Resources Policy 73 (2021) 102166

Contents lists available at ScienceDirect

Resources Policy

journal homepage: www.elsevier.com/locate/resourpol

Return connectedness among commodity and financial assets during the COVID-19 pandemic: Evidence from China and the US

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ARTICLE INFO

Keywords:
COVID-19
Time-varying connectedness
Commodities
Financial assets

ABSTRACT

In this paper, we explore the dynamics of the return connectedness among major commodity assets (crude oil, gold and corn) and financial assets (stock, bond and currency) in China and the US during recent COVID-19 pandemic by using the time-varying connectedness measurement introduced by Antonakakis et al. (2020). Firstly, we find that the total return connectedness of the US commodity and financial assets is stronger than that of the Chinese commodity and financial assets in most cases, and both of them increase rapidly after the outbreak of COVID-19. Secondly, gold is a net transmitter of return shocks in both the Chinese and the US markets before the burst of COVID-19 pandemic, while stock and currency become net transmitters of shocks in both markets after that. Thirdly, corn usually receives the shocks from other commodity and financial assets in both China and the US markets during the COVID-19 epidemic, and the shocks it receives peak during this period, making it the strongest net receiver of shocks. Fourthly, crude oil shifts from a net transmitter to a net receiver of shocks in China after the outbreak of COVID-19, but it remains to be a net transmitter of shocks in the US. Finally, bond changes from a net receiver to a net transmitter of shocks in China after the outbreak of the epidemic, but converts from a net transmitter to a net receiver of shock in the US. The interchangeable roles of the commodity and financial assets suggest flexible regulatory and portfolio allocation strategies should be applied by policy makers and investors.

1. Introduction

Achieving greater diversified asset allocation is an important strategic goal for portfolio managers and investors. It requires investors and portfolio managers to be fully aware of the knowledge about the connectedness (spillovers) between different asset classes. In the first half of 2020, the epidemic of COVID-19 caused a huge shock on global economic activity. During this period, the unemployment rate has increased significantly, the economic and financial uncertainties have surged, and the energy and financial assets have plummeted, leading to the chaos of international financial system, disrupting asset allocation and risk management and endangering global financial stability. As a result, the COVID-19 epidemic aroused new interests in systemic risk spillover in financial system in catastrophic events (Baig et al., 2021; Baker et al., 2020; Gormsen and Koijen, 2020; Haddad et al., 2020; Sharif et al., 2020; Zhang et al., 2020). However, with the financialization of commodity assets, investors have become more and more active in commodity markets, making commodity assets more and more important options for asset allocations along with traditional financial assets. So, understanding the formation mechanism of systemic risks across commodity and financial markets and how commodity and financial assets respond to shocks during the COVID-19 epidemic are of great implications for risk management, asset allocation and policy making.

Specially, China is the first country who reported the discovery of the COVID-19 epidemic. China reported the first COVID-19 infection on December 8, 2019. On January 23, 2020, Wuhan, a mega-city located in the central part of China, announced to lock down the city, further providing a signal for the accelerated spread of COVID-19. Influenced by this pandemic, the Chinese stock market fell sharply on February 3, 2020, with more than 3000 stocks limited down and both the Shanghai Exchange Composite index (SSEC) and the ShenZhen Stock Exchange

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https://doi.org/10.1016/j.resourpol.2021.102166
Received 2 September 2020; Received in revised form 17 May 2021; Accepted 25 May 2021
Available online 6 June 2021

Component Index (SZSE) experienced the biggest one-day-drop since 2015. To fight the COVID-19 epidemic and de-escalated the impact of COVID-19 epidemic on macroeconomy, the Chinese government quickly adopted various social prevention and control measures, and took the lead in resuming work and production. By April 8, Wuhan reopened, the epidemic in China was basically under control, the economy in China was also continuing to recover. However, in the US, the COVID-19 did not widely spread until March, and, the severity of the epidemic was not realized until March 12, 2020, when the US government declared a state of emergency for COVID-19. Due to failure of taking timely precautions and control measures, the number of infections and deaths caused by COVID-19 have been rising dramatically in the US since then, and eventually far surpassed those of other countries in the world. By mid-June 2020, the epidemic in the US had not yet been effectively controlled, this also severely impacted the development of the US economy. In summary, given the different situations of COVID-19 epidemic in China and the US and the various measures taken by them to fight COVID-19 epidemic, as well as the inherent differences in the characteristics of commodity and financial markets in China and the US, the time-varying return connectedness (spillovers) among commodity and financial assets of these two countries may also be distinct. So, it is important to explore the similarities and differences of the dynamics of return connectedness (spillovers) among commodity and financial assets in the Chinese and the US markets under the background of the COVID-19. Meanwhile, exploring the similarities and differences in return connectedness across commodities and financial assets in China and the US during the COVID-19 epidemic can provide important guide for investors and policy makers in risk management, asset allocation and policy adjustment under similar events. Further inspired by the researches of Wang and Chueh (2013), Kang et al. (2017), Yoon et al. (2019) and Zhang et al. (2019a,b), this paper focuses on analyzing the dynamics of the return connectedness (spillovers) among three major commodity assets (crude oil, gold and corn) and three major financial assets (stock, bond and currency) across the COVID-19 pandemic.

Since the outbreak of COVID-19, researches have explored the huge impacts of COVID-19 on economic and financial systems (Bai et al., 2020, 2021; Bai et al., 2020; Baker et al., 2020; Gormsen and Koijen, 2020; Haddad et al., 2020; Sharif et al., 2020; Zhang et al., 2020). Different from these works, we evaluate the time-varying responses of the systems composed of major commodity and financial assets in China and the US across the COVID-19 epidemic. This is an important task for existing COVID-19 related researches. In terms of research method, conditional correlation methods (Balcilar and Ozdemir, 2013; Chen et al., 2020; Dua and Tuteja, 2016; El Ghini and Saidi, 2016; Lei et al., 2019; Liang et al., 2020a; Liang et al., 2020b; Öztek and Öcal, 2017; Tsuji, 2020; Wei et al., 2017, 2020a, 2020b, 2021; Wright and Hirano, 2002; Zhang et al., 2019, 2020; Zhang et al., 2019a,b), Granger-causality (Balboa et al., 2015; Massa and Rosellón, 2020; Papana et al., 2017; Woźniak, 2016; Yang et al., 2021), copula models (Apergis et al., 2020; Boako et al., 2019; Kotkatvuori-Örnberg, 2016; Mensah and Premaratne, 2017; Rodriguez, 2007; Wen et al., 2012), and conditional value-at-risk (Ji et al., 2018a, 2019; Li and Wei, 2018; Mensi et al., 2017; Reboredo and Ugolini, 2015, 2016) are widely used to explore the characteristics of the information transmission between two variables/assets. Since Diebold and Yılmaz (2009, 2012, 2014)'s study which explore the connectedness across an asset system, a large body of literature realizes the importance of uncovering system spillovers in a large system (Ji et al., 2018b; Lundgren et al., 2018; Tiwari et al., 2020; Wang et al., 2020; Wei et al., 2019; Yoon et al., 2019; Zeng et al., 2019; Zhang, 2017). However, the dynamic connectedness network of Diebold and Yılmaz (2009, 2012, 2014) is measured using the rolling window method, implying that different settings of rolling-window sizes will result in unstable connectedness measures. Thereby, the method introduced in Antonakakis et al. (2020) successfully solves this problem by allowing the variance-covariance matrix to vary via a Kalman filter estimation with Koop and Korobilis (2014)'s forgetting factors. Besides, its loss of observations is much smaller than the one used in Diebold and Yılmaz (2009, 2012, 2014), the method of Antonakakis et al. (2020) can be very effective in dealing with short-sample datasets. So, Antonakakis et al. (2020)'s method is preferred in this paper to capture the time-varying return connectedness among the commodity and financial assets.

This paper is closely related to Bouri et al. (2021), however, it is different in the following aspects. Firstly, we consider not only the five assets used in Bouri et al. (2021), but also another more commodity asset, i.e., corn, to explore the spillover effects among three commodity assets (oil, gold and corn) and three financial assets (stock, foreign currency and bond). Secondly, the data employed in Bouri et al. (2021) are spot price index of S&P GSCI gold, S&P GSCI crude oil, MSCI World, USD index, and PIMCO Investment Grade Corporate bond index Exchange-Traded Fund, which are usually utilized to indicate the overall performances of international financial markets. However, our research focuses on the performances of commodity and financial market in two large counties, i.e., China and the US. Thus, we use both concrete futures and spot prices in these two countries instead of employing the international price indices. Finally, Bouri et al. (2021) do their analyses by comparing the empirical results before and after the outbreak of COVID-19 pandemic. Whereas we divide the full sample into five sub-samples according to four important time points, when several major events happen during the evolution of COVID-19 pandemic in both China and the US. This approach can offer us more accurate information about the connectedness dynamics among the assets during the pandemic, and provide more important guides for investors and policy makers in risk management, asset allocation and policy adjustment under similar public health emergencies. In addition, this paper supplies many explanations in details for the similarities and differences in connectedness of China and the US assets, which are of great importance for investors and policy makers. The empirical results show firstly that the dynamic return connectedness of the US market is stronger than that of the Chinese market in most cases, and both of them increase rapidly after the outbreak of COVID-19. Specially, the return connectedness of the US assets experiences two rapid increases after that, and reaches its peak at the second spike. Secondly, gold shifts from a net transmitter to a net receiver of return shocks in both the Chinese and the US market after the outbreak of COVID-19, while stock and currency become net transmitters of shocks in both markets after that. Meanwhile, stock was at one point the strongest source of shocks in both the Chinese and the US market. Thirdly, corn remains to act as a net receiver of shocks in both the Chinese and the US market after the outbreak of COVID-19 epidemic, and the shocks it receives peaked during this period, making corn the strongest net receiver of shocks. Another commodity asset, crude oil, turns from a net transmitter to a net receiver of shocks in China after the outbreak, but it is always a net transmitter of shocks in the US. Bond converts from a net receiver to a net transmitter of shock in China after the outbreak, but it changes from a net transmitter to a net receiver in the US.

The rest of this paper are constructed as below: Section 2 describes the methodology utilized in this paper, Section 3 depicts the data, Section 4 discusses the empirical results, Section 5 supplies explanations about the similar and different empirical findings in the Chinese and the US markets and Section 6 concludes this paper.

2. Methodology

In recent years, the method proposed by Diebold and Yılmaz (2009, 2012, 2014) is widely used to capture static and dynamic connectedness network across multiple assets. For this approach, the dynamic connectedness is constructed through the rolling-window vector autoregessive model (VAR), which has the drawback of unstable dynamic connectedness measurement with the different settings of rolling-window sizes. Different from this method, Antonakakis et al. (2020) constructs the dynamic connectedness network using the Kalman fitter based time-varying parameter VAR model. The advantage of Antonakakis et al. (2020)'s framework over Diebold and Yılmaz (2009, 2012, 2014)' approach is that it need not choose the size of rolling-window, making the dynamic connectedness captured by this method being more stable and robust. Moreover, Antonakakis et al. (2020)'s framework has no loss of observations in the estimation procedure, making it a more suitable approach for capturing the dynamic connectedness in small-sample datasets. Finally, the outliers caused by the underlying Kalman filter do not affect the final measures, thus the true parameter values can be more accurately estimated. Antonakakis et al. (2020)'s connectedness network is described as follows. First, we define a TVP-VAR(p) model with m variables as:

$$Y_t = B_t Z_{t-1} + \varepsilon_t \quad \varepsilon_t|\Omega_{t-1} \sim N(0, \Sigma_t) \tag{1}$$

$$vec(B_t) = vec(B_{t-1}) + \xi_t \quad \xi_t|\Omega_{t-1} \sim N(0, \Xi_t) \tag{2}$$

where, $Y_t = (y_{1,t}, y_{2,t}, \ldots, y_{m,t})^{'}$ is a $m \times 1$ vector at time t, $Z_{t-1} = (Y_{t-1}, Y_{t-2}, \ldots, Y_{t-p})^{'}$, p is the lag order, $B_t = (B_{1t}, B_{2t}, \ldots, B_{pt})$ is a $m\times mp$ dimensional parameter matrices and B_{it} is a $m \times m$ dimensional parameter matrices for ith lag order, $vec(B_t)$ is a $m^2p \times 1$ dimensional vector, representing the vectorization of B_t, ε_t and ξ_t are $m\times 1$ error vector and $m^2p \times 1$ dimensional error vector, respectively, Ω_{t-1} donates the information available until t-1, Σ_t and Ξ_t are $m \times m$ and $m^2p\times m^2p$ dimensional variance-covariance matrices for the error vector ε_t and ξ_t, respectively. Following Antonakakis et al. (2020), we select the lag order p by the AIC criterion, and the lag order for the Chinese and the US datasets are finally set to be 7 and 8, respectively.

Then, the multivariate Kalman filter is used to get the dynamic of B_t, Σ_t^B and Σ_t. The multivariate Kalman filter can be described as the following formula:

$$vec(B_t)\Big|Z_{1:t} \sim N\left(vec\left(B_{t|t-1}\right), \Sigma_{t|t-1}^B\right) \tag{3}$$

$$B_{t|t-1} = B_{t-1|t-1} \tag{4}$$

$$\varepsilon_t = y_t - B_{t|t-1}Z_{t-1} \tag{5}$$

$$\Sigma_t = \kappa_2\Sigma_{t-1|t-1} + (1-\kappa_2)\varepsilon_t^{'}\varepsilon_t \tag{6}$$

$$\Xi_t = \left(1-\kappa_1^{-1}\right)\Sigma_{t-1|t-1}^B \tag{7}$$

$$\Sigma_{t|t-1}^B = \Sigma_{t-1|t-1}^B + \Xi_t \tag{8}$$

$$\Sigma_{t|t-1} = Z_{t-1}\Sigma_{t|t-1}^B Z_{T-1}^{'} + \Sigma_t \tag{9}$$

where, κ_1 and κ_2 are forgetting factor and decay factor, respectively. Following Koop and Korobilis (2014) and Antonakakis et al. (2020), we set $\kappa_1 = 0.99$ and $\kappa_2 = 0.96$. B_t, Σ_t^B and Σ_t in this paper are updated by:

$$vec(B_t)\Big|Z_{1:t} \sim N\left(vec\left(B_{t|t}\right), \Sigma_{t|t}^B\right) \tag{10}$$

$$K_t = \Sigma_{t|t-1}^B Z_{t-1}^{'}\Sigma_{t|t-1}^{-1} \tag{11}$$

$$B_{t|t} = B_{t|t-1} + K_t\left(Y_t - B_{t|t-1}Z_{t-1}\right) \tag{12}$$

$$\Sigma_{t|t}^B = \left(I - K_t\right)\Sigma_{t|t-1}^B \tag{13}$$

$$\varepsilon_{t|t} = Y_t - B_{t|t}Z_{t-1} \tag{14}$$

$$\Sigma_{t|t} = \kappa_2\Sigma_{t-1|t-1} + \left(1-\kappa_2\right)\varepsilon_{t|t}^{'}\varepsilon_{t|t} \tag{15}$$

where, K_t is the Kalman gain.

The dynamic coefficients and variance-covariance matrices are used for the procedure of generalized forecast error variance decomposition (GFEVD). To calculate the GFEVD, the TVP-VAR is transformed into a TVP-VMA process by:

$$Y_t = B_t Z_{t-1} + \varepsilon_t = \sum_{h=0}^{\infty} A_{h,t}\varepsilon_{t-l}. \tag{16}$$

Then, the GFEVD can be written as:

$$\widetilde{\Phi}_{ij,t}(H) = \frac{\sum_{h=0}^{H-1}\Psi_{ij,t}(h)^2}{\sum_{j=1}^{m}\sum_{h=0}^{H-1}\Psi_{ij,t}(h)^2} \tag{17}$$

where $\widetilde{\Phi}_{ij,t}(H)$ is the H-step ahead GFEVD, donating the directional connectedness from variable j to variable i, $\Psi_{ij,t}(h) = \Sigma_{jj,t}^{-1/2}e_{i,t}{}'A_{h,t}\Sigma_t e_{j,t}$, $e_{i,t}$ and $e_{j,t}$ are the selection vector which have a value 1 for the ith and jth component and 1 for otherwise. Following Zeng et al. (2019) and Wang et al. (2020), H is set to be 100 in this paper. By construction, $\sum_{j=1}^{m}\widetilde{\Phi}_{ij,t}(H) = 1$ and $\sum_{i=1,j=1}^{m}\widetilde{\Phi}_{ij,t}(H) = m$.

Using Eq. (17), the total connectedness index (TCI) which quantifies the connectedness of the whole asset system can be measured as:

$$C_t(H) = \frac{\sum_{i,j=1,i\neq j}^{m}\widetilde{\Phi}_{ij,t}(H)}{\sum_{i=1,j=1}^{m}\widetilde{\Phi}_{ij,t}(H)}*100. \tag{18}$$

Then, the TO connectedness index, which quantifies the contribution of asset i to all other assets j can be defined as:

$$C_{i\to *,t}(H) = \frac{\sum_{j=1,j\neq i}^{m}\widetilde{\Phi}_{ji,t}(H)}{\sum_{i=1,j=1}^{m}\widetilde{\Phi}_{ji,t}(H)}*100. \tag{19}$$

Similarly, the spillovers received by asset i from all other assets j (FROM connectedness index) can be measured as:

$$C_{i\leftarrow *,t}(H) = \frac{\sum_{j=1,j\neq i}^{m}\widetilde{\Phi}_{ij,t}(H)}{\sum_{i=1,j=1}^{m}\widetilde{\Phi}_{ij,t}(H)}*100. \tag{20}$$

Then, we can obtain the net connectedness index from asset i to all other asset j by calculating the difference of the TO connectedness and the FROM connectedness of asset i:

$$C_{i,t} = C_{i\to *,t}(H) - C_{i\leftarrow *,t}(H). \tag{21}$$

The net connectedness index can quantify the net contribution of each assets to the whole asset system. It is also important to explore the net pairwise connectedness index, which describe the bidirectional relationships between two assets. The net pairwise connectedness index between asset i and asset j can be simply defined as the difference of the shocks transmitted from asset i to asset j and that transmitted from asset j to asset i, that is:

$$Net_{ij,t}(H) = \left(\frac{\widetilde{\Phi}_{ij,t}\left(H\right)}{\sum_{i=1,j=1}^{m}\widetilde{\Phi}_{ji,t}\left(H\right)} - \frac{\widetilde{\Phi}_{ji,t}\left(H\right)}{\sum_{i=1,j=1}^{m}\widetilde{\Phi}_{ji,t}\left(H\right)}\right)*100. \tag{22}$$

A positive $Net_{ij,t}(H)$ means that asset i is dominated by asset j.

3. Data

Following the works of Wang and Chueh (2013), Kang et al. (2017), Yoon et al. (2019) and Zhang et al. (2019a,b), three commodity assets and three financial assets, which are heavily traded in the world, are investigated in this paper. The three major commodity assets are crude oil, gold and corn, and the three financial assets consists of stock, bond and currency. For the Chinese market, we use the prices of crude oil futures in Shanghai International Energy Exchange (INE), gold futures of

Shanghai Futures Exchange (SFE), and corn futures in Dalian Commodity Exchange (DCE), the CSI 300 index and the 10-year Treasury bond futures in China Financial Futures Exchange (CFFEX), and the RMB-US dollar foreign exchange rate as data sample. For the US market, we consider the crude oil futures prices of New York Mercantile Exchange (NYMEX), the gold futures prices of New York Commodity Exchange (COMEX), the corn futures prices of CBOT, the S&P 500 index, the 10-year Treasury bond futures prices of Chicago Board of Trade (CBOT), and the US dollar index as data sample.[1]

The data sample covers the period from March 26, 2018 to June 12, 2020.[2] For comparison purposes, we collate data and remove the observations with missing dates in both the Chinese and the US markets. All the price series are transferred to natural logarithmic returns for the purpose of stationary. These return series for China and the US markets are shown in Fig. 1 and Fig. 2, respectively. Table 1 further presents the summary statistics of these series. As shown in Table 1, the standard deviations of the six assets in China are smaller than those in the US, indicating that the Chinese market exhibits lower price volatility and thus is safer than the US market. Besides, we find that crude oil and stock returns in both Chinese and the US markets are left skewed, while gold, bond and currency are right skewed. Specially, the corn asset is right skewed in China but left skewed in the US. The Kurtosis statistics of all asset series are larger than 3, indicating the peak and fat-tailed characteristics in the distribution of these series. The Jarque-Bera statistics reject the null hypothesis of normality for all series. The results of ADF (unit root) test show that all series are stationary, indicating that the use of TVP-VAR framework is appropriate. The Ljung-Box Q statistics show that the serial correlation exist in all series except for corn and currency returns in China and corn in the US.

3.1. Empirical results

3.1.1. Total connectedness

Fig. 3 shows the dynamics of the total return connectedness index among all six assets in China. We can see that the total return connectedness among commodity and financial assets in China fluctuates calmly (i.e., lower than 35%) over a long period of time before January 2020. But it increases sharply to the top value of about 50% after that time, which corresponds exactly to the date when Wuhan locked down the city. Interestingly, this increasing connectedness does not last long but declines quickly since March 2020. By the end of May 2020, it decreases to lower than 30%, which is close to the average level before the outbreak of COVID-19. Fig. 4 draws the dynamics of the total return connectedness index among all six assets in the US. There is a dramatic surge in total return connectedness in the US asset system at the end of January 2020, further followed by another spike in early March 2020. The high total connectedness of the US market did not last long, either. By May 2020, it also recovered to the normal level before the pandemic. In terms of overall pictures in China and the US, we find that the total connectedness in the US markets is stronger than that of the Chinese markets in most cases.

3.2. Net directional connectedness

In this sub-section, the time-varying net directional connectedness of each asset is calculated to show the net contribution of each asset to the asset systems in China and the US, respectively. A positive net directional connectedness index indicates that the corresponding asset transmits more shock to the whole system than it receives from the whole asset system, acting as a net transmitter of return shocks. Conversely, a negative net directional connectedness index indicates a net receiver of shocks.

Figs. 5 and 6 draw the dynamics of the net directional connectedness indices of commodity and financial assets in China and the US, respectively. Fig. 5 shows firstly that the net directional connectedness of the six assets in China are not always positive or negative, implying that these assets do not always play the role as a net transmitter or receiver of shocks in China. With regards to three commodity assets, crude oil and gold both shift from a net transmitter to net receivers of shock after the closure of Wuhan, and both become net transmitters again after mid-March. Differently, gold briefly reverts to its role as a net transmitter of shock in early March, but becomes a net receiver again when the US declared a state of emergency. However, it quickly re-emerges as a net transmitter of shocks again. As for corn, it acts as the net receiver of shock in most cases, and plays the role of a net receiver even after the closure of Wuhan, but the intensity of the shock continues to increase.

For three financial assets, they all convert from net receivers to net transmitters of shock after the closure of Wuhan. However, stock, bond and currency turn to be net receivers of shock in late April, mid-March and early March, respectively. The role of currency as a net receiver of shock remains unchanged since the early March, while stock and bond become net transmitters of shock again in late May.

In short, in China, corn remains to be a net receiver of shocks after the outbreak of COVID-19 epidemic, and the intensity of the shock it receives peaks after the outbreak. Crude oil and gold, however, changed from net transmitters to net receivers of shock after the closure of Wuhan, while three financial assets change from net receivers to net transmitters of shocks. Moreover, both crude oil and gold resume their roles as net transmitters of shock in the later stages. The three financial assets have also recovered their roles as net receivers of shock in the later stages.

Fig. 6 shows the net directional connectedness indices of commodity and financial assets in the US. Similarly, the role of the six assets in the US are not stable. Specially, the roles of all assets, except for crude oil and corn, have changed significantly after the outbreak of COVID-19. Across the three commodity assets in the US, crude oil and corn remain to be a net transmitter and a net receiver of shocks, respectively, after the outbreak of COVID-19 pandemic. Specifically, crude oil experiences two rapidly increases in its net connectedness during the COVID-19 epidemic, where the first surge happens after the US's declaration of state emergency for COVID-19, and the second spike appears in late April, accompanied with obvious slump in crude oil futures prices. As for corn, it acts the role of a net receiver of shock in the two months before the closure of Wuhan, the intensity of the shock strengthens heavily after that and peaks after the US's declaration of state emergency. Another commodity asset, gold, changes from a net transmitter to a net shock receiver of shock after the closure of Wuhan. However, gold temporarily turns back to a net transmitter in early March but quickly becomes a net receiver after the US declaration of state emergency. By early June, gold shows signs of returning to a net transmitter of shocks.

Across three financial assets in the US, stock and currency shift from net receivers to net transmitters of shock after the outbreak of COVID-19, while bond converts from a net transmitter to a net receiver. In particular, the transformation of stock happens after the closure of Wuhan, while the changes of bond and currency come up after the US's declaration of state emergency. Besides, by mid-June, stock and bond have not yet converted back to be net receiver and net transmitter of shock, respectively. However, currency turns to be a net receiver of shock at the end of April.

In short, crude oil and corn remain to be a net transmitter and a net receiver of shocks, respectively, in the US before and after the outbreak of COVID-19. However, gold and bond convert from net transmitters to net receivers of shocks in the US after the outbreak, while stock and currency shift from net receivers to net transmitters. Specially, the changes of gold and stock come up after the closure of Wuhan, while the transformations of bond and currency occur after the US's emergency

[1] These data are collected from RESSET database, Federal Reserve Bank of St. Louis and https://www.macrotrends.net.

[2] The data sample spans from March 26, 2018 to June 12, 2020 due to the fact that Chinese crude oil future (SC) was first launched on March 26, 2018.

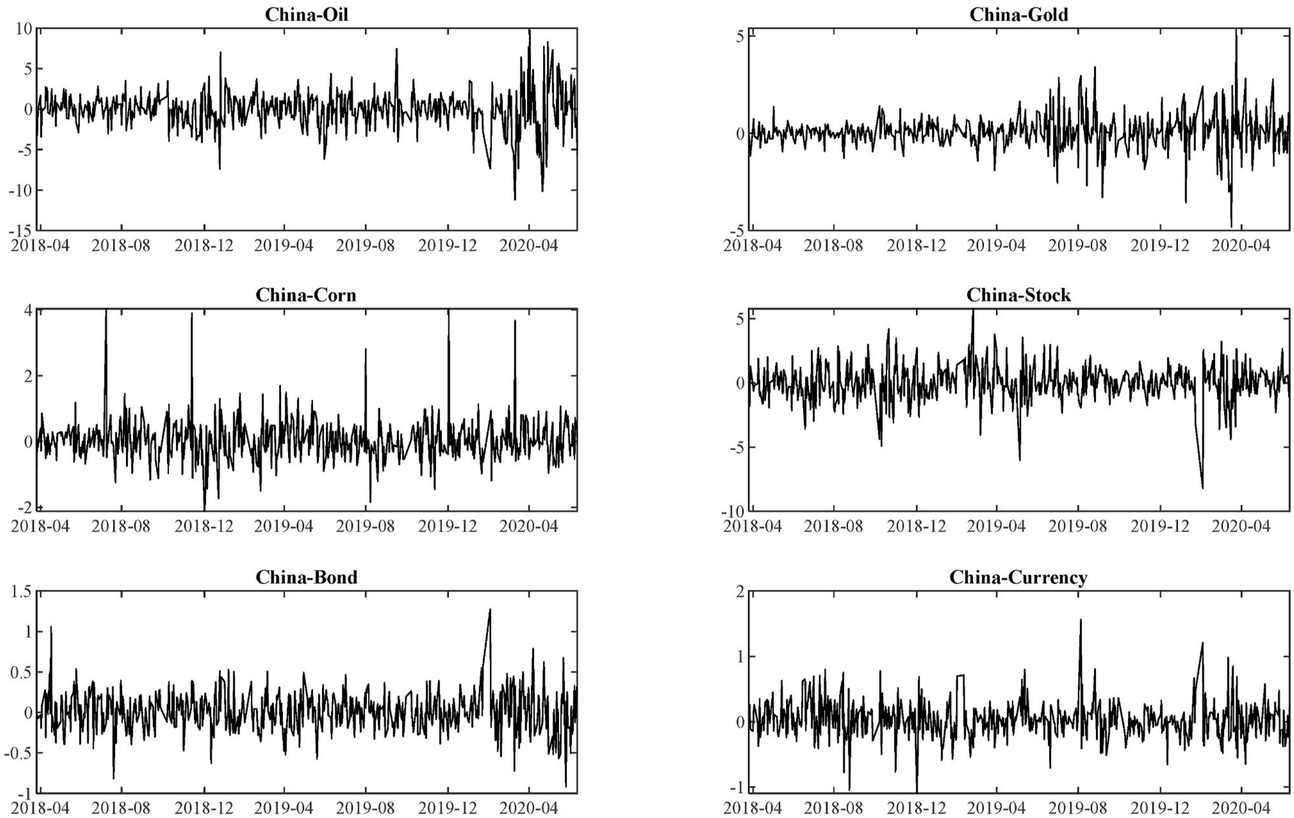

Fig. 1. Returns of commodity and financial assets in China.

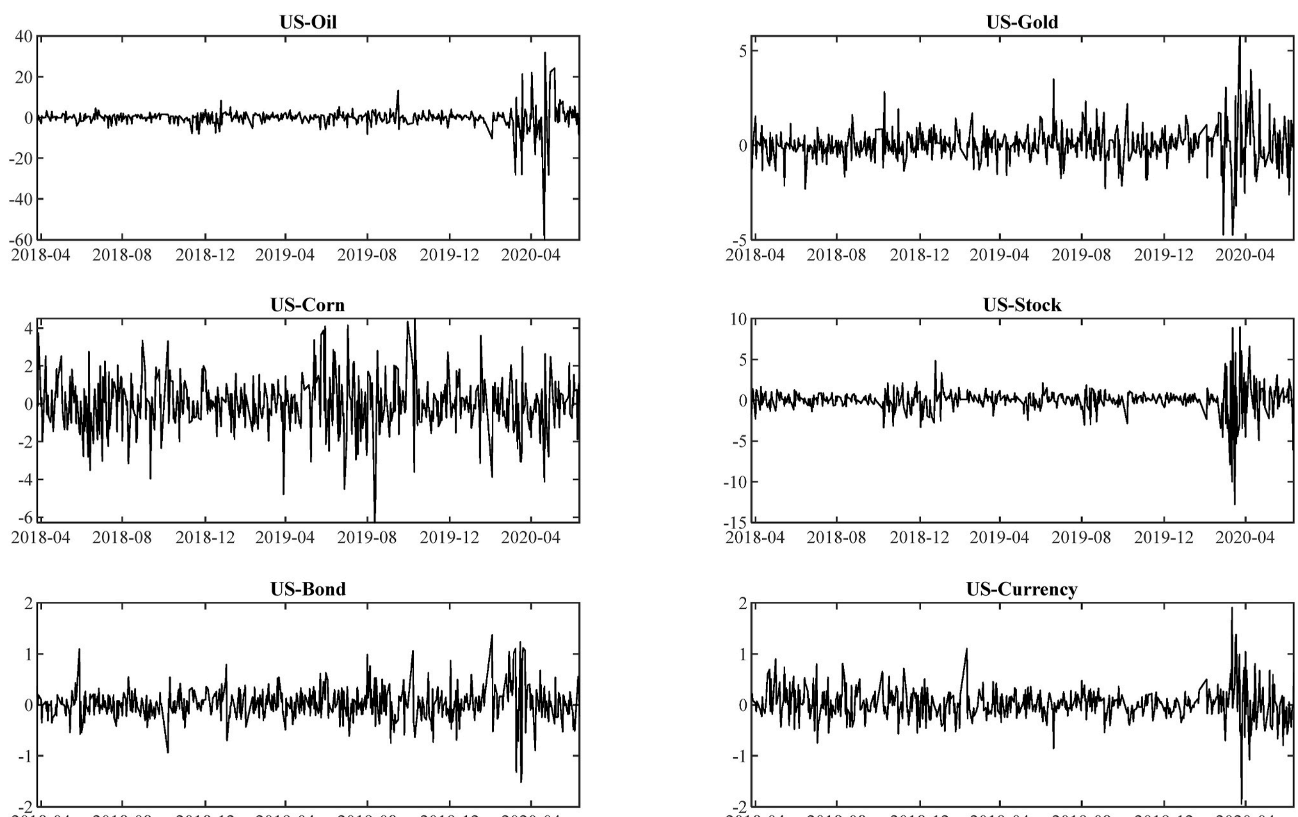

Fig. 2. Returns of commodity and financial assets in the US.

Table 1
Summary statistics.

	China-oil	China-gold	China-corn	China-stock	China-bond	China-currency	US-oil	US-gold	US-corn	US-stock	US-bond	US-currency
Mean	−0.093	0.069	0.034	0.006	0.014	0.024	−0.115	0.048	−0.024	0.026	0.027	0.021
Std.	2.381	0.892	0.656	1.403	0.248	0.289	5.222	0.968	1.399	1.646	0.324	0.321
Skew.	−0.338	0.093	1.601	−0.460	0.181	0.503	−2.732	0.419	−0.209	−0.996	0.096	0.362
Kurt.	6.358	8.906	12.041	6.579	4.909	5.857	46.132	10.169	4.849	17.829	6.500	8.981
JB	251.215***	747.816***	1970.485***	292.509***	80.875***	196.552***	40,481.868***	1115.762***	76.952***	4794.443***	263.079***	777.261***
ADF	−20.685***	−23.193***	−24.312***	−23.735***	−23.018***	−24.145***	−23.894***	−22.013***	−22.147***	−30.734***	−23.741***	−21.467***
Q (5)	11.148**	4.964	6.797	10.324*	3.738	6.719	30.729***	7.324	2.835	95.333***	8.762	17.692***
Q (10)	13.536	19.377**	9.269	10.871	18.726**	15.660	36.290***	30.202***	12.876	241.341***	23.200**	32.987***
Q (20)	26.224	36.304**	18.116	16.330	39.119***	25.190	64.214***	64.629***	27.561	302.435***	32.600**	43.997***

Notes: This table list the summary statistics of the financial assets and commodities in China and in US. "Mean" and "Std." summarize means and standard deviations, respectively. "Skew." and "Kurt." are the skewness and kurtosis, respectively. "JB" is the Jarque-Bera statistics for testing the null hypothesis of normality. "ADF" indicates the statistics of unit root test. Q(5), Q(10) and Q(20) are the Ljung-Box statistics of return series for up to 5th, 10th and 20th order serial correlation.

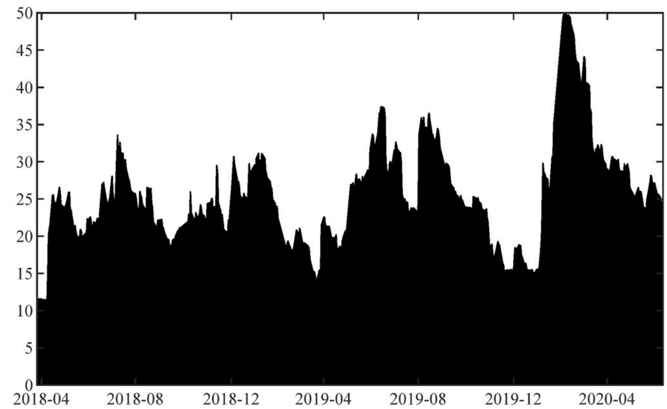

Fig. 3. Total return connectedness index among commodity and financial assets in China.

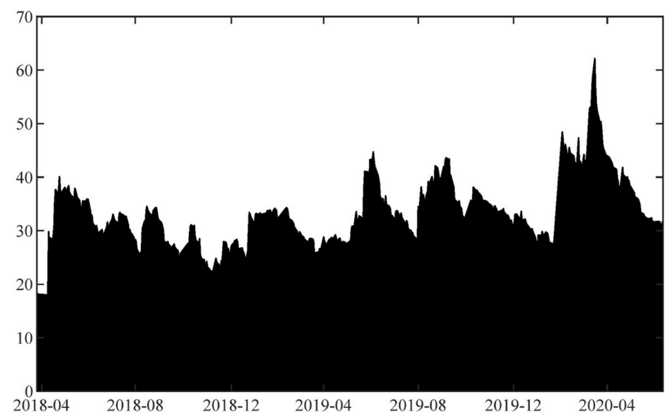

Fig. 4. Total return connectedness among commodity and financial assets in the US.

state. In the later stages of pandemic, gold returns to be the net transmitter of shock and currency also resumes its role as a net receiver of shock, while stock and bond do not return to the net transmitter and receiver of shocks, respectively.

3.3. Net pairwise directional connectedness

In this sub-section, the characteristics of net pairwise directional connectedness indices in China and the US asset system are explored. It can be seen from the analysis in Section 4.1 and 4.2, the closure of Wuhan (*January 23, 2020*) and the declaration of the US for an emergency state for COVID-19 (*March 12, 2020*) are two important events during the global COVID-19 pandemic. Besides, China reported the first COVID-19 infection on December 8, 2019, marking the burst of COVID-19 epidemic. Then, the reopen of Wuhan (*April 8, 2020*) indicated that the COVID-19 epidemic was basically under control in China. So, we divide the full sample into five sub-samples according to these important events and compute the average net pairwise directional connectedness during each period, and draw corresponding net pairwise directional connectedness networks to investigate the pairwise spillover characteristics during different periods.

The average connectedness measures among commodity and financial assets in China are listed in Table 2 and the corresponding net pairwise directional connectedness networks are drawn in Fig. 7. Table 2 and Fig. 7 show firstly that oil can dominate all the other five assets in period 0, but currency is dominated by all the other assets. Meanwhile, oil and currency transmit and receive about 2.4% and 1.6% net shocks from the whole asset system, respectively, becoming the strongest net

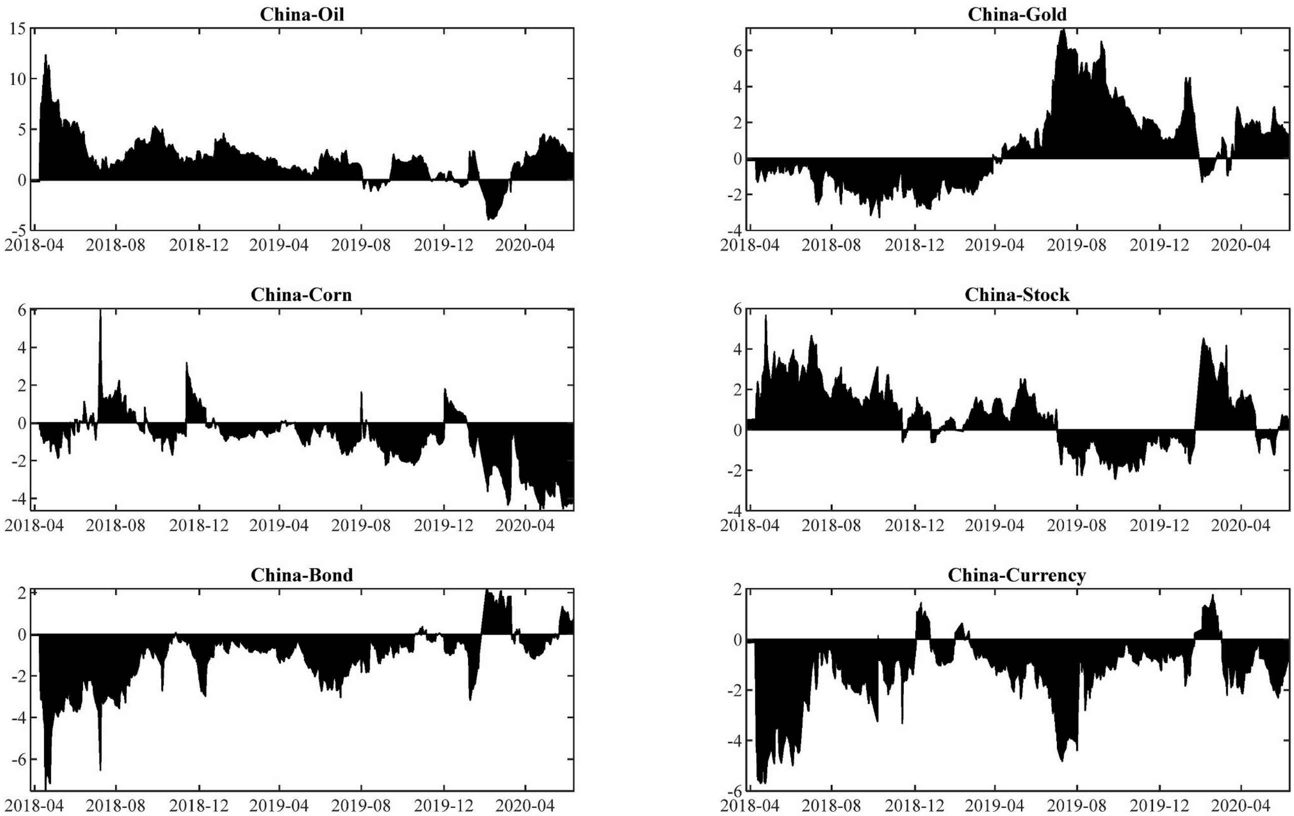

Fig. 5. Net directional connectedness index of commodity and financial assets in China.

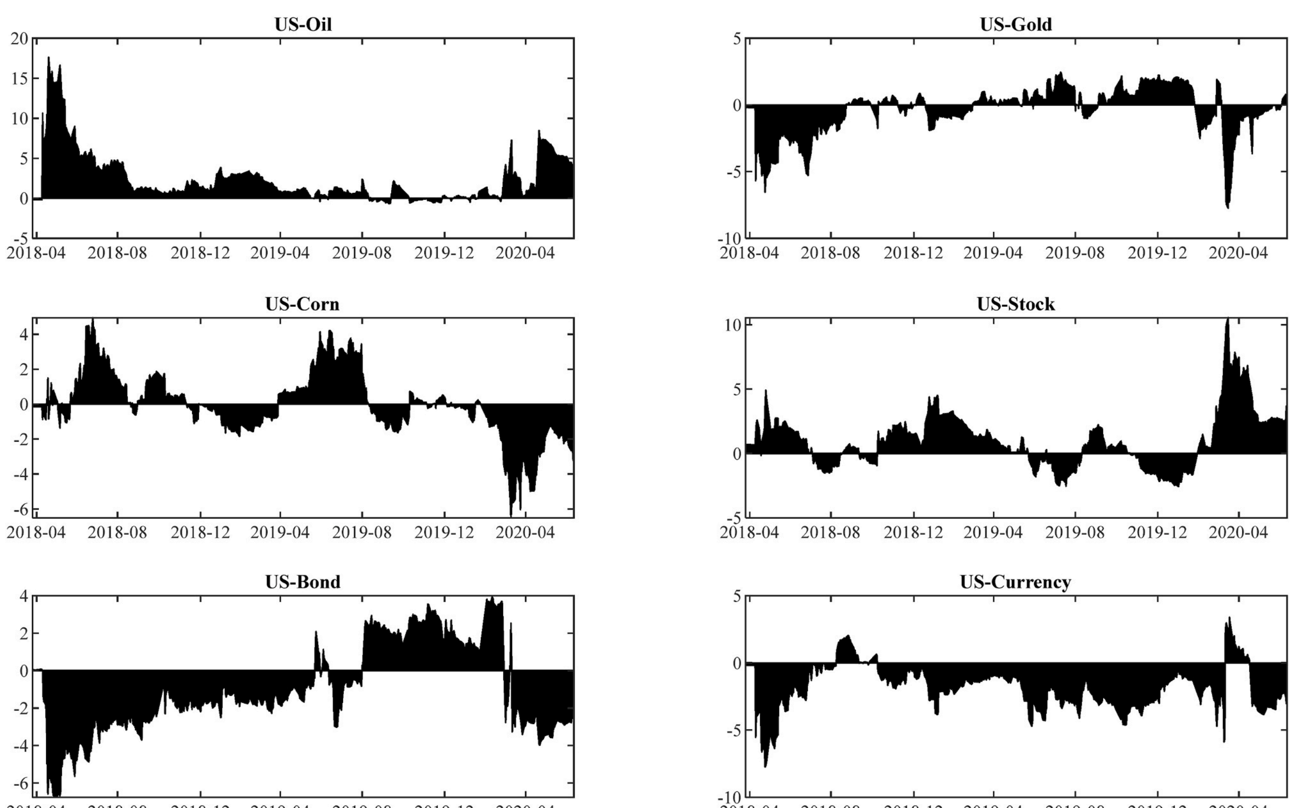

Fig. 6. Net directional connectedness of commodity and financial assets in the US.

Table 2
Average connectedness among commodity and financial assets in China.

	Oil	Gold	Corn	Stock	Bond	Currency	From
Period 0: 2018/03/27–2019/12/06							
Oil	85.4	4.6 (−0.3)	2.2 (−0.5)	3.8 (−0.2)	1.7 (−0.5)	2.2 (−0.8)	2.4
Gold	6.4 (0.3)	74.6	2.1 (−0.2)	7.1 (0.0)	4.3 (−0.2)	5.5 (−0.2)	4.2
Corn	5.0 (0.5)	3.3 (0.2)	81.7	4.1 (0.2)	2.2 (−0.3)	3.7 (−0.2)	3
Stock	5.3 (0.2)	7.0 (−0.0)	2.7 (−0.2)	72.0	5.5 (−0.5)	7.5 (−0.4)	4.7
Bond	5.0 (0.5)	5.7 (0.2)	4.1 (0.3)	8.2 (0.5)	73.5	3.6 (−0.0)	4.4
Currency	**<u>7.3 (0.8)</u>**	6.8 (0.2)	5.0 (0.2)	9.7 (0.4)	3.6 (0.0)	67.6	5.4
Contribution TO others	4.8	4.6	2.7	5.5	2.9	3.8	
NET directional connectedness	2.4	0.4	−0.4	0.8	−1.5	−1.6	TCI
NPDC transmitter	5.0	3.0	2.0	4.0	1.0	0.0	24.2
Period 1: 2019/12/09–2020/01/23							
Oil	78.0	13.7 (0.4)	1.5 (−0.1)	2.9 (−0.2)	1.9 (−0.4)	2.0 (−0.3)	3.7
Gold	11.4 (−0.4)	79.1	2.7 (−0.4)	2.2 (−0.6)	2.6 (−0.4)	1.9 (−0.5)	3.5
Corn	2.1 (0.1)	4.8 (0.4)	85.4	2.5 (0.1)	1.8 (−0.2)	3.3 (−0.3)	2.4
Stock	4.3 (0.2)	**<u>5.6 (0.6)</u>**	2.2 (−0.1)	75.2	4.6 (−0.1)	8.1 (0.1)	4.1
Bond	4.4 (0.4)	4.8 (0.4)	3.1 (0.2)	5.4 (0.1)	80.2	2.1 (0.1)	3.3
Currency	3.5 (0.3)	4.7 (0.5)	5.0 (0.3)	7.4 (−0.1)	1.7 (−0.1)	77.7	3.7
Contribution to others	4.3	5.6	2.4	3.4	2.1	2.9	
Net directional connectedness	0.6	2.1	0.0	−0.7	−1.2	−0.8	TCI
NPDC transmitter	4.0	5.0	2.0	2.0	0.0	2.0	20.7
Period 2: 2020/02/03–2020/03/12							
Oil	56.1	3.0 (0.1)	2.2 (−0.6)	**<u>16.9 (1.4)</u>**	15.2 (0.9)	6.5 (0.5)	7.3
Gold	2.5 (−0.1)	61.5	1.6 (−0.8)	11.6 (0.5)	11.4 (0.4)	11.4 (0.2)	6.4
Corn	5.6 (0.6)	6.6 (0.8)	77.0	4.4 (0.6)	3.8 (0.5)	2.6 (0.2)	3.8
Stock	8.8 (−1.4)	8.3 (−0.5)	0.6 (−0.6)	44.4	19.5 (−0.3)	18.4 (−0.5)	9.3
Bond	9.9 (−0.9)	9.0 (−0.4)	0.6 (−0.5)	21.4 (0.3)	46.2	13.0 (−0.1)	9.0
Currency	3.5 (−0.5)	10.0 (−0.2)	1.2 (0.2)	21.2 (0.5)	13.4 (0.1)	50.7	8.2
Contribution to others	5.0	6.2	1.0	12.6	10.5	8.7	
Net directional connectedness	−2.3	−0.3	−2.8	3.3	1.6	0.4	TCI
NPDC transmitter	1.0	2.0	0.0	5.0	4.0	3.0.	44.0
Period 3: 2020/03/13–2020/04/07							
Oil	69.6	2.8 (−0.4)	3.3 (−1.3)	17.5 (0.3)	1.2 (−0.0)	5.5 (−0.4)	5.1
Gold	5.0 (0.4)	74.9	2.3 (−0.6)	3.9 (0.0)	12.4 (−0.1)	1.6 (−0.9)	4.2
Corn	**<u>11.0 (1.3)</u>**	6.2 (0.6)	73.5	4.6 (0.4)	1.1 (0.0)	3.7 (0.0)	4.4
Stock	15.5 (−0.3)	3.8 (−0.0)	2.1 (−0.4)	60.4	9.3 (−0.3)	8.9 (−0.3)	6.6
Bond	1.4 (0.0)	13.0 (0.1)	1.1 (−0.0)	10.9 (0.3)	70.5	3.2 (−0.0)	4.9
Currency	7.7 (0.4)	7.2 (0.9)	3.5 (−0.0)	10.8 (0.3)	3.4 (0.0)	67.3	5.4
Contribution to others	6.8	5.5	2.0	7.9	4.6	3.8	
Net directional connectedness	1.7	1.3	−2.4	1.3	−0.3	−1.6	TCI
NPDC transmitter	4.0	3.0	0.0	5.0	2.0	1.0	30.6
Period 4: 2020/04/08–2020/06/12							
Oil	78.3	4.9 (−0.4)	0.6 (−1.5)	10.4 (−0.2)	2.4 (−0.2)	3.3 (−0.7)	3.6
Gold	7.2 (0.4)	79.7	2.0 (−0.9)	5.4 (−0.4)	4.1 (−0.2)	1.5 (−0.8)	3.4
Corn	**<u>9.9 (1.5)</u>**	7.5 (0.9)	70.1	3.6 (0.5)	4.9 (0.5)	4.1 (0.4)	5.0
Stock	13.0 (0.4)	6.5 (0.2)	0.6 (−0.5)	62.9	6.0 (−0.1)	10.9 (−0.2)	6.2
Bond	3.6 (0.2)	5.3 (0.2)	1.6 (−0.5)	6.7 (0.1)	78.8	3.9 (0.1)	3.5
Currency	7.6 (0.7)	6.5 (0.8)	1.7 (−0.4)	12.0 (0.2)	3.3 (−0.11)	69.0	5.2
Contribution to others	6.9	5.1	1.1	6.3	3.5	4.0	
Net directional connectedness	3.3	1.7	−3.9	0.2	−0.1	−1.2	TCI
NPDC transmitter	5.0.	4.0	0.0	3.0.	1.0	2.0.	26.9

Notes: This table presents the means of directional connectedness received by the asset in column 1 from the asset in line 1 over four periods. The "From" column lists the FROM connectedness. The "Contribution to others" row indicates the TO connectedness. The "Net directional connectedness" row reveals the total net connectedness of each assets. The numbers listed in "NPDC transmitter" line show the numbers of the asset in line 1 that act as a net transmitter among all pairwise directional connectedness. The numbers in the parentheses are NPDC connectedness. The largest NPDC connectedness are bolded and underlined.

transmitter and receiver of shocks during this period. This time, the net pairwise directional connectedness from crude oil to currency is much greater than the net pairwise directional connectedness of other asset pairs. At the beginning of COVID-19 outbreak (i.e., period 1), gold is a dominator to all the other five assets, but bond is dominated by all the other five assets. Besides, gold transmit about 2.1% net shocks to the whole asset system, and bond receive about 1.2% net shocks from the whole asset system, becoming the strongest net transmitter and receiver of shocks, respectively. This time, the net pairwise directional connectedness from gold to stock is the strongest one. It is worth mentioning that although some pairwise dominant relationships change in period 1, the total connectedness index is still at a low level of 20.7%, indicating that Chinese commodity and financial markets are not significantly affected in the early stage of the COVID-19 epidemic. In period 2, the dominant relationship of some asset pairs change again. This time, stock dominate all the other five assets, but corn is dominated by all the other five assets. This dominant relationship still exists in period 3. Meanwhile, corn is the strongest net receiver of shocks during both periods 2 and 3. However, stock is the strongest net transmitter of shocks only during period 2. In period 3, oil is the strongest net transmitter. Besides, in period 2, the net pairwise directional connectedness from stock to oil is the strongest one, but in period 3, the net pairwise directional connectedness from oil to corn is the strongest one. In period 4, corn remains to be dominated by all the other five assets, but this time, oil become the dominator to all the other five assets. Meanwhile, oil and corn are the strongest net transmitter and receiver of shocks during this period, respectively. This time, the net pairwise directional connectedness from oil to corn is still the strongest one. Finally, in general, only the dominant relationship from oil, gold and stock to corn as well as from stock to bond remain unchanged over the five periods. Referring to Ji et al. (2020)'s analysis, it may be the reason that corn and bond are relatively stable safe-haven assets during COVID-19 epidemic.

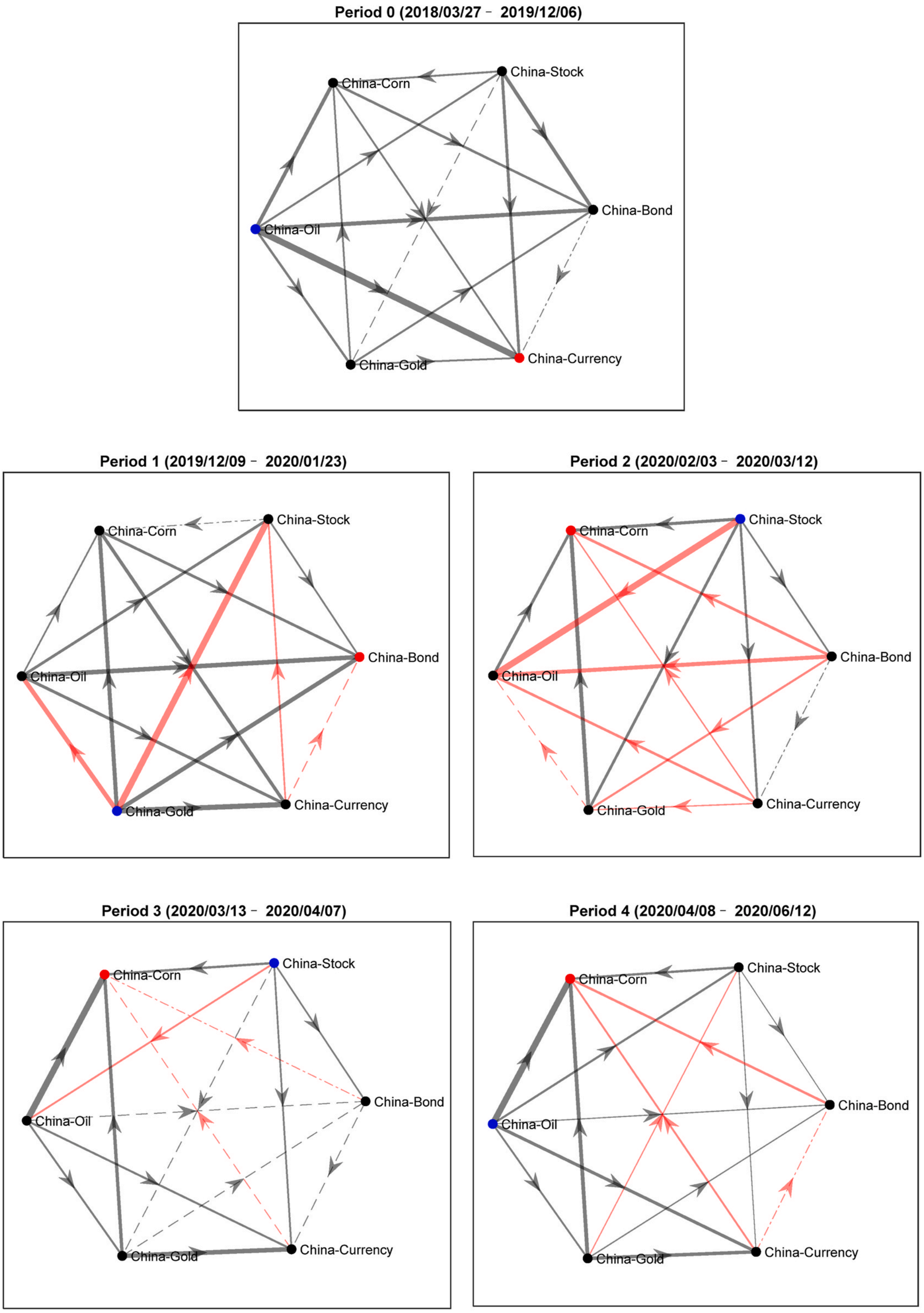

Fig. 7. Net pairwise directional connectedness in China. *Notes*: An asset that dominates the other 5 assets is marked with blue point. An asset that is dominated by the other 5 assets is marked with red point. The direction of the net pairwise directional connectedness indices between two assets which are different from Period 0 are drawn as red arrows. The net pairwise directional connectedness indices which are smaller than 0.1 are drawn as dotted arrows. The larger the net pairwise connectedness index, the wider the corresponding arrow. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

The average connectedness measures among commodity and financial assets in the US are present in Table 3 and the corresponding pairwise connectedness network is drawn in Fig. 8. Table 3 and Fig. 8 show firstly that oil can dominate all the other five assets in period 0, but currency is dominated by all the other five assets. Meanwhile, oil and currency are also the strongest net transmitter and receiver of shocks for the whole system, respectively, during this period. These findings are consistent with the situation in the Chinese market. Differently, in the

Table 3
Average connectedness among commodity and financial assets in the US.

	Oil	Gold	Corn	Stock	Bond	Currency	From
Period 0: 2018/03/27–2019/12/06							
Oil	79.5	2.5 (−0.4)	2.4 (−0.3)	7.3 (−0.1)	5.2 (−0.8)	3.1 (−0.7)	3.4
Gold	4.9 (0.4)	62.8	3.7 (0.2)	6.1 (0.2)	9.8 (−0.1)	12.7 (−0.2)	6.2
Corn	4.3 (0.3)	2.7 (−0.2)	85.3	2.5 (0.0)	2.4 (−0.3)	2.8 (−0.4)	2.5
Stock	8.1 (0.1)	4.9 (−0.2)	2.5 (−0.0)	65.1	12.7 (−0.1)	6.8 (−0.4)	5.8
Bond	**<u>9.8 (0.8)</u>**	10.6 (0.1)	4.4 (0.3)	13.4 (0.1)	58.0	3.8 (−0.2)	7
Currency	7.4 (0.7)	14.1 (0.2)	5.3 (0.4)	9.2 (0.4)	4.9 (0.2)	59.1	6.8
Contribution TO others	5.8	5.8	3.0	6.4	5.8	4.9	
NET directional connectedness	2.3	−0.4	0.6	0.6	−1.2	−2.0	TCI
NPDC transmitter	5.0	2.0	3.0	4.0	1.0.	0.0	31.7
Period 1: 2019/12/09–2020/01/23							
Oil	80.3	6.3 (0.4)	2.3 (−0.7)	2.6 (−0.1)	5.7 (0.4)	2.8 (−0.2)	3.3
Gold	3.6 (−0.4)	57.4	1.3 (−0.1)	9.5 (−0.9)	26.1 (0.0)	2.1 (−0.3)	7.1
Corn	6.3 (0.7)	1.7 (0.1)	85.6	2.0 (−0.0)	3.5 (0.1)	0.9 (−0.6)	2.4
Stock	3.4 (0.1)	**<u>15.0 (0.9)</u>**	2.1 (0.0)	60.7	15.2 (0.9)	3.6 (−0.0)	6.6
Bond	3.4 (−0.4)	25.9 (−0.0)	2.7 (−0.1)	9.7 (−0.9)	55.8	2.6 (−0.1)	7.4
Currency	3.8 (0.2)	4.2 (0.3)	4.3 (0.6)	3.9 (0.0)	3.4 (0.1)	80.4	3.3
Contribution to others	3.4	8.8	2.1	4.6	9.0	2.0	
Net directional connectedness	0.1	1.7	−0.3	−1.9	1.6	−1.2	TCI
NPDC transmitter	3.0	4.0	2.0	1.0	5.0.	0.0	30.0
Period 2: 2020/02/03–2020/03/12							
Oil	52.9	2.6 (−0.5)	3.7 (−0.9)	17.1 (0.1)	14.7 (0.2)	9.0 (−0.5)	7.9
Gold	5.5 (0.5)	64.2	2.3 (−0.5)	9.1 (0.7)	14.5 (0.7)	4.3 (−0.1)	6.0
Corn	9.1 (0.9)	5.6 (0.5)	67.1	7.1 (0.7)	6.7 (0.5)	4.5 (−0.1)	5.5
Stock	16.4 (−0.1)	5.0 (−0.7)	3.0 (−0.7)	48.3	18.9 (0.1)	8.4 (−1.2)	8.6
Bond	13.7 (−0.2)	10.2 (−0.7)	3.7 (−0.5)	18.5 (−0.1)	45.4	8.6 (−0.5)	9.1
Currency	12.1 (0.5)	5.2 (0.1)	5.3 (0.1)	**<u>15.3 (1.2)</u>**	11.7 (0.5)	50.3	8.3
Contribution to others	9.5	4.8	3.0	11.2	11.1	5.8	
Net directional connectedness	1.6	−1.2	−2.5	2.6	2.0	−2.5	TCI
NPDC transmitter	3.0	2.0	1.0	4.0	5.0	0.0	45.3
Period 3: 2020/03/13–2020/04/07							
Oil	51.3	6.4 (−1.0)	3.5 (−1.3)	21.1 (1.0)	4.7 (−0.3)	13.1 (0.0)	8.1
Gold	12.7 (1.0)	55.6	4.7 (−0.3)	14.1 (1.9)	2.8 (−0.0)	10.2 (1.3)	7.4
Corn	11.0 (1.3)	6.7 (0.3)	43.6	**<u>17.0 (1.9)</u>**	5.4 (0.3)	16.3 (0.5)	9.4
Stock	14.9 (−1.0)	2.4 (−1.9)	5.8 (−1.9)	48.7	10.1 (−1.8)	18.1 (−0.8)	8.6
Bond	6.5 (0.3)	3.1 (0.0)	3.9 (−0.3)	21.0 (1.8)	59.1	6.4 (0.7)	6.8
Currency	13.1 (−0.0)	2.7 (−1.3)	13.2 (−0.5)	22.7 (0.8)	2.1 (−0.7)	46.2	9.0
Contribution to others	9.7	3.5	5.2	16.0	4.2	10.7	
Net directional connectedness	1.6	−3.9	−4.2	7.4	−2.6	1.7	TCI
NPDC transmitter	3.0	2.0	0.0	5.0	1.0	4.0	49.3
Period 4: 2020/04/08–2020/06/12							
Oil	72.9	4.1 (−0.5)	14.2 (−1.3)	6.5 (−0.5)	0.9 (−0.9)	1.4 (−1.9)	4.5
Gold	6.9 (0.5)	75.7	1.8 (−0.9)	8.2 (1.0)	3.1 (−0.3)	4.3 (0.2)	4.0
Corn	22.0 (1.3)	7.2 (0.9)	53.5	9.1 (0.7)	2.2 (0.0)	5.8 (−0.4)	7.7
Stock	9.2 (0.5)	2.1 (−1.0)	4.9 (−0.7)	63.4	9.5 (−1.3)	10.8 (−0.7)	6.1
Bond	6.2 (0.9)	4.9 (0.3)	2.2 (−0.0)	17.6 (1.3)	64.2	5.0 (0.4)	6.0
Currency	**<u>13.1 (1.9)</u>**	3.3 (−0.2)	8.2 (0.4)	15.3 (0.7)	2.3 (−0.4)	57.8	7.0
Contribution to others	9.6	3.6	5.2	9.4	3.0	4.6	
Net directional connectedness	5.1	−0.4	−2.5	3.3	−3.0	−2.5	TCI
NPDC transmitter	5.0	2.0	1.0	4.0	1.0	2.0	35.4

Notes: This table presents the means of directional connectedness received by the asset in column 1 from the asset in line 1 over four periods. The "From" column lists the FROM connectedness. The "Contribution to others" row indicates the TO connectedness. The "Net directional connectedness" row reveals the total net connectedness of each assets. The numbers listed in "NPDC transmitter" line show the numbers of the asset in line 1 that act as a net transmitter among all pairwise directional connectedness. The numbers in the parentheses are NPDC connectedness. The largest NPDC connectedness are bolded and underlined.

US market, the net pairwise directional connectedness from oil to bond is the strongest one and is as high as 0.8%. In period 1, bond can dominate all the other five assets, but currency is dominated by all the other five assets. Meanwhile, in period 2, bond can still dominate all the other five assets and currency is still dominated by all the other five assets. However, in period 1 and period 2, gold and stock have the net directional connectedness at 1.7% and 2.6%, respectively, becoming the strongest net transmitter in these two periods. Besides, stock and currency have the net directional connectedness at −1.9% and −2.5% in period 1 and period 2, respectively, becoming the strongest net receiver in these two periods. The difference between the strongest net transmitter and receiver in period 1 and period 2 may due to the facts that the net pairwise directional connectedness from gold to stock is much higher than that of other asset pairs in period 1, while the net pairwise directional connectedness from stock to currency is much stronger than that of other asset pairs in period 2. Interestingly, Table 3 shows that the TCI in period 1 is not elevated compared to that in period 0, while the TCI in period 2 is elevated by about 15% compared to that in period 1, indicating that the US commodity and financial markets is not significantly affected in the early stage of the COVID-19 epidemic. However, the total connectedness across the US commodity and financial markets is on an upward trend as early as China announced the closure of Wuhan due to the COVID-19 epidemic. In period 3, stock can dominate all the other five assets with the net directional connectedness largest at 7.4%. Meanwhile, corn is dominated by all the other five assets with the smallest net directional connectedness at −4.2%. This time, stock and corn are the strongest net transmitter and net receiver of shocks, respectively, and the net pairwise directional connectedness from stock to corn is much larger than that of most other asset pairs. In period 4, crude oil becomes the dominator to all the other five assets and it is also the strongest net spillover transmitter. This time, bond is the strongest net spillover receiver because it has the smallest net directional

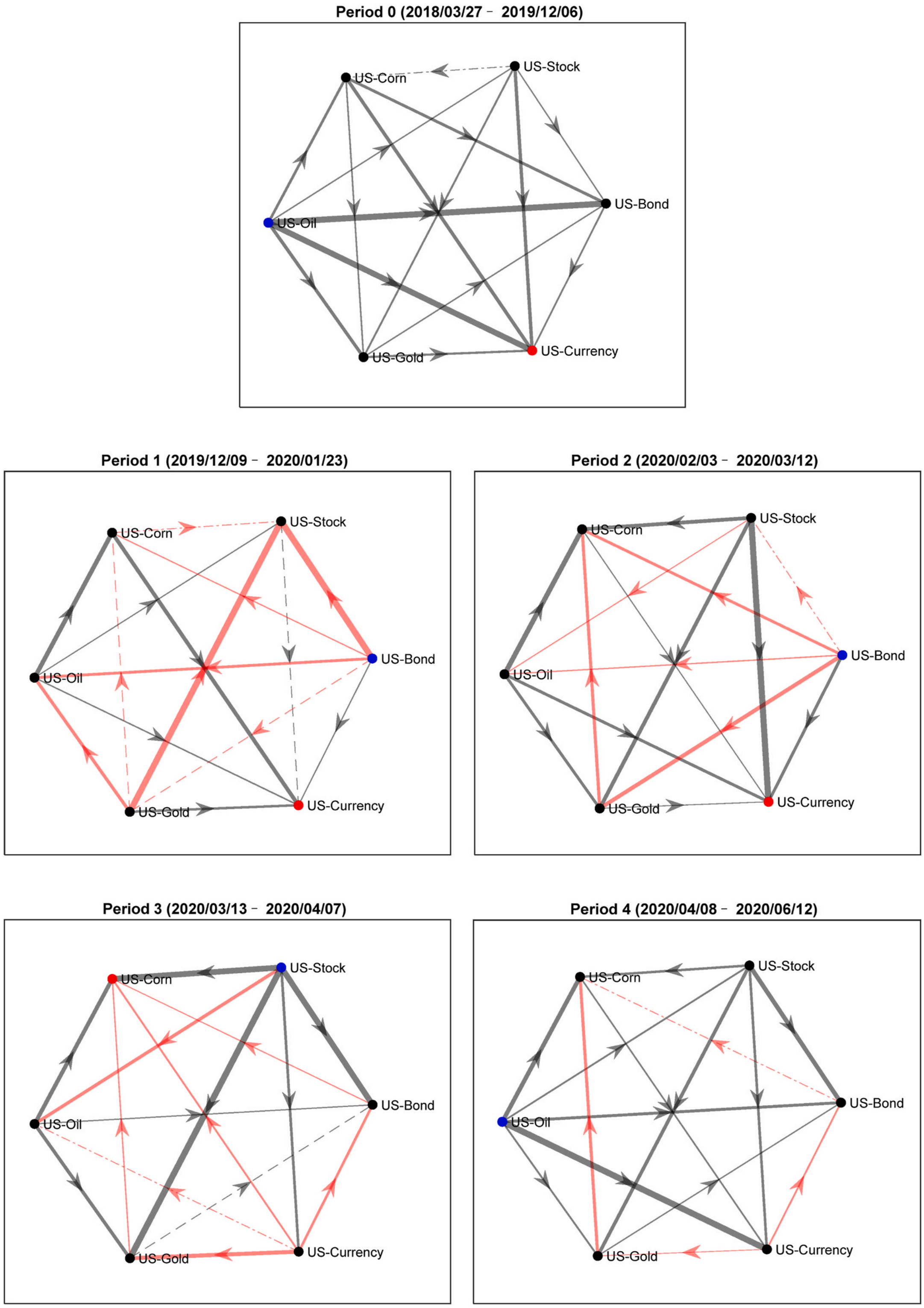

Fig. 8. Net pairwise directional connectedness of the US asset system. *Notes*: An asset that dominates the other 5 assets is marked with blue point. An asset that is dominated by the other 5 assets is marked with red point. The direction of the net pairwise directional connectedness indices between two assets which are different from Period 0 are drawn as red arrows. The net pairwise directional connectedness indices which are smaller than 0.1 are drawn as dotted arrows. The larger the net pairwise connectedness index, the wider the corresponding arrow. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

connectedness. Interestingly, in period 4, the net pairwise directional connectedness from oil to currency is the strongest one. Finally, in general, only the dominant relationship from oil to corn as well as from stock to currency remain unchanged over the five periods.

By analyzing the net pairwise directional connectedness indices, we find the following important similarities in the net pairwise spillover effects across commodity and financial markets in China and the US. Firstly, before the COVID-19 epidemic outbreak, oil can dominate all the other five assets and currency is dominated by all the other five assets in both the Chinese and the US markets. Meanwhile oil and currency are the strongest net transmitter and net receiver of shocks, respectively, in the two countries. Secondly, at the early stage of the COVID-19 epidemic, changes in the direction of net pairwise directional connectedness within the system do not lead to significant variations in the total connectedness index, and the net pairwise directional connectedness from gold to stock is higher than those of other asset pairs in both the Chinese and the US markets. Besides, at the beginning of the accelerated spread of the COVID-19 epidemic in China and the US (i.e., period 2 for China and period 3 for the US), stock can dominate all the other five assets and corn is dominated by all the other five assets. Meanwhile, stock and corn are the strongest net transmitter and receiver of shocks, respectively. Thirdly, in the period after Wuhan was reopened, oil can dominate all the other five assets in both the Chinese and the US markets and it is also the strongest net transmitter of shocks. Finally, in both the

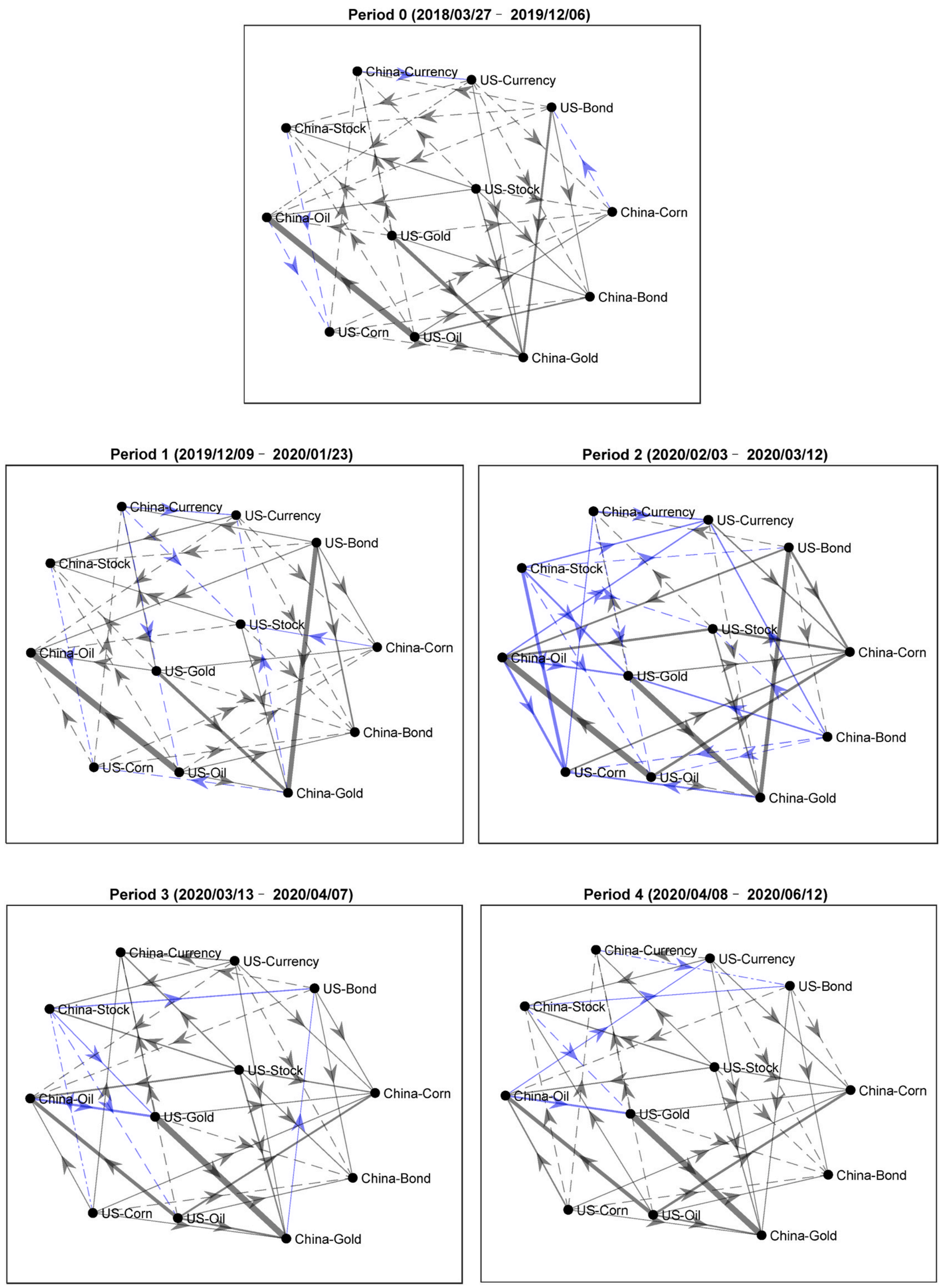

Fig. 9. Net pairwise directional connectedness between assets in China and the US. *Notes*: Net pairwise directional connectedness from assets in China to assets in the US is drawn with blue arrows. The net pairwise directional connectedness index smaller than 0.1 is drawn as dotted arrows. The larger the net pairwise connectedness index, the wider the corresponding arrow. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Chinese and the US markets, oil can always dominate corn.

Due to the differences in the economic structure and political environment between China and the US, the net pairwise connectedness across the commodity and financial markets in these two countries also present many different characteristics. For example, at the early stage of the COVID-19 epidemic, the Chinese bond is the strongest net receiver of shocks because of the safe-haven property of bond, but influenced by the inversion of the US bond return and recessionary fears, the US bond is a strong net transmitter of shocks for the US asset system. In the early days of Wuhan's closure, influenced by the strategy about stopping work and production as well as the personnel mobility control measures in China, the Chinese stock market risk increased and the demand for oil reduced, making the dominant relationship from the Chinese stock market to oil market far greater than those of other asset pairs. But in the US market, the dominant relationship of stock to currency is the strongest one. By March 2020, China's economy began to recover, but at this time, the spread of COVID-19 epidemic just began to accelerate globally, international crude oil prices fell and the risk in China's crude oil market increased significantly. As a result, it heightened the demand of risk aversion for crude oil market and made the net pairwise connectedness from oil to corn the strongest one. But in the US, the spread of COVID-19 accelerated in March 2020, and the stock market was greatly impacted, with increased demand for safe-havens, making the net pairwise directional connectedness from stock to corn the strongest one. By April 2020, in the Chinese market, the strongest net pairwise directional connectedness still occurred in the oil-to-corn direction, while in the US market, the strongest net pairwise directional connectedness occurred in the oil-to-currency direction.

3.4. Supplementary analysis

The previous findings in sub-sections show that the total connectedness characteristics of the US asset system have changed as early as the closure of Wuhan. This makes us wonder whether these changes in the US asset system are due to the spillover effects in the Chinese commodity and financial assets. So, we re-construct the connectedness network by incorporating all the 12 assets, focusing on the results of the pairwise directional connectedness between assets in China and in the US.

Fig. 9 draws the network of net pairwise directional connectedness of all 12 assets in China and in the US asset system. For the sake of clarity, we just illustrate the pairwise directional connectedness arrows between assets in China and in the US, without showing connectedness arrows between asset in the same country. Net return spillover from China (the US) to the US (China) are drawn as blue (grey) arrows. As can be seen in Fig. 9, during periods 0 and 1, there are net return spillover from the Chinese assets to the US assets. However, most of these net return spillovers are quite small, and only the net return spillover from the Chinese currency to the US currency and that from the Chinese corn to the US stock are greater than 0.1% in both periods 0 and 1. The main reason may be that the RMB-US dollar foreign exchange rate is an important component of the USD index. These findings imply that there is weak net return spillover effect from the Chinese market to the US market before the outbreak of COVID-19. During period 2, the direction of some net return spillovers has changed, and most of the net return spillovers from the Chinese assets to the US assets are larger than 0.1. These results suggest that the increased uncertainties in the Chinese asset system after the closure of Wuhan has indeed transmitted to the US asset system. By the third and the fourth periods, the net return spillovers from the Chinese assets to the US assets decrease due to the increased market risks in the US after the US declared a state of emergency. However, as can be seen in Fig. 3, the uncertainty in the US asset system due to the COVID-19 pandemic has limited impact on the Chinese asset system.

We can also find in Fig. 9 that Chinese crude oil always transmits more shocks to the US gold than it receives from the US gold. In addition, after the closure of Wuhan, Chinese stock always transmits more shocks to the US gold than it receives from the US gold. That's to say, the US gold can be treated as a safe-haven for Chinese stock and crude oil investors. Besides, Fig. 9 also shows that the net return spillovers from the US crude oil to the Chinese crude oil and from the US gold to the Chinese gold are always stronger than most of other net return spillovers. In other words, Chinese crude oil and gold prices are easily affected by outside oil and gold prices for the reason of high dependence on foreign imports of crude oil and gold in China.

3.5. Some explanations for the empirical findings

In this section, we further discuss the similarities and differences in the empirical findings between the Chinese and the US markets. Firstly, we find that the total return connectedness among commodity and financial assets in both the Chinese and the US markets increase greatly after the outbreak of the COVID-19. It indicates that the COVID-19 pandemic has significant impacts on both the Chinese and the US commodity and financial markets. Moreover, the total connectedness in the US markets is stronger than that of the Chinese markets in most cases, implying that portfolios using Chinese assets will be more effective than using assets in the US. Different from the Chinese markets, the total connectedness of the US markets experiences two spikes after the outbreak of COVID-19. The first surge of the total connectedness happens after the lock-down the Wuhan city. After this event, many other cities in China have successively implemented a series of measures to reduce the flow of people and control the source of infection of the epidemic. These actions have brought huge impacts on the Chinese economy, and triggered the total connectedness among the Chinese commodity and financial markets increasing rapidly. Although the COVID-19 has not yet spread widely to the US at that time, accompanied with sharp decline in trade volumes between China and the US, the enhanced systemic risks in China transmits stronger spillover effect to the US, leading to the increase of total connectedness in the US. The second surge of the total connectedness in the US occurs after the US's declaration of a state of emergency for COVID-19. At this time, the COVID-19 has spread largely in the US, sharply increasing the systemic risk in the US markets. However, by this time, the strict anti-epidemic actions taken by China have achieved remarkable effects through actively resuming work from the shocks of the COVID-19 epidemic. As a result, the total connectedness in China does not experience the secondary spike as the US does.

Secondly, gold shifts from a net transmitter to a net receiver of shock in both China and the US after the closure of Wuhan. In 2019, the long-term US Treasury bond interest rates falls several times, which leads to the rise in the gold price. Due to the tight correlation between the Chinese gold price and the US gold price, gold plays the role of net transmitter of shock in both the Chinese and the US markets before the outbreak of the COVID-19. However, after the outbreak of COVID-19, the economies of both China and the US are devastated during the epidemic, resulting in the risk aversion sentiment of investors and making gold play its role as a safe-haven. As a consequence, gold becomes a net receiver of shock after the outbreak. Specially, both the changes happen after the closure of Wuhan. This may because that the commodity and financial markets in both China and the US are less affected by the epidemic in the early stage of the COVID-19 epidemic, and the dwindling trade between China and the US allows the risk aversion sentiment in China transmitting to the US markets in the early stage after the closure of Wuhan. Differently, gold in China has resumed its role as a net transmitter of shock as early as March 2020 because the epidemic has been gradually under control in China, while gold in the US shows signs of resuming a net transmitter of shocks by June 2020.

Thirdly, corn remains a net receiver of shocks in both the China and the US after the outbreak of COVID-19 epidemic. In other words, corn usually passively receives shocks from other markets during the COVID-19 epidemic, implying that COVID-19 has no direct impact on corn price. In fact, the risk of agricultural commodities is directly affected by climatic factors to a greater extent instead of by infectious disease pandemic. This characteristic makes corn a relatively stable safe-haven during the COVID-19 epidemic (Ji et al., 2020), thus explaining the reason for why corn plays the role of a net receiver of shocks during the COVID-19 epidemic.

Fourthly, stock turns from a net receiver to be the strongest net transmitter of shocks in both China and the US after the outbreak of COVID-19. Specially, both of the changes happen after the closure of Wuhan. After Wuhan announces to lock down the city, most of the Chinese residents are requested staying at home and many enterprises shut down works until mid-February. These actions increase the uncertainty/risk of the Chinese stock market, making it the strongest shock source in China. Furthermore, due to the slashed trade between China and the US, the stock in the US also become a net transmitter of shock in the US after the closure of Wuhan. However, the COVID-19 does not spread widely in the US until March. The declaration of the state of emergency for COVID-19 in the US on March 12, 2020 has brought a huge impact on many industries in the US. This time, the unemployment rate rises sharply, some businesses goes bankrupt, and the panic sentiment of investors also infects sharply, which make stock market the most powerful origin of shock in the US. Differently, stock market in China resumes its role as a net receiver of shock in mid-April 2020, while the stock market in the US fails to recover its role as a net receiver of shock. That means that China has made remarkable achievements in controlling the spread of the epidemic, while the crisis in the US remains unresolved. Although stock in China becomes a source of shock again in late May 2020, it is not related to the epidemic, but is caused by the reason that Shanghai Stock Exchange and Shenzhen Stock Exchanges in China announced a circular on a pilot program to publicly issue short-term corporate bonds on May 21, 2020.

In addition, currency also changed from a net receiver to a net transmitter of shock in both the Chinese and the US market after the outbreak of COVID-19. The reason for this finding is that the risk aversion sentiment and the decline in risk appetite brought by the COVID-19 have made the RMB and the US dollar face the pressure of depreciation. To increase liquidity, both China and the US have adopted a series of monetary policies to maintain reasonable liquidity. Increased liquidity has helped to suppress the depreciation of currency, so that currency asset in both China and the US quickly revert to net receivers of shocks after being net transmitters. Differently, the change of the Chinese currency from a net receiver to a net transmitter occurs after the closure of Wuhan, while the change of the US currency from a net receiver to a net transmitter happens after the US declared a state of emergency for COVID-19. This is because that the epidemic does not spread widely in the US until March 2020.

The roles of the other two assets, crude oil and bond, as net transmitters or receivers of shocks are different in the Chinese and the US market before and after the outbreak of COVID-19. For crude oil asset, it usually acts as a net transmitter of shock in both the Chinese and the US market, however, it briefly changes to a net receiver of shock in China after the outbreak of COVID-19, but the role of it as a net transmitter hasn't converted in the US. Crude oil is a very important fossil energy and chemical raw material and plays an important role in economic activities. So, it is not surprising that crude oil is a net transmitter of shocks in most cases. As the largest crude oil importer in the world, China's crude oil futures prices are highly correlated to international crude oil prices. When Wuhan locked down the city on January 23, 2020, the oil demand has decreased significantly in China, driving the changes of international oil price to some extent. Meanwhile, the global epidemic had not yet spread widely at that time. Therefore, crude oil shifts to be a net receiver of shock in China after the closure of Wuhan, and with the COVID-19 epidemic is gradually under control in China, crude oil soon regains its role as a net transmitter. In the US, after the US declares a state of emergency, market participants' expectations for future crude oil demand fall sharply under the panic of the global spread of COVID-19. Meanwhile, Saudi Arabia launches an oil price war in March 2020. Under the combined effects of multiple factors, WTI crude oil futures prices begin to decrease and even fall to a negative number on April 20, 2020. This leads to an increasing shock of crude oil in the US market, making crude oil the strongest source of shocks in both China and the US after the reopen of Wuhan.

For bond, it converts from a net receiver to a net transmitter of shock in China after the outbreak of COVID-19, but changes from a net transmitter to a net receiver in the US. Bonds are usually less risky assets. Because of their hedging effect, they often passively accept shocks originating from other risky assets. So, bond asset acts as a net receiver of shock in China before the closure of Wuhan. After the outbreak, the revenue and profitability of many companies in China are greatly influenced, making investors concern more about the increasing credit risk. As a result, bond becomes a net transmitter of shock in China. With the COVID-19 being gradually under control in China, bond soon regains its status as a net receiver. In the US, the Treasury bond rate falls several times in the second half of 2019, making bond a major source of shocks in the US asset system before the US's declaration of state emergency for COVID-19. After that, the risk aversion sentiment of participants in crude oil and stock markets increases significantly, far outstripping their concerns about credit risk, making bond to be a net receiver of shocks in the US.

4. Conclusions

This paper explores the dynamics of the connectedness network among three major commodity assets and three financial assets in China and the US during the COVID-19 pandemic. Antonakakis et al. (2020)'s method is used to measure the dynamic connectedness. Our empirical results provide clear evidence of strong dynamic return connectedness among commodity and financial assets in both China and the US and the total connectedness in the US markets is stronger than that in China. Besides, the total return connectedness in the two countries increases sharply after the outbreak of the COVID-19. Differently, the total connectedness in the US markets experiences a second spike after the US's declaration of state emergency for COVID-19. Across all asset classes, gold shifts from a net transmitter of shocks to a net receiver in both China and the US after the outbreak of COVID-19, while stock and currency change from net receivers to net transmitter of shocks. In which, stock is at one point the strongest source of shocks in both the Chinese and the US markets. Moreover, corn remains to passively receives the shocks from other assets in both China and the US markets after the outbreak of COVID-19 epidemic, and the intensity of the shocks it receives peaks during this period, making corn at one point the strongest and important net receiver of shocks. Dissimilarly, crude oil converts from a net transmitter to a net receiver of shocks in China after the outbreak of COVID-19, but the role of it as a net transmitter of shocks does not change in the US. Bond alters from a net receiver to a net transmitter of shock in China after the outbreak, while it turns from a net transmitter to a net receiver in the US.

This paper has important implications for investors and policymakers in China and the US. Firstly, since high spillovers between different asset classes, i.e. commodity and financial assets, make it possible for systemic financial risk to surge rapidly to severe levels after the occurrences of major public health emergencies or economic Grey Rhino incidents. Investors should pay close attention to the subsequent development of these events and their possible adverse effects, identify the potential risks and stop losses timely. However, as a result of economic globalization, no country is immune to a public crisis. So, when making investment decisions, investors should keep eyes not only on local markets but on other related markets abroad. Moreover, investors should allocate portfolios by considering the similarities and differences in the time-varying connectedness characteristics of asset systems in different countries. Finally, the interchangeable roles of the commodity and financial assets suggest flexible regulatory strategies should be applied by policy makers to prevent systematic risk contagion.

CRediT authorship contribution statement

Xiafei Li: Writing – original draft, Software. **Bo Li:** Writing – review & editing. **Guiwu Wei:** Methodology, Software. **Lan Bai:** Methodology, Software, Writing – review & editing. **Yu Wei:** Writing, Methodology, Writing – review & editing. **Chao Liang:** Revision.

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 (17YJA790015, 17XJA790002, 18YJC790132, 18XJA790002), Science and Technology Innovation Team of Yunnan Provincial Universities (2019014) and Yunnan Fundamental Research Projects (202001AS070018).

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