COVID-19 and time-frequency spillovers between oil and sectoral stocks in China and US economies

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Abstract

This paper examines the volatility spillovers and the time-frequency dependence between crude oil and stock sectors of US and China using wavelet coherence and asymmetric bivariate BEKK GARCH models. We also rely on the effects of the recent global health crisis (COVID-19) on spillover effects and portfolio management. The results show evidence of strong positive co-movements between WTI oil and US sector stock returns at medium and low frequency particularly in 2020Q1. Oil leads the US sector stocks irrespective of frequencies. As for China, we find significant long-term co-movements between oil and Chinese sector stock returns (64-128 days). The lead-lag relationships between oil and Chinese sectors are mixed and frequency-sensitive. More importantly, the results show significant shocks and volatility transmission between oil and sector stock of US and China. The size and the intensity of shocks and volatility transmission is higher during the pandemic than before. The proportion invested in oil increased during the pandemic for US investors and decreased for Chinese investors. The hedging with oil is expensive for US sectors during the pandemic and cheap for Chinese sectors. Oil provides a better hedging effectiveness during the pandemic for US sectors (except Energy, Financials, and Utilities) and all Chinese sectors.

Keywords: COVID-19; industry sectors; spillovers; wavelet; asymmetric BEKK GARCH model; hedging

JEL classification: G14

Highlights

- Strong positive co-movements between oil and U.S. sectors at medium and low frequency.
- weak co-movements between oil and Chinese sectors at low frequencies.
- The size and the intensity of shocks and volatility transmission are higher during the pandemic.
- The hedging expensive for US sectors during the pandemic and cheapest for Chinese sectors.
- Oil provides a better hedging effectiveness during the pandemic for US and Chinese sectors.

1. Introduction

The ongoing COVID-19 pandemic has resulted in over 412,351,279 confirmed cases and 5,821,004 deaths as of 15th February 2022.[1] The damages of COVID-19 on the performance of stock and crude oil commodity markets are more pronounced than during the times of global financial crisis (GFC) in 2008 (Jebabli et al., 2021; Zhang and Hamori, 2021). The rapid spread of COVID-19 pandemic and its variants (from Delta to Omicron) brought government to undertake restrictive and precautionary measures (e.g., lockdown, social distancing, travel restrictions, reduction and stoppages of operational activities, and import/export disruption). These costly measures have intensified the uncertainty in financial and energy markets, increasing the uncertainty on these markets. In addition to the effects of COVID-19 pandemic, the Russia-Saudi Arabia oil price war has amplified the high uncertainty in oil market (Ma et al., 2021). Statistically speaking, the price of West Texas Intermediate (WTI) crude oil future contract#1 experiences a significant decline in March-April 2020 where the barrel declines from $28.7 in 16 March and $12.78 in 27 April. It is worth noting that the oil prices show a negative value ($-37.63 per barrel) in 20 April 2020. The low value of barrel continues in May 2020. The performance of the U.S. stock market showed the worst point decline (about 6,400 points for Dow Jones Industrial Average) in March 2020. This bad performance is the largest since the 1987 stock market crash (Mazur et al., 2021). The S&P500 index, as a benchmark for international investors, drops by 1.7% (4,357.73 points) in September 2021, which is the worst day since May 2021. On the other hand, the Shanghai index falls by 8% in February 2020 which is the largest daily price fall for more than

[1] https://covid19.who.int/

four years. It is evidenced that COVID-19 pandemic deepens the volatility in commodity and stock markets.

The high uncertainty level in both stock exchange and crude oil markets increases the panic, the investor fear, leading to irrational investor behaviors during the pandemic. Ashraf (2020) finds negative relationships between stock market performance and the growth in COVID-19 confirmed cases. He et al. (2020) find that the pandemic crisis has a negative and short impact on the stock markets of affected countries. The results are in line with the findings of Ichev and Marinč (2014) for Ebola pandemic. On the other hand, the financial liberalization is a main factor for an intensification of the information transmission among markets. Besides, the linkages among international markets vary over time and across frequencies (Rua and Nunes, 2009). These turbulences have important implications on recoupling hypothesis, herding behaviors and contagion effects (rapid spread from one market to another) and as a result on asset allocation fund and diversified portfolios. The hedging demand is mainly influenced by the increasing uncertainty and the herding of investors (Brock and Kleidon, 1992; Chien et al., 2013; Baltussen et al., 2021). The information spillover affects the short-term trading strategy and the demand of potential hedging assets to avoid trading losses (Kyle and Xiong, 2002). Fleming et al. (1998) and Kordes and Pritsker (1998) show that the cross-market hedging is related to volatility transmission between markets.

A large strand of empirical literature focuses on the oil-stock market nexus at the aggregate level (Ali et al., 2022; Cevik et al., 2020; Gomez-Gonzalez et al., 2021; Hung and Vo, 2021; Sadorsky, 2014; Souček and Todorova, 2013; Wang, 2020) whereas studies at disaggregate (or sectoral) level are few (Mensi et al., 2021a; Hernandez et al., 2022; Mensi et al., 2022). To the best of our knowledge, this is the first study that examines the relationships between oil and stock markets at sectoral level and their implications on an oil-stock portfolio management in the two largest economies in the globe: U.S. and China. This study is worthy of investigation given the political of conflict between the two largest economies in the globe. In addition, our work is important due the high turbulence in the oil prices and their strong impact on the expected cash flows of the listed companies. China and U.S. countries are largest dependent on oil. Bad and good news emanating from these two economies will strongly affect the oil price, leading to over/under reaction to equity investors. The aim of this study is threefold. First, we examine the heterogeneous and nonlinear relationships between crude oil and stock sector returns across different frequencies. Second, it investigates the asymmetric volatility transmission between the series under study before and during COVID-19 pandemic. Third, it analyzes the potential diversification benefits of an oil- stock portfolio before and during the ongoing global health crisis.

Our results show strong co-movements between stock price returns of the US and China industries for intermediate and low frequencies from February to April 2020. US and Chinese stock returns are in phase at both intermediate and low frequencies during COVID-19 period, suggesting a positive relationship between oil and stock sector returns. We notice that Chinese sectors are less dependent on oil price returns than US markets. Among all sectors, Utilities sector is the least dependent on oil shocks, suggesting a potential of diversification benefits. Using asymmetric BEKK model, we report risk transfer from oil to the majority of U.S. stock sectors before the pandemic (except Consumer Staples) and during the pandemic (except SP500, Consumer Discretionary, Consumer Services, and Utilities). Regarding China markets, we find evidence of bidirectional feedback between oil and both Energy and Health Care before the pandemic. There is a risk transmission from oil to Consumer Discretionary. However, we show during the ongoing pandemic an unidirectional volatility spillovers from oil to Consumer Services and spillover from sectors (Consumer Discretionary, Consumer Staples, Energy, Financials, Information Technology, and Health Care) to oil market. Moreover, the volatility spillovers between oil and U.S. markets are asymmetric whereas it is symmetric for China with few exceptions. The values of optimal portfolio weights indicate that investor should hold less oil asset than stocks before and during the pandemic for the two economies. Oil is a cheap hedge asset for both economies. However, it is cheapest for China during the pandemic. The hedging effectiveness using oil futures is significant during the pandemic for China. For the US markets, the results are mixed.

This study contributes to four streams of literature. First, it examines the impacts of COVID-19 on the frequency dynamics co-movements between US and Chinese stock sectors. Relying on frequency factor is important to understand the relationships between oil and stock markets sectors at short-, intermediate-, and long-terms. Institutional investors (hedge funds, mutual funds) are interested in the long-term oil-stock co-movements whereas retail investors (hedgers and speculators) focus on the short-term oil-stock co-movements. The wavelet approach is a suitable method to account for the heterogeneity of market participants. We notice that U.S. and China have the two largest stock markets in the world.[2] The investment in Chinese stock market is risky and characterized by high volatility and low returns (Su and Fleisher, 1998). Besides, the Chinese and U.S. stock markets have suffered, in the last decade, from successive crashes where the trade tension between US and China and has been amplified especially during the COVID-19 outbreak. Second, it investigates the bidirectional shocks and volatility transmission between oil and sectors before and during the COVID-19 using the asymmetric

[2] For more details on the stock exchange markets in China and US, the reader can visit http://www.szse.cn/, http://www.sse.com.cn/, and https://us.spindices.com/indices/equity/sp-500

BEKK-GARCH (1,1) model. Asymmetry is an important stylized fact, indicating that negative and positive shocks have different effects on the conditional volatility of oil and sectors, altering investor decision-making process. Third, this study focuses on oil-stock nexus not only at aggregate level but also at sectoral level. In fact, the effects of oil prices on industry sector performance depends on its dependence on oil market (Mensi et al., 2021a). Moreover, understanding the relationships between oil and stock markets at the sectoral level may provide a source of diversification gains for equity investors (Mensi et al., 2017). Broadstock and Filis (2014) argue that the oil-stock relationships depend on the type of oil shocks and the industrial sector. Finally, this study analyzes the hedging strategy and effectiveness of a mixed portfolio composed by crude oil futures and sectors before and during the pandemic. Specifically, we follow Kroner and Ng (1993) to describe the optimal oil proportion invested in an oil-stock portfolio. Besides, we analyze the hedge cost by Kroner and Sultan (1993) and hedging effectiveness using the methodology by Ku et al. (2007).

The remainder of this paper is organized as follows. Section 2 presents a review of literature addressed during the pandemic outbreak. Section 3 discusses the data and preliminary statistic results. Section 4 presents the methodology used in the paper. Section 5 states and discusses the empirical results. Section 6 concludes the paper.

2. Literature review: oil-stock nexus during the pandemic

A growing empirical literature tackles the return and volatility spillovers between crude oil and stock market during the COVID-19 pandemic. For example, Zhu et al. (2021) investigate the risk spillovers between crude oil futures (both West Texas Intermediate [WTI] and Europe Brent) and stock markets of U.S. and China economies during the COVID-19 period using a GARCHSK-

Mixed Copula-CoVaR-Network model. The authors find significant and stronger bidirectional risk spillovers between oil and Chinese market during the pandemic than before. This result is consistent with the findings of Zhang et al. (2021) in the context of Brazil, China, France, Germany, Hong Kong, Japan, Korea, Russia, UK, and U.S. countries. This result is also in line with Mensi et al. (2021b) where the authors examined the price switching spillovers between oil and both U.S. and Chinese stock markets before and during the pandemic. More importantly, the authors identify a low-volatility regime from January 2019 to February 2020 and high-volatility from March 2020 to May 2020. They also find that gold and stock markets are net contributors of spillovers in the low-volatility regime and shifts to net receivers during high-volatility regime. In contrast, Brent crude oil is a major receiver of spillovers in the low-volatility regime and contributor of spillovers during periods of high volatility regime. Using the spillover index methodology of Diebold and Yilmaz (2012, 2014), Mensi et al. (2021a) examine the spillovers between gold, oil and Chinese sector stocks during different crises (GFC, EDC, oil crisis and COVID-19). The authors find a high spillover during crisis periods than tranquil periods. Moreover, oil serves as a hedging instrument in China stock markets and its role is crisis-sensitive. This result corroborates the findings of Zhang et al. (2021) and Liao et al. (2021) who conclude stronger return and volatility spillovers between oil and international stock markets.

Zhang and Hamori (2021) consider the role of multi-scale factor to examine the spillovers between oil and stock markets in Japan, and Germany, Japan, and U.S. during the pandemic period. They find using the spillover index by Diebold and Yilmaz (2012) and Barunik, and Krehlik (2018) that the spillover patterns differ before and during the pandemic. The authors show evidence of return (volatility) spillover in the short (long) term. Similarly, Hung and Vo (2021) and examine the time-frequency co-movements and spillovers between strategic commodity (oil and gold) and

US stock market. The results show that the return spillover is higher during the pandemic than before. They also find positive co-movements between oil and US stock markets at medium and low frequencies. Jebabli et al. (2021) accounts for positive and negative (asymmetric) volatility spillovers between natural gas, Brent crude oil, and international global (MSCI world) and regional (MSCI Europe and Emerging) stock markets. The authors find asymmetric volatility spillovers between markets under study where the bad volatility spillover is stronger than the good volatility spillover. Wu et al. (2019) find a significant spillover within Chinese sector stock returns. the author find that industrial sectors are the main source of spillover in Chinese stock markets. Hernandez et al. (2022) examine the switching spillovers (low-volatility spillovers and high-volatility spillovers) between oil and U.S. stock sectors and show an intensification of spillovers during the COVID-19 period. Oil risk impact the spillover system in the high-volatility regime. These results are confirmed by Mensi et al. (2022) who find that oil and gold are net receivers of spillover in the system whereas the majority of EU subsectors are net contributors. The authors also show a jump in spillovers during the epidemic period.

Our paper adds to the literature by addressing the frequency co-movements and volatility spillovers between oil and stock sector returns of U.S. and China economies by relying on the impacts of the COVID-19. We focus on a sectoral level because the industrial sectors react differently to the oil shocks (Fang and Egan, 2018). Sectors are heterogonous in nature. Some sectors are offensives (cyclicals) and are less attractive for diversification purposes and others are defensive which are important for hedging strategies. For example, Narayan and Sharma (2011) show significant spillovers between oil and only energy, manufacturing and transportation sectors. This study also examines how COVID-19 virus affects the diversified portfolio gains and the hedging costs. Our study offers new insights on the relationships between oil and stock sector returns to traders, hedgers, mutual funds, and hedge funds.

3. Data and summary statistics

We use daily closing stock prices of China and U.S. Specifically, we consider the S&P 500 Index as a proxy of U.S. stock market and CSI 300 Index as a proxy of Chinese stock market. We also consider their ten corresponding sectors: Consumer Staples, Consumer Discretionary, Energy, Financials, Health Care, Industrials, Information Technology, Materials, consumer products and services, and Utilities. The CSI 300 Index and S&P 500 Index report the investment performance of the largest stocks traded in Shanghai and Shenzhen stock exchanges for China and US, respectively. These indices represent a benchmark for international investors on the financial health of global stock market. We also consider the reference WTI crude oil for the U.S. The sample period covers January 1, 2019 until May 21, 2021. We have selected this period to stress on the COVID-19 effects. This also eliminates the effects of other recent economic and energy crises. The data are compiled from the database of DataStream. We compute the continuously compounded daily returns on day t are defined as $R_t = \ln\left[\frac{P_t}{P_{t-1}}\right] \times 100$, where P_t and P_{t-1} stand for the price on day t and the one-day lag, respectively.

We plot in Figs. 1 and 2 the dynamic daily stock sectoral prices of US and China, respectively. As we can see in Panel A of Fig. 1, We observe that US sector prices show an upside trend from January 2019 until February 2020. A structural break in March 2020 is observed for all markets. This period corresponds to the announcement of World Health Organization (WHO) that COVID-19 is a global pandemic. We will select this breakpoint to split the entire sample period into two subperiods. After this sudden change, all series exhibit a significant upward. WTI price shows a significant drop in the first quarter of 2020 where the price reaches a negative value (-$36.98 per barrel) in April 20, 2021. The trajectory of Chinese sector stock prices shows an upside pattern after the WHO announcements with the exception of Consumer Staples, Financials. The time variations of daily price returns of oil and sector stock markets show high volatility clustering and fat tails, which is higher in China rather than U.S., indicating evidence of nonlinear price behaviors.

—— Insert Figs. 1 & 2 ——

Table 1 presents the descriptive statistics of stock price return series. We observe that the average returns are positive for all markets (except for Energy sector). The Information Technology sector exhibits the highest mean return for US sectors and Consumer Staples for Chinese sectors. The performance of Chinese sectors is better than their US counterparts. WTI oil shows positive average returns. The five out of ten US sector stock markets are riskier than the Chinese market (Energy, Financials, Industrials, Materials, and Utilities). WTI oil is more volatile than US and Chinese sectors. The skewness values are negative for all series, except Chines Utilities and WTI oil. This indicates asymmetry distribution (left skewed). The kurtosis values show evidence of fat tails and leptokurtic distributions. All return series are not normal according to the values of the Jarque Bera test. The results of ADF unit root and KPSS stationary statistic tests indicate that all return series are stationary. The Ljung Box test results show significant evidence of serial correlation. This result shows the appropriateness to use the GARCH family models.

Panels A and B of Fig. 2 display results of the unconditional correlations among all pairs. We observe a positive correlation between all pairs. More specifically, the correlation degree between WTI oil and US sectors ranges from 0.09 for Utilities to 0.48 for Energy whereas for Chinese economy it varies between 0.09 for Industrials to 0.16 for Information Technology. WTI oil is more correlated to US sectors than Chinese sectors. More interestingly, the correlations among US sectors are higher than among Chinese sectors. This result exhibits that US sectors are more integrated than those in china are.

—— Insert Table 1 ——

—— Insert Fig. 3 ——

4. Empirical methods

4.1 Wavelet coherence method

We are primarily interested in measuring the comovement between crude oil and sector stock markets in the time and frequency domain (i.e., short-term, medium-term and long-term). To achieve that, we utilize the wavelet coherence (WTC) technique (Torrence and Compo, 1998) a method characterized by localization in both time and frequency domains in turn allows to measure the strength of association between two time-series over sample period across different time frequencies. We define the cross-wavelet between the two series $x(t)$ and $y(t)$ as follows:

$$W_{xy}(\tau, s) = W_x(\tau, s)W_y^*(\tau, s), \qquad (1)$$

where τ refers to the location, s represents the scale, and * denotes the complex conjugate. The cross-wavelet shows a high common power by representing the local covariance between the time series at each scale.

To capture the co-movement between the two series, we define the wavelet coherence as:

$$R^2(\tau,s) = \frac{\left|S\left(\frac{1}{s}W_{xy}(\tau,s)\right)\right|^2}{S\left(\frac{1}{s}|W_x(\tau,s)|^2\right)S\left(\frac{1}{s}|W_y(\tau,s)|^2\right)}, \tag{2}$$

where S represents the smoothing operator and $0 \leq R^2(\tau,s) \leq 1$. Moreover, values closer to one (zero) indicate the presence of strong (weak) correlation between the two time series.[3] In the next step, we provide information about the positive and negative returns' co-movements, as well as the causal relationships between the two series, using the phase difference described by Torrence and Compo (1998) as:

$$\Phi_{xy}(\tau,s) = tan^{-1}\left[\frac{\mathrm{Im}\left|S\left(\frac{1}{s}W_{xy}(\tau,s)\right)\right|}{\mathrm{Re}\left|S\left(\frac{1}{s}W_{xy}(\tau,s)\right)\right|}\right], \text{ where } \Phi_{xy} \in [-\pi,\pi], \tag{3}$$

where lm and Re represent the imaginary and real parts of the smoothed cross-wavelet transformation, respectively. The phase difference is graphically shown by black arrow on the inside regions of wavelet coherence plots. Arrows pointing to the right mean that two series $x(t)$ and $y(t)$ are in phase or moving in a similar way. If arrows point to the left (antiphase), then two series are negatively correlated. Furthermore, the phase difference show the lead/lag relationship between two series $x(t)$ and $y(t)$. For example, arrows points to the right and up suggest that variable $x(t)$ is leading and the two variables are positively correlated; if arrows are pointing to the right and down, $y(t)$ is leading. On the other hand, arrows pointing to the left and up signify that the first series $x(t)$, is lagging and the correlation is negative, while arrows facing the left and down indicate the first series $x(t)$ is leading but with a negative correlation.

4.2 Asymmetric BEKK-MGARCH(1,1) model

Many empirical studies have captured the volatility spillover effects across different assets and

[3] On the wavelet coherence plots, the red colors represent strong co-movement, whereas the blue colors correspond to weak co-movement.

markets using several variants of the multivariate GARCH (MGARCH) models (Sadorsky, 2012, 2014; Gupta, et al., 2018; Tsuji, 2018; Katsiampa, et al., 2019; Belhassine, 2020; Sarwar, et al., 2020; Asl et al., 2021; Yousaf, 2021; Zhong and Liu, 2021). We analyze the volatility spillover effect between the crude oil and sector stock markets by using BEKK (Baba-Engle-Kraft-Kroner)-MGARCH model (Engle and Kroner, 1995). Unlike other variants of the MGARCH model, imposing other restrictions to the original model, such as the constant conditional correlation (CCC) of Bollerslev (1990) and the dynamic conditional correlation (DCC) of Engle (2002), the BEKK-MGARCH model is flexible to measure the positive definiteness of the variance-covariance matrix to capture both own- and cross volatility spillover effects and persistence. Thus, the BEKK-MGARCH model represents more parameters to be fully implement the interdependences of the conditional volatilities. However, the BEKK-MGARCH model do not capture an asymmetric volatility feature, i.e., volatility tends to rise more in response to negative shocks (bad news) than to positive shocks (good news) (Engle and Ng, 1993; Glosten et al., 1993; Kroner and Ng, 1998). We employ the asymmetric BEKK-MGARCH model to measure the asymmetric volatility spillover across crude oil and sector markets. The asymmetric BEKK-bivariate GARCH (1.1) model is written as:

$$R_{it} = \mu_i + \beta_i R_{it-1} + \varepsilon_{it},\ \varepsilon_{it}|\Omega_{t-1} \sim (0, \boldsymbol{H_t})$$

$$R_{it} = \begin{bmatrix} R_{o,t} \\ R_{s,t} \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \begin{bmatrix} R_{o,t-1} \\ R_{s,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{o,t} \\ \varepsilon_{s,t} \end{bmatrix} \tag{4}$$

where R_{it} is the (2×1) vector of returns for crude oil (o) and each sector (s) at time t, respectively, β_i is the coefficient matrix of first order autoregssive parameter and μ_i is a vector of constants. We assume that ε_{it} represents the random error terms for each market at time t with its corresponding (2×2) conditional variance-covariance matrix $(\boldsymbol{H_t})$.

From Eq. (1), the asymmetric BEKK-bivariate GARCH model is specified as:

$$\boldsymbol{H_t} = \boldsymbol{C'C} + \boldsymbol{A'}\varepsilon_{t-1}\varepsilon'_{t-1}\boldsymbol{A} + \boldsymbol{B'H_{t-1}B} + \boldsymbol{D'\Gamma_{t-1}\Gamma'_{t-1}D}, \quad (5)$$

where $\boldsymbol{H_t} = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix}$, $\boldsymbol{C} = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}$, $\boldsymbol{A} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$, $\boldsymbol{B} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$, $\boldsymbol{D} = \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}$,

$\varepsilon_{t-1}\varepsilon'_{t-1} = \begin{bmatrix} \varepsilon^2_{1t-1} & \varepsilon_{1t-1}\varepsilon_{2t-1} \\ \varepsilon_{2t-1}\varepsilon_{1t-1} & \varepsilon^2_{2,t-1} \end{bmatrix}$, $\boldsymbol{H_{t-1}} = \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix}$, $\boldsymbol{\Gamma} = \begin{bmatrix} min(\varepsilon_{1t}, 0) \\ min(\varepsilon_{2t}, 0) \end{bmatrix}$

where C is a lower triangular matrix. A is a (2×2) matrix of ARCH coefficients that capture the effects of shocks. B is a (2×2) matrix of GARCH coefficients that capture volatility effects. D is a (2×2) matrix of asymmetric coefficients that capture asymmetric response to shocks. The vector Γ_{t-1} is zero if $\varepsilon_t > 0$, and Γ_{t-1} is one if $\varepsilon_t < 0$.

From Eq (2), we define three types of spillover effects: shock spillover effect, volatility spillover effects and asymmetric shock spillover effects. First, shock spillover effects refer to the off-diagonal elements in matrix $\boldsymbol{A}$ (i.e., a_{12} and a_{21}) and capture a one-way causal link between past shocks in one market and the current volatility in another market. Second, volatility spillovers refer to the off-diagonal elements in matrix $\boldsymbol{B}$ (i.e., b_{12} and b_{21}) and capture a one-way causal link between past volatility in one market and the current volatility in another market. Finally, asymmetric shocks spillovers refer to the off-diagonal elements in matrix $\boldsymbol{D}$ (i. e., d_{12} and d_{21}) and measure the asymmetric response of the current conditional variance to past negative shocks from another market (i.e., "bad news" from another market). A negative value of elements in matrix $\boldsymbol{D}$ means that a negative shock (bad news) decreases volatility more than a positive shock (good news), while a positive value implies that a negative shock (bad news) increases volatility more than a positive shock.

The parameters of the asymmetric BEKK-bivariate GARCH model can be estimated by the maximum likelihood estimation method optimized with the BFGS algorithm. The log likelihood function $L(\theta)$ is expressed as:

$$L(\theta) = -T\log(2\pi) - 0.5\sum_{t=1}^{T}\log|H_t(\theta)| - 0.5\sum_{t=1}^{T}\varepsilon_t(\theta)'H_t^{-1}\varepsilon_t(\theta) \quad (6)$$

where T and θ are the number of observations and the vector of all the unknown parameters, respectively.

4.3. Optimal portfolio allocation and risk management

The dynamic of shocks and volatility transmission affects optimal portfolio allocation, risk management and hedging strategy between crude oil and sector markets. To construct optimal risk-minimizing portfolios, we compute the optimal portfolio weights (W_t^C) and optimal hedging ratios (β_t^C) using the asymmetric BEKK bivariate specifications. Following Kroner and Ng (1993), the optimal weights in a two asset portfolio are defined as:

$$w^c = \frac{h_t^S - h_t^{C,S}}{h_t^C - 2h_t^{C,S} + h_t^S}, \quad \text{with } w_t^C = \begin{cases} 0 & w_t^C < 1 \\ w_t^C & 0 \le w_t^C \le 1, \\ 1 & w_t^C > 1 \end{cases} \quad (7)$$

where h_t^C, h_t^S, and $h_t^{C,S}$ are the conditional volatility of the crude oil, conditional volatility of the sector stock market, and conditional covariance between the crude oil and sector markets at time t, respectively.

We also quantify the optimal hedge ratios to minimize the risk of sector-crude oil portfolio. By the application of the beta hedge method (Kroner and Sultan, 1993), the hedging of a long position (buy) of one dollar in the crude oil by a short position (sell) of β_t^C dollars in the sector markets:

$$\beta_t^C = \frac{h_t^{C,S}}{h_t^C}. \quad (8)$$

Finally, we estimate the hedging effectiveness of constructed portfolios that can be measured by comparing realized hedging errors (Ku et al. 2007), which are defined as follows:

$$HE = 1 - \frac{Var_{hedged}}{Var_{unhedged}}, \quad (9)$$

where, Var_{hedged} and $Var_{unhedged}$ represent the variance of hedged (sector and crude oil) and unhedged portfolios (crude oil), respectively. A higher hedging effectiveness (HE) value indicates a better investment strategy.

5. Empirical results and discussion

5.1. Frequency dynamics relationship analysis

Figs. 4 and 5 depict the wavelet coherence plots between oil and US and Chinese stock returns at aggregate and disaggregate level, respectively. As we can see in Fig. 4, the results show significant positive co-movements between oil and S&P500 index returns at low frequencies along almost all the sample period where the oil market leads the U.S. aggregate stock returns, suggesting evidence of contagion. The long-term investors mainly mutual and hedge funds should seek other alternative securities to hedge their position. The positive relationship indicates that both oil and U.S. stock markets are in-phase. Moreover, the correlation between these two markets exceeds 0.8. This result validates the recoupling hypothesis and indicates a drop in the diversification benefits using oil asset. Furthermore, we find evidence of medium co-movements during January-March 2019 under 8-16 days. This result reveals that medium-term investors can earns profit by adding oil futures to their stock portfolio. A strong co-movement is also observed from October 2019 to April 2020 under 8-64 days. Moreover, we observe a co-movement between oil and S&P500 returns during summer 2020 under 8 to 16 days. Our results are in line with the findings of Belhassine and Karamti (2021) who find a strong evidence of movements in U.S., China, Saudi Arabia, Russia, India, and Canada at low frequencies and weak co-movements at high frequencies.

As for the sectoral level, a strong co-movement between oil price returns and all U.S. sectors is observed before and during times of COVID-19 outbreak (Fig. 4), mainly at low frequencies (above 64 days). More interestingly, we observe heterogeneous responses of sector returns to oil prices. A weak co-movement at high and low frequencies is identified for Consumer Staples. As for the remaining sectors, we find evidence of little of insignificant co-movements with oil, except Energy sector. Specifically, oil and energy sectors co-move along the sample period irrespective of frequency. This result corroborates those of Ahmad et al. (2021) who find a strong effect between oil volatility as measured by OVX ad U.S. energy sector. We notice the first quarter of 2020 is the period where oil and sector pairs exhibit the highest dependence. This period corresponds to the first wave of COVID-19 where U.S government undertake strict measures to stop the spread of the virus. Overall, we find that, among all U.S. sectors, Utilities sector is the most immune against oil shocks at the long term. This expected result is explained by the fact that Utilities sector is a supplier of essential goods and services, making it a stable sector even during pessimistic phases. This result also confirms the findings of Ahmad et al. (2021).

As for China (see Fig. 5), the results are different to the U.S. markets. Specifically, we find moderate co-movements between oil and Chinese market at both medium and low frequencies. It is worth noting that oil leads the CSI300 index returns at medium frequency whereas it laggings behind the CISI300 index returns at low frequency between December 2019 and September 2020. As for sectors, the results show that the directions of the arrows at different scales and over the sample period are not the same across different sectors. This indicates that the lead-lag relationships are affected by the time investment horizons as well as the degree of dependence of each sector to oil market. Oil leads the Chinese Consumer Staples at high frequency in February 2020, at medium frequency between January and June 2019 at 64 days. A moderate correlation (0.6) between oil and Consumer Staples is observed at intermediate frequency between January 2020 and July 2020 as well as February 2021 and May 2021 where the correlation parameter increases to 0.8. All Chinese sectors exhibits strong co-movements with oil price returns at very low frequency along the sample period with the exception of Industrials, Information Technology and Consumer Services pre-COVID-19 crisis. Overall, we see that oil and the sector stock indexes are in phase. A weak continuous island of co-movement is observed at high frequency, indicating evidence of decoupling at high frequencies.

In sum, the absorption of oil shocks is heterogeneous for both U.S. and China, varies across sectors and sensitive to frequencies. This shows a nonlinear and heterogeneous relationships between oil and industrial sectors. In addition, Chinese investors are more comfortable in using oil futures to hedge their stock portfolio than U.S. investors.

—— Insert Figs. 4 & 5 here ——

5.2. Volatility transmission analysis

For an in-depth picture on the relationships between oil and stock sectors during the pandemic, we assess the direction and size of shocks and volatility transmission between the considered markets before and during the COVID-19 using the asymmetric BEKK GARCH model.[4] Tables 2-5 report the results of the bidirectional asymmetric shocks and volatility transmission between oil and stock sectors for U.S. and China economies before and during COVID-19 crisis, respectively. The parameter A_{ii} measures the impact of past own-shocks (own ARCH effects) in conditional volatility of market i and A_{ij} assesses cross-shock transmissions from market i to market j. B_{ii} and B_{ij} measures the own GARCH effects and cross-volatility

[4] It is worth noting that we used different GARCH models with different lag orders ranging from 0 to 2. We select the best-fit model by minimizing the Akaike Information Criteria.

transmissions from market i to market j, respectively. D_{ii} and D_{ij} account for asymmetries in market i and between markets i and j.

As we can see in Table 2, we show that past own-shocks has insignificant effects on the current conditional volatility of U.S. sectors before the pandemic with the exception of both Consumer Staples and Financials sectors where the past shocks (past news) affect negatively the conditional volatility of these two sectors. The results show investors can use past shocks to predict the volatility of the prices of Consumer Staples and Financials sectors. Besides, we find evidence of unidirectional shock transmission from U.S. Financials sector to oil market before the pandemic. For the remaining pairs, we observe insignificant own and cross-shocks transmission. On the other hand, we show that past own volatility of oil (B_{11}) and U.S. sector (B_{22}) contribute significantly and positively the conditional volatility of oil and sector returns. More importantly, we find strong evidence of bidirectional volatility transmission between oil and sectors (B_{12}) and B_{21}). More precisely, we find negative and significant volatility transmission from oil to SP500 index and both Consumer Staples, Health Care, Information Technology, and Consumer Service sectors. In contrast, the volatility transmission from these U.S. sectors to oil returns is positive. We find evidence of significant negative volatility transmission between oil and U.S Utilities and Materials. We notice that past volatility of sectors affects their current conditional volatility with the exception of Materials. The results reveal evidence of asymmetric response to negative shocks (or bad news) of own market for the sectors except Consumer Staples, Industrials and Materials (see the coefficient values of D_{22}). Looking at the cross-market asymmetric responses, we find that oil respond asymmetrically towards shocks of U.S. sectors except Consumer Staples, Energy, Financials, and Materials. In contrast, Consumer Staples, Financials, Industrials, and Utilities sectors rises more in response to bad shocks than good shocks emanating from oil market. This result exhibits the appropriate to relying on asymmetric responses when modelling the shocks and volatility transmission between oil and stock markets.

During the COVID-19 period (see Table 3), we find evidence of own-shock effects of oil on the current conditional volatility of oil market. This result is similar for all sectors with the exception of Consumer Staples, Health Care, and Industrials. Moreover, the magnitude of own-shock transmission increases during the times of COVID-19 crisis than before. We find evidence of unidirectional shock transmission from both SP500 index and Consumer Staples to oil and from oil to Consumer Staples, Financials, Industrials, and Utilities sectors. A bidirectional shock transmission is identified between oil and both Energy, Health Care, Technology, and Materials. As for the own volatility transmission (GARCH effects), we observe that past conditional volatility contributes to the increase of the current volatility of both oil and sectors. Furthermore, we find significant unidirectional volatility transmission from SP500 index, Consumer Discretionary, Consumer Services, and Utilities to oil market. In addition, oil transmits volatility to both Energy, Financials, Health Care, and Industrials markets. More interestingly, the result shows significant bidirectional volatility transmission between oil market and both Consumer Staples, Information Technology, and Materials sectors during COVID-19. The intensity of shock transmission increased during the pandemic than before whereas the results are mixed for the volatility transmission.

Tables 4 and 5 report the estimates of information transmission between oil and Chinese sectors before and during the COVID-19, respectively. As we can see in Table 4, we find evidence of unidirectional shock transmission from oil to Energy and Financials sectors before. In addition, the results show significant bidirectional volatility transmission between oil and both Energy and Health Care sectors. Conversely, unidirectional spillovers are obtained from oil to Consumer

Discretionary and from Financials sector to oil. For the remaining cases, the volatility transmission is statistically insignificant, indicating evidence of decoupling and diversification opportunities.

The matrix D reports the estimates of the asymmetric volatility spillover effects. The results show that the coefficients (D_{11}) is negative and significant for U.S. Consumer Discretionary, Information Technology and Utilities pre- pandemic period. This implies that good news increases the volatility in these three sectors. Conversely, the coefficient is positive and significant for U.S. Energy and Materials sectors, implying that bad news decreases the volatility in these markets. However, the coefficients of the remaining sectors are insignificant. The coefficient (D_{22}) is positive and significant for almost all cases, suggesting that negative news influence negatively the volatility in oil market. This result is consistent with the findings of the findings of Chen et al. (2020) who find a positive coefficient for the case of crude oil and rare earth markets. On the other hand, we report significant positive asymmetric bidirectional volatility spillovers between oil and Utilities and Information Technology sectors. In contrast, we show negative asymmetric volatility spillovers for the case of Industrials, implying bad news from Industrials/oil decreases the volatility oil/Industrials market. There are also asymmetric volatility spillovers from oil to both Consumer Staples Health Care, Industrials, and Consumer Service sectors. On other hand, we find asymmetric volatility spillovers from Consumer Staples and Financials sectors to oil market. The asymmetric spillover effects are more pronounced during the pandemic. This can be explained by the high panic, uncertainty, and the irrational behaviors of market participants. The values of coefficients (D_{11}) is positive and significant for all U.S. sectors (except Industrials and Information Technology). The coefficient (D_{22}) is also positive for all cases. This means that bad news increases the volatility in these markets. The asymmetric volatility spillovers is (see $D_{12}$and D_{21}) for all U.S. markets with the exception of Health Care sector. However, the asymmetric volatility spillovers are less evidenced for China. Before the pandemic, the coefficient see D_{12}(except Consumer Discretionary) and D_{21}(except Consumer Staples) are insignificant. Similarly, the coefficient (D_{22}) is also insignificant for all cases. The coefficient(D_{11}) is positive and significant for all sectors with the exception of Health Care. The result is almost similar during COVID-19. This result shows that the volatility spillover is symmetric between oil and Chinese sectors irrespective of the effects of COVID-19.

Finally, the last two rows of Tables 3-5 report the results of diagnostic tests (the Ljung–Box test for autocorrelation in the standardized squared returns). We find evidence against misspecification of our models as the null hypothesis of serial correlation is not rejected.

—— Insert Tables 2-5 ——

5.3. Portfolio management analysis

Table 6 presents the results of portfolio optimal weights ($\boldsymbol{w_t^C}$), hedge ratio ($\boldsymbol{\beta_t^C}$), and hedging effectiveness ($\mathbf{HE}$) for the whole period, before and during the pandemic. The results show for the whole period that the optimal weight is less than 50% for all pairs, suggesting that investors should hold more stocks than oil futures in their portfolio. This result persists for all sectors before and during the COVID-19 crisis. Specifically, we show that the optimal weight ranges between 0.028 for U.S. Energy sector and 0.162 for Information Technology before the pandemic. This indicates that an optimal allocation for oil futures in a $1 oil–Energy (Information Technology) portfolio of 2.8 (16.2) cents, with the remaining 97.2 (83.8) cent budget invested in the Energy (Information Technology). During the health crisis, it varies between 0.074 for Consumer Staples to 0.431 for Energy, suggesting that an investor should invest 7.4 (4.3) cents in oil and the 92.6 (56.9) cents in Consumer Staples (Energy). As for China, the optimal weight oscillates between 0.139 (0.121) for Utilities and 0.446 (0.336) for Information Technology before (during) the pandemic. We notice that the oil proportion invested in oil-stock portfolio is higher for China market than U.S. market for all sectors with the exception of both Energy and Utilities before and during COVID-19 crisis. More importantly, we observe that the proportion invested in oil asset increases during the pandemic for the U.S. aggregate index and all sectors except U.S. Health Care sector. This indicates that U.S. equity investors can consider oil futures as a diversifier asset. This result is opposite for the China where we find a decrease in the proportion invested in oil for all sectors with the exception of Financials and Utilities sectors.

For the whole period, the U.S. (Chinese) hedging ratio values are low and ranges between 0.001 (0.035) for Utilities and 0.45 (0.112) for Energy (Materials), indicating a highly effective hedge in the considered sector stocks using oil. For Utilities, this indicates that that $1 long in the oil portfolio should be hedged with 0.1 (3.5) cents in the U.S. (Chinese) Utilities to minimize risk. This result is in line with the findings of Arouri et al. (2011; 2012) for US and European stock sectors. It also confirms the results of Belhassine and Karamti (2021) who find low hedge ratio values for the case of oil-stock portfolio in countries heavily reliant on oil (India, China, Saudi Arabia, Russia, Canada, and U.S.). The hedging is expensive during the pandemic than before for all cases with the exception of both Health Care and Information Technology. This is due to the high performance of these two sectors during the pandemic. Our result is consistent with Dai and Zhu (2022) who conclude that COVID-19 increases the hedging costs. Moreover, oil is a cheap hedge for China than U.S. market mainly during the pandemic outbreak, since all average hedge ratio values are close to zero.

Finally, we quantify the hedging effectiveness (HE) by adding oil futures to each stock sector portfolio before and during the pandemic spread. The results exhibit that oil offers a HE for all cases independently to the effects of COVID-19. This result is consistent with Lin et al. (2021) who find time-varying positive hedge effectiveness between oil and stock markets of U.S. and China. For the case of U.S., we observe that the values of HE varies from 67.19% (55.8%) for Energy sector to 90.07% (90.19) for Consumer Staples sector before (during) COVID-19. This indicates that oil offers the lowest HE for the Energy sector and the highest HE for Consumer Staples before and during the COVID-19. As for China, we find that the oil provides the lowest highest HE to Consumer services (Utilities) sector before and during COVID-19. The HE values are higher during the pandemic than before for all Chinese sectors, indicating that oil offers the best HE during the ongoing pandemic. This is also true for all U.S. sectors with the exception of Energy, Financials and Utilities sectors. These findings are also in agreement with Samitas et al. (2022) for the case of fine wine and global markets. By comparing the HE between U.S. and China, we show that the HE is higher during the pandemic for the case of China. Before COVID-19, the result exhibits that oil offers the best HE for U.S. than China with the exception of Energy. This result is attributable to the fact that U.S. is more influenced by the price of energy sector than China. In addition, U.S. is the largest oil producer and consumer of energy.

—— Insert Table 6 ——

6. Conclusion and policy implications

The ongoing COVID-19 is one of the worst health crises that disrupted the world economic activities. The strict measure adopted by government has increased the uncertainty and instability in financial and commodity markets (Chang et al., 2020; Managi et al., 2022), making the investment decisions more complex. Examining the oil-stock linkages is a critical element to financial risk assessment. This paper examines the effects of COVID-19 outbreak on volatility spillovers and frequency co-movements between crude oil and 20 stock sectors in the two biggest economies in the world: US and China. It also investigates the impact of the pandemic on the portfolio management and hedging effectiveness. To achieve our objectives, we use the wavelet coherence and asymmetric BEKK GARCH models.

The results show using wavelet approach a time-frequency dependence between oil and sectors. A high dependence between oil and U.S. sectors is observed at intermediate and low frequencies. The highest dependence at low frequency is observed during the first wave of COVID-19 (January-April 2020). This period also corresponds to oil war between Russia and Saudi Arabia. U.S. Energy sector and oil are dependent at high frequencies. Among all U.S. sectors, we show that Utilities is the least dependent to oil shocks. Chinese sectors and oil price returns are weakly dependent at very low frequencies. At both high and intermediate frequencies, we observe insignificant co-movements between oil and sectors. Using the asymmetric BEKK GARCH models, we show significant bidirectional volatility transmission between oil and all U.S. sectors before the pandemic. The evidence of shock transmission is weak. As for China, we find evidence of bidirectional volatility spillovers from oil to both Energy, and Health Care sectors. In addition, a unidirectional volatility transmission from oil to Consumer Discretionary is showed. During the pandemic crisis, we observe strong evidence of own-shock and cross-shock transmission between oil and U.S. sectors. Conversely, we find insignificant transmission of shock (except Information Technology) and volatility (except consumer Services from oil to Chinese sectors during the crisis. However, the past shocks of Chinese sectors have insignificant impact on the oil shocks. A volatility transmission from Chinese sectors to oil is showed with the exception of Industrials, Materials, Consumer Services, and Utilities. The analysis of oil-sector portfolios shows oil is a cheap hedge for China and U.S. markets. In addition, oil futures offer the highest HE during the pandemic for the majority of portfolio in the U.S. case and for all portfolios for China market.

Our results offer new insights to policymakers, traders, hedgers, and institutional investors (mutual funds and hedge funds) during the financial and economic instability. U.S. investors can use oil for diversification purposes mainly at low frequency (1-4 trading days) at intermediate frequency (4-16 trading days). Long-term investors should find an alternative asset to oil as the co-movements between oil and stock sectors are high, limiting the diversification benefits. For the case of Chinese investors, oil is appropriate asset against downward stock price movements. Specifically, the low dependence between oil and Chinese sectors makes oil futures a good hedge for investors. The results of direction and the size of shock and volatility transmission help investors to identify the least vulnerable sector to oil volatility. This may help investor to cut the portfolio risk without lowering the expected returns. Our results may be of assistance to policymakers to undertake the appropriate and differentiating regulatory measures to stabilize the financial markets by controlling the cross-market risk transmission particularly during the pandemic crisis. To improve economic stability, U.S. policymakers should identify the most vulnerable sectors (e.g., Energy and Financials sectors) to oil volatility as sector's responsiveness to oil prices is heterogeneous.

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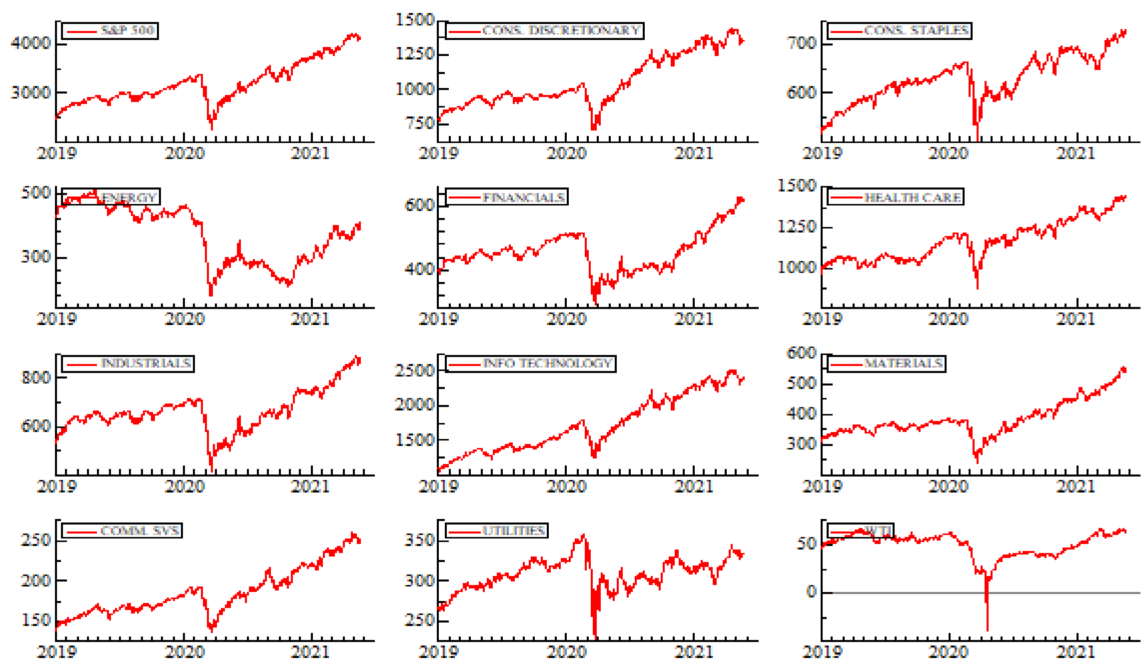
Panel A: U.S. sector and WTI prices



Panel B: U.S. sector and WTI returns

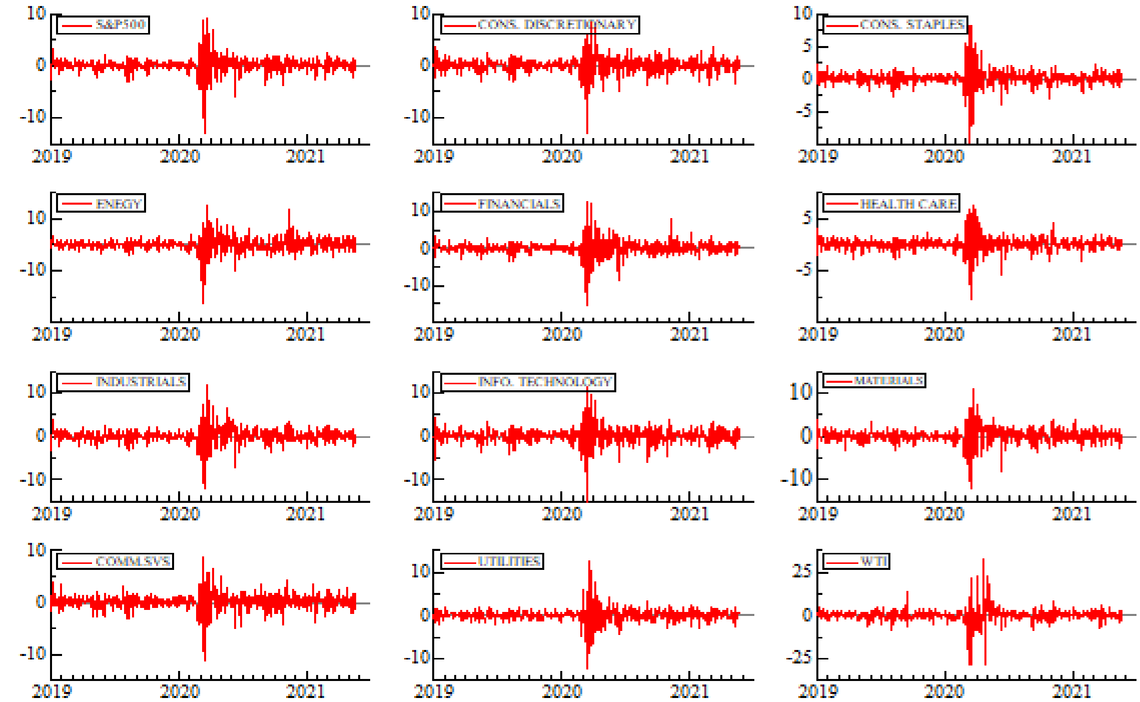
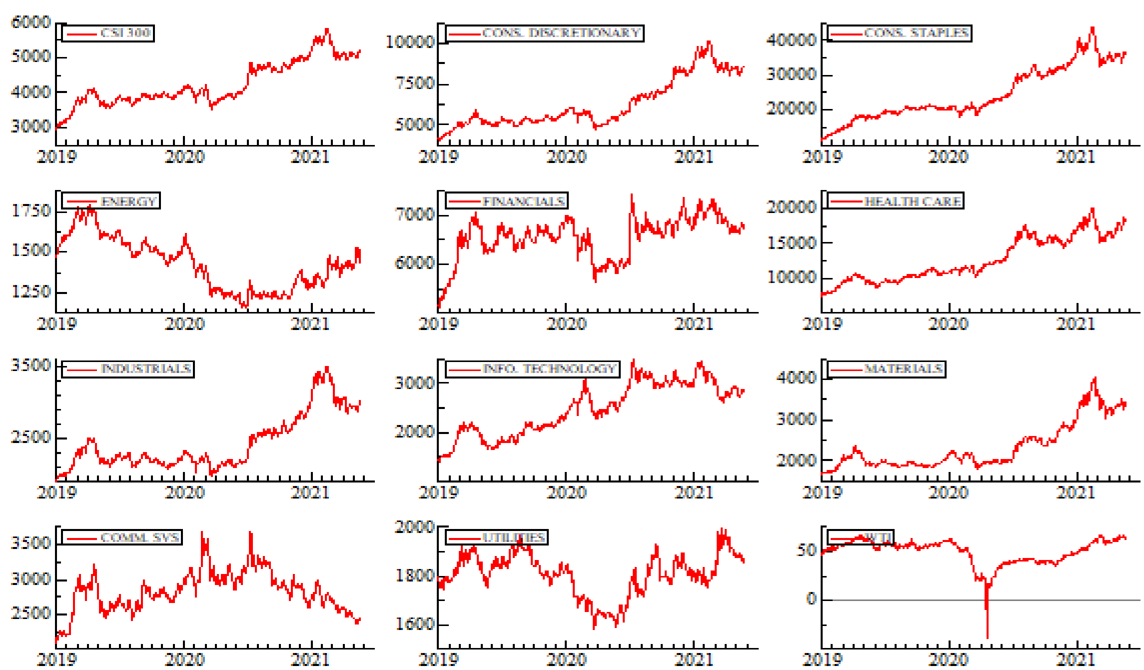


Fig. 1. Dynamics of US sector and WTI markets: (a) Prices; (b) Returns

Panel A: Chinese sector and WTI prices



Panel B: Chinese sector and WTI returns

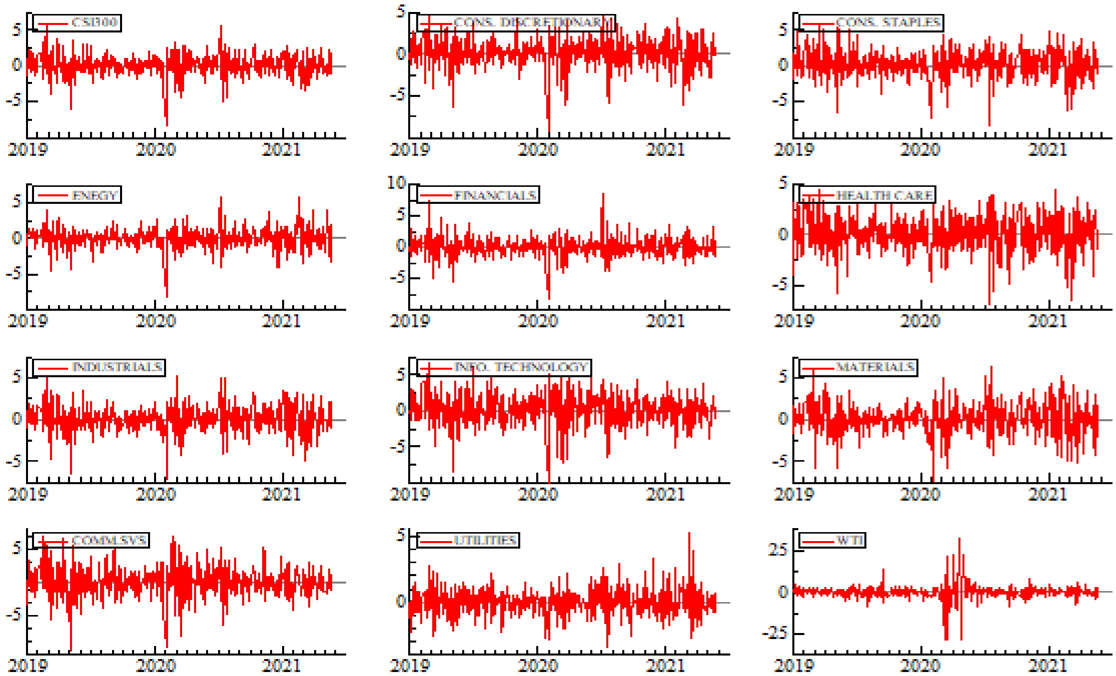
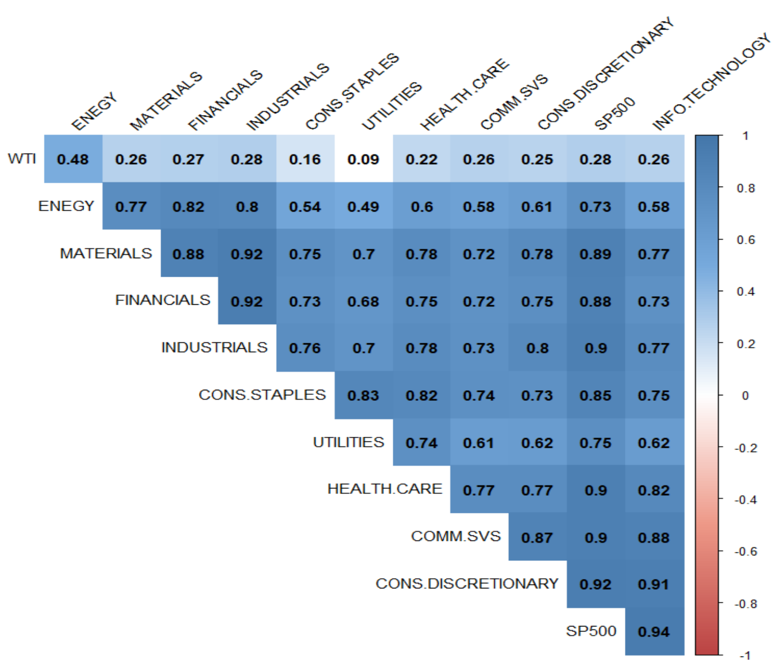


Fig. 2. Dynamics of Chinese sector and WTI markets: (a) Prices; (b) Returns

Panel A: WTI-U.S. sectors



Panel B: WTI- Chinese sectors

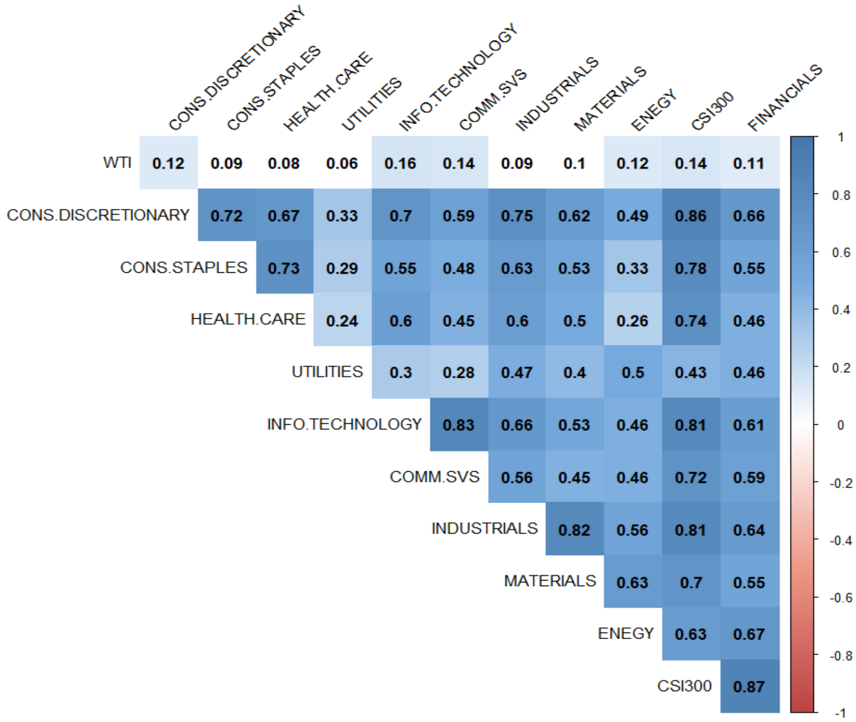
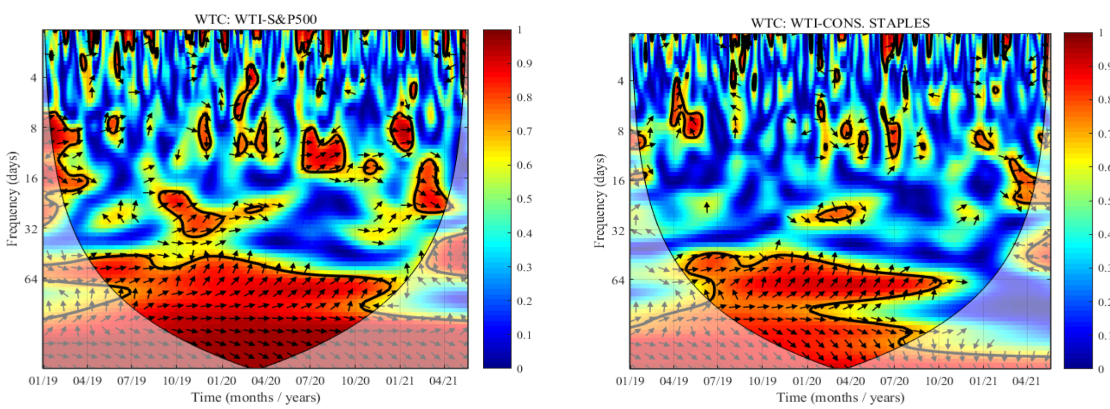
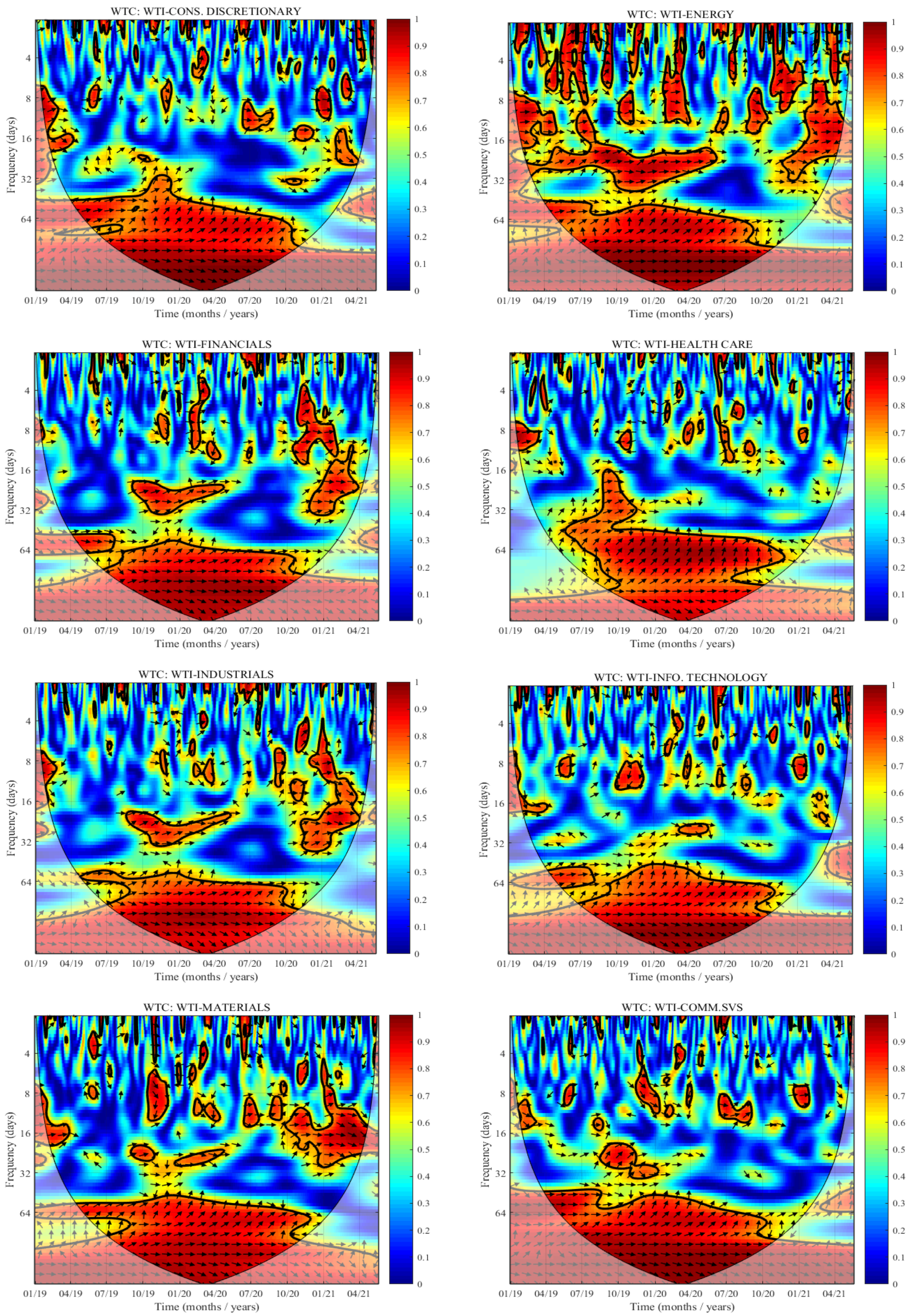


Fig. 3. Heatmap of the pairwise correlations

Notes: This figure exhibits a pairwise correlation matrix; (a) US sector-WTI; (b) China sector-WTI. The color intensity of the shaded boxes refers to the degree of correlation. Blue (red) indicates a positive (negative) correlation.




WTC: WTI-CONS. DISCRETIONARY
WTC: WTI-ENERGY
WTC: WTI-FINANCIALS
WTC: WTI-HEALTH CARE
WTC: WTI-INDUSTRIALS
WTC: WTI-INFO. TECHNOLOGY
WTC: WTI-MATERIALS
WTC: WTI-COMM.SVS
Frequency (days)
4
8
16
32
64
Time (months / years)
01/19
04/19
07/19
10/19
01/20
04/20
07/20
10/20
01/21
04/21
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

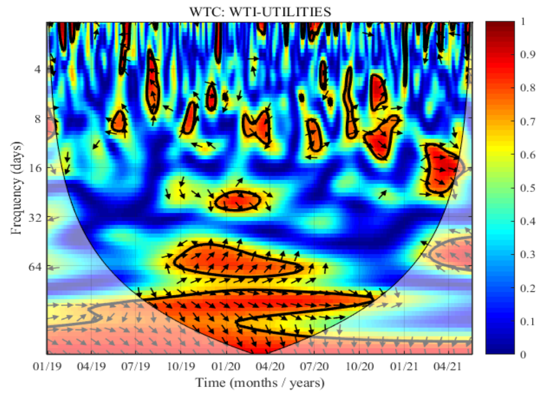
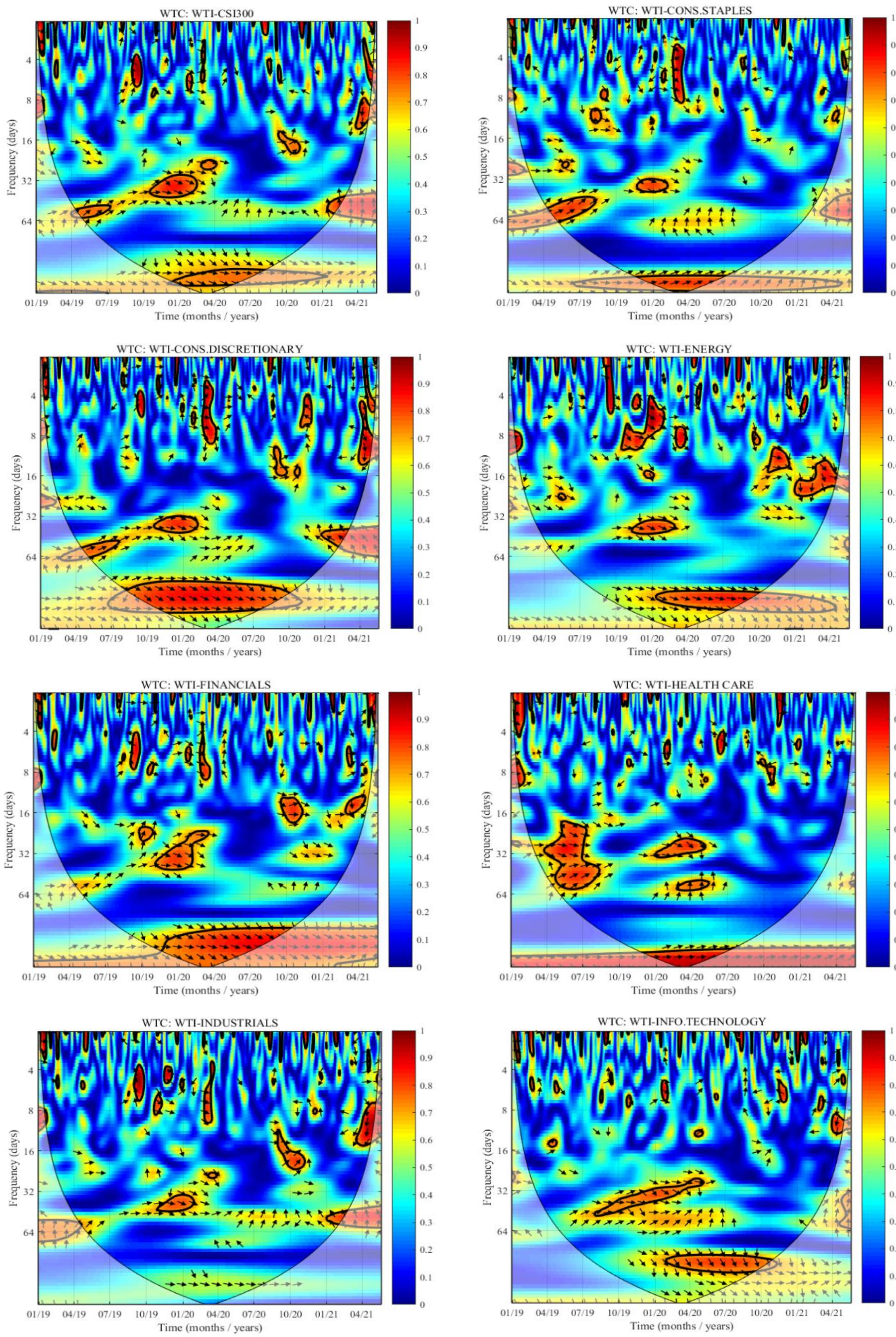


Fig. 4. Wavelet Coherence Plots for WTI and U.S. sector return pairs

Notes: This figure shows the wavelet coherence of US and China aggregate stock and ten sectoral stock indices. The frequency (in days) and time are given on the vertical and horizontal axis, respectively. The concept of wavelet coherence is similar to the square of the traditional correlation R^2. That is, the correlation values lie between 0 and 1, where 0 indicates no correlation and is shown by the blue color on the WTC plot, whereas1 denotes high correlation and is shown by the red droplets on the WTC plot. The arrows in coherence plot represent the lead/lag and in-out phase relationships. The east- (→) and west-facing (←) arrows show positive (variables are in phase) and negative (variables are out-of-phase or anti-cyclical effects) correlations, respectively.). Right-pointing, upwards arrows (↗) and left-pointing, downwards arrows (↙) indicate that US sector is leading, while the left-pointing, upwards arrows (↖) and the right-pointing, downwards (↘) arrows mean that US sector is lagging. The frequency is covered in days. The level of significance has been ascertained in the Monte Carlo simulation (for further explanations of the WTC plot, see Bredin et al. 2015).


WTC: WTI-CSI300
WTC: WTI-CONS.STAPLES
WTC: WTI-CONS.DISCRETIONARY
WTC: WTI-ENERGY
WTC: WTI-FINANCIALS
WTC: WTI-HEALTH CARE
WTC: WTI-INDUSTRIALS
WTC: WTI-INFO.TECHNOLOGY
Frequency (days)
Time (months / years)
01/19 04/19 07/19 10/19 01/20 04/20 07/20 10/20 01/21 04/21

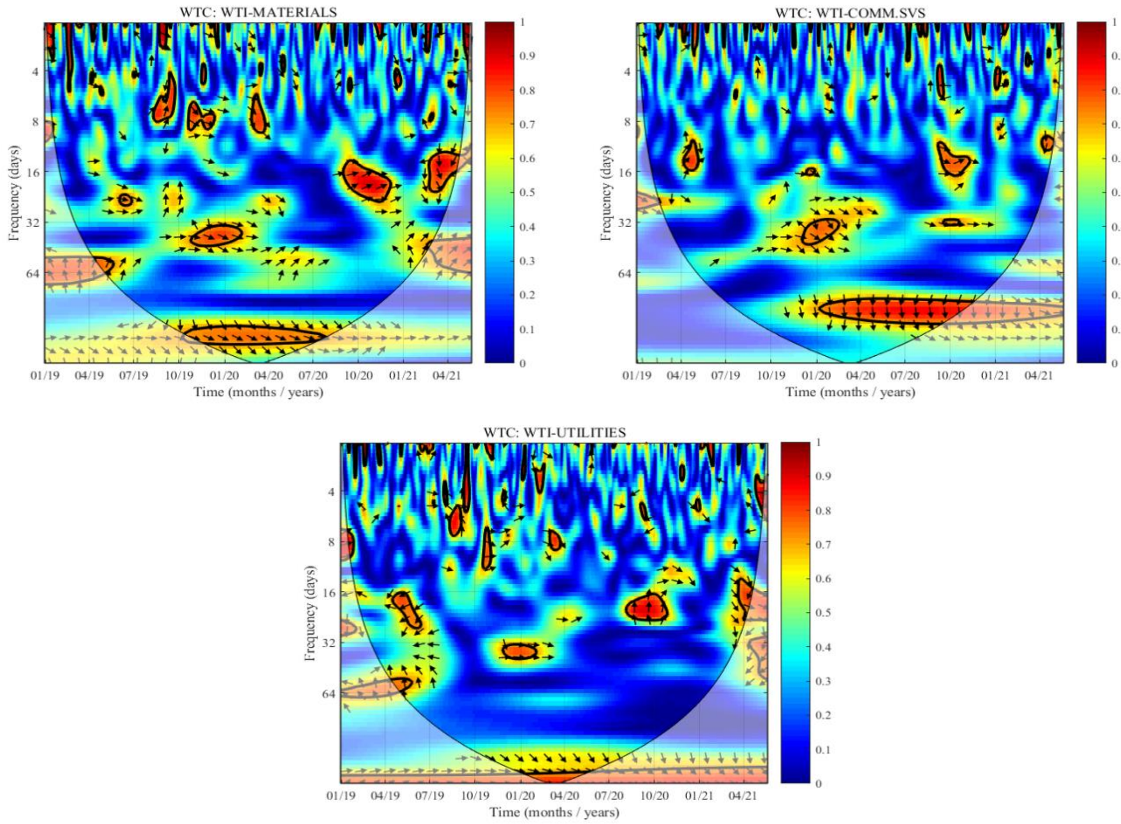


Fig. 5. Wavelet Coherence Plots for WTI and China's sector return pairs
Notes: See Fig. 4.

Table 1. Summary Statistics for United States and Chinese sector and WTI returns.

	Mean	Min	Max	Std. Dev	Skew	Kurt	Jarque Bera	Q^2 (24)	ADF	KPSS
Panel A: US sector										
SP500	0.0838	-12.76	8.968	1.546	-1.101	19.38	6868.4***	370.0***	-12.72***	0.0570
CONS. DISCRETIONARY	0.0906	-12.87	8.286	1.582	-1.276	15.84	4309.4***	193.3***	-12.74***	0.0526
CONS. STAPLES	0.0552	-9.69	8.074	1.258	-0.364	18.87	6345.8***	247.6***	-14.44***	0.0445
ENEGY	-0.0139	-22.41	15.11	2.734	-0.996	15.26	4518.6***	103.1***	-13.08***	0.1726
FINANCIALS	0.0753	-15.07	12.42	2.040	-0.713	15.32	4514.4***	236.5***	-12.95***	0.1612
HEALTH CARE	0.0610	-10.52	7.313	1.403	-0.467	14.32	3243.2***	342.8***	-13.38***	0.0362
INDUSTRIALS	0.0783	-12.15	12.00	1.793	-0.726	14.78	3541.9***	185.0***	-13.36***	0.1045
INFO. TECHNOLOGY	0.1304	-14.98	11.3	1.908	-0.731	14.81	3559.2***	318.1***	-13.80***	0.0366
MATERIALS	0.0897	-12.14	11.00	1.770	-0.793	13.47	2818.4***	204.5***	-13.28***	0.1166
COMM.SVS	0.0983	-11.03	8.802	1.551	-0.754	12.46	2308.1***	268.5***	-13.93***	0.0563
UTILITIES	0.0365	-12.26	12.32	1.711	-0.177	18.92	6375.8***	252.8***	-14.48***	0.0351
Panel B: China sector										
CSI300	0.0948	-8.208	5.777	1.355	-0.547	7.170	445.4***	31.16	-12.87***	0.0928
CONS. DISCRETIONARY	0.1264	-9.207	4.486	1.669	-0.694	5.671	217.2***	25.33	-13.70***	0.0664
CONS. STAPLES	0.1995	-8.282	5.770	1.794	-0.384	5.041	113.9***	33.19	-13.63***	0.1395
ENEGY	-0.0007	-8.074	5.824	1.298	-0.219	7.385	465.3***	18.81	-12.99***	0.1097
FINANCIALS	0.0461	-8.116	8.617	1.441	0.357	8.343	696.3***	36.55**	-12.60***	0.1431
HEALTH CARE	0.1479	-6.829	4.513	1.750	-0.480	3.854	39.56***	81.37***	-14.10***	0.0376
INDUSTRIALS	0.0768	-7.093	5.308	1.444	-0.329	5.700	185.1***	63.47***	-13.30***	0.0662
INFO. TECHNOLOGY	0.1183	-9.982	6.696	2.054	-0.459	5.031	119.0***	51.06***	-13.60***	0.1764
MATERIALS	0.1210	-7.243	6.330	1.718	-0.256	4.824	86.04***	135.0***	-13.10***	0.0847
COMM.SVS	0.0161	-10.27	7.117	2.066	-0.112	5.848	195.5***	97.26***	-13.64***	0.2110
UTILITIES	0.0081	-3.442	5.238	0.966	0.338	5.333	141.3***	62.80***	-15.82***	0.0553
Panel C: Oil										
WTI	0.1520	-28.22	31.96	4.093	0.085	25.33	11956. ***	386.7***	-16.74***	0.0725

Notes: The symbol *** indicates the significance at 1% level. ADF, and KPSS, are the (intercept-only) statistics of the Augmented Dickey and Fuller (1979), and the Kwiatkowski et al. (1992) tests, respectively.

Table 2. Estimation results of asymmetric BEKK-GARCH (1,1) model (Before COVID-19 period: U.S. sectors)

	WTI-SP500	WTI- CONS. DISCRETIONARY	WTI- CONS. STAPLES	WTI-ENEGY	WTI-FINANCIALS	WTI-HEALTH CARE	WTI-INDUSTRIALS	WTI-INFO. TECHNOLOGY	WTI-MATERIALS	WTI-COMM.SVS	WTI-UTILITIES
C_{11}	0.3627*** (0.1349)	-0.2579 (0.2261)	1.2731*** (0.1815)	0.2015 (0.1277)	0.5755*** (0.2064)	0.1032 (0.1313)	0.1070 (0.3789)	0.2863*** (0.1013)	0.1686 (0.2990)	0.2305 (0.2259)	0.1230 (0.0907)
C_{21}	0.0604 (0.0666)	-0.1589 (0.2178)	-0.2115*** (0.0636)	0.0842 (0.0674)	-0.2740*** (0.0658)	-0.0823 (0.0585)	0.1612*** (0.0528)	0.0433 (0.1021)	0.7722 (0.0756)	-0.0190 (0.1565)	0.5341*** (0.1191)
C_{22}	0.1246** (0.0547)	-0.0498 (0.5778)	0.00001 (0.2460)	0.00001 (0.0813)	0.00001 (0.2178)	0.00001 (0.1377)	0.0001 (0.7313)	-0.1202 (0.0817)	0.0001 (4.4409)	-0.1940*** (0.0587)	0.00001 (0.4732)
A_{11}	0.1053 (0.0757)	0.0228 (0.0228)	-0.2010* (0.1051)	0.00001 (0.1112)	-0.3233*** (0.0953)	0.00001 (0.0484)	0.0048 (0.0806)	-0.0003 (0.8428)	-0.1234 (0.0991)	0.0589 (0.0621)	-0.0164 (0.1048)
A_{12}	-0.0091 (0.0208)	0.0080 (0.0303)	0.0308 (0.0262)	0.00001 (0.0308)	0.0257 (0.0404)	0.00001 (0.0250)	0.0047 (0.0363)	0.00001 (0.0328)	0.1156*** (0.0426)	-0.0099 (0.0289)	0.0149 (0.0691)
A_{21}	-0.2287 (0.1805)	-0.0390 (0.1363)	-0.3210 (0.4053)	0.00001 (0.1526)	0.4477** (0.1804)	0.00001 (0.1399)	-0.0831 (0.2101)	0.0003 (0.7671)	1.0367*** (0.1870)	-0.2227 (0.1360)	0.0741 (0.4384)
A_{22}	0.0964 (0.1064)	0.1363 (0.1246)	0.2691*** (0.0794)	0.00001 (0.0768)	-0.0121 (0.1019)	0.00001 (0.0954)	-0.0669 (0.0851)	-0.0004 (1.2919)	0.3105* (0.1160)	0.1484 (0.0810)	0.0351 (0.2247)
B_{11}	0.9488*** (0.0210)	0.9629*** (0.0194)	0.3932*** (0.1333)	1.0688*** (0.0150)	0.8997*** (0.0492)	0.9863*** (0.0053)	0.9615*** (0.0353)	0.9673*** (0.0101)	0.6232*** (0.1179)	0.9622*** (0.0210)	0.9579*** (0.0081)
B_{12}	-0.0184** (0.0077)	-0.0318*** (0.0087)	0.0094 (0.0338)	0.0979*** (0.0091)	0.0609*** (0.0193)	-0.0182*** (0.0029)	0.2970*** (0.0187)	-0.0254*** (0.0060)	-0.1288** (0.0540)	-0.0231** (0.0102)	-0.0925*** (0.0207)
B_{21}	0.2031** (0.0800)	0.1902*** (0.0668)	1.2031*** (0.2433)	-0.2716*** (0.0286)	-0.0530 (0.1350)	0.1355*** (0.0291)	-1.3667*** (0.0797)	0.1108*** (0.0359)	-1.3875*** (0.2171)	0.2118*** (0.0782)	-0.3458*** (0.0629)
B_{22}	0.9289*** (0.0316)	0.9405*** (0.0381)	0.8557*** (0.0619)	0.8797*** (0.0172)	0.8300*** (0.0462)	0.9703*** (0.0121)	0.5633*** (0.0360)	0.9602*** (0.0160)	-0.1851 (0.2279)	0.9254 *** (0.0315)	-0.5603** (0.2187)
D_{11}	-0.0868 (0.0896)	-0.1636** (0.0654)	0.2624 (0.1840)	0.1532** (0.0686)	-0.0965 (0.2362)	-0.0773 (0.0536)	-0.1045 (0.0678)	-0.1172*** (0.0528)	0.6294*** (0.1325)	-0.0362 (0.0899)	-0.2035*** (0.0539)
D_{12}	0.0555** (0.0248)	0.0123 (0.0472)	0.0939*** (0.0243)	-0.0824 (0.0450)	0.0270 (0.0541)	-0.0953*** (0.0162)	-0.1389*** (0.0288)	0.1131*** (0.0284)	0.0541 (0.0740)	0.0722* (0.0372)	0.1099* (0.0600)
D_{21}	0.2523 (0.2255)	0.1660 (0.2000)	-2.6569*** (0.4781)	0.1829 (0.1321)	0.6120** (0.2742)	-0.0067 (0.1221)	-0.4157*** (0.1516)	0.2524** (0.1050)	-0.0330 (0.4530)	0.0486 (0.2075)	0.6838*** (0.1641)
D_{22}	0.3932*** (0.0890)	0.3898*** (0.1041)	0.1137 (0.1283)	0.2232*** (0.0762)	0.5133*** (0.1128)	0.3063*** (0.0457)	0.0696 (0.0766)	0.2527*** (0.0686)	0.3092 (0.1917)	0.3428*** (0.0989)	0.2203 (0.1726)
$Q_1^2(24)$	9.734 [0.995]	9.760 [0.995]	21.77 [0.592]	14.68 [0.930]	6.974 [0.999]	10.97 [0.471]	7.249 [0.999]	9.989 [0.994]	14.87 [0.924]	12.53 [0.973]	7.716 [0.999]
$Q_2^2(24)$	10.59 [0.990]	17.26 [0.837]	21.62 [0.601]	16.42 [0.872]	16.82 [0.856]	23.83 [0.471]	22.92 [0.524]	7.863 [0.999]	14.37 [0.937]	26.43 [0.331]	18.39 [0.783]

Note: This table presents the estimates of bivariate asymmetric BEKK-GARCH model. C(i,j) stands for the intercept. The parameters A(i,j) measure the one-day lag shock effects of each sector or oil on the current conditional volatility if i=j and the effects of shock spillovers if i≠j. The parameters B(i,j) stand for the effect of one-day lag conditional volatility on the current conditional volatility in each sector or oil if i=j and the effects of volatility spillovers if i≠j. The numbers in parentheses are standard errors. $Q_1^2(24)$ and $Q_2^2(24)$ refer to the Ljung–Box test for autocorrelation in the standardized squared returns. Subscript 1 denotes the parameters of returns on WTI crude oil. Subscript 2 denotes the parameters of returns on each US sector. ***, **, * represent 1%, 5%, and 10% significance, respectively.

Table 3. Estimation results of asymmetric BEKK-GARCH (1,1) model (COVID-19 period: U.S. sectors)

	WTI-SP500	WTI-CONS. DISCRETIONARY	WTI-CONS. STAPLES	WTI-ENEGY	WTI-FINANCIALS	WTI-HEALTH CARE	WTI-INDUSTRIALS	WTI-INFO. TECHNOLOGY	WTI-MATERIALS	WTI-COMM.SVS	WTI-UTILITIES
C_{11}	0.3932 (0.2414)	0.7652*** (0.1349)	0.7949*** (0.1443)	0.6343*** (0.1323)	0.5013*** (0.1116)	0.0122 (0.1244)	0.4973*** (0.1417)	0.4774*** (0.1683)	0.4968*** (0.1673)	0.4961*** (0.1258)	-0.0499 (0.1455)
C_{21}	0.4941*** (0.1487)	0.5412*** (0.0628)	0.4572*** (0.0449)	0.6686*** (0.2221)	0.1268 (0.1379)	0.2931*** (0.0534)	0.1173 (0.1199)	0.6064*** (0.0775)	0.7984*** (0.0905)	0.5772*** (0.1028)	-0.3811*** (0.0604)
C_{22}	0.00001 (0.2382)	0.00001 (0.1193)	0.00001 (0.1669)	0.5115*** (0.1469)	0.4442*** (0.0793)	-0.0002 (6.6554)	0.3438*** (0.0651)	0.00001 (0.2094)	0.00001 (0.2935)	0.00001 (0.3302)	0.00001 (2.0036)
A_{11}	0.1428** (0.0603)	0.3105*** (0.0555)	0.3847*** (0.0567)	0.3139*** (0.0570)	0.3190*** (0.0534)	0.2769*** (0.0572)	0.3127*** (0.0636)	0.2697*** (0.0500)	0.1754*** (0.0618)	0.2293*** (0.0541)	0.3060*** (0.0586)
A_{12}	-0.0740*** (0.0258)	-0.0633** (0.0251)	0.0209 (0.0190)	0.0626* (0.0378)	-0.0068 (0.0259)	-0.0388** (0.0176)	0.0072 (0.0288)	-0.0673*** (0.0239)	-0.1079*** (0.0344)	0.0002 (0.0216)	-0.0167 (0.0267)
A_{21}	-0.2484 (0.2214)	0.1199 (0.2102)	-0.8907*** (0.2797)	-0.1779** (0.0720)	-0.3954*** (0.1092)	-0.7843*** (0.1093)	-0.5521*** (0.1592)	0.4285*** (0.0972)	-0.3483*** (0.1223)	0.0191 (0.1498)	-0.8181*** (0.1100)
A_{22}	0.3700*** (0.1256)	0.2519*** (0.0795)	0.1014 (0.1083)	-0.2819*** (0.0644)	-0.3126*** (0.0810)	0.0466 (0.0724)	0.1636 (0.1146)	0.3864*** (0.1043)	0.2991** (0.1373)	-0.2381** (0.0997)	-0.1701** (0.0812)
B_{11}	0.9430*** (0.0300)	0.8587*** (0.0279)	0.8093*** (0.0367)	0.8663*** (0.0204)	0.8705*** (0.0183)	0.9243*** (0.0158)	0.8183*** (0.0344)	0.9035*** (0.0216)	0.9237*** (0.0159)	0.9034*** (0.0166)	0.8563*** (0.0239)
B_{12}	0.0193 (0.0164)	0.0255 (0.0160)	-0.0220* (0.0114)	-0.0477** (0.0185)	-0.0415*** (0.0141)	0.0176*** (0.0057)	-0.0374** (0.0170)	0.0207* (0.0106)	0.0285* (0.0153)	-0.0063 (0.0090)	-0.0015 (0.0176)
B_{21}	-0.3242** (0.1610)	-0.4775*** (0.0709)	-0.6243*** (0.1359)	0.0103 (0.0454)	0.0110 (0.0511)	-0.0362 (0.0572)	0.0854 (0.0600)	-0.2830*** (0.1037)	-0.2857** (0.1194)	-0.1870*** (0.0569)	-0.1076* (0.0637)
B_{22}	0.7288*** (0.1056)	0.7917*** (0.0273)	0.7195*** (0.0450)	0.8937*** (0.0444)	0.8716*** (0.0183)	0.8952*** (0.0224)	0.8947*** (0.0389)	0.7960*** (0.0438)	0.6282*** (0.0776)	0.8404*** (0.0497)	0.8819*** (0.0239)
D_{11}	0.2761* (0.1550)	0.2924*** (0.1116)	0.1077 (0.1216)	0.5620*** (0.1008)	0.3808*** (0.1084)	0.2125* (0.1223)	-0.5922*** (0.0931)	-0.3861*** (0.1112)	0.4528*** (0.0987)	0.4686*** (0.0907)	0.4774*** (0.0943)
D_{12}	0.0489 (0.0677)	0.1467*** (0.0399)	0.1110*** (0.0340)	0.2313*** (0.0806)	0.0548 (0.0476)	0.0367 (0.0381)	-0.1154** (0.0460)	-0.1423* (0.0749)	0.0736 (0.0576)	0.0750** (0.0350)	0.0772* (0.0459)
D_{21}	0.8081*** (0.2437)	0.7880*** (0.1992)	1.5713*** (0.4098)	0.0149 (0.1551)	0.3437* (0.1846)	0.1929 (0.2699)	1.1748*** (0.1700)	0.2108 (0.3109)	0.4497** (0.1996)	0.4276*** (0.1636)	-0.3510 (0.2378)
D_{22}	0.6378** (0.2750)	0.4103*** (0.0952)	0.6656*** (0.1324)	0.2935** (0.1185)	0.4438*** (0.1104)	0.4116*** (0.0944)	0.6426*** (0.0930)	-0.2859* (0.1684)	0.7765*** (0.1283)	0.3609*** (0.0878)	0.4062*** (0.0819)
$Q_1^2(24)$	26.06 [0.323]	26.84 [0.312]	24.37 [0.441]	27.12 [0.298]	25.79 [0.363]	25.12 [0.399]	29.68 [0.195]	29.43 [0.203]	28.65 [0.233]	25.25 [0.392]	27.91 [0.264]
$Q_2^2(24)$	16.29 [0.877]	15.99 [0.888]	13.47 [0.957]	17.93 [0.806]	14.52 [0.934]	8.493 [0.998]	18.84 [0.760]	8.761 [0.998]	14.63 [0.931]	21.38 [0.615]	23.82 [0.472]

Note: see notes of Table 2

Table 4. Estimation results of asymmetric BEKK-GARCH (1,1) model (Before COVID-19 period: China sectors)

	WTI-CSI300	WTI-CONS. DISCRETIONARY	WTI-CONS. STAPLES	WTI-ENEGY	WTI-FINANCIALS	WTI-HEALTH CARE	WTI-INDUSTRIALS	WTI-INFO. TECHNOLOGY	WTI-MATERIALS	WTI-COMM.SVS	WTI-UTILITIES
C_{11}	1.2925*** (0.4638)	1.4177*** (0.2879)	1.0171*** (0.2361)	0.00001 (0.1798)	1.5215*** (0.1174)	0.1003 (0.4209)	0.0419 (0.1125)	1.3281*** (0.4156)	1.0858*** (0.3716)	1.0924* (0.6540)	1.1457** (0.5312)
C_{21}	0.0679 (0.1392)	0.0703 (0.1287)	-0.0593 (0.1224)	0.00001 (0.2542)	0.1625** (0.0809)	1.1811*** (0.1483)	-0.1395* (0.0774)	0.0768 (0.3877)	0.0621 (0.1015)	0.1261 (0.2535)	0.1392 (0.1116)
C_{22}	0.00001 (0.2149)	0.00001 (0.3700)	0.00001 (0.3854)	0.00001 (0.1847)	-0.0001 (0.1868)	0.0003 (12.641)	0.00001 (0.3953)	0.4026 (0.3502)	0.0858 (0.1587)	0.2146 (0.2779)	0.00001 (0.0692)
A_{11}	0.1841 (0.1989)	-0.0521 (0.1387)	-0.1303 (0.1063)	0.0211 (0.0391)	0.3543*** (0.1140)	0.1531 (0.0889)	-0.0404 (0.0408)	0.1476 (0.1049)	0.1457 (0.1061)	-0.1324 (0.1197)	0.1261 (0.1148)
A_{12}	0.0041 (0.0282)	-0.0195 (0.0292)	0.0311 (0.9959)	0.0141 (0.0169)	0.0165 (0.0261)	-0.0074 (0.0624)	-0.0219 (0.0255)	0.0368 (0.5173)	0.0069 (0.0220)	0.0102 (0.0799)	0.0086 (0.0243)
A_{21}	-0.2996 (0.4131)	0.0973 (0.1393)	-0.0527 (0.1438)	-0.1039** (0.0525)	-0.9912*** (0.1773)	-0.0715 (0.1507)	-0.0750 (0.0586)	-0.1069 (0.1265)	-0.0624 (0.1014)	-0.0808 (0.0764)	-0.0701 (0.2078)
A_{22}	0.2321*** (0.0513)	0.3001*** (0.0452)	-0.1753*** (0.0374)	-0.1238*** (0.0326)	0.1773*** (0.0467)	0.0537 (0.1527)	0.2477*** (0.0552)	0.2393** (0.1030)	0.2500*** (0.0420)	0.2755*** (0.0574)	0.1429*** (0.0530)
B_{11}	0.6556** (0.3287)	0.6427*** (0.1734)	0.7941*** (0.0903)	0.9902*** (0.0051)	0.0539 (0.1625)	-0.0440 (0.2252)	0.9829*** (0.0050)	0.6658*** (0.2260)	0.7777*** (0.1499)	0.7860*** (0.2504)	0.7628*** (0.2316)
B_{12}	0.0040 (0.0423)	0.0681** (0.0277)	0.0324 (0.0304)	0.0079*** (0.0026)	-0.0251 (0.0422)	0.2803** (0.1266)	-0.0015 (0.0065)	0.0193 (0.1220)	0.0072 (0.0320)	0.0171 (0.0725)	-0.0261 (0.1761)
B_{21}	0.0734 (0.0778)	-0.0622 (0.0732)	0.0235 (0.0493)	-0.0372*** (0.0107)	0.1408** (0.0678)	1.3564*** (0.0934)	0.0251 (0.0196)	0.0262 (0.1199)	0.0179 (0.0487)	0.0132 (0.0459)	-0.1263 (0.0290)
B_{22}	0.9695*** (0.0137)	0.9286*** (0.0107)	0.9761*** (0.0110)	0.9896*** (0.0040)	0.9776*** (0.0108)	0.0844 (0.2193)	0.9612*** (0.0187)	0.9403*** (0.0661)	0.9634*** (0.0105)	0.9508*** (0.0208)	0.9725*** (0.0290)
D_{11}	0.5440*** (0.2090)	0.5061*** (0.1605)	0.2937** (0.1173)	0.2063*** (0.0551)	0.4870** (0.2258)	-0.1273 (0.1843)	0.2349*** (0.0523)	0.5200*** (0.1878)	0.4891*** (0.1460)	0.3784* (0.2003)	0.4808*** (0.1858)
D_{12}	-0.0154 (0.0541)	-0.1198** (0.0523)	-0.0438 (0.0523)	-0.0116 (0.0222)	0.0078 (0.0420)	0.0811 (0.0914)	0.0327 (0.0396)	-0.0791 (0.1526)	-0.0181 (0.0578)	-0.0911 (0.0853)	0.0504 (0.0421)
D_{21}	-0.0866 (0.2417)	-0.0081 (0.1510)	0.3750** (0.1557)	-0.1376 (0.0838)	-0.1798 (0.5832)	0.0564 (0.1724)	-0.1320 (0.0846)	-0.0222 (0.1104)	-0.1690 (0.1454)	0.0653 (0.0998)	-0.2517 (0.2878)
D_{22}	0.0035 (0.0035)	0.1467 (0.1468)	-0.0144 (0.0820)	0.0010 (0.0531)	0.0031 (0.0964)	0.6328 (0.1480)	-0.1132 (0.1167)	0.1348 (0.2184)	0.0271 (0.0869)	-0.0194 (0.1275)	-0.0045 (0.0946)
$Q_1^2(24)$	11.36 [0.989]	14.84 [0.925]	14.15 [0.043]	8.708 [0.998]	19.08 [0.747]	17.05 [0.846]	8.276 [0.998]	10.19 [0.993]	10.15 [0.994]	9.178 [0.997]	10.93 [0.989]
$Q_2^2(24)$	27.66 [0.274]	32.41 [0.446]	31.32 [0.144]	27.32 [0.289]	22.35 [0.558]	41.57 [0.014]	27.16 [0.297]	16.36 [0.874]	26.01 [0.352]	14.99 [0.921]	18.08 [0.799]

Note: see the Notes of Table 2.

Table 5. Estimation results of asymmetric BEKK-GARCH (1,1) model (COVID-19 period: China sectors)

	WTI-CSI300	WTI-CONS. DISCRETIONARY	WTI-CONS. STAPLES	WTI-ENEGY	WTI-FINANCIALS	WTI-HEALTH CARE	WTI-INDUSTRIALS	WTI-INFO. TECHNOLOGY	WTI-MATERIALS	WTI-COMM.SVS	WTI-UTILITIES
C_{11}	0.4375** (0.2055)	0.4560*** (0.1186)	0.6668*** (0.1242)	0.3835*** (0.1636)	0.5634*** (0.1458)	0.5424*** (0.1937)	0.4239** (0.1776)	0.4290*** (0.1360)	0.4590** (0.2304)	0.5774*** (0.1185)	0.5836*** (0.1267)
C_{21}	-0.0218 (0.3134)	-0.8722*** (0.2097)	0.7548*** (0.1423)	-0.3727 (0.3527)	0.0320 (0.1843)	0.5678*** (0.1952)	-0.0574 (0.2846)	-1.1870*** (0.2057)	0.1417 (0.5310)	0.1489 (0.1780)	0.1711 (0.2266)
C_{22}	0.4176*** (0.1147)	0.00003 (1.0971)	-0.00001 (1.8961)	0.3282 (0.4190)	0.5379*** (0.1372)	0.00001 (0.5462)	0.3377*** (0.1074)	0.00001 (3.3068)	0.4279*** (0.1445)	0.3295 (0.1332)	0.3632*** (0.1316)
A_{11}	0.2074*** (0.0631)	0.2540*** (0.0637)	0.2543 (0.0577)***	0.1611** (0.0684)	0.2266*** (0.0705)	0.2221*** (0.0626)	0.2164*** (0.0618)	0.2859*** (0.0617)	-0.2190*** (0.0613)	0.1947** (0.0773)	0.2442*** (0.0640)
A_{12}	-0.0046 (0.0100)	-0.0146 (0.0209)	-0.0106 (0.0151)	0.0017 (0.0114)	-0.0070 (0.0139)	-0.0097 (0.0126)	-0.0039 (0.0102)	-0.0577* (0.0314)	0.0008 (0.0128)	-0.0098 (0.0224)	-0.0036 (0.0074)
A_{21}	0.1526 (0.1271)	-0.0225 (0.1638)	-0.0497 (0.0851)	-0.1498 (0.1115)	-0.0566 (0.1227)	0.0433 (0.0954)	0.0709 (0.1196)	-0.0143 (0.0954)	0.0067 (0.1490)	-0.0676 (0.1292)	0.1340 (0.7377)
A_{22}	-0.2457*** (0.0723)	-0.0223 (0.1499)	-0.3218*** (0.0591)	0.3362*** (0.0896)	0.3426*** (0.0627)	-0.2282*** (0.0665)	-0.2856*** (0.0650)	0.0321 (0.1219)	0.3285*** (0.0741)	0.2520*** (0.0540)	-0.2973*** (0.0836)
B_{11}	0.8889*** (0.0223)	0.8755*** (0.0221)	0.8726*** (0.0222)	0.8875*** (0.0185)	0.8808*** (0.0234)	0.8880*** (0.0230)	0.8928*** (0.0203)	0.8639*** (0.0265)	0.8958*** (0.0216)	0.8775*** (0.0227)	0.8593*** (0.0236)
B_{12}	-0.0026 (0.0048)	0.0033 (0.0099)	0.00001 (0.0082)	0.0021 (0.0049)	-0.0008 (0.0063)	0.0001 (0.0052)	-0.0021 (0.0043)	0.0069 (0.0162)	-0.0059 (0.0059)	-0.0162** (0.0080)	-0.0009 (0.0042)
B_{21}	0.0791 (0.1005)	0.1641*** (0.0548)	-0.1398*** (0.0509)	0.1702** (0.0693)	0.0511*** (0.0822)	-0.0688*** (0.0638)	0.0418 (0.0745)	0.2038*** (0.0596)	0.0025 (0.1198)	-0.0025 (0.0585)	-0.0402 (0.1814)
B_{22}	0.8976*** (0.0384)	0.8430*** (0.0732)	0.8534*** (0.0432)	0.8739*** (0.0562)	0.8553*** (0.0594)	0.9223*** (0.0426)	0.9261*** (0.0275)	0.7351*** (0.0982)	0.9085*** (0.0410)	0.9431*** (0.0221)	0.8734*** (0.0500)
D_{11}	0.5745*** (0.0854)	0.5765*** (0.0799)	0.6206 (0.0327)	0.6356*** (0.0802)	0.6011*** (0.0898)	0.5718*** (0.0851)	0.5620*** (0.0752)	0.5405*** (0.0760)	0.5559*** (0.0863)	0.6824*** (0.0984)	0.7050*** (0.0832)
D_{12}	0.0140 (0.0187)	0.0199 (0.0315)	0.0263 (0.0327)	0.0060 (0.0179)	0.0121*** (0.0224)	0.0100 (0.0226)	0.0138 (0.0174)	0.0912** (0.0397)	0.0254 (0.0266)	0.0916*** (0.0337)	0.0171 (0.0174)
D_{21}	0.0208 (0.1823)	-0.0408 (0.1064)	-0.0431 (0.1411)	-0.1967 (0.1664)	-0.0434*** (0.1593)	0.0662 (0.1556)	0.1459 (0.1303)	-0.0395 (0.0989)	0.1057 (0.1077)	-0.2252 (0.2206)	-0.6262*** (0.1770)
D_{22}	0.2526*** (0.1057)	0.2688*** (0.0981)	0.0708 (0.1062)	0.0180 (0.1074)	0.1074 (0.1327)	0.1115 (0.1656)	0.1083 (0.1052)	0.3565*** (0.1089)	0.1211 (0.1408)	-0.0129 (0.1144)	-0.0314 (0.1439)
$Q_1^2(24)$	24.95 [0.408]	26.54 [0.326]	28.17 [0.252]	23.77 [0.474]	25.89 [0.358]	25.33 [0.388]	23.94 [0.464]	32.10 [0.124]	25.11 [0.399]	27.52 [0.281]	29.11 [0.215]
$Q_2^2(24)$	12.25 [0.976]	12.79 [0.969]	17.76 [0.814]	8.353 [0.998]	12.24 [0.977]	26,77 [0.315]	23.36 [0.866]	25.81 [0.771]	21.46 [0.611]	20.61 [0.661]	31.35 [0.1438]

Note: see the Notes of Table 4.

Table 6. Optimal portfolios' weights, hedge ratios, and hedging effectiveness

Portfolio Pairs	**Whole period**			**Before COVID-19**			**COVID-19 pandemic**		
Panel A: US sector-WTI	w_t^C	β_t^C	**HE**(%)	w_t^C	β_t^C	**HE**(%)	w_t^C	β_t^C	**HE**(%)
S&P500/WTI	0.0669	0.1146	84.06	0.0462	0.1054	**86.34**	0.0834	0.1219	83.78
CONS. DISCRETIONARY/WTI	0.1254	0.10822	84.14	0.0964	0.1004	82.12	0.1484	0.1144	**84.40**
CONS. STAPLES/WTI	0.0715	0.0426	90.15	0.0681	0.0424	90.07	0.0742	0.0428	**90.19**
ENEGY/WTI	0.2529	0.4595	57.12	0.0281	0.3839	**67.19**	0.4317	0.5195	55.80
FINANCIALS/WTI	0.1585	0.1441	71.82	0.1153	0.1280	**78.80**	0.1929	0.1568	70.91
HEALTH CARE/WTI	0.0956	0.0791	87.87	0.1022	0.0819	85.49	0.0904	0.0768	**88.18**
INDUSTRIALS/WTI	0.1240	0.1379	79.81	0.1118	0.1340	78.56	0.1337	0.1411	**79.97**
INFO. TECHNOLOGY/WTI	0.1912	0.1187	78.12	0.1627	0.1291	72.87	0.2138	0.1105	**78.81**
MATERIALS/WTI	0.1414	0.1474	80.56	0.1273	0.1355	79.15	0.1527	0.1568	**80.74**
COMM.SVS/WTI	0.1383	0.1048	85.39	0.1233	0.1011	79.98	0.1502	0.1078	**86.11**
UTILITIES/WTI	0.1539	0.0017	82.95	0.1293	-0.0033	**89.86**	0.1733	0.0057	82.08
Portfolio Pairs	**Whole period**			**Before COVID-19**			**COVID-19 pandemic**		
Panel B: China sector-WTI	w_t^C	β_t^C	**HE**(%)	w_t^C	β_t^C	**HE**(%)	w_t^C	β_t^C	**HE**(%)
CSI300 /WTI	0.2107	0.0964	91.35	0.2366	0.1044	76.05	0.1883	0.0894	**93.34**
CONS. DISCRETIONARY/WTI	0.3003	0.0932	88.28	0.3140	0.0977	71.11	0.2884	0.0893	**90.51**
CONS. STAPLES/WTI	0.3363	0.0959	86.74	0.3671	0.1031	61.27	0.3096	0.0896	**90.03**
ENEGY/WTI	0.2006	0.0923	91.93	0.2069	0.0959	80.05	0.1951	0.0893	**93.46**
FINANCIALS/WTI	0.2390	0.0827	87.53	0.2736	0.0915	64.36	0.2089	0.0752	**90.52**
HEALTH CARE/WTI	0.3225	0.0964	90.78	0.3284	0.0979	75.38	0.3174	0.0951	**92.77**
INDUSTRIALS/WTI	0.2485	0.0746	90.93	0.2576	0.0779	73.18	0.2405	0.0716	**93.25**
INFO. TECHNOLOGY/WTI	0.3877	0.1085	82.92	0.4463	0.1207	50.39	0.3369	0.0981	**87.19**
MATERIALS/WTI	0.3026	0.1123	88.34	0.2887	0.1104	73.47	0.3147	0.1139	**90.27**
COMM.SVS/WTI	0.3778	0.0731	83.15	0.4482	0.0853	50.17	0.3168	0.0626	**87.51**
UTILITIES/WTI	0.1298	0.0352	95.10	0.1393	0.0374	86.52	0.1216	0.0332	**96.21**