Economic Research-Ekonomska Istraživanja

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/rero20

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**To cite this article:** Yue Shang, Hongwen Cai & Yu Wei (2023) The impacts of infectious disease pandemic on China's edible vegetable oil futures markets: A long-term perspective, Economic Research-Ekonomska Istraživanja, 36:1, 2119425, DOI: 10.1080/1331677X.2022.2119425

**To link to this article:** https://doi.org/10.1080/1331677X.2022.2119425



Published online: 15 Sep 2022.

ECONOMIC RESEARCH-EKONOMSKA ISTRAŽIVANJA
2023, VOL. 36, NO. 1, 2119425
https://doi.org/10.1080/1331677X.2022.2119425



# The impacts of infectious disease pandemic on China's edible vegetable oil futures markets: A long-term perspective

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**ABSTRACT**

For the extremely important role of China in global edible vegetable oil market and its decisive measures in the epidemic controlling and stable economic recovery during the COVID-19 pandemic, the aim of this article is to inspect the quantitative impacts of infectious disease pandemic on the returns, volatilities and correlations of China's edible vegetable oil futures markets by using a DCC-MVGARCH-X model incorporating Baidu searching index as the proxy of pandemic severity. Our empirical results show that infectious disease pandemic does have significantly positive impacts on the returns and volatilities of China's soybean, canola and palm oil futures markets. Second, there are significant volatility spillover effects among the three vegetable oils, suggesting strong contagion effect from one oil market to the others. Third, soybean oil and palm oil show the largest correlation, while the dependence between canola oil and palm oil is the smallest one among the three pairwise correlations. Moreover, no matter to consider epidemic situation in China or in global environment, infectious disease pandemic has significant effects on these correlations.

**ARTICLE HISTORY**
Received 10 October 2021
Accepted 25 August 2022

**KEYWORDS**
Vegetable oil futures; infectious disease pandemic; COVID-19; Baidu index; DCC-MVGARCH

**JEL CODES**
Q50; O13; P18

## 1. Introduction

According to the reports of U.S. Department of Agriculture (USDA), China is currently the world's largest consumer of edible vegetable oils, followed by the EU and India. Among them, China's edible vegetable oil consumption in 2020 is 40.69 million tons, accounting for about 19.8% of the total global consumption. Furthermore, China is also the second largest producer of edible vegetable oils in the world. According to USDA, global edible vegetable oil production in 2019 and 2020 are 203.88 and 207.23 million tons, respectively, and this number in April 2021 is measured to be 212.04 million tons, increasing about 4.0% from 2019. This growth in

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edible vegetable oil production is particularly remarkable because we are suffering a global pandemic of COVID-19 since the beginning of 2020.[1] Based on the USDA submission, the main reason for this enhancement is that China's decisive epidemic controlling measures and its stable economic recovery, which in turn strengthen greatly the consumption expectations in global edible vegetable oil.

On the other hand, edible vegetable oil markets, like agriculture and other commodity markets, are susceptible to a variety of uncertainties, such as macroeconomic disturbances, supply-demand shocks, speculative profiteering, investor sentiment, new biotechnology and even extreme weather changes (Asafu-Adjaye, 2014; Bai et al., 2021; Chang, 2002; Chen et al., 2016; 2020b; Dodder et al., 2015; Jawid, 2020; Kandilov & Zheng, 2011; Kilic et al., 2009; Li et al., 2020; Minihan & Wu, 2014; Reese et al., 1993; Santangelo, 2018; Sills & Caviglia-Harris, 2015; Tubiello & Fischer, 2007; Wang et al., 2009; Wei et al., 2019; 2020; 2022; Xie et al., 2020; Yang et al., 2020; Zhang et al., 2017; 2019). Moreover, beyond these uncertainties, World Bank releases two reports in April and October 2020, named as "*A shock like no other: The impact of COVID-19 on commodity markets*" and "*Commodity Markets Outlook-Persistence of commodity shocks*," respectively, asserting that the infectious disease pandemic can cause shocks on the real economy and financial markets mainly by affecting both the supply and demand sides of commodity markets, and the duration and complexity of these effects are hard to predict.[2] In addition, for the extreme important role of agriculture commodity in fulfilling the demands of people's food, clothing and other basic well-being, we think it is very important for policy makers, producers, consumers and investors to learn the quantitative impacts of infectious disease epidemic on edible vegetable oil markets in a more general view.

By now, several researches have focused on the topic of price, volatility and volatility spillover dynamics in vegetable oil markets (Azam et al., 2020; Brümmer et al., 2016; Cui & Martin, 2017; In & Inder, 1997; Peri & Baldi, 2010; Santeramo & Searle, 2019; Ubilava & Holt, 2013; Xiong et al., 2017). For example, In and Inder (1997) investigate the long-run nexus between world vegetable oil prices by using a multivariate cointegration model, and find that most co-movements among vegetable oil prices are consistent with the high substitutability between vegetable oils. Brümmer et al. (2016) employ a common GARCH approach and a VAR model to identify volatility drivers and spillover effects among oil seeds and vegetable oils markets. They reveal that exchange rate volatility is a very important volatility driver of oil seeds and vegetable oils markets, while the hotly debated financialization of commodity markets is not. Cui and Martin (2017) address the important influence of expanded use of soybean oil biodiesel in U.S. on global vegetable oil markets. They point out that with various reasonable elasticity values for vegetable oil demand and demand substitution between soybean oil and palm oil, most vegetable oil substitution is likely to occur through substitution of palm oil. Xiong et al. (2017) examine the impact of China's growing meat demand and the industrialization of livestock on the vegetable oil market. Their research shows that soybean oil, a by-product of soybean processing, tends to crowd out other vegetable oils. In particular, they find that the market for non-soy vegetable oils is likely to shrink as long as the rapid pace of industrialization of more than 10% within China's livestock industry continues. Santeramo and

Searle (2019) estimate the cross-price elasticities of U.S. soybean and palm oil supply through a seemingly uncorrelated system of regression equations, and demonstrate a positive cross-price elasticity of palm oil imports to soybean oil prices and a positive response of soybean oil supply to higher palm oil prices. Recently, Azam et al. (2020) investigate the co-movement among palm, soybean, canola and sunflower oil prices by using wavelet-based analysis on a dataset from January 2003 to March 2018. They prove that palm oil shows a lower degree of relationship with other edible oils on all scales after 2015. Meanwhile, recent data show increased interdependence between soybean and canola oil. The multiple cross-correlations analysis suggests that soybean oil is a potential leader in the vegetable oil market, followed mainly by palm oil during the low-scale period. All in all, no researches have investigated the impacts of infectious disease pandemic on the edible vegetable oil markets. Furthermore, as noted above, the reports of World Bank point out that infectious disease pandemic can severely impinge on both the supply and demand sides of various commodity markets. Thus to quantify these influences can undoubtedly provide us a fresh perspective to better understand the impacts of public health emergency on the return, volatility and their correlations of edible vegetable oil markets, and help policy makers and investors in vegetable oil markets to make better regulation decisions and more effective portfolio allocation strategies.

In this research, therefore, we attempt to inspect the quantitative impacts of infectious disease pandemic on Chinese edible vegetable oil futures markets in three aspects: returns, volatilities and time-varying correlations between different categories of vegetable oils by using a dynamic conditional correlation multivariate generalized autoregressive conditional heteroskedasticity model (DCC-MVGARCH-X) model proposed by Engle (2002) and an internet searching index (Baidu index) to quantify the epidemic severity in a long-term data sample through November, 2013 to November, 2020. To the best knowledge of the authors, this article is first one to quantify the impacts of infectious disease pandemic on Chinese edible vegetable oil futures.

Since 2020, a huge amount of literature has focused on the effects of COVID-19 epidemic on agriculture industry or agriculture commodity markets (Adnan & Nordin, 2020; Albers et al., 2020; Biswal et al., 2020; Borgards et al., 2021; Elleby et al., 2020; Koppenberg et al., 2021; Larue, 2020; Lin & Zhang, 2020; Mahajan & Tomar, 2021; McNamara et al., 2020; Pan et al., 2020; Rajput et al., 2020; Ramakumar, 2020; Vo, 2020). For example, Elleby et al. (2020) analyze the impacts on global agricultural markets of the demand shock caused by the COVID-19 pandemic. They state that the sharp decline in economic growth causes a decrease in international meat prices by 7–18% in 2020 and dairy products by 4–7% compared to a usual situation. Following the slowdown of the economy, biofuel prices fall strongly in 2020, followed by their main feedstocks, maize and oilseeds. Although the income losses and local supply chain disruptions associated with the pandemic undoubtedly has led to an increase in food insecurity in many developing countries, global food consumption is largely unaffected due to the inelastic demand of most agricultural commodities and the short duration of the shock. Biswal et al. (2020) investigate the impact of COVID-19 pandemic on the livestock and poultry sectors in India, which has been one of the fastest-growing sectors in recent years. They find that the pandemic and the associated lockdown has not only caused enormous distress to the millions of poor and marginal farmers for saving their crops and/or livestock and thereby assuring their livelihoods but also impacted the overall poultry, dairy, and other livestock production systems and associated value chains, nutrition and health care, and labor availability. Rajput et al. (2020) find that agriculture industry is one of the least affected market so far by the COVID pandemic due to its indirect relation with economic activities. However, the ultimate impact of COVID-19 pandemic will greatly depend on the severity and duration of its outspread, but it is expected to have long-lasting implications. Borgards et al. (2021) study the overreaction behavior of 20 commodity futures, including wheat, corn, soybeans, soybean oil, cocoa, coffee, sugar and cotton, based on intraday data with a focus on the impact of the COVID-19 pandemic. They suggest that policymakers should anticipate environmental and climate risks to efficiently monitor the supply and demand of commodities, particularly agricultural and livestock commodities which are primary needs of the population. All these empirical works help us a lot to understand the present and potential effects of this COVID-19 pandemic on agriculture commodity markets.

To sum up, most extant researches focus on the short-term impacts of COVID-19 pandemic, and evaluate these impacts by just comparing the qualitative changes of market status, such as asset returns, volatilities or dependences, before and after the pandemic outbreak. Furthermore, most empirical studies ignore the rich information in internet searching index, which can directly capture the changes in people's sentiment during the pandemic and may do great help to quantify the pandemic severity (Chen et al., 2020a; Ding et al., 2020; Gong et al., 2020; Hou et al., 2020; Hu et al., 2020; Lee, 2020; Liang et al., 2020; Lyocsa et al., 2020; Wei & Wang, 2020; Xu et al., 2020). Moreover, no existing literature discusses the quantitative impacts of infectious disease pandemic on the Chinese edible vegetable oil futures, while China is by now the largest vegetable oil consumer and the second largest producer in the world. More importantly, China is the first country to officially report confirmed cases of COVID-19 infections, and is a decisive country to control the fast spreading of this pandemic in 2020. According to the report of National Bureau of Statistics of China, the GDP of China is 101,356.7 billion Yuan in 2020, an increase of 2.2% over last year at comparable prices, which is the only major economy in the world achieving positive GDP growth in 2020.[3] Thus, to understand the quantitative impacts of infectious disease pandemic on the returns, volatilities and correlations among Chinese edible vegetable oil futures is of great reference value for policy makers, producers, demanders and investors in this market.

Thus, this article contributes to extant literature in at least four ways: first, considering the important role of China in global economy and its large contributions in edible vegetable oil consumption and production, this article is the first one to investigate the impacts of infectious disease pandemic on the Chinese edible vegetable oil futures market. Second, different from existing researches focusing on *qualitative* changes in agriculture commodity markets just before and after the outbreak of COVID-19 pandemic, this article examines the *quantitative* effects of infectious disease pandemic on China's edible vegetable oil futures market in a relative long period through 2013–2020, which can offer us a more general view of how public health emergency may influence edible vegetable oil markets in China. Third, this article utilizes the Baidu searching index, the largest search engine in mainland China, as a proxy to quantify the pandemic severity, which is proved in many studies a sensitive and effective measurement for infectious disease epidemic and public sentiment (Chen et al., 2020a; Gong et al., 2020; Hou et al., 2020; Liang et al., 2020; Lyocsa et al., 2020; Wei & Wang, 2020). Finally, this article examines not only the pandemic impacts on returns and volatilities of edible vegetable oil futures, but also the volatility spillover effects and time-varying correlations among these oil futures during a long period from 2013 to 2020 by using the DCC-MVGARCH model with exogenous impactor proposed by Engle (2002).

The rest of this article is organized as follows: Section 2 introduces the GARCH-MIDAS model, Section 3 provides descriptive statistics of the data, Section 4 discusses the empirical results, and finally Section 5 concludes.

## 2. Methodology

In this study, we use the DCC-MVGARCH model of Engle (2002), instead of other commonly used MVGARCH approaches (e.g., BEKK or CCC) for these reasons: on the one hand, a well-known study by Caporin and McAleer (2012) provides a very comprehensive comparison of the statistical characteristics and practical applications of the BEKK and DCC MVGARCH models. They disagree with the fact that BEKK suffers from the typical "curse of dimensionality," while DCC does not. However, they point out that DCC is equivalent to a scalar BEKK model applied to standardized residuals, and each model can do virtually everything the other model can do. In addition, Caporin and McAleer (2012) note that DCC is more suitable for depicting conditional correlations than conditional covariances, while BEKK is more appropriate to explain conditional covariances. Since correlation coefficient takes values between $-1$ and $+1$ and is more easily understood than covariance, in this article, we focus on the impacts of infectious disease pandemic on the correlation coefficients instead of covariances among China's edible vegetable oil futures markets. On the other hand, Constant Conditional Correlation (CCC) MVGARCH is another usually adopted model to measure the volatility spillover effects among assets. However, its major drawback is that it sets the correlation between two assets to be fixed across the data sample, and thus cannot capture the time-varying dependence among different assets. Consequently, we choose DCC model instead of BEKK or CCC in our empirical examinations.[4]

Following Engle (2002), the logarithm return $r_{i,t}$ of an asset $i$ at time $t$ can be modeled as

$$r_{i,t} = \mu_{i,t} + \varepsilon_{i,t}, \tag{1}$$

$$\varepsilon_{i,t} = \sqrt{h_{ii,t}} \cdot z_{i,t}, \tag{2}$$

where $\mu_{i,t}$ is the conditional mean and $\varepsilon_{i,t}$ is the residual item as time $t$, respectively. Furthermore, residual $\varepsilon_{i,t}$ is a product of square root of conditional variance $h_{ii,t}$ and innovation item $z_{i,t}$, which is an independently and identically distributed random number with zero mean zero and unit standard deviation. For clarity, following Engle (2002), in a $n$-dimension DCC-MVGARCH(1,1) model with an exogenous impactor $X$, for example, Baidu index in this article, the conditional mean and conditional variance are calculated as:

$$\mu_{i,t} = \mu_{0i} + \gamma_i X_t, \quad i = 1, 2, \ldots, n, \tag{3}$$

$$h_{ii,t} = c_i + a_{ij} \sum_{j=1}^{n} \varepsilon_{j,t-1}^2 + b_{ij} \sum_{j=1}^{n} h_{jj,t-1} + \delta_i X_t. \tag{4}$$

Furthermore, the dynamic correlation coefficient $\rho_{ij,t}$ between assets $i$ and $j$ is defined as:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{h_{ii,t}}\sqrt{h_{jj,t}}}, \tag{5}$$

$$q_{ij,t} = (1-\varphi-\tau)\overline{q_{ij,t}} + \varphi q_{ij,t-1} + \tau\left(\frac{\varepsilon_{i,t-1}}{\sqrt{h_{ii,t-1}}}\right)\left(\frac{\varepsilon_{j,t-1}}{\sqrt{h_{jj,t-1}}}\right), \tag{6}$$

where $q_{ij,t}$ can be treated as the covariance between assets $i$ and $j$ at time $t$, and $\overline{q_{ij,t}}$ is the long-term mean of $q_{ij,t}$ (Engle, 2002). In these setting, we are extremely interested in four parameters: on the one hand, parameters $\gamma_i$ and $\delta_i$ indicate the quantitative impacts of exogenous variable, see Baidu index, on conditional return and volatility of asset $i$, respectively. On the other hand, $a_{ij}$ and $b_{ij}$ show the residual and volatility spillover effects of asset $j$ to $i$, respectively.

## 3. Data

As note in Section 1, China is now the largest consumer and the second largest producer of edible vegetable oil in the world. Furthermore, according to the statistics of Ministry of Agriculture and Rural Affairs of the People's Republic of China, China's edible vegetable oil consumption is about 38.18 million tons in 2019. In this total consumption, soybean oil, canola oil and palm oil account for about 47%, 21% and 13%, respectively. Thus, in this article, we choose these three major vegetable oil futures in China as our research objects. To be more specific, soybean oil and palm oil futures are traded in Dalian Commodity Exchange (DCE) and canola oil futures is traded in Zhengzhou Commodity Exchange (CZCE), respectively, and all the daily futures prices are recorded for contracts at the earliest specified delivery date.[5] In addition, as noted above, Baidu is the largest searching engine used in mainland China, and Baidu searching index is based on the search volume of internet users in Baidu. According to the different sources of Baidu search, the search index is divided into PC search index and mobile search index.[6] Therefore, with respect to the quantitative measurement of infectious disease pandemic, we choose Baidu searching index including three keywords, that is, viruses, influenza and infectious diseases, as our

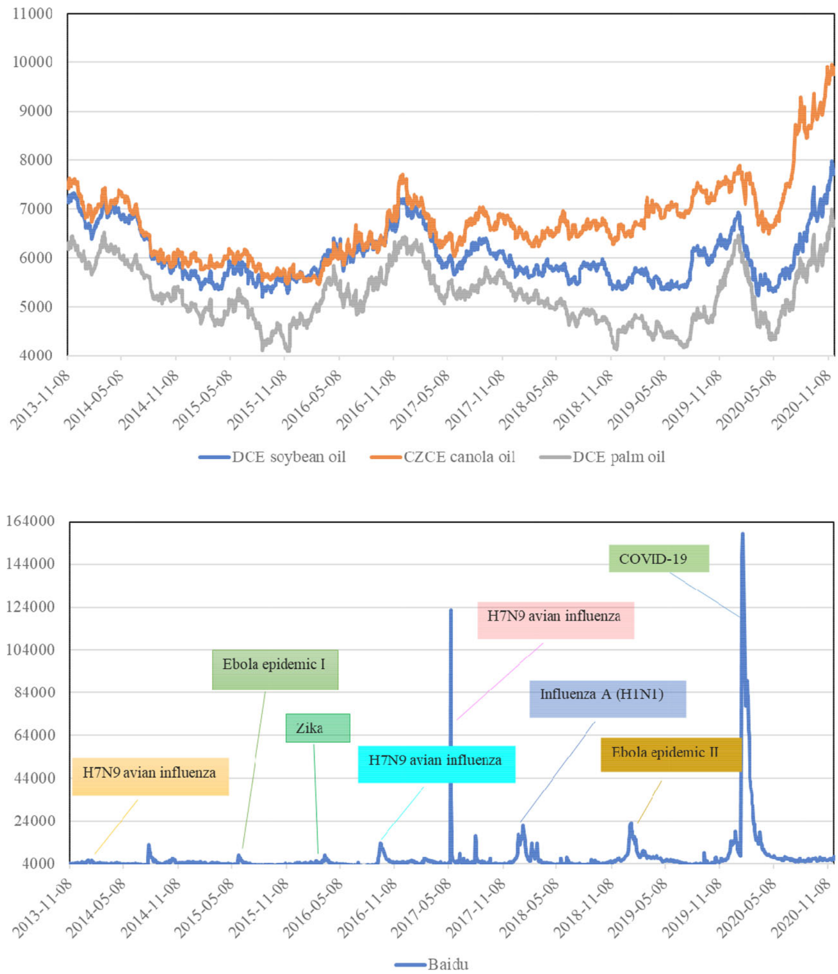


**Figure 1.** Time series plots of China's edible vegetable oil futures prices and Baidu index.
Source: The Wind Database and Baidu index company.

proxy and the searching area is limited within mainland China with both PC and mobile device terminals. The data sample are collected through 10 November, 2013 to 27 November, 2020, totally 1720 daily observations for each variable.

Figure 1 shows the time evolutions of the four daily oil futures prices and the Baidu searching index in the upper and lower panel, respectively. We can see that all the three vegetable oil futures prices present close connectedness among them and run relatively steady from 2013 to the first half of 2019, except for the period from November 2015 to May 2017. During this time, the three oil futures experience a relative turmoil period. For example, the soybean oil price climbs from the lowest price of about 5200 RMB at the beginning of November 2015 to the highest one of nearly 7200 RMB at the end of December 2016, and then falls sharply from the top to about 5600 RMB in May 2017. In addition, since the second half of 2019, oil prices go up sharply due to the production decrease in major palm oil producers of Indonesia and Malaysia as well as the soybean imports decline from the US. Then with the outbreak of COVID-19 pandemic, oil prices drop dramatically since January

**Table 1.** Descriptive statistics of all the vegetable oil returns and Baidu index growth rate.

| | Soybean oil | Canola oil | Palm oil | Baidu |
|---|---|---|---|---|
| Obs. | 1720 | 1720 | 1720 | 1720 |
| Mean | 4.68e-05 | 1.56e-04 | 4.68e-05 | 3.71e-04 |
| Maximum | 0.0459 | 0.0614 | 0.0835 | 3.3274 |
| Minimum | −0.064142 | −0.065242 | −0.0711 | −1.2448 |
| Standard deviation | 0.0103 | 0.0101 | 0.0130 | 0.1466 |
| Skewness | −0.0424 | −0.2824 | 0.0453 | 8.6248 |
| Kurtosis | 5.5149 | 7.2453 | 5.8710 | 186.8459 |
| Jarque-Bera | 453.78*** | 1314.47*** | 591.32*** | 2443607.29*** |
| *Q* (5) | 10.1670* | 5.1708 | 3.9534 | 28.1344*** |
| *Q* (10) | 15.0401 | 8.2494 | 10.4002 | 31.0301*** |
| *Q* (20) | 24.5539 | 26.0538 | 24.4828 | 40.7608*** |
| ARCH (5) | 2.5932** | 5.7823*** | 4.4751*** | 7.4393*** |
| ARCH (10) | 3.1285*** | 3.6554*** | 4.2047*** | 3.7012*** |
| ARCH (20) | 3.2417*** | 2.4435*** | 3.7172*** | 1.8321** |
| ADF | −40.8140*** | −41.3255*** | −41.6180*** | −44.1089*** |
| P-P | −40.8030*** | −41.3237*** | −41.6065*** | −44.0964*** |

Notes: The Jarque–Bera statistic tests for the null hypothesis of normality in sample returns distribution. *Q* (*n*) is the Ljung-Box statistics of the return series for up to *n*th order serial correlation. ARCH (*n*) represents the non-heteroskedasticity (ARCH effect) statistics with lags *n*. ADF and P-P are statistics of Augmented Dickey-Fuller and Phillips-Perron unit root test based on least AIC criterion, respectively. ***, ** and * indicate rejection at the 1%, 5% and 10% significance level, respectively.
Source: Author Estimation.

2020 till about May 2020. After that, with China's decisive pandemic control and stable recovery in domestic demand, oil prices surge quickly to their all-time peaks in November 2020. At the same time, the lower panel of Figure 1 shows the Baidu searching index incorporating three keywords as viruses, influenza and infectious diseases. We can see clearly that this Baidu index reacts promptly with the occasional outbreaks of infectious disease pandemic through the whole data sample. This view verifies the validity of using Baidu searching index as the proxy in measurement of pandemic severity. Then, all these daily data are transferred to logarithm returns (i.e. growth rate) and the descriptive statistics are listed in Table 1.

Table 1 shows that, first, all the oil return series have near-zero means with about 1% standard deviations, while Baidu index growth rate has much larger stand deviation of about 14%, indicating greater fluctuation in international searching index than edible vegetable oil prices. Second, we find negative skewness in soybean and canola oil return distributions but positive skewness in palm oil and Baidu index. Furthermore, all return distributions have kurtosis larger than 3, revealing the leptokurtic and fat-tailed features in these distributions. These non-normality characteristics are also proved by the Jaque-Bera statistics. Third, the Ljung–Box Q statistics suggest that oil return series have no auto-correlations up to at least 20 days, while Baidu index has very strong auto-correlation. Fourthly, the ARCH statistics show that all the return series have significant heteroskedasticity effects up to 20 days. Finally, Augmented Dickey–Fuller and Phillips–Perron unit root tests indicate that all the return series are stationary that can be modeled without further transformation.

## 4. Empirical analysis

In this section, we investigate the quantitative impacts of infectious disease pandemic on the returns, volatilities, and correlations of China's vegetable oil futures markets.

According to the report, "*A shock like no other: The impact of COVID-19 on commodity markets*," released by IMF in April 2020, infectious disease pandemic, such as the recent COVID-19 epidemic, can shock the agriculture commodity markets in two major ways: (1) Disruptions in supply chains. Some mitigation measures create a wedge between consumers and producers of commodities. For example, disruptions in food supply chains may lead to concerns about food security, which in turn may trigger hoarding by consumers. This could push up prices at the consumer level. (2) Disruptions to agricultural commodity production. Agriculture production can be impacted by a shortage of available inputs due to mitigation measures. If large numbers of people are subject to movement restrictions, including across borders, the labor available for commodity production may be curtailed. This is of great concern for agricultural production, especially in developed economies, which rely heavily on migrant workers who may no longer be able to travel. Another report of IMF released in October 2020, "*Commodity Markets Outlook-Persistence of commodity shocks*," further points out that the permanent shocks by COVID-19 pandemic accounts for two-thirds of the variability in annual agricultural commodity prices of 2020.[7] Following these reports, we think that infectious disease pandemic, measured by Baidu index in this article, should have positive impacts on the returns and volatilities of China's vegetable oil futures markets. However, in China, there is a very large difference in the self-sufficiency of these three vegetable oils. Therefore, infectious disease pandemic may have quite different impacts on the correlations among these oil futures.

As noted in Section 2, the DCC-MVGARCH-X model originally proposed by Engle (2002) can depict not only the effects of infectious disease pandemic proxied by Baidu index on the returns and volatilities of three major vegetable oils, but can also capture the time-varying correlations among the three futures. Table 2 reports estimation results of the DCC-MVGARCH-X model through the whole data sample from 10 November, 2013 to 27 November, 2020.

We can see in Table 2 that, first, most of the parameters are significant except for the constant items in conditional mean equations, suggesting that the DCC-MVGARCH-X model fits very the impacts of infectious disease pandemic on the three Chinese vegetable oil futures. Second, in terms of pandemic impacts on vegetable oil markets, the $\gamma$ coefficients in conditional mean Equation (3) are all significantly positive at 1% levels, indicating that more serious infectious disease pandemic will drive higher vegetable oil prices. That means more dramatic pandemic may raise more worries of supply shortages in oil markets, which contribute to more vegetable oil reserves and then push the oil price up. Furthermore, the $\delta$ coefficients in conditional variance Equation (4) are significantly positive at 1% level for soybean and palm oil futures, while it is not significant for canola oil. The reason for this result is that, the Chinese average self-sufficiency rate of edible vegetable oil is about 30% at the end of 2019. Regarding to the three major oils, the self-sufficiency rate for soybean oil is lower than 20% and palm oil even depends entirely on imports in China. However, the self-sufficiency rate for canola oil in China is as high as nearly 65% for the fact that China is the biggest canola oil producer in the world with the planting area of rapeseed reaches 113 million mu and the total rapeseed production of about

**Table 2.** Estimation results for DCC-MVGARCH-X model through the whole data sample (November, 2013–November, 2020).

| | Soybean oil ($i=1$) | Canola oil ($i=2$) | Palm oil ($i=3$) |
|---|---|---|---|
| $\mu_{0i}$ | −7.2321e-06 | 1.1513e-05 | −6.8822e-05 |
| | (1.3104e-04) | (1.3873e-04) | (1.5361e-04) |
| $\gamma_i$ | 0.0044*** | 0.0037*** | 0.0041*** |
| | (0.0013) | (0.0013) | (0.0015) |
| $c$ | 2.9965e-05*** | 1.1255e-05*** | 4.9596e-05*** |
| | (3.8180e-06) | (7.9600e-07) | (1.2480e-06) |
| $a_{i1}$ | −0.0296*** | 0.0576*** | 0.1580*** |
| | (0.0108) | (0.0060) | (0.0187) |
| $a_{i2}$ | 0.1052*** | −0.0085* | 0.1568*** |
| | (0.0100) | (0.0051) | (0.0100) |
| $a_{i3}$ | 0.0312*** | 0.1044*** | −0.1507*** |
| | (0.0102) | (0.0062) | (0.0220) |
| $b_{i1}$ | 0.3054*** | −0.0041 | 0.1324*** |
| | (0.0085) | (0.0056) | (0.0010) |
| $b_{i2}$ | 0.2854*** | 0.1331*** | −0.1106*** |
| | (0.0315) | (0.0087) | (0.0030) |
| $b_{i3}$ | 0.0294** | 0.6509*** | 1.0947*** |
| | (0.0121) | (0.0046) | (0.0295) |
| $\delta_i$ | 3.4027e-05** | 3.3160e-06 | 9.6328e-05*** |
| | (1.4189e-05) | (6.2150e-06) | (1.8379e-05) |
| $\varphi$ | 0.8437*** | | |
| | (0.0193) | | |
| $\tau$ | 0.0852*** | | |
| | (0.0041) | | |
| *Diagnostic test* | | | |
| $Q$ (5) | 5.3310 [0.3768] | 4.8010 [0.4406] | 2.5010 [0.7763] |
| $Q$ (10) | 11.8320 [0.2964] | 6.4630 [0.7750] | 9.3310 [0.5009] |
| $Q$ (20) | 19.6280 [0.4814] | 18.2480 [0.5711] | 24.0290 [0.2411] |
| ARCH (5) | 0.3641 [0.8733] | 0.8078 [0.5439] | 1.9451* [0.0839] |
| ARCH (10) | 0.6786 [0.7452] | 0.7609 [0.6668] | 1.3495 [0.1984] |
| ARCH (20) | 1.4176 [0.1032] | 0.9411 [0.5337] | 2.7961*** [0.0000] |

Notes: The upper panel of this table reports the estimation results of the DCC-MVGARCH-X model with three oil returns and a Baidu index as exogenous impactor. The numbers in parentheses are standard errors. The lower panel of this table shows the diagnostic tests on the standardize residuals of three China's edible vegetable oil futures returns. $Q$ ($n$) is the Ljung-Box statistics of the series for up to $n$th order serial correlation. ARCH ($n$) represents the non-heteroskedasticity (ARCH effect) statistics with lags $n$. The numbers in square brackets are the $p$-values of the corresponding tests. ***, ** and * indicate the rejections of null hypothesis at 1%, 5% and 10% significance level, respectively.
Source: Author Estimation.

14.930 million tons at 2019.[8] Therefore, we can see that the infectious disease pandemic has significant positive impacts on the price volatilities in Chinese soybean and palm oil futures, and the effects for palm oil (i.e. 9.6328e-05) is about three times larger than that for soybean oil (i.e. 3.4027e-05), but it has no obvious influence on the volatility of canola oil futures price. Third, almost all the residual and volatility spillover coefficients, $a_{ij}$ and $b_{ij}$ $(i \neq j)$ are significant in this estimation, implying strong cross-impacts of one market's return and volatility on those of the other markets. In specific, the volatility spillover effect of canola oil on soybean oil (indicted by $b_{12}$) is about 0.2854 and the effect of palm oil on soybean oil (indicted by $b_{13}$) is just 0.0294. Then the volatility spillover effect of soybean oil on canola oil (indicted by $b_{21}$) is not significant but the effect of palm oil on canola oil (indicted by $b_{23}$) is as large as 0.6509. In addition, the spillover strength of soybean oil on palm oil is 0.01324 while this effect of canola oil on palm oil is −0.1106, indicating that large canola oil volatility at $t$-1 time may cause small volatility in palm oil at $t$ time. Then

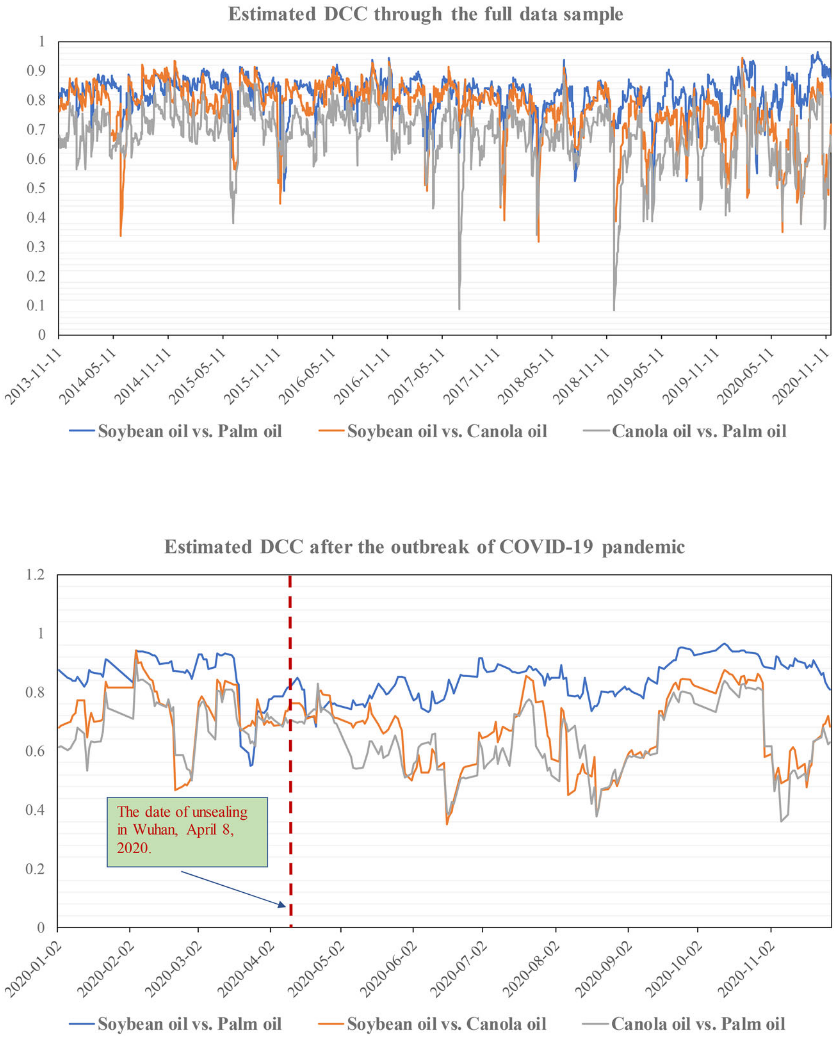


**Figure 2.** Dynamic correlation coefficients among three vegetable oils. The upper panel is based on the full data sample (November, 2013–November, 2020), and the lower panel is through the start time of the COVID-19 outbreak (January, 2020) to November, 2020.
Source: Authors.

the DCC parameters, that is, $\varphi$and $\tau$, capturing the time-varying correlations among the three oils are significant with estimation values of equal 0.8437 and 0.0852, respectively. It means that strong persistence in the connections of the three vegetable oil futures, and the estimated DCC is presented in Figure 2. We can see that the DCC among the three oil futures show tight fluctuation patterns. Generally speaking, soybean oil and palm oil in China shows the largest dependence, while the dependence between canola oil and palm oil is the smallest. As noted above, this outcome is based on the fact that over 80% soybean oil and nearly all palm oil consumed in China depends on imports, but only about 35% of canola oil relies on imports. Finally, the diagnostic tests with both Ljung–Box $Q$ and ARCH tests for the three standardized residuals indicate that these standardized residuals do not have significant autocorrelation and ARCH effects in most situations, suggesting that the DCC-MVGARCH-X model is generally adequate in capturing the conditional volatilities and correlations in China's edible vegetable oil futures markets.

In summary, the estimation results based on the whole data sample indicate good fitness of the DCC-MVGARCH-X model in depicting the impacts of infectious disease pandemic on the returns and volatilities of the three Chinese edible vegetable oil futures, and the time-varying correlations among them. Furthermore, to investigate whether the COVID-19 pandemic has significant effect on the dynamic correlations among the three oil futures, we conduct the regressions according to the suggestions of Chiang et al. (2007), Dutta (2018), Dutta et al. (2020) and Wen et al. (2012) as follows:

$$\hat{\rho}_{ij,t} = \theta_0 + \theta_1 COVID1_t + \theta_3 Crisis_t + u_t, \tag{7}$$

$$\hat{\rho}_{ij,t} = \theta_0 + \theta_2 COVID2_t + \theta_3 Crisis_t + u_t, \tag{8}$$

where $\hat{\rho}_{ij,t}$ is the DCC coefficients estimated in the DCC-MVGARCH-X model. To be more accurate for China's real conditions, *COVID*1 is a dummy variable that takes value of one through 1 January, 2020 to 7 April, 2020, and zero otherwise. This setting of end day for COVID-19 pandemic in China is based on the fact that on 8 April, 2020, the Chinese government officially announced the lifting of the lockdown on the city of Wuhan on April 8, 2020. Wuhan is the first city in China to report confirmed cases of COVID-19 and the city with the most severe COVID-19 pandemic in China. Its unsealing means a major victory in the battle against this epidemic in China. This fact is also identified by the Baidu searching index revealed in the bottom panel of Figure 1. Moreover, to ensure robustness in our results, we further use another dummy variable, *COVID*2 to take the value of one through 1 January, 2020 to the present day, which is common setting for pandemic time period in recent literature (Adekoya et al., 2021; Bai et al., 2021; Borgards et al., 2021; Dutta et al., 2020; Dwita Mariana et al., 2021; Mensi et al., 2020; Salisu et al., 2021; So et al., 2021). In addition, as suggested by Dutta (2018) and Dutta et al. (2020), *Crisis* is also a binary variable depicting the turmoil period, i.e., November 2015 to May 2017, in the Chinese vegetable oil futures markets. At this period, for example, the soybean oil price climbs from the lowest price of about 5200 RMB at the beginning of November 2015 to the highest one of nearly 7200 RMB at the end of December 2016, and then falls sharply from the top to about 5600 RMB in May 2017, which is also proved be to a volatile period in the top panel of Figure 1. Table 3 reports the estimation results for regressions of Equations (7) and (8) with three pair-wise DCC coefficients among the three oil futures.

In general, Table 3 shows clear evidence of significant impacts of infectious disease pandemic on the dynamic correlations among the three oil futures, and the market turmoil period also has clear influences on the correlations in soybean-canola oil and canola-palm oils. To be more specific, firstly in Panel A, both $\theta_1$ and $\theta_2$ parameters are significantly negative with estimated values of −0.0319 and −0.0961, respectively, indicating that both dummy variables, *COVID*1 and *COVID*2, have inverse influences

**Table 3.** Testing for the impacts of infectious disease pandemic on dynamic correlation coefficients through the whole data sample (November, 2013–November, 2020).

| | Regression of Eq. (7) | | | | Regression of Eq. (8) | | | |
|---|---|---|---|---|---|---|---|---|
| | Estimate | Standard error | *t*-statistic | *p*-value | Estimate | Standard error | *t*-statistic | *p*-value |
| Panel A: Soybean-Canola oil | | | | | | | | |
| $\theta_0$ | 0.7631*** | 0.0027 | 285.9178 | 0.0000 | 0.7752*** | 0.0025 | 304.6198 | 0.0000 |
| $\theta_1$ | −0.0319** | 0.0134 | −2.3889 | 0.0169 | | | | |
| $\theta_2$ | | | | | −0.0961*** | 0.0087 | −10.9598 | 0.0000 |
| $\theta_3$ | 0.0434*** | 0.0069 | 6.2833 | 0.0000 | 0.0313*** | 0.0069 | 4.5633 | 0.0000 |
| Panel B: Soybean-Palm oil | | | | | | | | |
| $\theta_0$ | 0.8179*** | 0.0017 | 493.1318 | 0.0000 | 0.8151*** | 0.0017 | 467.9988 | 0.0000 |
| $\theta_1$ | 0.0312*** | 0.0119 | 2.6212 | 0.0088 | | | | |
| $\theta_2$ | | | | | 0.0290*** | 0.0052 | 5.5666 | 0.0000 |
| $\theta_3$ | −0.0116 | 0.0074 | −1.5543 | 0.1201 | −0.0088 | 0.0075 | −1.1757 | 0.2397 |
| Panel C: Canola-Palm oil | | | | | | | | |
| $\theta_0$ | 0.6751 | 0.0027 | 246.5859 | 0.0000 | 0.6808*** | 0.0028 | 240.6795 | 0.0000 |
| $\theta_1$ | 0.0236** | 0.0117 | 2.0277 | 0.0426 | | | | |
| $\theta_2$ | | | | | −0.0338*** | 0.0081 | −4.1714 | 0.0000 |
| $\theta_3$ | 0.0249*** | 0.0059 | 4.1941 | 0.0000 | 0.0193*** | 0.0060 | 3.2248 | 0.0012 |

Notes: Regressions of Eq. (7) is $\hat{\rho}_{ij,t} = \theta_0 + \theta_1 COVID1_t + \theta_3 Crisis_t + u_t$ and Eq. (8) is $\hat{\rho}_{ij,t} = \theta_0 + \theta_2 COVID2_t + \theta_3 Crisis_t + u_t$, respectively. The linear regression estimation is made by Least Squares with heteroscedasticity-consistent (Eicker-White) standard errors. ***, ** and * indicate the rejections of null hypothesis at 1%, 5% and 10% significance level, respectively.
Source: Author Estimation.

on the time-varying dependence between soybean and canola oils. This result verifies the fact that, no matter under the Chinese specific local condition (*COVID*1) or the global environment (*COVID*2), infectious disease pandemic does have strong negative impacts on the correlations between soybean and canola oils. Secondly, in Panel B, we observe that both *COVID*1 and *COVID*2 give significant positive effects on the correlation between soybean oil and palm oil futures. The possible reasons for the different (negative/positive) impacts of infectious disease pandemic on these two dynamic correlations are as follows: the canola oil has a relative high degree of self-sufficiency rate of about 65% in China, while the self-sufficiency rate for soybean oil is only about 20% and the palm oil relies almost entirely on imports. Thus, canola oil price in China is less influenced by external shocks (e.g., infectious disease pandemic, foreign supply decrease, etc.), but the prices of soybean and palm oil are highly affected by such effects together. Furthermore, China is the only major economy in the world achieving positive GDP growth in 2020, and is less impacted by the COVID-19 pandemic than other countries. The stable economic recovery and relative high degree of self-sufficiency rate of canola oil in China may cause the correlation between canola oil and soybean oil (indicated in Panel A of Table 3) negatively affected by COVID-19 pandemic, which is different from the one between soybean oil and palm oil (indicated in Panel B of Table 3) positively affected by COVID-19 pandemic. In addition, we can also see in the upper panel of Figure 2 that the dynamic correlation coefficients for pairs of soybean-canola oil and canola-palm oil (indicated by orange line and gray line, respectively) are generally smaller than the one for soybean-palm oil (blue line), and after the breakout of COVID-19 pandemic, we find the DCC coefficients of the three oil pairs show clear divergent trends in some time periods as demonstrated in the lower panel of Figure 2. In summary, the relatively independent fundamentals in canola oil market may cause the negative impacts of COVID-19 pandemic on the DCC between canola oil and the other two oil futures. This outcome is also observed in Panel C of Table 3, where the *COVID*2 parameter is estimated to be $-0.0338$ at 1% significance level. Finally, the $\theta_3$ coefficients depicting the impacts of *Crisis* (i.e. the turmoil period of world vegetable oil futures markets) are estimated to be significantly positive on the DCCs of soybean-canola oil and canola-palm oil pairs, further indicating that vegetable oil price crisis will strengthen the dependence among these oil markets. All in all, we find that infectious disease pandemic in both Chinese domestic and global circumstances have significant impacts on the time-varying correlations among the Chinese edible vegetable oil futures and these impacts can be specific for different pairs of oil combinations.

## 5. Conclusions

This article investigates the quantitative impacts of infectious disease pandemic on returns, volatilities and time-varying correlations among three major edible vegetable oil futures in China for the reason that China is now the largest consumer and the second largest producer of edible vegetable oils in the world. In addition, China's decisive epidemic controlling measures and stable economic recovery during this COVID-19 pandemic contribute greatly to the consumption and production in global edible vegetable oil market. The empirical results show that, first of all, generally speaking, infectious disease pandemic has significantly positive impacts on the returns, volatilities and connections of China's soybean, canola and palm oil futures. To be more specific, the pandemic has the largest impact on the price volatility in Chinese palm oil futures, about three times greater than that on soybean oil futures. In addition, the canola oil futures volatility is the least affected by infectious disease pandemic for its relative high degree of self-sufficiency rate of about 65%, while the self-sufficiency rate for soybean oil in China is only about 20% and the palm oil relies almost entirely on imports. Secondly, there are significant volatility spillover effects among the three vegetable oils, suggesting strong contagion effect from one oil market to the others. Thirdly, the soybean oil and palm oil in China shows the largest dependence, while the correlation between canola oil and palm oil is the smallest one among the three pair-wise correlations. Moreover, no matter to consider epidemic situation in China or in global environment, infectious disease pandemic has significant effects on these correlations.

These empirical findings have several import policy and economic implications as follows: for policy makers, the strong evidence of positive pandemic impacts on returns and volatilities of China's edible vegetable oil futures remind them to adopt more flexible adjustment in policies when facing public health emergencies. Prompt and effective regulations can stabilize people's expectations and thus help to mitigate the pandemic shocks to the markets. For example, the Chinese National Food and Strategic Reserves Administration (NFSRA) has introduced a series of measures to stabilize the supplies in grain and edible oil markets after the outbreak of COVID-19, for example, on 20 October 2020, NFSRA puts 300,000 tons of national reserve canola oil in the market, providing positive effect on stabilizing market expectations.[9] In turns, the steady performance of the vegetable oil markets helps to stabilize oil productions and consumptions, just as we have seen in China. Regarding to vegetable oil producers, to hedge the obvious risks from infectious disease pandemic is very necessary in their production process. During infectious disease pandemic, in general, high price volatilities are usually seen and thus they must actively adopt oil derivatives to hedge the market risks through reducing possible losses in price fluctuations. Finally, in terms of risk managements for China's vegetable oil investors, the significant positive impacts of infectious disease pandemic on the returns and volatilities of China's vegetable oil markets suggest that, investors should consider seriously to add this new risk factor, infectious disease pandemic, into their risk management applications, and understand that quantifying the infectious disease pandemic is very necessary in measuring and managing the market risk of their vegetable oil portfolios. To be specific, we find that the effect of infectious disease pandemic on the volatility of palm oil price is about three times larger than that on soybean oil, indicating that investors should be proactive in reducing their positions in palm oil during severe epidemics. Then, the evidence of no significant impact of infectious disease pandemic on the volatility of canola oil futures remind the investors that canola oil futures can be used as a hedge asset to reduce the increasing volatility/market risk in other vegetable oil futures affected by infectious disease pandemic. Moreover, we find that COVID-19 pandemic has a negative impact on the time-varying correlation between soybean oil and canola oil futures, while it has a positive effect on the DCC between soybean oil and palm oil, implying that vegetable oil portfolio allocated mainly by canola oil and soybean oil assets is less susceptible to the recent COVID-19 pandemic and is more attractive for investors to achieve better returns and lower market risks.

However, there are some additional research directions that deserve further discussion: for example, the DCC-MVGARCH model used in this article can only depict the linear correlation among assets. The nonlinear dependency among vegetable oil futures markets may be more important for policy makers and portfolio managers to understand the complicated relationships among them. Thus, employing nonlinear tools to measure the impacts of infectious disease pandemic on vegetable oil futures markets may be an interesting topic in the future. In addition, the recent Russia-Ukraine conflict has also had a huge impact on the global agricultural futures market (including the edible vegetable oil futures market), making it a critical research topic to examine the influence of the overlapping geopolitical and war conflicts on the agricultural futures market, in addition to the infectious disease epidemic.

## Acknowledgements

The authors are grateful for the financial support from the National Natural Science Foundation of China (71671145, 71971191), Humanities and social science fund of ministry of education of China (18YJC790132), Science and Technology Innovation Team of Yunnan Provincial Universities (2019014) and Yunnan Fundamental Research Projects (202001AS070018).

## Disclosure statement

Yue Shang, Hongwen Cai, Yu Wei declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

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## Data availability statement

All the data used in this article are confidential and available by subscription from the Wind Database [https://www.wind.com.cn/] and Baidu index company [http://index.baidu.com].

## Notes

1. https://www.ers.usda.gov/data-products/oil-crops-yearbook/
2. https://www.worldbank.org/en/research/commodity-markets
3. http://www.stats.gov.cn/english/PressRelease/202112/t20211220_1825480.html
4. We also employ the BEKK and CCC models to estimate the data sample, but find that these two models fit the data not as well as DCC model does. These estimation results are available upon request.
5. For instance, for DCE soybean oil, each contract expires on the 10th trading day of the contract month. After a contract expires, the nearest expiration contract for the remainder of that calendar month is the second following month.
6. http://index.baidu.com/
7. https://www.worldbank.org/en/research/commodity-markets
8. http://shipin.people.com.cn/gb/n1/2020/1026/c85914-31905930.html
9. More reports can be found in the official website of NFSRA, such as http://www.lswz.gov.cn/html/xinwen/2020-01/30/content_248786.shtml; http://www.lswz.gov.cn/html/xinwen/2020-03/10/content_249621.shtml

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