impact of the emergence of COVID-19 on the cross-correlations of multifractal characteristics between the Brent Crude Oil and agricultural future markets. COVID-19 began to appear in December 2019 and gradually showed a trend of pandemic. In this article, we choose December 1, 2019 as the cut-off point, and select two samples, one period of which is from July 30, 2019 to November 30, 2019, we call it Period 1, and the other period from December 1, 2019 to April 3, 2020, we call it Period 2. The closing price time series of Brent Crude and agricultural futures for period 1 and 2 are shown in Fig. 7. The statistics of the time series in two periods are illustrated in Table 3. According to the length of each subsample, we set the scale s ranges from 5 to 15, the value of order q is $q = -10, -9, \ldots, 9, 10$.

As shown in Fig. 8, all the $H_{xy}(q)$ in period 1 and 2 decrease with the increasing of q, showing the cross-correlations of multifractality exist between the crude oil market and all the agricultural future markets in both period 1 and 2. In addition, we see that $H_{xy}(q)$ decrease fast with q varies from -10 to 0, suggesting there exists small fluctuations, while large fluctuations exist in the series pair when $0 < q < 10$. Futhermore, according to Table 4, all the $H_{xy}(2)$ are larger than 0.5, implying that there exists strong positive persistence of cross-correlations between the time series of the Brent Crude market and all agricultural future markets in both period 1 and 2. Besides, we observe that in period 1, the persistence of series pair LCO-LWB is the strongest, meaning that the fluctuations in the crude oil market will has the greatest impact on the future returns of wheat future market. However, under the influence of COVID-19, the fluctuations in the crude oil market will has the greatest impact on the future returns of orange juice market since the persistence of series pair LCO-OJ is the largest. This may be due to the indirect effect of COVID-19 on transportation in orange juice transportation. Besides, all the $H_{xy}(2)$ in period 2 are larger than in period 1, indicating a stronger persistence under the influence of COVID-19.

Table 3
Descriptive statistics for each subsample.

Period	Commodity	Code	Exchange	Min	Max	Mean	σ	Skewness	Kurtosis
	Brent crude	LCO	ICE	56.23	69.02	61.07	2.20	0.50	3.58
	London Surgar	LSU	ICE	301.50	347.80	327.52	14.31	-0.4026	1.72
Period 1	London Wheat	LWB	ICE	129.75	148.75	138.40	4.26	0.26	2.23
	USA Cotton #2	CT	ICE	57.77	65.86	61.92	2.59	-0.01	1.52
	USA Orange Juice	OJ	ICE	93.40	105.25	99.36	2.37	0.07	3.03
	Brent crude	LCO	ICE	22.74	68.91	53.65	14.44	-0.99	2.52
	London Surgar	LSU	ICE	335.80	451.00	376.94	30.00	0.43	1.87
Period 2	London Wheat	LWB	ICE	138.60	165.70	149.27	5.16	0.54	3.91
	USA Cotton #2	CT	ICE	48.85	71.43	64.86	6.07	-1.27	3.48
	USA Orange Juice	OJ	ICE	93.50	121.65	99.96	6.83	2.07	6.25
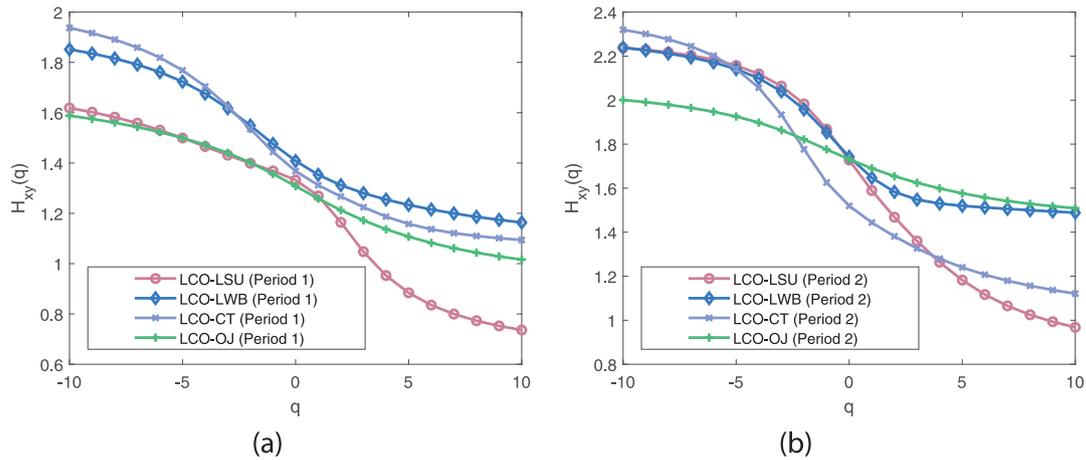
Fig. 8. Nonlinear relationship between $H_{xy}(q)$ and q for crude oil and agricultural futures in (a) period 1, and (b) period 2.
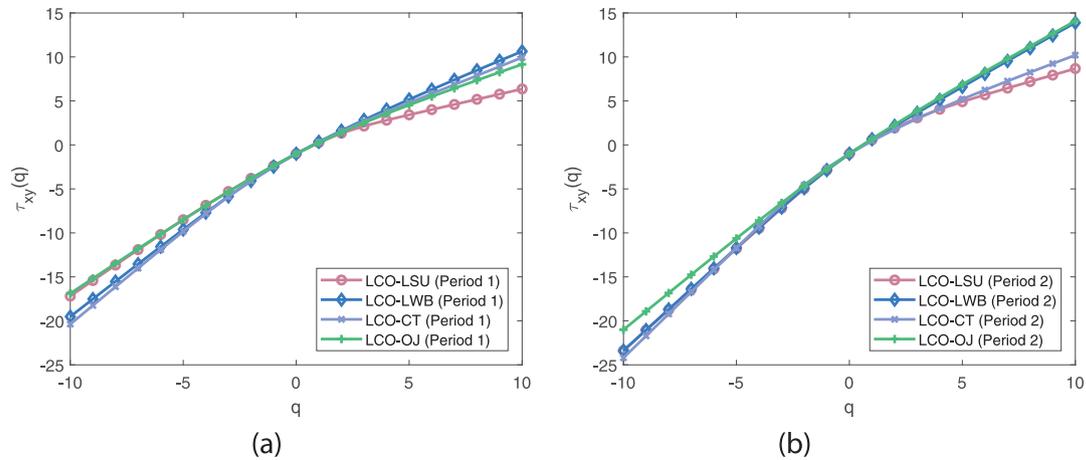
Fig. 9. Relationship between $\tau(q)$ and q for crude oil and agricultural futures in (a) period 1, and (b) period 2.

Table 4
Cross-correlation exponents of multifractality for crude oil and agricultural futures in period 1 and period 2.

Period	Series Pair	$H_{xy}(2)$	$\Delta H_{xy}(q)$	$\Delta \alpha_{xy}$
	LCO-LSU	1.1643	0.8827	1.1786
	LCO-LWB	1.3119	0.6881	0.9234
1	LCO-CT	1.2669	0.8435	1.1098
	LCO-OJ	1.2126	0.5721	0.8013
	LCO-LSU	1.4681	1.2701	1.5823
	LCO-LWB	1.5833	0.7500	0.9349
2	LCO-CT	1.3811	1.1993	1.5800
	LCO-OJ	1.6543	0.4918	0.6627

By comparing $\Delta H_{xy}(q)$ in Fig. 8 and Table 4, in both period 1 and 2, $\Delta H_{xy}(q)$ of LCO-LSU is the largest, which imply the cross-correlations of multifractality between crude oil and sugar future market is the strongest among other four agricultural future markets. In addition, the cross-correlations of all the agricultural futures increased in period 2 except the orange juice.

The same conclusion can also be obtained by comparing the curvature of the curves in Fig. 9 and comparing $\Delta \alpha_{xy}$ in Fig. 10 and Table 4. The experimental results show that COVID-19 has a great impact on the cross-correlation of multifractal property between crude oil and most selected agricultural future markets.
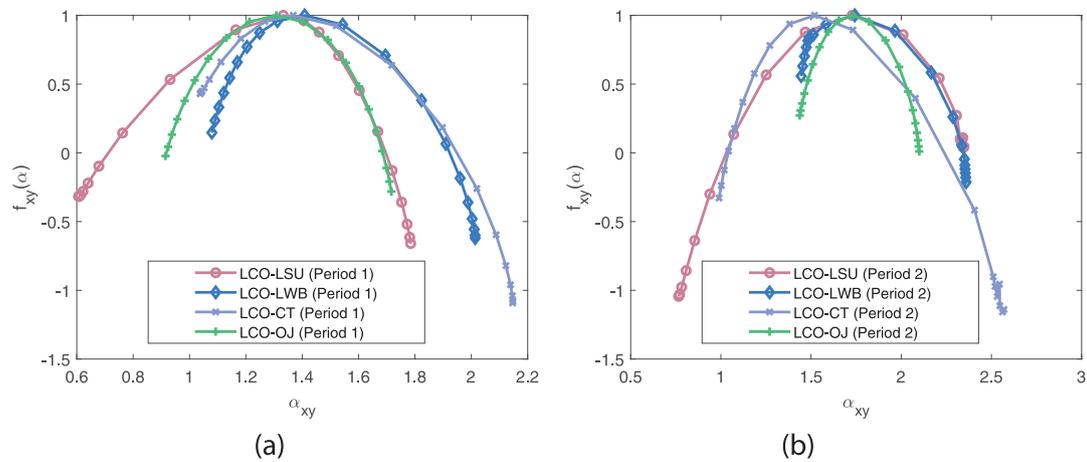
Fig. 10. The multifractal spectra for crude oil and agricultural futures in (a) period 1, and (b) period 2.

5. Conclusions

In this study, we investigated the cross-correlations between crude oil and agricultural futures markets such as London Sugar, London Wheat, USA Cotton #2, and USA Orange Juice futures. Firstly, DCCA coefficients were employed to test there exists cross-correlations between the time series of crude oil and agricultural futures. Afterwards, MF-DCCA approach was utilized to further analyze the cross-correlations between the Brent crude oil and agricultural futures. The computed $\Delta H_{xy}(q)$ and $\Delta \alpha_{xy}$ indicated that the time series pair LCO-LSU has the strongest cross-correlation. Besides, the sources of the cross-correlations were envisaged and discussed. We also analyzed the impact of COVID-19 on the cross-correlations of multifractality between crude oil and agricultural futures. The values of $H_{xy}(2)$ showed that the feature of positive persistence became stronger after the emergence of COVID-19, and $\Delta H_{xy}(q)$ and $\Delta \alpha_{xy}$ calculated in period 1 and 2 showed the cross-correlations of multifractality between crude oil and sugar future market is the strongest. Furthermore, we observe that the cross-correlations of almost all the agricultural futures behave stronger in period 2 than that in period 1, which imply that COVID-19 has an impact on the cross-correlation of multifractality between Brent Crude Oil and selected agricultural future markets.

Declaration of Competing Interest

The authors declare that there is no conflict of interests regarding the publication of this article.

References

[1] Chang TH, Su HM. The substitutive effect of biofuels on fossil fuels in the lower and higher crude oil price periods. Energy 2010;35:2807–13.

[2] Campiche J. L., Bryant H. L., Richardson J. W., Outlaw J. L.. Examining the evolving correspondence between petroleum prices and agricultural commodity prices. 2007.

[3] Natanelov V, Alam MJ, McKenzie AM. Van huylenbroeck g. is there co-movement of agricultural commodities futures prices and crude oil? Energy Policy 2011;39(9):4971–84.

[4] Du X, Cindy LY, Hayes DJ. Speculation and volatility spillover in the crude oil and agricultural commodity markets: a bayesian analysis. Energy Econ 2011;33(3):497–503.

[5] Kantelhardt JW, Zschiegner SA, Koscielny-Bunde E. Multifractal detrended fluctuation analysis of nonstationary time series. Physica A 2002;316:87–114.

[6] Shao W, Wang J. Does the "ice-breaking" of south and north korea affect the south korean financial market? Chaos Soliton Fract 2020;132:109564.

[7] Lahmiri S. Multifractal analysis of moroccan family business stock returns. Physica A 2017;486:183–91.

[8] Wang J, Kim J, Shao W. Investigation of the implications of 'haze special law' on air quality in south korea. Complexity 2020.

[9] Lahmiri S, Bekiros S. Chaos, randomness and multi-fractality in bitcoin market. Chaos Soliton Fract 2018;106:28–34.

[10] He LY, Chen SP. Multifractal detrended cross-correlation analysis of agricultural futures markets. Chaos Solitons Fract 2011;44(6):355–61.

[11] Lahmiri S. Multifractals in western major stock markets historical volatilities in times of financial crisis. Fractals 2017;25(01):1750010.

[12] Gajardo G, Kristjanpoller WD, Minutolo M. Does bitcoin exhibit the same asymmetric multifractal cross-correlations with crude oil, gold and DJIA as the euro, great british pound and yen? Chaos Solitons Fract 2018;109:195–205.

[13] Lahmiri S. Multifractal in volatility of family business stocks listed on casablanca stock exchange. Fractals 2017;25(02):1750014.

[14] Stavroyiannis S, Babalos V, Bekiros S, Lahmiri S, Uddin GS. The high frequency multifractal properties of bitcoin. Physica A 2019;520:62–71.

[15] Zhou WX. Multifractal detrended cross-correlation analysis for two nonstationary signals. Phys Rev E 2008;77:166–211.

[16] Dai M, Hou J, Gao J, Su W, Xi L, Ye D. Mixed multifractal analysis of china and US stock index series. Chaos Solitons Fract 2016;87:268–75.

[17] Wang J, Shao W, Kim J. Cross-correlations between bacterial foodborne diseases and meteorological factors based on MF-DCCA: A case in South Korea. Fractals 2020. https://doi.org/10.1142/S0218348X20500462

[18] Liu L. Cross-correlations between crude oil and agricultural commodity markets. Physica A 2014;395:293–302.

[19] Shadkhoo S, Jafari GR. Multifractal detrended cross-correlation analysis of temporal and spatial seismic data. Eur Phys J B 2009;72:679–83.

[20] Zebende GF. DCCA cross-correlation coefficient: Quantifying level of cross-correlation. Physica A 2011;390:614–18.