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Directional spillover effects and time-frequency nexus between oil, gold and stock markets: Evidence from pre and during COVID-19 outbreak

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ABSTRACT

The Covid-19 crisis has been spread rapidly throughout the world so far. However, how deep and long the turbulence would depend on the success of solutions taken to deter the spread of Covid-19, the impacts of government policies may be prominent to alleviate the current crisis. In this article, we investigate the spillover effects and time-frequency connectedness between S&P 500, crude oil prices, and gold asset using both the spillover index of Diebold and Yilmaz (2012) and the wavelet coherence to evaluate whether the time-varying dynamic return spillover index exhibited the intensity and direction of transmission during the Covid-19 outbreak. Overall, the present results shed light on that in comparison with the pre-Covid-19 period, and the return transmissions are more apparent during the Covid-19 crisis. More importantly, there exist significant dependent patterns about the information spillovers among the crude oil, S&P 500, and gold markets might provide significant implications for portfolio managers, investors, and government agencies.

1. Introduction

There are two pressing issues that the global economy is facing: the novel coronavirus (Covid-19) pandemic outbreaks Wuhan (Hubei region from China) onset December 2019 and the current oil price slump, which has caused severe devastation both in human lives and increasing economic costs. Both severe shocks would commence a long-run economic crash and drive many countries across the world into recession. Also, the novel coronavirus is quite infectious and activates a large amount of the real economy and financial markets. Oil prices witnessed a dramatic fall in April 2020 during the Covid-19 period, while the global oil markets have experienced a slight decrease with the Covid-19 pandemic outbreaks and started an upside trend at the beginning of February 2020 (Mensi, Sensoy, Vo, & Kang, 2020).

Furthermore, the Covid-19 outbreak is referred to as a source of systematic risk. As a result, it is necessary to implement further study on the financial impacts of the Covid-19 outbreak. Our first contribution to the existing literature is the evaluation of the comovements between crude oil price and gold market and S&P 500 stock index before and during the Covid-19 outbreak. This is the first study focusing on this subject. The selection of three assets (gold, oil, and stock S&P 500) is because that the most actively traded commodities in the world are oil

and gold, and S&P 500 is one of the most actively traded and diversified stock indices (Baruník, Kočenda, & Vácha, 2016). Oil, gold, and S&P 500 witnessed profound dissimilarities in leverage, making them highly attractive from a financial perspective. These common assets have acquired further diversification strategies and share similar statistical characteristics with other popular assets (Arfaoui & Rejeb, 2017; Baruník et al., 2016; Bouri, Shahzad, Roubaud, Kristoufek, & Lucey, 2020). As a result, a systematical understanding of the comovement of the three conventional financial assets has essential meaning for investors, portfolio managers, and policymakers.

As documented by the Commodity Futures Trading Commission during the Covid-19 period, the investment capital rate had fluctuated between \$8,992,846 and \$11,908,620 in the US through index investment. This low investment flow, along with episodes of the crude oil price variation, has resulted in a heated debate among academics and policymakers in connection with the effects of the Covid-19 outbreak on the associations among gold, crude oil, and stock markets. The discussion mainly bases on the premise that if the financial stress influences the prices of the commodity, financial traders' trading should change their portfolio diversifications.

In this scenario, the current paper is the first endeavor to analyze how the Covid-19 crisis affects the comovements between crude oil price

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and gold market and S&P 500 stock index before and during the Covid-19 periods. To this end, we utilize both the spillover index of [Diebold and Yilmaz \(2012\)](#) and the wavelet coherence, which allow us to measure the directional of spillover and lead-lag interplay among different variables in the pre and during Covid-19 periods. Compared with the related literature, the most significant advantage of these methods is that dynamic and directional. We could evaluate the extent of information spillover and volatility interrelatedness across assets at any particular date ([Bouri, Lien, Roubaud, & Shahzad, 2018](#); [Maghyreh, Awartani, & Bouri, 2016](#)). Besides, the application of the wavelet coherence framework unveils the comovement across gold, stock, and oil market indices at different frequencies. This approach captures slow and existent connectedness, allowing for a more nuanced understanding of the interconnectedness among markets than standard methods that only consider the time domain perspective ([Bouri, Demirer, Gupta, & Pierdzioch, 2020](#)). More precisely, we use wavelet analysis to capture the intercorrelation between the examined series and within the different frequency bands and time-scales, which means that depending on differences in heterogeneous expectations and different perception of risk, global investors should be cautious about their investment decision over investment horizons ([Baruník et al., 2016](#); [Hung, 2020](#)). We also analyze the net spillovers of each variable and between each pair of variables to identify which market is net transmitter and recipients of spillovers before and during the Covid-19 crisis.

Our significant empirical findings can be summarized as follows. First, the intercorrelation among three assets is relatively low in the pre-COVID-19 period, but during the Covid-19 outbreak, it remarkably increases. The change in the pattern is more pronounced after decisive structural breaks occur after the World Health Organization (WHO) announcement in January 2020. Second, the directional spillovers before and during the Covid-19 crisis are different and vary over time. Third, we show the difference between intercorrelation and contagion among assets and measure their degree and direction at various investment horizons; mainly, the heterogeneity in the relationship is very prominent during the Covid-19 outbreak. Finally, by comparing and contrasting the multiple influences between the pre-COVID-19 period and during the Covid-19 outbreak, we can provide significant implications for investors, policymakers, and portfolio managers in connection with risk management across various regimes.

The remainder of this paper is organized as follows. [Section 2](#) represents the related literature. [Section 3](#) discusses the methodology used and the data. [Section 4](#) provides empirical results and policy recommendations. [Section 5](#) concludes the study.

2. Related literature

The Covid-19 outbreak is an unprecedented shock to the world economy. Given the extent of the Covid-19 crisis, the dynamic connectedness in asset prices has received much attention on account of their relevance to financial connectedness, portfolio diversification, and cross-speculation ([Baruník et al., 2016](#)). Our study stands at the crossroad of three strands of the literature, the first centering on the oil-stock relationship, the second investigating oil-gold connectedness, and the third tackling the interplay between stock and gold prices.

[Bouri, Demirer, et al. \(2020\)](#) report a positive impact of a daily newspaper-based index of uncertainty with regard to infectious diseases (EMVID) for the volatility of the global oil market. At the same time, [Mensi et al. \(2020\)](#) look into the influences of Covid-19 on the multifractality of gold and oil prices based on upward and downward trends and show that the gold (oil) market is more inefficient during downward (upward) trends prior to the outbreak. By contrast, the results reveal that gold (oil) is more inefficient during upward (downward) trends during the Covid-19 outbreaks, which means that global oil and gold markets are inefficient.

The Covid-19 effects are occasionally compared to the global financial crisis of 2008 that numerous articles have studied in the

interdependence, contagion, and spillover effect literature. Within the first line of research, [Ferreira, Pereira, da Silva, and Pereira \(2019\)](#) examine the detrended cross-correlation coefficient between oil price and stock markets and provide evidence that before the global financial crisis, the relationship is low, but increase in the oil-stock nexus after the crisis. [Wen, Wang, Ma, and Wang \(2019\)](#) discover the significant asymmetry in the spillover effect when examining the volatility spillovers between oil and stock markets. Similarly, [Bagirov and Mateus \(2019\)](#) confirm the persistence of the interplay between oil and European stock markets. [Ma, Zhang, Ji, and Pan \(2019\)](#) study the interdependence between WTI oil price and the returns of listed firms in the US energy sector. The authors suggest the vital role of industrial-level standard information in the interplay between oil prices and the stock market, and individual stock returns have significant impacts on WTI oil prices. More recently, [Li, Semeyutin, Lau, and Gozgor \(2020\)](#) recuperate the time-varying interconnectedness between oil price and volatility index for emerging market economies. This paper reports that Kazakhstan is more sensitive to the volatility index and oil price volatility. [Wang, Ma, Niu, and He \(2020\)](#) confirm that there exist the causal associations between crude oil and BRICS stock markets, and indicate that the impact of oil price changes on the stock markets is statistically significant.

The interrelatedness between crude oil and gold markets reveals its turn, the persistence of a reverse causality situation. For example, [Bassil, Hamadi, and Mardini \(2019\)](#) test the long-run relationship between the daily prices of oil and gold and provide evidence that oil-gold connectedness has varied over time and is subject to two or five regime changes. [Dutta, Bouri, and Roubaud \(2019\)](#) rely on various methodologies and uncover the causal interaction between the global oil market and the precious metals and gold miners markets. [Balcilar, Ozdemir, and Shahbaz \(2019\)](#) examine the causal interactions between oil and gold using a time-varying causality test and reveal that the causality links to oil and gold exhibit substantial time variation. Similarly, [Elie, Naji, Dutta, and Uddin \(2019\)](#) use copulas techniques to look into the pivotal roles of gold and crude oil as safe-haven assets against extreme down movements in clean energy stock markets. They suggest that both crude oil and gold are no more than weak safe-haven assets for clean energy markets. Another interesting paper, [Bampinas and Panagiotidis \(2015\)](#) investigate the causal links between the global oil market and gold spot prices pre and post the global financial crisis in 2008. The findings uncover that causality is linear and unidirectional from oil to gold in the pre-crisis period, while a bidirectional nonlinear causality connectedness emerges in the post-crisis period. Similar findings are reported by [Bampinas and Panagiotidis \(2015\)](#), [Narayan, Narayan, and Zheng \(2010\)](#) contribute to the futures market by exploring that gold and oil spot and futures markets up to the maturity of 10 months are cointegrated.

Another strand of research has investigated the impact of stock markets on gold prices. With a focus on extreme dependencies and resorting to a copula approach, [Boako, Tiwari, Ibrahim, and Ji \(2019\)](#) successfully capture a co-jump of gold and stock market returns, which means that diversification attributes of gold. In the same vein, [Tiwari, Adewuyi, and Roubaud \(2019\)](#) resort to quantile on quantile regression and notice a weak positive dependence in all quantiles of gold and stock markets during 2002–2018 in seven emerging countries. At the same time, [Baur and Kuck \(2019\)](#) perform three new properties of gold and show that there is a fast reaction of gold prices to extreme negative stock returns. [Bouri, Roubaud, Jammazi, and Assaf \(2017\)](#) put forward significant bi-directional influences between gold and the Chinese and Indian stock markets.

In the bulk of the literature that investigates the interdependence among crude oil, gold, and stock markets ([Basher & Sadorsky, 2016](#); [Bouri, Jain, Biswal, & Roubaud, 2017](#); [Bouri, Lien, Roubaud, & Shahzad, 2018](#); [Huang, An, Gao, & Huang, 2016](#); [Husain, Tiwari, Sohag, & Shahbaz, 2019](#); [Jain & Biswal, 2016](#); [Raza, Shahzad, Tiwari, & Shahbaz, 2016](#); [Tursoy & Faisal, 2018](#)), these papers find significant causal

linkages among them by using different econometric methodologies. More recently, [Miladifar, Mohamadi, and Akbari Moghadam \(2020\)](#) examine the nonlinear nexus between oil price and gold and stock market indices during upward and downward movements using the Markov Switching Bayesian VAR model. The results show that during periods of declining oil prices, gold and stock markets considerably increase in value. [Lin, Kuang, Jiang, and Su \(2019\)](#) examine the risk contagion among the crude oil market, gold, and stock market in China and Europe. The authors suggest that unidirectional risk contagion running from the crude oil market and a gold asset to the stock markets is found and from European stock markets to the crude oil prices in irregular events, while there is a bidirectional risk contagion among them in extreme events. [Maghyreh et al. \(2016\)](#) explore the oil-equity implied volatility relationships using the spillover index framework and show that there are the bi-directional information transmissions between the two markets. Similarly, [Bouri, Lien, Roubaud, and Hussain Shahzad \(2018\)](#) reveal strong and persistent quantile predictability when the crude oil implied volatility is low.

Financial stress might be depicted as adverse economic forces that are responsible for macroeconomic uncertainty conditions in a real-world economy ([Das, Kumar, Tiwari, Shahbaz, & Hasim, 2018](#)). [Hakio and Keeton \(2009\)](#) indicate that the aggregated positions of commodity index traders and hedge funds experienced considerable and negative position corresponds to rises in the VIX in a wide range of commodity futures markets during the recent financial crisis. In another study, [Mollick and Assefa \(2013\)](#) analyze the impact of a vast amount of information, including equity VIX volatility, inflation expectations, interest rates, gold prices, and the USD/Euro exchange rate on the US stock markets. They categorize their sample into three sub-periods and find that the US stock returns are negatively influenced by oil prices and the USE/Euro before the financial crisis. On the other hand, crude oil prices have a positive impact on the stock returns in the subsample of mid-2009 onwards. [Nazlioglu, Soytaş, and Gupta \(2015\)](#) investigate the dynamic volatility spillovers between oil prices and financial stress and support evidence on risk transfer from oil prices to financial stress in the pre-and post-crisis periods and long-lived impacts during the crisis. In another study on the nexus Gold, Crude Oil, Stocks with Financial Stress, [Das et al. \(2018\)](#) conclude that there is a bidirectional causality in terms of mean and variance for gold and crude oil with financial stress.

None of these articles concentrates, nevertheless, in the new situation created by the Covid-19 crisis. Therefore, the present study would fill this gap and analyze the connectedness and the lead-lag structures between crude oil price, gold asset, and S&P 500 index before and during the Covid-19 outbreak. To the best of our knowledge, this is the first paper addressing the time-frequency interplay among major markets under investigation.

3. Methodology

In our paper, we use both the spillover index and the wavelet coherence approaches. We briefly introduce the empirical methods used throughout the article in this section. The spillover index approach developed by [Diebold and Yilmaz \(2012\)](#) is employed to identify the dynamic net directional spillover effects across these series. The wavelet time-frequency domain framework allows for different forms of localization, especially addressing the non-stationary time series ([Baruník et al., 2016](#)). In this way, we can examine the comovements and lead-lag interplay between assets using pairwise plots of wavelet coherence. Therefore, both techniques provide more rigorous results than conventional methodologies because the spillover index allows for measurement of spillover in returns across multiple assets, while wavelet analysis yields information in both the time and frequency dimensions ([Dahir et al., 2018; Kang, Uddin, Troster, & Yoon, 2019](#)).

3.1. Spillover index approach

Following [Diebold and Yilmaz \(2012\)](#), a covariance stationary n variables VAR(p) can be written:

$$y_t = \sum_{i=1}^p \phi_i y_{t-i} + \varepsilon_t \tag{1}$$

Where $y_t = \sum_{i=1}^n A_i \varepsilon_{t-i}$, $A_i = \phi_1 A_{j-1} + \phi_2 A_{j-2} + \dots + \phi_p A_{j-p}$, ϕ_i are $n \times n$ coefficients matrix, ε_t is the vector of error terms.

The H-step-ahead generalized forecast-error variance decomposition can be written as:

$$\phi_{ij}^g(H) = \frac{\sigma_{ij} \sum_{h=0}^{H-1} (e_i' A_h \sum e_i)^2}{\sum_{h=0}^{H-1} (e_i' A_h \sum A_h e_i)} \tag{2}$$

Where, \sum denotes the variance matrix of the error vector, σ_{ij} is the standard deviation of the idiosyncratic error term for the j^{th} market. Finally, e_i is the selection vector with one as the i^{th} components, and zero otherwise.

To gain a unit sum of each row of the variance decomposition, we normalize each entry of the variance decomposition matrix by row sum as

$$\tilde{\theta}_{ij}^g = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^n \theta_{ij}^g(H)} \tag{3}$$

where $\sum_{j=1}^n \tilde{\theta}_{ij}^g(H) = 1$ and $\sum_{i,j=1}^n \tilde{\theta}_{ij}^g(H) = n$

We can calculate the total directional connectedness, which measures the spillovers of volatility transmission across different financial markets.

$$S^g(H) = \frac{\sum_{i,j=1, i \neq j}^n \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^n \tilde{\theta}_{ij}^g(H)} \times 100 = \frac{\sum_{i,j=1, i \neq j}^n \tilde{\theta}_{ij}^g(H)}{N} \times 100 \tag{4}$$

We compute the directional volatility spillovers received by the market i from all other markets j using the normalized components of the variance decomposition matrix.

$$S_i^g(H) = \frac{\sum_{j=1, j \neq i}^n \tilde{\theta}_{ij}^g(H)}{\sum_{j=1}^n \tilde{\theta}_{ij}^g(H)} \times 100 = \frac{\sum_{i,j=1, i \neq j}^n \tilde{\theta}_{ij}^g(H)}{N} \times 100 \tag{5}$$

Likewise, the direction of spillover from variable i to and from all other variable j is written as

$$S_i^g(H) = \frac{\sum_{j=1, j \neq i}^n \tilde{\theta}_{ji}^g(H)}{\sum_{j=1}^n \tilde{\theta}_{ji}^g(H)} \times 100 = \frac{\sum_{i,j=1, i \neq j}^n \tilde{\theta}_{ji}^g(H)}{N} \times 100 \tag{6}$$

Net total directional connectedness is the difference of equation (5) and (6):

$$S_i^g(H) = S_i^g(H) - S_i^g(H) \tag{7}$$

3.2. Wavelet coherence

The nexus between oil price, gold asset, and stock markets can be analyzed through time scales by taking into consideration the widely used wavelet coherence. According to [Nagayev, Disli, Inghelbrecht, and Ng \(2016\)](#), the wavelet techniques allow us to estimate the lead-lag relationship between financial data during various regimes without having to subdivide the data into different sample periods. A brief note

on wavelet coherence is defined as follows:

$$R_n^2(S) = \frac{|S(s^{-1}W_n^{XY}(s))|^2}{S(s^{-1}|W_n^X(s)|^2)S(s^{-1}|W_n^Y(s)|^2)} \quad (7)$$

where S denotes a smoothing operator in time and scale. Smoothing is achieved by convolution in time and scale.

$$S(W) = S_{scale}(S_{time}(W_n(s))) \quad (8)$$

where S_{scale} and S_{time} stand for smoothing on the wavelet frequency and time scales. Smoothing operator we use in this study is the Morlet wavelet, so the more suitable definition is given by Torrence and Webster (1999):

$$S_{time}(W) = \left(W_n(s) * c_1 \frac{\pi^{-\frac{1}{2}}}{s} \right) \Big|_s \text{ and } S_{scale}(W)_s = (W_n(s) * c_2 \Pi(0.6s))_s \Big|_n \quad (9)$$

where the rectangle function denotes Π ; c_1 and c_2 represent normalization constants.

The wavelet coherence coefficient measures the local linear connectedness between two stationary time series at each scale and ranges $R_n^2(s) \in [0, 1]$.

$W_n^{XY}(s)$ is the cross-wavelet power. It refers to as the local covariance between the two-time series at each scale. Given time series $x(t)$ and $y(t)$, the cross-wavelet power can be expressed as

$$W_n^{XY}(s) = W_n^X(s)W_n^{*Y}(s) \quad (10)$$

where $W_n^X(s)$ and $W_n^{*Y}(s)$ are continuous wavelet transforms of two time series $x(t)$ and $y(t)$. The symbol * represents a complex conjugate.

The wavelet coherence phase can be written as

$$\phi_n^{XY}(s) = \tan^{-1} \left(\frac{I\{S(s^{-1}W_n^{XY}(s))\}}{R\{S(s^{-1}W_n^{XY}(s))\}} \right) \quad (11)$$

where I is the imaginary and R denotes real parts of smooth power spectrum.

3.3. Data

We aim to analyze the rapidity and intensity of the dynamic association among crude oil (WTI), gold (GOLD) and stock (SP) markets before and after WHO announces the COVID-19 outbreak on 30 January 2020, we take daily data spanning the period from January 2018 to April 2020. The whole examination period is subdivided into two sub-periods: Pre-COVID-19 period: 2 January 2018 to 30 January 2020, the Covid-19 period: 31 January 2020 to 23 April 2020. The selection of the sub-periods is based on the downward trend in oil prices during the Covid-19 outbreak pandemics. This is in line with the work of Nazlioglu et al. (2015) and Mollick and Assefa (2013), oil-financial stress and oil-

stock relationships are served in 2008. Their findings unveil that when oil prices are employed, separate estimations are necessary before, at, and after 2008. Moreover, the findings also shed light on changing interdependence across examined variables for three subsamples. All the price time series are obtained from the Bloomberg database. We calculate the logarithmic returns of the selected indices. Table 1 reports the descriptive statistics for the variables under investigation.

As we can see from Table 1, the GOLD and S&P 500 exhibit positive average daily returns, while the figure for WTI is negative over the sample period shown. However, there are changes in the mean of returns before and during Covid-19.

Furthermore, we observe that all the selected returns are skewed and far from normally distributed. The Jarque-Bera test statistics have also confirmed this property. More importantly, the unconditional volatility of all the return series is measured by standard deviations, and the sample variance dramatically increases during the Covid-19 period.

Table 2 provides the estimation results of the Markov Switching Autoregressive model (MS-AR) for each of the time series. We can observe that the standard deviation coefficients are statistically significant at 1% level, and their values indicate the existence of two different regimes. The first regime represents the pre-COVID-19 period, while the second regime presents the Covid-19 outbreak. Table 2 also represents the probability of being in each regime. It is obvious that the low volatility regime 1 is more persistent than the high volatility regime 2. Besides, the mean of duration in days for each regime (d_1 and d_2) affirm the existence of two regimes.

Fig. 1 depicts the raw series in which each market fluctuates. In general, we can see that all series follow a similar trend over the study period.

4. Empirical results

4.1. Spillover analysis

The depiction of the static spillover index for returns of the three markets is represented in Table 3. Besides, we also compute the average directional spillovers and net spillovers before and during the Covid-19 outbreak. This might offer some straightforward insights into spillover effect transmission trends across the above-mentioned markets. All results are based on a daily vector autoregressive model of order 4, identified employing generalized variance decompositions of 10-day-ahead forecast errors. In Table 3, the $(i, j)^{th}$ entry in each panel is the estimated contribution to the 10-day-ahead forecast error variance of variable i coming from shocks to market j . The diagonal components ($i = j$) capture own-variable spillovers f returns within and between markets, while ($i \neq j$) the off-diagonal opponents illustrate the clear properties of pairwise spillovers. In addition, the column "From others" and row "Contribution to others" demonstrate the total spillovers to (received by) and from (transmitted by) each market series. The net return spillover row provides the difference in total directional spillovers, and the

Table 1
Descriptive statistics of daily returns.

| | Mean | Max | Min | Std. Dev | Skew. | Kurt. | JB | Obs. |
|--------------------------------|----------|----------|---------|----------|----------|----------|-----------|------|
| Panel A. Pre-COVID-19 outbreak | | | | | | | | |
| WTI | 0.020454 | 24.53098 | -14.986 | 4.320124 | 0.118353 | 5.225793 | 109.1803* | 523 |
| GOLD | 0.037774 | 8.976122 | -7.6860 | 1.949065 | -0.02086 | 4.839368 | 73.76515* | 523 |
| S&P 500 | 0.034301 | 4.840318 | -4.1842 | 0.936799 | -0.6169 | 6.629252 | 320.2021* | 523 |
| Panel B. Covid-19 outbreak | | | | | | | | |
| WTI | -0.99608 | 34.88181 | -26.447 | 10.16997 | 0.467065 | 5.393355 | 15.40174* | 56 |
| GOLD | 0.638462 | 14.13273 | -12.765 | 4.563678 | -0.02113 | 4.128321 | 2.974757 | 56 |
| S&P 500 | -0.25307 | 8.968323 | -10.906 | 4.091904 | -0.29456 | 4.055258 | 3.40814 | 56 |
| Panel C. Full sample | | | | | | | | |
| WTI | -0.07786 | 34.88181 | -26.447 | 5.175662 | 0.236250 | 9.655889 | 580.5482* | 579 |
| GOLD | 0.095871 | 14.13273 | -10.906 | 2.333281 | 0.182359 | 7.891948 | 6930.392* | 579 |
| S&P 500 | 0.006507 | 8.968323 | -12.765 | 1.546949 | -0.95629 | 19.84079 | 1074.144* | 579 |

Notes: * denotes significance at the 1% level.

Table 2
Estimation results for the MS-AR model.

| | WTI | GOLD | S&P 500 |
|--------------|------------------------|------------------------|-------------------------|
| C_1 | -0.102332 (0.183365) | 0.049982 (0.087860) | -0.325689 (0.235981) |
| C_2 | -0.012422 (2.264145) | 0.463987 (0.618003) | 0.117279*** (0.030403) |
| AR(1) | 0.015071 (0.042596) | 0.011129 (0.045280) | -0.066727 (0.045680) |
| σ_1^2 | 1.414647*** (0.140047) | 0.585806*** (0.056558) | 1.053582** (0.073164) |
| σ_2^2 | 2.571030*** (0.140047) | 1.543133*** (0.119307) | -0.462419*** (0.045036) |
| P_{11} | 0.905301 | 0.984562 | 0.945469 |
| P_{22} | 0.937551 | 0.991943 | 0.981835 |
| d_1 | 212.8122 | 64.77648 | 55.05078 |
| d_2 | 16.01308 | 9.254351 | 18.33829 |
| $Q^2(36)$ | 36.036 [0.0420] | 48.977[0.059] | 49.331[0.055] |

Notes: Standard errors are represented in parentheses. d_1 and d_2 denote the average duration for the examined variables to be in regime 1 and in regime 2, respectively. p -values are given in brackets.

*, **, *** denotes significance at the 1%, 5% and 10% level.

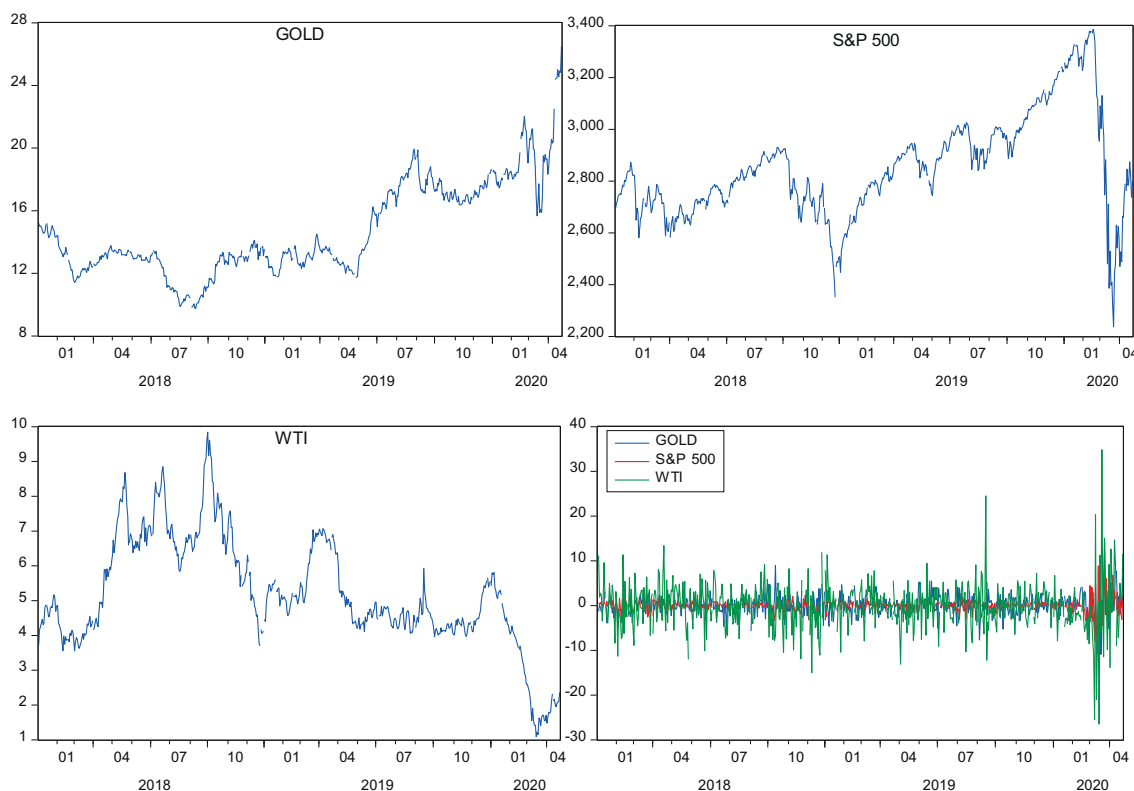


Fig. 1. Original time series and returns of the selected variables.

total spillover index is approximately equal to the grand off-diagonal column sum (or row sum) regarding the grand column sum including diagonals, expressed in percentage points.

Table 3 reports the total static spillover index among the selected markets, decomposed by transmitters and recipients of return spillovers in both periods under consideration. The key substantive figure is the total spillover index; it documents an average of 11.7% and 38.5% for return forecast error variance results from the pre-COVID-19 and during Covid-19. This simply means that the bi-directional return spillovers across examined markets are higher in the Covid-19 outbreak period than in the pre-COVID-19. Looking at the directional spillover transmitted “to”, S&P 500 is the highest contributor to other markets, contributing 16.8%, followed by WTI (15.4%) and GOLD (2.8%), respectively in the pre-COVID-19 period, while WTI is the highest contributor to other markets during the Covid-19 period. More specifically, WTI and S&P 500 are net recipients since their contributions to the other markets are less than what they receive from other markets in

the pre-COVID-19 period, while they are not true during the Covid-19 outbreak. Similarly, GOLD is the recipient of return spillovers with the net value of -22.3% in the Covid-19 outbreak, but it is the transmitter of return transmissions amounted to 1.6% in the pre-COVID-19 period. Overall, different determinants and measures have contributed to the increased spillover effects coming from the Covid-19 outbreak. The total directional connectedness is more significant and increased profoundly during the Covid-19 outbreak, this rise was due to the intensification of crisis effect transmission between the three markets.

Next, we look into the time-varying behavior of total return spillovers during the Covid-19 outbreak. Our model is estimated using the 200-day rolling sample and 10-day-ahead forecast errors. It is crucial to take into account cyclical movements and variations in transmissions that could not be estimated by the findings shown in Table 3. Fig. 2 depicts the time dynamics of the total return spillovers during the research period, calculated based on the Diebold and Yilmaz (2012). Total return spillovers show the cyclical movements and bursts over

Table 3
Total directional return spillovers.

| | WTI | S&P 500 | GOLD | From others |
|------------------------------|-------|---------|-------|--------------------------------|
| Panel A: Pre-COVID-19 period | | | | |
| WTI | 83.34 | 15.72 | 0.94 | 16.7 |
| S&P 500 | 15.31 | 82.84 | 1.85 | 17.2 |
| GOLD | 0.10 | 1.12 | 98.78 | 1.2 |
| Contribution to others | 15.4 | 16.8 | 2.8 | 35.0 |
| Contribution including own | 99.7 | 98.8 | 101.6 | Spillover index = 11.7% |
| Net spillovers | -0.3 | -1.2 | 1.6 | |
| Panel B: Covid-19 period | | | | |
| WTI | 65.68 | 26.47 | 7.85 | 34.3 |
| S&P 500 | 20.96 | 63.97 | 15.07 | 36.0 |
| GOLD | 27.58 | 17.59 | 54.83 | 45.2 |
| Contribution to others | 48.5 | 44.1 | 22.9 | 115.5 |
| Contribution including own | 114.2 | 108.0 | 77.7 | Spillover index = 38.5% |
| Net spillovers | 14.2 | 8.0 | -22.3 | |

time, suggesting a significant degree of integration between the markets. The graph shows that total spillovers vary over time and respond to economic events. More importantly, the return spillovers reached a peak of nearly 32% during the Covid-19 outbreak, which corresponds to the slowdown in global economic activity. Specifically, the cyclical movements and bursts in spillovers are associated with the Covid-19 outbreak, and we would see the intensity existing return spillover effects across the crude oil, gold, and S&P 500 markets. These outcomes are in line with the hypothesis of market contagion in the literature that the periods of financial distress trigger large return spillovers in these markets.

In order to identify which markets are net receivers and net givers of spillovers during the sample period, we estimate the time-varying net returns spillovers based on 200-day rolling windows, as indicated in Fig. 3. The net return spillover is computed by subtracting directional “to” spillovers from directional “from” spillovers. Net spillovers show the total sum of the net-pairwise directional spillovers expressed as a net-receiver (negative) and net-giver (positive), respectively.

Fig. 3 represents the sign of the time evolution of the net return spillover among crude oil, gold and S&P 500 markets over time. Throughout the visual inspection of these figures, the S&P 500 and WTI series are net recipients of risks, whereas the gold market is a net transmitter of shocks in the pre-Covid-19 period. In contrast to the results for the pre-Covid-19 period, crude oil and S&P 500 markets are the transmitters of return spillovers, reaching a maximum level of approximately 32% during the Covid-19 outbreak. And the gold market is a net recipient of return spillovers during a certain period. It is consistent with the results in Table 3. It seems that return spillovers are unidirectional spillovers among the selected markets under examination because the given graphs for each indicator perform a magnitude of negative and positive values over time. Overall, the net return spillovers fluctuated with a high spike during the Covid-19 outbreak. The bar graphs suggest

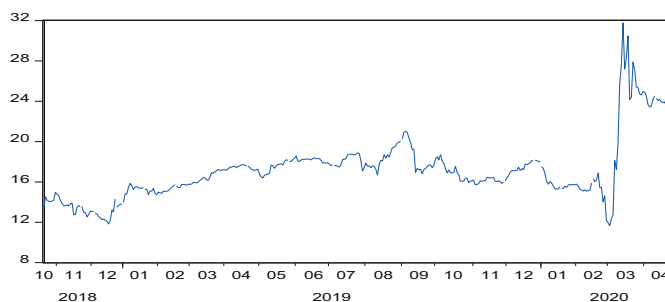


Fig. 2. Total return spillover indices.

positive (net transmitter) value and negative (net recipient) values before and during the Covid-19 outbreak. This outcome supports the findings of Bampinas and Panagiotidis (2015), who indicate that there are strong links and unidirectional spillover from oil to gold after the global financial crisis.

4.2. The wavelet coherence

We employ wavelet analysis to assess the dynamic connectedness among the examined markets because wavelet frameworks are powerful specifications that allow us to capture comovements between the selected variables quickly (Dahir et al., 2018). We utilize wavelet coherence to investigate comovement and the lead-lag correlation structures among the market returns. More precisely, wavelet coherence can explore how much two-time series co-vary and estimate the relative phase of different time sequences in present time-frequency spaces (Hung, 2020). Fig. 4 plots the estimated wavelet coherence and the phase difference for all pairs of variables under consideration. The horizon axis illustrates the time elements, and frequency components are shown on the vertical axis. The horizontal axis covers the pre-COVID-19 period from January 2018 to January 2020, corresponding to 50 and 500, and the Covid-19 outbreak between February 2020 to April 2020, corresponding to 10 and 50. By contrast, the frequency scales on the vertical axis are found on daily units spanning from 4-to 128-day scales for the pre-COVID-19 period and from 4-to 16-day scales for the Covid-19 outbreak. The colour code captures interdependence level between the pair of series. Areas with significant interrelatedness are represented by warmer colours (yellow), while cooler colours (blue) regions illustrate the two series are less dependent. Cool areas beyond the significant regions indicate frequencies and time with no relationship in the variables. Both zones over time and scales where the pairs of relevant indices co-move together significantly can be determined or otherwise, corresponding to the domestic correlation spanning from 0 to 1.

Wavelet coherence sheds light on the interconnectedness in index pairs, while the dynamic linkages of series are identified by looking lead-lag structure through various investment horizons. An arrow in the wavelet coherence plots describes the direction of intercorrelation and cause-effect interactions. A phase difference of zero explains that the two variables move together on a particular scale. Arrows point to the

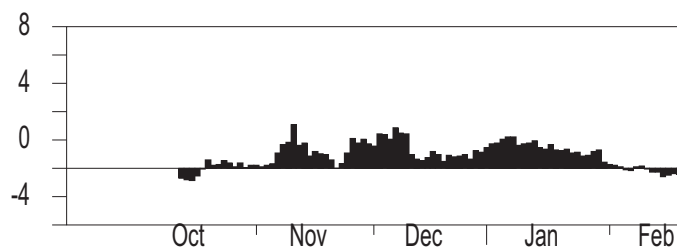


Fig. 3. Net volatility spillovers, three asset classes.

(a) Pre-Covid-19

(b) Covid-19 outbreak

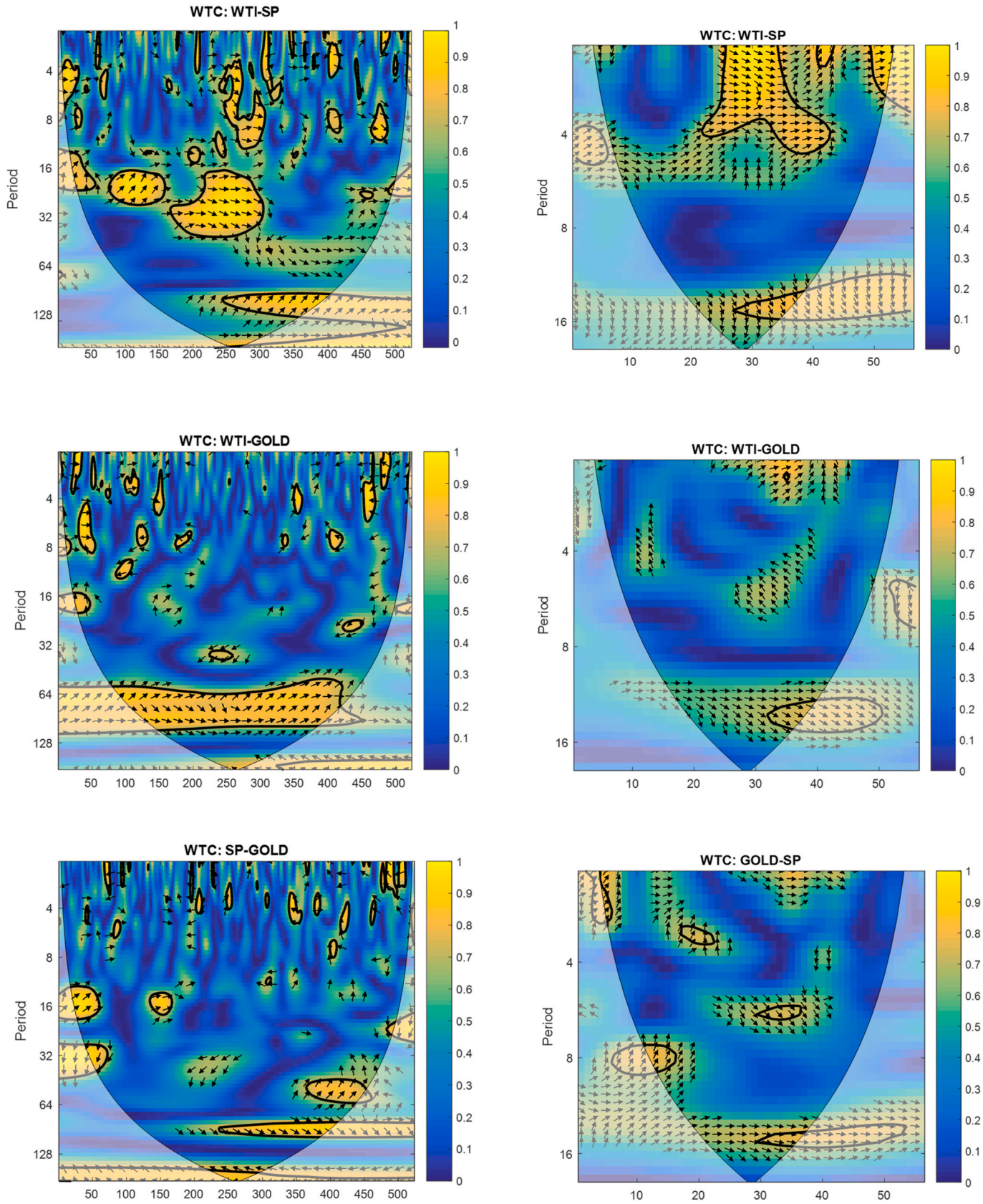


Fig. 4. Wavelet coherence plots, pairwise estimates.

right, and the left suggests that the two series are in-phase and out-phase, respectively. An in-phase wavelet phase difference shows that the return series move in the same direction (positive relationship), while they move in the opposite direction when two variables are in out of phase (negative correlation).

To further analyze the associations, Fig. 4 describes the phase difference and wavelet coherence among series under investigation. We observe the persistence of small regions of significant interconnection at the beginning, the mid and the end of the sample period. Overall, the wavelet coherence plots indicates that crude oil, gold, and stock indices highlight clear relationships through time and frequency domain. In the pre-COVID-19 period, the associations between WTI and S&P 500, GOLD exhibit high coherence, which exists at the medium and long run; nevertheless, the highest level of associations was stated at scales spanning from 64-to-128-day scales, and the arrows are mostly pointed to the left where crude oil prices are leading. On the other hand, comovements between S&P 500 and gold markets reveal a weak connectedness, and there are some areas with significant wavelet coherence in 64- and-128-day scales corresponding to the periods December 2019 and January 2020 when Chinese authorities announced the novel coronavirus incurred in Wuhan. These findings reinforce the past studies (Bouri, Jain, et al., 2017; Husain et al., 2019; Tursoy & Faisal, 2018).

The contagion during the Covid-19 outbreak, three markets under study seem to react to bad news coming from the Covid-19 pandemic outbreak, Chinese authorities announced the novel virus that causes fatal human on 31 December 2020. Furthermore, another high coherence regions are determined in mid-February, corresponding to several Covid-19 pandemics bad news; namely, the first patient death in the US was reported on 28 February 2020. We also find significant coherence by the end of the sample period. This situation might be as a result of the impact of the dramatic drop in oil prices and Covid-19 fears.

Looking at the case of WTI-SP, wavelet coherence plot also demonstrates the persistence of strong coherence regions at the onset of the Covid-19 pandemics and by the end of April 2020 corresponding to a constant rise of the infected counts around the world and the free fall of oil prices. The arrows are predominantly pointed up and to the right showing that crude oil prices are leading, implying that oil prices are positively correlated with the S&P 500 market. By contrast, gold market has a weak relationship with crude oil and stock markets during the Covid-19 outbreak. Several islands with low wavelet coherence are statistically significant in 4- and 8- and 16-day scales. These findings are apparently impacted by several episodes of the Covid-19 outbreak. In the significant islands, we note the phase-related information, as indicated by arrows. Obviously, the arrows turn leftward and downward, suggesting that the gold market and crude oil and stock markets are negatively correlated, and WTI and S&P 500 lead GOLD. This scenario represents an apparent fact that in turbulent periods since crude oil prices fall and gold prices increase, investors should pay attention to gold as a safe haven. The finding supports the studies of Baur and Kuck (2019), Bagirov and Mateus (2019), and Li et al. (2020). This significant co-variation can be seen during the Covid-19 outbreak, and the gold asset might play a prominent role as a safe haven during extreme stock and crude oil market movements. Further, there exist significant dependent patterns about the information spillovers between the crude oil and gold markets might provide several valuable information for portfolio managers, investors, and government agencies (Chen & Xu, 2019). Das et al. (2018) argue that the existing investors increasingly rebalance their portfolios to reduce downside risks by transferring investments to the gold that is viewed as safe-haven assets during the occasions of higher financial stress like the Covid-19 outbreak. This scenario is known as a flight to quality. Cheng, Kirilenko, and Xiong (2015) also demonstrate that financial traders mitigate their net long positions and change in the commodities markets during the crisis in response to variations in market distress. At the same time, Nazlioglu et al. (2015) reveal that economic activity slows down in times of high

financial stress, resulting in low energy demand and decreasing oil prices. Put it in another way, financial stress would give rise to change investors' portfolios, and this would influence the stock, gold, and crude oil markets.

From a financial view, the increasing of oil, gold, and S&P 500 stock market return coherence during the Covid-19 outbreak period, in particular at low and high frequencies, supports the contagion hypothesis through these periods. Our findings are typically similar to some recent analogous studies, such as Bouri, Shahzad, et al. (2020) and Mensi et al. (2020), who suggest that financial markets exhibit a significant increase in comovement during the Covid-19 outbreak in comparison with other periods.

From an asset management perspective, the findings of this paper reveal the significant short-term influence of Covid-19 on the S&P 500 and crude oil markets. We would believe the contingency of further government interventions, once the US financial markets will be able to recuperate in the long run. At the same time, asset managers and individual investors should know how to grasp market variation and systematic risk in connection with the Covid-19 outbreak.

5. Conclusion

The Covid-19 crisis has been spread rapidly throughout the world so far. However, how deep and long the turbulence would depend on the success of solutions taken to deter the spread of Covid-19, the impacts of government policies may be prominent to alleviate the current crisis. The economic and social costs of the Covid-19 pandemics involve in the society, policymakers, market participants, and investors. In this article, we investigate the spillover effects and time-frequency connectedness between S&P 500, crude oil prices, and gold assets using both the spillover index of Diebold and Yilmaz (2012) and the wavelet coherence. The sampling period is from 2018 to 2020. The first period covers the pre-COVID-19 period from 1 January 2018 to 30 January 2020. The second period is the Covid-19 period from 31 January 2020 to 23 April 2020, which was characterized by widespread Covid-19. More specifically, we evaluate whether the time-varying dynamic return spillover index exhibited the intensity and direction of transmission during the Covid-19 outbreak.

This study is one of the pioneer papers that examines the effects of the Covid-19 pandemic on the fluctuation of the three major assets, including the S&P 500 index, crude oil prices, and gold markets. Therefore, our findings offer several significant pieces of evidence.

The results represent that the S&P 500 and WTI series are net recipients of risks, whereas the gold market is a net transmitter of shocks in the pre-COVID-19 period. In contrast to the results for the pre-COVID-19 period, crude oil and S&P 500 markets are the transmitters of return spillovers, reaching a maximum level of approximately 32% during the Covid-19 outbreak. Also, the gold market is a net recipient of return spillovers during a specific period. Moreover, our wavelet coherence analysis unveils that in the pre-COVID-19 period, the associations between WTI and S&P 500, GOLD exhibit high coherence, but comovements between S&P 500 and gold markets reveal a weak connectedness. The contagion during the Covid-19 outbreak, there is the existence of strong and positive associations between crude oil and S&P 500 markets. Besides, the results also suggest the gold asset might play a prominent role as a safe haven during extreme stock and crude oil market movements.

Overall, the present results shed light on that in comparison with the pre-COVID-19 period, and the return transmission is more apparent during the Covid-19 crisis. More importantly, there exist significant dependent patterns about the information spillovers among the crude oil, S&P 500, and gold markets might provide urgent prominent implications for portfolio managers and global investors.

The Covid-19 pandemic is indicated by a remarkable increase extent of dependencies among indexes under consideration. The timing of these variations differs radically for the three pairs, in particular, the

unprecedented response of the stock market as crude oil and stock markets are found to be strongly correlated under the Covid-19 outbreak. Moreover, the Covid-19 outbreak can further impact oil market because of the travel limitations across the world. This phenomenon is crucial for oil companies as well as companies in the transportation and hospitality industries. During the Covid-19 period, and from various investment horizons perspectives, all three assets might be employed in a well-diversified portfolio less often than popular perception could have it. Further, investors need to employ risk management strategies to protect against dramatic variations in the stock sensitive to oil prices. Three asset prices exhibit strong and positive associations during the Covid-19 crisis that would provide the prediction of future pricing behaviors in these markets based on past information for investors and market participants.

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Declaration of Competing Interest

None.

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