



Connectedness of stock markets with gold and oil: New evidence from COVID-19 pandemic

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ABSTRACT

This paper sets out to explore the impact of COVID-19 pandemic on the dynamic connectedness among gold, oil and five leading stock markets by applying a new DCC-GARCH connectedness approach. We find stronger connectedness between these markets during the COVID-19 pandemic than in the pre-pandemic period. We also find that during this pandemic, gold is a receiver of shocks from the five stock markets, whereas the oil is a net transmitter of shocks.

1. Introduction

The COVID-19 pandemic is having a great impact on global financial markets. Because of this turmoil, global financial markets have experienced heavy losses and the kind of deep changes that have not been seen since the 2008 financial crisis (Cembalest, 2020). Assessing connectedness between financial markets during this outbreak has been a remarkable challenge facing researchers and policymakers because it helps them to analyze the behavior of the markets facing this major event, prepare plans and strategies to minimize the financial effects of the COVID-19 outbreak, and make well-founded and informed decisions about global portfolio diversification opportunities.

As economic activity came to a halt during lockdowns in nearly all industrialized economies, oil prices fell dramatically due to the significant decline in global demand. For instance, the US reference crude oil's price (West Texas Intermediate) had fallen by 37 USD per barrel by 20 April 2020. While oil price volatility tends to influence the world economy negatively, gold prices have shown a clear upward trend. Oil and gold are strategic for investors as they are usually included in their asset portfolios. Oil, as a highly volatile commodity, presents valuable information in forecasting financial asset prices. Conversely, gold is regularly regarded as a safe-haven asset during periods of turmoil (Baur and Lucey, 2010). Accordingly, oil and gold are, theoretically, strongly associated with stock markets. Therefore, an accurate assessment of the linkages between oil, gold, and stock markets may aid investors in their portfolio allocation during the crisis period.

Many empirical studies that have examined relationships between financial markets have confirmed that the COVID-19 pandemic has influenced the degree of connectedness between these markets. For instance, So et al. (2021) used dynamic financial networks based on stock return correlations to examine the connectedness between financial networks in Hong Kong during the COVID-19 outbreak. They found that network connectedness within the financial network increased during the outbreak. Similarly, Zhang

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et al. (2020) found that the pandemic is having important repercussions on global financial markets. Specifically, they showed that the linkages between global stock markets exhibited obviously different patterns during the pandemic period. In the same vein, Bissoondoyal-Bheenick et al. (2020) investigated the impact of the pandemic on the connectedness between stock returns and volatility. They provided empirical evidence that the connectedness between these two became significantly more marked as the COVID-19 outbreak increased in severity. In the same line, Costa et al. (2021) examined sectoral connectedness in the US using data from 2013 to the end of 2020. They showed that total connectedness has experienced a dramatic increase during the outbreak.

This paper contributes to the existing literature of connectedness between financial markets by assessing the impacts of the COVID-19 pandemic on the dynamic connectedness among gold, oil, and five leading stock markets. For this purpose, we use Gabauer's (2020) DCC-GARCH connectedness approach to evaluate the total and net connectedness between financial markets. This approach offers a number of advantages. First, it allows us to overcome the major drawbacks of the rolling window analysis, namely the arbitrary choice of the window size in most cases and the loss of observations. Second, it lets us test whether or not the propagation mechanism is time-varying. To our knowledge, this is the first research to apply this novel approach to investigating the connectedness between financial markets. Our focus on gold and oil was motivated by several factors. First, there are a few empirical studies linking oil and gold to financial markets during the COVID-19 pandemic (Zhang and Hamori; 2021; Wang et al., 2021; Drake, 2021). Second, oil prices experienced high volatility during the period of turmoil. The connection between oil and the financial markets is highlighted by this volatility and uncertainty. Third, since ancient times, stock investors have considered gold a safe haven and have used it to protect against market instabilities and financial turbulence. Gold contributes to reducing connectedness between financial markets when it is used this way by acting as a shock damper during periods of turmoil.

Our findings show a stronger connectedness among gold, oil and the selected stock markets during the COVID-19 pandemic than in the pre-pandemic period. Our results also reveal that gold is a receiver of shocks from the five stock markets, whereas oil is a transmitter of shocks during the outbreak. The increased connectedness among the considered commodities and stock markets has been due to the intensification of the transmission of the crisis effect between them. Overall, these findings support the hypothesis in the literature of market contagion, which suggests that periods of financial crisis generate large return connectedness among commodities and stock markets.

The remainder of this paper is organized as follows: Section 2 outlines the econometric specifications and data description, while Section 3 reports and discusses the paper's empirical findings. Finally, Section 4 concludes and discusses policy implications.

2. Data and methodology

2.1. Data

Daily data spanning from 14 November 2018 to 24 March 2021 were collected from Bloomberg database to explore the patterns of dynamic connectedness between oil, gold and five of the world's largest stock markets in the pre and during the COVID-19 pandemic periods. The decision to focus on these stock markets was motivated by the following reasons. First, the stock markets that are considered are among the world's ten largest stock markets. Second, all of these markets have been severely affected during the

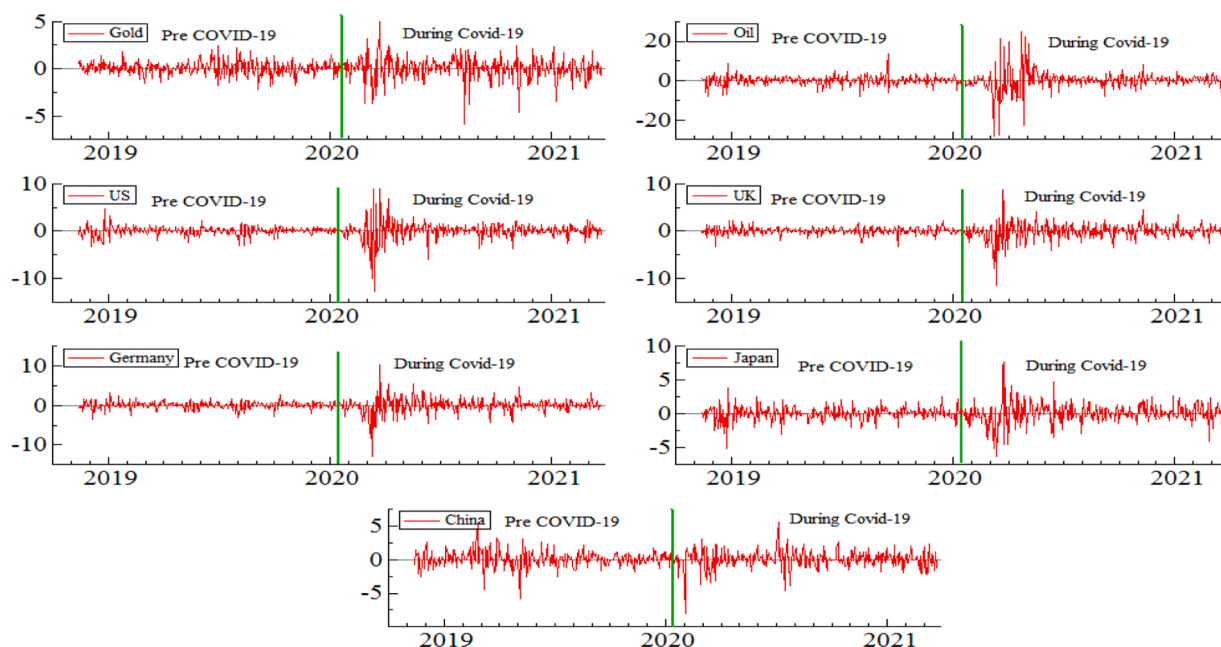


Fig.1. Returns evolution of gold, oil and the five selected stock markets.

COVID-19 pandemic and experienced losses of between 30 and 42% of their value (Yarovaya et al., 2020; Zhang et al., 2020).

As suggested by Wan et al. (2021), we consider 20 January 2020 as the start date of the pandemic period. Fig. 1 depicts the daily evolution of the returns of the series considered in our analysis.

2.2. Methodology

This paper employs the DCC-GARCH connectedness approach proposed by Gabauer (2020). It is based on the volatility impulse response function (VIRF) that represents the impact of a shock in variable "i" on variable j's conditional volatilities. The VIRF can be written as

$$\Psi^g = VIRF(J, \delta_{j,t}, F_{t-1}) = E(H_{t+j} \setminus \varepsilon_{j,t} = \delta_{j,t}, F_{t-1}) - E(H_{t+j} \setminus \varepsilon_{j,t} = 0, F_{t-1}) \tag{1}$$

where $\delta_{j,t}$ is a selection vector with a one at the j^{th} position and zero otherwise.

Conditional variance-covariance forecasting by using the DCC-GARCH model is at the core of VIRF and can be done by iteration in three steps.

First, using the GARCH(1, 1), the conditional volatilities ($D_{t+h} \setminus F_t$) can be predicted by

$$E(h_{i,t+1} \setminus F_t) = \omega + \alpha \delta_{i,t}^2 + \beta h_{i,t} = 1, \tag{2}$$

$$E(h_{i,t+h} \setminus F_t) = \sum_{i=0}^{h-1} \omega(\alpha + \beta)^i + (\alpha + \beta)^{h-1} E(h_{i,t+h-1} \setminus F_t) h > 1, \tag{3}$$

As a second step, $E(Q_{t+1} \setminus F_t)$ is forecasted by

$$E(Q_{t+1} \setminus F_t) = (1 - a - b)\bar{Q} + au_t u'_t + bQ_t h = 1 \tag{4}$$

$$E(Q_{t+1} \setminus F_t) = (1 - a - b)\bar{Q} + aE(u_{t+h-1} u'_{t+h-1} \setminus F_t) + bE(Q_{t+h-1} \setminus F_t) h > 1 \tag{5}$$

where $E(u_{t+h-1} u'_{t+h-1} \setminus F_t) = E(Q_{t+h-1} \setminus F_t)$ allows to predict the dynamic conditional correlations as suggested by Engle and Shepard (2001).

In the third step, the dynamic conditional variance-covariances are predicted by

$$E(R_{t+h} \setminus F_t) \approx diag \left[E \left(q_{iit+h}^{-\frac{1}{2}} \setminus F_t \right), \dots, \left(q_{NNt+h}^{-\frac{1}{2}} \setminus F_t \right) \right] E(Q_{t+h} \setminus F_t) diag \left[E \left(q_{iit+h}^{-\frac{1}{2}} \setminus F_t \right), \dots, \left(q_{NNt+h}^{-\frac{1}{2}} \setminus F_t \right) \right], \tag{6}$$

$$E(H_{t+h} \setminus F_t) \approx E(D_{t+h} \setminus F_t) E(R_{t+h} \setminus F_t) E(D_{t+h} \setminus F_t). \tag{7}$$

The generalized forecast error variance decomposition (GFEVD) is then computed using the VIRF and is interpreted as the variance share of one variable explains on others. The normalized variance share is computed by

$$\tilde{\phi}_{ij,t}^g(J) = \frac{\sum_{t=1}^{J-1} \Psi_{ij,t}^{2,g}}{\sum_{j=1}^N \sum_{t=1}^{J-1} \Psi_{ij,t}^{2,g}} \tag{8}$$

where $\sum_{j=1}^N \tilde{\phi}_{ij,t}^g(J) = 1$ and $\sum_{i,j=1}^N \tilde{\phi}_{ij,t}^g(J) = N$.

By employing the GFEVD, it is possible to construct the total connectedness index (TCI) as follows:

$$C_i^g(J) = \frac{\sum_{i,j=1, i \neq j}^N \tilde{\phi}_{ij,t}^g(J)}{N} \tag{9}$$

The total connectedness presented in Eq. (9) allows finding the spillovers that variable "i" transmits to variables "j" (total directional connectedness), which are calculated by:

$$C_{i \rightarrow j,t}^g(J) = \frac{\sum_{i,j=1, i \neq j}^N \tilde{\phi}_{ij,t}^g(J)}{\sum_{j=1}^N \tilde{\phi}_{ij,t}^g(J)} \tag{10}$$

The total directional connectedness from others is computed by

$$C_{i \leftarrow j,t}^g(J) = \frac{\sum_{i,j=1, i \neq j}^N \tilde{\phi}_{ij,t}^g(J)}{\sum_{j=1}^N \tilde{\phi}_{ij,t}^g(J)} \tag{11}$$

The difference between the two previous measures allows computing the net total connectedness used to describe the influence of the variable "i" on the studied network, which can be presented by

$$C_{i,t}^g = C_{i \rightarrow j,t}^g(J) - C_{i \leftarrow j,t}^g(J) \tag{12}$$

Finally, Gabauer (2020) defines the net pairwise directional connectedness (NPDC) between variable "i" and variable "j" by

$$NPDC_{ij} = \tilde{\phi}_{ji,t}^g(J) - \tilde{\phi}_{ij,t}^g(J) \tag{13}$$

A negative value of NPDC_{ij} indicates that variable "i" is dominated by "j", whereas a positive value indicates the opposite.

3. Empirical results

3.1. Connectedness tables

Tables 1 and 2 illustrate the average dynamic connectedness measures among gold, oil, and the five studied stock markets before and during the COVID-19 pandemic. Table 1 shows that the total connectedness (TCI) between gold and the five stock markets increased during the COVID-19 pandemic, reaching 37.09% against 32.98% in the pre-COVID-19 period. Table 2 shows that the TCI between oil and the stock markets also increased during the COVID-19 pandemic (45.78% vs. 37.09% before the outbreak). Overall, the results indicate that the studied markets are moderately inter-connected and that the TCI among them increased during the pandemic period. In addition, our findings suggest that oil becomes the main net transmitter during the COVID-19 pandemic period while gold acts as the main net receiver, which receives from all studied stock markets.

3.2. Dynamic total connectedness

Figs. 2 and 3 display the dynamic total connectedness (TCI). Fig.2 indicates the TCI between gold and the five stock markets spanned approximately between 25 and 43% before the pandemic and from 30 to 60% during it. Therefore, the TCI sharply increased instantly after COVID-19 was declared a pandemic by the World Health Organization (WHO), indicating this event significantly affected the connectedness between gold and the selected stock markets. Regarding oil with these stock markets, the total connectedness index is approximately between 28 and 40%. Fig.3 shows that this index increased during the pandemic, peaking at over 60% shortly after the pandemic was declared.

Overall, our findings show that COVID-19 has influenced the connectedness level between the gold market and the studied stock markets, and between the oil market and these markets, as well. This outcome is owed to the amplification of crisis effect transmission between them. These findings are consistent with the hypothesis of market contagion in the literature, suggesting that periods of financial crisis generate large return connectedness between commodities and stock markets.

To provide evidence concerning the statistical significance of the total connectedness increase, we tested the following hypothesis

$$\begin{cases} H_0 : \mu_{Before} = \mu_{During} \\ H_1 : \mu_{Before} \neq \mu_{During} \end{cases}$$

where μ_{Before} is the average total connectedness index before the COVID-19 pandemic and μ_{During} is the average total connectedness index during the COVID-19 pandemic. The appropriate procedure to test the null hypothesis of the equality of these means is the Satterthwaite-Welch *t*-test (Welch, 1947) because it takes into account the unequal variances condition. The results of this test, reported in Table 3, show that the null hypothesis is rejected for both submarkets, gold-stock markets and oil-stock markets.

Table 1

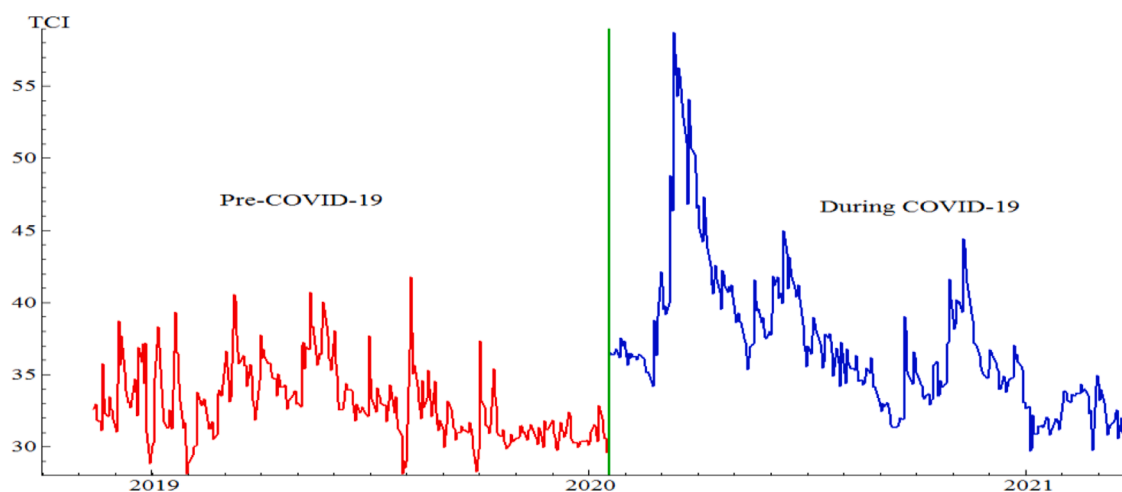
Dynamic connectedness measures between gold and studied stock markets based on 60-day-ahead forecasts.

	Gold	US	UK	Germany	Japan	China	FROM
Panel 1.a Pre-COVID-19 period							
Gold	88.10	3.89	1.48	4.26	1.71	0.57	11.90
US	2.55	57.92	10.65	20.79	3.06	5.03	42.08
UK	1.61	15.69	41.91	30.78	3.07	6.94	58.09
Germany	2.54	16.14	16.12	52.96	2.79	9.46	47.04
Japan	1.35	3.26	2.16	3.60	70.76	18.86	29.24
China	0.09	1.20	1.09	2.72	4.41	90.49	9.51
Contribution to others	8.13	40.17	31.50	62.15	15.04	40.86	197.86
NET directional connectedness	-3.77	-1.91	-26.59	15.11	-14.19	31.35	TCI
NPDC transmitter	4.00	2.00	5.00	1.00	3.00	0.00	32.98
Panel 1.b During COVID-19 period							
Gold	91.93	1.87	0.68	1.41	0.76	3.34	8.07
US	0.76	50.66	16.63	26.83	3.25	1.88	49.34
UK	0.10	9.82	42.67	38.10	7.54	1.77	57.33
Germany	0.10	11.22	27.41	54.44	5.52	1.31	45.56
Japan	0.17	3.80	13.59	14.68	59.87	7.89	40.13
China	1.16	2.72	4.31	4.69	9.26	77.86	22.14
Contribution to others	2.30	29.44	62.62	85.70	26.33	16.18	222.57
NET directional connectedness	-5.77	-19.90	5.29	40.14	-13.80	-5.95	TCI
NPDC transmitter	5.00	2.00	1.00	0.00	3.00	4.00	37.09

Table 2

Dynamic connectedness measures between oil and stock markets based on 60-day-ahead forecasts.

	Oil	US	UK	Germany	Japan	China	FROM
Panel 2.a Pre-COVID-19 period							
Oil	97.17	0.70	0.41	0.35	0.22	1.15	2.83
US	22.63	46.17	8.38	16.38	2.44	3.99	53.83
UK	22.30	12.22	33.31	24.19	2.47	5.52	66.69
Germany	11.29	14.51	14.58	48.42	2.58	8.63	51.58
Japan	9.36	2.98	1.99	3.31	65.07	17.28	34.93
China	10.83	1.05	0.96	2.37	3.86	80.94	19.06
Contribution to others	76.41	31.45	26.32	46.60	11.57	36.58	228.93
NET directional connectedness	73.58	-22.37	-40.37	-4.98	-23.36	17.52	TCI
NPDC transmitter	0.00	3.00	5.00	2.00	4.00	1.00	38.15
Panel 2.b During COVID-19 period							
Oil	86.65	3.39	3.92	4.29	1.02	0.74	13.35
US	29.95	35.87	11.75	18.78	2.25	1.39	64.13
UK	21.85	7.43	33.64	29.65	5.97	1.46	66.36
Germany	18.58	8.90	22.44	44.42	4.54	1.12	55.58
Japan	11.90	3.08	11.88	12.61	53.33	7.19	46.67
China	11.59	2.06	3.46	3.63	7.84	71.42	28.58
Contribution to others	93.87	24.86	53.45	68.96	21.61	11.90	274.65
NET directional connectedness	80.52	-39.27	-12.91	13.39	-25.05	-16.68	TCI
NPDC transmitter	0.00	3.00	2.00	1.00	4.00	5.00	45.78

**Fig.2.** Total connectedness index between gold and the five stock markets.

3.3. Dynamic net connectedness

In this section, we analyze the net connectedness dynamic patterns of the studied markets. Figs. 4 and 5 display the net total directional connectedness index over the compared periods. The main results emerging from these figures follow. First, the results highlight that the net connectedness of all studied markets peaked during the COVID-19 pandemic, in a behavior similar to the total connectedness index presented in the previous section. From these figures, it is evident that the net connectedness behavior has significantly changed during the pandemic compared to the pre-COVID-19 period. Second, Fig. 4 shows that gold is a receiver of shocks from the five stock markets. More specifically, gold becomes a receiver of shocks after a short period of being a transmitter for the US. For the UK stock market, it becomes a net transmitter during the COVID-19 period. In the case of Germany, gold remains as a transmitter of shocks, but to a stronger extent during the COVID-19 period. For the Japanese stock market, gold seems to have a similar behavior during the two considered periods. When it comes to the Chinese stock market, gold becomes a receiver of shocks during the first months of COVID-19 after being a net transmitter during the pre-pandemic period. Finally, similar behavior is found when considering the oil returns with the five stock markets. As shown in Fig. 5, oil exhibits a higher net connectedness index during the pandemic period. It remains a net transmitter of shock to all five selected stock markets during the entire pandemic period.

The findings of the dynamic net connectedness replicate how stock markets react with oil and gold in periods of crisis. During the COVID-19 pandemic, the combination of stagnant production and high economic uncertainty generated increasing volatility in oil prices, making this strategic commodity the largest transmitter of shock to stock markets. Individual investors' pessimism boosts investment in gold, which is commonly viewed as a primary safe-haven asset, making this commodity the largest receiver of shock from stock markets.

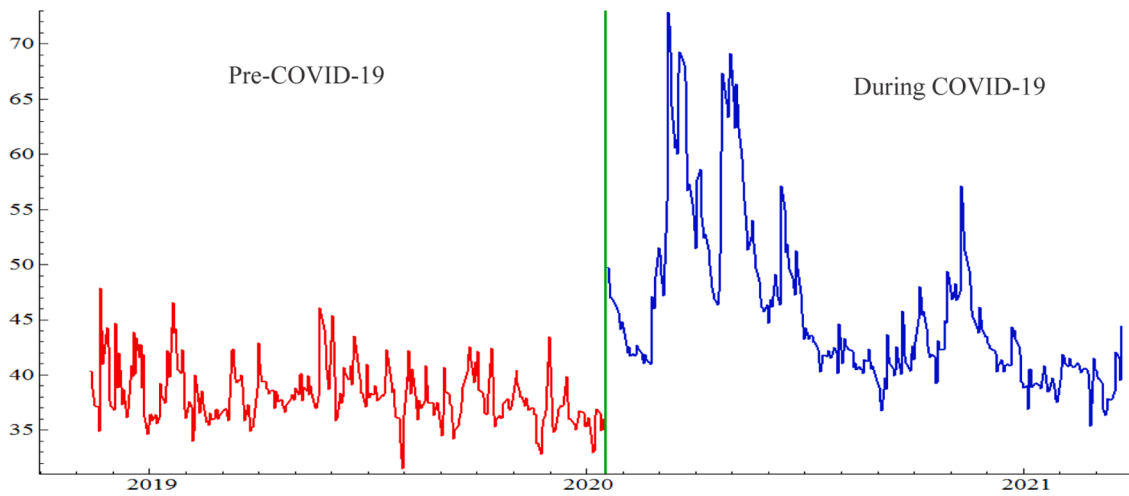


Fig.3. Total connectedness index between oil and the five stock markets.

Table 3
Satterthwaite-Welch t-Test results.

Statistics	Gold and stocks	Oil and stocks
Mean Pre COVID-19	32.976	45.557
Mean During COVID-19	37.095	38.154
S.D Pre COVID-19	2.526	7.436
S.D during COVID-19	4.962	2.546
Satterthwaite-Welch test	12.980***	-17.014***
p-value	0.000	0.000

Note. Statistical significance: * at 10%, ** at 5% and *** at 1%

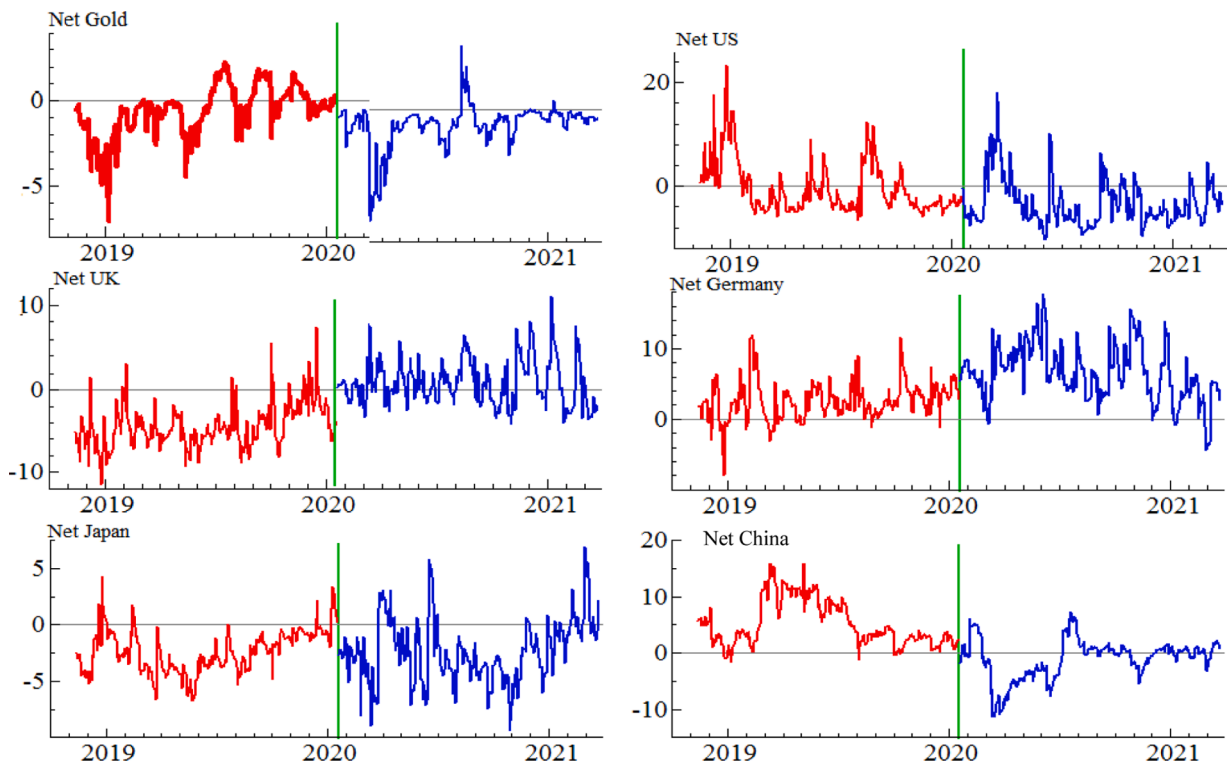


Fig.4. Net connectedness index for gold and the five stock markets-

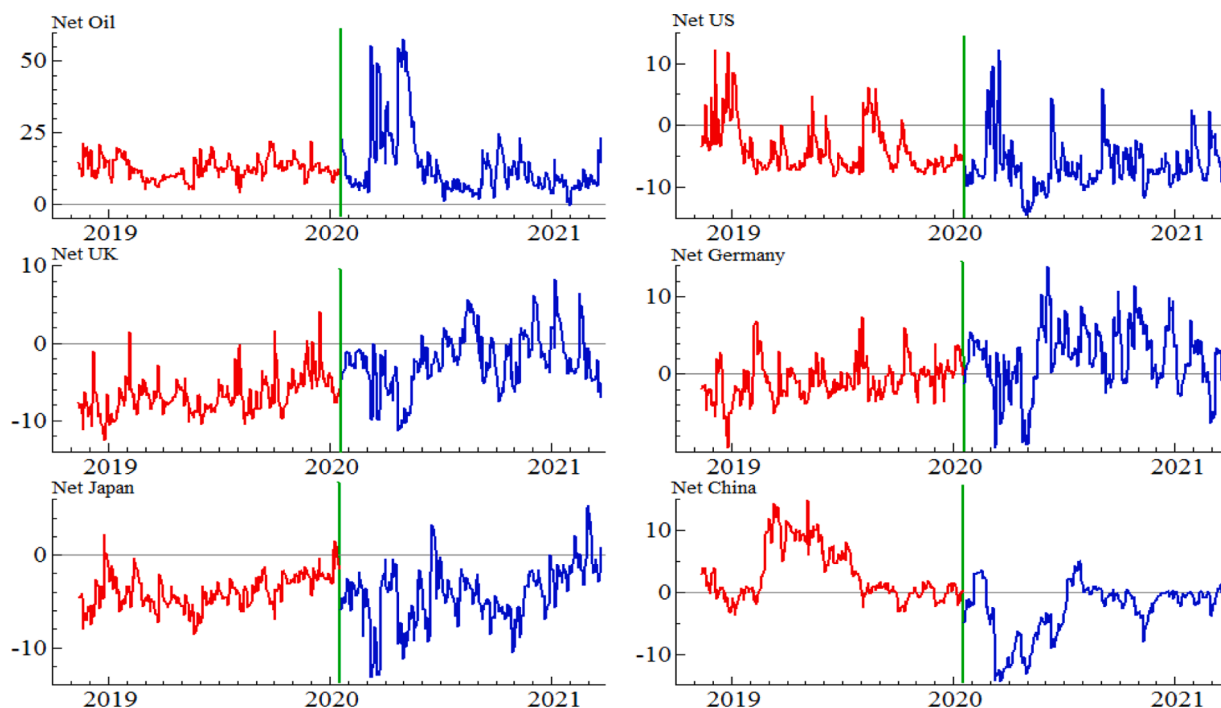


Fig.5. Net connectedness index for oil and the five stock markets.

As we proceeded for the total connectedness, we employed the Satterthwaite-Welch procedure to check whether the dynamic net connectedness has significantly changed during the COVID-19 outbreak by testing the following hypothesis.

$$\begin{cases} H_0 : \mu_{i, Before} = \mu_{i, During} \\ H_1 : \mu_{i, Before} \neq \mu_{i, During} \end{cases}$$

where $\mu_{i, Before}$ is the average net connectedness index of the market "i" before the COVID-19 pandemic and $\mu_{i, During}$ is the average net connectedness index of the market "i" during the COVID-19 outbreak. The results reported in Table 6 reveal that the change in net connectivity among the markets studied is statistically significant except for the Japanese stock market.

4. Conclusions

This paper investigates the effects of the COVID-19 pandemic on the dynamic connectedness between gold, oil and five leading stock markets. Using a new DCC-GARCH connectedness approach, we found that the COVID-19 pandemic increased the connectedness among oil, gold and the five selected stock markets. Our results also show that gold is a receiver from the five stock markets, whereas oil is a transmitter of shocks during this outbreak. These outcomes are associated with the hypothesis of market contagion, suggesting that the periods of financial distress induce large return connectedness in several asset markets. More specifically, during the COVID-

Table 6
Satterthwaite-Welch t-test for the net connectedness measures.

	Mean	S.D	Satterthwaite-Welch test			p-value
	Pre	During	Pre	During	Stat	
Panel A						
Gold	-0.628	-0.961	1.46	1.290	2.960**	0.003
US	-0.317	-0.317	4.979	4.568	7.790***	0.000
UK	-4.431	0.881	2.637	2.7652	-24.465***	0.000
Germany	2.518	6.690	2.712	4.038	-15.050***	0.000
Japan	-2.365	-2.300	1.882	2.817	-0.336	0.736
Panel B						
Oil	12.262	13.419	3.601	11.606	-1.671*	0.095
US	-3.728	-6.545	3.874	3.904	8.986***	0.000
UK	-6.728	-2.151	2.391	3.549	-18.772***	0.000
Germany	-0.830	2.231	2.475	4.169	-11.083***	0.000
Japan	-3.893	-4.175	1.785	3.144	1.368	0.171

Notes: The asterisk *, **, *** are the significance levels at 1, 5 and 10%.

19 period, the global uncertainty caused by the contagion has influenced the structural connectedness patterns between the markets under investigation. Furthermore, the dynamic net connectedness findings replicate how stock markets respond to oil prices and gold in periods of crisis.

The results from this study have policy implications that could potentially be important to stock investors and policymakers. For instance, policymakers should be aware of the links between oil and gold and their effect on financial markets when preparing strategies to reduce connectedness between stock markets during pandemics.

Declaration of Competing Interest

Noureddine Benlagha and Salaheddine El Omari declare no conflicts of interest in this manuscript.

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