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Impact of COVID-19 outbreak on multi-scale asymmetric spillovers between food and oil prices

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\section*{ABSTRACT}

This paper analyzes the time-frequency spillover effects between food and crude oil markets, two particularly important commodity markets, under the impact of the pandemic. Using the BK frequency domain spillover index and the rolling window method, we explore the spillover effects between the food and crude oil markets under the influence of COVID-19, and compare the changes of spillover effects in each market before and during the pandemic. Based on the network connectedness method and the Bayesian structural time series method, we further reveal the changes of the pairwise spillover effects between markets on different time scales. Our study shows that the food-oil market system has the strongest spillover effect in the short term, and the spillovers during the pandemic are significantly weaker than that under the financial crisis. In addition, the pandemic has significantly increased the impact of corn on the crude oil market, but reduced its spillovers on soybeans and rice. Finally, during the COVID-19 period, the wheat market is likely to receive more spillovers from other markets, particularly corn and soybeans. These findings are of great significance for market participants with different horizons to understand the spillover effects of food and oil markets under the impact of the pandemic and to avoid the risk transmission across markets or assets.

\section*{1. Introduction}

The COVID-19 outbreak at the end of 2019 has triggered a global economic recession and caused a series of socio-economic problems such as currency devaluation, falling wages, and rising unemployment. These serious consequences have led to violent fluctuations in global commodity markets, particularly in energy and food markets, which are sensitive to economic activities and market shocks. Specifically, the global food supply chain system has been directly affected, and with the continuous impact of the pandemic, whether the global food crisis will break out again has attracted attention. On the other hand, the pandemic crisis has significantly reduced global demand for crude oil and resulted in negative oil prices for the first time in history. It is worth noting that the financialization of commodity markets could further amplify the uncertainty in crude oil markets and major food markets such as rice, wheat, corn, and soybeans under the pandemic, which may exacerbate market volatility (Duc Huynh, Burggraf and Nasir, 2020; Hamadi et al., 2017; Shaikh and Huynh, 2021; F. Wu, Zhao, Ji and Zhang, 2020). As two basic materials and strategic resources for people’s production and life, food and crude oil have penetrated into all aspects of economic development. In the context of the COVID-19, price fluctuations in the two markets, which affect the politics, economy, people’s livelihood, military and diplomacy of countries around the world, have aroused widespread concern in the market.

In the past few decades, especially since the subprime mortgage crisis in 2007, the prices of food and oil have fluctuated violently and showed a clear and consistent linkage. In fact, many studies have proved this linkage relationship and indicated that it can be significantly affected after the financial or food crisis (Han et al., 2015; Debdatta Pal and Mitra, 2018; D. Zhang and Broadstock, 2020). The food and oil markets can be linked through multiple channels (Cheng and Cao, 2019). For example, the production and transportation of food depend on the input of crude oil. Some foods, such as corn and soybeans, are raw materials for biofuels that can be used as important substitutes for crude oil. This in turn may trigger competition between food crops and energy crops for land and fertilizer. In addition, the financialization of commodity markets has made food and crude oil markets more closely linked to satisfy investors’ need for diversified investment tools, which may exacerbate cross-market risk spillovers. Given their previous prominence in post-crisis situations, it is worth exploring whether the spillovers...
between food and crude oil markets will change significantly before and during the pandemic in the context of COVID-19’s global impact. Will the pandemic crisis have a stronger impact on the relationship between food and oil markets than the financial crisis? What role do different food markets play in spillovers across markets or assets? Do the spillover effects between the two markets vary over time scales? This study aims to answer these questions by re-examining the multi-scale and time-varying spillover effects and connectedness between the two.

Exploring the spillover performance of the two major global commodity markets in different contexts can provide important reference for policymakers to effectively regulate and formulate policies, timely reduce such cross-market risk spillover, avoid triggering more serious global market turbulence, and ensure the stable development of global economy. In addition, with the financialization of commodity markets, the spillovers between food and oil markets will reduce the effectiveness of diversified portfolios. The findings of this paper are of great significance for investors looking for potential investment opportunities in commodity markets to understand the spillover interaction between these markets and to formulate a reasonable portfolio.

Consideration that the conclusions of previous studies devoted to exploring the spillover effect and the causal relationship between the two are unclear (Al-Maadid et al., 2017; Avalos, 2014; Fowowe, 2016; Mokni and Ben-Salha, 2020; Nwoko et al., 2016; Debattata Pal and Mitra, 2017; Vu et al., 2019). Recent studies have revealed that the linkage effect between crude oil and food markets is nonlinear and asymmetric (Cha and Bae, 2011; Rafiq and Bloch, 2016; Shahzad et al., 2018; Yip et al., 2020). Given the above nonlinear characteristics and ambiguous conclusions, we believe that possible hidden information needs to be mined from the frequency domain perspective to further reveal the spillover effects between food and oil markets. On the one hand, the multiple channels linking the crude oil and food markets will work on different time scales. On the other hand, different participants have different horizon preferences in the market. For example, hedgers or arbitrageurs mainly focus on the long-term portfolios, while speculators mainly focus on the short-term portfolios. Therefore, given that market prices are the specific reflections of multiple participants trading at different times and scales, the complex linkage effect between crude oil and food markets may be multi-scale asymmetric. In addition, the main channels for the linkage between crude oil and different varieties of food are also different. For example, the biofuel channel plays an important role in the linkage between crude oil and major energy crops such as corn and soybeans, while the cost channel plays an important role in the linkage between crude oil and major food crops such as rice and wheat. Therefore, the nonlinear spillover effects between different varieties of food and crude oil may also be different.

Based on this, the dynamic and frequency-domain spillover effects between global crude oil and food markets as well as the impact of COVID-19 are analyzed by using daily data of WTI (hereafter crude oil), rice, wheat, corn and soybean futures markets from January 22, 2007 to March 3, 2021. First, we use the frequency spillover index (BK method) of Barunik and Krehlik (2018) to explore the risk roles of each market in the food-oil market system on different time scales in the subsamples before and during the pandemic, and compare the changes caused by COVID-19. Second, to further capture the dynamic spillovers between food and oil markets, we combine rolling window to understand and compare the impact of the financial crisis and the pandemic crisis, providing a more comprehensive and visual picture of spillover changes. Finally, a Bayesian structured time series approach based on paired spillover index is used to reveal the spillover transmission effect between food and oil markets on different time scales in the samples before and during the pandemic, and then the Bayesian structured time series method is combined to provide an estimated counterfactual time series to evaluate the potential impact of COVID-19 on the pairwise spillover index between food and oil markets.

This paper would extend the previous studies from the following aspects. First, it may be misleading to draw conclusions about the relationship between food and oil markets from a linear perspective (Cheng and Cao, 2019; Ibrahim, 2015). In this paper, the spillover effect between food and oil markets is effectively measured by the BK frequency domain spillover index. This method has been widely used in other literatures (Balli et al., 2019; Huynh et al., 2020; Liu et al., 2020). Based on the spectrum representation of variance decomposition, the BK method can not only fully quantify the details of spillovers, calculate the direction and accurate strength of the connectedness between different variables in the system, but also effectively capture the spillover effects of heterogeneous frequency shocks, thus providing more insight into the persistence of the effects of different degrees (Barunik and Krehlik, 2018). Subsequently, we further assess the potential impact of COVID-19 on spillovers between major crops and crude oil using a Bayesian structured time series approach based on paired spillover index. Our results are more targeted to provide market participants with a reference map to avoid cross-market risk spillovers.

Second, existing research work focuses on a relatively limited time or index data and lacks the quantification of the magnitude and direction of multi-scale asymmetric spillover effects, particularly in the context of crises including financial crisis and pandemic crisis (Hung, 2021; Kang et al., 2019; D. Pal and Mitra, 2020). Our sample period covers the global financial crisis, which provides a more comprehensive performance of the spillovers and helps us to get a clearer picture of the relative impact of the pandemic. Moreover, on the one hand, given the high degree of integration of agricultural markets, price fluctuations of a certain food are likely to be transmitted to others (Naziqolju and Soytas, 2012). Therefore, our analysis covers major energy and food crops (Chandio et al., 2019; Ciaian and Kancs, 2011; Nguyen, 2020; Debattata Pal and Mitra, 2019; Shahzad et al., 2018). On the other hand, since futures prices are widely used as investment tools, the futures prices used in this paper contain more available information than spot prices or index prices, so they are more suitable for exploring spillover effects between markets (Natanelov et al., 2011). Therefore, our results are relevant to a larger group of investors and policymakers and provide stronger empirical evidence.

Third, our results provide new insights into the spillover effects between food and oil markets in the context of the pandemic. Stronger spillover levels in the short term mean that different market participants, especially speculators, should pay more attention to the financial channels on which cross-market influences depend to avoid risk transmission. Notably, we find that the impact of COVID-19 crisis on the spillovers between food and oil markets is significantly weaker than that of the financial crisis. However, the pandemic has caused significant changes in the spillovers between food crops, especially energy crops, and crude oil. During the pandemic, the role of soybeans as a transmitter of net spillovers has increased (except in the short-term), and the net spillovers of corn have also changed significantly over different time scales. While the role of rice as a net receiver has diminished, so has crude oil in the short term. But the wheat market has suffered more spillovers from other markets. Further analysis of the pairwise spillover index of the food-oil market shows that under the influence of COVID-19, the spillover effects of corn and soybeans on the crude oil market have increased significantly over a longer time scale.

The rest of this paper is structured as follows. The second part summarizes the previous literature. The third part introduces the methods and data adopted in this paper. The fourth part is the empirical results of the spillovers between food and crude oil markets in the context of the pandemic. The last part gives our conclusions and provides the corresponding policy implications.

2. Literature review

Under the pandemic crisis, many scholars believe that COVID-19 has had a significant impact on all aspects of the world economy (Goodell, 2020; Nicola et al., 2020; Sharif et al., 2020). Some scholars focus on the impact of the crisis on individual markets such as financial and commodity markets (Karamti and Belhassine, 2021; Mensi et al., 2020;
Naeem et al., 2021; Sadefo Kamdem et al., 2020). Of course, there are also concerns about the impact of the COVID-19 crisis on the oil market (Atri et al., 2021; Borgards et al., 2021). Adedeji, Ahmed, and Adam (2021), however, argues that the impact of the pandemic on Brent, WTI and oil prices in China, Nigeria is short-term and weak. At the same time, some scholars have analyzed the impact of the COVID-19 on the spill-over effects between markets. Most of these studies focus on financial markets (Farid et al., 2021; Kinateder et al., 2021; Yarovaya et al., 2021; D. Zhang, Hu and Ji, 2020), and spillovers and dependencies between financial markets and commodity markets (Amat et al., 2021; Bahloul and Khemakhem, 2021; Le et al., 2021). Some studies have also examined spillovers between energy and other markets. For example, Lin and Su (2021) finds that the spillover effect between energy markets is affected by the pandemic, and the connectedness between markets shows a significant temporary enhancement. W. Zhang and Hamori (2021) finds that the impact of COVID-19 shock on the linkage relationship between crude oil and stock markets is significantly higher than that of financial crisis. B.-B. Wu (2020), using the quantile perspective, shows that the asymmetrical influence between crude oil and China’s commodity markets is significantly affected by the pandemic. Hung (2021) argues that spillovers between oil and food markets are clearly affected by the pandemic. Y. Sun, Mirza, Qadeer, and Hsueh (2021), on the other hand, shows that during the COVID-19 period, the prices of agricultural products and oil are not affected by the shocks caused by these two markets.

In previous studies on the food and crude oil markets, early scholars mostly focus on the one-way spillover effect of crude oil on the food markets and find that the food markets are positively influenced by the crude oil market (Baffes, 2007; Dillon and Barrett, 2015; Koirala, Mishra, D’Antoni and Mehnhorn, 2015; Paris, 2018; Taghizadeh-Hesary et al., 2019). Moreover, quite a few studies support that the spillover effects become more obvious after the food crisis (Nazlioglu et al., 2013; Wang et al., 2014). However, when discussing the spillover effects of different agricultural products on the crude oil market, the conclusions of the previous literature are contradictory. For example, the research of Chang and Su (2010) and Zafeiriou et al. (2018) both show that the crude oil market has a significant impact on the corn and soybean markets. Chen, Kuo, and Chen (2010) concludes that prices of corn, soybeans and wheat are affected by oil prices. The study of Balcombe and Rapsomanikis (2008) proves that oil prices are the driving factor for sugar prices in Brazil in the long run. However, Nwoko et al. (2016) finds no long-term relationship between oil and the food prices when analyzing the impact of oil prices on the prices of corn, rice, sorghum, soybean and wheat in Nigeria. Fernandez-Diaz and Morley (2019) supports that there is indeed a volatility spillover between the crude oil market and the corn market, but not between the soybean and sugar markets.

Some studies explore the correlation between the two markets, and most scholars use traditional econometric models such as GARCH, VAR and cointegration analysis to provide evidence of spillovers between crude oil and food markets (Al-Maaddi and Baraghli et al., 2020; Chiou-Wei et al., 2019; McFarlane, 2016; Rezitis, 2015), and some other studies such as Ji et al. (2018) and Tiwari et al. (2018) also support the linkage between oil and agricultural product markets by using copula model and wavelet coherence analysis respectively. Based on the Copula model, VAR and CoVAR methods, Hanif et al. (2021) concludes that there is an asymmetric risk spillover behavior between oil prices and some major food price indices. Some scholars also believe that the linkage between crude oil and agricultural products markets has become more obvious after the food crisis (Avalos, 2014; Du et al., 2011; Lucotte, 2016; Debdattra Pal and Mitra, 2018). In contrary, a number of studies support the neutral view that there is no spillover effect between crude oil and food markets (Baumeister and Kilian, 2014; Fowowe, 2016; Gardebroek and Hernandez, 2013; M. Kaltioglu and Soytas, 2011; Reboredo, 2012).

Of course, there are also studies on the causal relationship between oil and food markets, but there is no consensus on the conclusions. Some studies suggest that there is only a one-way causality from oil to food markets (Nazlioglu et al., 2011; Debdattra Pal and Mitra, 2017; Sarwar et al., 2020). In addition, the research of Nwoko et al. (2016) shows that the one-way Granger causality of oil to grain market depends on the variety of grains. More specifically, there is one-way causality of oil to corn and soybeans, but not to rice and wheat. In contrast, the studies of Baumeister and Kilian (2014) and Vu et al. (2019) consider the causal effect of the food market on oil, arguing that the expansion of agricultural production may lead to an increase in oil prices. Some other studies confirm the existence of a two-way causal relationship between food and oil markets (Mokni and Ben-Salla, 2020; Rezitis, 2015; Wei Su et al., 2019). Karakotosios, Katrakildis, and Kroupis (2021) finds only a unidirectional linear causality from oil to food prices, but under a nonlinear framework, a causality from food to oil markets is found. In addition, Mokni and Ben-Salla (2020) finds that the Granger causality between oil and food prices not only shows asymmetry, but also varies with different quantities. However, there are also studies that argue the absence of a causal relationship between oil and food markets (Fowowe, 2016; Gilbert, 2010; M. S. Kaltioglu, U, 2009; Nazlioglu and Soytas, 2011).

Consider the fact that the time series data of the oil and food markets are composed of components on different time scales and the influence channels between the two markets operate on different time scales (Huang et al., 2016; X. Sun, Chen, Wang and Li, 2020). From a frequency domain perspective, we use BK spillover index combined with the rolling window method, the network connectedness method and the Bayesian structural time series method to obtain the information of time series on different time scales, thus revealing the spillover effects between the global major food and crude oil futures markets under the impact of COVID-19.

3. Methodology and data

3.1. BK frequency spillover method

In this paper, BK spillover index proposed by Barunik and Kréhlik (2018) is used to explore the overall and directional spillover level of food and oil market system. Considering that different market participants have different preference horizons, BK frequency spillover method can provide a clear reference for market spillover effects on different time scales.

Since the BK method is an extension of the DY method, we first briefly introduce the DY spillover index. The DY method measures connectedness by the forecast error variance decomposition (FEVD) of generalized vector autoregression model (VAR). By considering a covariance stable N-variate process \( x_t = (x_{t1}, ..., x_{tn}) \), which can be expressed in the form of VAR (p) as follows:

\[
X_t = \sum_{i=1}^{p} \Phi_i X_{t-i} + \varepsilon_t. \tag{1}
\]

To simplify the above equation, we can express the above model as follows: \( \Phi(L)X_t = \varepsilon_t \), \( \Phi(L) = |I_p - \Phi_1L - \Phi_2L^2 - \cdots - \Phi_pL^p| \). The identity matrix, \( \varepsilon_t \) represents the error term with the covariance matrix \( \Sigma \). If the above VAR process is stable, it can be expressed as the moving average (MA) process in Equation (2):

\[
X_t = \Psi(L)\varepsilon_t, \tag{2}
\]

where, \( \Psi(L) \) can be calculated by \( \Phi(L)^{-1} \). In this paper, considering that the VAR model does not include exogenous variables which are not entered into the model, we introduce the structured lasso penalty in Formula (3), which can well deal with large optimization problems. The \( \lambda \) represents non-negative penalty parameters, and \( P_j(\Phi) \) is the group penalty structure of endogenous coefficient.
\[
\min \sum_{i=1}^{n} \left| X_i - \sum_{i=1}^{p} \Phi_i X_{i-i} \right|^2 + \lambda P_2(\Phi_i)
\]

According to the above VAR model, the generalized FEVD can be expressed as:

\[
\Theta_{ij}(H) = \frac{\sigma_{ij}}{\sum_{i=1}^{N} \sigma_{ii}^{2}} \left( \Psi_i \Sigma \right)_{ij}^2.
\]

The above formula can be used to calculate the contribution of \( j_{th} \) variable in the system to the forecast error variance of \( i_{th} \) variable at the forecast horizon \( H \). In equation (4), \( \Psi_i \) is a \( n \times n \) lag \( h \) matrix of coefficients, and \( \sigma_{ij} = (\Sigma)_{ij} \). By standardizing it, the following equation can be obtained:

\[
\tilde{\Theta}_{ij}(H) = \frac{\Theta_{ij}(H)}{\sum_{i=1}^{n} \Theta_{ii}(H)}
\]

with \( \sum_{j=1}^{n} \Theta_{ij}(H) = 1 \) and \( \sum_{i=1}^{n} \Theta_{ij}(H) = N \). Finally, Equation (5) is used to measure the connectedness of the \( j_{th} \) variable on the \( i_{th} \) variable at the forecast horizon \( H \).

The DFM method above does not consider the connectedness in the frequency domain. On this basis, the BK frequency domain spillover method proposes that the spectral representation of variance decomposition should be based on the frequency response to the impact, rather than the impulse response. Therefore, in the BK method, the coefficient \( \Psi_i \) is estimated by using the frequency response function:

\[
\Psi(e^{j\omega}) = \sum_{k=0}^{n} e^{-j\omega k} \Psi_k, i = \sqrt{-1},
\]

where, \( w \) represents the frequency. Then, the power spectrum assigned to frequency component \( w \) in \( X_t \) can be expressed as:

\[
S_{x}(w) = \sum_{k=0}^{w} E(X_{t-k} e^{-j\omega k}) = \Psi(e^{j\omega}) \Sigma \Psi(e^{j\omega}).
\]

Therefore, based on the frequency response function, the generalized FEVD obtained at a given frequency \( w \) can be expressed as:

\[
(\Theta(w))_{ij} = \frac{\sigma_{ij} \sum_{j=0}^{n} (\Psi e^{j\omega} \Sigma)^2_{ij}}{\sum_{j=0}^{n} (\Psi e^{j\omega} \Sigma)^2_{ii} (\Psi e^{j\omega} \Sigma)^2_{jj}}.
\]

In Equation (8), \( (\Theta(w))_{ij} \) denotes the spillover effect of the \( j_{th} \) variable on the \( i_{th} \) variable at frequency \( w \). Similarly, Standardize the above equation:

\[
\tilde{\Theta}(w)_{ij} = \frac{(\Theta(w))_{ij}}{\sum_{j=1}^{N} (\Theta(w))_{ij}}
\]

The following formula holds: \( \sum_{j=1}^{N} (\Theta(w))_{ij} = 1 \), \( \sum_{j=1}^{N} (\Theta(w))_{ij} = N \).

Then, in the frequency band \( d = (f1, f2) \), the accumulated connectedness is:

\[
\tilde{\Theta}_{ij}(d) = \int_{f1}^{f2} \tilde{\Theta}(w)_{ij} dw.
\]

Accordingly, the overall connectedness of the system in frequency band \( d \) is as follows:

\[
C^d = \sum_{j=1}^{n} \left( \tilde{\Theta}_{ij}(d) \right) = 1 - \sum_{j=1}^{n} \left( \tilde{\Theta}_{ij}(d) \right).
\]

The directional spillover index can be measured as:

\[
C^d_{ij} = \sum_{j=1}^{n} \left( \tilde{\Theta}_{ij}(d) \right)
\]

\[
C^d_{ji} = \sum_{j=1}^{n} \left( \tilde{\Theta}_{ij}(d) \right).
\]

In the above equation, \( C^d_{ij} \) measures the contribution of all other variables in the system to the forecast error variance of variable \( i \) in the frequency band \( d \). \( C^d_{ji} \), on the other hand, measures the contribution of variable \( i \) to the forecast error variance of all the other variables in the system. Therefore, the Net connectedness of a certain variable \( i \) is expressed as:

\[
C^d_{i-Net} = C^d_{ij} - C^d_{ij,From}.
\]

We can also obtain the paired connectedness between variables \( i \) and \( j \) in the system:

\[
C^d_{ij} = \left( \tilde{\Theta}_{ij} \right) - \left( \tilde{\Theta}_{ij} \right).
\]

In addition, by spectral weight \( \Gamma(d) \), BK method also provides the contribution proportion of a given frequency band \( d \) to the system as follows:

\[
\bar{C}^d = C^d \cdot \Gamma(d) = \frac{\sum_{j=1}^{n} \tilde{\Theta}_{ij}(d)}{\sum_{j=1}^{n} \tilde{\Theta}_{ij}(d)} = \frac{\sum_{j=1}^{n} \tilde{\Theta}_{ij}(d)}{n}.
\]

Finally, by adding up the connectedness of each band, the sum obtained is equal to the overall connectedness of the system obtained by DFM method.

### 3.2 Data

To fully explore the effects of COVID-19 on the time-frequency correlation and spillover transmission between crude oil and several major food markets, the sample period covers futures prices of WTI (crude oil) and four major food markets from January 22, 2007 to March 3, 2021. Among them, the food markets include food crops (rice and wheat) and energy crops (corn and soybeans). In this paper, December 1, 2019, the earliest known COVID-19 case, is used as the separation date for samples before and during the pandemic. Therefore, the two sub-sample periods are: (i) pre-sample, from January 22, 2007 to November 29, 2019, and (ii) during-sample from December 2, 2019 to March 3, 2021. Since returns provide more comprehensive market information, the lognormal difference form of price series is adopted in this paper to represent returns, that is, \( r_t = \ln P_t - \ln P_{t-1} \). Table 1 shows the statistical description of food and oil markets. We find that crude oil is the most volatile of all markets, which is more obvious in the post-sample. In the food markets, rice has the most stable performance in the pre-sample, and soybeans in the post-sample. All markets are characterized by spikes and skewness and do not follow normal distribution, which can also be further proved by J-B test results. In addition, ADF test results show that all data are stable.
4. Empirical results

4.1. Static spillovers

Through the analysis of frequency domain spillover table (Table 2), the process of spillover transmission between oil and food markets on different time scales can be quantified. The frequency bands 1 to 5 correspond to time scales of 1–2 days, 2–4 days, 4–8 days, 8–16 days, and more than 16 days, respectively. Based on the results, first, overall, we find that the overall spillover index fluctuates between 1.79% and 16.06% (pre-sample) and 1.39%–0.54% to 2.89%. This means that most investors behave similarly in the short term, while the spillovers received by net receivers are weakened. Notably, the wheat market appears to have been significantly affected. Under the pandemic, the spillovers of wheat received are significantly enhanced, and there is even a role reversal from the net transmitter to the net receiver of spillovers. This means that COVID-19 tends to exacerbate the effects of spillovers from other markets on the wheat market.

Finally, a positive net spillover index (Net) indicates that the market is a net transmitter, which is more likely to have an impact on others; otherwise, it is a net receiver and is more susceptible to the influence of others. We find that the impact of the pandemic has not changed the roles of corn and soybeans as net spillo-transmitters and crude oil and rice as net spillo-receivers. However, under the influence of COVID-19, the spillovers of net transmitters are enhanced on all time scales except the short term, while the spillovers received by net receivers are weakened. Notably, the wheat market appears to have been significantly affected. Under the pandemic, the spillovers of wheat received are significantly enhanced, and there is even a role reversal from the net transmitter to the net receiver of spillovers. This means that COVID-19 tends to exacerbate the effects of spillovers from other markets on the wheat market.

4.2. Dynamic spillovers

4.2.1. Results of dynamic spillover index

The static spillover analysis provides the overall results of the average spillover between oil and agricultural futures markets. However, the direction or extent of spillovers between markets may change throughout the sample period, with a high degree of uncertainty. Therefore, in view of the fact that the static spillover table cannot effectively capture the time-varying spillover characteristics between markets during the sample period, we further analyze the dynamic connectedness of oil and food markets throughout the sample period through a rolling window. Fig. 1 (a, b, c, d, e) shows the dynamic changes of the overall spillover index under different time scales.

The global characteristics of the overall spillover index in different frequency bands indicate that the food and oil markets are sensitive to the spillover effects between markets, and the impact on the food and oil markets in the short term will cause more obvious transmission. The overall spillover index fluctuates the most in the short term, ranging from 5.04% to 25.08%, while on the long time scale, i.e., 8–16 days, the overall spillover index is the weakest, with fluctuations ranging from 0.54% to 2.89%. This means that most investors behave similarly in the short term and more variously in the medium to long term when investing in assets. On the other hand, the following findings can be obtained by further analyzing the local characteristics of the overall spillover index on different time scales. The overall spillover index of each frequency band reaches the weakest at the end of August 2014.
## Table 2
Static spillover indices of food and oil price returns.

### Panel A: Pre-sample

|               | FROM_ADD | FROM_WTH |
|---------------|----------|----------|
| **Freq 1:** The spillover table for band: 3.14 to 1.57 Roughly corresponds to 1 days – 2 days. |          |          |
| WTI           | 44.21    | 0.98     |
| rice          | 44.00    | 1.69     |
| wheat         | 1.69     | 1.77     |
| corn          | 1.77     | 2.83     |
| soybean       | 2.83     | 1.45     |
| TO ABS        | 1.45     | 2.79     |
| TO WTH        | 2.79     | -0.46    |
| Net           | -0.46    | -0.40    |

### Panel B: During-sample

|               | FROM_ADD | FROM_WTH |
|---------------|----------|----------|
| **Freq 1:** The spillover table for band: 1.57 to 0.79 Roughly corresponds to 2 days to 4 days. |          |          |
| WTI           | 45.53    | 0.45     |
| rice          | 50.79    | 0.58     |
| wheat         | 37.74    | 0.41     |
| corn          | 5.49     | 0.65     |
| soybean       | 0.65     | 0.31     |
| TO ABS        | 0.31     | 2.68     |
| TO WTH        | 2.68     | -0.19    |
| Net           | -0.19    | -0.20    |

### Panel C: Post-sample

|               | FROM_ADD | FROM_WTH |
|---------------|----------|----------|
| **Freq 1:** The spillover table for band: 0.79 to 0.39 Roughly corresponds to 4 days to 8 days. |          |          |
| WTI           | 5.31     | 0.13     |
| rice          | 50.79    | 0.14     |
| wheat         | 37.74    | 0.24     |
| corn          | 5.49     | 0.38     |
| soybean       | 0.65     | 0.31     |
| TO ABS        | 0.31     | 2.62     |
| TO WTH        | 2.62     | -0.04    |
| Net           | -0.04    | -0.05    |

### Panel D: Aside-sample

|               | FROM_ADD | FROM_WTH |
|---------------|----------|----------|
| **Freq 1:** The spillover table for band: 0.39 to 0.20 Roughly corresponds to 8 days to 16 days. |          |          |
| WTI           | 5.31     | 0.13     |
| rice          | 50.79    | 0.14     |
| wheat         | 37.74    | 0.24     |
| corn          | 5.49     | 0.38     |
| soybean       | 0.65     | 0.31     |
| TO ABS        | 0.31     | 2.62     |
| TO WTH        | 2.62     | -0.04    |
| Net           | -0.04    | -0.05    |
The performance of the dynamic net spillover index of each market given that markets is bidirectional and asymmetric. In addition, in most periods, indicating that the spill transfer between crude oil and food futures each market on different time scales changes in magnitude over time, the overall spillover index. On the other hand, the net spillover index of the most in the short term, which is consistent with the performance of Fig. A1-A5. We find that the net spillover index of each market fluctuates markets in the medium to long term (F3, F4 and F5). We find that these

Table 2 (continued)

| WTI | rice | wheat | corn | soybean | FROM_ABS | FROM_WTH |
|-----|------|-------|------|---------|----------|----------|
| 10.51 | 0.01  | 0.02  | 1.08 | 0.26  | 0.27  | 2.31  |
| 0.01  | 11.72 | 0.01  | 0.12 | 0.01  | 0.03  | 0.27  |
| 0.01  | 0.01  | 8.71  | 1.56 | 1.59  | 0.63  | 5.34  |
| 0.73  | 0.07  | 1.27  | 7.08 | 2.73  | 0.96  | 8.08  |
| 0.19  | 0.01  | 1.36  | 2.87 | 7.45  | 0.89  | 7.46  |
| 0.19  | 0.02  | 0.53  | 1.13 | 0.92  | 2.79  |        |
| 1.59  | 0.17  | 4.47  | 9.48 | 7.74  |        |        |
| Net  | -0.09 | -0.01 | -0.10| 0.17  | 0.03  |        |

Freq 1: The spillover table for band: 3.14 to 1.57 Roughly corresponds to 1 days–2 days.

Note: From_ABS (To_ABS) measures frequency connectedness, which represents contribution from (to) other markets. From_WTH (To_WTH) measures within market connectedness, which weights the power of the From_ABS (To_ABS) at the corresponding frequency. Net, derived from To_ABS minus From_ABS, measures the net contribution of this market to all other markets. The bottom right corner of the static spillover table gives the overall spillover index for different frequency bands, which is the sum of From_ABS (To_ABS) and measures the total spillover effect for all markets in the system.

during the Oil Depression, and the overall spillover level of the sample after 2013 is significantly lower than before. This means that the impact of COVID-19 on spillovers between food and crude oil markets has been overestimated. In fact, we find that overall spillovers during the pandemic are significantly weaker than during the financial crisis.

4.2.2. Dynamic net spillovers

After discussing the overall spillover effects between food and oil markets, it is necessary to further analyze the net spillover effects of a certain market. The time-varying net spillover results are shown in Fig. A1-A5. We find that the net spillover index of each market fluctuates the most in the short term, which is consistent with the performance of the overall spillover index. On the other hand, the net spillover index of each market on different time scales changes in magnitude over time, indicating that the spill transfer between crude oil and food futures markets is bidirectional and asymmetric. In addition, in most periods, the performance of the dynamic net spillover index of each market given by the rolling window is consistent with the results of the static net spillover table, but it also captures some changes missing in the static spillover analysis.

We find that rice and crude oil mainly act as net recipients of spillovers, and the role of the rice market is more stable. In the oil market, we can see the short-term and long-term effects of the financial crisis on this market are different. Specifically, the crisis has made crude oil vulnerable in the short term to net spillovers from other markets. But over a longer time scale, crude oil shows net spillovers on other markets. In addition, as global oil prices declines sharply from the fourth quarter of 2014 to January 2016, the market also shows net spillovers on other markets. In 2014 to January 2016, the market also shows net spillovers on other markets. But over a longer time scale, crude oil shows net spillovers on other markets. In

4.3. Pairwise analysis

4.3.1. Results of network connectedness

Fig. 2 shows the network connectedness between markets in the system based on the paired net spillover index. Fig. 2 (a)–(e) shows the spillover transfer structure of markets in the pre-sample on different time scales, and Fig. 2 (f) shows the spillover transfer structure among the markets in the during-sample, which means that the transfer structure on all time scales becomes consistent after the impact of COVID-19.

In the pre-COVID-19 sample, the most active spillovers in the short term are from corn to all other markets and from soybeans to crude oil markets. In the medium and long term, corn has the strongest impact on the soybean and rice markets, followed by the spillover effect of wheat
on crude oil and rice markets. Examining the paired spillover effects between different food markets and crude oil, we find that in the medium to long term, corn, soybeans, and wheat have stronger spillover effects on the crude oil market, while the rice market is less affected by the oil market. However, in the shorter term, the impact of wheat on crude oil has weakened to the weakest of the three, indicating that the impact of wheat on the crude oil market will be weaker in the short term but will be significantly stronger in the medium to long term. Moreover, it is worth noting that in the shortest term (F1), we find that the rice has a weak spillover effect on the oil market. This shows that in the short term, the oil market acts as a receiver of spillovers from food markets, but on all other time scales, the oil market receives spillovers from the wheat, soybean and corn markets on the one hand and passes the spillover risks to the rice market on the other.

During the COVID-19 pandemic, spillovers between the corn market and other markets are significantly impacted. The spillover effect of corn on the crude oil market and wheat market has been significantly enhanced, and the spillover effect on the soybean and rice market has

Fig. 1. Time varying overall spillover index in different frequency bands. Note: Fig. 1 shows the dynamic characteristics of the overall spillover index of the food-oil market system over different time scales. The horizontal axis accounts for the time factor and the vertical axis for the overall spillover levels.
been significantly weakened. In addition, the impact of soybeans on the wheat market has also changed. During the pandemic, the weak effect of wheat on the soybean market is turned into a strong spillover effect of soybean on the wheat market.

4.3.2. Bayesian posterior estimates

A causal impact analysis based on Bayesian inference is presented to estimate the possible impact of COVID-19 on the pairwise spillover index between food and oil markets. The results are shown in Table 3. The posterior causal inference consists of the following steps: the model is estimated using pre-pandemic data, and then the time series during the pandemic impact is simulated based on the observed values. Finally, the impact of the pandemic is analyzed according to the difference between the predicted and actual values.

Regarding the spillover between the rice and the crude oil market, in the short term, namely F1, the pandemic has turned the rice market affected by the spillover of the crude oil market into a spillover transmitter. On all other time scales, the spillover effect of crude oil on the rice market has become stronger under the impact of the pandemic. However, these effects do not show statistical significance. The impact of the pandemic on spillover effect between the wheat and crude oil markets is also not statistically significant. In the short term, the pandemic has reduced the spillover effect of crude oil on the wheat market. On all other timescales, the wheat market has less impact on the crude oil market. In addition, in F2, the wheat market has changed from the spillover transmitter of the crude oil market to its spillover receiver. Notably, the spillover effect of corn on the crude oil market under the influence of COVID-19 is significantly enhanced on all time scales, and all effects are statistically significant. In terms of the spillover between the soybean and crude oil market, the spillover effect of the soybean market on the crude oil market increases in the short term, but it is not statistically significant. On all other time scales, the pandemic turns the soybean market affected by the crude oil market into a spillover transmitter, and at the 10% significance level, the effect is significant over the long term.

4.4. Robustness test

To test the robustness of the results, we use Brent crude instead of West Texas Intermediate (WTI) to analyze spillovers between food and
Table 3

Results of posterior estimates (inference) of the causal impact of COVID-19 on food-oil market.

| Rice—WTI      | Actual Prediction | Absolute effect | Relative effect | P     |
|---------------|-------------------|-----------------|-----------------|-------|
| F1 [95% CI]  | 0.022             | -0.0053 [-0.18, 0.17] | 0.027 [-0.15, 0.2] | -514% [2818%, 3814%] | 0.3923 |
| F2 [95% CI]  | -0.03             | -0.0039 [-0.05, 0.042] | -0.026 [-0.072, 0.02] | 658% [1845%, -521%] | 0.1465 |
| F3 [95% CI]  | -0.024            | -0.0017 [-0.062, 0.061] | -0.022 [-0.084, 0.038] | 1278% [4929%, -2229%] | 0.2539 |
| F4 [95% CI]  | -0.015            | -0.00083 [-0.043, 0.043] | -0.014 [-0.058, 0.028] | 1735% [6933%, -332%] | 0.2640 |
| F5 [95% CI]  | -0.02             | -0.001 [-0.027, 0.056] | -0.019 [-0.077, 0.036] | 1910% [7522%, -2557%] | 0.2600 |

| Wheat—WTI    | Actual Prediction | Absolute effect | Relative effect | P     |
|---------------|-------------------|-----------------|-----------------|-------|
| F1 [95% CI]  | -0.0046           | -0.0088 [-0.073, 0.055] | 0.0042 [-0.06, 0.068] | -48% [676%, -770%] | 0.4577 |
| F2 [95% CI]  | -0.0019           | 0.0056 [-0.046, 0.061] | -0.0075 [-0.063, 0.044] | 133% [1100%, 786%] | 0.4043 |
| F3 [95% CI]  | 0.00075           | 0.0065 [-0.019, 0.033] | -0.0057 [-0.033, 0.02] | -88% [503%, 307%] | 0.3613 |
| F4 [95% CI]  | 0.00063           | 0.0043 [-0.0072, 0.016] | -0.0036 [-0.016, 0.0078] | -85% [366%, 184%] | 0.2815 |
| F5 [95% CI]  | 0.00086           | 0.0055 [-0.012, 0.023] | -0.0047 [-0.022, 0.012] | -85% [-398%, 224%] | 0.3277 |

| Corn—WTI     | Actual Prediction | Absolute effect | Relative effect | P     |
|---------------|-------------------|-----------------|-----------------|-------|
| F1 [95% CI]  | 0.14              | 0.04 [-0.065, 0.15] | 0.096 [-0.012, 0.2] | 241% [30%, 505%] | 0.0364** |
| F2 [95% CI]  | 0.087             | 0.00025 [-0.05, 0.052] | 0.086 [0.034, 0.14] | 34093% [13921%, 55140%] | 0.0012** |
| F3 [95% CI]  | 0.028             | 0.002 [-0.031, 0.037] | 0.026 [-0.0088, 0.06] | 1352% [-450%, 3059%] | 0.0635*  |
| F4 [95% CI]  | 0.021             | 0.002 [-0.014, 0.019] | 0.019 [0.0019, 0.035] | 944% [97%, 1747%] | 0.0146** |
| F5 [95% CI]  | 0.03              | 0.0028 [-0.02, 0.026] | 0.027 [0.0041, 0.05] | 994% [148%, 1817%] | 0.0135** |

| Soybean—WTI  | Actual Prediction | Absolute effect | Relative effect | P     |
|---------------|-------------------|-----------------|-----------------|-------|
| F1 [95% CI]  | 0.038             | 0.027 [-0.037, 0.091] | 0.011 [-0.054, 0.075] | 42% [200%, 279%] | 0.3813 |
| F2 [95% CI]  | 0.011             | -0.00082 [-0.033, 0.032] | 0.012 [-0.021, 0.044] | -1458% [2536%, -5317%] | 0.2457 |
| F3 [95% CI]  | 0.0081            | -0.0014 [-0.024, 0.022] | 0.0095 [-0.014, 0.032] | -696% [1029%, -2337%] | 0.2224 |
| F4 [95% CI]  | 0.0089            | -0.00044 [-0.015, 0.015] | 0.0094 [-0.0057, 0.024] | -2141% [1299%, -5468%] | 0.1187 |
| F5 [95% CI]  | 0.014             | -0.00037 [-0.021, 0.021] | 0.014 [-0.0069, 0.035] | -3918% [1873%, -9463%] | 0.0976*  |

Note: Column 1 is the average value of actual data; Column 2 is the average value of predicted data; Column 3 is the absolute impact; Column 4 is the relative impact; Column 5 is the probability of the trailing region and the 95% confidence interval is in parentheses.

* represents a significance level of 5%.
* represents a significance level of 10%.

The spillover effect of rice remains the weakest. In addition, spillovers from soybean to Brent crude oil decrease over time scales, while the opposite is true for wheat, which is consistent with previous findings. Another aspect is the performance in the sample during COVID-19. The main findings are also consistent with previous empirical research results. That is, under the pandemic, the impact of corn on wheat and Brent crude oil has increased, but on soybeans and rice has weakened. Moreover, the impact of soybeans on wheat has become obvious.

(i) The spillover effect is stronger in the short term. In addition, the spillover effect of the food-oil market system is significantly stronger during the financial crisis than during the COVID-19 crisis.

(ii) Brent crude and rice mainly act as receivers. Further dynamic spillover results show that the role of the rice market is more stable.

(iii) Under the influence of the COVID-19, the wheat market tends to be more susceptible to spillovers, and soybeans, as the second most stable net spillovers transmitter, will become more active. It is worth noting that by tracking dynamic spillovers, we find an interesting phenomenon that these two markets are basically transmitters of net spillovers in the early sample period, and mainly receivers in the late sample period.

(iv) Corn has always been the most prominent market, acting as the strongest transmitter of net spillovers.

(v) Regarding the characteristics of pairwise spillover indices, one is the performance in the pre-sample. The most obvious spillovers in the short term are from corn to all other markets and from soybeans to Brent crude. In the medium to long term, the results are slightly different, with the most prominent performance still being the impact of corn on the soybean and rice markets, however, followed by the spillover received by Brent crude. Focusing on the paired spillover effect between food and oil, we find that

5. Conclusions and implications

This paper analyzes the spillover effects between food and crude oil markets under the influence of COVID-19 based on the daily returns of the futures market from January 22, 2007 to March 3, 2021. To understand the impact of the pandemic, we use the BK frequency domain spillover index to analyze the static spillover performance in the subsamples before and during the COVID-19. Then, combined with the rolling window method, we capture the time-varying spillover effects between food and crude oil markets, covering the financial crisis and COVID-19 period, which provide a comprehensive spillover characteristics. Finally, this paper explores the pairwise spillover index between the food and oil markets in the context of COVID-19. Based on the test results, the reliability of the main findings is generally confirmed:

1. The results of all tables and figures for robustness test are available upon request.
food and oil markets on different time scales by using the network connectedness method and Bayesian structured time series method, and further analyzes the impact of the pandemic on the pairwise spillover index. Our research is of great significance for market participants with different perspectives and preferences to reasonably formulate diversified portfolio strategies, timely and effectively respond to the changes brought about by the pandemic, and avoid cross-market risk spillovers.

The main conclusions of this paper are as follows. First, the overall and directional spillover levels perform strongest in the short term and weakest on the time scale of 8–16 days. This supports the conclusion of Nazlioglu et al. (2013) that the spillovers between crude oil and food markets are sensitive. In addition, the overall spillover effects of the food and oil market system do not fluctuate significantly during the COVID-19 period and remains significantly weaker than the overall spillover effects during the financial crisis. Therefore, we believe that the impact of the pandemic on the spillover of food-oil market is not strong, which is consistent with the findings of Adesoji et al. (2021), indicating that the impact of the pandemic on oil markets is short and weak. Our findings show that the impact on the food and oil markets will have a more pronounced transmission in the short term.

Second, on the one hand, for the receivers of net spillovers, we find that the wheat market has become a stable net receiver of spillovers on all time scales after the COVID-19 shock, and the spillovers it receives is significantly stronger, mainly from the corn and soybean markets. This is consistent with the findings of Fernandez-Perez et al. (2016) that corn has a strong influence on wheat. In addition, crude oil and rice markets are both receivers, although the role of rice is significantly diminished on all time scales after the COVID-19 pandemic, especially the spillover effect from the corn market has weakened. However, compared to crude oil, it is a more stable receiver of net spillovers. On the other hand, for the transmitter of net spillovers in the system, corn has always been the most active market. Since the COVID-19, the spillover effect of corn in the medium term has been significantly stronger, and the soybean market, which is also a net transmitter, has shown a stronger net spillovers on time scales except for the short term. In fact, the study of Grieb (2015) also believes that the corn market plays an important role in the spillover effect between commodities. Notably, we find that the spillover effect of corn on the soybean market has been significantly weakened. This means that the pandemic has had an impact on the previous strong correlation between these two energy crops (Debdatta Pal and Mitra, 2019). Moreover, it is worth noting that the time-varying spillover indices show that the corn and oil markets tend to change their normal roles as the transmitter and receiver of spillovers respectively in the event of their deep declines, except in the short run, when their roles are relatively stable. Finally, the pairwise spillover index between the food and crude oil markets indicates that the spillover effect of corn on the crude oil market is enhanced during the pandemic crisis, and the statistical significance of this finding is further supported by Bayesian inference in the medium to long term. In addition, crude oil is significantly affected by soybeans on a longer time scale. This further supports the conclusions of Karakotsios et al. (2021) and Y. Sun et al. (2021) that the crude oil market is subject to spillover effects from energy crops, which can be explained by biofuel and commodity financialization channels.

Our findings have the following policy implications for different market participants to understand the spillover effects of the food and oil markets in the pandemic crisis and to mitigate the cross spillover effects between markets or assets. Specifically, the stronger spillovers of the food-oil market system in the short term mean that regulators need to timely prevent cross-market or cross-asset linkages that rely on financial channels, so as to formulate better policy optimization measures and maintain market stability. In addition, special attention should be paid to the spillover effects of the two energy crops, corn and soybeans, during the pandemic, especially the strong spillover effects on the crude oil market over the longer term. This cross-market spillovers may further affect the production costs of all agricultural products and make food prices more expensive, thus amplifying the fluctuations in food market and may even trigger a food crisis. Therefore, policymakers should strengthen the information supervision of the corn and soybean markets, and re-formulate strategies based on the correlation between energy crops and crude oil markets to prevent food crises caused by cross-market risk spillovers. For investors, it is of great significance to understand the spillover effects between the food and oil markets for their portfolio risk management. Based on our findings, corn and soybeans have significant spillover effects on wheat and crude oil under the impact of the pandemic, while the spillover relationship between the rice market and all other markets is weak. Given the increased interaction between the commodity markets, the possibility of diversifying commodity investment strategies to increase risk hedging has been reduced. Therefore, when designing diversified portfolio strategies, investors can refer to the above findings to formulate the desired risk hedging strategies, adjust the portfolio reasonably, and seek new investment opportunities.

Credit author statement

Yan Cao: Methodology; Software; Formal analysis; Investigation; Writing-Original Draft; Writing-Review & Editing. Sheng Cheng: Conceptualization; Methodology; Software; Writing-Review & Editing; Supervision.

Declaration of competing interest

None.

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Appendix A

Note: The figure shows the dynamic characteristics of the net spillover over time from this market to all other markets in the food-oil market system, as explained in the static spillover table, which is obtained by subtracting From_ABS from To_ABS. The horizontal axis is the timeline and the vertical axis is the net spillover index. The other figures in the appendix follow this note.
Fig. A1. Net spillovers (WTI).
Fig. A2. Net spillovers (rice).
Fig. A3. Net spillovers (corn).
Fig. A4. Net spillovers (wheat).
Fig. A5. Net spillovers (soybean).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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