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Media coverage of COVID-19 and its relationship with climate change indices: A dynamic connectedness analysis of four pandemic waves

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ABSTRACT

This study explores the impact of the COVID-19 media coverage index (MCI) on the return and volatility connectedness of five MSCI Climate Changes Indices (the USA, Emerging Markets (EMU), Japan, Europe, and the Asia Pacific). The sample period was from 11 March 2020–19 January 2022, divided into sub-samples based on four waves of the COVID-19 pandemic. Thus, we use the time-varying parameter vector autoregression (TVP-VAR) model besides the frequency-dependent connectedness network approach. The key findings are as follows. First, the results demonstrate that the MCI is a net receiver of shocks in all waves, and the highest level of connectedness occurs in the first wave. The findings concerning volatility are similar, with the majority of MSCI Climate Change Indices being net transmitters, potentially indicating the severity of the pandemic. Second, estimating the short-, medium-, and long-term return network connectedness indicates the dominance of strong-term connectedness suggesting the spread of shocks within a week. Our results are robust by replacing MCI with Panic Index (PI). These results have implications for investors and policymakers.

1. Introduction

The novel coronavirus health crisis has significantly influenced the returns and volatility of financial markets (Cheng et al., 2022), creating an unprecedented situation in several countries due to the failure of government policies in managing the repercussions of the crisis (Alshater et al., 2021). This has caused panic among individual and institutional investors, influencing their buying and selling decisions (Aggarwal et al., 2021; Atri et al., 2021; Padungsaksawasdi & Treepongkaruna, 2021). To monitor the impact of the pandemic on the returns and volatility of financial markets, researchers have developed specific COVID-19 news-related indices, such as the media coverage index (MCI), to identify relevant news, especially during a crisis (García, 2013).

Recently, there has been increasing interest in global warming and climate change, which has led to the emergence of sustainable stock indices and the concept of Socially Responsible Investments (SRI). Investors have started to consider low-carbon assets (Monasterolo & De Angelis, 2020) and Environmental, Social, and Governance (ESG) (Clementino and Perkins, 2021) as appealing investment opportunities, attracting an increasing number of investors (Cortez et al., 2009). Several indices dedicated to socially responsible investment have been created, such as the Dow Jones Sustainability Index (DJSI), KLD Analytics, the FTSE4Good Index, and Morgan Stanley Capital International (MSCI). From the MSCI series, we are interested in the index related to climate change (MSCI Climate Change). This index was launched in June 2020 and includes companies that are part of the low-carbon economy.

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With the increasing interest in climate change, a greater understanding of the performance of these indices is important. The pandemic has presented a unique opportunity to study the impact of market sentiment, as proxied by the media coverage index (MCI), on the returns and volatility of climate change indices.

Since the outbreak of the COVID-19 pandemic, literature has focused on the pandemic's impact on financial contagion and equity returns and volatilities (Adekoya & Oliyide, 2021; Akhtaruzzaman et al., 2021; Gubareva, 2021). Many researchers have employed COVID-19 news-related indices for various objectives. For example, Gubareva and Umar (2020) studied the impact and interdependence of the Media Coverage Index (MCI) on the volatility and returns of 11 bond indices using the wavelet approach. Akhtaruzzaman et al. (2022) and Umar & Gubareva (2021b) studied the influence of the MCI on Environmental, Social, and Governance (ESG) indices and found a significant role of the MCI in the volatility of the studied ESG indices. Umar and Gubareva (2021a) studied the influence of the MCI on the volatility of Islamic equity indices and found coherence between the MCI and Islamic stock movements. Furthermore, Umar et al. (2021c) studied the dynamics of selected cryptocurrencies with the MCI, along with additional studies about the role of the MCI on commodity markets, short stocks, and other aspects. Bolton et al. (2020) found that the health crisis caused by the COVID-19 virus and climate change have common elements and argue that the crisis has highlighted interest in sustainability. Moreover, the COVID-19 pandemic offers a great opportunity for businesses to shift towards more genuine and authentic Corporate Social Responsibility (CSR) and contribute to addressing urgent global social and environmental challenges (He and Harris, 2020).

However, the current literature lacks research on the interconnection between climate change indices on one side and the impact of the media coverage index on their performance.

Akhtaruzzaman et al. (2022) have shown that there is a dynamic connection between the COVID-19 media coverage index (MCI) and ESG leader indices. However, it is unclear how precisely this connection functions or how significant its impact will be. MSCI has published articles on how COVID-19 will affect carbon emissions and how to combat global warming,[6] suggesting a possible spillover effect between COVID-19 coverage and MSCI climate change indices due to the pandemic's impact on global markets and investor sentiment. News related to the pandemic has been shown to cause panic, stress, and uncertainty, leading to extreme spillover effects in financial assets. Furthermore, there is an increasing emphasis on climate transition indices, funds, and products in response to the threat of climate change. During the COVID-19, MSCI ESG indexes were contrasted with their parent indexes[7] and COVID-19 coverage may have an impact on investor behavior and ultimately, investments in climate change indices. Both COVID-19 and climate change have a significant impact on society and the economy, which can be attributed to three factors. The first factor is changes in public perceptions and behavior. Media coverage of COVID-19 can influence how people perceive and respond to public health issues, including those related to climate change. The pandemic has brought attention to underlying environmental and social factors that contribute to the spread of diseases, such as air pollution and global travel. This has increased demand for sustainable investments, which are tracked by MSCI climate change indices, and driven investment flows towards companies that are taking steps to address both climate change and public health risks. The second factor is the impact of COVID-19 on the performance of companies that are included in MSCI climate change indices. Due to decreased demand and supply chain disruptions, businesses in the energy and transportation sectors have been particularly hard hit by the pandemic. The performance of the MSCI climate change indices, which track the performance of businesses across various sectors, has been impacted as a result. The third channel is through changes in policy and regulation. Media coverage of COVID-19 can influence policymakers and regulators to introduce new policies or regulations to address public health and environmental challenges. This can then impact the performance of companies included in MSCI climate change indices that are taking steps to address these issues.

This study aims to bridge this gap by investigating the relationship between pandemic-driven market sentiment and indices representative of the low-carbon economy, with a focus on the environmental dimension of socially responsible investment. Specifically, the study explores the relationship between COVID-19 media coverage and the MSCI Climate Change Indices in five major regions during the pandemic. The study also examines the net receiver and net transmitter of return and volatility spillovers and analyzes the short-, medium-, and long-term connectedness networks in the time and frequency domains. Additionally, the study investigates the relationship among media sentiment, panic index, and short selling of the MSCI indices during the COVID-19 health crisis, providing valuable insights for investors and stakeholders. The COVID-19 pandemic has attracted scholars' attention to the behavior of various financial assets (Akhtaruzzaman, Boubaker, & Umar, 2022; Salisu, Vo, & Lawal, 2021). During times of financial or geopolitical turbulence, media coverage may significantly influence investor sentiment. This paper adds to this literature by documenting climate change indices' reactions to the pandemic, providing valuable insights for responsible investors pursuing investments in climate change indices. The findings of this study will also benefit researchers interested in understanding the impact of market sentiment on financial assets during times of crisis.

This study makes several contributions to the literature. First, it contributes to the literature on the COVID-19 health crisis by investigating the role of MCI in the returns and volatilities of equity markets. This helps to understand the stock market's reaction to the pandemic. Second, the paper fills an existing gap related to the dynamic interdependence between MCI and MSCI Climate Change indices, which is an important topic given the strong interest in climate indices. Third, it disentangles the net receiver and net transmitter of return and volatility spillovers during the current pandemic, providing insights to policymakers, portfolio managers, and investors to diversify their portfolios. Fourth, it augments the time-varying parameter vector autoregressive (TVP-VAR) connectedness methodology with the frequency-dependent connectedness networks approach of Ellington and Barunik (2020) to examine the short-, medium-, and long-term connectedness networks at diverse time scales, which has been rarely examined.

Understanding the frequency linkages among financial agents is vital as they behave differently in their investment perceptions (Barunik and Křehlík, 2018). To estimate the connectedness between assets in different frequency horizons, such as short, medium, and long-term, the frequency connectedness (BK) approach was developed by Barunik and Křehlík (2018). Recent studies have focused on measuring frequency linkages among various assets, including Ferrer et al. (2018), Kang et al. (2019), Polat (2019), Naeem et al. (2020), Fousekis and Tzaferi (2021), and Jiang and Chen (2022). However, in our study, we use a novel methodology to analyze frequency-based connectedness. We employ the approach of Ellington and Barunik (2020), which uses a locally stationary TVP VAR model and Quasi-Bayesian Local Likelihood (QBLL) methods to construct frequency-dependent connectedness networks. This approach allows for the estimation of time-varying and locally stationary connectedness networks, accurate and reliable estimation of the model parameters, and construction of frequency-dependent connectedness networks. Our study estimates the transitory and permanent linkages between the returns and volatilities in the four COVID-19 waves, focusing on frequency-dependent returns and volatilities transmissions among the indices. The Bayesian framework of this approach

[6] https://www.msci.com/www/blog-posts/will-coronavirus-reduce/01758503407

[7] https://www.msci.com/www/blog-posts/msci-esg-indexes-during-the/01781235361

allows us to incorporate prior shrinkage and estimate uncertainty from the network's posterior distribution. This is the methodology's main difference from conventional approaches that provide only point estimates by bootstrapping confidence intervals. Moreover, this approach does not suffer from dimensionality and inference issues. Our study supplements the work of Akhtaruzzaman et al., (2021) and Umar and Gubareva (2021b), who examine the impact of MCI on ESG indices, and Haroon and Rizvi (2020) and Cepoi (2020), who examine the effect of media on the market and industry level, respectively.

This study presents several interesting findings. First, the study shows that there is a higher dynamic return connectedness than volatility connectedness, with medium to high spillover between various MSCI Climate Change Indices and the MCI. This suggests that the returns of the markets are more related than the volatility of the markets. Second, the study finds that the highest average total connectedness indices among both return and volatility series were observed in the first pandemic wave, indicating that the markets reacted more strongly during the first wave of the pandemic than in the following waves. This is consistent with previous studies (Umar et al., 2022b). Third, the study reveals that the MCI is a net receiver of shocks for return spillovers in all waves, contrary to the expectation that information transmission is from the MCI to the MSCI Climate Change Index. However, the MCI is a net transmitter of volatility shock in the second and fourth waves, indicating that the relationship between the indices is more complex than previously thought, and the MCI may be influenced by other factors in addition to the MSCI Climate Change Indices. Fourth, the study distinguishes the different behaviors of the indices in the COVID-19 waves and shows how the market reacted differently during the different waves of the pandemic and how the behavior of the indices changed during this period. Fifth, the study suggests potential contagion effects in financial markets due to the high connectedness between returns and volatility of financial markets, consistent with previous studies (So et al., 2020; Bouri et al., 2021; Benlagha and El Omari, 2022). Thus, our results support the expectation that investors pursue sustainable investments as a hedging strategy. Finally, the study shows that geographical proximity plays a role in measuring the connectedness of climate change indices, and the findings support geographical market segmentation. This suggests that the relationship between the indices varies depending on the region and that the market behavior in different regions is not the same. This finding is unsurprising and signifies that geographical proximity plays a role in measuring the connectedness of climate change indices.

The frequency-dependent network structure revealed several interesting findings. Firstly, short-term (transitory) return linkages were found to be larger relative to medium and long-term (persistent) interdependencies only during the first wave, while links in the medium term appeared to be stronger for all other waves. This is consistent with the idea that the relationship between indices is more disrupted in shorter horizons. This finding demonstrates that shorter horizons dominate both return and volatility spillovers and is in line with previous studies (Polat, 2021; Alshater et al., 2022; Umar et al., 2022b; Umar et al., 2022c). Secondly, the short-term total connectedness index (TCI) peaked on 30 June 2020 (43.39 %) during the first wave, while the TCIs for the medium and permanent connections peaked respectively on 10 December 2021 (32.27 %) and 13 November 2020 (26.91 %) during the third wave. Thirdly, the results suggest that Europe and the EMU transmit the largest spillovers using short-term network connectedness topologies for both returns and volatilities, while the MCI propagates the lowest total spillovers. Fourthly, Europe and the EMU exhibit close association for returns and volatilities in every period, indicating that investment horizons can be a source of risk.

The remainder of this paper is organized as follows. Section 2 presents the data. Section 3 explains the methodology used in this study. Section 4 provides the empirical results, and Section 5 concludes the paper.

2. Data

Our dataset consists of daily prices of five MSCI Climate Change Indices (USA, EMU, Japan, Europe, and the Asia Pacific) collected from Refinitiv. We use the RavenPack Coronavirus MCI to measure media coverage of the pandemic and the Panic Index (PI) to measure panic and hysteria led by the pandemic as a robustness test.[8] The returns are calculated as the first difference of the logarithmic price, whereas volatility is estimated using 10-day rolling historical volatility. The historical volatility is calculated as the annualized standard deviation of log returns of closing prices in a 10-day rolling window. The 10-day rolling historical volatility, which was extensively used by researchers, analysts, and traders in determining portfolio strategies, is used for two reasons. First, it is a measure of past performance and a statistical measure of the dispersion of returns. Second, it allows for a more long-term interpretation of risk (Umar et al., 2022a).

The sample period was from 11 March 2020[9] to 19 January 2022, starting from when the coronavirus began affecting countries before being officially declared a global pandemic by the WHO. Following (Iftimie et al., 2021), this period was divided into four waves to track the pandemic evolution[10]: The first wave (11 March 2020–30 June 2020), the second wave (1 July 2020–15 October 2020), the third wave (1 November 2020–31 March 2021), and the fourth wave (1 December 2021–19 January 2022). Table 1 presents the descriptive statistics for the entire sample period.

Notably, the USA MSCI Climate Change Index has the highest mean (2384.20) among MSCI indices, whereas Europe has the lowest mean value of 1285.37 over the study period. The average value of MCI is 69.97, indicating that 70% of news is related to the pandemic. All the MSCI Climate Change Indices and the MCI have negative skewness values, indicating a fatter tail on the left side of their distribution. Kurtosis statistics propose the leptokurtic nature of asset returns. Excess Jarque-Bera (JB) values indicate that the series are non-normally distributed. Fig. 1 displays the dynamics of MSCI Climate Change Indices and the MCI from 11 March 2020–19 January 2022.

All MSCI Climate Change Indices surged from the second half of March 2020, following a common trend. The MSCI indices peaked in late 2021 (EMU in November 2021, and Japan in September 2021) or early 2022 (Europe and the USA in January 2022, and the Asia Pacific in February 2022). The MCI skyrocketed following the official announcement of COVID-19 as a pandemic, reaching its peak on 4 April 2020 (82.95).

3. Methodology

We apply two methodologies to measure both the time and frequency-based connectedness using the time-varying parameter vector autoregressive (TVP-VAR) model (Antonakakis et al., 2020) and the frequency approach (Ellington and Barunik, 2020).

Both methodologies have several advantages over other methods used in previous literature, particularly wavelet-based methods. One major advantage is that these approaches can handle time-varying volatility in the data, which is a common feature of many economic and financial time series. Second, they can capture the dynamic interactions between different variables in the data, rather than just focusing on individual time series. Third, they can provide more accurate and reliable predictions of future trends and patterns in the data, as they are

[8] See Appendix Table A1 for more details.

[9] The official announcement of the COVID-19 pandemic by the World Health Organization (WHO) on 11 March 2020.

[10] The first two waves were selected following Iftimie et al. (Iftimie et al., 2021), while the third and fourth waves were selected by tracking the pandemic evolution (https://coronavirus.jhu.edu/data/new-cases) and focusing on the trends in the total cases.

Table 1
Summary statistics for MSCI climate change indices and MCI.

	Mean	Maximum	Minimum	Skewness	Kurtosis	Jarque-Bera
USA	2384.20	3031.22	1355.05	-0.35	-0.88	25.36***
EMU	1362.72	1644.98	881.36	-0.32	-1.01	28.99***
Japan	1461.39	1720.03	1016.80	-0.57	-0.90	42.69***
Europe	1285.37	1522.85	894.36	-0.27	-1.01	26.26***
Asia Pasific	1473.81	1715.27	1020.13	-0.81	-0.52	59.10***
MCI	69.97	82.95	55.86	-0.18	-0.86	17.24***

Notes: *** indicates 1 % significance level.

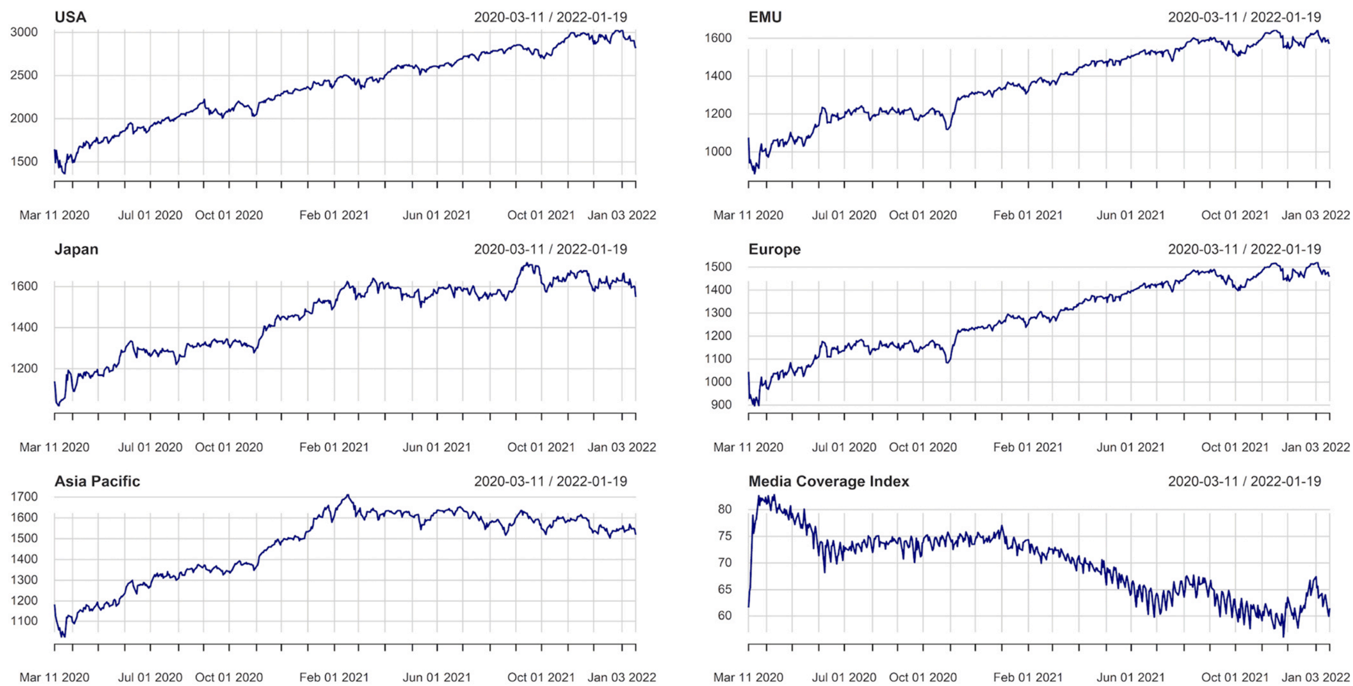

Fig. 1. Dynamics of MSCI Climate Change Indices and the MCI.

able to account for the non-linear and non-stationary nature of many time series. Moreover, the second model's advantage is that it allows us to uncover spillovers while accounting for the investment horizons of market participants that often vary across frequencies. Such an analysis allows for a more comprehensive and detailed exploration of the frequency components of the data. This is especially useful for economic and financial applications, where the data is often characterized by high volatility and non-stationary behavior. It is also useful and informative as it allows traders, investors, risk managers, and arbitragers to adjust their portfolios and risk management strategies according to their investment horizons.

Although several studies have examined the frequency-domain connectedness using Baruník and Křehlík (2018), only a limited number of studies have examined the frequency-based connectedness network based on the TVP-VAR model by implementing the methodology of Ellington and Barunik (2020). These two approaches have some different features, while they both compute connectedness in different frequency horizons. First, the latter employs a locally stationary TVP VAR model using Quasi-Bayesian Local Likelihood (QBLL) methods to construct frequency-dependent connectedness networks. This methodology provides a more powerful and flexible framework for exploring frequency-based connectedness that allows for the estimation of time-varying and locally stationary connectedness networks, while Baruník and Křehlík (2018) approach uses a simpler framework based on cross-correlations between frequency bands. Additionally, the use of QBLL methods allows for a more accurate and reliable estimation of the model parameters, which can improve the overall performance of the connectedness analysis. This methodology can provide a more accurate and reliable analysis of the frequency-based connectedness in the financial markets and other complex systems.

3.1. Time-varying parameter vector autoregressive connectedness

We investigate the nexus between the MSCI Climate Change Indices and MCI using the time-varying parameter vector autoregressive (TVP-VAR) model by Antonakakis et al. (2020), which extends the originally proposed dynamic connectedness by Diebold and Yilmaz (2009); Diebold and Yilmaz (2012). Using the TVP-VAR model has three main advantages: (1) there is no loss of observations, (2) it can handle low-frequency data, and (3) it does not depend on an arbitrary selection of the rolling window size. Specifically, we apply this methodology to analyze the pandemic's degree of influence on the returns and volatilities of the MSCI Climate Change Index, as measured by the MCI.

The TVP-VAR model is specified as follows:

$$y_t = \beta_t z_{t-1} + u_t,\ u_t \sim N(0, S_t), \tag{1}$$

$$vec(\beta_t) = vec(\beta_{t-1}) + v_t,\ v_t \sim N(0, R_t), \tag{2}$$

where y_t and z_{t-1} are $N \times 1$ and $Np \times 1$ dimensional vectors, respectively. $\beta_t$is $N \times Np$ dimensional time-varying coefficient matrix, while u_t is $N \times 1$ dimensional error disturbance vector with an $N \times N$ time-varying variance-covariance matrix S_t. Finally, v_t is $N^2p \times 1$ dimensional error matrix, with an $N^2p \times N^2p$ time-varying variance-covariance matrix of the error term R_t.

We use the Wold theorem (Eq. 3) to transform the TVP-VAR into the TVP-vector moving average (VMA) to calculate the generalized impulse response function (GIRF) and generalized forecast error variance decomposition (GFEVD) developed by Koop et al. (1996) and Pesaran and Shin (1998).

$$y_t = A_t u_{t-1} + u_t. \tag{3}$$

Due to shocks to variable j, we focus on the h-step error variance in forecasting variable i.

$$\widetilde{\varphi}^g_{ij,t}(h) = \frac{\sum_{t=1,}^{h-1} \widetilde{\psi}^{2,g}_{ij,t}}{\sum_{i=1}^{N} \sum_{t=1,}^{h-1} \widetilde{\psi}^{2,g}_{ij,t}}, \tag{4}$$

where $\widetilde{\varphi}^g_{ij,t}(h)$ denotes the h-step ahead of GFEVD, $\widetilde{\psi}^g_{ij,t}(h) = S^{-\frac{1}{2}}_{ij,t} A_{h,t} \Sigma_t u_{ij,t}$; $\sum_{j=1,}^{N} \widetilde{\varphi}^g_{ij,t}(h) = 1$ and $\sum_{i,j=1,}^{N} \widetilde{\varphi}^N_{ij,t}(h) = N$.

The total connectedness index (TCI) is constructed from GEVD, as follows:

$$C^g_t(h) = \frac{\sum_{i,j=1,i\neq j}^{N} \widetilde{\varphi}^g_{ji,t}(h)}{\sum_{i,j=1}^{N} \widetilde{\varphi}^g_{ji,t}(h)} \times 100. \tag{5}$$

Eq. (6) measures the 'total directional connectedness to others' (TO), or the degree to which a shock in variable i affects the other variable j.

$$TO_{jt} = C^g_{i\to j,t}(h) = \frac{\sum_{j=1,i\neq j}^{N} \widetilde{\varphi}^g_{ji,t}(h)}{\sum_{i,j=1}^{N} \widetilde{\varphi}^g_{ji,t}(h)} \times 100. \tag{6}$$

Eq. (7) measures the 'total directional connectedness from others' (FROM), or the influence all other variables j have on variable i.

$$FROM_{jt} C^g_{i\leftarrow j,t}(h) = \frac{\sum_{j=1,i\neq j}^{N} \widetilde{\theta}^g_{ij,t}(h)}{\sum_{i,j=1}^{N} \widetilde{\theta}^g_{ij,t}(h)} \times 100 \tag{7}$$

Finally, Eq. (8) measures the 'net total directional connectedness' (NET) to indicate whether a variable is a net transmitter driving the network (positive value) or a net receiver driven by the network (negative value).

$$NET_{jt} = TO_{jt} - FROM_{jt} = C^g_{i\to j,t}(h) - C^g_{i\leftarrow j,t}(h) \tag{8}$$

3.2. The frequency-based TVP-VAR network connectedness

Given that TVP-VAR is useful to estimate the spillover effects in the time domain, it is important to determine whether the results are coincident across different frequency domains. Ellington and Barunik (2020) introduced a dynamic network form, which indicates the effects of transitory and persistent shocks from i on the future variance of j.

This methodology employs a locally stationary TVP-VAR model by using Quasi-Bayesian Local Likelihood (QBLL) methods. The framework of the methodology embodies prior shrinkage and estimating uncertainty from the posterior distribution of the network. Additionally, this methodology is not influenced by dimensionality issues with inference. This novel structure of this approach is more advantageous than the conventional methodologies that employ only point estimates by bootstrapping for confidence intervals. All in all, this approach estimates connectedness networks in different frequency horizons.

The model is defined as follows:

Let's define $(Y_{t,T})_{1\le t\le T, T\epsilon N}$ with $Y_{t,T} = (Y^1_{t,T}, \ldots, Y^N_{t,T})^T$, where t denotes the time index and T as the "sharpness of the local approximation of the time series $(Y_{t,T})_{1\le t\le T, T\epsilon N}$ by a stationary one" (Ellington and Barunik, 2020).

(Ellington and Barunik, 2020) structure $(Y_{t,T})_{1\le t\le T, T\epsilon N}$ as follows:

$$Y_{t,T} = \varphi_1(t/T) Y_{t-1,T} + \ldots + \varphi_p(t/T) Y_{t-p,T} + \epsilon_{t,T}, \tag{9}$$

where $\epsilon_{t,T} = \Sigma^{-\frac{1}{2}}(t/T)\rho_{t,T}$ with $\rho_{t,T} \sim NID(0, I_N)$, and $\varphi(t/T) = (\varphi_1(t/T), \ldots, \varphi_p(t/T))^T$are time-varying autoregressive coefficients. At fixed time neighborhood of $v_0 = t_0/T$, a stationary process $\widetilde{Y}_t(v_0)$ approximates the process $Y_{t,T}$ as

$$\widetilde{Y}_t(v_0) = \varnothing_1(v_0)\widetilde{Y}_{t-1}(X_0) + \ldots + \varnothing_p(v_0)\widetilde{Y}_{t-p}(v_0) + \pi_t \tag{10}$$

with $t \in \mathbb{Z}$ and suitable regularity conditions $|Y_{t,T} - \widetilde{Y}_t(v_0)| = O_p(|t/T - v_0| + 1/T)$ are satisfied. The time-varying $VMA(\infty)$ representation of the process is given as:

$$Y_{t,T} = \sum_{h=-\infty}^{\infty} \Psi_{t,T}(h)\pi_{t-h} \tag{11}$$

here $\Psi_{t,T} \approx \Psi(t/T, h)$ is a stochastic process with $\sup_l \| \Psi_t - \Psi_l \|^2 = O_p(h/t)$ for $1 \le h \le t$ as $t \to \infty$. The spectral density of $Y_{t,T}$ at frequency, d is defined as:

$$S_Y(v, w) = \sum_{h=-\infty}^{\infty} E[\widetilde{Y}_{t+h}(v)\widetilde{Y}_t^T(v)]e^{-iwh} = \{\Psi(v)e^{-iw}\}\Sigma(v)\{\Psi(v)e^{+iw}\}^T \tag{12}$$

Let $Y_{t,T}$ is a weakly locally stationary process with $\sigma^{-1}_{kk}\sum_{h=0}^{\infty}[\Psi(v)e^{-iw}\Sigma(v)]_{j,k} < \infty, \forall j, k$. The time-frequency variance decompositions of the jth variable at a rescaled time $v = t_0/T$ due to shock in ith variable on the frequency band $d = (a, b)$: a, $b\epsilon(-\pi, \pi)$, $a < b$ form a dynamic adjacency matrix

$$[\theta(v, d)]_{j,i} = \frac{\sigma^{-1}_{kk}\int_a^b |[\Psi(v)e^{-iw}\Sigma(v)]_{j,k}|^2 dw}{\int_{-\pi}^{\pi}[\{\Psi(v)e^{-iw}\}\Sigma(v)\{\Psi(v)e^{+iw}\}^T]_{j,j} dw} \tag{13}$$

We normalize each element in the row of the network by the corresponding row sum:

$$[\widetilde{\theta}(v, d)]_{j,k} = [\theta(v, d)]_{j,k} / \sum_{i=1}^{N}[\theta(v)]_{j,k} \tag{14}$$

4. Empirical results

The empirical analysis is conducted as follows. The first part investigates the static and dynamic spillover effects of both the return and volatility in the time domain using TVP-VAR. The second part explores the spillover effects in the frequency domain using (Ellington and Barunik, 2020).

4.1. Time-based connectedness

4.1.1. Dynamic connectedness

The first step was to estimate the time-varying return connectedness among the MSCI Climate Change Indices and the MCI for the four COVID-19 pandemic waves using TVP-VAR connectedness analysis. Fig. 2 demonstrates that the TCI for the first COVID-19 wave fluctuated between 79.83 % and 81.66 %. It increased slightly between March 15th and March 18th, 2020. The index dropped moderately before peaking on June 30th, 2020 (81.66 %). The TCI reached considerably low values during the second wave and oscillated between 49.08 % and

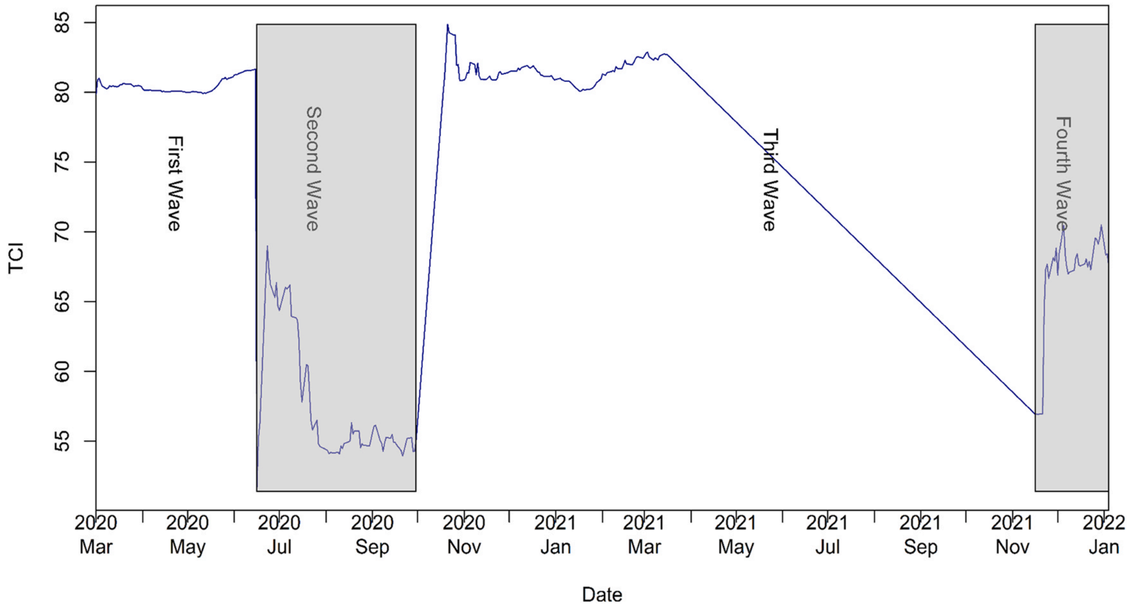

Fig. 2. Dynamic returns connectedness of the MSCIs and the MCI for the four COVID-19 pandemic waves.

59.46 %. It peaked on July 21st, 2020, coinciding with the global spread of the Delta variant. During the third wave, TCI fluctuated between 77.39 % and 80.56 %, and it increased in the fourth wave from 65.09 % to 73.02 % approximately, peaking on January 11th, 2022. This sharp rise in return connectedness can be associated with the emergence of the Omicron variant in late November 2021. Thus, the highest TCI observed during the first wave suggests that a significant increase in vaccination globally or alleviating the virus's symptoms may reduce interconnectedness in subsequent periods.

Because the virus was still new and little was known about its spread and impact, the first wave of outbreaks was marked by a high level of uncertainty and unpredictability. This may have led to a stronger connectedness, as investors may have been more reactive to news and information about the pandemic. As the outbreak progressed and more information became available, the impact of MCI may have decreased. For example, in the second and third waves of outbreaks, investors may have become more accustomed to the impacts of the pandemic and may have incorporated this information into their investment strategies. In the fourth wave of the outbreak, the situation might be different as the pandemic is still ongoing and the number of cases and deaths are increasing, but on the other side, the vaccination is being distributed, and the possibility of having a new normal is coming into sight. This could lead to a change in investors' perceptions and expectations about the future, which could affect the level of connectedness. Thus, the level of connectedness changes based on the four waves of outbreaks, as investors' perceptions and expectations about the pandemic and its impacts may evolve.

The second step involved estimating the average spillovers among the return series for the four waves, as presented in Table 2. The four key factors are the average TCI, unidirectional spillovers, total spillovers to and from a particular asset, and net directional spillovers for individual assets. The first COVID-19 wave indicated that, on aggregate, MSCI Climate Change Indices propagated more (77.02 %) to the MCI than they received (49.89 %). All MSCI indices were net transmitters of shocks, whereas the MCI was the persistent net receiver. The Asia Pacific was the largest transmitter of risk (88.54 %), followed by Europe (88.17 %). On the other hand, the MCI received the least from the MSCI indices. This finding is not surprising and signifies the prominent roles of the Asia Pacific and Europe in transmitting return shocks during the first wave. The directional spillovers and TCI were considerably low compared to the first wave, which can be related to a significant drop in the COVID-19 mortality rates. During the second wave, the USA, Europe, and the Asia Pacific maintained their roles as net risk transmitters, whereas EMU, Japan, and the MCI became net receivers. It should be noted that the second wave corresponds to the discovery of the SARS-CoV-2 Delta variant and the pandemic's rapid spread in the United States, Europe, and Asia Pacific. Therefore, our findings of these countries transmitting the highest return spillovers to the other nodes can be related to this. Likewise, the Asia Pacific catalysts had the highest risk (80.28 %) compared to others, and the MCI received the lowest risk from the MSCI Climate Change Indices. The TCI in the third wave was higher compared to the second wave. As clearly shown in Fig. 2 and in line with our result, the overall TCI skyrocketed in October 2020 with the emergence of the Delta variant. Cumulatively, MSCI indices transmitted more (76.96 %) to the MCI than they received (37.32 %). All MSCI indices were net transmitters of shocks, whereas the MCI was a net receiver. Japan received the highest risk spillovers to and from other indices (80.02 % and 93.67 %, respectively). This finding is rather surprising yet consistent with that of Karako et al. (2021). Finally, the MCI and the Asia-Pacific were net receivers during the fourth wave, whereas the other MSCI indices (USA, EMU, Japan, and Europe) were the net transmitters. Europe transmitted the largest spillovers, while Asia-Pacific received the lowest spillovers from the other indices. It should be noted that the Omicron variant originated in this period, and the number of identified cases, particularly in Europe, notably surged during this wave. However, the MCI continued to be a net risk receiver but transmitted considerably higher spillovers to the MSCI indices (particularly for the EMU and Europe) compared to the other waves. Cumulatively, the MSCI indices transmitted more (69.03%) to the MCI than they received (36.07%).

The results once again support that the relationship is based on the four waves of outbreaks. The reasons for this are twofold. First, as the pandemic progressed and more information became available, investors may have become more accustomed to the impacts of the pandemic and

Table 2
Average returns connectedness results for the MSCIs and the MCI.

First COVID-19 Wave	USA	EMU	Japan	Europe	Asia Pacific	MCI	FROM
USA	19.34	17.41	16.71	18.13	18.1	10.3	80.66
EMU	17.03	18.81	17.64	18.68	17.98	9.87	81.19
Japan	17.01	18.15	18.82	18.15	18.11	9.78	81.18
Europe	17.76	18.39	17.45	18.7	17.97	9.72	81.3
Asia Pacific	17.74	17.94	17.38	18.17	18.54	10.22	81.46
MCI	16.44	14.9	14.27	15.04	16.38	22.98	77.02
Contribution TO others	85.98	86.8	83.46	88.17	88.54	49.89	482.83
NET directional connectedness	5.31	5.6	2.27	6.87	7.08	-27.14	**TCI = 80.4**
Third COVID-19 Wave	**USA**	**EMU**	**Japan**	**Europe**	**Asia Pacific**	**MCI**	**FROM**
USA	21.09	16.55	18.94	16.87	19.57	6.98	78.91
EMU	17.68	20.49	18.83	20.16	15.55	7.3	79.51
Japan	18.43	17.49	19.98	17.27	18.27	8.56	80.02
Europe	18.13	20.18	18.35	20.57	15.93	6.85	79.43
Asia Pacific	20.16	15.37	19.42	15.81	21.61	7.63	78.39
MCI	14.88	12.6	18.13	12.36	19	23.04	76.96
Contribution TO others	89.27	82.17	93.67	82.47	88.31	37.32	473.22
NET directional connectedness	10.36	2.66	13.66	3.04	9.92	-39.65	**TCI = 78.8**

Second COVID-19 Wave	USA	EMU	Japan	Europe	Asia Pacific	MCI	FROM
USA	57.25	6.56	7.56	5.35	4.66	18.62	42.75
EMU	6.55	37.03	1.78	34.61	1.47	18.55	62.97
Japan	4.68	9.73	55.22	10.78	15.07	4.54	44.78
Europe	5.28	37.7	2.86	39.15	1.42	13.59	60.85
Asia Pacific	4.37	10.35	14.22	9.16	53.29	8.61	46.71
MCI	21.49	15.39	0.84	12.07	0.68	49.53	50.47
Contribution TO others	42.37	79.73	27.27	71.97	23.3	63.9	308.54
NET directional connectedness	15.87	-2.04	-6.96	0.83	16.76	-24.46	**TCI = 52.9**
Fourth COVID-19 Wave	**USA**	**EMU**	**Japan**	**Europe**	**Asia Pacific**	**MCI**	**FROM**
USA	33.66	16.99	16.59	21.12	4.28	7.36	66.34
EMU	16.02	28.03	12.32	27.35	4.06	12.22	71.97
Japan	20.5	15.49	31.93	18.53	10.2	3.35	68.07
Europe	19.11	25.25	14.66	26.9	3.26	10.81	73.1
Asia Pacific	16.09	12.93	16.9	12.31	39.44	2.33	60.56
MCI	15.35	19.25	9.19	19.92	5.58	30.7	69.3
Contribution TO others	87.07	89.91	69.67	99.24	27.39	36.07	409.34
NET directional connectedness	20.73	17.95	1.59	26.14	-33.17	-33.23	**TCI = 68.2**

Notes: This table reports the average connectedness results for the returns. Pairwise spillovers and total connectedness indices (TCIs) are also provided.

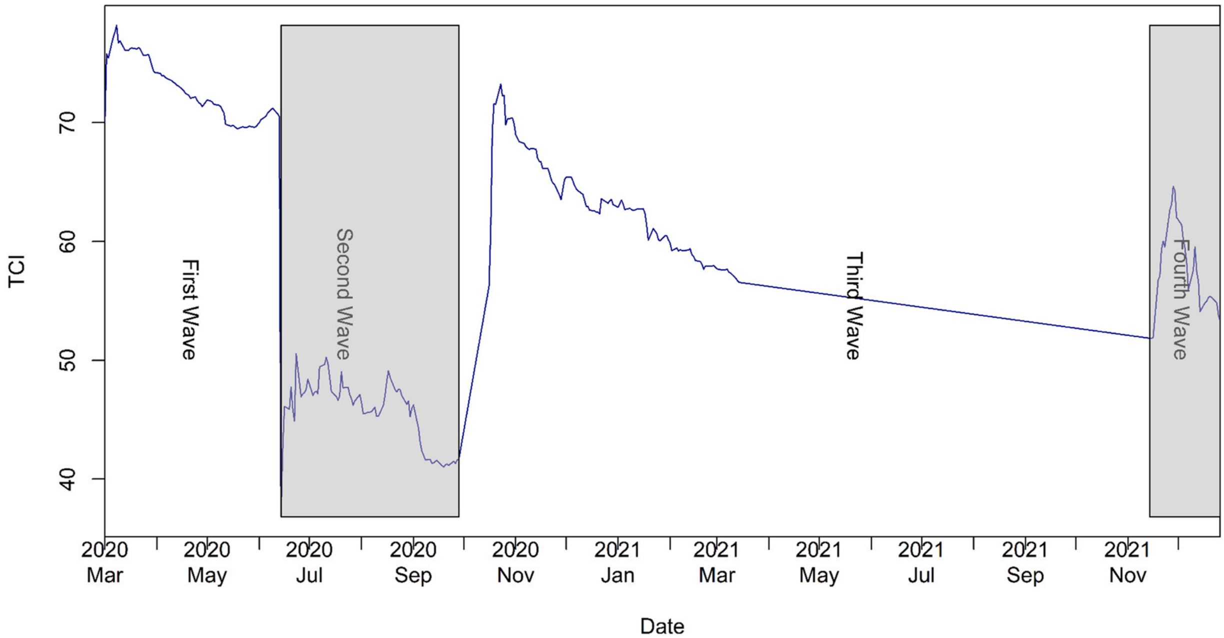

Fig. 3. Dynamic volatilities connectedness of the MSCIs and the MCI for the four waves of the COVID-19 pandemic.

may have incorporated this information into their investment strategies, which could lead to a decrease in the impact of MCI on the returns and volatility correlations of the MSCI climate change indices over time. Second, the economic and financial impacts of the pandemic have been significant, and investors may have been more focused on the pandemic and its effects on the economy and the stock market, rather than on other factors such as climate change. This could have led to a decrease in the impact of MCI on the returns and volatility connectedness of the MSCI climate change indices, as investors may have been more focused on the pandemic than on other factors. As for why MCI would be a net receiver of spillover, it is because the media coverage of an event or phenomenon is a key factor in shaping public perception and opinion. The more coverage an event receives, the more likely it is to be considered important and to have an impact on public opinion and behavior. In the case of the COVID-19 pandemic, extensive media coverage has likely played a significant role in shaping public perception and opinion about the pandemic, as well as its economic and financial impacts. This extensive media coverage has likely led to the pandemic having a large impact on the economy and the stock market. As a result, the MCI, which reflects the level of media coverage of the pandemic, would be a net receiver of spillover from the pandemic.

Figs. A1–A4 depict the total net time-varying connectedness of the returns for the four COVID-19 waves, detailing the third step. The MCI was the net receiver of shocks, receiving a significant magnitude at the end of the wave (Fig. A1). Sharing a common trend, the USA and the Asia Pacific were the net transmitters of return shocks during the first wave. This finding is not surprising since the pandemic first emerged in the Asia-Pacific region and has spread around the globe since then. Furthermore, the United States was the first in identifying the “infodemic” in the first wave (Chhibber-Goel et al., 2021). Japan propagated noteworthy net return shocks, particularly in March 2020, and this finding can be attributed to the close geographical proximity of Japan to the origin of the virus. Additionally, Europe and EMU were net transmitters of shocks from April 2020 until the end of the period.

Expectedly, the USA and the Asia Pacific kept their roles as the net transmitters of shocks during the second wave, owing to the heightened severity of the pandemic in these regions. It is worth noting that India, one state located in the Asia region, experienced a remarkable surge of cases in this wave. Europe was the net receiver between July and August 2020 and a net transmitter of risk between August and October 2020 (Fig. A2). This finding can be associated with the significant surge in COVID-19 cases in Europe because the Delta variant emerged in this period. Except for the MCI and the PI, all returns in the third wave were net shock transmitters. This finding is most probably due to the emergence of the Delta variant in the previous wave and the rapid spread of the identified cases of the pandemic in the third wave. Finally, all MSCI returns except those from Asia Pacific kept their roles as net transmitters of shock (Fig. A4). On the other hand, the Asia Pacific was the net recipient of shocks in the fourth wave. This finding is rather surprising, yet can be related to the alleviation of the pandemic in this region or lifting Covid test requirements.[11] Furthermore, the MCI and the PI were the net recipients of return shocks in all waves.

4.2. TVP-VAR volatility connectedness

Fig. 3 shows the overall volatility and its time-varying connectedness for the four waves. The TCI increased significantly between March and April 2020, peaking on March 26, 2020 (80.32 %). It then decreased and remained stable at approximately 76 % for the remainder of the first wave. The TCI increased significantly at the start of the second wave, peaking at 56.29 % on September 3, 2020. By the end of the second wave, it had dropped to 46.57 %. During the third wave, the TCI fluctuated between 50% and 64%, with a peak on 18 December 2020 (63.29 %). It then fell to 52.56 % on February 26th, 2021. A massive increase was observed during the fourth wave, starting on 7 December 2021. The TCI sharply surged from 65.16 % to 72.75 % on 14 December 2021 and peaked on 11 January 2022 (73.02 %). This significant increase was probably triggered by the notable surge of Omicron cases during the fourth wave.

Table 3 presents the average spillover results for the volatilities. During the first wave, Japan and the MCI were net receivers, while the USA, the EMU, Europe, and the Asia Pacific were the net transmitters of shock. The TCI was 76.78, indicating strong volatility connectedness. The USA was the largest transmitter of shocks to the other indices (92.19 %), followed by the EMU (91.63 %) and Europe (91.5 %). This finding is consistent with the significant increase in

[11] See, https://www.ft.com/content/abefb06e-a5a7–432b-85bf-b3250b53-836f.

Table 3
Average connectedness results for the volatilities of the MSCIs and the MCI.

First COVID-19 Wave	USA	EMU	Japan	Europe	Asia Pacific	MCI	FROM
USA	20.61	19.23	14.01	19.17	16.47	10.51	79.39
EMU	19.85	20.37	12.43	20.16	16.29	10.91	79.63
Japan	18.19	17.87	21.25	18.4	19.79	4.5	78.75
Europe	19.66	20.14	12.76	20.13	16.65	10.66	79.87
Asia Pacific	18.07	18.88	15.04	18.92	19.86	9.23	80.14
MCI	16.42	15.51	4.76	14.86	11.35	37.1	62.9
Contribution TO others	92.19	91.63	58.99	91.5	80.56	45.81	460.69
NET directional connectedness	12.8	12	-19.75	11.63	0.41	-17.09	**TCI = 76.78**

Second COVID-19 Wave	USA	EMU	Japan	Europe	Asia Pacific	MCI	FROM
USA	57.25	6.56	7.56	5.35	4.66	18.62	42.75
EMU	6.55	37.03	1.78	34.61	1.47	18.55	62.97
Japan	4.68	9.73	55.22	10.78	15.07	4.54	44.78
Europe	5.28	37.7	2.86	39.15	1.42	13.59	60.85
Asia Pacific	4.37	10.35	14.22	9.16	53.29	8.61	46.71
MCI	21.49	15.39	0.84	12.07	0.68	49.53	50.47
Contribution TO others	42.37	79.73	27.27	71.97	23.3	63.9	308.54
NET directional connectedness	-0.38	16.76	-17.52	11.12	-23.41	13.43	**TCI = 51.42**

Third COVID-19 Wave	**USA**	**EMU**	**Japan**	**Europe**	**Asia Pacific**	**MCI**	**FROM**
USA	35.29	11.8	15.07	15.3	21.6	0.93	64.71
EMU	17.32	35.93	5.37	35.46	5.63	0.29	64.07
Japan	17.62	9.81	39.04	12.5	19.75	1.28	60.96
Europe	19.01	32.5	6.56	34.71	6.93	0.29	65.29
Asia Pacific	25.22	2.77	20.85	5.02	44.3	1.83	55.7
MCI	5.96	3.1	6.75	3.65	8.71	71.83	28.17
Contribution TO others	85.14	59.98	54.6	71.93	62.62	4.62	338.9
NET directional connectedness	20.43	-4.09	-6.36	6.64	6.93	-23.54	**TCI = 56.48**

Fourth COVID-19 Wave	**USA**	**EMU**	**Japan**	**Europe**	**Asia Pacific**	**MCI**	**FROM**
USA	27.48	19.93	4.51	21.59	13.6	12.89	72.52
EMU	17.21	27.86	1.9	26.94	5.53	20.57	72.14
Japan	14.56	13.36	26.56	15.08	20.92	9.51	73.44
Europe	18.48	26.1	3.04	26.63	8.07	17.69	73.37
Asia Pacific	18.89	12.8	17.78	15.85	28.65	6.03	71.35
MCI	13.99	24.18	0.32	22.8	1.86	36.84	63.16
Contribution TO others	83.13	96.38	27.55	102.27	49.98	66.68	425.99
NET directional connectedness	10.61	24.23	-45.89	28.89	-21.37	3.52	**TCI = 71**

Notes: This table reports the average connectedness results for the volatilities. Pairwise spillovers and total connectedness indices (TCIs) are also provided.

Fig. 4. Connectedness network graphs for returns.

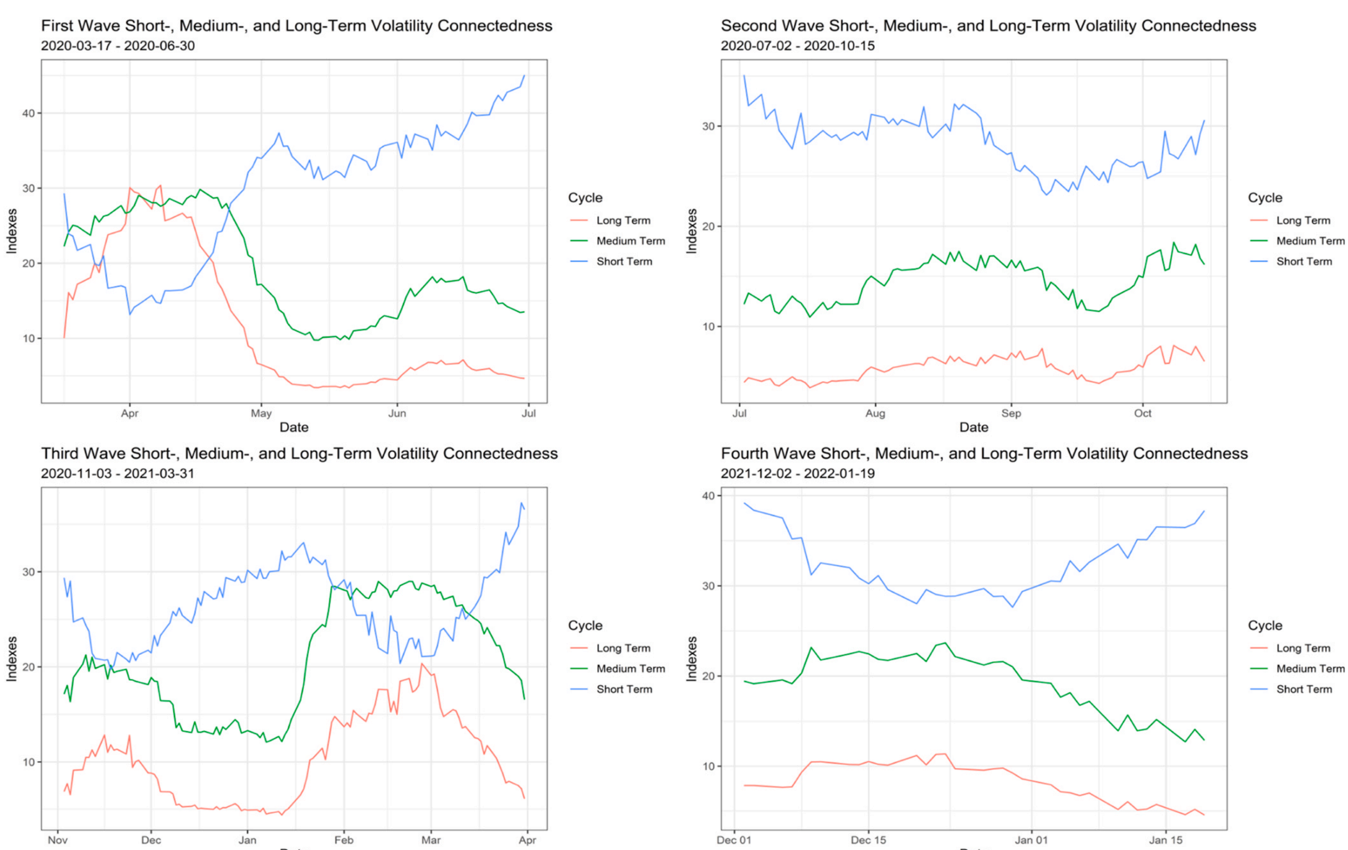

Fig. 5. Connectedness network graphs for volatilities.

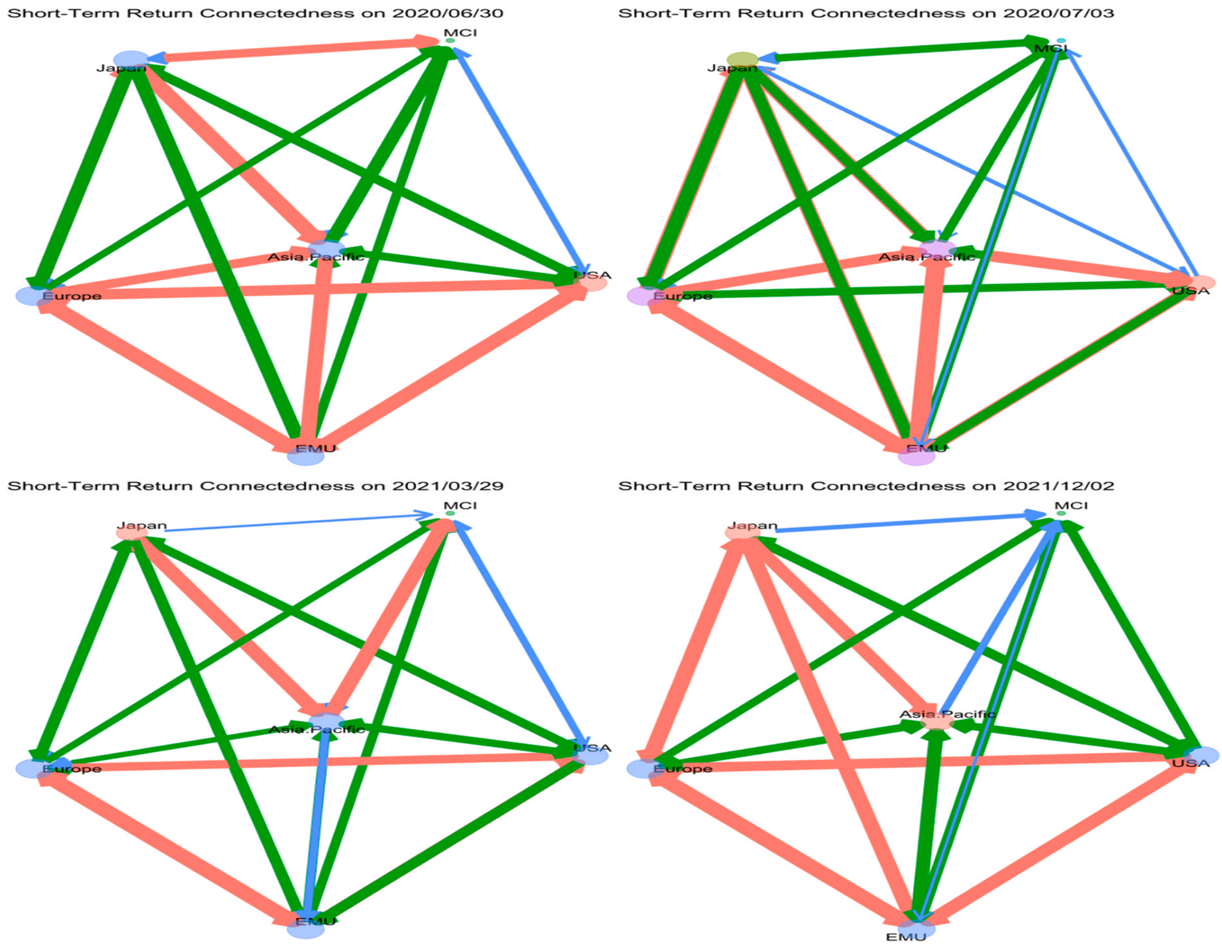

Fig. 6. Short-term network connectedness topologies for the returns.

the number of SARS-CoV-2 cases in these regions. In contrast, the MCI received the lowest spillovers from the MSCI indices. In the second wave, the EMU, Europe, and MCI were the net transmitters of shocks, while the Asia Pacific, Japan, and the USA were the net recipients. The EMU was the largest transmitter of shocks (79.73 %), followed by Europe (71.97 %), which can be attributed to the rapid spread of Delta variants across Europe. Notably, the MCI transmitted significant spillovers to the MSCI indices, indicating a remarkable increase in media coverage of COVID-19. The USA received the lowest spillovers from other indices (42.75 %), followed by Japan (44.78 %).

Overall, the third and fourth waves of COVID-19 showed a different pattern of volatility connectivity compared to the first and second waves. The USA, Europe, and the Asia Pacific were net transmitters in the third wave, while the EMU, Japan, and the MCI were net receivers. In the fourth wave, Europe and EMU were the net transmitters, while the USA and Japan were the net propagators of shock, with Asia Pacific as the persistent net receiver. The TCI was 56.48 % in the third wave, and the USA was the largest transmitter and recipient of shocks. The MCI received the lowest spillovers from the MSCI indices. In the fourth wave, Europe was the largest transmitter of shocks (102.27 %), followed by the EMU (96.38 %). Japan was the largest recipient of shocks, while the MCI received the lowest spillovers from the MSCI indices. This finding can be related to the amplification of COVID-19 cases owing to the Omicron variant in Europe and the EMU. Japan was the largest recipient of shocks (73.44 %), while the magnitudes of spillovers received by other MSCI indices were relatively close. The MCI received the lowest spillovers from the MSCI indices (63.16 %).

Fig. A5 shows that, except for the USA, all volatility indices were net transmitters of shocks during the first wave. The USA flipped its role from net transmitter to net recipient of shocks after April 2020. This finding is very similar to the spillover results for the returns, indicating the role of these countries in transmitting volatility shocks and being in line with their rank in terms of the identified SARS-CoV-2 cases in the first wave. Fig. 6 shows that in the second wave, Europe, EMU, and the US were net transmitters of volatility shock, whereas Asia Pacific and Japan were either net receivers or net transmitters of shock depending on the wave's duration. It is worth remarking that they were the net transmitters of shocks at the end of the wave, most probably due to the emergence of the Delta variant.

Fig. 7 reports that all MSCI indices except for Japan were the net transmitters of volatility shocks. Likewise, the results for the returns, this finding can be related to the emergence of the Delta variant in the second wave and the rapid spread of the pandemic in the third wave in these regions. Finally, only Europe and EMU were the net transmitters of volatility shocks in the fourth wave, while the USA and Japan were the net propagators of shocks over most of the wave, explaining the marked impact of the Omicron variant on the volatilities of these MSCI indices in the fourth wave. Conversely, and similar to the result for the returns, Asia Pacific was the persistent net receiver. Additionally, the MCI and the PI were the net recipients of volatility shocks in all waves.

4.3. The frequency-based TVP-VAR network connectedness

4.3.1. The frequency-dependent network connectedness indices

Using the frequency-dependent network connectedness of Ellington and Baruník (2020), we estimated the short-. medium-, and long-term

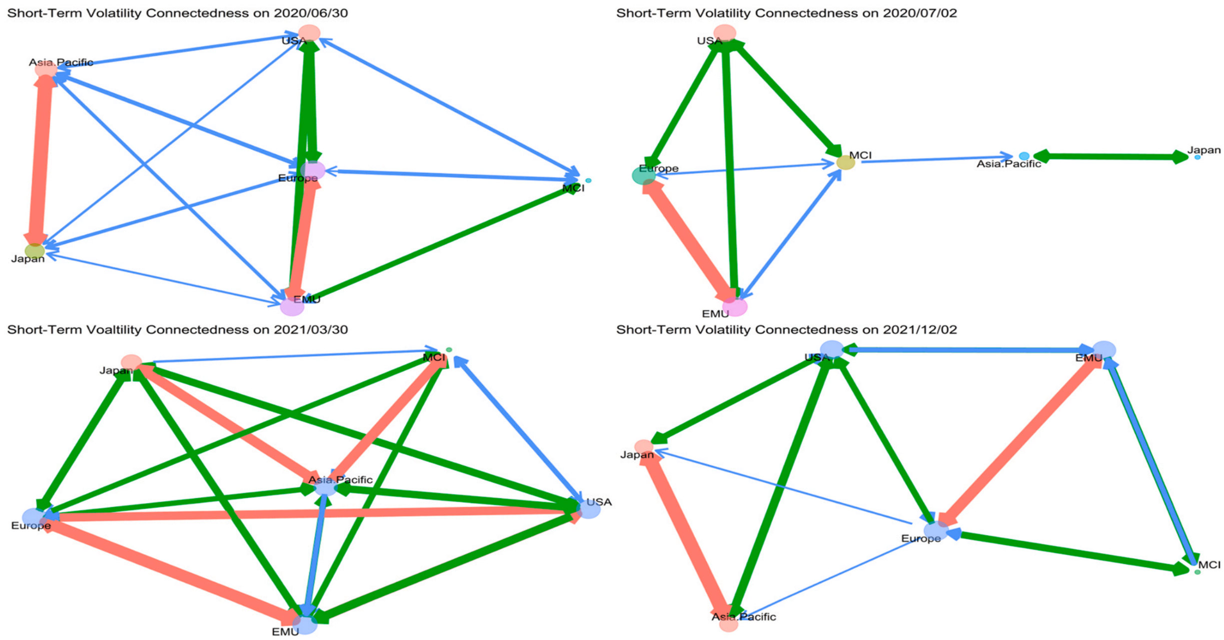

Fig. 7. Short-term network connectedness topologies for the volatilities several results emerged based on the network topology of returns. First, the MCI propagated the lowest total short-term spillovers to the MSCI Climate Change Index returns in all network topologies, ranging from 0.021 in the second and fourth waves to 0.0494 in the first wave. This finding is not surprising since most of the shocks within the system were transmitted among the MSCI indices. Second, the period affected the index that transmitted the most short-term spillovers to other nodes. While the top three indices in all periods were Europe, the Asia Pacific, and the EMU, their rankings were not the same. Europe transmitted the most short-term spillovers to other nodes in the first and third waves at 0.0978 and 0.0526, respectively, while it was second in the second and fourth waves at 0.0625, respectively. This finding is unsurprising given the significant escalation of identified COVID-19 cases during the first and third waves, as well as the negative effects on Europe's economic/financial system accompanied by lockdowns. Moreover, the EMU was one of the most influenced regions by the adverse effects of the pandemic. However, the Asia Pacific has the highest total spillovers to other nodes in the second and fourth waves at 0.0631, while transmitting the second-largest spillover in the first wave (0.0958) and the third-largest in the third wave (0.0487). Furthermore, EMU was third-placed in transmitting spillovers during all waves except the third. Third, the Europe-EMU pair maintained the highest directional spillovers, while the MCI-USA pair had the lowest during all waves except the fourth. This finding indicates that geographical proximity plays a significant role in spillovers among returns. In the fourth wave, Japan and the MCI had the lowest interdependence, proposing a low level of short-term linkages between the media coverage and Japan's MSCI index.

connectedness[12] among returns and volatilities for the four COVID-19 waves as shown in Figs. 4 and 5, respectively.

The first wave returns connectedness networks indicated that transitory linkages were relatively larger than persistent interdependencies, signifying that the interlinkages were more pronounced in the short term. The medium-term connections are larger relative to the transitory and permanent connections indices in the second, third, and fourth waves.

The third wave graph reveals a similarity in patterns of the transitory and persistent spillovers. Finally, the short- and medium-term connections were stronger than the long-term linkages in the fourth wave.

Based on the frequency-based volatility network connectedness indices, Fig. 5 indicates the following results: (i) the transitory linkages were tighter than the persistent interdependencies during the major portion of wave durations; (ii) the medium and long-term connectedness indices displayed similar patterns in all waves; and (iii) the short-term connectedness index tends to amplify at the end of each wave.

4.3.2. The short-term connectedness networks for returns

Following Ellington and Baruník (2020), we examined the connectedness network topologies at a turbulent time for each COVID-19 wave. We estimated the network topologies of the short-term connectedness for each wave when the short-term connectedness peaked (30 June 2020, 3 July 2020, 29 March 2021, and 2 December 2021, respectively)[13] considering several short-term shock spills, particularly during the burst episodes. Figs. 6 and 7 present the network topologies for returns and volatilities for returns, respectively.

Considering the network topologies of volatilities, the results are remarkably similar to those obtained from the return topologies. First, the MCI maintained the lowest total short-term spillovers to MSCI index returns, ranging from 0.021 in the second wave to 0.0504 in the fourth wave. Second, Europe recorded the highest transmission of short-term spillovers to other nodes during all waves except the second wave. This finding signifies Europe's prominent role in the short-term volatility connectedness network and is in line with previous studies (Umar et al., 2021c). Third, the Europe-EMU pair maintained its highest directional spillovers in all waves (similar to the return results), in addition to the EMU-USA pair, while the pair with the lowest directional spillover depended on the wave, with it being the Japan-MCI pair in the third and fourth waves.

4.4. Robustness test

To strengthen our analysis, we conducted a robustness test by using an alternative proxy for COVID uncertainty. Specifically, we followed Haroon and Rizvi (2020) and used Ravenpack's Panic Index

[12] Transitory-, medium-term, and Persistent connectedness roughly reflect 1–5 days (1 day up to 1 week), 5–20 days (1 week up to a month), and 20 + days (more than 1 month), respectively.

[13] In this figure, arrows indicate the direction of the connectedness, the size, and the color (red, green, and blue, respectively) of the lines represent the magnitude of the interdependencies, and the sizes of the vertices are represented by total TO spillovers pertaining to that node.

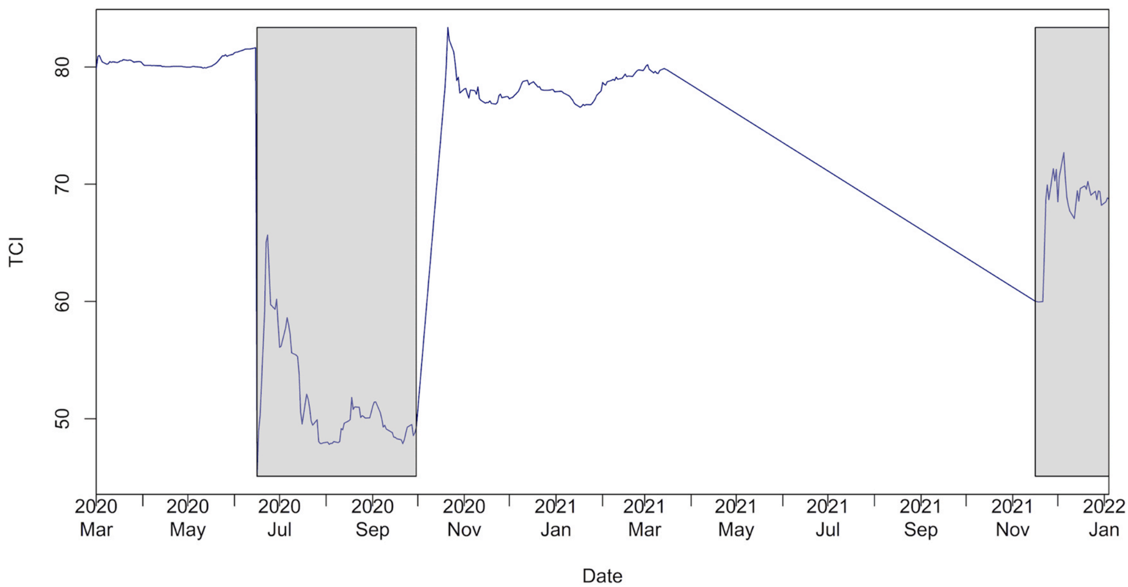

Fig. 8. Dynamic returns connectedness of MSCIs and PI for the four COVID-19 pandemic waves.

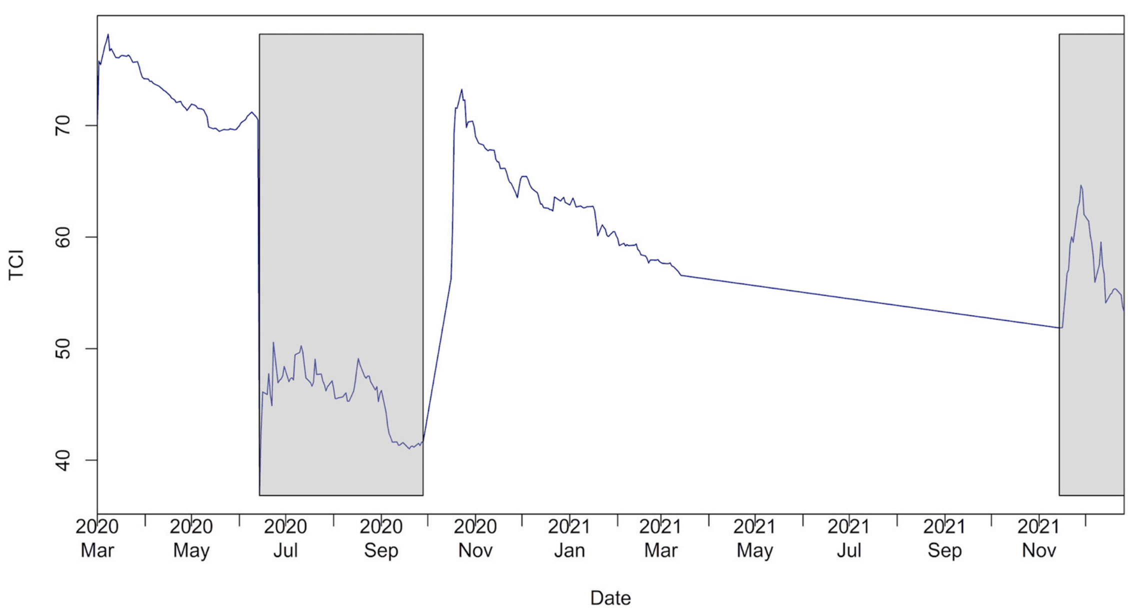

Fig. 9. Dynamic volatilities connectedness of the MSCIs and the PI for the four waves of the COVID-19 pandemic.

(PI) as a proxy for Covid-19 induced panic. We then re-estimated the connectedness system by replacing the MCI with the PI in the TVP-VAR model. Figs. 8 and 9 display the TCI of the system comprising PI and the MSCI indices for the four COVID waves for return and volatility, respectively. Both figures exhibit a similar pattern to the ones in Figs. 2 and 3, confirming our previous findings of time-varying connectedness.

Tables 4 and 5 present the average connectedness results for the MSCIs and the PI for return and volatility, respectively. The results are comparable to our primary findings in Tables 2 and 3, indicating that our findings are robust and accurate.[14] The TCI was highest in the first wave and lowest in the second wave. All MSCI Climate Change indices transmitted more to the PI than they received. Although the PI was a persistent net receiver in all waves, the MSCI indices were the net transmitters. Furthermore, the magnitudes and signs of the average spillovers are similar to those given in Tables 2 and 3.

Finally, we computed the short-, medium-, and long-term connectedness between returns and volatilities of MSCIs and the PI for the four COVID-19 waves, as shown in Figs. 10 and 11, respectively. The results exhibit very similar patterns to those given in Figs. 4 and 5, indicating the accuracy of our estimates.

[14] The net time-varying connectedness for the MSCIs and the PI returns are not provided to save space. They are available upon request.

Table 4
Average returns connectedness results for the MSCIs and the PI.

First COVID-19 Wave								Second COVID-19 Wave							
	USA	EMU	Japan	Europe	Asia Pacific	PI	FROM		USA	EMU	Japan	Europe	Asia Pacific	PI	FROM
USA	19.1	17.21	16.52	17.92	17.89	11.36	80.9	**USA**	44.87	1.19	18.37	1.39	33.29	0.9	55.13
EMU	16.95	18.74	17.58	18.61	17.91	10.21	81.26	**EMU**	2.61	45.86	2.93	42.03	5.18	1.38	54.14
Japan	16.93	18.06	18.73	18.06	18.03	10.19	81.27	**Japan**	22.68	3.42	39.69	5.83	28.21	0.16	60.31
Europe	17.57	18.2	17.27	18.5	17.78	10.68	81.5	**Europe**	2.05	40.95	5.01	44.47	5.38	2.13	55.53
Asia Pacific	17.63	17.83	17.27	18.06	18.42	10.79	81.58	**Asia Pacific**	32.06	3.86	22.34	4.53	36.74	0.47	63.26
PI	18.44	15.45	14.58	16.74	16.51	18.28	81.72	**PI**	9.01	4.25	11.77	4.96	7.1	62.93	37.07
Contribution TO others	87.52	86.76	83.21	89.39	88.11	53.23	488.23	**Contribution TO others**	68.42	53.66	60.42	58.74	79.17	5.05	325.45
NET directional connectedness	6.62	5.49	1.94	7.89	6.54	-28.49	**TCI = 81.37**	**NET directional connectedness**	13.28	-0.48	0.11	3.21	15.91	-32.02	**TCI = 54.24**
Third COVID-19 Wave								**Fourth COVID-19 Wave**							
	USA	**EMU**	**Japan**	**Europe**	**Asia Pacific**	**PI**	**FROM**		**USA**	**EMU**	**Japan**	**Europe**	**Asia Pacific**	**PI**	**FROM**
USA	21.92	17.2	19.68	17.54	20.33	3.32	78.08	**USA**	36.15	18.09	17.83	22.61	4.88	0.44	63.85
EMU	18.3	21.24	19.5	20.9	16.08	3.98	78.76	**EMU**	17.36	31.03	13.54	30.12	4.9	3.05	68.97
Japan	19.36	18.37	21	18.14	19.2	3.93	79	**Japan**	21.1	15.71	33.26	18.88	10.87	0.18	66.74
Europe	18.71	20.85	18.94	21.25	16.42	3.83	78.75	**Europe**	20.59	27.84	15.89	29.61	3.78	2.29	70.39
Asia Pacific	20.93	15.95	20.17	16.41	22.43	4.1	77.57	**Asia Pacific**	16.21	11.67	17.93	11.12	42.01	1.05	57.99
PI	11.61	12.68	13.88	12.46	16.71	32.66	67.34	**PI**	16.54	13.38	14.04	15.61	7.57	32.86	67.14
Contribution TO others	88.92	85.06	92.16	85.45	88.74	19.17	459.49	**Contribution TO others**	91.81	86.69	79.22	98.34	32	7.02	395.07
NET directional connectedness	10.84	6.3	13.16	6.7	11.17	-48.17	**TCI = 76.58**	**NET directional connectedness**	27.96	17.72	12.48	27.95	-26	-60.12	**TCI = 65.84**

Table 5
Average connectedness results for the volatilities of the MSCIs and the PI.

First COVID-19 Wave								Second COVID-19 Wave							
	USA	EMU	Japan	Europe	Asia Pacific	PI	FROM		USA	EMU	Japan	Europe	Asia Pacific	PI	FROM
USA	25.14	15.94	17.99	17.88	18.71	4.33	74.86	**USA**	68.54	4.71	16.6	6.42	2.18	1.56	31.46
EMU	13.91	23.87	18.2	22.78	20.58	0.66	76.13	**EMU**	8.76	45.17	2.79	40.56	1.47	1.24	54.83
Japan	15.91	18.74	23.51	19.58	19.14	3.12	76.49	**Japan**	13.34	11.58	57.27	15.28	1.27	1.27	42.73
Europe	15.01	22.36	18	23	20.61	1.02	77	**Europe**	8.43	38.56	4.87	43.69	1.46	2.98	56.31
Asia Pacific	15.22	20.9	18.71	21.04	22.46	1.68	77.54	**Asia Pacific**	14.1	3.62	2.62	0.94	65.5	13.22	34.5
PI	13.3	5.92	17.07	8.28	11.02	44.42	55.58	**PI**	4.37	4.73	13.95	4.64	26.07	46.24	53.76
Contribution TO others	73.35	83.85	89.97	89.56	90.06	10.81	437.59	**Contribution TO others**	49	63.19	40.84	67.84	32.45	20.28	273.6
NET directional connectedness	-1.51	7.72	13.48	12.56	12.52	-44.77	**TCI = 72.93**	**NET directional connectedness**	17.54	8.36	-1.9	11.53	-2.05	-33.48	**TCI = 45.6**
Third COVID-19 Wave								**Fourth COVID-19 Wave**							
	USA	**EMU**	**Japan**	**Europe**	**Asia Pacific**	**PI**	**FROM**		**USA**	**EMU**	**Japan**	**Europe**	**Asia Pacific**	**PI**	**FROM**
USA	37.75	17.15	11.85	16.53	16.06	0.67	62.25	**USA**	47.95	23.69	4.4	23.48	0.21	0.27	52.05
EMU	19.48	30.43	11.04	29.28	8.07	1.7	69.57	**EMU**	21.11	35.36	6.61	33.29	0.83	2.79	64.64
Japan	20.26	17.69	27.24	16.96	17.72	0.13	72.76	**Japan**	6.22	10.57	48.65	14.36	5.68	14.51	51.35
Europe	18.36	29.46	10.44	30.63	9.1	2.01	69.37	**Europe**	20.09	31.28	10.25	33.5	0.83	4.05	66.5
Asia Pacific	18.35	10.13	17.4	12.36	41.4	0.36	58.6	**Asia Pacific**	8.26	5.36	8.14	5.47	55.14	17.63	44.86
PI	8.26	5.72	11.96	5.85	13.26	54.94	45.06	**PI**	7.49	10.48	21.99	13	12.81	34.22	65.78
Contribution TO others	84.71	80.16	62.7	80.98	64.21	4.87	377.62	**Contribution TO others**	63.17	81.38	51.39	89.6	20.36	39.26	345.17
NET directional connectedness	22.46	10.59	-10.07	11.61	5.6	-40.19	**TCI = 62.94**	**NET directional connectedness**	11.12	16.75	0.04	23.1	-24.5	-26.51	**TCI = 57.53**

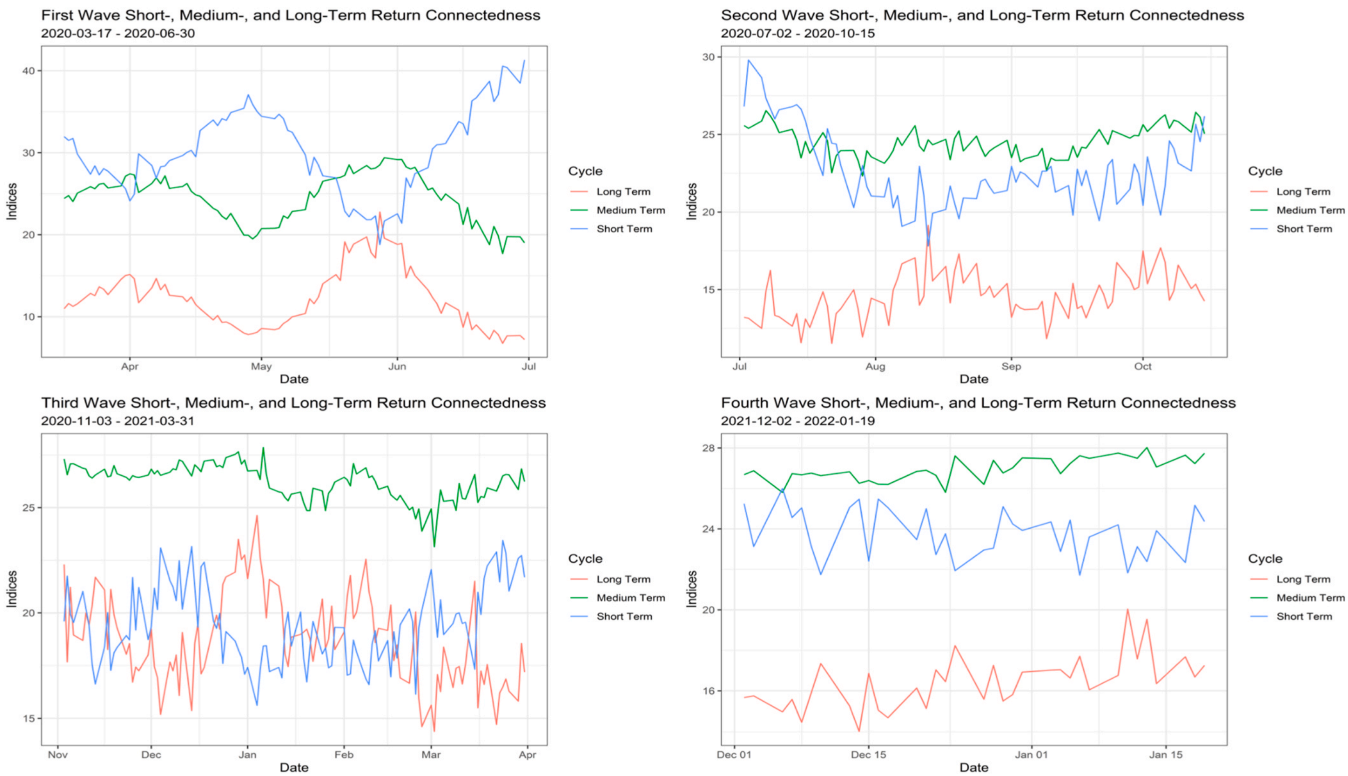

Fig. 10. Connectedness network graphs for returns of the MSCIs and the PI.

Fig. 11. Connectedness network graphs for volatilities of the MSCIs and the PI.

5. Conclusion

This study contributes to advanced knowledge in two main areas: (i) the dynamic connectedness of MSCI Climate Change indices; and (ii) the impact of the Covid-19 pandemic on their connectedness. We use the pandemic media coverage index (MCI) as a proxy for investors' sentiment during the pandemic. As a robustness test, we replace MCI with the panic index (PI). Thus, this study investigates the static and dynamic return and volatility connectedness between the MCI and five MSCI Climate Change Indices encompassing the USA, emerging markets, Japan, Europe, and the Asia Pacific from March 11, 2020, to January 19, 2022. The return and volatility dynamic connectedness measures are estimated for all four waves using the TVP-VAR-based approaches of Antonakakis et al. (2020) (time connectedness) and Ellington and Barunik (2020) (frequency connectedness). This study enhances the literature on connectedness by offering new research on the impact of pandemic-related news on the connectedness of financial market networks.

First, the dynamic time connectedness analysis results reveal that the overall return and volatility connectedness of the system is high, indicating strong interactions among the variables in the system. Second, the results show a connection between the degree of spillovers and the occurrence of major events, represented by a significant increase in TCI. TCI was highest during the first wave and lowest during the second wave. Thus, the connectedness had increased significantly with the escalation of the pandemic outbreak and more specifically during the onset of the pandemic. Third, the results highlight that MSCI Climate Change indices are integrated, indicating that the hedging and diversification benefit from MSCI climate indices is minimal during a crisis period. Fourth, MCI kept its role as a net receiver during the sample period, while MSCI indices had different roles depending on the period. Thus, heterogeneity occurred in the role of MSCI climate indices. Fifth, in the frequency domain, it is evident that the level of volatility connectedness among the variables was significantly greater in the short term (1–5 days) than in the long term. This indicates that the markets respond quickly to shocks in the first few trading days. Finally, the connectedness decreased during the second wave, which might indicate that during recovery, investors may benefit from diversification.

Our study has relevant implications for policymakers, investors, and future research. Firstly, policymakers should pay attention to media monitoring and regulation related to COVID-19, particularly during the pandemic period. Policymakers can use our results to design policies to reduce connectedness during pandemic-related turbulence. Secondly, investors should be cautious in designing cross-geographical hedging strategies during a global crisis like the COVID-19 pandemic. Knowing the intensities of directional spillover effects on these markets can help investors choose the best investment portfolio to reduce their risk and maximize their profits. Our study can aid portfolio investors in making decisions regarding optimal asset allocation. Finally, policymakers should focus on time-varying spillover effects among variables as they are strongly associated with international conditions. This information can improve portfolio decisions, design hedging strategies, and maintain financial stability.

Our study can also motivate further research. The ongoing COVID-19 pandemic can profoundly and persistently influence every sector. Future research could explore whether COVID-19 media-related indices have different impacts on diverse sectors. Additionally, collecting high-frequency financial data to calculate realized volatility can help uncover the contribution of jumps in the network of spillovers during COVID-19. Lastly, alternative techniques could be used to measure the portfolio implications of including such investments in a portfolio choice framework.

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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.

Appendix

See Table A1 and Figs. A1-A8.

Table A1
Index description.

Index	Description
MSCI USA Climate Change Index	The MSCI USA Climate Change Index includes large and mid-cap 584 securities of the U.S. equity markets.
MSCI EMU Climate Change Index	The MSCI Emerging Markets Climate Change Index includes 1269 large and mid-cap securities across 25 Emerging Markets (EM) countries (Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Kuwait, Malaysia, Mexico, Peru, Philippines, Poland, Qatar, Russia, Saudi Arabia, South Africa, Taiwan, Thailand, Turkey, and United Arab Emirate).
MSCI Japan Climate Change Index	The MSCI Japan Climate Change Index includes 251 large and mid-cap securities of the Japanese equity markets.
MSCI Europe Climate Change Index	The MSCI Europe Climate Change Index includes 403 large and mid-cap securities across 15 Developed Markets (DM) in Europe (Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the UK.)
MSCI Asia Pacific Climate Change Index	The MSCI AC Asia Pacific Climate Change Index includes 1394 large and mid-cap securities across 5 Developed Markets (DM) countries (Australia, Hong Kong, Japan, New Zealand, and Singapore) and 8 Emerging Markets (EM) countries (China, India, Indonesia, Korea, Malaysia, the Philippines, Taiwan, and Thailand) in Asia Pacific region
Media Coverage Index (MCI)	It is the percentage of news sources that cover the coronavirus. The index ranges between 0 and 100. The value of 50 on a particular day implies that 50% of all news providers cover the COVID–19.
Coronavirus Panic Index (PI)	It measures panic through the level of news that reflect panic or hysteria led by a coronavirus. It ranges between 0 and 100, with 0 meaning 0% news concerning panic and coronavirus and 100 meaning vice versa.

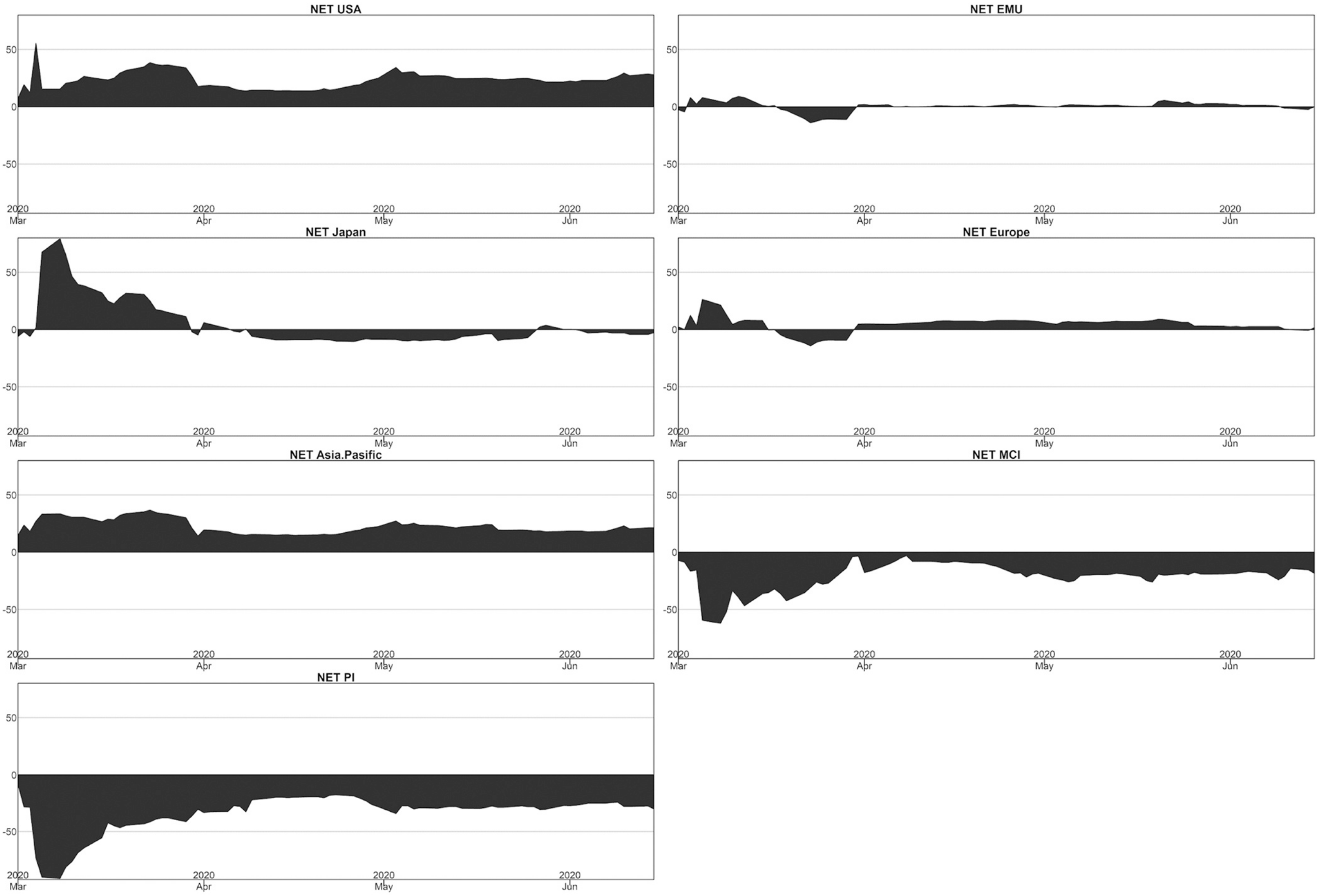

Fig. A1. Total time-varying net returns connectedness for the first COVID-19 wave.

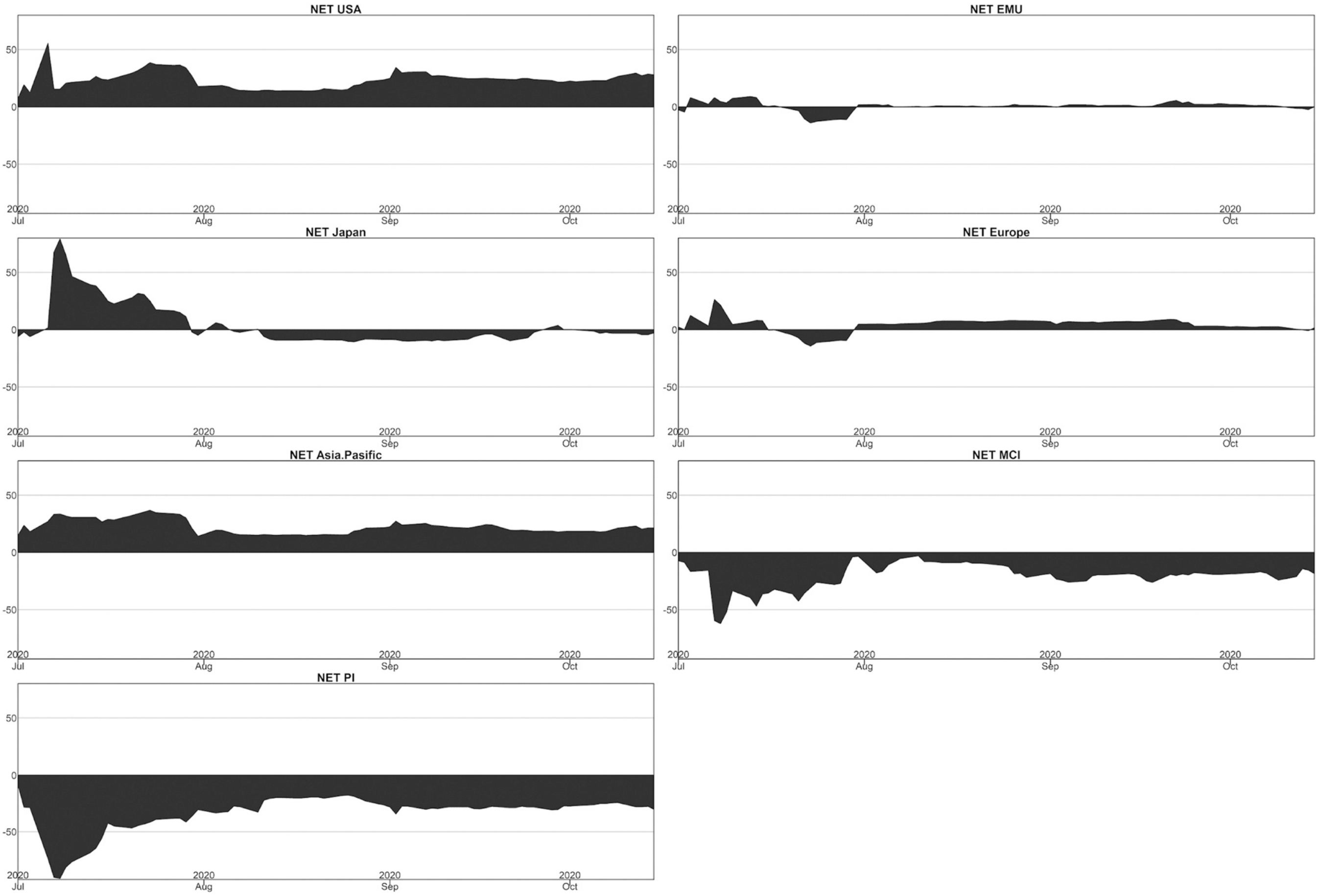

Fig. A2. Total time-varying net returns connectedness for the second COVID-19 wave.

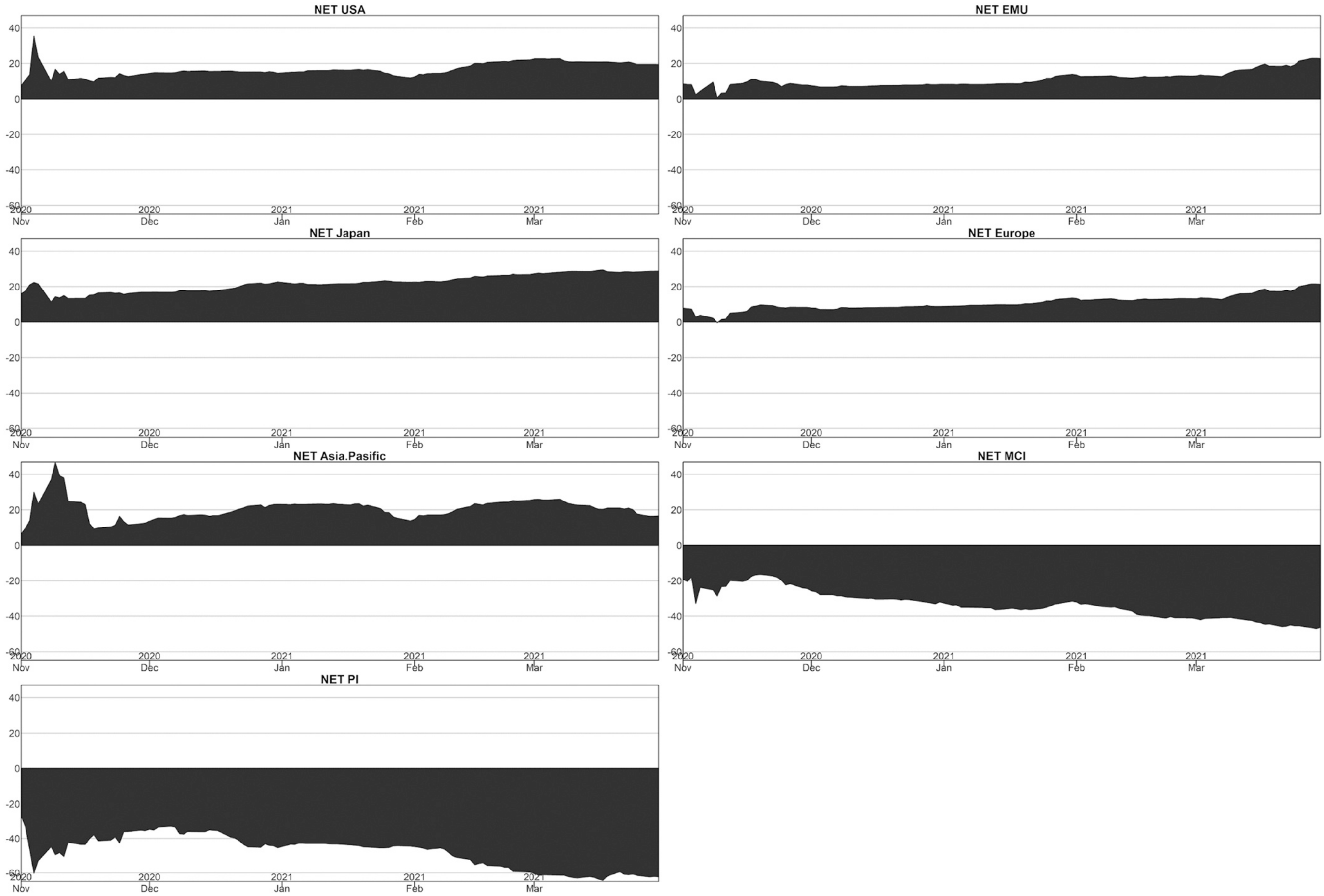

Fig. A3. Total time-varying net returns connectedness for the third COVID-19 wave.

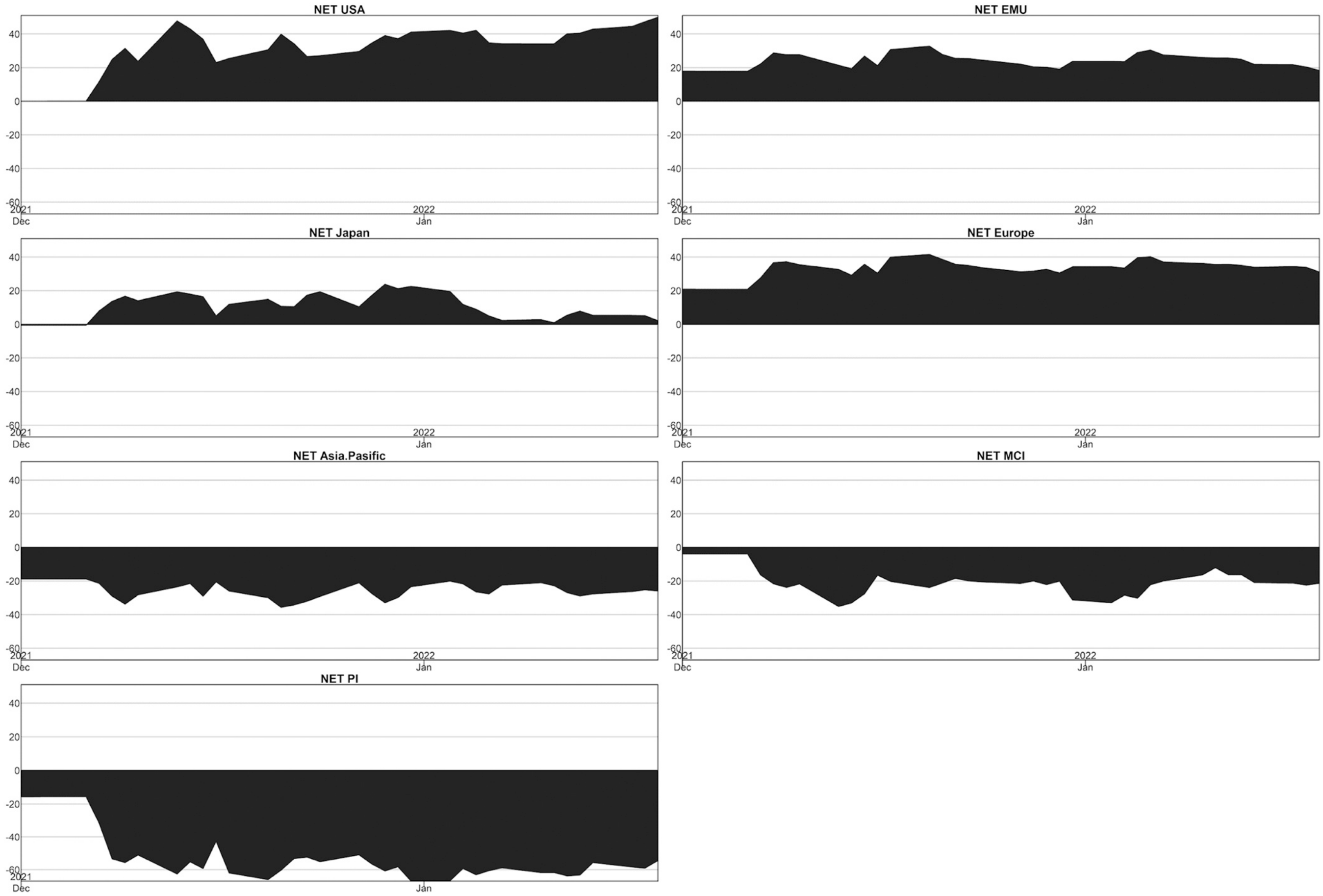

Fig. A4. Total time-varying net returns connectedness for the fourth COVID-19 wave.

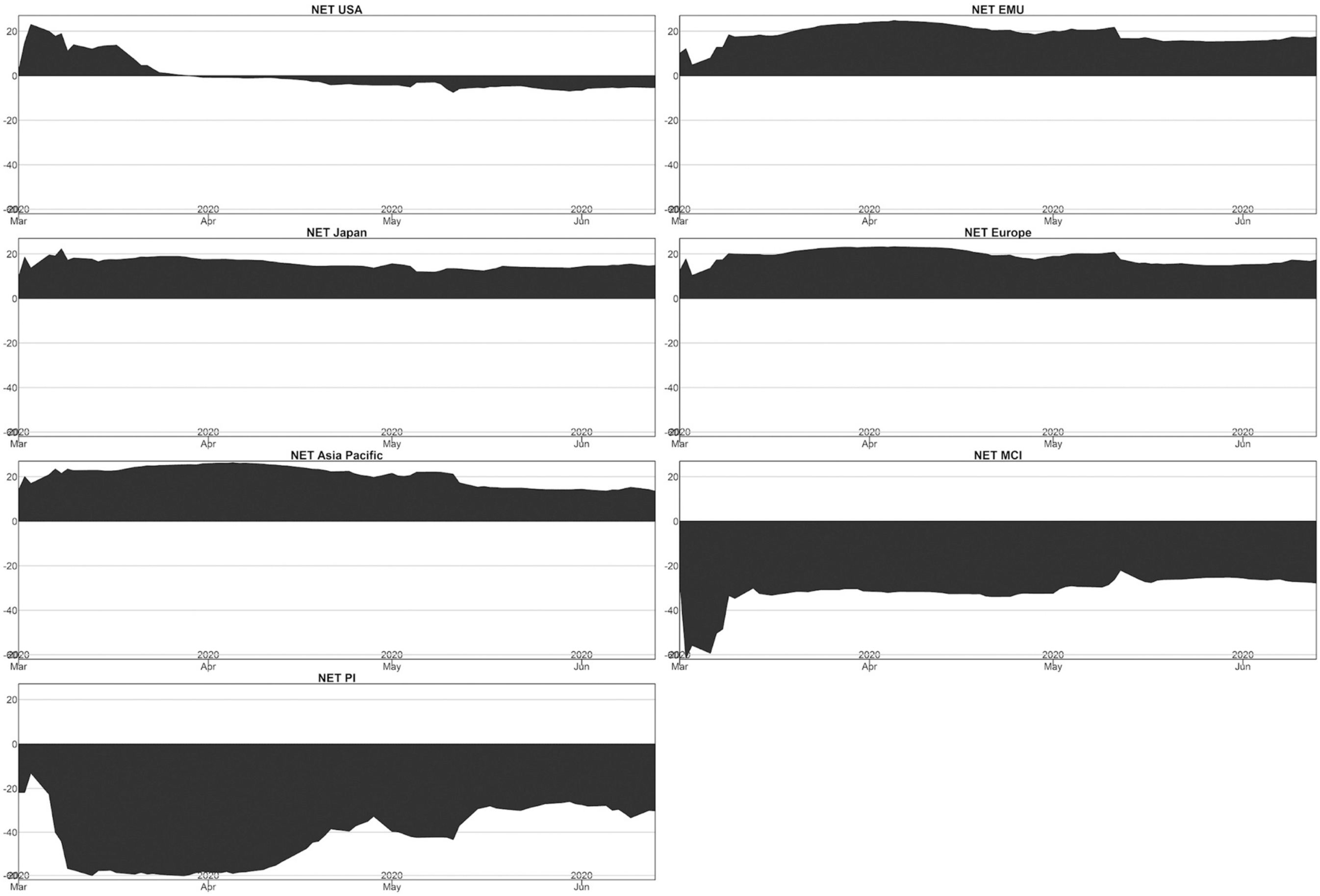

Fig. A5. Total time-varying net volatility connectedness for the first COVID-19 wave.

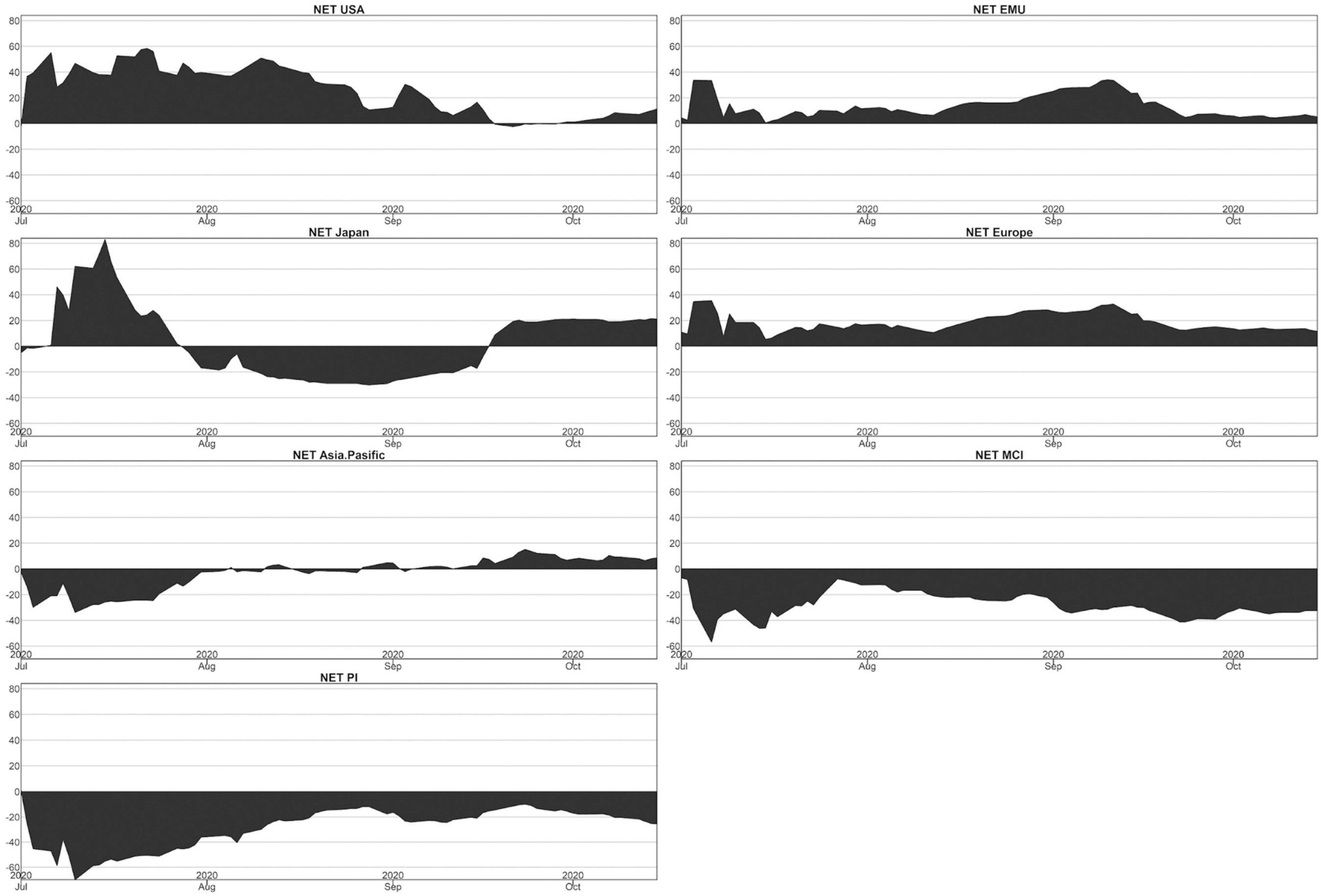

Fig. A6. Total time-varying net volatility connectedness for the second COVID-19 wave.

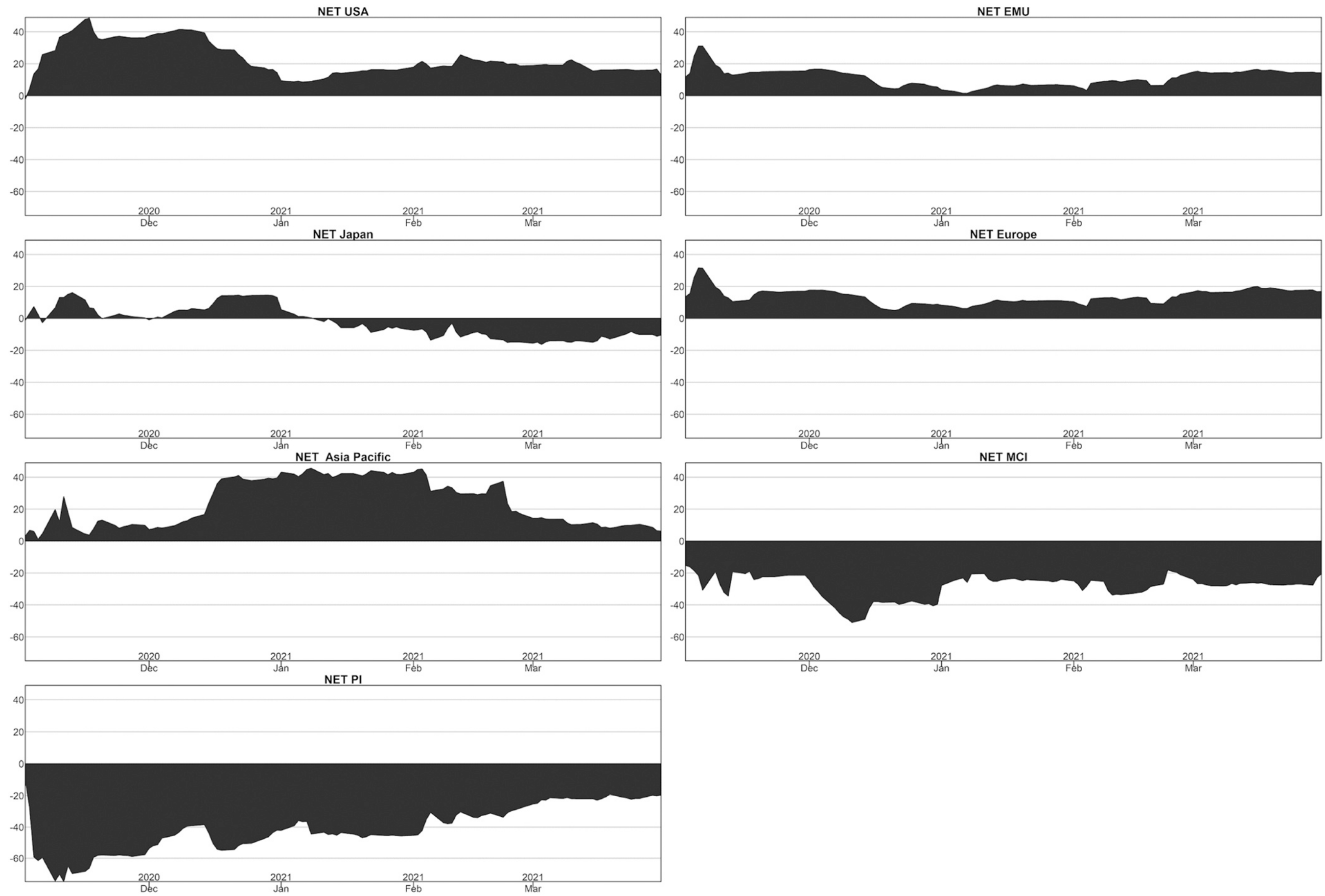

Fig. A7. Total time-varying net volatility connectedness for the third COVID-19 wave.

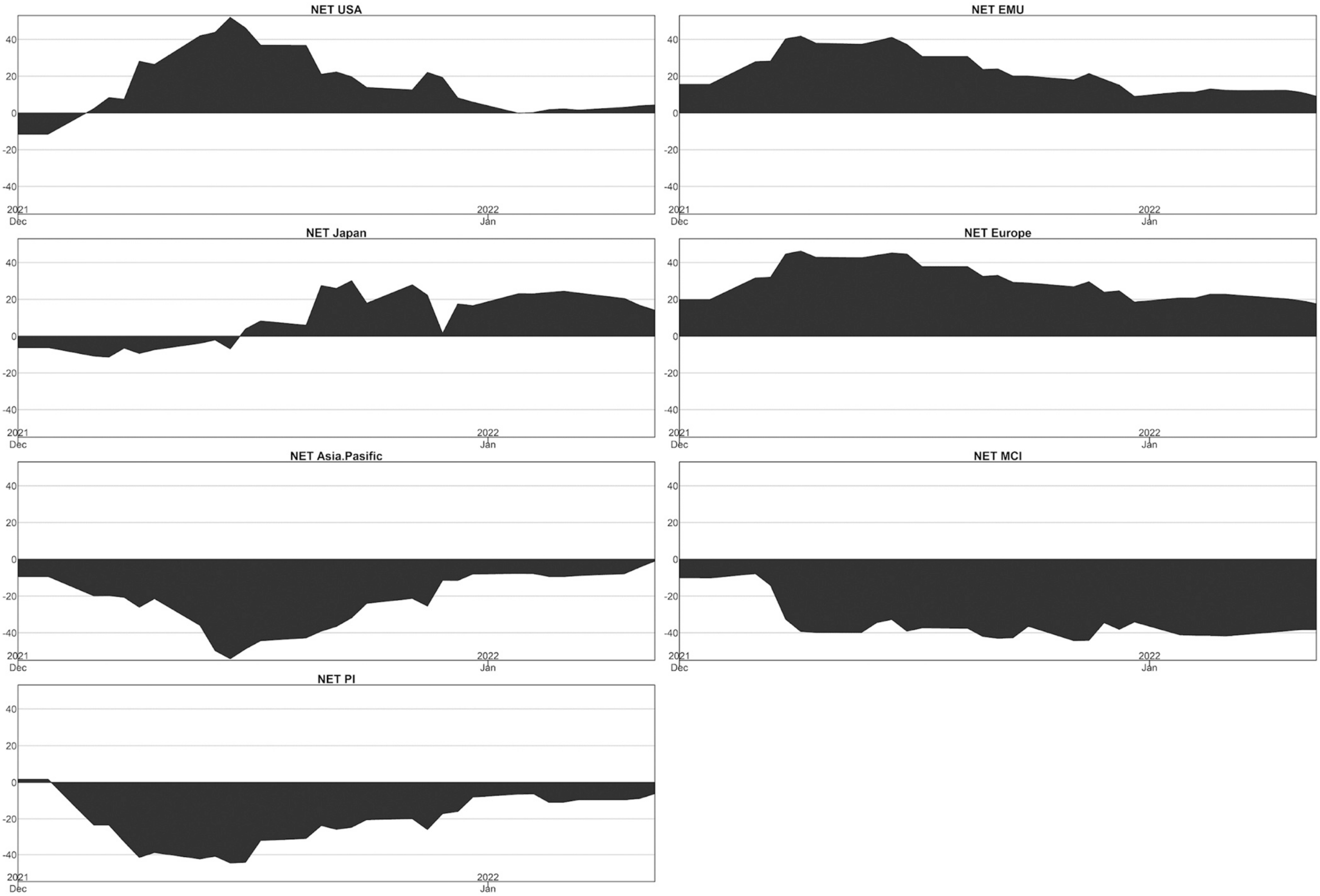

Fig. A8. Total time-varying net volatility connectedness for the fourth COVID-19 wave.

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