Asymmetric spillover and network connectedness between crude oil, gold, and Chinese sector stock markets

Walid Mensi a, b, Abdel Razzaq Al Rababa’a c, Xuan Vinh Vo d, Sang Hoon Kang e,⁎

a Department of Economics and Finance, College of Economics and Political Science, Sultan Qaboos University, Muscat, Oman
b Institute of Business Research, University of Economics Ho Chi Minh City, Viet Nam
c Faculty of Economics and Administrative Sciences, Yarmouk University, Irbid 21163, Jordan
d Institute of Business Research and CFVG, University of Economics Ho Chi Minh City, Vietnam
e Department of Business Administration, Pusan National University, South Korea

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A B S T R A C T
This paper examines the asymmetric return spillovers between crude oil futures, gold futures and ten sector stock markets of China. The results show using the spillover index of Diebold and Yilmaz (2012, 2014) time-varying asymmetry spillovers among commodity and the ten sectors. Industrials and consumer discretionary sectors are the largest contributor and receiver of spillovers in the system. In addition, basic materials sector is a net contributor of spillovers whereas oil futures, gold futures and the remaining sectors are net receiver of spillovers. Furthermore, the bad return spillovers dominate the good return spillovers. The asymmetry spillovers are influenced by the global financial and European crises (GFC & ESDC), oil price crash and global health crisis (COVID-19 outbreak). Equity investors benefit from adding gold and oil to their individual equity markets. Moreover, the hedging is sensitive to the GFC & ESDC, oil price crash, and COVID-19 outbreak. Finally, the highest hedging effectiveness occurs during COVID-19 spread for the case of oil futures. The result is similar for gold under only good spillovers and it is highest during recovery period under bad spillovers.

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1. Introduction

This paper aims to examine the asymmetry in return spillovers between gold futures, West Texas Intermediate (WTI) crude oil futures, and aggregate (CSI 300 sector index) and ten disaggregate Chinese stock index returns (Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Information Technology, Materials, Telecommunications Services, and Utilities). A portfolio risk analysis during tranquil and turbulent episodes is performed.

Monitoring the spillovers between commodity (gold and oil) and stock markets remains a timely topic to study given the high uncertainty in stock markets and the occurrence of energy and financial crises. On the other hand, asymmetry is an important stylized fact (Black, 1976; Christie, 1982; Nelson, 1991; Bekaert and Wu, 2000). More importantly, the intensity and direction of positive and negative return spillovers have been little addressed on the recent empirical literature. A deepen study of asymmetry in return spillovers between commodity and stock markets has significant practical implications, especially for investors that have diversification as a goal. Moreover, analyzing the positive and negative return spillover provides market participants a valuable information on the interactions between commodity and stock markets which enhance the portfolio risk management during different market regimes. Using aggregate price returns to study the spillover among markets may hide a valuable information in terms of risk management. Decomposing the aggregate stock price returns into positive and negative returns provides thus an accurate information on the effective hedging strategies during extreme downside stock price movements as market participant’s reactions differ during downside and upside market conditions.

The increasing integration and the financial liberalization has increased the speed of information transmission among stock markets, leading to a contagion effect. Equity investors face a serious challenge to monitor the risk of their portfolio and estimate the prospective performance (Erb and Harvey, 2006). Besides, fund allocations and portfolio risk management require an accurate modeling for the spillover effects among market value of equity securities. The last few years have been marked by a significant decrease of the diversification benefits in stock markets. This phenomenon leads equity investors to seek alternative assets to hedge their positions during turbulent periods. On
the other hand, the financialization of commodities has attracted a special attention of equity investors, hedge funds and academicians. Among commodities, crude oil and gold represent the two strategic commodities for monetary policies and economic development. Recently, market participants find in oil and gold the new profitable alternative assets for risk management (Gorton and Rouwenhorst, 2006; Chang et al., 2010; Dwyer et al., 2011; Erb and Harvey, 2006; Silvennoinen and Thorp, 2013; Naem et al., 2020).

However, oil market is vulnerable to economic, financial and geopolitical factors which explain its high volatility. Moreover, oil prices impact the movements of market share prices through different channels. The microeconomic theoretical framework argues that oil prices affect the stock prices through the expected cash flows and the cost of capital. More precisely, a rise in oil prices augments the cost of production which result in reduction of the firm’s expected cash flows and as a result the market stock prices (Fisher, 1930; Williams, 1938).

Besides, the changes in interest rates are dependent to the uncertainty level in oil market (Jones and Kaul, 1996). The central banks adjust the interest rates given the changes in oil prices in order to control the inflation rates (Basher and Sadorsky, 2006).

Numerous empirical studies have examined the relationships between oil and stock markets (Sadorisky, 1999; Nanadha and Faff, 2008; Park and Ratti, 2008; Björnlund, 2009; Filis et al., 2011; Mensi et al., 2013; Wang et al., 2013). The first strand of literature reports evidence of time-varying multiscale relationships between oil and stock market returns (Jiang and Yoon, 2020). Further, the responsiveness of stock markets to oil prices depends on whether the country is oil importing or oil exporting (Wang et al., 2013). A second strand of literature used a variety of multivariate generalized autoregressive conditional heteroskedasticity (GARCH) models to analyze the dynamic conditional correlations, and the transmission of returns and volatility between crude oil and stock markets (Arouri et al., 2011; Sadorisky, 2012; Mensi et al., 2013; Lin et al., 2014; Basher and Sadorsky, 2006; Yang et al., 2016; Yu et al., 2020). A third strand of literature examines the dependence structure (upper and lower tail dependence) between crude oil and stock markets (Sukcharoen et al., 2014; Li and Wei, 2018; Nguyen and Bahtti, 2018; Ji et al., 2020). Despite the multiplicity of empirical methods, the results are mixed.

Compared to financial assets (stock share, currency, and bond), the empirical studies on gold was negligible for a long time (Lucy, 2011). Market participants pay a special attention on gold in the last few years particularly during the onset of the 2008–2009 global financial crisis (GFC) (O’Connor et al., 2015). As a good store of value, the performance of gold is impressive during turbulent periods. Previous studies validate the strong role of yellow metal as an excellent hedge and safe haven for period of high inflation level (McCown and Zimmerman, 2006; Oxman, 2012; Beckmann and Czudaj, 2013; Hoang et al., 2016; Salisu et al., 2020; Adeptoka et al., 2020) and extreme negative returns of stock exchange markets (Baur and McDermott, 2010; Baur and Lucy, 2010; Juntila et al., 2018).1 The safe haven property of gold against stock market risk exposure during crash and crisis episodes is commonly accepted by the literature. Combining gold and stock shares thus reduce the portfolio risk without losing the mean returns. For example, Morema and Bonga-Bonga (2020) use the vector autoregressive (VAR) GARCH model based on the framework of asymmetric dynamic conditional correlation (ADDC) to examine the volatility spillover between South African stock markets and commodity (gold and oil) markets. The authors find evidence of volatility spillover between South African stock market and both gold and oil markets and provides the diversification benefit of gold and stock portfolio during the global financial crisis. This result is in line with the findings of Al-Yahyae et al. (2019) where the authors show that precious metals offer better hedging strategies over energy markets for Gulf Cooperation Council stock markets. More recently, Mensi et al. (2021a) show that recent oil price crash and time horizons affect the dependence structure and systemic risk between energy (crude oil, natural gas, and gasoline) and MENA stock markets. They also show that the stock markets of the oil-exporting MENA countries are more affected by the energy price shocks than the oil-importing MENA countries. Using the Barunik and Krelik (2018) methodology, Mensi et al. (2021b) investigate the dynamic frequency spillovers between gold, oil futures, and developed and BRICS stock markets. The results reveal that the short-term volatility spillovers are higher than their long term counterpart. Moreover, the hedging effectiveness in BRICS markets is more pronounced than in developed markets irrespective to the time horizons. More importantly, gold futures offer a higher hedging effectiveness than oil and at both short- and long-runs.

The recent literature shows that not only the financial crisis affects the stock returns and the directional spillovers among markets but also the health crisis influences negatively the stock returns (Bakas and Triantafyllou, 2020). The rapid spread of COVID-19 pandemic,2 causing more than 108.8 million confirmed cases and 2.39 million deaths, has increased the uncertainty and the risk in both financial and commodity markets. Ashraf (2020), Harjoto et al. (2020), Liu et al. (2020) and Ichiev and Marinč (2018) report negative impact of COVID-19 epidemic on stock and commodity returns. Sharif et al. (2020) show that the relationships between COVID-19 spread, oil price shocks, geopolitical uncertainty index, economic uncertainty index, and US stock markets vary over frequencies where the oil leads the US market at low and high scales. In addition, the impact of the COVID-19 spread on the geopolitical risk is higher than on the US economic uncertainty. Devising successful funds allocation, portfolio management and hedging strategies requires a better understanding on how one market spill over another market.

We contribute to the existing empirical literature in three main ways. First, we analyze the spillovers between gold, crude oil, and aggregate and disaggregate stock markets in China. For a deep analysis, our study distinguishes between negative and positive returns spillovers among markets which allows us to account for asymmetry factor. Second, we evaluate the added value of gold and crude oil to an individual equity portfolio. Specifically, we quantify the optimal weights, hedge ratio and hedging effectiveness of commodity-stock sector portfolio. The analysis is carried not only for the whole period but also under different subperiods: before the GFC and European debt crisis (ESDC), during the GFCs and ESDC, during recovery period, during oil price crash, and during COVID-19 pandemic spread. Empirically, we apply the spillover index of Diebold and Yilmaz (2012, 2014) (hereafter, DY). This empirical method determines the directional and the extent of spillover from one market to another. It measures the proportion of contribution/receipt of risk to/from other markets. It also identifies whether a market is a net receiver or net receiver of spillover. Overall, it identifies the source of contagion.

The results show time varying returns spillovers. Industrials and consumer discretionary sectors are the main contributors and receivers of total spillover in the system. Commodities and seven of ten sectors (exception for industrials, materials and consumer discretionary sectors) are net receiver of spillovers. The spillover effect between sectors and crude oil is higher as compared with its counterpart between the equities equity shocks and the gold market. The bad return spillovers dominate the good returns spillovers, indicating asymmetry spillovers. The gap between positive spillovers and negative spillovers increase during GFC and ESDC, the recent oil price crash in 2014–2015 as well as the COVID-19 crisis. COVID-19 transmits negative signals to the markets, leading to a jump in negative spillovers. The analysis of portfolio management show that adding commodity to equity portfolio reduces the risk level. Gold provides a better hedging effectiveness than oil.

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1 Capie et al. (2005) and Kaul and Sapp (2006) shows that gold is a safe haven against the US dollar.

2 The World Health Organization (WHO) officially announced the new coronavirus (COVID-19) to be a global epidemic in March 11, 2020.
during tranquil and turbulent periods. The hedging is more expensive during GFCs and ESDC period. More importantly, the hedging strategy changes according to market trend (positive and negative returns).

The remainder of this study is followed as sections. Section 2 discusses the spillover index method of DY. Section 3 describes the data and construct the daily positive and negative returns. Section 4 discusses the empirical results of symmetric and asymmetric spillover index and illustrate the connectedness network in different regimes. Section 5 provides concluding remarks.

2. Methodology

Following Diebold and Yilmaz (2012), we construct a return spillover index matrix using the generalized VAR (GVAR) framework. Let return series, $X_t$, be a covariance stationary VaR ($p$) process as follows:

$$X_t = \sum_{-1}^{p} \phi_i X_{t-i} + \epsilon_t$$

where $X_t$ represents a vector of $N \times 1$ endogenous variables, $\phi_i$ are $N \times N$ autoregressive coefficients matrix and $\epsilon \sim (0, \Sigma)$ is a vector of independent and identically distributed disturbances with zero and $\Sigma$ covariance matrix. The representation of the above VAR process can be written as:

$$X_t = \sum_{-1}^{\infty} \sum_{i=1}^{N} B_i \epsilon_{t-i}$$

The $N \times N$ coefficient matrices $B_i$ obey a recursion of the form $B_i = \phi_1 B_{i-1} + \phi_2 B_{i-2} + \ldots + \phi_p B_{i-p}$ with $B_0$ being the $N \times N$ identity matrix and $B_0 = 0$ for $i < 0$. Based on the H-step ahead forecasting error variance decomposition (FEVD) framework (Koop et al, 1996; Pesaran and Shin, 1998), we can define own variance components and cross variances components, in which the latter is the spillover index $\theta_{ij}(H)$ follows:

$$\theta_{ij}(H) = \frac{\sigma_{ij}^{-1} \sum_{h=0}^{H-1} (e_i \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i \Sigma e_j)^2}$$

where $\Sigma$ is the covariance matrix of the vector of errors $\epsilon$, and $\sigma_{ij}$ is the standard deviation of the error term of the $j^\text{th}$ equation and $e_i$ is a selection vector, where the $i^\text{th}$ element is one and the remaining elements are zero. We further standardize the spillover index measured in Eq. (3) as follows:

$$\tilde{\theta}_{ij}(H) = \theta_{ij}(H) / \sum_{j=1}^{N} \theta_{ij}(H)$$

with $\sum_{j=1}^{N} \tilde{\theta}_{ij}(H) = 1$ and $\sum_{j=1}^{N} \tilde{\theta}_{ij}(H) = N$ by construction. $\tilde{\theta}_{ij}(H)$ provides the magnitude of pairwise directional connectedness from $j$ to $i$ at horizon $H$. Using the contributions from the variance decomposition approach, we compute the total spillover index, $C(H)$ as follows:

$$C(H) = \frac{\sum_{j=1}^{N} \tilde{\theta}_{ij}(H)}{\sum_{j=1}^{N} \theta_{ij}(H)} \times 100 = \frac{\sum_{j=1}^{N} \tilde{\theta}_{ij}(H)}{N} \times 100$$

To analyze the contributions of a particular sector, we aggregate partially “total spillover” in both “FROM” and “TO” versions. The directional connectedness $C_{ij}(H)$ from all equity returns to each commodity returns $i$ is computed as:

$$C_{ij}(H) = \frac{\sum_{j=1}^{N} \tilde{\theta}_{ij}(H)}{\sum_{j=1}^{N} \theta_{ij}(H)} \times 100 = \frac{\sum_{j=1}^{N} \tilde{\theta}_{ij}(H)}{N} \times 100$$

Similarly, the directional connectedness $C_{i*}(H)$ from each commodity $i$ to all equity returns is expressed as:

$$C_{i*}(H) = \sum_{j=1}^{N} \tilde{\theta}_{ij}(H)$$

Finally, we obtain the net directional connectedness transmitted from sector $i$ to all other sectors as:

$$C_i(H) = C_{i*}(H) - C_{i-}(H)$$

To visualize the connectedness network across markets, we convert all sector connectedness into networks. Following the interpretations of Diebold and Yilmaz (2014, 2016), the variance decomposition matrix is referred as the adjacency matrix of a weighted directed network. The elements of the matrix are considered as the pairwise directional connectedness, $C_{ij}(H)$; the row sums of the matrix (node-in degrees) are our directional connectedness “FROM”, $C_{i*}(H)$; and the column sums of the matrix (node-out degrees) are directional connectedness “TO”, $C_{*j}(H)$.

3. Data

This study considers the 10 sub-indices of the CSI 300 sector index, namely CSI 300 index (CSI 300), Consumer Discretionary index (CONS DISCRE), Consumer Staples index (CONS STAPLE), Energy index (ENERGY), Financials index (FINANCIALS), Health Care index (HLTH CARE), Industrials index (INDUSTRIALS), Information Technology index (INFO TECHN), Materials index (MATERIALS), Telecommunications Services index (TELECOM SVC), and Utilities index (UTILITIES). We also consider two strategic commodity futures markets, gold futures (GOLD) and WTI crude oil futures (CO1). The commodities are traded in Chicago Mercantile Exchange (CME) trade commodities. Our sample data are obtained from the Database stream and cover the period from 4th January 2005 to 15st May 2020. The sample period includes important economic events such as 2008–2009 GFC, 2010–2012 ESDC, 2014 great oil bust, and the COVID-19 outbreak.

We calculate continuously compounded daily returns by taking the difference in the logarithm percentage of two consecutive prices, defined as $r_t = \ln(P_t/P_{t-1}) \times 100$. In addition, we investigate the asymmetric spillover between sector equity and commodity markets in terms of the positive and negative returns. It is widely observed that asset returns present asymmetric response to good news and bad news. In order to measure the asymmetric risk spillover, we decompose the aggregate returns into positive and negative returns. The positive and negative returns are defined as:

$$r_t^+ = \begin{cases} r_t, & \text{if } r_t > 0 \\ 0, & \text{otherwise} \end{cases}$$

$$r_t^- = \begin{cases} r_t, & \text{if } r_t < 0 \\ 0, & \text{otherwise} \end{cases}$$

where $r_t^+$ and $r_t^-$ denote the positive and negative returns, respectively. The sum of $r_t^+$ and $r_t^-$ is the aggregate returns ($r_t$) before the GFC and European debt crisis (ESDC), during the GFCs and ESDC, during

3 The industrial sector includes mining and ore processing (textiles and apparel, cement, chemical, fertilizers, ships, aircraft). The consumer discretionary sector is the largest sector in terms of market capitalization and contains the e-commerce, automotive, education, and travel & luxury. Consumer staples sector is composed by food, beverages, and tobacco. Energy sector includes companies involved in the exploration and development of oil and gas drilling, oil or gas reserves, and refining. Financial sector includes bank firms, insurance companies, consumer finance firms, credit card companies, stock brokerage, and government sponsored enterprises. The healthcare sector includes industries such as health, ecology, medical facility, and equipment. The information technology sector includes industries such as software, information transmission, and technology services. The materials sector englobes industries in manufacture chemicals, building materials and paper products (chemicals, glass, paper, forest products, construction materials, packaging products, metals, minerals and mining companies). Telecommunications sector include firms operating in social media, internet, streaming, gaming, and telecom industries. The utility sector embodies electricity, natural gas, and water firms.
recovery period, during oil price crash, and during COVID-19 pandemic spread.

Fig. 1 depicts the price returns of oil, gold and stock sectors. We divide the whole period into five subperiods: (i) Pre-GFC period (January 4, 2005–June 29, 2007); (ii) during GFC and ESDC period (July 2, 2007–December 31, 2012); (iii) Recovery period (January, 4 2013–May 30, 2014); (iv) Great oil bust period (June 3, 2014–December 31, 2019); (v) COVID-19 break period (January 2, 2020–May 15, 2020). The graphical evidence shows significant fat tails and volatility clustering. These stylized facts are more pronounced during financial crisis, oil price crash and COVID-19 pandemic relative to the recovery or pre-financial crisis periods. Besides, oil is widely affected by the COVID-19 pandemic spread whereas gold and health care sectors are the least affected markets by the pandemic. Crude oil is severely affected by the epidemic spread whereas health care sector and gold are less affected. This result may be attributable the slow demand of oil during lockdowns and traffic control. By contrast, Gold futures contract play a crucial role for investors during turbulent periods. The healthcare sector benefit from the epidemic. Masks, medicine, protective clothing, and other medical supplies are in urgent need. Therefore, investors’ optimistic expectations about the healthcare sector.

Table 1 reports the descriptive statistics of price returns of gold, crude oil, and CSI300 index and their ten sectors. The mean returns are positive for all markets, except for oil. Among all sectors, consumer staples exhibit the highest average returns whereas energy sectors have the lowest average returns. Oil and information technology are
Fig. 1 (continued).
high risky markets whereas gold is the least risky market. The skewness values are negative for all return series, indicating left skewed series. The kurtosis values are high, indicating leptokurtic behavior. The statistics of Jarque Bera rejects the null hypothesis of normal distributions. The empirical statistics of the Ljung-Box test supports evidence of auto-correlations of returns series. The unit root tests of ADF, PP and Zivot-Andrew show that all return series are stationary. Table 2 reports the preliminary statistics for positive and negative returns. The results show that the standard deviations for all markets are higher under negative returns than positive returns. More importantly, the negative return series are more leptokurtic than the positive return series. Positive and negative return series deviate from normal distributions and are stationary.

Fig. 2 displays the results of unconditional correlations among price returns of gold, oil and stock markets. We observe that Chinese sectors are weakly correlated with gold and oil. For gold, the correlation degree varies from 0.01 for telecommunication service to 0.09 for materials. As for oil, it ranges from 0.09 for health care and utilities to 0.14 for energy. This result reveals the importance of these two strategic commodities for risk management. In contrast, we find high correlations among sectors, indicating high integrations among Chinese sectors.

4. Empirical results

4.1. Total spillover index

Table 3 reports the matrix of total static spillover index of the Chinese sectors, oil and gold markets. Specifically, the main diagonal of the matrix summarizes information on the contribution of shocks in market i to the own forecast error variance. The off-diagonal column sums (“To”) along with row sums (“From”) show the entire directional connectedness to all variables in the system from i and from all others to i, respectively. The bottom right corner, “Total,” indicates the total connectedness. The row “Net” is the total sum of the net-pairwise directional spillover expressed as a negative (positive) value to denote for the net-recipient (net-transmitter).

Overall, the table shows that roughly 74% of the forecast error variances can be attributed to the return spillovers among the asset classes. More analysis seems to uncover the differences in the results between sectors. Noticeably, shocks associated with the industrials and consumer discretionary sectors are the main contributors to the spillover of other elements. Among these, the industrial sector’s shock is found to lead other equities and commodities with 103%. Industrials sector transmit nearly the same proportion of shocks to the rest of sector whereas it transmits a negligible portion of spillovers to commodity markets. Surprisingly, these abovementioned sectors again appear to be the main receivers of shocks from others (87.4% for industrials and 87.1% for consumer discretionary). Besides, Table 3 also shows that the gold market is the least influenced by the shocks from the equities and oil market, supporting evidence of decoupling hypothesis. This finding contradicts that Raza et al. (2016) who found a strong connectedness between the gold volatility and the Chinese market.

Additionally, we identify the net contributors and net recipients of shocks. For example, all the variables are net receivers of shocks except the aggregate index, industrials, consumer discretionary and basic materials industries. The spillover effect between sectors and crude oil is higher as compared with its counterpart between the equity shocks and the oil market. Our finding for the stronger impact on oil market is consistent with that documented in the existing literature (e.g., Morema and Bonga-Bonga, 2020, among others). The lowest

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4 The sample study in Raza et al. (2016) comprises the BRIC counties. Their analysis also concerns the impact of the oil and gold prices and their volatilities on the stock returns. Their study shows that the volatility of the gold market had a negative and significant impact on the Chinese stock returns. Oil volatility, however, is found to leave insignificant influence on the Chinese market.
## Table 2
Summary descriptive statistics and unit root tests for positive and negative returns.

<table>
<thead>
<tr>
<th></th>
<th>CSI 300</th>
<th>FINANCIALS</th>
<th>CONS STAPLE</th>
<th>INDUSTRIALS</th>
<th>CONS DISCRE</th>
<th>INFO TECHN</th>
<th>HLTH CARE</th>
<th>MATERIALS</th>
<th>UTILITIES</th>
<th>TELECOM SVC</th>
<th>ENERGY</th>
<th>GOLD</th>
<th>CO1</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Positive returns</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean (%)</td>
<td>0.6284</td>
<td>0.7058</td>
<td>0.7085</td>
<td>0.6721</td>
<td>0.7079</td>
<td>0.8269</td>
<td>0.7100</td>
<td>0.7352</td>
<td>0.5702</td>
<td>0.7896</td>
<td>0.7092</td>
<td>0.4171</td>
<td>0.7906</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>1.013</td>
<td>2.521</td>
<td>1.111</td>
<td>1.085</td>
<td>1.080</td>
<td>1.240</td>
<td>1.116</td>
<td>1.147</td>
<td>0.968</td>
<td>1.311</td>
<td>1.201</td>
<td>0.683</td>
<td>1.431</td>
</tr>
<tr>
<td>Skewness</td>
<td>2.495</td>
<td>2.531</td>
<td>2.305</td>
<td>2.529</td>
<td>2.227</td>
<td>2.067</td>
<td>2.333</td>
<td>2.238</td>
<td>2.727</td>
<td>2.556</td>
<td>2.584</td>
<td>3.044</td>
<td>3.792</td>
</tr>
<tr>
<td>PP</td>
<td>103.4</td>
<td>85.88 ***</td>
<td>62.09 ***</td>
<td>112.0 ***</td>
<td>101.1 ***</td>
<td>95.18 ***</td>
<td>102.2 ***</td>
<td>123.7 ***</td>
<td>126.7 ***</td>
<td>83.20 ***</td>
<td>100.9 ***</td>
<td>75.04 ***</td>
<td>55.57 ***</td>
</tr>
</tbody>
</table>

| **Panel B: Negative returns** |         |            |             |             |             |            |           |           |           |             |        |       |     |
| Mean (%)             | 0.5872  | 0.6537     | 0.6203      | 0.6471      | 0.6584      | 0.7969     | 0.6382    | 0.7122    | 0.5525    | 0.7546      | 0.6984 | 0.3795 | 0.7968 |
| Std. Dev.            | 1.141   | 1.231      | 1.112       | 1.324       | 1.445       | 1.185      | 1.314     | 1.095     | 1.366     | 1.278       | 0.717  | 1.573 | 1.573 |
| Kurtosis             | 15.81   | 15.68      | 15.66       | 16.25       | 15.33       | 9.300      | 15.24     | 14.05     | 19.57     | 12.48       | 14.58  | 23.36 | 64.56 |
| Jarque-Bera Q (20)   | 46.65   | 89.89 ***  | 60.61 ***   | 71.84 ***   | 73.21 ***   | 60.57 ***  | 70.20 *** | 72.59 *** | 72.88 ***  | 64.90 ***   | 86.30 *** | 50.10 *** | 63.38 *** |
| ADF                  | -67.88  | -67.93     | -62.84      | -66.52      | -64.28      | -62.47     | -63.16    | -64.82    | -65.48    | -61.93      | -64.86 | -60.54 | -72.17 |

Notes: Q (20) refers to the empirical statistics of the Ljung-Box test for the autocorrelation of returns series. ADF (PP) denotes the empirical statistics of the augmented Dickey-Fuller (1979) (Phillips-Perron (1988)) unit root test. Zivot-Andrews (1992) tests for the null hypothesis that the series has a unit root with a structural break. ** and *** indicate significance at the 5% and 1% levels, respectively.
Overall impact of 9.4% from all variables in the system to the gold market again confirms this result. Consistent with Yang et al. (2016)’s observations, a comparison between the shocks from sectors to oil and gold markets reveals the strongest spillover with the energy sector. The resulted index values are then found to be 0.67 and 1.66%, respectively. Apparently, the reverse strong relationship also exists from the oil to the energy markets with 0.61%. Yet, this evidence of two-ways relationship contradicts the previous finding of Ping et al. (2018) who documented only one-way effect from the Chinese energy sector to fuel oil market. This opposing result might be attributed to the degree of variations in the sectoral returns and commodities prices over time.

To address this issue, we re-examine the connectedness in two separate analyses; for the positive returns (Table 4) and negative returns (Table 5).

The overall results of total spillover matrix for positive returns reported in Table 4 almost resemble those obtained from the full sample analysis summarized in Table 3. For example, the shocks originated from industrials, consumer discretionary and basic materials sectors to oil markets are 11.86, 10.5, and 7.63%, respectively. This reveals that these sectors are the main drivers of oil market volatility. Similarly, the spillover effects to gold markets from the same sectors are 9.95%, 7.91%, and 7.59%, respectively. These results indicate that the energy sector has the highest impact on both oil and gold markets. The heat map of the pairwise correlations in Figure 2 shows a linear unconditional correlation matrix across the precious metal and currency markets under investigation. The color intensity of the shaded boxes refers to the degree of correlation. Blue (red) indicates a positive (negative) correlation.

Table 3
Total return spillover matrix across Chinese sector and commodity returns.

<table>
<thead>
<tr>
<th></th>
<th>CSI 300</th>
<th>FINANCIALS</th>
<th>CONS</th>
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<th>INFO TECHN</th>
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<th>TELECOM SVC</th>
<th>ENERGY</th>
<th>GOLD</th>
<th>CO1</th>
<th>FROM</th>
</tr>
</thead>
<tbody>
<tr>
<td>CSI 300</td>
<td>11.86</td>
<td>9.95</td>
<td>7.63</td>
<td>10.5</td>
<td>10.06</td>
<td>7.91</td>
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Notes: This table is based on vector autoregressions of order 1 (as determined by the Schwarz information criterion), generalized variance decompositions of 10-day-ahead forecast errors.
Notes: See Table 3.

their positions within the system. Conversely, notice that the net transmitters and receivers of shocks preserve more relative to oil. Concerning the net spillover impact, we find the shocks from equities to commodities. That is, clearly the impacts of New results appear now when it comes to evaluating the size of the other variables in the system tend to bring the largest impact of 81.5%. Likewise, surprises from the telecommunication on continue to lead the spillover process with the largest corresponding index values. Surprises from the telecommunication on other variables in the system tend to bring the largest impact of 81.5%. New results appear now when it comes to evaluating the size of the shocks from equities to commodities. That is, clearly the impacts of the financial, consumer staples and healthcare sectors on the gold are more relative to that on oil. Concerning the net spillover impact, we also notice that the net transmitters and receivers of shocks preserve their positions within the system. Confirming the previous analysis over the full sample period, the energy sector remains the main transmitter of shocks to the oil and gold markets. Nevertheless, the response from oil seems to decrease now to 0.97% from its previous level of 1.66%.

Turning the attention to the analysis with the negative returns in Table 5, we observe the following. First, the influence of the equities shocks on oil is still higher than on gold. Second, the responses of both equities to the negative returns are clearly larger relative to their counterparts when then the positive returns are considered. This result indicates that the total negative return spillover dominates the total positive returns spillovers. This observation supports the existing argument in the literature on the role of information asymmetry in examining the risk contagion between the gold and stock markets (Lin et al., 2019; El Abed and Zardoub, 2019). It contradicts those previously made arguments for the possibility of using the gold as a safe haven against the stock BRICs markets (e.g., Mensi et al., 2018). It, however, becomes in consistent with Zhang et al. (2020a, 2020b) and others). However, the results suggest that the commodities-stocks portfolios (Juntilla et al., 2018; Ji et al., 2020; Sarwar et al., 2020, among others). However, the results suggest that the commodities-stocks portfolios (Juntilla et al., 2018; Ji et al., 2020; Sarwar et al., 2020, among others). However, the results suggest that the commodities-stocks portfolios (Juntilla et al., 2018; Ji et al., 2020; Sarwar et al., 2020, among others). However, the results suggest that the commodities-stocks portfolios (Juntilla et al., 2018; Ji et al., 2020; Sarwar et al., 2020, among others). However, the results suggest that the commodities-stocks portfolios (Juntilla et al., 2018; Ji et al., 2020; Sarwar et al., 2020, among others). However, the results suggest that the commodities-stocks portfolios (Juntilla et al., 2018; Ji et al., 2020; Sarwar et al., 2020, among others). However, the results suggest that the commodities-stocks portfolios (Juntilla et al., 2018; Ji et al., 2020; Sarwar et al., 2020, among others).
4.2. Rolling windows analysis

Indeed, one key drawback of the static spillover index exercise is that it assumes a stable interlinkage between the variables of the study over time. This, in turn, ignores the excess variations in the equities-commodities relationships which might arise throughout the turmoil periods (Mensi et al., 2018; Kang et al., 2019). In addition, Diebold and Yilmaz (2012) argued that financial market conditions tend to fluctuate over time. Henceforth, applying a single fixed-parameter model over the full sample period can be misleading. The spillover analysis can accordingly be biased. In order to deal with this issue, we conduct a rolling window-based analysis using both the symmetric and asymmetric properties. The later investigates whether the spillover depends on the sign of the return series. We perform the rolling analysis over a 250-day sliding window size.

4.2.1. Symmetric risk spillovers

Fig. 3 depicts the time-varying symmetric spillover index across Chinese sector and commodity markets. Noticeably, the connectedness has been moderately intensified during the global financial crisis (Kang et al., 2017; McIver and Kang, 2020). The index value decreased after that until the end of the Chinese stock market crash period in 2016, the time when the spillover index inclined to a level of about 70%. It starts increasing again to approach its previous highest value in 2017. This indicates evidence of contagion effects as defined by Forbes and Rigobon (2002). Following this fluctuation, the spillover value sharply falls to reach its lowest level during 2018 before attaining another maximum level of approximately 80% throughout the COVID-19 outbreak period. This finding is in consistent with Akhtaruzzaman et al. (2021) who observed a high degree of financial contagion between stock markets during the pandemic period. The results in Fig. 3(a) indicates that the 2008 global financial crisis and the COVID-19 recessionary periods bring almost the same impact on the Chinese-Commodities spillover pattern. This finding triggers the need for a careful portfolio diversification during both global health and financial crisis episodes. To examine the variations in total spillover index further, we consider the directional spillovers. A close look at the analysis in Fig. 3(b) shows that the spillover from all stocks to gold almost resembles that to oil market during the GFC and ESDC period. These two commodities then started reacting in a different way in post-crisis period. The spillover from stocks to gold reached the

5 This, however, contradicts Ping et al. (2018) who found evidence of less correlation between the oil and the Chinese energy stock market during the financial crisis. There finding then emphasizes on the importance of considering sectoral data when examining the connectedness between the stock markets and commodities. Some differences in the spillover are expected to appear across the sectoral analysis.

6 Corbet et al. (2021) also found that COVID-19 has a long lasting influence on the Chinese agricultural, energy and financial markets. They also documented a pronounced impact from the COVID-19 on the price of Bitcoin in a directional spillover analysis. Their analysis involved estimating the directional connectedness between the Coronavirus, the equity markets and some commodities markets. They performed a directional analysis between each pair with the COVID-19 being included as main variable of interest.
maximum level in the beginning of 2011 which coincide with the Greater Chinese Democratic Jasmine Revolution. The connectedness between stocks and oil also maximized during this period indicating to the high uncertainty in the Chinese economy at that time. China is among the top five of largest oil producers by 4.89 million barrels per day and ranked the second oil consumers by 13.57 million barrels per day after the US (19.96 million barrels per day). Surprisingly, COVID-19 pandemic tends to push the directional spillover from stocks to oil to its highest level which is attributable to lockdown adopted by the Chinese government on January 23, 2020. This evidence appears to be little once the gold market is considered in the analysis.

Fig. 3(c) concerns the reversed spillover impact from commodities to stocks. The new results are similar to those previously obtained in Fig. 3(b) with only few exceptions. That is, oil to all stocks spillover attained all time highest record of 29% during the GFC period. Other peak points in this relationship can also be observed in 2011 and throughout the COVID-19 period, respectively. However, the magnitude of the spillover from oil during the virus outbreak is less relative to that originated from stocks. Fig. 3(c) also shows that the spillover from gold to stocks showed the tendency to increase after 2012 reaching the highest value one year later in 2013. This particular evidence during that time perhaps can be explained by the increase in the Chinese policy uncertainty in 2012 following the announcement of "The 12th Five-Year Plan". The subsequent reforms comprised a series of programs such as deposit insurance and market exit mechanism for financial companies (Wang et al., 2020). This in turn can specifically maximize uncertainty level in the Chinese stock markets.

4.2.2. Asymmetric return spillovers

Fig. 4 displays the evolving asymmetric spillover index with the positive and negative returns. Overall, Fig. 4(a) reveals a similarity in the time-varying nature of both sub-indexes. With a close look at the index, the value of the positive spillover appears slightly lower than the negative counterpart all over the sample period. However, an exception continues to appear where the negative shocks declines after 2012. This can possibly reflect the uncertainty associated with the release of "The 12th Five-Year Plan" in China. The variation at the end of the sample period confirms the role of COVID-19 where we can observe an increase in the gap between the values of the two indexes. This indicates that the impact of negative shocks maximized throughout the coronavirus period. This finding supports the previous argument made by Corbet et al. (2020) regarding the role of the COVID-19, as a black swan, in establishing the information asymmetry in the Chinese markets. Their time-varying spillover analysis uncovers distinct variations from the stock to oil and dollar markets as the effect of the COVID-19 gets worse. Such an explanation for that is attributed to the early recognition of the danger of the virus by the domestic investors. This, in turn should be reflected on the investment behavior of investors in the market. That is later on, investors tend to absorb the negative news more and move their investment between the stock and commodity markets accordingly before ending with intensifying the negative spillover at the later stages of the pandemic. Generally, the result here complements the most recent one by Guo et al. (2021) regarding the risk contagion between the financial markets during the pandemic period. In line with their finding, negative shocks can maximize the prevailing risk in the market and easily transmit from one market to another. Additionally, Guo et al. (2021) found that the number of risk takers in the market are larger the risk averse during the pandemic. This also has to be one reason behind negative shocks transmission since the pandemic started.

Turning the attention to the directional spillovers in the subsequent panels in the figure also reveals an interesting story. Positive spillovers from (Fig. 4(b)) and to (Fig. 4(c)) have averages of almost 20 and 10 percentages, respectively. These values are below the ones from the negative spillovers reported in Fig. 4(d) and (e). Noticeably, sectoral negative shocks are also embedding into the oil market during both the global and Chinese crises in 2008 and 2016. Considering the negative shocks also confirms the spikes in the relation from (to) the oil returns. Yet, the striking features appear in 2010 and 2020 with the maximum level being in the later period. Between these, the index has the minimum value in 2016. This observation indicates to the importance of disentangling the impact of negative and positive shocks when examining the spillover between the sectoral market returns and commodities over time. Henceforth, the asymmetric spillover evidence confirms the previous findings of Xu et al. (2019) and BenSaid (2019) on the role of exogenous shocks in producing the asymmetric responses in stock market volatility. Our analysis, however, confirms the directional relation either from (or) to oil market. It also reveals a greater connectedness between commodities and the sectoral Chinese stock markets during the COVID-19 period when more efficient trading strategies can be formulated. This, in turn can contradict the recent finding of Donadelli et al. (2017) where dangerous infectious diseases in the US are found not to trigger the rational trading on Wall Street. They specifically observe that the impacts of these diseases are stronger in large pharmaceutical companies' stocks.

4.3. Robustness tests

Fig. 5 presents the robustness test of positive returns (Panel A) and negative returns (Panel B). We estimate different H-step-ahead forecasting days with 10-, five, and two-day with 200- and 250-day rolling windows, respectively. As shown in Fig. 5, the positive returns (Panel A) and negative returns (Panel B) of total spillover indices appear to have similar patterns irrespective of different forecasting days and windows. Thus, total spillover indices are robust to the size of rolling windows or to the selection of the forecast horizon. Similar alternative values are also adopted as robustness tests by several previous studies (Diebold and Yilmaz, 2009; Kang et al., 2017; Mensi et al., 2020; Maitra et al., 2021).

4.4. Network connectedness

Figs. 6–8 illustrate pairwise and net-pairwise directional connectedness between the sectoral market returns and commodities throughout the sample period. The connectedness network aims at providing the relevant information about senders or receivers as well as the strength of connectedness. In all figures, the color of the node specifically shows the nature of the market. For instance, the red (green) color of nodes indicates the most significant transmitter (recipient) within the network. The size of the node indicates the economic size of the connectedness between the pair of markets under consideration. Moreover, the arrow thickness also reflects the strength of the directional connectedness.

The net pairwise connectedness in Fig. 6 partially confirms the results in Table 3 for observing most of shocks transmission from the total CSI 300 and industrial indexes to the oil market. We also note that gold market receives less shocks from the sectors relative to those embedded into the oil market. However, the shocks originated from the energy sector to both commodities markets almost disappeared with the new analysis. Within this system, the industrials sector became the second strong transmitter of shocks to other sectors but not to the commodities. Overall, a significant unidirectional spillover from industrials and consumer discretionary sectors to the remaining sectors.

7 https://www.eia.gov/tools/faqs/faq.php?id=709&t=
8 This supports the previous finding in Table 3 for the high spillover between the stocks and crude oil.
9 Their study investigated the time varying Kurtosis, Skewness and volatility spillover in three stages of the COVID pandemic namely July 1-Nov 16/2019, November 17-December 30/2019 and December 31 to April 10, 2020. They found more time varying volatility spillover in the last two stages when considering Chinese A and B stock markets along with commodity markets.
Financial and telecommunication sectors are very sensitive to the performance of CSI 300 index.

Results in Figs. 7 and 8 resemble those observed in Table 3 for the strong interlinkages between the negative sectoral returns and the crude oil market. That is, shocks from all sectors went through to the oil market while the reverse is not true. Interestingly again, Fig. 8 (b) shows that during the COVID-19 period, the magnitude of connectedness is intensified once the investor considers the shocks from...
Fig. 5. Robustness test of total spillover indices: (a) Panel A: Positive returns; (b) Panel B: Negative returns. Notes: The total spillover indices are calculated by re-estimating the four-order VAR approach using 200- and 250-day rolling window estimates with 10-, 5-, and 2-day forecast horizons.
industrial, consumer discretionary, financial and basic materials sectors.\textsuperscript{10} We also observe a little evidence in the same panel for the shocks moving from the energy to the oil market. These cross sectional differences between sectors confirms the recent finding of Bouri et al. (2021) regarding the changes in the structure of asset connectedness during the pandemic outbreak. This observation can also be noticed in the asymmetric network of COVID-19 with the positive returns. However, the gold market remains weekly connected with the sectoral returns though with little evidence when considering the positive returns of the industrial sector during the virus pandemic period.

The results from the network connectedness exercise indicate that investment in commodities can have a less correlation of returns with the equity market. Doing that should provide better diversification benefits. However, our finding for the strong connectedness between the oil and some sectors contradicts Antonakakis et al. (2018) and Kang et al. (2019). This new result can be mainly justified by including the COVID-19 period in the sample as well as performing our asymmetric and sectoral analyses. In other words, while the pandemic is spreading out, the uncertainty arises and an efficient trading strategy involves considering the sign of the stock returns and switching between sectors to reach a better portfolio hedging.

Overall, the strong evidence of stocks-commodities interlinkages during the COVID-19 suggests analyzing the comparable results in the literature with other crises periods. Contrast to our result, Bouri et al. (2016) found little evidence of spillover from oil to the Jordanian stock market sectors during the Arab spring period. We also contradict Bouri et al. (2017a) who documented less causality in variance between the Chinese stock market and the international oil market after the after reform of the oil prices in 2013. Yet, this finding is partially reversed by Weng et al. (2018) for the distinct role of oil pricing reform in affecting the uncertainty in the Chinese sectoral stock market. The less directional spillover from the stock to gold market throughout the pandemic is also opposite to its counterpart in Bouri et al. (2017b). Another contradictory finding with respect to this is also documented by Shahani and Paliwal (2020) for the bidirectional between gold and Nifty 50 stock market during the COVID-19 period. Specifically, the causality from the stock market implied volatility in China to gold is found to peak at all investment horizons during the European debt crisis on September 2012. Our finding of less volatility spillover from gold is inconsistent with the study of Pandey and Vipul (2018). Their analysis proved the ability of gold volatility to transmit to the stock BRICS stock markets after the GFC period.\textsuperscript{11}

Regarding the asymmetric spillover pattern during the pandemic period, our study contrasts Sheikh et al. (2020) who found strong spillover with the positive shocks of gold and not oil after the GFC. Again, these contradictory outcomes seem to be driven by different investment behavior across the sub periods. By adopting the asymmetric VAR model, Okorie and Lin (2020) tends to contradict our conclusion regarding the unidirectional spillover from oil to stock markets. Their analysis considered the Nigerian stock market proved the bidirectional spillover without dividing the sample into market states.

To sum up, the conducted analyses so far make new enlightenments regarding the role of COVID-19 in pricing discovery. It clearly shows that Chinese stock market sends signals into the oil and gold markets with less evidence the other way around. More interestingly asymmetric spillover is more obvious throughout the pandemic period, implying that negative return stock-commodity spillover is much stronger relative to that associated with the positive returns. That means the contagious effect of coronavirus is catastrophic and even exhibits a domino effect. This last argument becomes in line with Baumöhl et al. (2020) who investigate the financial contagion between banks following the pandemic.

4.5. Portfolio analysis

Our empirical results provide evidence of risk spillovers across the commodity and stock sector markets under consideration and have important implications for efficiently maintaining diversified portfolios and risk management. Practically, developing an optimal portfolio on the basis of risk management and portfolio allocation decisions requires a preliminary and accurate estimation of the temporal covariance matrix. To manage the commodity–stock market more efficiently, we use the estimated results of the multivariate DCC-GARCH model,\textsuperscript{12} which helps investors make optimal portfolio allocation decisions by constructing dynamic risk-minimizing hedge ratios. We therefore quantify the optimal portfolio weights and the hedge ratios for designing optimal hedging strategies at the positive and negative returns, respectively.

First, we assume that an investor holds a set of stock assets and seeks to hedge their position against unfavorable effects using commodity assets. Specifically, we follow Kroner and Ng (1998) to define the portfolio weight of the commodity asset holdings as follows:

\[ w_C = \frac{h_C^S - h_C^S}{h_C^S - 2h_C^S + h_C^S} \times \text{with } w_C = \begin{cases} 0 & w_C^+ < 1 \\ w_C^+ & 0 \leq w_C^+ \leq 1 \\ 1 & w_C^+ > 1 \end{cases} \]  

(10)

where \( h_C^S, h_C^S, h_C^S \) are the conditional volatility of the commodity markets, conditional volatility of the stock market, and conditional co-variance between the commodity and stock markets at time \( t \), respectively. For each commodity–stock pair, all information needed to compute the weight \( w_C \) is obtained from the DCC-GARCH model.

Following Kroner and Sultan (1993), we quantify the beta hedge to minimize the risk of this stock–commodity portfolio. We therefore measure the degree of hedging of a long position (buy) of one dollar in the commodity market by a short position (sell) of \( \beta_C^S \) dollars in the stock markets. The hedging ratio \( \beta_C^S \) (HR) is computed as:

\[ \beta_C^S = \frac{h_C^S}{h_C^S} \]  

(11)

\[ \text{for all } i \in \{1, 2, \ldots, N\}, \quad \text{with } h_C^S = \text{the conditional volatility of the commodity asset holding at time } t. \]

\[ \text{where } \beta_C^S, h_C^S, h_C^S, \text{ and } h_C^S \text{ are the conditional volatility of the commodity markets, conditional volatility of the stock market, and conditional co-variance between the commodity and stock markets at time } t, \text{ respectively. For each commodity–stock pair, all information needed to compute the weight } w_C^+ \text{ is obtained from the DCC-GARCH model.} \]

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(11)

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\[ \text{where } \beta_C^S, h_C^S, h_C^S, \text{ and } h_C^S \text{ are the conditional volatility of the commodity markets, conditional volatility of the stock market, and conditional co-variance between the commodity and stock markets at time } t, \text{ respectively. For each commodity–stock pair, all information needed to compute the weight } w_C^+ \text{ is obtained from the DCC-GARCH model.} \]
The hedging effectiveness (HE) of the constructed portfolios can be assessed by comparing the realized hedging errors (Ku et al., 2007) defined as:

\[
\text{HE} = 1 - \frac{\text{Var}_{\text{hedged}}}{\text{Var}_{\text{unhedged}}}
\]  

where the variance of the hedge portfolio (Var_{hedged}) is the variance of the returns of the weighted portfolio of a commodity and stock (PF II), whereas that of the unhedged portfolio (Var_{unhedged}) is that of the returns of the benchmark portfolio (PF I). A higher HE ratio implies stronger hedging effectiveness as measured by the reduction in the portfolio’s variance, implying that the associated investment policy can be deemed a superior hedging strategy.

To complement the analysis in the previous sections, we examine portfolio hedging strategy with the positive and negative equity returns. Table 6 reports the optimal portfolio weights, average HR (long/short) and HE of the portfolios under consideration with the positive equity returns. These three statistics are reported for the whole sample period and sub-periods, covering for example the pre-GFC and ESDC, during the GFC & ESDC period, recovery period, recent oil price crash and the COVID-19 period. The table reports the HR for each long/short pair, with a one-dollar long position in equity market (i.e. stock market sector) and one dollar short position in the gold market. Obviously, the results in the table reveal that the amount of investment in the gold market is more relative to the stocks in almost all investment scenarios. Taking as an example, the telecommunication-gold pair for the whole period, we show that the optimal weight is 0.94, suggesting that the optimal weight of gold holding in a one-dollar gold–telecommunication portfolio should be 94%, with the remainder of 7% invested in the telecommunication stocks. For every one dollar, the investors invest 94 cents in gold and 7 cents in telecommunication stock shares. This indicates the preference of investing the money in gold as a safe haven investment regardless of the market state. By evaluating the cost of hedging, we notice that the optimal HR ranges from a maximum value of 1.3257 for telecommunication sector during the great oil bust period to a minimum of 0.435 for utilities throughout the COVID-19 period. A hedge ratio of 0.435 implies that one dollar long in gold should be shorted by about 43 cents of the utilities. From these two observations, high (low) value of the HR reflects an expensive (cheaper) hedge.
Specifically, the expensive value of the hedge represents the case where the investor needs to take a long position by buying in the stock market and a short position (sell) in the gold market.

Interestingly, Table 6 also shows that the sticking with the utilities-gold investment plan produces the lower proportion of investment in the gold market, HR and hedging effectiveness in all market states. Yet, the only exception here is before the GFC & ESDC the time when investors in the markets found themselves under pressure to allocate of 75.13% to the gold market to get the lowest HR. Also a consistent evidence in the table proves the need to invest in the telecommunication-gold portfolio to reach the highest level of the hedging effectiveness. This new evidence again violates for the period preceding Pre-GFC & ESDC where the highest HE % is associated with the industrial-gold combination.

An overall comparison between Tables 6 and 7 suggests that investors tend to hold more gold when the stock market prices are decreasing. This striking finding can be explained by high uncertainty in stock markets during the crises periods (Juntilla et al., 2018) and investor risk appetite in the equity market (Gülsèven and Ekcì, 2016; Qadan, 2019). Furthermore, Table 6 continues in providing similar results regarding the appropriateness of investing in the utilities sector along with gold market. Specifically, combining between these two investment makes a favorable situation with the lowest HR and highest HE.

This again does not hold before the global and European turbulent periods. During these periods, however, the consumer staples-gold combination seems encouraging for the investor to gain the lowest (highest) HR (HE %). Our general finding for the potential of hedging from the stock-gold here supports contradicts the recent evidence of Trabelsi et al. (2020) who conducted their analysis using Indian stock market sectoral indices. It however supports the other existing findings in the literature for the potential of using gold as a safe haven (e.g., Flavin et al., 2014; Bilgin et al., 2018; Gozgor et al., 2019).

Tables 6 and 9 provide similar portfolio hedging analysis with the oil market using the positive and negative returns, respectively. Essentially, the results suggests more holding of stocks than oil all the time. This evidence can be mostly observed during the COVID-19 period possibly due to the decrease in the oil demand leading to a significant downward oil price at the time of the pandemic. A close look at the tables reveals that under negative return spillover during the pandemic, adding oil yields highest HE ratio. Furthermore, the hedging expensive is clearly minimum during the oil crash period regardless of the sign of the equity returns. This finding contradicts Ashfaq et al. (2020) who observe a significant stock-oil shock correlation during the oil crisis period. Conversely, the hedging seems to be the most expensive throughout the GFC & ESDC period only when the negative returns are considered in the analysis. For the positive returns, this evidence tends to exist after the financial crisis. Our finding here complements that of Ji et al. (2020) since they found that the variations in the BRCs stock returns-oil depend on the shock types in the oil market. That, however, is found to reflect on the conditional value-at-risk in the markets. The variations of oil-stock performance over time also confirms the results of Elsayed et al. (2020) who also documented a higher hedging ratio during the global crisis period. Further evidence for the stock-oil time-varying relation is also found in Belhassine (2020). Other relatively close findings in the literature include Chang et al. (2011) who observed a flight-to-quality from oil to bonds in the crisis regime.

Analyzing the oil-stock results more reveals some interesting results. Specifically, more (less) investment in the basic utilities (oil) market remains again the most appropriate for investors to generate the lowest HR. That is also proved to make the hedging more effective relative to the situations being observed with other hedging scenarios. These results are observed during all sub-periods but not in the pre-global and European crises periods. This finding should confirm that the Chinese basic utilities sector is a preferable hedging instrument for investors at least in the last seven years. In contrast, the hedging with negative returns became the most expensive when the investment is made in the information technology sector. This evidence prevails across all sub-periods even over the full sample period. Lastly, analyzing the results in Tables 6–9 reveal lower cost of hedging and higher hedging effectiveness with the oil market relative to the gold market.

Notes: This table summarizes the results of the optimal weights and hedge ratios. The numbers in bold indicate the hedged portfolio with the highest variance reductions.
5. Conclusions

This paper contributes to the existing literature on commodity and stock markets by examining the asymmetric returns spillovers between Chinese sector stocks (aggregate CSI 300 index, Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Information Technology, Materials, Telecommunications Services, Utilities) and two commodity futures markets (gold futures and WTI crude oil futures) using the DY methodology.

The results show significant time varying spillovers. Industrials and consumer discretionary sectors are the main contributors and receivers of total spillover in the system. Commodities and seven of ten sectors (exception for industrials, materials and consumer discretionary sectors) are not receivers of spillovers. The spillover effect between sectors

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Table 7

Optimal portfolios’ weights, hedge ratios, and hedging effectiveness of sector-gold pair under negative returns.

<table>
<thead>
<tr>
<th>Portfolio pairs</th>
<th>Whole period</th>
<th>Pre-GFC &amp; ESDC</th>
<th>GFC &amp; ESDC</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>wt</td>
<td>βC HE(%)</td>
<td>wt</td>
</tr>
<tr>
<td>CSI 300/ GOLD</td>
<td>0.8377</td>
<td>1.1288</td>
<td>14.55%</td>
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<tr>
<td>FINANCIALS/ GOLD</td>
<td>0.8543</td>
<td>1.1862</td>
<td>11.19%</td>
</tr>
<tr>
<td>CONS STAPLE/ GOLD</td>
<td>0.8433</td>
<td>1.1366</td>
<td>20.21%</td>
</tr>
<tr>
<td>INDUSTRIALS/ GOLD</td>
<td>0.8942</td>
<td>1.2253</td>
<td>10.40%</td>
</tr>
<tr>
<td>CONS DISCRE/ GOLD</td>
<td>0.8971</td>
<td>1.2322</td>
<td>10.86%</td>
</tr>
<tr>
<td>INFO TECHN/ GOLD</td>
<td>0.9578</td>
<td>1.4604</td>
<td>4.74%</td>
</tr>
<tr>
<td>UTILITIES/ GOLD</td>
<td>0.6887</td>
<td>1.0361</td>
<td>25.02%</td>
</tr>
<tr>
<td>MATERIALS/ GOLD</td>
<td>0.9121</td>
<td>1.3091</td>
<td>9.116%</td>
</tr>
<tr>
<td>TELECOM SVC/ GOLD</td>
<td>0.9273</td>
<td>1.3875</td>
<td>11.53%</td>
</tr>
<tr>
<td>ENERGY/ GOLD</td>
<td>0.8993</td>
<td>1.2735</td>
<td>10.22%</td>
</tr>
</tbody>
</table>

Table 8

Optimal portfolios’ weights, hedge ratios, and hedging effectiveness of sector-gold pair under positive returns.

<table>
<thead>
<tr>
<th>Portfolio pairs</th>
<th>Whole period</th>
<th>Pre-GFC &amp; ESDC</th>
<th>GFC &amp; ESDC</th>
</tr>
</thead>
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<tr>
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<td>wt</td>
<td>βC HE(%)</td>
<td>wt</td>
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</tr>
</tbody>
</table>

Notes: See Table 6.
negative spillovers increase during GFC and ESDC, the recent oil price shocks declines after 2012. The gap between positive spillovers and negative spillovers appears slightly lower than the negative counterpart all over the sample period. However, an exception continues to appear where the negative spillover return metric spillover show that the value of the positive spillover appears to be highest during times of commodity market stress.

The spillover from all sectors to gold almost resembles that to oil market spillovers. In contrast, the spillovers from oil to gold and other commodities of the commodity market is higher as compared with its counterpart between the financial and commodity market. This in turn should help in gaining real benefits out of the stock-commodity pairs. (ii) The hedging effectiveness with the commodities varies over time and it reaches the maximum level during the COVID-19 period with the oil market. This in turn should help in gaining real benefits out of the stock-commodity portfolios in specific time periods. (iii) A combination of the basic utilities-commodity pair, when contrast with other pairs can provide higher return (lower cost) potential over time especially after the European debt crisis period. (iv) There is still a potential to revise the assumption of the safe haven and hedging of the stock-commodities combination while considering other stock markets and hedging positions such as the short hedging. (v) Investors should take into account the sign of stock market returns for accurate portfolio risk management. Generally, the negative returns of the Chinese stock markets are quite capable of causing excess volatility of the crude oil market, this could be a component of strategic analysis employed by the Chinese stock market participants in deciding the right position and gaining a profit in the market.

On the other hand, policy makers and portfolio managers can react to our results in various ways. First, non-conventional actions are needed to reduce the impact of the spillover during the pandemic period such as increasing the transaction cost though, this might cause series long-run problems, conversely short selling might be extensively
allowed to for a better expectation for the future asset prices. This could then result in better pricing opportunities in both the stock and commodities markets and a reduction in the herdng behavior between them. Third, portfolio managers need to be informed that oil is an optimal hedging instrument for only specific sectors. Henceforth, diversification can be more profitable if sectors less subject to spillover are overweighted in portfolios. Lastly, portfolio managers can also examine the spillover in a firm level for those most affected sectors while also considering the market capitalization of the companies inside assuming that the performance of small firms might be more affected by the pandemic than others.

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Appendix A. Supplementary data

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References


