



COVID–19 media coverage and ESG leader indices

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ABSTRACT

This study examines the dynamic connectedness between COVID–19 media coverage index (MCI) and ESG leader indices. Our findings provide evidence that MCI plays a role in facilitating the transmission of contagion to advanced and emerging equity markets during the pandemic. The connectedness between MCI and ESG leader indices is more pronounced around March and April 2020 at the peak of the pandemic. The US is a net receiver of shocks reaffirming that it was the most affected country during the pandemic. Our results provide implications for investors, portfolio managers, and policymakers in mitigating financial risks during the pandemic.

1. Introduction

The COVID–19 pandemic has been under continuous media limelight around the world—traditional and social media alike. Apart from the media, academic (e.g., Johns Hopkins University COVID–19 dashboard¹) and corporate initiatives (e.g., COVID–19 Government Response Tracker,² the mobility index by Apple,³ and Google trends on COVID–19⁴) have been instrumental in reporting COVID–19 cases. The abundant flow of news on COVID–19 may influence investors' sentiment, given that they may overreact to such information during the period of stress (see Barberis et al., 1998). Tetlock (2007) finds that media pessimism negatively affects stock prices. Fang and Peress (2009) show that media coverage affects stock returns. Groß-Klußmann and Hautsch (2011) argue that the use of artificial intelligence for reading and interpreting news to make financial decisions become a viable trading strategy. Existing studies also show that news sentiment is helpful to investors for asset allocation (Frijns and Huynh, 2018; Griffith et al., 2020; Heston and Sinha, 2017). In particular, sentiment from the media affects stock return during recessions than it does in normal periods (Garcia, 2013).

Since the outbreak of the COVID–19 pandemic, literature is ever-growing on the effects of the pandemic in financial contagion (Akhtaruzzaman et al., 2021a; Adekoya and Oliyide, 2020; Banerjee, 2021; Choi, 2020; Just and Echaust, 2020; Papadamou et al., 2020; So et al., 2020), the safe-haven property of gold and cryptocurrencies (Akhtaruzzaman et al., 2021b; Baur and Dimpfl, 2020;

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¹ See, <https://coronavirus.jhu.edu/map.html>

² See, <https://www.bsg.ox.ac.uk/research/projects/coronavirus-government-response-tracker>

³ See, <https://covid19.apple.com/mobility>

⁴ See, <https://trends.google.com/trends/explore?q=covid-19>

Corbet et al., 2020; James et al., 2020), oil risk exposure (Akhtaruzzaman et al., 2020; Corbet et al., 2020; Mensi et al., 2020; Salisu et al., Usman, 2020; Sharif et al., 2020), exchange rate prediction (Aslam et al., 2020), and lockdown effects (Ceballos et al., 2020; Goolsbee and Syverson, 2020; Narayan et al., 2020). Haroon and Rizvi (2020) find that the overwhelming panic caused by news during the pandemic increases equity returns volatility, particularly those of sectors that are most affected by the pandemic. Lyócsa et al. (2020) find that high Google search volumes for COVID-19 predict high stock market volatility. Umar and Gubareva (2020) find a high coherence between the COVID-19 Panic Index and EUR, GBP, RMB, and leading cryptocurrencies during the pandemic. Cepoi (2020) finds that media coverage decreases stock returns for middle to superior quantiles of the return distribution but has no effects on the inferior ones. However, there is limited literature on how the COVID-19 media coverage index (MCI) influences the volatility of environmental, social, and governance (ESG) leader indices from advanced and emerging equity markets.⁵ Our study fills this void in the literature.

We use the MSCI ESG leader indices as the proxy for ESG investments. Sustainable investment has been growing globally. Global sustainable investments stood at USD30.7 trillion in 2018, recording an increase of 34% in two years (Global Sustainable Investment Alliance, 2018). They also account for a considerable share of professionally managed assets in the world, ranging from 18% in Japan to 63% in Australia and New Zealand in 2018.⁶ The remarkable growth of ESG investments around the world motivates our study to examine the dynamic connectedness between the MCI and ESG leader indices during the pandemic.

The current study extends previous literature in several ways. First, it contributes to the growing literature on how the COVID-19 MCI impacts the volatility of ESG leader indices from advanced and emerging equity markets and supplements the work of Umar and Gubareva (2021), who use a time-frequency wavelet analysis to examine how the media coverage of the COVID-19 pandemic influences the volatility of ESG leader indices. In contrast to their wavelet analysis, we use a novel approach known as the time-varying parameter Vector Autoregressive model (TVP-VAR) suggested by Diebold and Yilmaz (2009, 2012, 2014) and Antonakakis and Gabauer (2017) to measure spillovers. The TVP-VAR model has a number of computational advantages, including the choice of the rolling windows size, insensitivity for outliers, and applicability of low-frequency data. Our study also supplements the work of Haroon and Rizvi (2020) and Cepoi (2020), who examine the effect of media on the market and industry level, respectively. Second, our study disentangles the net transmitters and net receivers of volatility spillovers during the pandemic, which provides investors with insights on how to diversify their portfolios.

The empirical results provide interesting findings. The results demonstrate that MCI plays a role in facilitating the transmission of shocks during the pandemic. The pronounced connectedness between ESG leader indices and MCI is evident around March and April, matching with the declaration of COVID-19 as a pandemic by the WHO and the steep decline in stock indices globally. The US appears to be a net receiver across the network except for February and May, echoing that the US is the most affected country during the pandemic.

The rest of the paper is organized as follows. Section 2 presents data and methodology. Section 3 provides the results, and Section 4 concludes.

1. Data and methodology

1.1. Data

The historical volatility series of ESG leader indices for advanced and emerging markets are from DataStream. The media coverage index (MCI) is from Ravenpack.⁷ The data start date coincides with the introduction of MCI by Ravenpack (January 1st, 2020) and ends on April 21st, 2021. The emerging markets include Brazil, China, India, Russia, and South Africa, whereas advanced markets include the US and the UK. We have included the European Market Union (EMU) ESG leader index to represent more countries in the study.

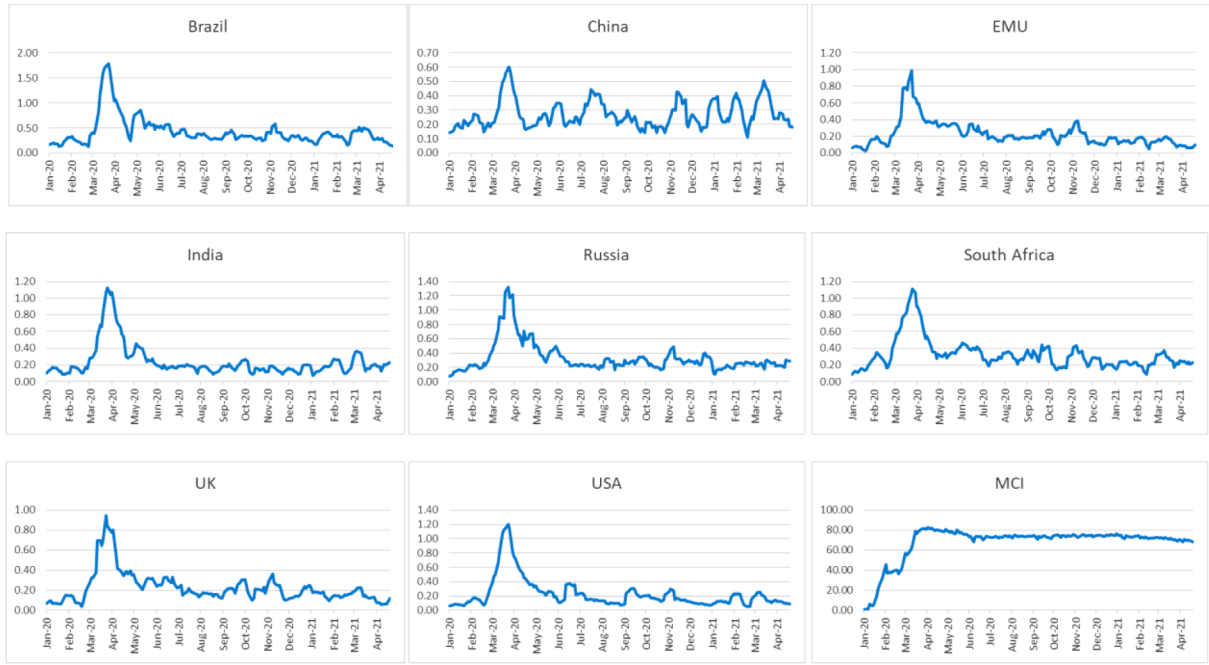
1.2. Empirical strategy

We apply the time-varying parameter Vector Autoregressive model (TVP-VAR). Diebold and Yilmaz (2014) model is applied, among others, to measure spillovers in stock indices (Diebold and Yilmaz, 2014), financial and commodity markets (Yoon et al., 2019), and housing prices (Zhang and Fan, 2019). The connectedness framework's popularity is mainly attributable to its ability to provide researchers and practitioners with an easy to comprehend network analysis in both static and dynamic time series. The static approach employs a VAR model on the whole dataset, whereas the dynamic approach applies a rolling-window VAR approach. Antonakakis and Gabauer (2017) suggest a dynamic model built on a TVP-VAR approach where the rolling window size does not impact the results. The additional advantages of the TVP-VAR model include applicability for low-frequency data, not losing observations, and not requiring an arbitrary selection of the rolling window size. We apply the TVP-VAR model and use two-day non-overlapping periods' volatility

⁵ The classification of Advanced and Emerging countries is based on the FTSE country classification (<https://www.ftserussell.com/equity-country-classification>).

⁶ Assets with sustainable investment strategies account for the 26% of investments assets under professional management in the US in 2018 (Global Sustainable Investment Alliance, 2018).

⁷ Ravenpack uses all news sources related to the COVID-19 to calculate the Coronavirus MCI. 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 related stories. (<https://coronavirus.ravenpack.com/>). The timestamp for the MCI is 00:00:00 (hh:mm:ss) Coordinated Universal Time (UTC).



Note: The figure shows the volatility of the ESG leaders indices and the media coverage index.

Fig. 1. Volatility of ESG leader indices and MCI. Note: The figure shows the volatility of the ESG leaders indices and the media coverage index.

indices to control for the asynchronous trading issue since markets in our study are in different time zones (see Baumöhl et al., 2018; Forbes and Rigobon, 2002).^{8,9}

We estimate a TVP-VAR (1) using the Bayesian information criterion (BIC) as below:

$$z_t = B_t z_{t-1} + u_t \quad u_t \sim N(0, S_t) \quad (1)$$

$$\text{vec}(B_t) = \text{vec}(B_{t-1}) + v_t \quad v_t \sim N(0, R_t) \quad (2)$$

where z_t , z_{t-1} , and u_t are $k \times 1$ dimensional vector and B_t and S_t are $k \times k$ dimensional matrices. $\text{vec}(B_t)$ and v_t are $k^2 \times 1$ dimensional vectors while R_t is a $k^2 \times k^2$ dimensional matrix. We calculate the H-step ahead generalized forecast error variance decomposition (GFEVD) (see Koop et al., 1996; Pesaran and Shin, 1998). Using the Wold theorem, we convert a TVP-VAR model into a TVP-VMA model by applying the following equality:

$$z_t = \sum_{i=1}^p B_{it} z_{t-i} + u_t = \sum_{j=0}^{\infty} A_{jt} u_{t-j} \quad (3)$$

The (scaled) GFEVD normalizes the (unscaled) GFEVD, $\theta_{ij,t}^g(H)$ so that each row sums up to unity. Hence, $\tilde{\theta}_{ij,t}^g(H)$ is the influence variable j on the variable i in terms of its forecast error variance share, representing the pairwise directional connectedness from j to i .

$$\theta_{ij,t}^g(H) = \frac{S_{ii,t}^{-1} \sum_{t=1}^{H-1} (e_i' A_t S_t e_j)^2}{\sum_{j=1}^k \sum_{t=1}^{H-1} (e_i' A_t S_t e_j)^2} \quad \tilde{\theta}_{ij,t}^g(H) = \frac{\theta_{ij,t}^g(H)}{\sum_{j=1}^k \theta_{ij,t}^g(H)} \quad (4)$$

e_i is a selection vector, with one as the i^{th} element and zero, otherwise with $\sum_{j=1}^k \tilde{\theta}_{ij,t}^g(H) = 1$ and $\sum_{i=1}^k \tilde{\theta}_{ij,t}^g(H) = k$.

Diebold and Yilmaz (2012, 2014) measure the connectedness using GFEVD as below:

$$TO_{jt} = \sum_{i=1, i \neq j}^k \tilde{\theta}_{ij,t}^g(H) \quad (5)$$

⁸ Authors thank an anonymous referee for his/her helpful comments that motivate this empirical strategy to deal with the asynchronous trading issue.

⁹ For a detailed discussion on return alignment and non-synchronous trading issues, please see Baumöhl and Lyócsa (2012), Baumöhl and Výrost (2010), and Výrost, Lyócsa and Baumöhl (2015).

Table 1

Descriptive statistics and correlation matrix.

Panel A: Descriptive statistics									
	BRAZIL	CHINA	EMU	INDIA	RUSSIA	SOUTH AFRICA	UK	US	MCI
Mean	−0.0001	0.0041	0.0034	0.0045	0.0071	0.0023	0.0027	0.0021	67.8401
Median	−0.0064	−0.0019	0.0106	0.0000	−0.0026	0.0026	0.0022	−0.0052	73.6050
Maximum	1.0199	0.5289	0.8906	0.6818	0.5447	0.8460	0.9779	1.0398	82.5900
Minimum	−0.5047	−0.6052	−0.8437	−0.9778	−1.0245	−0.7244	−0.6311	−0.7326	0.3000
Std. Dev.	0.2086	0.1889	0.2437	0.2377	0.1959	0.2038	0.2210	0.2358	17.2446
Skewness	1.5706	−0.1165	0.3235	−0.3923	−0.4841	0.1695	0.4657	1.2275	−2.5984
Kurtosis	9.1985	3.7811	6.1817	5.4019	7.3238	6.0353	5.9324	8.5293	9.0862
Jarque–Bera	342.04 ^a	4.71 ^b	74.67 ^a	45.22 ^a	139.07 ^a	66.07 ^a	67.06 ^a	259.25 ^a	453.68 ^a
Observations	170	170	170	170	170	170	170	170	170
Panel B: Correlation matrix									
	BRAZIL	CHINA	EMU	INDIA	MCI	RUSSIA	SOUTH AFRICA	UK	US
BRAZIL	1.0000	0.1966 ^a	0.2339 ^a	0.2800 ^a	−0.0824	0.2496 ^a	0.2933 ^a	0.1890 ^b	0.2647 ^a
CHINA		1.0000	0.1744 ^b	0.2624 ^a	−0.1055	−0.0588	0.1724 ^b	0.1336 ^c	0.1845 ^b
EMU			1.0000	0.4773 ^a	−0.0973	0.4324 ^a	0.6100 ^a	0.7101 ^a	0.4100 ^a
INDIA				1.0000	−0.0503	0.3437 ^a	0.3296 ^a	0.4003 ^a	0.2844 ^a
MCI					1.0000	−0.1525 ^b	−0.0732	−0.0906	−0.1167
RUSSIA						1.0000	0.4958 ^a	0.3851 ^a	0.0841
SOUTH AFRICA							1.0000	0.4981 ^a	0.2414 ^a
UK								1.0000	0.3841 ^a
US									1.0000

Notes: Panel A: Jarque-Bera test is conducted to check the normality of the volatility of ESG leader indices and the Media Coverage Index (MCI). Augmented Dickey-Fuller (ADF) test is conducted to check the unit root of variables. a, b and c represent significance at 1%, 5% and 10%, respectively.

Note: Panel B: a, b and c represent significance at 1%, 5% and 10%, respectively.

Table 2

Average connectedness table.

	Brazil	China	EMU	India	Russia	South Africa	UK	US	MCI	FROM
Brazil	74.4	1.7	7.6	5.4	5.8	6.8	5	4.9	1.1	38.1
China	3.2	74.5	7.3	7	5.6	5.5	4.2	4.1	1.2	38
EMU	4	1.8	44.2	8.4	7.4	15.3	22.1	8.7	0.6	68.3
India	3.8	3.9	12.1	57.9	8.2	10.7	8.5	6.4	1	54.6
Russia	3.1	0.7	11.6	7.3	60.7	13.6	9.1	1.6	4.9	51.8
South Africa	4.1	2.5	17.9	8.6	10.7	48.2	13.4	4.8	2.4	64.3
UK	2.1	1.2	25.4	6.1	5.6	12.6	48.5	10.3	0.8	64
US	4.4	2.5	14.9	5.1	1.1	5.6	13.7	63.1	2.1	49.4
MCI	0.1	0.5	0.3	0	1.3	0.1	0.2	0.6	109.4	3.1
Contribution TO others	24.8	14.8	97	47.8	45.7	70.2	76.1	41.2	14.1	431.7
NET directional connectedness	−13.3	−23.2	28.6	−6.8	−6.1	5.8	12.1	−8.1	11.1	TCl: 35.5

Notes: The results are based on a TVP-VAR model with a lag length of order one and a 10 step-ahead generalised forecast error variance decomposition and estimated using the following equations:

$$TO_{jt} = \sum_{i=1, i \neq j}^k \tilde{\theta}_{ij,t}^g(H) \quad (5).$$

$$FROM_{jt} = \sum_{i=1, i \neq j}^k \tilde{\theta}_{ji,t}^g(H) \quad (6).$$

$$NET_{jt} = TO_{jt} - FROM_{jt} \quad (7).$$

$$TCI_t = k^{-1} \sum_{j=1}^k TO_{jt} - k^{-1} \sum_{j=1}^k FROM_{jt} \quad (8).$$

TO_{jt} in Eq. (5) represents a shock to all variables, known as the total directional connectedness to others while $FROM_{jt}$ in Eq. (6) represents a shock from all variables, known as the total directional connectedness from others. NET_{jt} in Eq. (7) measures the net directional connectedness to indicate whether it is a net transmitter or net receiver. TCI_t in Eq. (8) is a total connectedness index.

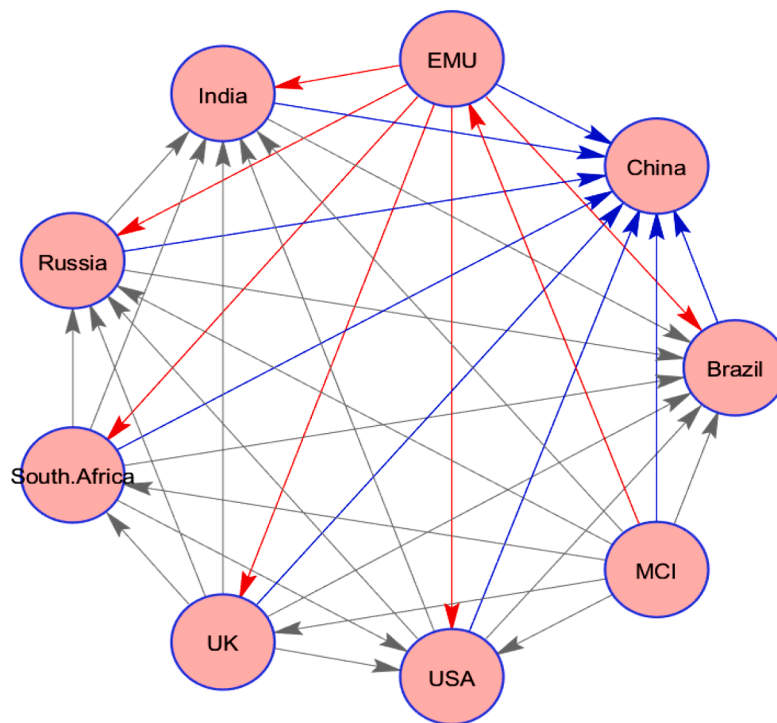


Fig. 2. Average pairwise connectedness of the system. Note: The figure shows the average net pairwise directional connectedness of each pair: the volatility of ESG leader indices and the MCI. The base of the edge indicates the source of spillover, and the head of the edge shows the recipient of the spillover.

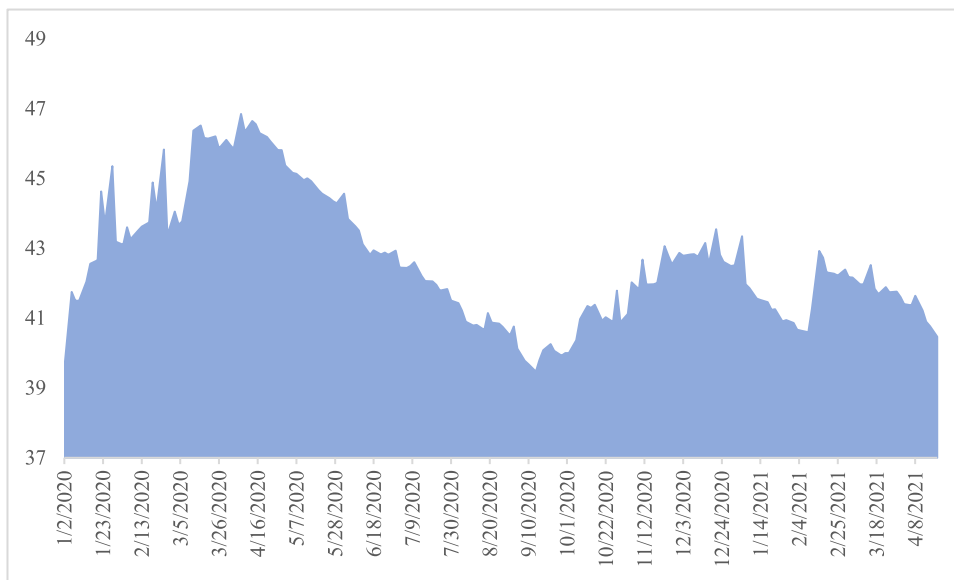


Fig. 3. Dynamic total net connectedness. Note: The results are based on a TVP-VAR model with a lag length of order one and a 10 step-ahead generalised forecast error variance decomposition.

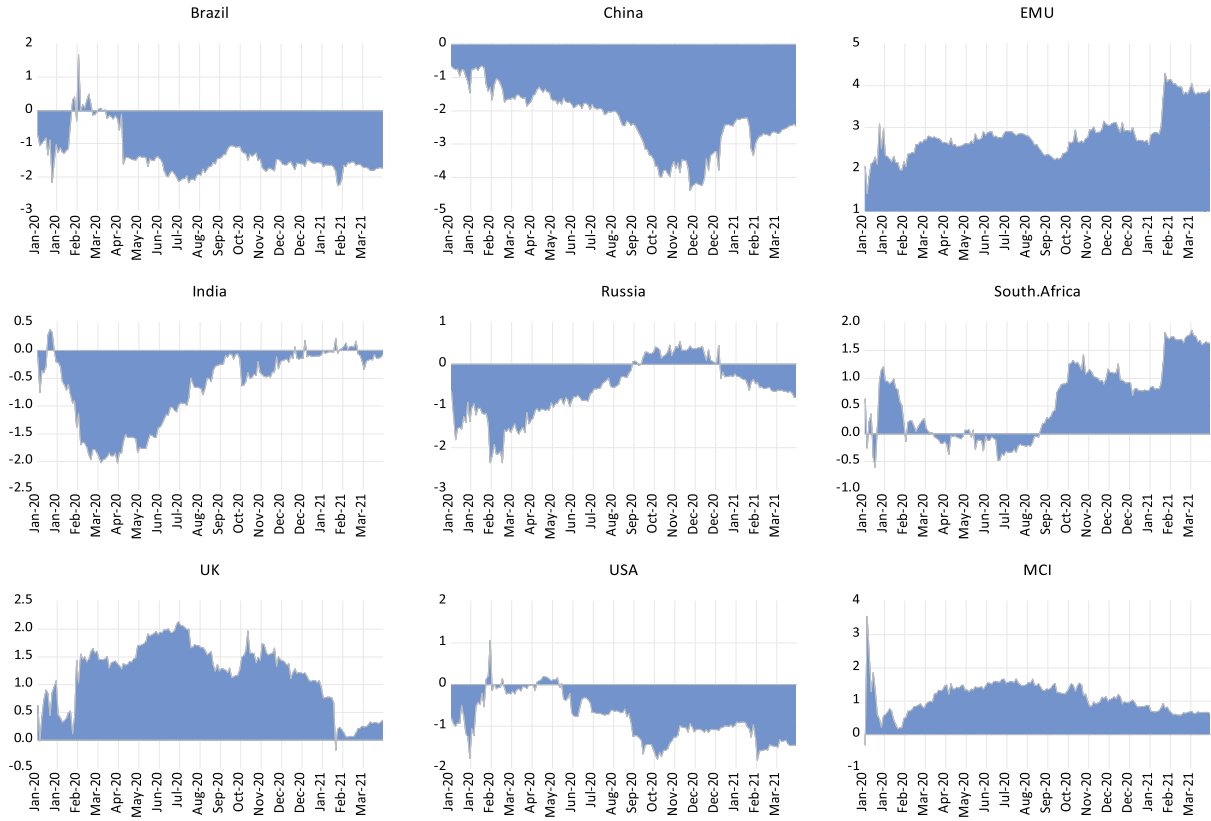


Fig. 4. Net total directional connectedness. Note: The figure shows the time-varying net directional connectedness of the volatility of ESG leader indices and the MCI.

$$FROM_{jt} = \sum_{i=1, i \neq j}^k \tilde{\theta}_{ji,t}^g(H) \quad (6)$$

$$NET_{jt} = TO_{jt} - FROM_{jt} \quad (7)$$

$$TCI_t = k^{-1} \sum_{j=1}^k TO_{jt} - k^{-1} \sum_{j=1}^k FROM_{jt} \quad (8)$$

TO_{jt} in Eq. (5) represents a shock to all variables, known as the total directional connectedness to others while $FROM_{jt}$ in Eq. (6) represents a shock from all variables, known as the total directional connectedness from others. NET_{jt} in Eq. (7) measures the net directional connectedness to indicate whether it is a net transmitter or net receiver. TCI_t in Eq. (8) is a total connectedness index.

2. Empirical results

2.1. Descriptive statistics

The change in the EMU ESG leader indices' volatility appears to reach its highest values during the sample period, followed by the UK. Fig. 1 shows that ESG leader indices' volatility is highest during the peak of the COVID-19 pandemic in the second half of March. The MCI reached the highest level during the same period, indicating the coherence between the MCI and volatility of ESG indices. The skewness and kurtosis of all volatility series indicate the non-normality. The Jarque-Bera test confirms the non-normality. MCI is negatively correlated with the volatility series of ESG leader indices (see Table 1). The highest positive correlation is between the UK and EMU leader ESG indices, followed by that between EMU and South Africa.

2.2. Average and dynamic total connectedness measures

The total connectedness index (TCI) value in Table 2 indicates that the comovements of ESG leader indices and MCI are moderate during the sample period as they account only for 35.5% of the total forecast error variance of the network. EMU, South Africa, the UK

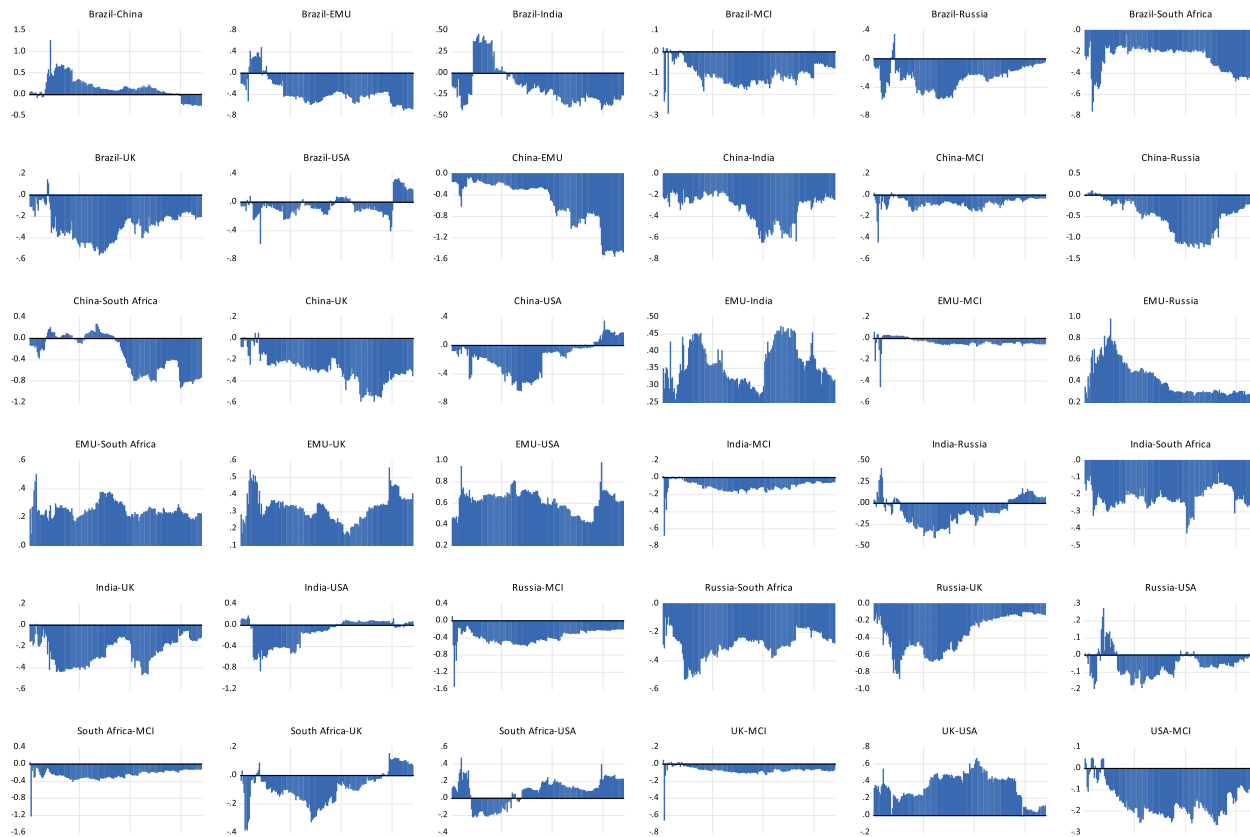


Fig. 5. Net pairwise directional. Note: The figure shows the time-varying net pairwise directional connectedness between the volatility of ESG leader indices and the MCI.

ESG leader indices, and MCI appear to be the net transmitters of shocks during the pandemic, while Brazil, China, India, Russia, and the US appear to be net receivers (see Fig. 2). Fig. 3 provides the spillover plots for total net connectedness for ESG leader indices and MCI. The results from Fig. 3 demonstrate that the overall volatility spillover was higher at the pandemic's peak in March and April, matching with the declaration of COVID-19 as a pandemic by the WHO and a large drop in stock indices globally.¹⁰ However, the overall volatility spillover dropped after April when the fiscal and monetary measures to lift the economy by the respective governments were implemented.

2.3. Net total connectedness

Total net connectedness indicates the difference between the transmitting and the receiving shocks of ESG leader indices and MCI. The positive values of the shaded areas in Fig. 4 correspond to periods when a particular index plays a net-transmitting role, while negative values show the periods when an index receives spillover, on net terms, from others. Fig. 4 (Net total directional connectedness) provides several interesting findings. MCI always appears to be a net transmitter across the network, highlighting the role of MCI in facilitating the transmission of financial contagion. On the other hand, the US appears to be a net receiver across the network except in February and May, echoing that the US is the most affected country during the pandemic.

2.4. Net pairwise connectedness

While the net total directional connectedness measure can be informative, it may suppress interesting stories between MCI and ESG leader indices during the pandemic. To examine further the net connectedness between MCI and ESG leader indices, we plot the pairwise results. Fig. 5 provides the net pairwise directional connectedness measures of spillovers between MCI and ESG leader indices. We find several interesting results on the pattern of spillover during the pandemic. The US leader index is a net transmitter of spillovers to India and Brazil in the beginning and most part of the pandemic. However, at the latter part of the pandemic, Brazil and India become the net transmitter to the US, reflecting that both Brazil and India have been severely affected by the pandemic in recent weeks. Likewise, South Africa is a net receiver from the UK in the beginning and most part of the pandemic. South Africa turns a net transmitter to the UK in the latter part of the pandemic when South Africa is hard hit by the pandemic and when the South Africa's strain of COVID-19 has become one of the dominant strains globally.

3. Robustness checks

We apply alternative specifications to check the robustness of our results. We have re-estimated and generated average connectedness table, average pairwise connectedness of the system, dynamic total net connectedness, net total directional connectedness, and net pairwise directional using data on daily frequencies instead of non-overlapping two-day frequencies. We find that results from daily data are qualitatively similar to those from two-day non-overlapping periods.¹¹

4. Conclusion

The COVID-19 pandemic disrupted the global economy. Our study provides evidence of how media coverage plays a role in facilitating the transmission of contagion. It uses a TVP-VAR model to examine the spillover and overcome the shortcoming of the small size of the rolling window. The pronounced connectedness between ESG leader indices and MCI is evident around the pandemic's peak in March and April, matching with the declaration of COVID-19 as a pandemic by the WHO and the massive global decline in stock indices. The US appears to be a net receiver across the network, reiterating that the US is the most affected country during the pandemic. Our results provide implications for global investors, portfolio managers, and policymakers in analyzing the shock transmission among ESG equity indices and media during the pandemic. Policymakers need not only monitoring the total connectedness but also evaluating directional spillover between financial assets. When the monitoring tool to assess shock transmission is in place, policymakers can design timely policy interventions to mitigate spillover risk from the connectedness of financial assets. Also, understanding the media's role in facilitating the transmission of shocks during the crisis period is critical for global investors, portfolio managers, policymakers, and other market participants to adopt strategies successfully to mitigate risks during the crisis. Our study is limited to see the effects of the COVID-19 media coverage on the ESG volatility indices. Future research is needed on this topic, particularly the effects of search volume intensity on the ESG volatility indices during the pandemic.

Authors statement

Md Akhtaruzzaman: Conceptualization, Methodology, Formal Analysis, Investigation, Writing-Original Draft, Writing-Review & Editing. Sabri Boubaker: Conceptualization, Methodology, Formal Analysis, Investigation, Writing-Original Draft, Writing-Review & Editing. Zaghum Umar: Conceptualization, Data Curation, Methodology, Software, Validation, Writing-Review & Editing.

¹⁰ This result is consistent with Adekoya and Oliyide (2020).

¹¹ Table A1 and Figures A1–A4 have been provided in the Internet Appendix.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.frl.2021.102170](https://doi.org/10.1016/j.frl.2021.102170).

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