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The transition of the global financial markets' connectedness during the COVID-19 pandemic

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ABSTRACT

This study contributes to the literature on financial research under the presence of the COVID-19 pandemic. Fresh evidence emerges from using two novel approaches, namely network analysis and wavelet coherence, to examine the connectedness and comovement of financial markets consisting of stock, commodity, gold, real estate investment trust, US exchange, oil, and Cryptocurrency before and during the COVID-19 onset. Moreover, unlike the previous studies, we seek to fill a gap in the literature regarding the ex-post detection of COVID-19 crises and propose the Markov-switching autoregressive model to detect structural breaks in financial market returns. The first result shows that most financial markets entered the downtrend after January 30, 2020, coinciding with the date the World Health Organization (WHO) declared the COVID-19 pandemic as a Public Health Emergency of International Concern. Thus, it is reasonable to use this date as the break date due to COVID-19. The empirical result from network analysis indicates a similar connectedness, or the network structure, in other words, among global financial markets in both the pre-and during COVID-19 pandemic periods. Moreover, we find evidence of market differences as the MSCI stock market plays a central role while Cryptocurrency presents a weak role in the global financial markets. The findings from the wavelet coherence analysis are quite mixed and illustrate that the comovement of the financial markets varies over time across different frequencies. We also find the main and most significant period of coherence and comovement among financial markets to be between December 2019 and August 2020 at the low-frequency scale (>32 days) (middle and long terms). Among all market pairs, the oil and commodity market pair has the strongest comovement in both pre-and during the COVID-19 pandemic phases at all investment horizons.

1. Introduction

With the high and growing comovement and integration of the global financial markets in this age, the use of diversification strategy for minimizing investment risk has become more limited. Consequently, studies on the relations among different financial markets and asset returns will be of utmost importance in providing leading indicators and frameworks for both investors and policymakers desiring to predict future economic conditions and make financial management plans accurately and effectively (McMillan, 2019). The cross-asset and cross-market relationships have received extraordinary interest from academics and research scholars (such

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as Kazemilari & Djauhari, 2015; Maneejuk & Yamaka, 2019; McMillan, 2019; Rahman, Khudri, Kamran, & Butt, 2021; Billio, Casarin, Costola, & Iacopini, 2021), particularly since the burst in the USA of the 2008–9 Financial Crisis. However, the results from previous studies fail to provide a clear-cut conclusion as well as consensus on the relationships among different financial assets. This is because the cross-market relations are dependent on the time-definite and perhaps location-specific economic conditions. For example, investors during the time of economic normality will have a positive sentiment regarding financial markets and thus invest accumulatively in stock, cryptocurrency, foreign exchange, government bond, gold, and futures markets. This, in turn, will generate a positive comovement of these financial markets. On the contrary, during the economic recession, investors have a negative expectation about the performance of certain financial markets, and they might try to reduce the risk of financial loss by reducing their holding of risky assets like stock and Cryptocurrency and investing more in government bonds and gold. This will result in a negative relationship between markets. Besides, the cross-asset correlation can also vary in degree in different periods (Maneejuk & Yamaka, 2019). Therefore, knowledge of the association between or among financial assets is vital for understanding investors' behavior and applying it to predict the behavior of asset returns and their correlations.

Several previous studies paid great attention to the connectedness structure (or pattern) of and the correlations among financial markets, particularly after the rise of the 2008–2009 global financial crisis. Generally, studies on the relationships between financial markets in the past can be distinguished into two orientations. The first focuses on the cross-country correlation concerning a particular category of financial markets such as stock (Osu, Okonkwo, Uzoma, & Akpanibah, 2020; Younis, Longsheng, Basheer, & Joyo, 2020), foreign exchange (Yang, Cai, Zhang, & Hamori, 2016), and Cryptocurrency (Qiao, Zhu, & Hau, 2020). The other deals with the cross-asset correlation, for example, between stock and bond returns (Chiang, 2020; Park, Park, & Ryu, 2020), foreign exchange rates, and oil prices (Liao, Shi, & Xu, 2018); among stock, oil, and gold markets (Zhao & Wang, 2021), stocks, bonds, and commodities (Nguyen, Naeem, Balli, Balli, & Vo, 2021), and Cryptocurrency, stock, gold, and oil (Gajardo, Kristjanpoller, & Minutolo, 2018). These previous works revealed both positive and negative correlations between/among different financial assets, but which can be at different degrees, directions, and times. The possible reason is that the cross-asset interdependences have time-varying characteristics (Maneejuk & Yamaka, 2019). As supported by McMillan (2019) and Zhao and Wang (2021), they found that the change in relations between and among financial markets is largely determined or driven by the global economic conditions at that time.

As previous studies have provided many pieces of evidence that the cross-asset relations can change at any time and the connectedness structure or the relationships are generally shaped by the influence of economic situations in or before that period, we become interested in exploring the dynamic connectedness of various financial markets in the recent years in the presence of the COVID-19 pandemic. The spread of COVID-19 has contributed tremendous social and economic impacts on virtually all parts and systems of a country and the world. For example, the lockdown and travel restriction measures just by themselves are likely to continue giving adverse impacts on the tourism industry and its market participants for a long time (Billio et al., 2021). Nowadays, the global financial markets are also experiencing the dramatic impacts of the COVID-19 pandemic (Zhang, Hu, & Ji, 2020). Therefore, it becomes our interest to get an insight into the relationships between various financial markets during the COVID-19 pandemic and how and in what way the connectedness or network of each financial market of our interest is affected.

In this study, we aim to examine the connectedness during the COVID-19 pandemic among seven selected financial markets, including stock, commodity, gold, real estate investment trust, US exchange, oil, and Cryptocurrency. To this purpose, we employ three econometric techniques for data analysis comprising 1) the Markov switching autoregressive model to detect the date of structural breaks in financial market returns 2) the network analysis to determine the network relations among the seven selected financial markets and establish the relative importance or the position of each market in the global financial markets and 3) wavelet coherence to understand the interaction between two assets and its change or evolution over time and across frequencies. Hence, this research performs a more comprehensive analysis of dynamic comovement and connectedness of global financial markets than previous works. We use the data spanning from January 1, 2019 to June 30, 2021 to cover the pre-outbreak and the pandemic periods for comparison of the financial market connectedness in these two time intervals. It is our conviction that the findings from the study on the seven leading financial markets from three assessment approaches will be useful for other research scholars wishing to investigate the connectedness involving other asset markets and for investors hoping to make more efficient their investment portfolio allocation.

The rest of this paper is structured as follows. A literature review of correlations among the financial markets during the COVID-19 pandemic is provided in Section 2. Section 3 explains the data and methodologies employed in this study. Section 4 presents the empirical results and discussion, while Section 5 gives conclusions and recommendations.

2. Literature review

After the outbreak of the COVID-19 pandemic, tremendous attempts have been made to empirically examine the impacts of COVID-19 on the financial markets as well as the transmission of the COVID-19 effects from one market in chain reactions to other markets. Corbet, Hou, Hu, and Oxley (2021) contended that the COVID-19 pandemic has made many economic activities come to a halt with a statistically significant decline in both supply and demand in the market particularly the energy market resulting in a large drop in oil prices. Sharif, Aloui, and Yarovaya (2020) provided evidence of the unprecedentedly great impact of global oil prices' volatility and shock due to COVID-19 on the stock market with spillover effects on such related industries as transportation and tourism. Zhang et al. (2020) explored the COVID-19 impacts on financial markets all over the world and found the negative effects huge and in all markets as the pandemic had led to a significant increase in market volatilities. Their finding was subsequently supported by Albulescu (2021) that examined the effects of COVID-19 in financial markets and found the US confirmed deaths from COVID-19 to intensity the volatility in the S&P500 stock market as well as the foreign exchange market. Meanwhile, Bazán-Palomino and Winkelried (2021) revealed that foreign exchange markets did not show turbulent volatilities in response to the COVID-19 pandemic unlike during the

time of previous global financial crisis. However, movements in foreign exchange markets were found closely related to those in stock and energy markets with the volatility spillovers coming particularly from the crude oil market (Corbet et al., 2021).

Vidal-Tomás (2021) investigated the movements of 69 digital currencies in the cryptocurrency market using the network analysis method and found the market did not react instantly to the WHO's declaration of COVID-19 as a pandemic on March 11, 2020 but the cryptocurrency network began changing at a significant level after the pandemic had hit every corner of the globe for a while. The study by Goodell and Goutte (2021) using the wavelet coherence analysis found that the growing number of COVID-19 fatalities caused the rise in Bitcoin price in the post April 4, 2020 period and that virtually all digital currencies in the cryptocurrency market reacted positively to the pandemic levels with comovements in the same direction. Caferra and Vidal-Tomás (2021) made a comparison between stock and cryptocurrency market dynamics during the COVID-19 pandemic, confirming that the cryptocurrency market was hardly affected negatively by COVID-19 and that cryptocurrencies had shown the properties of being a good hedging asset for investment during this stressful situation. In contrast, Dutta, Das, Jana, and Vo (2020) considered Cryptocurrency not able to compete with gold as an ideal safe-haven asset during the COVID-19 crisis. Furthermore, Corbet, Larkin, and Lucey (2020) provided a piece of evidence from their study on the correlations among gold, Cryptocurrency, and stock market supporting the previous observation that gold is better than Cryptocurrency as a hedging instrument against the risky stock assets. Similarly, Conlon and McGee (2020) analyzed the relationship between Bitcoin and S&P 500 at the onset of the COVID-19 outbreak and determined that Bitcoin could not be used to reduce the risk of investment in the S&P 500 market.

It is evident from the above review that substantial attempts have been made to examine the impacts of the COVID-19 pandemic on financial markets and the relations among financial markets during this stressful event. However, the study results have not reached a consensus with the findings being different depending on the time or duration and the type of assets or financial markets of the investigators' interest. Moreover, the previous studies under this review are confined to the time of the COVID-19 outbreak and spread and limited to the relationship between some types of financial markets only. Therefore, the present researchers determine to widen the scope of the investigation to encompass more types of financial assets and examine whether the COVID-19 pandemic had impacts on the connectedness among different global financial markets by considering the data that covers the pre- and the COVID-19 periods. Furthermore, most of the studies mentioned above have focused only on the time domain, while information derived from the frequency domain has been neglected during the COVID-19 pandemic. Hence, we distinguish our work from those in the literature by employing the wavelet coherence technique to investigate the comovement among global financial markets over time and across frequencies.

3. Methodology and data

3.1. Network analysis

The network theory is derived from the graph theory (Kazemilari & Djauhari, 2015), which allows us to understand networks' structural characteristics and to analyze the complex pattern of relationships among different units in terms of the connectivity and the interrelations of the underlying structure (Hevey, 2018). We thus apply a network diagram analysis to provide a more intuitive view of the interconnection among financial markets (Boginski, Butenko, & Pardalos, 2006). Note that although the network analysis has been proposed to deal with the complex relationship among the variables, in this study, it is still reasonable to employ the network analysis in highlighting simple relationships among seven financial markets. This is due to (1) the overall structure of financial markets and the roles played by each market in the network can be analyzed in a manner that other statistical approaches cannot provide (Hevey, 2018). The network analysis also enables us to obtain the three centrality criteria: betweenness centrality, degree centrality, and closeness centrality. The results obtained from these criteria could give another view of market linkages. (2) It enables us to have a better picture or another perspective in understanding the connections or linkages among the units (Liu, 2021) and Chai et al., 2011).

In this study, a network is defined by $G = (V, E)$, where V is the number of nodes (markets) in the network, E is a set of connections or edges. To build the network, we need to know the edge weight or distance between all pairs of correlation coefficients (Stanley & Mantegna, 2000), which can be expressed as.

$$d_{ij} = \sqrt{2(1 - \rho_{ij})}, \tag{1}$$

where ρ_{ij} is the correlation coefficient between returns of markets i and j. In this network analysis, we consider the network nodes' centrality using three centrality criteria, consisting of betweenness centrality, degree centrality, and closeness centrality.

1) Betweenness centrality

The betweenness centrality measures the degree to which nodes stand between each other. In other words, it detects the number of times a market acts as a bridge along the shortest path between two other markets. If the market has a high betweenness centrality, this indicates that this market has played a vital role in coordinating the information among financial markets. The betweenness centrality of market k can be expressed mathematically as.

$$BC(k) = \sum_{ij \in V}^{n} \frac{g(i,j|k)}{g(i,j)}, \tag{2}$$

where $g(i,j|k)$ is the shortest path connecting market i to j that passes through market k and $g(i,j)$ is the shortest path connecting market

i to$j$. Note that n is the number of nodes or markets in the network and in this study, we consider 7 financial markets.

2) Degree centrality

    The degree centrality of a node (market) in a network is the number of direct links that node (market) has with other node (market). Thus, the higher degree centrality indicates the market is more central. This degree centrality of market k can be defined as.

$$DC(k) = \sum_{i=1}^{n} \alpha(i,k),$$ (3)

where $\alpha(i,k) = 1$ if market i is connected with market$k$, but if market i is not connected with market$k$,$\alpha(i,k) = 0$.

3) Closeness centrality

    Closeness centrality is the average shortest distance from one node (market) to all the other nodes (markets). It measures how close a market to all other markets. The higher closeness index, the more powerful the market is. Specifically, if the closeness centrality is high, the spread of information from market k to all others is fast.

$$CC(k) = \sum_{i=1}^{n} d(i,k)/(n-1),$$ (4)

where $d(i,k)$ is the shortest distance between i and k based on the sum of the weights.

3.2. Wavelet coherence

    Most financial analyses are normally performed in the time domain (time horizon) and generally with a neglect of the frequency domain (frequency of the data) (Das, 2021). In fact, there are different types of investors, considering those with an investment horizon of several minutes, hours, days, weeks, months, and years. Therefore, apart from the time domain, there is a frequency domain, which represents various investment horizons (Baruník, Vácha, and Krištoufek, 2011). In this study, we take into account both time and frequency domains in the analysis of the comovement among global financial markets. Since the wavelet coherence technique which is one of the most popular methods in signal analysis (Orhan, Kirikkaleli, and Ayhan, 2019) has been employed to decompose the data into the time and frequency domains (He, Gokmenoglu, Kirikkaleli, & Rizvi, 2021), we can examine the comovements and correlations among global financial markets in different frequencies and times using it. This approach provides insightful information of inter-linkages based on either market fundamentals or transitory volatility (Ftiti, Guesmi, Teulon, & Chouachi, 2016).

    By definition, wavelet is simply a wave which can be stretched over time (t) to obtain frequency constitutes (f) (Omane-Adjepong, Ababio, and Alagidede, 2019). In this study, we consider the return of the market as a wave stretching over time and the trading horizons as the frequency domain. Meanwhile, coherence is defined as the comovement between paired financial markets. To derive the wavelet coherence, following Torrence and Compo (1998), we define the cross wavelet transform of two time series of markets $i(t)$ and $j(t)$ as.

$$W_{ij}(t,f) = W_i(t,f)W_j^*(t,f),$$ (5)

where $W_i(t,f)$ and $W_j^*(t,f)$ are the continuous wavelet transforms and "" is a **complex conjugate.** Torrence and Webster (1999) explained that the square of $W_{ij}(t,f)$ can be used to explain the local covariance between series over each scale; however, it cannot be used to present the comovement between the markets. So, they proposed squared wavelet coherence, which can be constructed as.

$$R^2(t,f) = \frac{\left| S\left(f^{-1}W_{ij}(t,f)\right) \right|^2}{S\left(s^{-1}|W_i(t,f)|^2\right)S\left(s^{-1}|W_j(t,f)|^2\right)},$$ (6)

where S is the smoothing operator and $R^2(t,f)$ is the localized coherency coefficient over time–frequency with ranges between 0 and 1. If $R^2(t,f)$ is close to 1, this indicates the high correlation between markets $i(t)$ and $j(t)$ at time$t$. If $R^2(t,f)$ is close to zero, this indicates the low correlation between markets $i(t)$ and $j(t)$ at time$t$. However, $R^2(t,f)$ does not provide the direction of the correlation. We thus consider the wavelet coherence phase difference to differentiate the positive correlation from the negative one (Torrence & Compo, 1998).

$$\Phi_{ij}(t,f) = \tan^{-1}\left(\frac{Im\{S(s^{-1}W_{ij}(t,f))\}}{Re\{S(s^{-1}W_{ij}(t,f))\}}\right),$$ (7)

where Im and Re are the imaginary operator and real parts operator, respectively. In this study, we illustrate a bi-dimensional plot with the black arrows showing the phase differences and causality between two markets. For example, $\rightarrow$ and $\leftarrow$ indicate that markets $i(t)$ and $j(t)$ have a positive and negative relationship, respectively. Moreover, means that market $i(t)$ leads market$j(t)$, while means that market $j(t)$ leads market$i(t)$.

3.3. Markov-switching autoregressive model

In this section, we discuss the Markov switching autoregressive (MS-AR) model, which is used to investigate the recovery of various global financial markets. This model enables us to divide the time series into two or more market regimes (Hamilton, 1989) and also provide the probability of staying in each regime. In this study, two market regimes are assumed (market upturn and market downturn regimes). The model is written as.

$$r_t = \phi_{0,S_t} + \sum_{m=1}^{P} \phi_{m,S_t} \{r_{t-m}\} + \varepsilon_t \sigma_{S_t},$$

(8)

where ϕ_{0,S_t}, ϕ_{m,S_t} and σ_{S_t} are intercept term, regime-dependent autoregressive, and variance at state or regime $S_t = 1, 2$. r_t and r_{t-m} are the return of market at time t and $t-1$, respectively. ε_t is the error term at time t. S_t is the unobserved discrete state or regime variable at time t and it is governed by the first-order Markov process $P(S_t = a, b | w_{t-1}, \Phi)$ (w_{t-1} is all information at time $t-1$ and Φ is the set of unknown parameters in Eq.9) and the transition matrix Q is as follows:

$$Q = \begin{bmatrix} p_{11} & 1-p_{22} \\ 1-p_{11} & p_{22} \end{bmatrix},$$

(10)

where $p_{ab} = P(S_t = a | S_{t-1} = b)$, $a, b = 1, 2$ is the probability of switching from regime a to b and $\sum_{b=1}^{2} p_{ab} = 1$.

3.4. Data

In this study, we analyze the cross correlation among seven financial markets, using the market return series and the variable names as in the parentheses, consisting of MSCI All Country World Index (MSCI), GSCI commodity index (GSCI), Gold, Real estate investment trust (REIT), US dollar index (USD), Brent oil (OIL) and Cryptocurrency (Bitcoin:BTC). All daily data are collected from https://www. Investing.com covering the period from January 2019 to June 2021. Table 1 presents summary statistics for these market return series. We observe that BTC has the highest standard deviation, while USD has the lowest. We also observe that all market returns show a higher standard deviation than mean return and exhibits non-normality (indicated by the Jarque-Bera test). These characteristics indicate the high volatility of the financial markets. Furthermore, we conduct the Augmented-Dicky Fuller (ADF) test to examine the stationarity of our return series and the result shows a significant ADF statistic, implying that all series are stationary.

4. Results

Before performing the analysis using the selected methodological approaches, we employ the MS-AR to detect and confirm the presence of structural change due to COVID-19. Then, the data are divided into two sub-periods: pre- and during the COVID-19 pandemic. The study results are reported in four sub-sections.

4.1. Analysis of structural change in financial markets using the Markov switching autoregressive (MS-AR) method

Our first objective, again, is to explore whether there is a structural change in the connectedness and correlation among financial markets before and during the COVID-19 pandemic. To achieve this, the MS-AR is used. The analysis of structural change of financial markets using the MS-AR model begins with the determination of an appropriate lag indexed by m to include 3 lags and the number of Regime labeled by S_t to include 2 regimes (upturn and downturn). Table 2 presents the estimation results of the candidate models for describing the behavior of each financial market and the optimal model for each market is chosen upon the lowest BIC value. As seen from Table 2, the optimal model for every financial market has $S_t = 2$ and $m = 1$.

Consequently, the MS-AR(1) model was estimated individually for BTC, GOLD, GSCI, MSCI, OIL, REIT, and USD; and the results are reported in Table 3. The estimated values of the constant term for all markets for Regime 1 ($\phi_{0,S_{t=1}}$) are positive and greater than those

Table 1
Summary statistics of market returns.

	BTC	GOLD	GSCI	MSCI	OIL	REIT	USD
Mean	0.0035	0.0005	0.0002	0.0007	0.0005	0.0005	−0.0001
Median	0.0021	0.0012	0.0014	0.0014	0.0028	0.0016	−0.0001
Maximum	0.2008	0.0363	0.0762	0.0806	0.1908	0.0825	0.0159
Minimum	−0.4973	−0.0589	−0.1252	−0.1000	−0.2798	−0.1932	−0.0170
Std. Dev.	0.0494	0.0099	0.0164	0.0123	0.0322	0.0182	0.0037
Skewness	−1.5595	−0.7437	−1.5692	−1.6442	−1.6038	−2.3095	0.2994
Kurtosis	20.9319	7.0112	16.6465	22.3267	24.3173	29.6554	5.3302
Jarque-Bera	8668.4820	478.9041	5130.6830	10056.7700	12160.0600	19149.9900	151.4603
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
ADF-test	−27.430***	−23.579***	−25.052***	−6.924***	−22.929***	−13.873***	−22.871***

Note: "***" denotes rejection of the null hypothesis at the 1% significance level.

for Regime 2($\phi_{0,S_{t=2}}$), and hence we can define Regime 1 ($S_t = 1$) to be the upturn state and Regime 2 ($S_t = 2$) as the downturn state. To predict how long each regime can persist, we look at the values of transition probabilities or the parameters p_{11}, p_{22}. For example, BTC has $p_{11} = 0.631$ meaning that there is a 63.1 % probability that BTC will remain in upturn market state while it has $p_{22} = 0.788$ indicating a 78.8 % chance for it to remain in the downturn market. Therefore, BTC has a slightly greater likelihood to be in the downturn market regime than in the upturn market regime for the period 2019/1–2021/6. Meanwhile, the chance that BTC will shift from being in the upturn market to the downturn market is 36.9 % as $p_{12} = 1 - 0.631 = 0.369$ and from being in the downturn market to the upturn market is 21.2 % as $P_{21} = 1 - 0.788 = 0.212$. Compared to other financial markets, REIT possesses the highest regime persistence with the probabilities of $p_{11} = 0.996$ or 99.6 % chance and $p_{22} = 0.978$ or 97.8 % chance of staying in regimes 1 and 2, respectively.

The analysis of the presence of structural change for the seven considered assets provided the results as graphically shown in Fig. 1. The smoothed probabilities of Regime 1 or the upturn state estimated from the MS-AR model, plotted to the left of the red dashed line that separates the time series into pre and during COVID-19 parts, explain the patterns of financial market recovery from the previous low for the seven assets. For example, USD has high probabilities, although not quite stable and certain, to be in the booms throughout the pre Covid-19 period. Its probabilities to be a bull market dropped following the COVID-19 outbreak and causing USD to go downturn abruptly but only for a short while before returning to its pre COVID-19 position. On the contrary, REIT has the probabilities close to 100 % to be in the booms throughout the pre-COVID-19 period and can be viewed as a secured and safe-haven asset for its providing investors a stable income stream (Ngene, Manohar, & Julio, 2020). However, the REITs' earnings were also affected by the COVID-19 crisis in the early phase with a slow recovery trend afterward. Therefore, we can perceive the difference in price movements in the boom-and-bust cycle of these two classes of financial markets. During the pre-COVID-19 period which is the upturn phase, USD returns showed constant fluctuations while REIT returns were rather stable. After a bust due to the pandemic, the USD market could recover before the REIT market which took a longer time to resume its normality.

The GOLD market seems to benefit from the COVID-19 pandemic when investors shifted their investment in other assets to buy more gold due to the hedging properties of gold as a commodity and as a safe-haven asset in time of crisis (Ozturk, 2020), driving GOLD to the boom levels despite rather high price swings and volatilities. However, Akhtaruzzaman, Boubaker, Lucey, and Sensoy (2021) noted that gold lost its hedging and safe-haven properties during the second phase of the pandemic (March 17, 2020– April 24, 2020) due to the state intervention in the affected countries using various financial and fiscal policy measures to encourage economic activities. Hence, investors and portfolio managers should keep themselves informed and updated about the pertinent government intervention schemes such that they can rebalance the share of gold in their investment portfolios appropriately and determine the ranking of the other financial markets in terms of their capability or speed to recover. Among the pandemic-affected financial markets, the fastest recovering one is USD followed by GSCI, OIL, MSCI, and REIT in descending order. While suggesting earlier that GOLD seemed to benefit from the pandemic, we could not make any conclusion about BTC market recovery because the smoothed probabilities of BTC plotted in Fig. 1 show a very similar pattern of volatilities for both pre and during COVID-19 series.

From the findings presented above, we can provide a piece of advice concerning investment strategies or portfolio allocation particularly for investors having limited capacity to face the risk of investment loss or those having the speculative purpose. These investors should consider focusing first and foremost on the USD market during the pandemic turmoil because the USD market can

Table 2
The calculated BIC for the MS-AR model in various variants.

Market	S_t	1	2
	m	BIC	
BTC	1	−1982.627	**−2162.041**
	2	−1977.947	−2140.053
	3	−1973.896	−2116.996
GOLD	1	−3999.755	**−4057.272**
	2	−3993.413	−4031.519
	3	−3987.028	−4006.139
GSCI	1	−3365.807	**−3623.886**
	2	−3359.367	−3600.088
	3	−3353.714	−3574.387
MSCI	1	−3738.323	**−4169.835**
	2	−3763.527	−4153.103
	3	−3759.193	−4135.483
OIL	1	−2518.381	**−2922.868**
	2	−2511.958	−2903.636
	3	−2505.518	−2880.373
REIT	1	−3248.74	**−3776.076**
	2	−3275.02	−3758.231
	3	−3270.158	−3733.64
USD	1	−5246.427	**−5268.954**
	2	−5244.766	−5254.011
	3	−5238.37	−5237.959

Note: Bolded number = the lowest BIC value, *m* = the number of Lag, and S_t = the number of State or Regime.

Table 3
Estimation results of the optimal MS-AR model for each financial market.

	BTC		GOLD		GSCI		MSCI		OIL		REIT		USD	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
$\phi_{0,S_{t-1}}$	0.006	0.005	0.001***	0.0004	0.001*	0.0005	0.001***	0.0003	0.002*	0.001	0.001***	0.0004	0.0001	0.0002
$\phi_{1,S_{t-1}}$	−0.099	0.080	−0.019	0.041	0.011	0.047	0.069	0.046	0.058	0.047	−0.017	0.045	−0.121**	0.053
$\phi_{0,S_{t-2}}$	0.003*	0.001	−0.001	0.001	−0.007	0.004	−0.002	0.002	−0.005	0.007	−0.004	0.005	−0.001	0.001
$\phi_{1,S_{t-2}}$	−0.078*	0.044	0.218	0.133	−0.055	0.110	−0.19**	0.092	0.089	0.099	−0.199	0.005	0.923***	0.117
p_{11}	0.631		0.644		0.986		0.979		0.981		0.996		0.895	
p_{22}	0.788		0.327		0.915		0.919		0.907		0.978		0.294	

Note *: significant at the 0.10 level, **: significant at the 0.05 level, ***: significant at the 0.01 level.
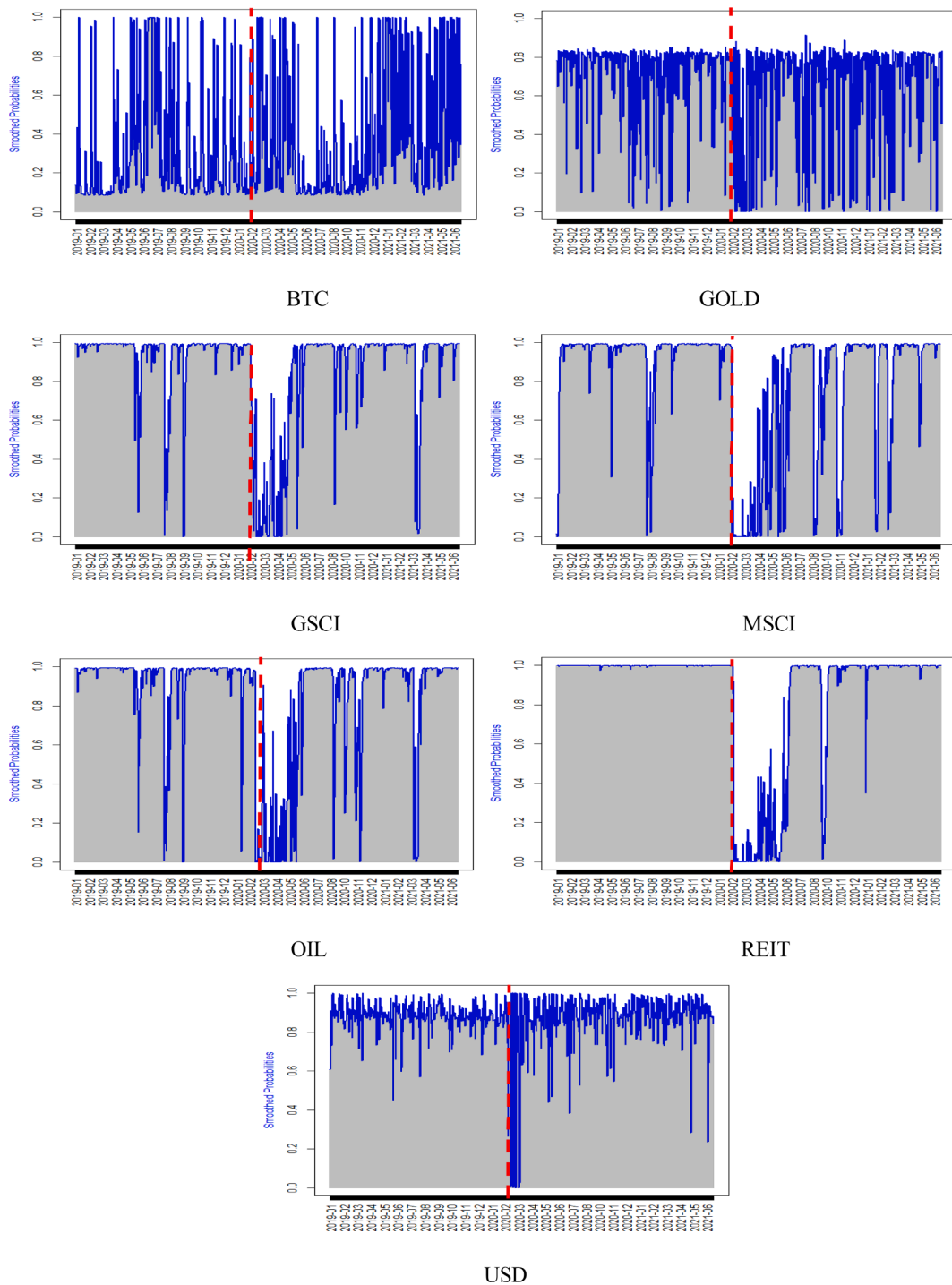
Fig. 1. The boom and bust cycle of the considered financial markets in the period 2019/1–2021/6 (with the red dashed line corresponding to January 30, 2020, the date the WHO declared COVID-19 a pandemic (Shiferaw, 2021; and Fernandez-Perez et al., 2021). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

recover from the downturn relatively faster than other markets with the properties of currencies like the US dollar as a tangible asset that can be shorted advantageously. When REIT shows a recovering trend, such risk-avert investors can move their funds from USD to invest in REIT which has stability and low volatility risk. Meanwhile, investing or not in BTC perhaps deserves careful thought from investors before they make the decision because the levels and volatilities of the returns in the BTC market are unique and unlike those in other financial markets that are influenced by the states of economic crisis and information.

The overall analysis suggested that most financial markets entered the downtrend after January 30, 2020, corresponding to the date the World Health Organization (WHO) declared the COVID-19 pandemic as a Public Health Emergency of International Concern (Shiferaw, 2021; and Fernandez-Perez, Gilbert, Indriawan, & Nguyen, 2021). Thus, it is reasonable to use this date as the break date in our comovement and connectedness analysis. We then divide that data into two sub-periods, before the COVID-19 pandemic (January 4, 2019, to January 30, 2020) and during the COVID-19 pandemic (February 1, 2020, to June 30, 2022).

4.2. Correlations between financial markets

We calculated the simple correlation between financial markets in pair to find the degree and direction of their relationships and to determine later whether the simple correlation results are compatible with the results obtained from the analysis employing the more complex and refined methodologies. The calculated correlations of paired financial markets are presented in Table 4 for three different data sets namely whole, pre COVID-19, and during COVID-19 data set. Apart from the numeric values, the simple correlations are also shown with colored background where green indicates low correlation (0>|correlation|>0.5), yellow means moderate correlation (0.5>| correlation |>0.8), and red is high correlation with |correlation|>0.80.

As shown in Table 4, the market return correlations of seven pairs of financial markets for the January 1, 2019 – June 30, 2021 period are mostly low (green) except the MSCI – REIT pair which has a correlation as high as 0.815 (red).

The correlations of returns of most financial market pairs based on pre-COVID data and those based on during-COVID data are quite similar in trend characteristics. The exceptions are the GSCI-MSCI pair in which the correlation during the pre-COVID period is low at 0.3618, but the comovement becomes stronger with the value of 0.5005 (yellow) during the COVID-19 period; and the MSCI-REIT pair in which the pre-COVID correlation is 0.3619 but the COVID period correlation becomes as high as 0.8587 (red). This observed change in the relationship between financial markets over time can be explained according to Chiang (2020) and Park et al. (2020) that the correlation between the risky asset and low-risk assets will be strong in the event of an economic crisis because investors will replace the risky asset with safe haven one to minimize their financial risk. In our study, REIT can generate a steady income stream for investors

Table 4
Correlations between financial markets in terms of return using different data sets.

	BTC	GOLD	GSCI	MSCI	OIL	REIT	USD
Whole period							
BTC	1.0000						
GOLD	0.1913	1.0000					
GSCI	0.1517	0.0553	1.0000				
MSCI	0.2957	0.1157	0.4752	1.0000			
OIL	0.1558	0.0080	0.2683	0.3933	1.0000		
REIT	0.2349	0.1415	0.3347	0.8150	0.2787	1.0000	
USD	-0.0635	-0.2838	-0.0184	-0.0911	0.0330	-0.0781	1.0000
Pre-COVID crisis period							
BTC	1.0000						
GOLD	0.2111	1.0000					
GSCI	-0.0192	-0.1693	1.0000				
MSCI	-0.1191	-0.2507	0.3618	1.0000			
OIL	0.0008	-0.1820	0.1977	0.3207	1.0000		
REIT	-0.0298	0.1636	0.0163	0.3619	0.0453	1.0000	
USD	-0.1191	-0.0192	-0.1400	-0.0298	0.2111	0.0008	1.0000
During COVID crisis period							
BTC	1.0000						
GOLD	0.1860	1.0000					
GSCI	0.2114	0.1154	1.0000				
MSCI	0.4028	0.1836	0.5005	1.0000			
OIL	0.2029	0.0501	0.2859	0.4048	1.0000		
REIT	0.2976	0.1423	0.3863	0.8587	0.3077	1.0000	
USD	-0.0354	-0.2160	-0.0165	-0.1087	0.0361	-0.0940	1.0000

Note: Red: |correlation| >0.8, Yellow: 0.5> |correlation| >0.8, Green: 0> |correlation| >0.5.

while MSCI generates variable stock returns. Therefore, it is possible to make primary conclusions that the pandemic can change the relationship between financial markets and that the correlation changes in various pairs of financial markets tend to be in the same direction. However, the pairs of financial markets containing USD exhibit different investors' behavior, as possibly supported by Liao et al. (2018), who stated that the USD market was directly impacted by market sentiment following the outbreak of the financial crisis in 2008 because the panic in financial markets made investors consider USD a safe haven asset, particularly in a turbulent time. However, it is not possible now to perceive the apparent relationship between USD and other financial assets. Thus, in the next sub-section, this study ventures into performing a network analysis to unveil the connectedness among major global financial markets in terms of their returns.

4.3. Network analysis of major global financial markets

This sub-section first presents a network diagram analysis to illustrate the direction and magnitude of the connections among financial markets in terms of their returns. In Fig. 2, the nodes symbolized by orange circle correspond to the seven financial markets, and the edges represented by a grey line convey the information on the link between nodes or financial markets. To make it easy to understand, this study distinguishes lines into three representations, the thick grey line indicating a high correlation between markets, the thin grey line indicating a low correlation between markets, and the red line corresponding to the link between market *i* and market *j* indirectly through market *k* (see the elaboration in 3.1).

Our network analysis was done for two periods: pre COVID-19 and during COVID-19. For the pre COVID-19 period, we found GSCI to play a connecting role in three pairs of financial markets relations namely USD-OIL, REIT- BTC, and MSCI-GOLD which is in line with the result reported in Table 5 that the betweenness of GSCI is measured 3. By the measure of edge thickness, GSCI and MSCI appear to have strong connectedness with REIT as indicated by the thickest linking lines. For the COVID-19 period, we observed, overall, that the connectedness between financial markets in the outbreak period changed slightly from that in the pre COVID-19 episode in the form of topological characteristics. However, there is an obvious change in the strength of correlation of each market pair as indicated by the change in the thickness of the linking line. This means that the correlation values of financial market returns differ between the two periods which is consistent with the study finding of McMillan (2019) that the cross-asset relations and correlations can change particularly consequential to the emergence of an economic crisis that has a widespread impact. Chiang (2020) and Park et al. (2020) further added that, during the economic crisis, the correlation between returns of risky assets will get lower while that between returns of risky and safe-haven assets will become higher because investors tend to increase the proportion of low-risk assets in their investment portfolio to minimize loss from the high market uncertainty. Thus, the finding from our study also shows that the COVID-19 pandemic can lead to the structural change in the cross-asset correlations just like the previous economic crises had done.

From the above network analysis, we can present in Table 5 the evaluated connectedness between financial markets using the three centrality indices including degree, betweenness, and closeness. Before COVID-19, it can be seen that MSCI was the most powerful market with the closeness centrality value of 0.1262 followed by GSCI with the value of 0.0498 while BTC has the lowest closeness centrality measured at 0.0238 indicating it has virtually no connectivity with the other global financial markets. During the COVID-19 pandemic, we found MSCI to remain the closest to other markets with BTC remaining the least related with the others. The difference in market influence can be explained by the different market features. MSCI represents a stock market mobilizing significant capital for various business sectors with an enormous market capitalization and a large number of investors; thus, its change or movement will affect other financial markets tremendously. Meanwhile, BTC represents a cryptocurrency market participated mostly by speculators, influenced largely by its supply and demand as well as participants' sentiment, with the high price and market volatilities compared to
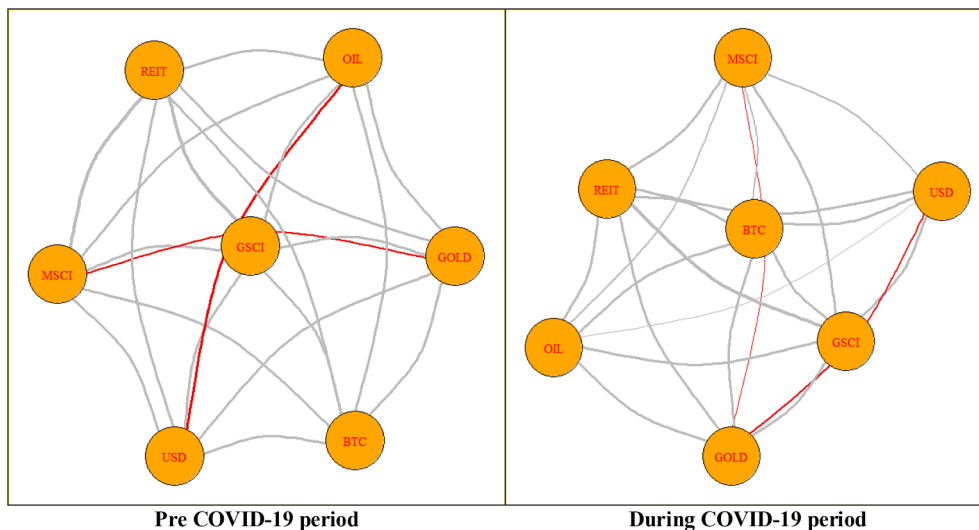

	Pre COVID-19 period	During COVID-19 period

Fig. 2. Network analysis of interrelations among financial markets in the pre and the during COVID-19 pandemic periods.

Table 5
Financial markets' connectedness by centrality measures.

	Degree	Betweenness	Closeness
Before COVID-19			
BTC	6	0	0.0238
GOLD	6	0	0.0398
GSCI	6	3	0.0498
MSCI	6	0	**0.1262**
OIL	6	0	0.0274
REIT	6	0	0.0324
USD	6	0	0.0760
During COVID-19			
BTC	6	1	0.0238
GOLD	6	0	0.0405
GSCI	6	1	0.0503
MSCI	6	0	**0.1542**
OIL	6	0	0.0275
REIT	6	0	0.0326
USD	6	0	0.0799

gold and foreign exchange; thus, it becomes less connected with other financial markets (Baur, Dimpfl, & Kuck, 2018).

However, the network analysis could not provide an understanding of the difference between the short-term and long-term reactions of the financial markets and the clear direction of the cross-asset relations. To seek a further understanding, we performed a wavelet coherence analysis and presented the results in the next sub-section.

4.4. Wavelet coherence analysis

The wavelet coherence analysis of the global financial markets was undertaken to get an insight into their comovements in the time and the frequency domains. The data are distinguished into the series for the times before COVID-19 and during COVID-19, and for different trading frequencies. The findings on the comovement of each pair of financial markets' returns are illustrated in Fig. 3 with the frequency scale (high to low frequency bands) being represented by the vertical axis and the time scale (January 1, 2019- June 30, 2021) by the horizontal axis. The intensity of comovement is color-coded (dark red to dark blue color corresponding to high to low intensity; see spectral wavelength chart on the right of the image). Shown in panels in Fig. 3 are also the island-like areas and arrows. The regions within the black contour lines represent the areas where the comovements of the market pair have been found at the 5 % significance level for the corresponding frequency bands and time intervals, while the arrows explain the casualty between two markets (see explanation in sub-section 3.2).

The results from our wavelet coherence analysis as shown in Fig. 3 unveil the time-varying relationship of each market pair with the comovements growing stronger (dark red) and statistically significant (within the contour lines) in 2019/12–2020/1 for the high frequency 32-day data and the low frequency 128-day data. Such strong comovements occurred around the time the WHO declared COVID-19 a pandemic on January 30, 2020 (Fernandez-Perez et al., 2021) and supported the findings of McMillan (2019), Chiang (2020), and Park et al. (2020) that the correlations and comovements among financial markets increased with the emergence of adverse economic events due to the contagious herding behavior among investors when markets are highly uncertain.

We can observe from the wavelet coherence plot that BTC and USD have a weak relationship as the blue spectra are predominant with no statistical significance for both pre and during COVID-19 periods, particularly for the frequency scales higher than 32 days. However, the correlations during 2019/12-/2020/12 in the 8–32 days bands are rather strong, negative, and significant which are consistent with the study results of Bhuiyan, Husain, and Zhang (2021), and Mokni and Ajmi (2021). The arrows in the plot suggest BTC was influenced by USD at the beginning of 2020 but it turned to lead USD (↘) at the end of 2020. For other pairs, the interpretation of connectedness between financial markets from the wavelet coherence plot can be done in the same way as for BTC-USD. Overall, we can draw the conclusions from our wavelet coherence analysis as follows.

1) BTC has a weak linkage with other financial markets as indicated by the large proportion of blue spectra. According to Vukovic, Maiti, Grubisic, Grigorieva, and Frömmel (2021), BTC is linked to low-risk market but not considered a safe-haven asset for preventing investment risk because the cryptocurrency market is highly sensitive to economic changes and market uncertainty while predominantly participated by speculators. However, we found that BTC has some connection with GOLD at a certain time and frequency scales, taking alternately between them the roles of movement leader and follower. Our finding is compatible with that of Siddique, Kayani, and Ashfaq (2021) who found BTC to have weak relations with other hedge assets but some connectedness with GOLD particularly during the time of the COVID-19 pandemic; because investors can reduce the potential risk in their investment portfolios from an adverse event by buying BTC and GOLD as the hedge assets (Ozturk, 2020). Moreover, the present researchers detected the slight connectedness of BTC with REIT and MSCI during the period 2019/4–2020/8 at the 64–128 days bands.
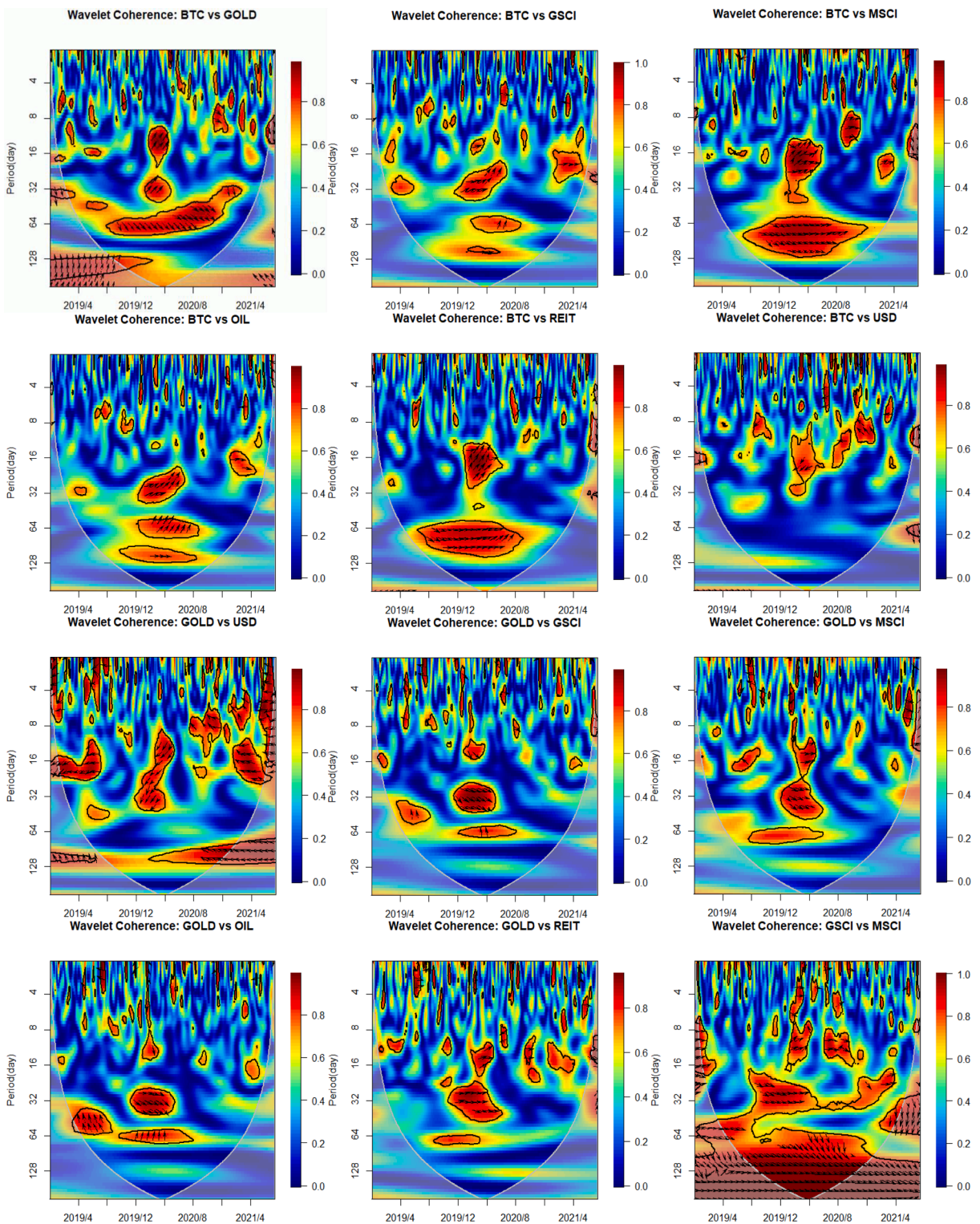
Fig. 3. Wavelet power spectra of the considered financial markets' returns for the periods from June 2019 to June 2021 and the 4–128 days bands.

2) GSCI has shown to have connectedness with other financial markets at all frequencies indicating the importance of commodities as a safe-haven asset that can draw the interest of investors in other markets to invest in GSCI during the time of politico-economic uncertainties because both risk and return of investing in commodities are not overly high or overly low. Thus, GSCI is appropriate as a hedge or safe-haven asset in portfolio diversification (Batten, Ciner, & Lucey, 2010), Interestingly, the comovement between
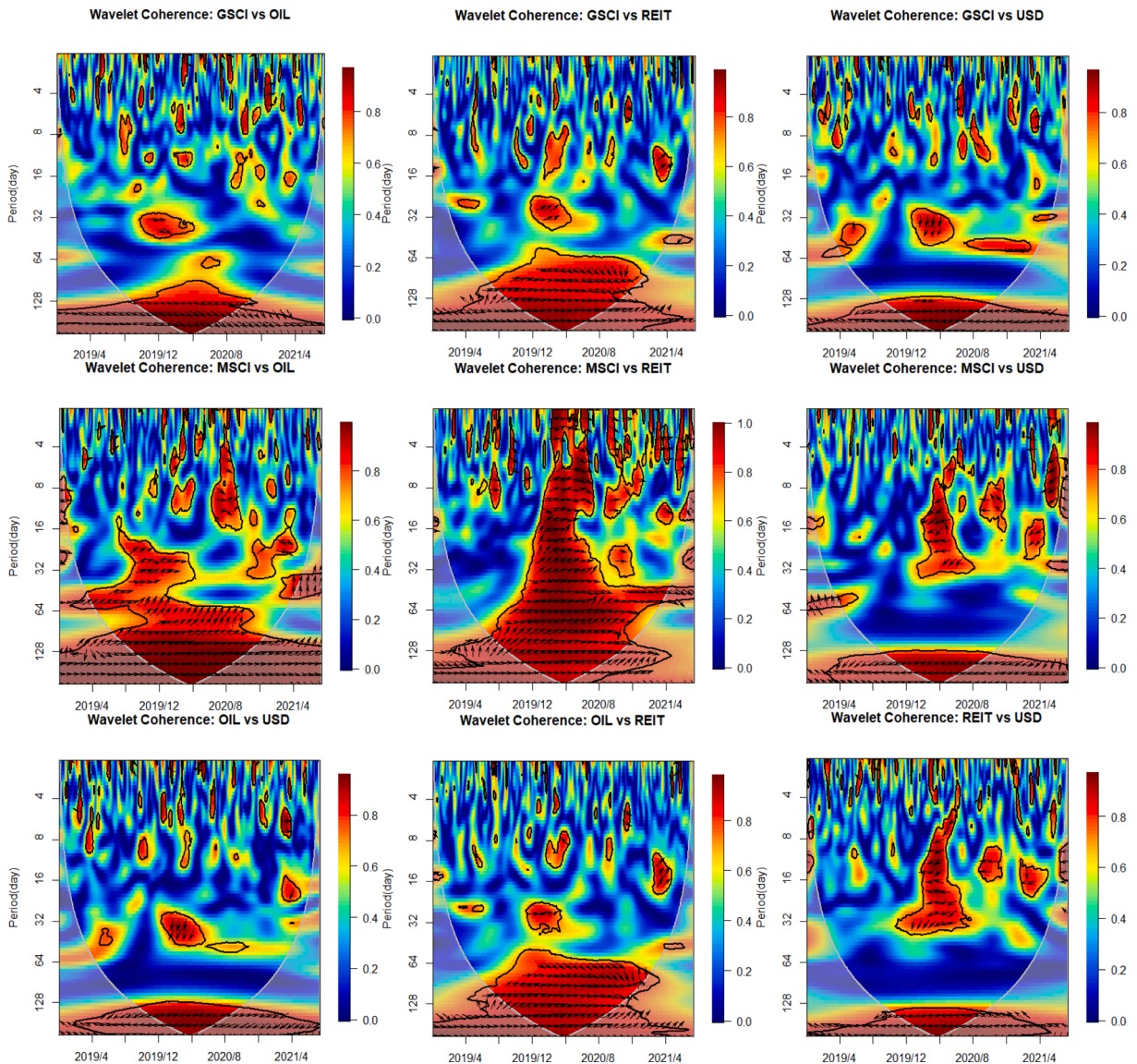
Fig. 3. (*continued*).

GSCI and MSCI is remarkably strong statistically significant in the 64–128 days bands for the period from 2019 to 2021/6. Because the comovement is positive with GSCI having a lag relationship with MSCI indicating the high influence of the equity market on commodity market at all times, investors and portfolio managers should consider whether or not to include both assets in the portfolio. It is important to note the finding of Bahloul and Khemakhem (2021) of the rather significant volatility spillovers between financial markets especially during the COVID-19 pandemic. Our study, however, found the strong comovement at the statistical significance level between GSCI and OIL for the 128-day frequency during the period from the year 2019 to 2021/6 only, with the arrows running to the right and downward indicating the positive comovement of commodity indices with oil prices being the volatility transmitter. Thus, our finding is consistent with the study result of Chen, Chiu, and Hsiao (2021) that confirms the positive correlation between commodity and oil prices because the oil price is generally the main part of the total shipment cost of commodities.

3) MSCI has the strongest connectedness with most other financial markets and in all periods. It is also interesting to note that the connectedness between MSCI and REIT is highly strong for all frequencies during the period from 2019/12 to 2020/8, indicating the comovement between the equity market and the real estate market that investors must consider because holding both assets at the same time might damage the risk diversification and prevention ability of the portfolio (Chong, Miffre, & Stevenson, 2009). MSCI also has a strong positive comovement with OIL in the 128 days band and is significant from 2019 to 2021/6, with the arrows running from it to affect OIL. Our results concur with the finding of O'Donnell, Shannon, and Sheehan (2021) about the positive

correlation or comovement between oil prices and MSCI, particularly during the COVID-19 pandemic as the demand for oil decreased due to the economic recession (MSCI is considered an economic indicator).

4) USD exhibits negative relations with all other financial markets, especially at the onset of the COVID-19 outbreak in the 32–64 days bands and the 128-day band with MSCI, GSCI, and REIT. This finding aligns with that of Antoniadis, Sariannidis, and Kontsas (2018), indicating the inverse relationship between the USD and other financial markets because the US dollar is the main reserve currency and viewed as a safe-haven currency to lower the portfolio risk and thus preferred for investment when economic and financial market conditions are uncertain and volatile.

5) Most financial markets alternately played the roles of sender and receiver of the spillover effects throughout the time and frequency domains of this study; and thus, we perceive that none of the considered financial markets can act as a market leader lastingly. Besides, we found that the relations or comovements among the studied assets can change all the time, and so can their magnitude and direction. Also interesting is our observation that the correlations of many pairs of financial markets turned higher at the time when COVID-19 was declared a pandemic and then began getting lower in early 2021. Such weakening dependency is probably due to the recovery of financial markets and the return to economic normality after the pandemic has brought about an adaptation to the "new normal" culture, and this proposition will be tested and analyzed in the next sub-section.

5. Conclusions and recommendations

5.1. Conclusions

This study employed two econometric techniques to examine the connectedness and relationships among seven global financial markets for the pre and during COVID-19 periods. Besides, it analyzed whether there exists the structural change accelerated by Covid-19 in each financial market.

In the first part, we use the MS-AR model to detect and confirm the presence of structural market change. The results indicated structural changes in all markets(except BTC) after January 30, 2020, corresponding to the date the WHO declared the COVID-19 pandemic as a Public Health Emergency of International Concern. We also investigated the recovery speed to the normality of each asset market and compared the recovery performance among markets when time proceeded in the COVID-19 pandemic period. Throughout the pre-COVID-19 period, USD fluctuated all the time in contrast to REIT, which showed a very small fluctuation. Surprisingly, the recovery from the pandemic shock was faster for USD than for REIT during the COVID-19 pandemic regime. Our findings demonstrate that the highly volatile financial markets like the USD in time of normality can recover well and relatively faster from the crisis, thus, allowing the investors in international currencies to feel pain from the potential financial loss just for a brief time. Meanwhile, the quite stable markets like REITs preferred by many investors during the economic normality once disrupted by the global crisis might change the market sentiment of some investors that had endured the pain of loss or risk-potential during the lengthy pandemic period up to the point of their withdrawal from the real estate market before the investment climate becomes normal. However, the responses of investors to the structural changes in different financial markets depend on investor sentiment toward risk and the capability of investors or portfolio managers to reallocate assets and reduce portfolio risk. Furthermore, despite enormous information for estimating the market recovery speed, we still have to be aware that the historical levels or movements of prices or market returns of an asset cannot provide a guaranteed level of future prices or returns of that asset. Thus, investors should keep monitoring the movements of various pertinent variables before deciding to invest in particular assets or markets (Dimitrios & Vasileios, 2015). From our study, among the five financial markets hit by the pandemic shock, the fastest recovering market is USD, followed by GSCI, OIL, MSCI, and REIT in descending order. While GOLD seemed to benefit from COVID-19, the BTC market was considered not influenced by the prevailing pandemic because its volatilities for both pre and during COVID-19 data series are quite remarkably similar in features leading to no concrete conclusion on the BTC market's recovery.

The second part of the study involves the network analysis to understand the connectedness and strength of correlations among the seven considered markets. It was found that the COVID-19 pandemic did not alter the connectedness structure among markets, but the relationship between markets in each pair was strengthened or weakened to different degrees.

The third part concerns the in-depth investigation of market connectedness in the time–frequency domain using the wavelet coherence technique. The cross-asset connectedness was found to be slightly different across the market pairs. It is interesting to note that the GSCI-OIL pair exhibits a very strong correlation for all data frequencies while OIL acted as the leader of the GSCI market; for example, the increase or decrease of OIL returns will cause the change in the GSCI returns in the same direction because oil is the main component of commodities' transportation cost (Chen et al., 2021). We also found BTC to have not much relationship with other financial markets, which is in line with the study result of Conlon and McGee (2020) that the BTC market had a connection with traditional asset markets for both pre and during the COVID-19 periods.

5.2. Recommendations

The following conclusions are drawn from our findings reported above.

1) As MSCI has shown to take a leading role in the global financial markets throughout the COVID-19 prevailing period, investors in other assets and governments of various countries should give the highest priority to getting an insightful understanding of the roles of different equity markets and their relations with other markets.

2) At the onset of the COVID-19 outbreak, the comovement between markets grew stronger and positively at the statistically significant levels for practically all pairs of the global financial markets. The exception is the USD market which was found to correlate negatively with other markets during the pandemic regime for the 32–64 days frequencies, implying that USD can be used as a hedging asset in the short and medium run.

3) The analysis of market recovery reveals that the USD market recovered from the bust relatively faster than the others; and, thus, the risk-avert investors can consider investing primarily in this market during the economic recession. In the meantime, precaution should be taken by risk-avert investors whether or not to invest in the BTC market due to the irregular market volatilities of various cryptocurrencies, making it difficult to differentiate between the upturn and the downturn phase.

4) OIL and GSCI have shown their rather high correlations throughout the entire studied period with OIL taking the causal role because crude oil constitutes the main component of the transportation cost of commodities (meat, livestock, and agricultural types). In this connection, the government should implement fuel price intervention to prevent rising consumer prices and inflation.

6. Availability of data and materials

The datasets analyzed during the current study are available at Thomson Reuter DataStream.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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