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Return and Volatility Connectedness and Spillovers of ESG Indexes across Markets

Anaspree Chaiwan[1] and Chaiwat Nimanussornkul[2]

[1]Associate Professor Doctor, Faculty of Economics, Chiang Mai University, Mueang, Thailand
[2]Assistant Professoe Doctor, Faculty of Economics, Chiang Mai University, Mueang, Thailand
[1]anaspree@gmail.com, [2]chaiwatnim@gmail.com

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ABSTRACT
Recently, Environmental, Social, and Governance (ESG) have been transitioned from optional to essential for sustainable economy and development not only in country scale but also in global scale. ESG becomes a rapid growth of indexing as the Index Industry Association (IIA) reported the ESG indexes number globally increased by 55 percent in 2022. Since global investors, also funds integrate ESG to make a decision for the portfolio investment. Regulators and policymakers also make an attention on the indexes. Therefore, many companies disclose ESG information and release ESG reports to present their participation and ESG performance. The indexes provide the average returns and risks of selected companies. They are early warning indicators for opportunities creating to avoid losses. Then, returns and volatilities would help investors to evaluate its performance. This issue is essential to analyze the connectedness across ESG indexes. It is also important to figure out the linkage of returns and risk spillovers from one market to others because the globally financial system. The time varying parameter – vector autoregressive (TVP-VAR) is employed to examine return and volatility connectedness of global ESG indexes in both advanced and emerging markets from 2020 to 2024. The linkage of return and volatility spillovers across markets would guide the investors for adjusting their portfolio. Also, the regulators would monitor the global financial stability.

KEYWORDS: ESG Indexes, Volatility spillover, Advanced markets, Emerging markets, TVP-VAR

I. Introduction

In a recent year, trending of world economy highly targets about sustainable (green) finance, environmental, social, and governance (ESG) investing especially in emerging markets. [7] of IMF reports that it is rapidly growth of sustainable finance in advanced markets, but not in emerging markets. The environmental, social, and governance (ESG) investing in emerging markets have been increasing in magnitudes as well as among markets. They also report that the volumes of green bond grow about 20 percent. The sustainability markets outside China, e.g. Chile, Peru, and Mexico are proportioning about 12 percent of gross domestic products. The growth of ESG markets is an opportunity for investors to gain from investing, however, there are also higher risks. Moreover, the number of ESG indexes reported by the Index Industry Association (IIA) increased by 55 percent all over the world in 2022. This report showed the growing significant of ESG in financial sectors as well as the real-world sectors.
Environmental, social, and governance (ESG) stock indexes are more interesting for portfolio and fund managers and investors since it was high market value in several stock markets. It has been supporting by policy makers and regulators, for example, a tax deduction. Previous empirical research has provided consistent evidence for connectedness and volatility spillovers across major stock markets. [4] studied the return and volatility connectedness among assets consisting of cryptocurrency, crude oil, clean energy, and stocks during 2013 to 2021 by time-varying parameter model. The study showed shock transmit from clean energy and stocks to cryptocurrency and oil. The finding also found the substantially connectedness among cryptocurrency with other assets during the crisis of COVID-19 pandemic. Other studies, for example, [13] showed low-frequency components of stocks in US and UK markets having high volatility spillovers transmitters. Although other markets receive spillover effects. Therefore, they concern about the volatilities of market returns especially in the short terms that effecting by bubbles, liquidity tightening expectations, and financial policy. [11] investigated the

dynamic volatility connectivity of important environmental, social, and governance (ESG) stock indexes of US, Latin America, Europe, the Middle East and Africa, and Asia Pacific markets. They show the shock transmitters among ESG stock indexes in the Middle East Africa, and Latin America. Whereas the United States and Asia Pacific are net volatility receivers that convincing with Wang et al. They also show the high volatiles that relevance to portfolio management in Middle East Africa and Asia Pacific region or emerging markets. [10] applied TVP-VAR to study the dynamics mechanism among globally assets (equity, cryptocurrency, and commodities) during COVID-19 crisis. They found the different spillovers between events and time-frequency. Therefore, the study suggests the policymakers to concern about return and volatility spillover between markets during the period of crises. [12] also indicated high performance of EGS indexes portfolios generated by the minimum time-frequency domain volatility connectedness especially during extreme events as the pandemic. They find the connectedness changes among the ESG indexes' volatilities than returns in Europe and North America stock markets. Thus, it is importance for portfolio management to examine volatility spillovers among market retunes for different time-frequency dynamics, as the low-frequency markets may be high risk and volatiles.

This study proposes the empirical framework for investigating the return and volatility spillovers of ESG indexes across advanced and emerging markets in terms of a country level. Advanced markets are consisting of Australia, Canada, Hong Kong, Japan, Switzerland, UK, and US. Emerging markets are consisting of China, India, Korea, Taiwan, and Thailand. We extends the literatures by applying the time varying parameter vector autoregression (TVP-VAR) approach for measuring the dynamic correlation of return and volatility of ESG Indexes across both advanced and emerging markets. Additionally, the study investigates the existence of volatility connectedness and spillovers since 2020 that was a peak crisis of COVID-19. It would provide a reference for investors to invest in the market and helps regulators to formulate regulations that promote financial stability.

The structure of this paper is broken down as the introduction section, data section, methodology section, the empirical results section, and the conclusion and implications section that show the discussion from the results and policy recommendation.

II. Data

This study employs daily time series data of MSCI ESG LEADERS Indexes in advanced and emerging markets from January 2020 to April 2024. The data sets are consisting of twelve countries' ESG Indexes e.g. Australia, Canada, Switzerland, Hong Kong, Japan, the United Kingdom, the United States, China, India, Korea, Thailand, and South Africa. The indexes are calculated to the return series for estimation as $r_{it} = \log(x_{it})/\log(x_{it-1})\times 100$ totally including 1,120 time-series observations. All variables included in this study are described in Table 1.

Table 1 Variable Description

Variables	Description
AU	Australia ESG Leaders return
CA	Canada ESG Leaders return
CH	Switzerland ESG Leaders return
HK	Hong Kong ESG Leaders return
JP	Japan ESG Leaders return
UK	UK ESG Leaders return
US	USA ESG Leaders return
CN	China ESG Leaders return
IN	India ESG Leaders return
KR	Korea ESG Leaders return
TH	Thailand ESG Leaders return
ZA	South Africa ESG Leaders return

Table 2 shows that six series consisting with AU, CA, CH, JP, US, and IN have a positive average return. Whereas the series that have a negative average return are HK, UK, CN, KR, TH and ZA. Additionally, CN has the highest variance with the negative average return and the lowest variance with the positive average return is JP during the sample period. Most series are significantly right skewed, or the median is smaller than the mean whereas only three series are left skewed. According to the normality test of [9], all series are significantly non-normal distributions. The Augmented Dickey-Fuller (ADF) unit root test of [6] evident all return series are stationary at 1% significance level.

Table 2 Summary Statistics

Variables	Mean	Std. Dev.	Maximum	Minimum	Skewness	Kurtosis	Jarque-Bera	ADF Test
AU	0.002	1.528	8.408	-11.503	-1.044	12.465	**4,383**	**-22.369**
CA	0.009	1.435	11.564	-13.944	-1.325	24.870	**22,649**	**-11.322**
CH	0.020	1.208	7.416	-11.786	-0.791	13.271	**5,040**	**-33.221**
HK	-0.042	1.402	6.749	-6.900	-0.071	5.369	**262.9**	**-33.387**
JP	0.005	1.169	6.983	-6.422	0.037	5.587	**312.5**	**-33.061**
UK	-0.008	1.325	8.912	-13.248	-0.917	16.457	**8,607**	**-33.344**
US	0.042	1.415	9.460	-12.925	-0.750	16.430	**8,522**	**-9.584**
CN	-0.047	2.007	15.649	-9.626	0.467	8.036	**1,224**	**-32.119**
IN	0.038	1.344	9.785	-14.736	-1.511	23.327	**19,708**	**-13.349**
KR	-0.029	1.862	12.326	-14.514	0.012	9.920	**2,234**	**-21.843**
TH	-0.040	1.338	7.574	-11.461	-1.117	17.787	**10,436**	**-12.580**
ZA	-0.026	1.947	8.292	-11.818	-0.496	6.851	**738.0**	**-32.147**

Entries in bold are significance at 5% significance level.
Notes: Skewness test of [1]; Kurtosis test of [2]; JB normality test of [9]; ADF unit root test of [6].

III. Methodology

This paper employed the time varying parameter – vector autoregressive (TVP-VAR) model to evaluate the connectedness and spillover in return and volatility across ESG market indexes. This model allows the variance-covariance matrix to vary overtime via a Kalman filter estimation. The advantage of TVP-VAR is that it does not need to arbitrarily select a window size and has more precise calculation of the generalized forecast error variance decomposition (GFEVD).

The TVP-VAR model of order p for ESG stock indexes is as (1).

$$y_t = B_t z_{t-1} + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \Sigma_t) \tag{1}$$
$$vec(B_t) = vec(B_{t-1}) + v_t, \qquad v_t \sim N(0, \Omega_t)$$

where y_t is $k \times 1$ vector of endogenous variables, $z_{t-1} = (y_{t-1}, y_{t-2}, \ldots, y_{t-p})$ is $kp \times 1$ vector. $B_t = (B_{1t}, B_{2t}, \ldots B_{pt})$ and B_{it} are $k \times kp$ and $k \times k$ dimensional matrices, respectively. Σ_t and Ω_t are time varying variance-covariance matrices with dimension $k \times k$ and $k^2p \times k^2p$, respectively. ε_t is $k \times 1$ vector, $vec(B_t)$ and v_t are vectors with dimension $k^2p \times 1$. This model allows parameters B_t and the relationship across markets to vary over time. Moreover, the variance and covariance matrices are also time varying.

The Kalman filter algorithm is employed to estimate the accurate parameter B_t. Base on generalized impulse response function (GIRF) and generalized forecast error variance decompositions (GFEVD), the time varying parameters and time varying variance-covariance are used to estimate the generalized connectedness.

To calculate GIRF and GFEVD, the TVP-VAR has to convert to its TVP-VMA model based on Wold representation theorem. The TVP-VMA of [3] is as (2).

$$y_t = \sum_{j=0}^{\infty} A_{jt} \varepsilon_{t-j} \tag{2}$$

where A_{jt} is $k \times k$ dimensional matrix.

The GIRFs $(\Psi_{ij,t}(H))$ are the responses of all variables j, with a shock in variable i. The differences between a H step ahead forecast is computed when variable i is shocked or not. The calculation of effect of the difference to the shock in variable i is (3).

$$GIRF_t(H, \delta_{j,t}, \Gamma_{t-1}) = E(y_{t+H} | e_j = \delta_{j,t}, \Gamma_{t-1}) - E(y_{t+J} | \Gamma_{t-1}) \tag{3}$$

$$\Psi_{ij,t}(H) = \frac{A_{H,t} \Sigma_t e_j}{\sqrt{\Sigma_{jj,t}}} \frac{\delta_{j,t}}{\sqrt{\Sigma_{jj,t}}}, \qquad \delta_{j,t} = \sqrt{\Sigma_{jj,t}}$$

$$\Psi_{ij,t}(H) = \Sigma_{jj,t}^{-\frac{1}{2}} A_{H,t} \Sigma_t e_j$$

where e_j is m × 1 selection vector with unity in the j^{th} position and zero otherwise. The GFEVD ($\tilde{\phi}_{ij,t}(H)$) demonstrate the influence variable j on variable i in terms of its forecast error variance share, called pairwise directional connectedness from j to i. The variance shares are normalized that mean all variables explain variable i's forecast error variance sum up to 100% and calculated by (4).

$$(\tilde{\phi}_{ij,t}(H)) = \frac{\Sigma_{t=1}^{H-1}\Psi_{ij,t}^{2}}{\Sigma_{j=1}^{m}\Sigma_{t=1}^{H-1}\Psi_{ij,t}^{2}} \tag{4}$$

with $\Sigma_{j=1}^{m}\tilde{\phi}_{it,t}(H) = 1$ and $\Sigma_{i,j=1}^{m}\tilde{\phi}_{it,t}(H) = m$. The numerator is the cumulative effect of a shock in variable i and the denominator is a cumulative effect of all the shocks. The GFEVD represents the total connectedness index by (5).

$$C_t(H) = \frac{\Sigma_{i,j=1,i\neq j}^{m}\tilde{\phi}_{ij,t}(H)}{\Sigma_{i,j=1}^{m}\tilde{\phi}_{ij,t}(H)} \times 100 = \theta\frac{\Sigma_{i,j=1,i\neq j}^{m}\tilde{\phi}_{ij,t}(H)}{m} \times 100 \tag{5}$$

The connectedness index illustrates the spillover of a shock in one variable to other variables. Firstly, total directional connectedness variable i to all other variables j, called total directional connectedness to others, is defined as (6).

$$C_{i\to j,t}(H) = \frac{\Sigma_{j=1,i\neq j}^{m}\tilde{\phi}_{ji,t}(H)}{\Sigma_{j=1}^{m}\tilde{\phi}_{ji,t}(H)} \times 100 \tag{6}$$

Secondly, the total directional connectedness variable i receives from all other variables j, called total directional connectedness form others, is defined as (7).

$$C_{i\leftarrow j,t}(H) = \frac{\Sigma_{j=1,i\neq j}^{m}\tilde{\phi}_{ij,t}(H)}{\Sigma_{i=1}^{m}\tilde{\phi}_{ij,t}(H)} \times 100 \tag{7}$$

Finally, the net total directional connectedness is obtained by subtract total directional connectedness to others from total directional connectedness from others as (8).

$$C_{i.t} = C_{i\to j,t}(H) - C_{i\leftarrow j,t}(H) \tag{8}$$

The positive $C_{i,t}$ means the variable i influences the network more than itself being influenced. While a negative $C_{i,t}$ means the variable i is driven by the network.

IV. Empirical Results

To illustrate the average dynamic connectedness of ESG Indexes among twelve stock markets; seven return series in advanced markets and five return series in emerging markets, this study applies the time varying parameter – vector autoregressive based on impulse response function and generalized forecast error variance decompositions for the connectedness index estimation.

Table 3 shows the return spillovers of twelve ESG indexes in the globally stock markets. The estimations represent that the previous period return of nine stock markets significantly spillover to Australia's current period return. Secondary, eight stock markets' return at the past time spillover to US's current period return, while only three stock markets' return at the past time spillover to Japan's and Switzerland's current period return with the significance level. Therefore, the investors should concentrate when they decide to invest in Australia and US ESG stock markets. In addition, the US has the highest impact magnitude that spillovers to India (0.33), Japan (0.30), China (0.29), Korea (0.29), the UK (0.23), and Thailand (0.21). Meanwhile, India is the negative impacts spillover to all markets. When considering the return spillovers to the network, it appears that the past return of Japan and India ESG indexes affect to other 10 markets, equally. The past return of US ESG indexes also spillovers to other 8 markets. Japan, India, and the US can consequently assume to be the essential markets for investors. Nonetheless, the past return of Hong Kong ESG indexes affect only one market. This is inferred that if a few investors who investing in Hong Kong markets and only if they are not interesting to invest in other markets or to invest in the small volume. In other words, Hong Kong ESG return in the previous period would affect only in its system.

Table 3 Return Estimations

	Advanced markets							Emerging markets				
	AU	CA	CH	HK	JP	UK	US	CN	IN	KR	TH	ZA
AU_{t-1}	**-0.483**	**-0.135**	**-0.085**	-0.052	**-0.101**	**-0.102**	**-0.107**	-0.103	0.059	-0.013	0.053	**-0.133**
	0.043	**0.044**	**0.036**	0.042	**0.032**	**0.040**	**0.042**	0.061	0.038	0.051	0.039	**0.060**
CA_{t-1}	**0.172**	-0.042	0.004	0.050	-0.004	0.104	-0.118	0.055	-0.042	**0.194**	-0.070	**0.188**
	0.062	0.063	0.053	0.061	0.047	0.058	0.061	0.089	0.056	**0.074**	0.057	**0.087**
CH_{t-1}	0.081	0.019	-0.070	**0.143**	0.077	0.009	0.012	**0.233**	-0.015	**0.146**	0.048	0.028
	0.055	0.056	0.047	**0.054**	0.042	0.051	0.055	**0.079**	0.049	**0.066**	0.050	0.077
HK_{t-1}	0.036	0.036	0.031	-0.073	-0.025	0.045	**0.095**	-0.107	0.011	-0.033	0.006	-0.027
	0.041	0.042	0.035	0.041	0.031	0.039	**0.041**	0.059	0.037	0.050	0.038	0.058
JP_{t-1}	**0.276**	**0.202**	**0.132**	0.062	-0.048	**0.188**	**0.146**	**0.153**	**0.164**	**0.169**	**0.158**	**0.263**
	0.043	**0.044**	**0.037**	0.043	0.033	**0.040**	**0.043**	**0.062**	**0.039**	**0.052**	**0.040**	**0.061**
UK_{t-1}	**0.148**	-0.030	-0.066	0.062	**0.192**	**-0.107**	-0.005	-0.042	0.023	0.114	**0.135**	0.053
	0.058	0.060	0.050	0.057	**0.044**	**0.054**	0.058	0.084	0.052	0.070	**0.053**	0.082
US_{t-1}	**0.285**	**0.113**	**0.298**	0.082	**0.305**	**0.232**	-0.056	0.097	**0.330**	**0.240**	**0.214**	0.089
	0.049	**0.050**	**0.042**	0.049	**0.037**	**0.046**	0.049	0.071	**0.044**	**0.059**	**0.045**	0.069
CN_{t-1}	-0.056	-0.037	-0.047	**0.056**	-0.010	-0.040	**-0.075**	0.069	-0.006	0.040	-0.011	0.014
	0.029	0.030	0.025	**0.029**	0.022	0.027	**0.029**	0.042	0.026	0.035	0.027	0.041
IN_{t-1}	**-0.195**	**-0.210**	-0.061	**-0.187**	-0.056	**-0.126**	**-0.174**	**-0.233**	**-0.190**	**-0.236**	**-0.212**	**-0.253**
	0.043	**0.044**	0.036	**0.042**	0.032	**0.040**	**0.042**	**0.061**	**0.038**	**0.051**	**0.039**	**0.060**
KR_{t-1}	**0.094**	**0.107**	0.030	-0.012	-0.008	0.050	**0.129**	-0.037	**-0.066**	**-0.170**	-0.047	0.025
	0.031	**0.032**	0.026	0.030	0.023	0.029	**0.031**	0.045	**0.028**	**0.037**	0.028	0.043
TH_{t-1}	**-0.126**	**-0.106**	-0.061	**-0.081**	-0.024	**-0.082**	**-0.103**	-0.081	**-0.152**	-0.074	**-0.103**	-0.080
	0.042	**0.043**	0.035	**0.041**	0.031	**0.039**	**0.041**	0.060	**0.037**	0.050	**0.038**	0.058
ZA_{t-1}	**0.081**	0.058	0.023	**0.104**	0.033	-0.004	**0.084**	**0.117**	**0.106**	**0.146**	**0.083**	0.005
	0.032	0.033	0.027	**0.031**	0.024	0.030	**0.032**	**0.046**	**0.029**	**0.038**	**0.029**	0.045
Constant	-0.006	0.011	0.008	-0.044	-0.007	-0.018	0.053	-0.053	0.026	-0.037	-0.045	-0.027
	0.041	0.042	0.035	0.040	0.031	0.038	0.040	0.058	0.037	0.049	0.037	0.057

The two entries for each parameter are their respective estimates and standard errors. Entries in bold are significance at 5% significance level.
Note: Results estimated by TVP-VAR model with lag length of order one (BIC).

Table 4 shows countries transmit shocks to others (influencing the network more than itself being influenced), also receive shocks from others. The average value of the total connectedness index (TCI) is 59.31%. This implies the percent of the forecast error variance within this network is about 59.31 from cross-market errors. By the net directional connectedness from highest to lowest effects to others, they are Canada, South Africa, the United Kingdom, Australia, the United States, and Switzerland. In contradiction, countries that influenced by networks are in Asia region. From the most to least receiving effects, they are Japan, Hong Kong, China, Korea, Thailand, and India, respectively. The results show the interesting remarks about the own contribution. Networks that have the most effects to themselves are in Asia. China is the highest within the network itself with 41.03% then Hong Kong (40.05%), Japan (36.20%), Thailand (34.33%), India (31.82%), and Korea (29.33%). Considering the averaged pairwise connectedness, contribution of each return error to the forecast error variance of one specific country occurs in the same region. In the opposite direction, one specific country responses to innovation (receiving the shocks) in respective another country. For example, in the North America, Canada transmits the shocks to US about 19.78% and receives the shocks from US about 15.57%. In Asia, Hong Kong transmits the shocks to China about 16.26% and receives the shocks from China about 16.30%. In Europe, UK transmits the shocks to Switzerland about 16.39% and receives the shocks from Switzerland about 13.92%. By conclusion, this network of ESG Indexes is high co-movement, considerably when it is in the same region.

Table 4 Averaged Joint Connectedness Results.

	AU	CA	CH	HK	JP	UK	US	CN	IN	KR	TH	ZA	FROM
AU	24.75	12.71	7.09	3.23	4.24	10.34	10.35	2.31	5.51	5.55	4.94	8.99	61.26
CA	10.17	23.82	10.07	1.52	2.17	11.98	15.57	2.06	6.17	2.88	4.77	8.81	80.19
CH	7.19	12.85	29.57	0.99	2.24	16.39	10.86	1.72	4.41	1.53	3.03	9.21	64.72
HK	5.61	4.15	3.17	40.05	2.56	3.88	2.84	16.3	2.7	7.75	4.01	6.99	52.06
JP	6.76	9.98	7.39	2.15	36.2	8.32	13	1.66	2.03	5.39	1.84	5.27	44.18
UK	9.5	12.73	13.92	1.6	2.19	25.31	9.47	1.42	6.24	2.68	4.71	10.23	72.82
US	7.83	19.78	9.49	0.73	2.11	10.7	28.47	1.93	6	2.36	4.15	6.46	71.49
CN	3.86	4.09	3.04	16.26	1.8	2.55	3.65	41.03	3.46	7.59	4.07	8.61	52.74
IN	6.99	8.94	5.79	2.09	2.12	8.57	8.17	2.54	31.82	5.68	9.75	7.54	51.91
KR	7.78	8.93	5.77	5.55	4.56	6.8	7.86	5.73	4.99	29.33	5.32	7.36	53.04
TH	7.02	7.56	5.16	3.36	2.12	8.12	5.75	3.31	10.31	6.35	34.33	6.61	48.12
ZA	9.48	10.44	8.68	3.82	2.21	11.26	6.42	5.62	5.86	3.94	4.44	27.82	59.14
TO	70.68	96.45	68.43	35.52	24.36	85.07	80.8	38.36	49.61	44.47	43.9	74.03	711.68
Inc.Own	106.93	135.97	109.14	81.35	64.52	124.22	122.42	85.64	89.51	81.04	85.37	113.9	TCI
NET	9.42	16.27	3.7	-16.54	-19.83	12.25	9.31	-14.38	-2.3	-8.57	-4.23	14.88	59.31

Note: Results estimated by TVP-VAR model with lag length of order one (BIC) and GFEVD.

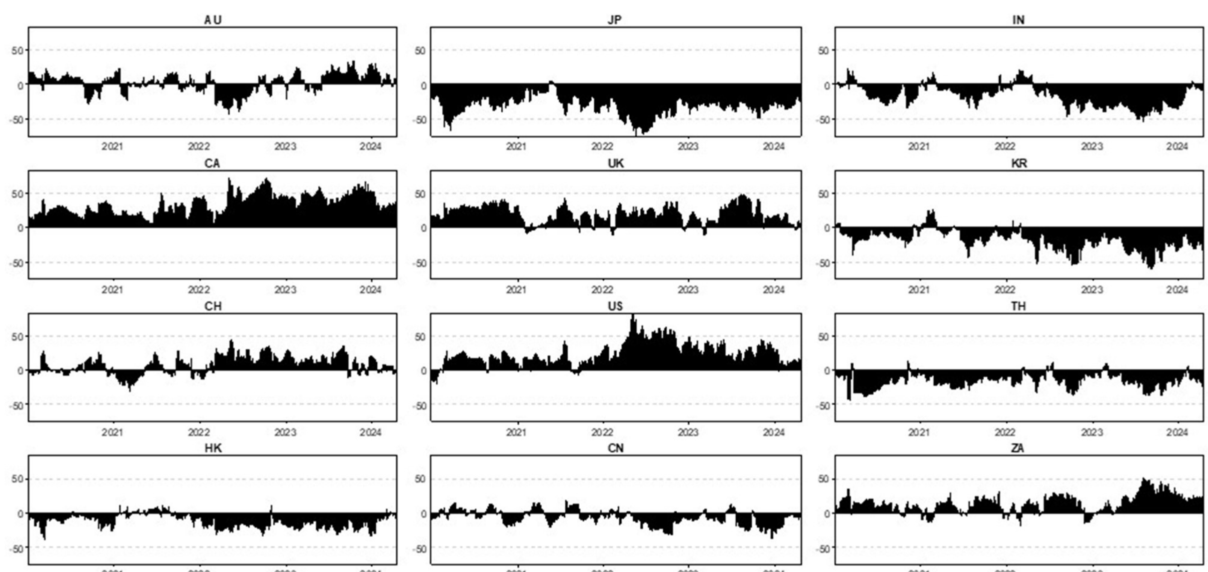

Figure 1 Dynamic net total directional connectedness plot

The results obviously show the dynamic net connectedness transmissions, the positive direction correspond to the dynamic transmitter and the negative direction correspond to the dynamic receiver. The entries samples show that all ESG markets are strongly interconnected since the connectedness changing over time as shown in Figure 1. Canada, the UK, the US, Switzerland, and South Africa are clearly dominate the market while Hong Kong, Japan, China, India, Korea, and Thailand are driven by the market. By considering the results of the dynamic net connectedness transmissions, it is noted that most countries in Asia are determined as the net receivers. Top ten largest economies in 2024 by [7] e.g. the US, the first ranking, the UK, the sixth ranking, and Canada, the tenth ranking, are determined as the major net transmitters of spillover shocks in the system. However, Australia could play both roles as a net transmitting role or a net receiving role — given periods since the late of year 2022, it appears to be a net transmitting role. Finally, the dynamic volatility spillovers as shown in Fig.1, it represents that Canada, the US, and Japan ESG stock indexes having the significant spillovers in terms of magnitude during the period of the study (2020-24).

V. Conclusion and Implications

In this study, the time varying parameter – vector autoregressive (TVP-VAR) model is applied to estimate the interconnectedness across globally ESG stock market indexes. This approach is the normalization technique that allows investigating the joint connectedness among series' volatilities that cloud be changing over time. The data used in the analysis are the daily return series of twelve countries' ESG indexes consisting of Australia, Canada, Switzerland, Hong Kong, Japan, the United Kingdom, the United States, China, India, Korea, Thailand, and South Africa from January 2020 to April 2024, totally 1,120 observations.

In the return equations, there are return spillover across the market. However, Japan and Switzerland are less spillover from other markets, in terms of number of markets, it is implied that the investors should sensibly consider three markets when they are investing in Japan and Switzerland. While in contrast, Australia and the US is depending on nine and eight markets, respectively. India market's return has a negative spillover to all markets and the US has the highest magnitude affecting to other markets. Therefore, India and the US returns might be in consideration as well. For the volatility connectedness, the results indicates that most of indexes' volatilities are strongly interconnected. The advanced markets have positive net connectedness except Hong Kong and Japan, while emerging market are net receiver except South Africa. This mean advanced market in North America and Europe and emerging market in Africa are transmitter, whereas Asia market is receiver. Our findings show not only a direction (positive/negative) but also the substantial connectedness of Canada, the US, and Japan spillover to the network, thus this is an opportunity for investors to manipulate the risk in these markets. Additionally, the system-wide dynamic connectedness is heterogeneous over time. The finding could help the investors, speculators, or fund managers to have more information in the ESG markets. This information could be used to make the decision in investing, speculating, managing, and hedging in their portfolio's risk and returns. This information of the dynamic values is assured to achieve their optimization purposes. Furthermore, insight information of major drivers of the volatility spillovers would help investors/fund managers to minimize or diversify the risk across markets. ESG indexes return spillover is used as warning indicators that the previous market returns will affect to the current market returns. In conclusion, the volatility connectedness shows the time varying effect of positive and negative shocks from ESG markets around the world, then the investors/fund manager should concentrate the shocks from other markets all the time to manage portfolio efficient.

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