Financial Innovation

RESEARCH Open Access

Analyzing time–frequency connectedness between cryptocurrencies, stock indices, and benchmark crude oils during the COVID-19 pandemic

Majid Mirzaee Ghazani[1*], Ali Akbar Momeni Malekshah[1] and Reza Khosravi[1]

*Correspondence: majidmirzaee@kntu.ac.ir

[1] Department of Industrial Engineering, K. N. Toosi University of Technology, Tehran, Iran

Abstract

We used daily return series for three pairs of datasets from the crude oil markets (WTI and Brent), stock indices (the Dow Jones Industrial Average and S&P 500), and benchmark cryptocurrencies (Bitcoin and Ethereum) to examine the connections between various data during the COVID-19 pandemic. We consider two characteristics: time and frequency. Based on Diebold and Yilmaz's (Int J Forecast 28:57–66, 2012) technique, our findings indicate that comparable data have a substantially stronger correlation (regarding return) than volatility. Per Baruník and Křehlík' (J Financ Econ 16:271–296, 2018) approach, interconnectedness among returns (volatilities) reduces (increases) as one moves from the short to the long term. A moving window analysis reveals a sudden increase in correlation, both in volatility and return, during the COVID-19 pandemic. In the context of wavelet coherence analysis, we observe a strong interconnection between data corresponding to the COVID-19 outbreak. The only exceptions are the behavior of Bitcoin and Ethereum. Specifically, Bitcoin combinations with other data exhibit a distinct behavior. The period precisely coincides with the COVID-19 pandemic. Evidently, volatility spillover has a long-lasting impact; policymakers should thus employ the appropriate tools to mitigate the severity of the relevant shocks (e.g., the COVID-19 pandemic) and simultaneously reduce its side effects.

Keywords: Time–frequency, COVID-19, Wavelet coherence, Spillover, Volatility

Introduction

Following the onset of the COVID-19 pandemic, numerous countries enacted stringent policies that substantially reduced economic activity. The pandemic induced global economic turmoil, triggering a pronounced contagion effect on various financial sectors, such as banking, insurance, and equity markets (Goodell 2020). This phenomenon has captured the attention of scholars seeking to investigate the repercussions of the COVID-19 outbreak on financial markets (Akhtaruzzaman et al. 2021; Youssef et al. 2021; Zhang et al. 2020). The prevailing COVID-19 outbreak has influenced many assets, thereby shaping the dynamics of international financial markets (Özdemir 2022; Salisu and Obiora 2021; Shahzad et al. 2021).

In contrast, the transformation of the commodities market, exemplified by the financialization of commodities, has attracted the scrutiny of stock traders, hedgers, and researchers. Among strategic commodities crucial to the economic advancement of sophisticated industrial societies, crude oil is particularly significant. The COVID-19 outbreak has heightened uncertainty, and the resultant financial market shock has been unparalleled. In May 2020, for example, concomitant with the global proliferation of the COVID-19 pandemic, there was an anomalous decline in global crude oil prices, and West Texas Intermediate (WTI) futures prices plunged to their lowest level in four years. A large corpus of literature (e.g., Elsayed et al. 2020; Jiang et al. 2020; Malik and Umar 2019; Mestre 2021; Shahzad et al. 2017; Rehman et al. 2022; Ha 2023; Kumar et al. 2023) illustrates the interconnectedness of crude oil and other financial market assets. The dynamic relationship between crude oil and financial markets, particularly during economic fragility and distress, has also been meticulously documented (e.g., Batten et al. 2019; Ha 2023; Kumar et al. 2023; Rao et al. 2022).

The interconnections among financial markets, especially globally, constitute essential elements. These connections are commonly influenced by the spillover effects of volatility and returns, and carry substantial implications for investors. It is critical to thoroughly examine spillovers, both in terms of returns and volatility, between commodity markets, but with a specific focus on crude oil and equity markets. This topic is particularly relevant for portfolio managers actively pursuing diversification strategies and maintaining a watchful stance in anticipation of energy and financial crises.

Cryptocurrencies have garnered significant attention from academics, practitioners, and investors across multiple asset classes (Hasan et al. 2022; Rehman 2020; Mensi et al. 2020). Cryptocurrency markets have grown significantly over the past few years. As of August 2022, over 20,000 cryptocurrencies were traded compared with just over 600 in January 2016; the total market capitalization has crossed US$ 1 trillion. Investors prefer to use cryptocurrencies as a hedge against risks caused by other financial markets (e.g., equity markets), and they attempt to diversify their holdings to mitigate these financial risks (Jiang et al. 2021; Ji et al. 2019; Conlon et al. 2020; Kumah et al. 2021). However, the relationship between cryptocurrencies and equity markets remains a subject of contention (e.g., Gambarelli et al. 2023; Ha 2023; Kumar et al. 2023; Rao et al. 2022), and integrating markets that trade traditional financial assets (e.g., stocks, bonds) and cryptocurrencies will depend on resolving this issue.[1] There are studies focusing on the relationships between cryptocurrencies and commodity markets.[2]

Clearly, a comprehensive analysis of the behavior of a variety of assets (both traditional and digital) and their relationship in terms of the intensity of the spillover effect is essential (especially in the event of significant shocks, such as COVID-19). Several methods have been proposed to analyze spillover effects. Let us consider Diebold and Yilmaz

[1] See, for example, Aharon et al. (2021), Baur and Lucey (2010), Köchling et al. (2019), Kumah and Odei-Mensah (2021), Bouri et al. (2018), Caferra (2022); Kumah et al. (2022).

[2] See, for example, Ji et al. (2019), Panagiotidis et al. (2019), Kumah and Mensah (2022), Rehman and Apergis (2019), Bouri et al. (2018), White et al. (2020), Mensi et al. (2019), Foroutan and Lahmiri (2022), Kang et al. (2019), Kumah and Odei-Mensah (2022).

(2012), who implement concepts such as variance decomposition (VD) and vector auto regression (VAR). However, this method neither accounts for the frequency component nor examines the interconnections in different periods (from short to long term). More recent studies have investigated the time–frequency components simultaneously; Baruník and Křehlík (2018), for example, attempt to overcome the aforementioned limitation this way. In their approach, the Fourier transform was used to convert Diebold and Yilmaz's (2012) model results into a frequency–dynamics framework. We similarly point to studies by Arif et al. (2021), Iqbal et al. (2022), Liu et al. (2022), Dai et al. (2022), Mensi et al. (2022), and Umar et al. (2022), who utilized the aforementioned approaches to investigate the spillover.

These studies nevertheless neglect scenarios in which the data have a non-stationary characteristic (e.g., financial data)—a problem that becomes challenging when we want excessive manipulation to provide stationary data. Additionally, the existence of time-varying fluctuation over time justifies a need for implementing methods that account for a lead-lag structure among the variables, which most studies have overlooked. Significant structural breakdowns in the data are another issue observed in financial data, and using traditional methods in this context does not lead to a favorable result (Ghazani et al. 2022).

Studies have also failed to sufficiently analyze dynamic and evolving behaviors with respect to the intensity of connectedness between the data in the area of spillover and interconnection among markets. We solve these limitations in the literature through our investigation.

Our main contributions are summarized as follows. First, we utilized the implications of a phase difference method (wavelet coherence) and spillover to analyze approaches in the time–frequency domain (Baruník and Křehlík 2018; Diebold and Yilmaz 2012). We consider this to be an exhaustive analysis. Second, we considered the time-varying interdependence between various assets by employing a rolling window approach with varying periods in order to investigate the dynamic behavior of mutual interconnection in the lead-lag structure across various assets (particularly in the COVID-19 period).

The remaining paper is organized as follows. Section "Literature review" details the literature review, section "Data and methodology" presents the data and the methodology, section "Empirical findings" describes empirical results, and section "Conclusions and policy implications" concludes.

Literature review

We review studies that investigate the behavior of financial markets in troubled conditions and assess their relationships in these circumstances. Some studies specifically focus on analyzing the relationship between assets (primarily stocks) in various financial markets (e.g., Hong et al. 2021; Iqbal et al. 2022; Liu et al. 2022; Loughran and McDonald 2023; Tiwari et al. 2018; Arif et al. 2021). We also look at studies that analyze the interdependence of commodities and other assets across markets (e.g., Dai et al. 2022; Mensi et al. 2022, 2021; Umar et al. 2022; Wei et al. 2022; Ali et al. 2022; Zhang and Hamori 2021; Ferrer et al. 2021), as well as studies investigating the interdependence between cryptocurrencies and other financial assets (e.g., Kumar et al. 2022; Agyei et al. 2022; Qureshi et al. 2020; Balcilar et al. 2022; Arouxet et al. 2022; Bhuiyan et al. 2021).

Through this review, we offer an in-depth evaluation of the concepts presented in the literature.

Interconnections among securities

Hong et al. (2021) investigated the relationship between COVID-19 and the instability of stock price volatility and return predictability in the United States from January 1, 2019, to June 30, 2020, using the methodologies of Bai and Perron (1998), Elliot and Müller (2003), and Xu (2013). The results confirm a single break in the price volatility and return predictability of the S&P 500 and Dow Jones Industrial Average. The breakpoint coincides with the COVID-19 pandemic, and return predictability and price volatility show significant amplification following the break.

Iqbal et al. (2022) investigated the asymmetric spillovers (returns and volatility) between global sustainable investments for fourteen country-level Dow Jones Sustainability Indices between 2005 and 2021. They utilized the Diebold and Yilmaz (2012), Diebold and Yılmaz (2014), Baruník and Křehlík (2018), and Diebold and Yilmaz (2018) methods to analyze time–frequency connectivity. Their findings reveal substantial time–frequency asymmetries in return spillovers across several short- and long-run areas, especially during the COVID-19 outbreak.

Liu et al. (2022) investigated the volatility spillover among global equity markets during the COVID-19 outbreak using the connectedness methods of Diebold and Yilmaz (2012) and Baruník and Křehlík (2018), as well as volatility data from sixteen different equity markets. Evidently, COVID-19 pandemic significantly exacerbated the effects of risk contagion on global financial markets. Loughran and McDonald (2023) analyzed all 2018 10-K filings and found that less than one-fourth of the documents mentioned COVID-19-related terms. They also discovered a correlation between the incorporation of COVID-19-related terms in financial statements and realized returns during the COVID-19 period.

Arif et al. (2021) analyzed the time–frequency interdependence between clean energy and conventional investments in equity and energy markets during the COVID-19 pandemic by applying the Diebold and Yilmaz (2012) and Baruník and Křehlík (2018) methods to a sample from January 2008 to July 2020. Their findings demonstrated a superior connection between selected data during the COVID-19 outbreak.

Interdependence of commodities and other assets

Ha (2023) scrutinized the interconnections among different types of financial assets and commodities, including equities, gold, crude oil, and cryptocurrency, by applying several Bayesian VAR models. Ha decomposed the models into various time horizons (short, medium, and long run) to analyze the dynamic interlinkages between these markets before and during the COVID-19 pandemic periods. Both short- and medium-term trends revealed that equity, crude oil, and gold markets all receive shocks transmitted to these markets by the selected cryptocurrencies. In the long-term horizon, the cryptocurrency and gold markets were identified as shock transmitters.

Dai et al. (2022) analyzed the volatility spillover effects and evolving relationships between gold, WTI crude oil, and the Chinese equity markets by employing the Diebold and Yilmaz (2012) and Diebold and Yılmaz (2014) techniques established on the time-varying parameter VAR model. The results reveal an extraordinary degree of interdependence between data, and the general volatility spillover experiences a sudden increase during severe crises. They further determined that gold and WTI are the net recipients of the shocks, while all Chinese equity markets are net transmitters; the oil industry had the lowest returns and one of the lowest word counts related to the pandemic; and the oil industry firms barely mentioned pandemic risk in their shareholder disclosure statements (despite being severely affected by the pandemic). Clearly, managers failed to emphasize their exposure to COVID-19 risks. Dai et al. thus concluded that oil executives should have warned their shareholders about the industry's enormous downside risk during the catastrophic pandemic.

Utilizing the Baruník and Křehlík (2018) and wavelet coherency methods, Mensi et al. (2022) assessed the time-varying and frequency spillovers between WTI crude oil, global Green Bonds (GBs), and G7 equity markets. The spillovers proved to be time-varying and shock-sensitive. During the onset of the COVID-19 pandemic, a significant increase in spillover was also observed. The wavelet analysis revealed substantial correlations between GBs and both G7 equity markets and oil. In the medium and long terms, as well as during the COVID-19 outbreak, GBs and oil triggered equity market fluctuations.

Umar et al. (2022) analyzed the correlation between the volatility of certain stocks and fossil fuels during the COVID-19 outbreak. They matched the impact of financial catastrophes (e.g., the 2008 Global Financial Crisis and COVID-19 pandemic) in inciting the volatility interdependence of energy markets. They utilized Diebold and Yilmaz's (2012) and Baruník and Křehlík's (2018) techniques. Their findings indicate a tenuous correlation between the volatility of clean energy stocks and fossil fuels. Before and during the COVID-19 outbreak, Ali et al. (2022) applied the wavelet technique to reveal a robust correlation between specific equity and oil futures markets. They discovered low-frequency positive co-movements during the COVID-19 period.

Connectedness between cryptocurrencies and other assets

Gambarelli et al. (2023) used daily data from 2018 to 2022 in the European equity markets to examine the interconnection between cryptocurrencies and gold in different conditions on the market and the hedging efficacy of cryptocurrencies in managing the risk of portfolios. They implemented linear and nonlinear autoregressive distributed lag approaches to evaluate the intensity of connection in different short and long periods.

Kumar et al. (2023) examined the interconnection among cryptocurrencies, commodities, and select equity markets with respect to risk and returns under the COVID-19 pandemic and the Russian–Ukraine war. They implemented the time-varying parameter VAR method by changing the structure of Diebold and Yilmaz's (2012) technique, revealing a high level of connectedness during COVID-19, which was persistent for an extended period.

Agyei et al. (2022) proposed a time–frequency framework based on wavelet techniques for analyzing the degree of connectivity and the lead-lag relationship between six cryptocurrencies and the cryptocurrency-implied volatility index (VCRIX). The relationship between cryptocurrencies and VCRIX was substantial and predominantly positive across various investment time horizons. Rao et al. (2022) examined the nexus and the connectedness between different indices of equities, bonds, commodities, and

Bitcoin from August 2011 to July 2021 (covering the pre- and post-COVID-19). They employed the time-varying parameter VAR and quantile regression approaches to recognize the effect of events on different assets and analyzed the nexus between assets under uncertain conditions. The selected markets proved to be intensely connected, with the expectation that they will only expand in the post-pandemic future. Before the pandemic, emerging markets and the MSCI World indices contributed to most shocks to other variables.

Zhang and Hamori (2021) used the Diebold and Yilmaz's (2012) and Baruník and Křehlík's (2018) methods to examine the volatility and return spillovers between the COVID-19 outbreak, stock, and crude oil markets. They demonstrated that the return spillover is predominantly short term, whereas the volatility spillover is primarily long term. Mensi et al. (2021) investigated the return spillovers between crude oil, gold, and ten Chinese sector equity markets using Diebold and Yilmaz's (2012) and Diebold and Yilmaz's (2014) techniques. They concluded that the industrial and consumer discretionary sectors are the most critical spillover transmitters and receivers. In addition, their findings indicate that the crash in oil prices, 2008 Global Financial Crisis, and outbreak of COVID-19 affected asymmetric spillovers.

From 2016 to 2018, Qureshi et al. (2020) investigated the dynamics of multiscale interdependencies among the top five cryptocurrencies using wavelet-based analyses. The results confirmed the short- and long-term market integration of several cryptocurrency pairs. Balcilar et al. (2022) used time–frequency integration methods based on network analysis to investigate the volatility interdependence between 27 emerging stock markets and seven cryptocurrencies for the pre- and post-COVID-19 pandemic. After the outbreak of COVID-19, they found an increasing risk spillover among emerging market stocks and cryptocurrencies. Calculations of time-varying connectedness validated the significant impact of the COVID-19 pandemic. Arouxet et al. (2022) examined long-term memory in return and volatility by employing a high-frequency time series of seven of the most prominent cryptocurrencies for the pre- and post-COVID-19 outbreak. Using the wavelet transform method, they discovered that the long memory of returns was only marginally affected during the peak of the COVID-19 pandemic.

The literature review clearly reveals gaps in research. The research on the time–frequency domain and volatility transmission network between new asset classes (cryptocurrencies) and traditional asset classes (commodities and stocks) is limited and scarce. We thus highlight a novel perspective by focusing on the substantial time-varying variation in the lead-lag structure during the COVID-19 period. It should also be noted that dynamic behavior analysis and the time-varying interdependence among different assets have received less attention in the literature. We address these issues by employing the rolling window methodology with varying time intervals.

Data and methodology

We examine the descriptive analysis of data in this section. The data consist of daily spot return series [calculated as a logarithmic difference in prices, i.e., $r_t = (\ln p_t - \ln p_{t-1})$] for selected benchmark stock indices (Dow Jones Industrial Average and S&P 500), cryptocurrencies [Bitcoin (BTC from here on) and Ethereum (ETH from here)], and crude oils (WTI and Brent). We can observe the evolution

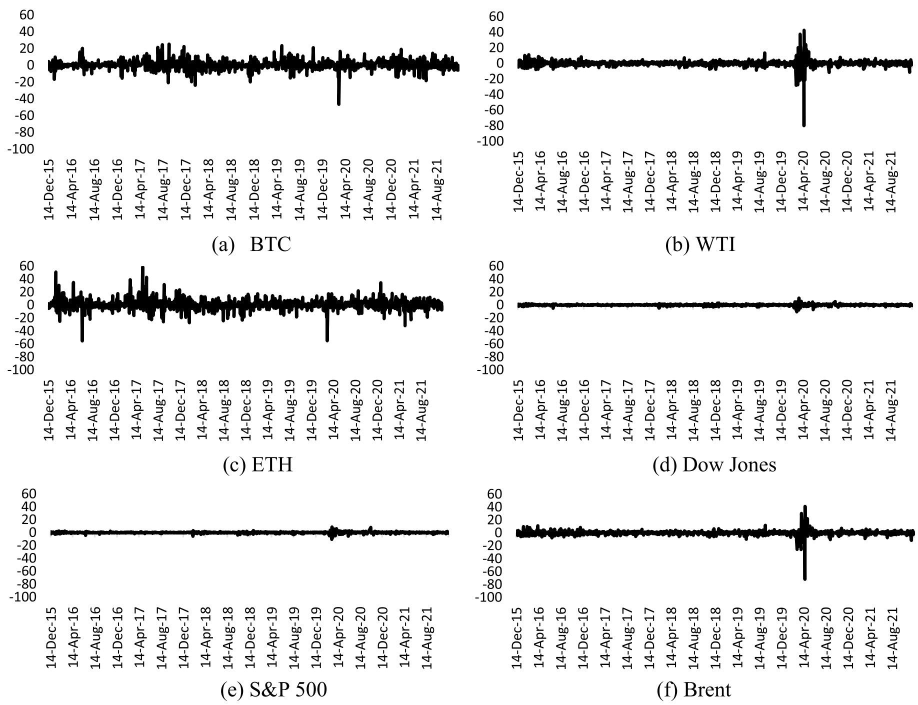

Fig. 1 Behavior of the return series

of the return series in the Fig. 1. The information for cryptocurrencies was obtained from investing.com; stock indices and crude oil data were obtained from Yahoo Finance. The data span from 14 December 2015 to 13 December 2021.

We selected both Brent and WTI crude oil prices because, first, they are international energy sector benchmarks and considered reference prices in many commodity markets. Second, each of the crude oils represents a specific market (e.g., Brent crude is the benchmark used for the broader light oil market, i.e., Europe, Africa, and the Middle East, while WTI is the benchmark for the U.S. light oil market) and in total cover more than 90% of the market. Other countries also regularly apply Brent and WTI benchmarks to value their crude oil.

Table 1 shows the descriptive analysis of the return series. All of the series present negative skewness (except for Ethereum). Brent prices have the most notable degree of skewness. The intensity of kurtosis is incredible for all the data, but for WTI, confirming its excess kurtosis. In general, and based on the mentioned statistical findings, all information presents features of a non-normal distribution, and the significant results of the Jarque–Bera test statistics validate it.

Figure 2 illustrates the volatility behavior for each data. We employ the autoregressive moving average-generalized autoregressive conditional heteroscedasticity (ARMA-GARCH) model to compute the volatilities of data. We consider the residual series resulting from ARMA-GARCH models for six return series. The fluctuations of the Ethereum return series are higher than that of other assets from the beginning. Looking at the results, in early 2020, when the COVID-19 pandemic began, the return fluctuations peaked and increased substantially.

Table 1 Descriptive statistics of return series

	BTC	WTI	ETH	Dow Jones	S&P500	Brent
Mean	0.3655	0.0528	0.6472	0.0564	0.0658	0.0556
Median	0.2517	0.1435	0.1637	0.0966	0.0965	0.1746
Max	25.3490	42.5832	58.6810	10.7643	8.7956	41.2023
Min	−46.4730	−79.9517	−55.3296	−10.5232	−10.4236	−71.7519
Std. Dev	5.1337	4.3076	7.7879	1.2172	1.1182	3.8966
Skewness	−0.3690	−4.0701	0.2926	−0.7475	−0.6779	−4.1412
Kurtosis	11.7846	113.1058	13.1259	19.0201	18.7574	109.7688
Jarque–Bera	4125.3	647,062.5	5461	13,742.2	13,277.8	608,769.3
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

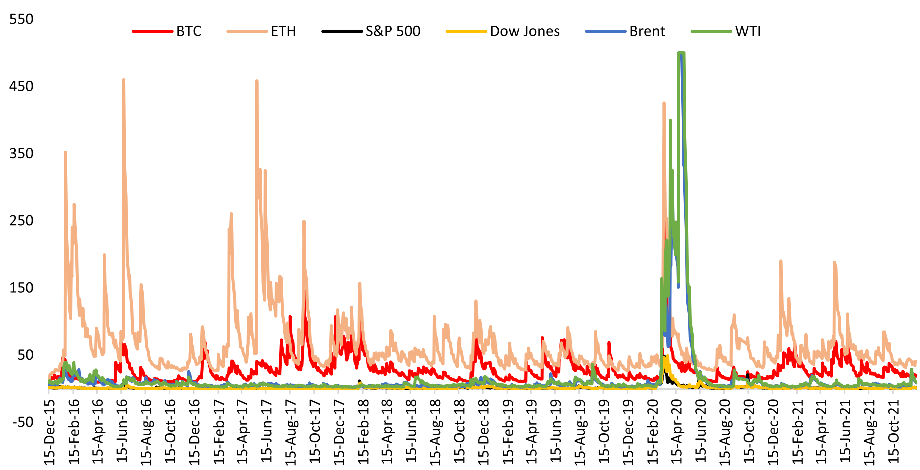

Fig. 2 Dynamics of return volatility

Table 2 Estimation result for ARMA-GARCH specification

	BTC	WTI	ETH	Dow Jones	S&P 500	Brent
γ	0.4791*	0.1777**	0.3578*	0.0945*	0.1108**	0.1749**
$AR(1)$	0.9782**	−0.9356**	0.8705**	−0.9739**	−0.7342**	−0.8406**
$AR(2)$	–	−0.7126**	–	–	0.4631*	−0.6621**
$MA(1)$	−0.9687**	0.9133**	−0.8380**	0.9638**	0.6786**	0.7892**
$MA(2)$	–	0.4986**	–	–	0.8981*	0.6064*
$MA(3)$	–	−0.0082*	–	–	−0.6941**	–
μ	1.5493*	0.3395**	4.1785*	0.0551**	0.0540**	0.3165*
φ_1	0.1185**	0.1739**	0.1226**	0.2452**	0.2932**	0.1746**
θ_1	0.8353**	0.7980**	0.8255**	0.7217**	0.6912**	0.7997**
$Q(20)$	28	19	22	24	31	36
Probability	0.2152	0.3561	0.4123	0.7165	0.6881	0.1418
$Q^2(20)$	21	16	13	20	24	19
Probability	0.5617	0.4228	0.3987	0.4418	0.1171	0.2511

** and * represent statistical significance at the 1% and 5% levels, respectively. *Q* (20) and *Q*2 (20) are the Ljung–Box statistics with 20th lags for the standard residuals and standard residuals squared, respectively

Based on the Akaike information criterion (AIC), Table 2 presents the fittest model for selected data in ARMA-GARCH specification and the optimum lag structure for each data and related empirical results. We show the best-fitting model in the ARMA-GARCH approach for each of the six return series based on the lowest number of AIC criteria. As evident from Table 2, the selected data have the following specifications: Bitcoin, Ethereum, and Dow Jones industrial index have ARMA-GARCH (1, 1), WTI and S&P500 index have ARMA-GARCH (2, 3), and Brent has ARMA-GARCH (2, 2) structures.

Rolling window method

The number of observations available to estimate the parameters in the modeling process might sometimes be too insufficient for a statistically robust estimation. An innovative approach called rolling analysis can be employed to address this challenge. This approach also offers a dynamic data view and helps detect fluctuations of patterns over time. It can also assist in finding seasonal patterns, trends, and other vital characteristics of the time series.

We construct a time series utilizing samples of sequential observations. For example, let us consider a series of returns $\{r(t)\}_{t=1}^{T}$ from which the target is to estimate an accumulated return over a period Δs. In the context of a rolling analysis, where rather than dividing the sample into $T/\Delta s$ equally sized non-overlapping sub-samples, the aggregated returns are analyzed by moving the window forward one observation at a time. The number of aggregated Δs returns for this approach then becomes $T - \Delta s + 1$, which is considerably larger than $T/\Delta s$, for $\Delta s < T$. Assume that $\{r(t)\}$ is a stationary time series. Then, the rolling returns, represented by $\{\widetilde{r}(t)\}$, is described as

$$\tilde{r}^{(\Delta s)}(z) := \sum_{t=z}^{z+\Delta s-1} r(t).$$

Analyzing methods

We suggest two approaches—frequency domain spillover methods and wavelet coherence—to examine the connection among data. The features and advantages of these approaches are debated in detail as follows.

Diebold and Yilmaz (2012)

To calculate spillovers, Diebold and Yilmaz (2012) integrate the generalized forecast error variance decomposition (GFEVD) and the extended VAR models, which creates a connectivity idea. The k-variable VAR (q) model can be thought of as Eq. (1):

$$x_t = \sum_{i=1}^{q} \varphi_i x_{t-i} + e_t, \tag{1}$$

where φ represents the $k \times k$ coefficient matrices and x_t represents the $k \times 1$ vector of the utilized variables at time t. The vector moving average ($MA(\infty)$) can also be used to alter the VAR process in our investigation. Assume that the roots of $|\varphi(z)|$ are outside a unit's circle in Eq. (2):

$$x_t = B(l)e_t, \tag{2}$$

where $B(l)$ is a $k \times k$ matrix of infinite lag polynomials formed by substituting $\varphi(l) = [B(l)]^{-1}$. Because the order of variables in the VAR model can alter the variance decomposition or impulse response results, Diebold and Yilmaz (2012) used the generalized VAR structure proposed by Koop et al. (1996) and Pesaran and Shin (1998) to ensure variance decomposition independence from ordering. The U-step-ahead GFEVD can be described in the following way using the framework in Eq. (3):

$$(\theta_U) = \frac{\sigma_{kk}^{-1} \sum_{u=0}^{U} \left((B_u E)_{jk}\right)^2}{\sum_{u=0}^{U} \left(B_u E B_u'\right)_{jj}}. \tag{3}$$

where $\sigma_{kk} = (E)_{kk} \cdot (\theta_U)_{jk}$ describes the share of the model's kth variable to the variance of forecast error of the component j at horizon u and B_u is a $k \times k$ coefficient matrix of the polynomial at lag u. Each entry is normalized by the sum of the rows in the form of Eq. (4):

$$\widetilde{\theta}_{jk}(U) = \frac{\theta_{jk}(U)}{\sum_{k=1}^{M} \theta_{jk}(U)}. \tag{4}$$

The pairwise spillover from k to j at horizon U is indicated by $\widetilde{\theta}_{jk}(U)$, which is utilized to evaluate the spillover impact from market k to j.

The total spillover index, which calculates the contribution of shock spillovers across variables to the total forecast error variance, is calculated as follows:

$$SP(U) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{M} \widetilde{\theta}_{ij}(U)}{\sum_{i,j=1}^{M} \widetilde{\theta}_{ij}(U)} \times 100. \tag{5}$$

All other variables j have a directional spillover effect on variable i, which is assessed as

$$SP_{i.}(U) = \frac{\sum_{\substack{j=1 \\ i \neq j}}^{M} \widetilde{\theta}_{ij}(U)}{\sum_{j=1}^{M} \widetilde{\theta}_{ij}(U)} \times 100. \tag{6}$$

Similar to the directional spillover from the market i to all other markets j, the directional spillover from the market i to all other markets j is calculated as:

$$SP_{.i}(U) = \frac{\sum_{\substack{j=1 \\ i \neq j}}^{M} \widetilde{\theta}_{ji}(U)}{\sum_{j=1}^{M} \widetilde{\theta}_{ji}(U)} \times 100. \tag{7}$$

Net spillovers from market i to all markets j can be estimated as the difference among gross shocks sent to and received from all other markets, given these directional spillovers:

$$SP_i(U) = SP_{.i}(U) - SP_{i.}(U). \tag{8}$$

Baruník and Křehlík (2018)

In the Diebold and Yilmaz (2012) method, we examine correlation for the total period. In comparison, the Baruník and Křehlík (2018) method enables us to check the correlation among the variables in different time frames (including the short, medium, and long terms) by determining various frequencies. They applied the Fourier transform to convert the Diebold and Yilmaz (2012) model results into a frequency dynamics technique. The frequency response function is derived by performing a Fourier transformation on the coefficients $B_u : B\left(e^{-iw}\right) = \sum_u e^{-iwu} B_u$, where $i = \sqrt{-1}$. The generalized causation spectrum across the frequency range $w \in (-\pi, \pi)$ is written as Eq. (9):

$$\left(g(w)\right)_{jk} = \frac{\sigma_{kk}^{-1}\left|\left(B\left(e^{-iw}\right)E\right)_{jk}\right|^2}{\left(B\left(e^{-i\omega}\right)EB'\left(e^{iw}\right)\right)_{jj}}, \tag{9}$$

where $B\left(e^{-iw}\right) = \sum_u e^{-iwu} B_u$ is the Fourier transform of the impulse response B_u. The element of the jth variable's spectrum at the w frequency due to shocks in the kth variable is $\left(g(w)\right)_{jk}$, which should be stressed. Within the causality of frequency, we might clarify the shape of Eq. (9) for the variety since the divisor holds the spectrum of the jth variable at a particular frequency w. To reap the generalized decomposition of variance decomposition in the frequency dynamics, we can weight $\left(g(w)\right)_{jk}$ by the frequency contribution of the jth variable variance. This weighting function is written in Eq. (10):

$$\xi_j(w) = \frac{\left(B\left(e^{-iw}\right)EB'\left(e^{iw}\right)\right)_{jj}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}\left(B\left(e^{-iw}\right)EB'\left(e^{iw}\right)\right)_{jj} d\tau}. \tag{10}$$

It shows the jth variable's power at a specific frequency, that is, a constant value of 2π at all frequencies. Formally, the frequency band $b = (a, c) : a, c \in (-\pi, \pi), a < c$ is constructed.

Under the frequency band b, the GFEVD is:

$$\theta_{jk}(b) = \frac{1}{2\pi}\int_a^c \xi(w)\left(g(w)\right)_{jk} dw. \tag{11}$$

However, Eq. (11) must still be adjusted. On the frequency range $b = (a, c) : a, c \in (-\pi, \pi), a < c$, the scaled GFEVD can be thought as Eq. (12):

$$\widetilde{\theta}_{jk}(b) = \frac{\theta_{jk}(b)}{\sum_k \theta_{jk}(\infty)}, \tag{12}$$

where $\widetilde{\theta}_{jk}(b)$ is the pairwise spillover at frequency band b. Additionally, on the frequency band b, the total overflow (frequency interdependence) can be defined as Eq. (13):

$$SP(b) = \left[\frac{\sum \widetilde{\theta}(b) - T\left\{\widetilde{\theta}(b)\right\}}{\sum \widetilde{\theta}(\infty)}\right] \times 100. \tag{13}$$

$T\{.\}$ denotes the trace operator and $\sum\widetilde{\theta}(b)$ is the sum of all influences in the $\widetilde{\theta}(b)$ matrix. The total spillover frequency splits the total spillover into various frequency portions and can be used for the total spillover (SP) calculated using the Diebold and Yilmaz (2012) model. Similarly, the two-directional spillovers in frequency dynamics can be defined as follows:

Directional Spillovers with Frequency (From): $SP_{k.}(b) = \sum_{\substack{j=1 \\ j\neq i}}^{M} \widetilde{\theta}_{kj}(b)/M \times 100.$

The market's spillover from all other markets at frequency band b is measured by frequency directional spillovers (from) and $SP_{.k}(b) = \sum_{\substack{j=1 \\ j\neq i}}^{M} \widetilde{\theta}_{jk}(b)/M \times 100$ for frequency directional spillovers (To). The market's spillover to all other markets at frequency band b is measured by frequency directional spillovers (to).

Wavelet analysis

A close examination of the literature shows that time–frequency domain techniques have been used to estimate the correlation between variables. However, these traditional approaches cannot be robust if the data are non-stationary. Indeed, significant structural breakdown(s) in datasets has (have) harmed the outcomes of standard time-domain analysis (Ghazani et al. 2022). Meanwhile, wavelet techniques, which permit one-dimensional time data to be split into the two-dimensional time–frequency domain, have been suggested as a critical innovation to overcome these constraints (Kirikkaleli and Gokmenoglu 2020). A multiscale mindset suggests using a common framework to indicate frequency-dependent behavior while evaluating any data linkage, as in our case.

We may find specific places in the time–frequency domain where sudden variations in the co-movement of the investigated series occur and are identical to standard correlation using this approach. The wavelet (φ) has its origins in the Morlet wavelet family. The Morlet wavelet, invented by Goupillaud et al. (1984), is the type of wavelet used in this investigation. The wavelet model (φ) is a modification of the Morlet wavelet (Eq. 14).

$$\varphi(t) = \pi^{-0.25} e^{-i\omega t - 0.5t^2} \quad t = 1, 2, 3, \ldots, T. \tag{14}$$

A wavelet's scale (s) and location (l) are two different characteristics. The l parameter helps obtain the precise position by moving the wavelet throughout time, but the s parameter tries the stretched wavelet to limit distinct frequencies. The $\varphi_{l,s}$ is obtained from the φ in the following.

$$\varphi_{l,s}(t) = \frac{1}{\sqrt{s}}\varphi\left(\frac{t-l}{s}\right), \quad l, s \in \mathbb{R}, s \neq 0. \tag{15}$$

As a function of l and s, φ can generate a continuous wavelet. Also, in Eq. 16, $Rel(t)$ presents appropriate series, where

$$Q_w(l,s) = \int_{-\infty}^{\infty} Rel(t)\frac{1}{\sqrt{s}}\varphi\left(\frac{\bar{t}-l}{s}\right)dt. \tag{16}$$

The φ coefficient has been added to the modified version of the times series $Rel(t)$:

$$Rel(t) = \frac{1}{S_\varphi}\int_0^\infty \left[\int_{-\infty}^\infty \left|Q_w(i,j)\right|^2 di\right]\frac{dj}{j^2}. \tag{17}$$

The wavelet power spectrum (WPS) concept was applied in this work to obtain extra information (e.g., the scale of the time series) concerning the variables:

$$WPS_w(l,s) = \left|Q_w(l,s)\right|^2. \tag{18}$$

In light of the concerns addressed in this area, we used the wavelet coherence method because, unlike other methods. it lets us describe any association between the two series $\alpha(t)$ and $\beta(t)$ in time–frequency linkages. In this case, the cross wavelet transform (CWT) of the selected series can be defined as follows:

$$CWT_{\alpha\beta}(l,s) = CWT_\alpha(l,s)\overline{CWT_\beta(l,s)}, \tag{19}$$

where $CWT_\alpha(l,s)$ and $CWT_\beta(l,s)$ denote the CWT of two different series $\alpha(t)$ and $\beta(t)$, respectively. According to Orhan et al. (2019), the equation for squared wavelet coherence is as follows:

$$WC^2(l,s) = \frac{\left|Sm(s^{-1}Q_{\alpha\beta}(l,s)\right|^2}{Sm\left(s^{-1}\left|Q_\alpha(l,s)\right|^2\right)Sm\left(s^{-1}\left|CWT_\beta(l,s)\right|^2\right)}. \tag{20}$$

With $0 \le \mathrm{WC}^2(l,c) \le 1$, Sm depicts the smoothing method over time. When $\mathrm{WC}^2(l,c)$ approaches 1, the variables correlate with a specific scale, highlighted in red and enclosed by a black line in the figures. If $\mathrm{WC}^2(l,c)$ is 0, no connection (shown in blue color) between the series is indicated (Kirikkaleli and Ozun 2019).However, when $\mathrm{WC}^2(l,c)$ is measured, it is impossible to distinguish between positive and negative correlation numbers. To solve this problem, Torrence and Compo (1998) created a technique to assess wavelet coherence using several indicators to examine the oscillatory nature of two time series. The wavelet coherence difference phase's relevant equation is written as follows:

$$\theta_{\alpha\beta}(l,s) = \tan^{-1}\left(\frac{IMAG\left\{Sm\left(z^{-1}CWT_{\alpha\beta}(l,s)\right)\right\}}{REA\left\{Sm\left(z^{-1}CWT_{\alpha\beta}(l,s)\right)\right\}}\right). \tag{21}$$

Figure 3 shows that the black arrows explain wavelet coherence (phase difference) results. As rightward arrows indicate, the wavelet coherence phase difference moves towards 0 when two time series illustrate a positive correlation. However, the arrows point to the left when the two series correlate negatively. A downward arrow denotes that the primary variable is ahead of the secondary by π, and vice versa.

Empirical findings

We now check and analyze the behavior of selected data in the current study through the suggested methods to answer our research questions, that is, what is the intensity of the connection among the selected data in different markets during shocks (e.g., the

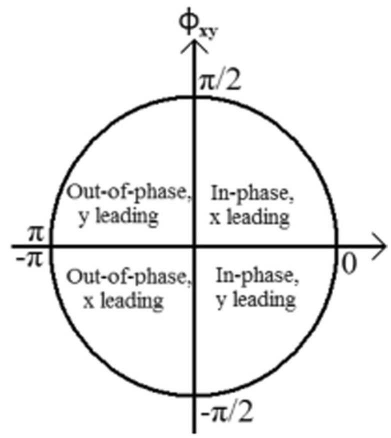

Fig. 3 Schematic phase difference structure

COVID-19 pandemic)? Further, is there a difference between the results obtained when analyzing the return and volatility of variables?

Dynamic analysis of total connectedness

The degree of total connectedness in returns and volatilities has been presented through rolling windows with two different sizes (200 and 300, following Ferrer et al. 2021; Arif et al. 2021; Tiwari et al. 2018) to confirm the robustness of our results.

Figure 4 shows the behavior of returns over time (window size 200). Moving from the short to the long term reveals a noticeable decrease in the total connectedness in the returns. The diagram that displays the long-term interconnection (in gold line) has been placed at the lowest level compared with other series (short and medium terms). On March 12, 2020, as the COVID-19 pandemic commenced, we observe a peak in connectedness that coincides with the significant decline in stock markets.

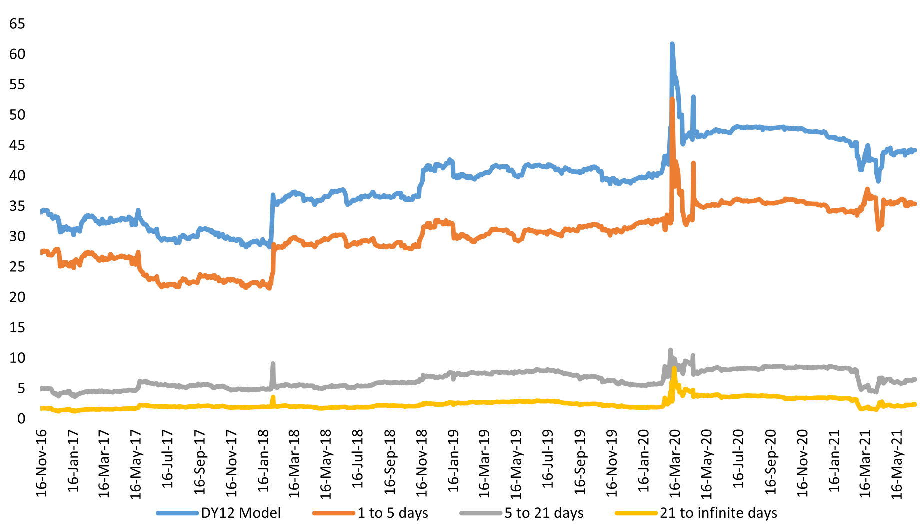

Fig. 4 Dynamic total return connectivity developments with a window length of 200 based on the frameworks proposed by Baruník and Křehlík (2018) and Diebold and Yilmaz (2012)

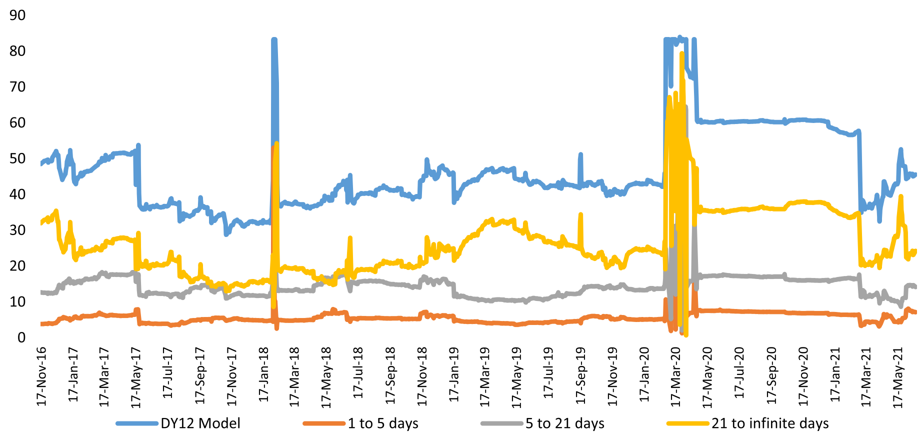

Fig. 5 Dynamic total volatility connectivity developments with a window length of 200 based on the frameworks proposed by Baruník and Křehlík (2018) and Diebold and Yilmaz (2012)

Figure 5 shows the total connectedness in terms of volatility among data by implementing a rolling window approach with a size of 200. Moving from the short to the long term increases the total connectedness because the diagram that presents the short-term interconnection has been placed at the lowest level compared with other series (medium and long terms). We observe two notable movements in the time series in Fig. 5. The first movement was recognized on February 5, 2018, due to the comments of the head of the Bank for International Settlements (BIS) about the threat of Bitcoin, which triggered a drop of almost 25% in the price of Bitcoin and caused observing a peak in volatility connectedness on February 6, 2018. Another significant fluctuation is detected in March 2020, when the COVID-19 pandemic began. We also realize a climax in volatility connectedness, which coincides with the historic collapse of the stock markets.

By moving toward a longer time window (300), we observe the replication of certain trends in the previous specific periods (February 2018 and March 2020) (see Figs. 6 and 7). The only difference in this relationship, compared with the previous one, is a slight and non-noticeable decrease in the intensity of the relationship at all time points, indicating that the choice of a different rolling window length does not disturb the robustness of connectedness results.

Spillover analysis

We now discuss the analysis of the returns and volatility spillover among data. Each variable's mutual effect on other study variables is investigated in this framework. According to Table 3, based on the Diebold and Yilmaz (2012) method, similar (in the same category) data have a higher correlation (in terms of return) with each other; according to Table 4, this is not the case in volatility. There exist several studies that mention this phenomenon (e.g., Zhang and Hamori 2021; Naeem et al. 2022; Toyoshima and Hamori 2018). Bitcoin, for example, is most impacted by the S&P 500 (22.43%), while Ethereum is most impacted by Bitcoin. However, stock indices and crude oils, like returns, have the most significant impact on their peers in volatility.

Tables 3 and 4 show that Bitcoin and Ethereum returns have the same effect on each other (23.71% vs 23.48%). In comparison, Bitcoin has a more significant impact on

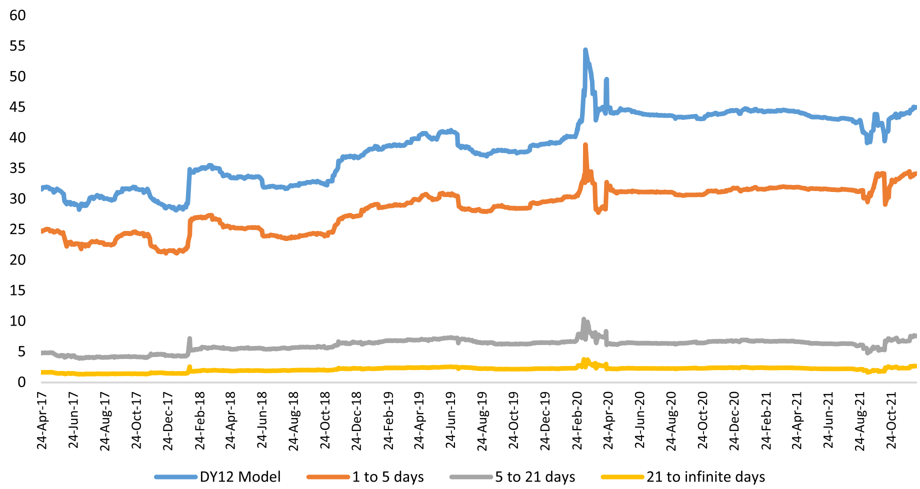

Fig. 6 Dynamic total return connectivity developments with a window length of 300 based on the proposed frameworks by Baruník and Křehlík (2018) and Diebold and Yilmaz (2012)

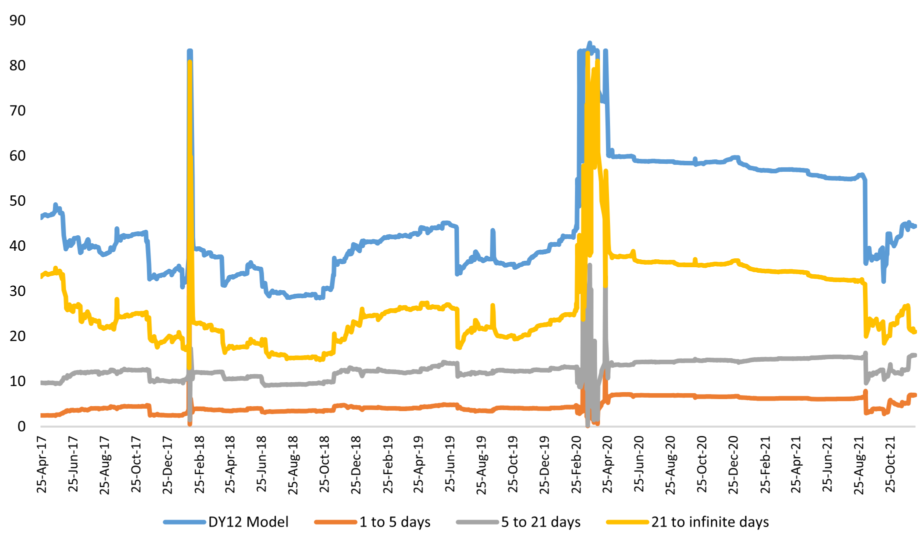

Fig. 7 Dynamic total volatility connectivity developments with a window length of 300 based on the proposed frameworks by Baruník and Křehlík (2018) and Diebold and Yilmaz (2012)

Table 3 Diebold and Yilmaz Return Spillover

	Bitcoin	Ethereum	S&P 500	Dow Jones	Brent	WTI	FROM
Bitcoin	73.64	23.48	1.13	0.96	0.4	0.4	4.39
Ethereum	23.71	74.18	0.83	0.97	0.18	0.12	4.3
S&P 500	0.84	0.71	74.23	18.88	3.41	1.93	4.3
Dow Jones	1.04	0.91	26.04	60.16	6.63	5.23	6.64
Brent	0.64	0.25	2.44	5.34	55.35	35.98	7.44
WTI	0.53	0.17	0.94	3.61	37.24	57.51	7.08
TO	4.46	4.25	5.23	4.96	7.98	7.28	**34.16**

The bold numbers show the aggregate impacts

The sum of the numbers in each row and each column, except the "From" column and the "To" row, is 100. The numbers in each row indicate how others influence the return data of that row. The numbers in each column indicate how the return of that column affects other data. The numbers in the "From" column equal the average effect a specific row's return data takes from the rest. The numbers in the "To" row are equal to the average impact of a particular column's return data on the rest

Table 4 Diebold–Yilmaz volatility spillover

	Bitcoin	Ethereum	S&P 500	Dow Jones	Brent	WTI	FROM
Bitcoin	53.93	9.45	22.43	13.88	0.12	0.18	7.68
Ethereum	12.83	75.21	7.77	4.11	0.03	0.05	4.13
S&P 500	1.85	0.58	53.61	43.63	0.14	0.2	7.73
Dow Jones	2.73	0.84	29.97	65.97	0.22	0.26	5.67
Brent	0.04	0.03	2.68	7.18	46.14	43.93	8.98
WTI	0.07	0.05	3.54	9.15	43.7	43.48	9.42
TO	2.92	1.83	11.07	12.99	7.37	7.44	**43.61**

The bold numbers show the aggregate impacts

The sum of the numbers in each row and each column of the table, except the "From" column and the "To" row, is 100. The numbers in each row indicate how the volatility of that row is affected by other data. The numbers in each column indicate how the volatility of that column affects other data. The numbers in the "From" column are equal to the average effect of that row's volatility taken from the rest of the data. The numbers in the "To" row are equal to the average impact of that column's volatility on the rest of the data

Ethereum in terms of volatility (12.83% vs 9.45%). Following the stock indices returns, the effect of the S&P 500 on the Dow Jones is more significant (26.04% vs 18.88%), while volatility is quite the opposite (29.97% vs 43.63%). For the crude oil returns, Brent is slightly superior in impact (37.24% vs 35.98%) but almost equal in volatility (43.70% vs 43.93%). Total connectedness is generally higher in the volatility section than in return (43.61% vs 34.16%).

The results in Table 3 reflect those in Fig. 8. The thickness of the arrows indicates the intensity of the effect of a specific variable on the other one. The direction of the arrows also specifies the course of the relationship between the two variables. The highest relationship is visible between the two benchmark crude oils. Then, the Dow Jones Industrial Average and S&P 500 stock indices are placed in the following positions of spillover intensity, and finally, the two selected cryptocurrencies of the study.

Concerning the volatility results and based on Fig. 9, we observe the highest spillover between the two crude oils, but we find a significant change in the spillover intensity between the two stock indices. Its amount from the Dow Jones index to the S&P 500 reaches 43.63%. Also, the volatility spillover from stock indices to cryptocurrencies significantly increases, reflecting the impact of the changes and fluctuations of the stock markets on these two cryptocurrencies.

According to Tables 5 and 6, based on the Baruník and Křehlík (2018) method, total connectedness in the returns decreases from the short to long term (25.84% vs 2.20%). In comparison, volatility is the opposite (3.48% vs 28.61%). This finding specifies that volatility spillover has an enduring impact. Interestingly, in terms of the return data in Table 5, for cryptocurrencies and in the short term, the effect of Bitcoin on Ethereum is slightly more significant (19.18% vs 18.43%); in the medium and long terms, it is the opposite (3.35% vs 3.72% and 1.19% vs 1.32%). In the case of indices returns, the effect of the S&P 500 is stronger. In the long term, we observe a stronger impact of the S&P 500 versus the Dow Jones. Finally, for crude oil return and in the short term, Brent significantly affects WTI (32.91% vs 28.39%); the opposite is true for the medium and long terms (3.27% vs 5.67% and 1.06% vs 1.92%, respectively).

Interestingly, regarding the volatility in Table 6, the indices in the short term reveal that the effect of the S&P 500 on Dow Jones is slightly higher (1.29% vs 1.19%), but the

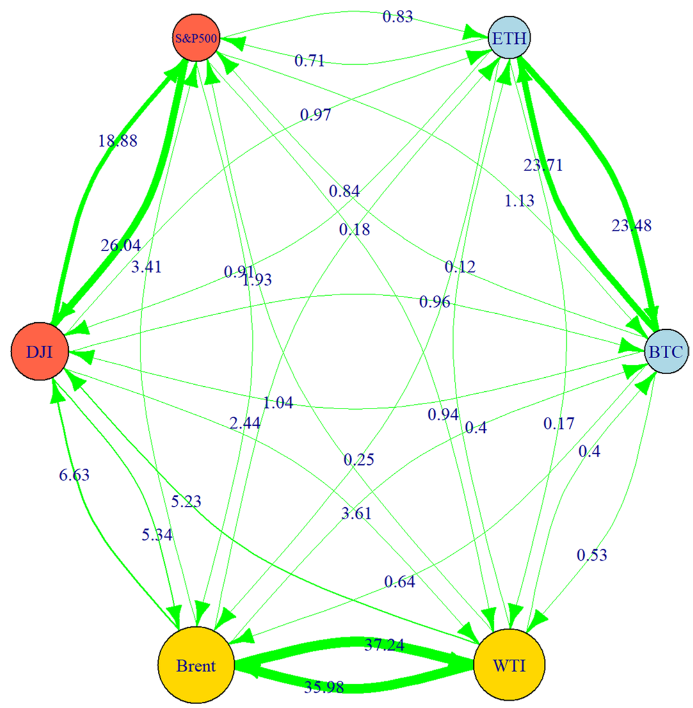

Fig. 8 Directional return spillovers in networks using the Diebold and Yilmaz (2012) method

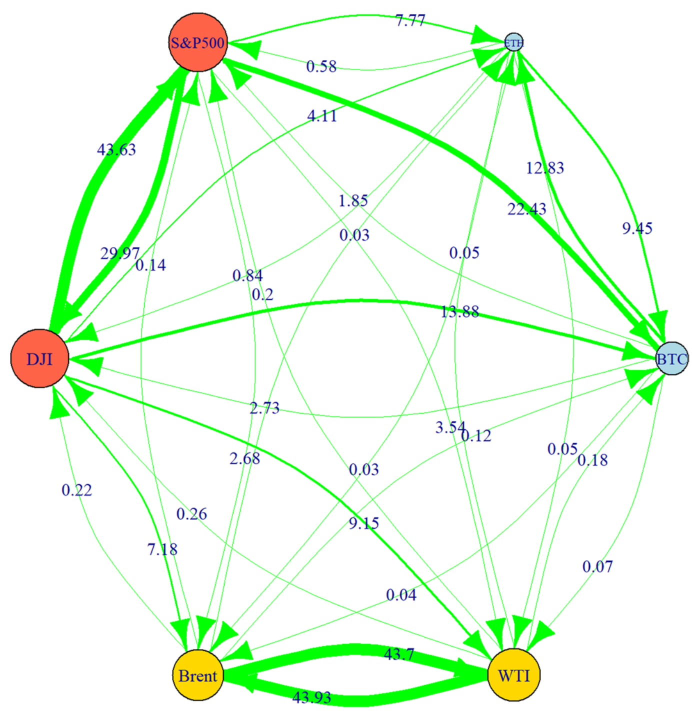

Fig. 9 Directional volatility spillovers in networks using the Diebold and Yilmaz (2012) method

Table 5 Barunik–Krehlik return spillover

	Bitcoin	Ethereum	S&P 500	Dow Jones	Brent	WTI	FROM
Short-term frequency: 1 to 5 days							
Bitcoin	58.84	18.43	0.75	0.71	0.3	0.34	3.42
Ethereum	19.18	58.55	0.51	0.74	0.14	0.11	3.45
S&P 500	0.37	0.4	60.57	14.18	1.81	0.92	2.95
Dow Jones	0.51	0.51	15.42	48.48	4.18	4.07	4.12
Brent	0.3	0.15	1.51	4.27	45.59	28.39	5.77
WTI	0.33	0.13	0.52	2.95	32.91	50.04	6.14
TO	3.45	3.27	3.12	3.81	6.56	5.64	**25.84**
Medium-term frequency: 6 to 21 days							
Bitcoin	11.01	3.72	0.28	0.18	0.08	0.04	0.72
Ethereum	3.35	11.58	0.23	0.16	0.03	0.01	0.63
S&P 500	0.34	0.22	10.05	3.46	1.17	0.73	0.99
Dow Jones	0.37	0.27	7.78	8.57	1.76	0.82	1.83
Brent	0.25	0.07	0.67	0.78	7.32	5.67	1.24
WTI	0.14	0.03	0.3	0.48	3.27	5.64	0.7
TO	0.74	0.72	1.54	0.85	1.05	1.21	**6.11**
Long-term frequency: more than 22 days							
Bitcoin	3.79	1.32	0.1	0.06	0.03	0.02	0.25
Ethereum	1.19	4.05	0.08	0.06	0.01	0	0.22
S&P 500	0.13	0.09	3.6	1.25	0.43	0.28	0.36
Dow Jones	0.16	0.12	2.84	3.11	0.69	0.34	0.69
Brent	0.1	0.03	0.25	0.29	2.44	1.92	0.43
WTI	0.05	0.01	0.12	0.18	1.06	1.83	0.24
TO	0.27	0.26	0.56	0.31	0.37	0.43	**2.2**

The bold numbers show the aggregate impacts

This table was obtained from the results in Table 3. The numbers in each cell of Table 3 are divided into three parts, placed in three sub-tables of Table 5. These numbers show the return spillover in three terms (short, mid, and long term). For example, the numbers in row 1 and column 2 in the three sub-tables of Table 5 are equal to 18.43, 3.72, and 1.32, respectively. Their total number is 23.48, which is equal to row 1 and column 2 in Table 3

opposite is true for the medium and long term (5.63% vs 7.11% and 23.04% vs 35.33%). In the case of the volatility of cryptocurrencies, Bitcoin has a more significant impact on Ethereum. In the case of crude oils, the effect of WTI on Brent is more significant in the short term (5.50% vs 4.86%). In the medium term, they have an almost equal effect on each other (15.86% vs 15.63%). However, in the long term, the impact of Brent on WTI is substantial (23.21% vs 22.58%).

Figure 10 shows the behavior of relationships between the study data in the Baruník and Křehlík (2018) approach. Subfigures [a–c] show the results of return spillovers in three periods (long, medium, and short terms, respectively). Here, and similar to the return spillover, we observe that by moving toward the long term, the degree of influence of the benchmark crude oil prices from themselves and the intensity of their mutual relationship decreases. Regarding other data, the intensity of mutual spillovers decreases as time increases. The subfigures [d–f] show the results of the volatility spillover analysis.

As stated before, we observe the contrasting behavior with respect to the intensity and the extent of volatility spillover. Moving toward the long term (22 days and above) increases the volatility of spillovers among the data. That is, the shocks are mainly effective in the long term, and their impact increases (contrary to the result obtained in the

Table 6 Baruník– Křehlík volatility spillover

	Bitcoin	Ethereum	S&P 500	Dow Jones	Brent	WTI	FROM
Short-term frequency—1 to 5 days							
Bitcoin	6.6	1.15	2.24	0.48	0.01	0.02	0.65
Ethereum	1.7	10.21	0.98	0.19	0	0	0.48
S&P 500	0.53	0.13	9.06	1.19	0.04	0.06	0.32
Dow Jones	0.28	0.07	1.29	3.54	0.01	0.01	0.28
Brent	0	0	0	0.06	5.83	5.5	0.93
WTI	0	0	0.02	0.07	4.86	5.04	0.83
TO	0.42	0.22	0.76	0.33	0.82	0.93	**3.48**
Medium-term frequency—6 to 21 days							
Bitcoin	16.62	3.03	7.22	2.93	0.03	0.07	2.21
Ethereum	4.04	23.89	2.88	1.1	0.01	0.02	1.34
S&P 500	0.92	0.22	17.38	7.11	0.03	0.03	1.38
Dow Jones	0.59	0.13	5.63	9.92	0.09	0.09	1.09
Brent	0.01	0	0.12	0.48	16.87	15.86	2.74
WTI	0	0	0.27	0.58	15.63	15.36	2.75
TO	0.93	0.56	2.69	2.03	2.63	2.68	**11.52**
Long-term frequency—more than 22 days							
Bitcoin	30.71	5.28	12.97	10.48	0.08	0.09	4.82
Ethereum	7.09	41.11	3.91	2.81	0.01	0.02	2.31
S&P 500	0.4	0.23	27.17	35.33	0.07	0.11	6.02
Dow Jones	1.86	0.64	23.04	52.51	0.12	0.17	4.31
Brent	0.04	0.03	2.55	6.65	23.44	22.58	5.31
WTI	0.07	0.05	3.25	8.5	23.21	23.07	5.85
TO	1.57	1.04	7.62	10.63	3.91	3.83	**28.61**

The bold numbers show the aggregate impacts

This table was obtained from the results in Table 4. The numbers in each cell of Table 4 are separated into three parts, placed in three sub-tables of Table 6. These numbers show volatility spillover in three terms (short, medium, and long term). For example, the numbers in row 1 and column 2 in the three sub-tables of Table 6 are equal to 1.15, 3.03, and 5.28, respectively. Also, their total number is 9.45, which is equal to row 1 and column 2 in Table 4

case of return analysis). We interpret this phenomenon following Baruník and Křehlík (2018), who clarify that periods of high-frequency connectivity exist when markets appear to process information swiftly and steadily. In this case, a shock to one asset in the system would have a short-term effect. That is, the shockwaves persist for extended periods when the relation is generated at lower frequencies. Barunik and Krehlik contend that, since volatility is generated after a return, volatility requires more time to transmit from one market to another, which justifies the behavior among data during the time.

Wavelet power spectrum

We now present the results of the wavelet analysis. The frequency range is from 2 to 444 days, and the results are comprehensive and provide good coverage in terms of historical viewpoints. Figure 11 illustrates the WPS of each series, where the black contour defines the 5% significance level. The WPS is an indicator that represents particular periods, with each time series showing more volatility than the other times. The colors in the power spectrum fluctuate from blue to red, indicating the lowest to the highest power spectrum (Kirikkaleli 2021). The Brent data indicate that the turbulence intensity

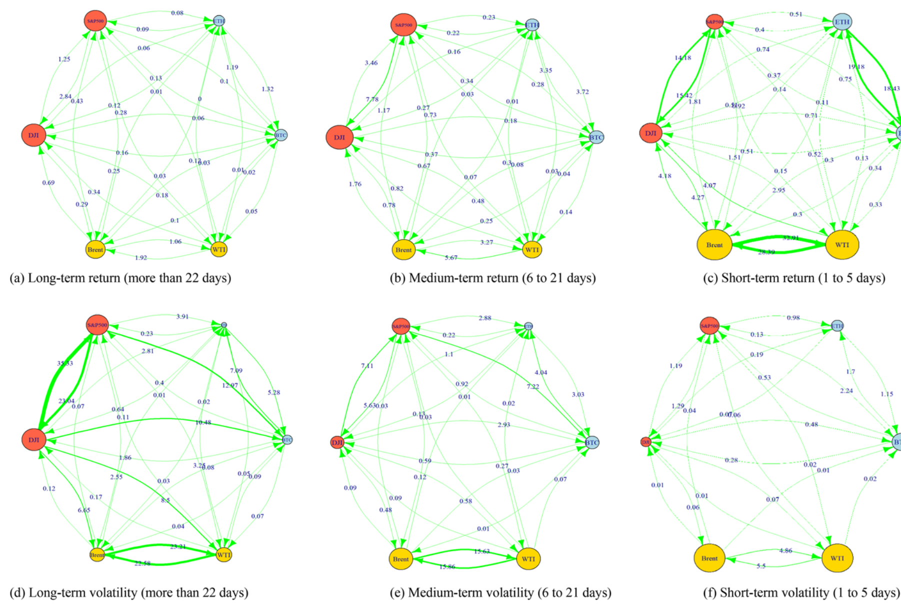

Fig. 10 Directional connectedness based on the Baruník and Křehlík (2018) method; **a**–**c** for return and **d**–**f** for volatility spillovers

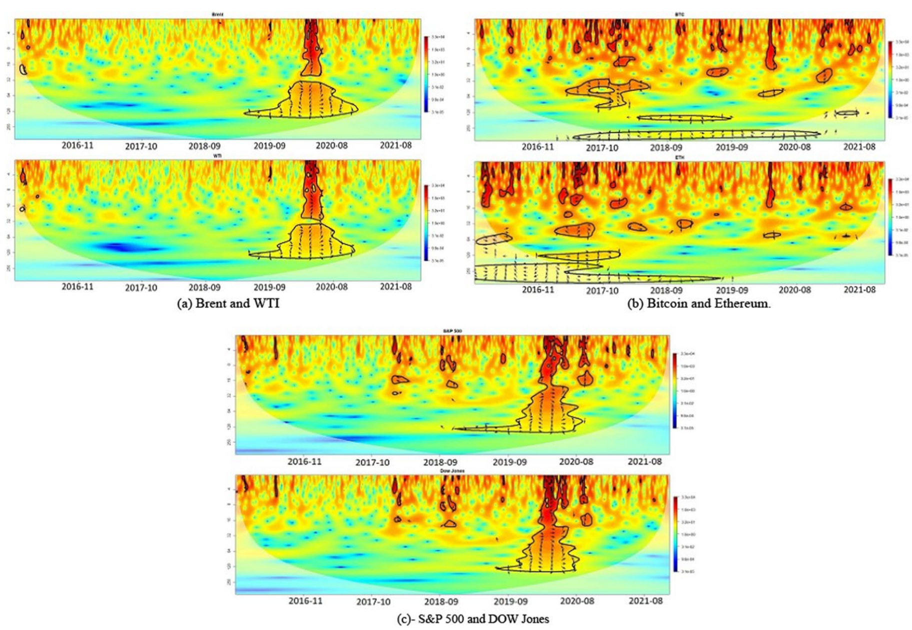

Fig. 11 WPS for daily return series for all of the data

is more pronounced at shorter frequencies up to 32. Suddenly, in the period 700 to 1050, we see a sharp increase in turbulence, visible from frequency 0 to 128. This period coincides with the COVID-19 pandemic. Observing the behavior of WTI reveals a significant similarity between the behavior of this data and that of Brent. Thus, we observe severe turbulence during the COVID-19 outbreak. This is also evident in the enclosed parts of Fig. 11a.

Analysis of WPS behavior in the case of BTC shows that, with increasing frequency, we observe a decrease in turbulence. At different times, the turbulence intensifies in enclosed areas that have taken the shape of an island. However, contrary to the observed behavior of the two benchmark crude oils, there are no significant fluctuations or changes in the data during the COVID-19 pandemic. We also observe data changes at some frequencies (more than 256) that are visible in the points enclosed in Fig. 11b. Examining ETH, we observe similarities in this behavior compared with BTC. In particular, the downward trend of the turbulence decreases with increasing frequency. However, a significant difference between Ethereum and Bitcoin is the high turbulence intensity from the initial to the medium-time range of observations. For the S&P 500, as in the previous data, the turbulence intensity decreases with increasing frequency level, such that the frequency of more than 32 turbulence events is significantly reduced.

The only exception to this discussion is the observations from 620 to 1000. Therefore, we observe extreme turbulence in the S&P 500 index. This coincides with the time of occurrence and prevalence of COVID-19. This result is illustrated in Fig. 11c as an enclosed area. Crucially, let us look at the Dow Jones results; we find strong similarity in the S&P 500 behavior. That is, it is a mirror image of the S&P 500. We also observe a decrease in the turbulence intensity as the frequency increases. Turbulence increased significantly in the Dow Jones and S&P 500 indices, indicating the impact of this crisis on the market during the COVID-19 pandemic. The direction of the arrows is similar to their behavior with respect to the S&P 500 index.

Wavelet coherency analysis

Examining the results from the WTC (Fig. 12) shows that, in all pair combinations of data, there is a strong relationship between 650 and 1100, which coincides with the outbreak of COVID-19 worldwide. This phenomenon is shown in the enclosed areas of the figures. The only exception to this conclusion is the behavior of BTC–ETH. The

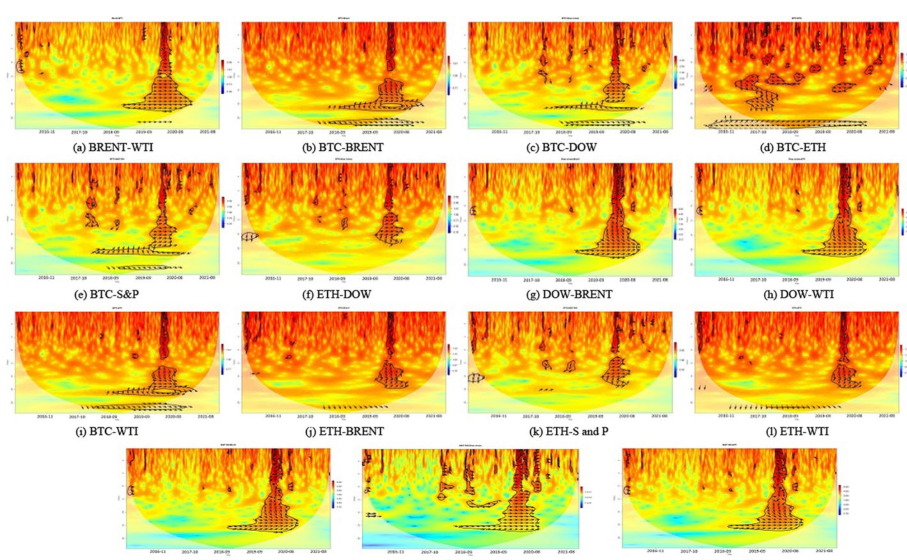

Fig. 12 The wavelet coherency between each pair of data

BTC–ETH relationship is strong but scattered at different frequencies and periods. In addition, the intensity of the relationship, marked in red, is visible in the figure. A broad enclosed region is observed at a frequency close to 512, which includes the most relevant observations. The direction of most of the arrows is to the right. This finding indicates a positive relationship between these two variables. Regarding the causal relationship between these two variables, based on the direction of the arrows, we see the alternating direction of the arrow angles, which indicates the lead and lag of each variable at different time points. Nevertheless, the critical point here is the absence of a strong relationship in the period coinciding with the COVID-19 outbreak, which is contrary to the results of other studies.

Another point inferred from the results is that the extent of coherence and connection decreases with an increase in frequency. This can be seen from the change in color in the figures from red to blue. This indicates a decrease in the level of connection between the data.

A new issue that emerges from examining these figures is the specific behavior of Bitcoin for each combination of study data. This is illustrated in Figs. (b), (c), and (e). In the aforementioned figures, there are three enclosed and separate areas (in the form of islands), indicating a strong connection between the data. These areas can be identified through observations between 600 and 1100, which includes the period of the COVID-19 pandemic.

Another point is the direction of causality between variables. Sometimes, the direction of the arrow is in the form of $\searrow$, which indicates that x is the lead of y. In periods, it has been in the form of $\rightarrow$, which indicates their synchronized movement. In some cases, the direction is shown as $\nearrow$, which indicates that y is the lead of x.

Moreover, by examining the direction of the arrows, one can observe a variety of behaviors. The figures show that the specific behavior of the paired combinations of data in the frequency range of 128. Accordingly, the direction of the arrows fluctuates in this range, and the direction of the arrows changes from $\searrow$ to $\nearrow$ or vice versa. At frequencies close to 128 Hz, the direction of the arrows becomes $\rightarrow$, indicating that the two variables are in phase and have a positive relationship.

Discussion

We find interesting similarities when comparing the results obtained from the methods proposed in the current study. For example, the results of the wavelet and spillover methods show a stronger connection between the selected data during the COVID-19 pandemic, which the Figs. 4 and 5 of the Baruník and Křehlík (2018) approach and the enclosed parts in Figs. 11 and 12 of the wavelet analysis verify. The connection between the S&P 500 and Bitcoin, and at the next level with Ethereum, is noticeable in terms of volatility spillovers.

We can refer to this phenomenon as the growing acceptance of crypto-related platforms and instruments in stock markets or, more generally, increasing cryptocurrency (mainly Bitcoin) adoption by institutional and retail investors, many of whom have positions in both crypto and equity markets. Indeed, these activities support co-movements, especially in terms of volatility in recent years and during volatile market conditions, such as the COVID-19 pandemic.

Another point that can be outlined is that in the context of wavelet analysis, in most cases, the highest level of coherence was detected between variables in the frequency range of 50–70. Based on the investigation carried out in this research, it was found that by applying two different time windows (200 and 300), the extent of spillover between variables did not change significantly (in the time window 200, we observe an insignificant upper level of spillover in comparison to 300, which is not noticeable), confirming the robustness of the selected approaches in the current study. Another point inferred from the results is the unusual behavior of cryptocurrencies, particularly around February 2018. At this point, we can see an increase in the intensity of volatility in both Bitcoin and Ethereum, which the results of wavelet (in the enclosed area in the interval of observation 500) and spillover analysis at this specific time confirm. One of the most critical events in this timeframe was the shock instigated by comments from the head of the BIS regarding the threats posed by Bitcoin. In the next steps, it is suggested to investigate market efficiency in each of the selected datasets and analyze the effect of the mutual relationship between them on the extent of efficiency.

Conclusions and policy implications

The outbreak of COVID-19 caused tremendous changes in the economies of countries and international markets. This shock seems to have affected the interconnections between markets and the intensity of this connectedness. Investors' interest in accepting cryptocurrencies has forced them to scrutinize their relationships with other markets. This study contributes to the literature on interconnections across diverse markets by investigating the return and volatility spillovers among selected and benchmark crude oils, stock indices, and cryptocurrencies. In the last decade, cryptocurrencies have gradually become important financial assets that are considered a significant part of diversified investment portfolios today. Therefore, their correlation analysis compared to other common financial assets worldwide under different conditions is necessary to choose a suitable portfolio of assets to cover risk. For this purpose, we employed the time-domain (Diebold and Yilmaz 2012), frequency dynamics (Baruník and Křehlík 2018), and wavelet coherence approach to check the relationship between the return and volatility of the mentioned assets.

Our main findings show that, based on the Diebold and Yilmaz (2012) method, similar data have a much higher correlation (in terms of returns), which is not the case when dealing with volatility. Generally, the total connectedness is higher in the volatility section than in the returns section (43.61% vs 34.16%). Based on the Baruník and Křehlík (2018) method, pertaining to returns, data of the same type are most dependent on each other, and as we go from short to long term, the correlation and relationship between asset returns decrease. However, this was not the case for volatility. In particular, Bitcoin follows the S&P 500 index more than Ethereum in terms of volatility; however, in stock indices and crude oils, the data of the same type still follow each other the most. In addition, unlike returns, when analyzing volatility, the degree of correlation and connection increases from the short term to the long term. In addition, through moving window analysis, we can easily see a sudden increase in the correlation between the mentioned assets, both in return and volatility, during the COVID-19 outbreak.

By utilizing the wavelet power spectrum, we infer that, in line with the findings from the spillover analysis, the decrease in volatility intensity coincides with the increasing frequency level. A notable phenomenon is the sudden surge in volatility across all datasets (except for Ethereum and Bitcoin) from 700 to 1050. This specific range matches that of the outbreak of the COVID-19 pandemic. We discovered a different method for Ethereum and Bitcoin. Contrary to the behavior of the other data, there was no significant fluctuation in the two selected cryptocurrencies during the COVID-19 pandemic and we did not observe a substantial change.

In the context of the wavelet coherence analysis and all combinations of data, we observed a strong interconnection that coincided with the COVID-19 outbreak. The only exception was the behavior of BTC-ETH. In examining the relationship between BTC-ETH, we observe strong but scattered relationships at different frequencies and periods. In addition, most of the arrows are directed to the right. This finding indicated a positive relationship between these two variables.

Nevertheless, the significant point here is the absence of a strong relationship in the period coinciding with the COVID-19 outbreak, contrary to results obtained from other research data. Moreover, the results show a specific behavior of Bitcoin with each combination of data, particularly during the period matching the COVID-19 pandemic.

These results have several practical implications for portfolio managers, policymakers, investors and researchers. First, because returns and risk are the two main components in investors' decisions to create an asset portfolio, a better understanding of these two variables over time is essential. The findings show that the return and risk spillovers among the variables are different and in opposite forms. In addition, investors have better modified their strategies, which is consistent with diverse market circumstances because of the dynamic features of portfolio weights and optimal hedge ratios. Portfolio managers and investors should consider this when designing optimal asset portfolios. Second, based on the results of the wavelet analysis, cryptocurrencies can be considered to play a unique role in portfolio diversity.

Since cryptocurrencies are characterized by significant spillovers and represent an outstanding level of return and volatility, they can be considered a source of uncertainty compared with commodities such as crude oil, which are regularly considered hedging or safe-haven assets. Therefore, including cryptocurrencies into portfolios regularly collected from traditional financial assets (particularly stocks and fixed income) offers significant diversification benefits. Third, our findings show that return spillovers occur frequently in the short term, while volatility spillovers occur regularly in the long term. This finding indicates that volatility spillovers have long-lasting impacts. Therefore, policymakers and regulators should use appropriate tools that, while alleviating the severity of relevant shocks (such as the COVID-19 pandemic), can dampen their effects.

Abbreviations

TVP-VAR	Time-varying parameter vector auto regressive
WTI	West texas intermediate
GFEVD	Generalized forecast error variance decomposition
VAR	Vector auto regressive
MA	Moving average
CWT	Cross wavelet transform
WPS	Wavelet power spectrum

Acknowledgements
Not applicable.

Author contributions
MMG: Conceptualization, Data curation, Methodology, Investigation, Writing–original draft, Formal analysis. AAMM: Software, editing, Methodology (Spillover analysis). RK: Software, Visualization, Investigation, Methodology (Wavelet analysis). All authors read and approved the final manuscript.

Funding
The authors declare that this research received no specific financial support from any funding agency in the public, commercial, or not-for-profit sectors.

Availability of data and materials
The datasets used and/or analyzed during the current study are available upon request.

Declarations

Competing interests
The authors declare that they have no competing interests.

Received: 23 September 2022 Accepted: 27 February 2024
Published online: 18 June 2024

References
Agyei SK, Adam AM, Bossman A et al (2022) Does volatility in cryptocurrencies drive the interconnectedness between the cryptocurrencies market? Insights from Wavelets. Cogent Econ Financ 10:2061682
Aharon DY, Umar Z, Vo XV (2021) Dynamic spillovers between the term structure of interest rates, bitcoin, and safe-haven currencies. Financ Innov 7:1–25
Akhtaruzzaman M, Boubaker S, Sensoy A (2021) Financial contagion during COVID–19 crisis. Financ Res Lett 38:101604
Ali SRM, Mensi W, Anik KI et al (2022) The impacts of COVID-19 crisis on spillovers between the oil and stock markets: evidence from the largest oil importers and exporters. Econ Anal Policy 73:345–372
Arif M, Hasan M, Alawi SM, Naeem MA (2021) COVID-19 and time-frequency connectedness between green and conventional financial markets. Glob Financ J 49:100650
Arouxet MB, Bariviera AF, Pastor VE, Vampa V (2022) Covid-19 impact on cryptocurrencies: evidence from a wavelet-based Hurst exponent. Phys A Stat Mech Appl 596:127170
Bai J, Perron P (1998) Estimating and testing linear models with multiple structural changes. Econometrica 66(47):78
Balcilar M, Ozdemir H, Agan B (2022) Effects of COVID-19 on cryptocurrency and emerging market connectedness: empirical evidence from quantile, frequency, and lasso networks. Phys A Stat Mech Appl 604:127885
Baruník J, Křehlík T (2018) Measuring the frequency dynamics of financial connectedness and systemic risk. J Financ Econ 16:271–296
Batten JA, Kinateder H, Szilagyi PG, Wagner NF (2019) Time-varying energy and stock market integration in Asia. Energy Econ 80:777–792
Baur DG, Lucey BM (2010) Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. Financ Rev 45:217–229
Bhuiyan RA, Husain A, Zhang C (2021) A wavelet approach for causal relationship between bitcoin and conventional asset classes. Resour Policy 71:101971
Bouri E, Das M, Gupta R, Roubaud D (2018) Spillovers between Bitcoin and other assets during bear and bull markets. Appl Econ 50:5935–5949
Caferra R (2022) Sentiment spillover and price dynamics: Information flow in the cryptocurrency and stock market. Phys A Stat Mech Appl 593:126983
Conlon T, Corbet S, McGee RJ (2020) Are cryptocurrencies a safe haven for equity markets? An international perspective from the COVID-19 pandemic. Res Int Bus Financ 54:101248
Dai Z, Zhu H, Zhang X (2022) Dynamic spillover effects and portfolio strategies between crude oil, gold and Chinese stock markets related to new energy vehicle. Energy Econ 109:105959
Diebold FX, Yilmaz K (2012) Better to give than to receive: predictive directional measurement of volatility spillovers. Int J Forecast 28:57–66
Diebold FX, Yılmaz K (2014) On the network topology of variance decompositions: measuring the connectedness of financial firms. J Econ 182:119–134
Elliott G, Müller UK (2003) Optimally testing general breaking processes in linear time series models
Elsayed AH, Nasreen S, Tiwari AK (2020) Time-varying co-movements between energy market and global financial markets: Implication for portfolio diversification and hedging strategies. Energy Econ 90:104847
Ferrer R, Benítez R, Bolós VJ (2021) Interdependence between green financial instruments and major conventional assets: a wavelet-based network analysis. Mathematics 9:900
Foroutan P, Lahmiri S (2022) The effect of COVID-19 pandemic on return-volume and return-volatility relationships in cryptocurrency markets. Chaos Solitons Fractals 162:112443
Gambarelli L, Marchi G, Muzzioli S (2023) Hedging effectiveness of cryptocurrencies in the European stock market. J Int Financ Mark Inst. Money 84:101757
Ghazani MM, Khosravi R, Barak S (2022) Nexus of COVID-19 and carbon prices in the EU emission trading system: evidence from multifractal and the wavelet coherence approaches. Environ Sci Pollut Res 27:41293–41308

Goodell JW (2020) COVID-19 and finance: agendas for future research. Financ Res Lett 35:101512
Goupillaud P, Grossmann A, Morlet J (1984) Cycle-octave and related transforms in seismic signal analysis. Geoexploration 23:85–102
Ha LT (2023) An application of Bayesian vector heterogeneous autoregressions to study network interlinkages of the crude oil and gold, stock, and cryptocurrency markets during the COVID-19 outbreak. Environ Sci Pollut Res 30:68609–68624
Hasan M, Naeem MA, Arif M et al (2022) Liquidity connectedness in cryptocurrency market. Financ Innov 8:1–25
Hong H, Bian Z, Lee C-C (2021) COVID-19 and instability of stock market performance: evidence from the US. Financ Innov 7:1–18
Iqbal N, Naeem MA, Suleman MT (2022) Quantifying the asymmetric spillovers in sustainable investments. J Int Financ Mark Inst Money 77:101480
Ji Q, Bouri E, Lau CKM, Roubaud D (2019) Dynamic connectedness and integration in cryptocurrency markets. Int Rev Financ Anal 63:257–272
Jiang Y, Lie J, Wang J, Mu J (2021) Revisiting the roles of cryptocurrencies in stock markets: a quantile coherency perspective. Econ Model 95:21–34
Jiang Y, Tian G, Mo B (2020) Spillover and quantile linkage between oil price shocks and stock returns: new evidence from G7 countries. Financ Innov 6:1–26
Kang SH, McIver RP, Hernandez JA (2019) Co-movements between Bitcoin and Gold: a wavelet coherence analysis. Phys A Stat Mech Appl 536:120888
Kirikkaleli D (2021) Analyses of wavelet coherence: financial risk and economic risk in China. J Financ Econ Policy 13:587–599
Kirikkaleli D, Gokmenoglu KK (2020) Sovereign credit risk and economic risk in Turkey: empirical evidence from a wavelet coherence approach. Borsa Istanbul Rev 20:144–152
Kirikkaleli D, Ozun A (2019) Co-movement of political risk and sovereign credit risk: a wavelet coherence analysis for Argentina, Brazil, and Venezuela. Soc Sci Q 100:2094–2114
Köchling G, Müller J, Posch PN (2019) Does the introduction of futures improve the efficiency of Bitcoin? Financ Res Lett 30:367–370
Koop G, Pesaran MH, Potter SM (1996) Impulse response analysis in nonlinear multivariate models. J Econ 74:119–147
Kumah SP, Abbam DA, Armah R, Appiah-Kubi E (2021) African financial markets in a storm: cryptocurrency safe havens during the COVID-19 pandemic. J Res Emerg Mark 3:60–70
Kumah SP, Mensah JO (2022) Are cryptocurrencies connected to gold? A wavelet-based quantile-in-quantile approach. Int J Financ Econ 27:3640–3659
Kumah SP, Odei-Mensah J (2021) Are Cryptocurrencies and African stock markets integrated? Q Rev Econ Financ 81:330–341
Kumah SP, Odei-Mensah J (2022) Do cryptocurrencies and crude oil influence each other? Evidence from wavelet-based quantile-in-quantile approach. Cogent Econ Financ 10:2082027
Kumah SP, Odei-Mensah J, Baaba Amanamah R (2022) Co-movement of cryptocurrencies and African stock returns: a multiresolution analysis. Cogent Bus Manag 9:2124595
Kumar A, Iqbal N, Mitra SK et al (2022) Connectedness among major cryptocurrencies in standard times and during the COVID-19 outbreak. J Int Financ Mark Inst Money 77:101523
Kumar S, Jain R, Balli F, Billah M (2023) Interconnectivity and investment strategies among commodity prices, cryptocurrencies, and G-20 capital markets: a comparative analysis during COVID-19 and Russian-Ukraine war. Int Rev Econ Financ 88:547–593
Liu Y, Wei Y, Wang Q, Liu Y (2022) International stock market risk contagion during the COVID-19 pandemic. Financ Res Lett 45:102145
Loughran T, McDonald B (2023) Management disclosure of risk factors and COVID-19. Financ Innov 9:1–9
Malik F, Umar Z (2019) Dynamic connectedness of oil price shocks and exchange rates. Energy Econ 84:104501
Mensi W, Al Rababa'a AR, Vo XV, Kang SH (2021) Asymmetric spillover and network connectedness between crude oil, gold, and Chinese sector stock markets. Energy Econ 98:105262
Mensi W, Naeem MA, Vo XV, Kang SH (2022) Dynamic and frequency spillovers between green bonds, oil and G7 stock markets: Implications for risk management. Econ Anal Policy 73:331–344
Mensi W, Rehman MU, Maitra D et al (2020) Does bitcoin co-move and share risk with Sukuk and world and regional Islamic stock markets? Evidence using a time-frequency approach. Res Int Bus Financ 53:101230
Mensi W, Sensoy A, Aslan A, Kang SH (2019) High-frequency asymmetric volatility connectedness between Bitcoin and major precious metals markets. North Am J Econ Financ 50:101031
Mestre R (2021) A wavelet approach of investing behaviors and their effects on risk exposures. Financ Innov 7:1–37
Naeem MA, Karim S, Uddin GS, Junttila J (2022) Small fish in big ponds: connections of green finance assets to commodity and sectoral stock markets. Int Rev Financ Anal 83:102283
Orhan A, Kirikkaleli D, Ayhan F (2019) Analysis of wavelet coherence: service sector index and economic growth in an emerging market. Sustainability 11:6684
Özdemir O (2022) Cue the volatility spillover in the cryptocurrency markets during the COVID-19 pandemic: evidence from DCC-GARCH and wavelet analysis. Financ Innov 8:1–38
Panagiotidis T, Stengos T, Vravosinos O (2019) The effects of markets, uncertainty and search intensity on bitcoin returns. Int Rev Financ Anal 63:220–242
Pesaran HH, Shin Y (1998) Generalized impulse response analysis in linear multivariate models. Econ Lett 58:17–29
Qureshi S, Aftab M, Bouri E, Saeed T (2020) Dynamic interdependence of cryptocurrency markets: an analysis across time and frequency. Phys A Stat Mech Appl 559:125077
Rao A, Gupta M, Sharma GD et al (2022) Revisiting the financial market interdependence during COVID-19 times: a study of green bonds, cryptocurrency, commodities and other financial markets. Int J Manag Financ 18:725–755
Rehman MU (2020) Do bitcoin and precious metals do any good together? An extreme dependence and risk spillover analysis. Resour Policy 68:101737

Rehman MU, Ahmad N, Vo XV (2022) Asymmetric multifractal behaviour and network connectedness between socially responsible stocks and international oil before and during COVID-19. Phys A Stat Mech Its Appl 587:126489
Rehman MU, Apergis N (2019) Determining the predictive power between cryptocurrencies and real time commodity futures: Evidence from quantile causality tests. Resour Policy 61:603–616
Salisu AA, Obiora K (2021) COVID-19 pandemic and the crude oil market risk: hedging options with non-energy financial innovations. Financ Innov 7:1–19
Shahzad SJH, Bouri E, Kang SH, Saeed T (2021) Regime specific spillover across cryptocurrencies and the role of COVID-19. Financ Innov 7:1–24
Shahzad SJH, Naifar N, Hammoudeh S, Roubaud D (2017) Directional predictability from oil market uncertainty to sovereign credit spreads of oil-exporting countries: evidence from rolling windows and crossquantilogram analysis. Energy Econ 68:327–339
Tiwari AK, Cunado J, Gupta R, Wohar ME (2018) Volatility spillovers across global asset classes: evidence from time and frequency domains. Q Rev Econ Financ 70:194–202
Torrence C, Compo GP (1998) A practical guide to wavelet analysis. Bull Am Meteorol Soc 79:61–78
Toyoshima Y, Hamori S (2018) Measuring the time-frequency dynamics of return and volatility connectedness in global crude oil markets. Energies 11:2893
Umar M, Farid S, Naeem MA (2022) Time-frequency connectedness among clean-energy stocks and fossil fuel markets: comparison between financial, oil and pandemic crisis. Energy 240:122702
Wei Y, Zhang Y, Wang Y (2022) Information connectedness of international crude oil futures: evidence from SC, WTI, and Brent. Int Rev Financ Anal 81:102100
White R, Marinakis Y, Islam N, Walsh S (2020) Is Bitcoin a currency, a technology-based product, or something else? Technol Forecast Soc Change 151:119877
Xu K-L (2013) Powerful tests for structural changes in volatility. J Econ 173:126–142
Youssef M, Mokni K, Ajmi AN (2021) Dynamic connectedness between stock markets in the presence of the COVID-19 pandemic: does economic policy uncertainty matter? Financ Innov 7:1–27
Zhang D, Hu M, Ji Q (2020) Financial markets under the global pandemic of COVID-19. Financ Res Lett 36:101528
Zhang W, Hamori S (2021) Crude oil market and stock markets during the COVID-19 pandemic: evidence from the US, Japan, and Germany. Int Rev Financ Anal 74:101702

Publisher's Note