PressAcademia
www.pressacademia.org/journals/jbef
JBEF
ISSN 2146-7943
Journal of Business, Economics and Finance YEAR 2024 VOLUME 13 ISSUE 2

TIME-VARYING CONNECTEDNESS BETWEEN GREEN MARKETS AND CABLE NEWS-BASED ECONOMIC POLICY UNCERTAINTY: EVIDENCE FROM A TVP-VAR CONNECTEDNESS APPROACH

DOI: 10.17261/Pressacademia.2024.1943
JBEF- V.13-ISS.2-2024(4)-p.88-98

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Date Received: August 29, 2024 **Date Accepted:** December 7, 2024

To cite this document
Gungor, S., (2024). Time-varying connectedness between green markets and cable news-based economic policy uncertainty: evidence from a TVP-VAR connectedness approach. Journal of Business, Economics and Finance (JBEF), 13(2), 88-98.
Permanent link to this document: http://doi.org/10.17261/Pressacademia.2024.1943

ABSTRACT

Purpose- Governments and businesses worldwide are actively driving the growth of green finance (GF) markets as part of their goals towards a natural, sustainable, zero-carbon economy. Along with the turbulent events and developments in global markets, economic policy uncertainty (EPU) levels are constantly increasing, leading to significant spillover shocks on various economic and financial factors. Accordingly, this research aims to identify the dynamic connectivity between cable news-based EPU (TVEPU) and green asset returns, considering the period between 01.10.2014 and 30.09.2024.

Methodology- This research employs the TVP-VAR connectedness method to examine the nexus between TVEPU and the returns of green assets. This approach enables the estimation of a generalized connectedness procedure using variance-covariance matrices and time-varying coefficients. Additionally, by applying Wold's representation theorem, it calculates generalized impulse response functions (GIRF) and variance decompositions (GFEVD) to predict the connectedness indices between the variables.

Findings- First, we observe that the Fossil Fuel Reserves Free index has the highest influence on other indices while the TVEPU index has the lowest impact on other indices. Second, we find that shocks from international events and news significantly increase the sensitivity of the spillover effects between green assets and TVEPU. Third, we demostrate that the Green Bond (GB) market is a net shock receiver; simultaneously, the Fossil Fuel Reserves Free, Sustainability World and Environmental and Social Responsibility indices are net shock transmitters. Moreover, the findings demonstrate that the net spillover of TVEPU, Global Clean Energy, Carbon Emission Allowances (CEAs) and Renewable Energy and Clean Technology indices changes over time. Fourth, we determine that TVEPU has a meagre impact on the returns of green stocks (GSs) and GBs.

Conclusion- This research provides strong evidence that news from wired news networks also impacts uncertainty shocks, emphasising that green asset investors should determine their portfolio diversification and hedging strategies by considering this factor.

Keywords: TVEPU, green financial markets, sustainable assets, dynamic connectedness, TVP-VAR based connectedness technique.
JEL Codes: D53, E60, Q56.

1. INTRODUCTION

Since the early 2000s, the international community has consistently accepted the critical need to address climate challenges and transition to a zero-carbon economy. Key frameworks like the Paris Agreement established in 2015 emphasise limiting global heat spikes, enhancing climate resilience and advancing sustainable progress. At the same time, the growth of the environmental movement has drawn significant attention to green markets, which aim to achieve carbon neutrality and support sustainability initiatives (McCollum et al., 2018; Iacobuţă et al., 2022).

Early efforts by the international financial sector to align financial power with ecological benefits were adapted to address global climate challenges. This event led to the development of GF as an economic factor. GF markets facilitate funding green energy initiatives by offering financial services and operational capital. Within this framework, GBs, called climate bonds, are stable-income instruments primarily used to support environmental conservation and climate change projects. Banks play an essential role in enabling companies and governments to provide financing for projects with favourable ecological outcomes. Additionally, GSs are often associated with businesses that focus on renewable and alternative energy, waste reduction, sustainable transport, recycling, aquaculture, pollution control and organic farming. On the macro side, this situation is grounded in the collective rationality that corresponds to the attempts of World states to eliminate climate risks (Kazlauskiene et al., 2017; Berrou et al., 2019).

GF serves as both a crucial enabler and a fundamental prerequisite for sustainable development programs, supporting green technologies and fostering environmental accountability. Simultaneously, the growth of green markets reflects a collective commitment to building an eco-friendly society and mitigating global warming. At the micro level, this approach is grounded in individual rationality, aligning with companies' voluntary actions to preserve the environment (Braouezec and Joliet, 2019; Madaleno et al., 2022).

Over the past 25 years, the rapid succession of international events has heightened global economic uncertainty, prompting nations to examine its effects on the broader economy and asset markets. This growing concern has driven EPU to unprecedented levels worldwide, influencing asset markets directly and indirectly. Elevated uncertainty impacts firms' operations and profitability through the direct channel, resulting in asset price volatility. Indirectly, uncertainty increases investors' concerns about future economic growth, leading to a significant fall in stabilised asset values (Bansal and Shaliastovich, 2010; Luo and Zhang, 2020). However, green assets are also vulnerable to the influence of the EPU. This condition discourages buying behaviour in the green asset market because the increase in EPU will likely deteriorate expectations and hamper the forecasting ability of financial institutions and investors. Investors also face more significant valuation uncertainty, information costs and information asymmetry when uncertainty is high.

Against the continuous and increasing EPU background, lenders and stakeholders are becoming more conservative and applying tighter issuance criteria for green assets, thus limiting the availability of financing for projects. However, green asset markets offer a hedge against EPU by attracting long-term investors who prioritize sustainable development and are less likely to make impulsive decisions during market fluctuations (Nagar et al., 2019; Wei et al., 2021). Consequently, identifying instruments to ensure coherence and balance between green asset markets and EPU remains a critical frontier. Therefore, this paper explores the dynamic interconnectedness between TVEPU and green asset returns.

This research makes two substantial contributions to the existing literature. First, since EPU is not directly observable, previous studies have constructed it in various ways: by analyzing political and economic events (Hong and Kostovetsky, 2012), mining uncertainty using macroeconomic indicators and financial market data, constructing it from news reports on reputable platforms (Baker et al., 2016), and developing EPU using artificial intelligence from large US cable news networkssuch as Fox News, MSNBC and CNN (Hong et al., 2021; Bergbrant and Bradley, 2022). The Pew Research Centre reported that the primary source of American political information is about 3% newspaper-based sources and about 16% cable news. This observation is an imperative factor that triggers uncertainty (Bergbrant and Bradley, 2022). Furthermore, the growing level of factors such as the COVID-19 pandemic, FED interest rate hikes, trade policy war with China, Russia-Ukraine and Israel-Palestine wars, and the collapse of Silicon Valley Bank, which are driving US uncertainty indices from cable news networks, is highly likely that such factors will affect the green asset market. Secondly, Campbell and Shiller (1991) argued that the time-varying market price of risks and available information on financial asset returns have predictive power for future financial asset returns. Therefore, this paper utilises factors that enhance forecasting power by providing an experimental testbed for the influence of systematic uncertainty on green asset returns with the help of a TVP-VAR connectedness model.

The other sections of this paper are organised as follows: Section 2 summarizes the existing literature on the topic, followed by Section 3, which outlines the research methods. Section 4 reports and analyses the empirical results, and finally, Section 5 offers a theoretical interpretation of the policy implications and results.

2. LITERATURE REVIEW

As environmental challenges continue to grow, researchers have shown increasing interest in green financial markets. Theoretically, EPU can lead to both upside and downside movements in the prices and yields of green assets, affecting investors' perceptions of a company's growth potential and possibly reducing their desire to engage in the green market (Pástor and Veronesi, 2013). As a result, the association between green markets and EPU has been extensively analysed in the literature, often using indicators derived from newspapers or cable news.

Pham and Nguyen (2022) examined the sensitivity of the GB market to US EPU using TVP-VAR and Markov regime-switching models. Their results indicated that GBs protect against uncertainty during periods of low uncertainty, but their hedging effectiveness decreases when uncertainty is high. Syed et al. (2022), employing NARDL models, investigated the asymmetric nexus between US EPU, global GBs, and the green energy index. They found that a positive shock in EPU negatively affects GBs, whereas a negative shock enhances their performance.

Wei et al. (2022) employed wavelet-based and multiscale quantile analyses to examine the link between EPU and the GB markets. Their results suggested a non-linear and time-varying causality from EPU to the GB market. Using quantile causality analysis, Lin and Su (2023) investigated the tail dependence of GB markets in the US and China with EPU and financial uncertainty. They concluded that financial uncertainty affects the US GB market more significantly, while EPU influences the Chinese market.

Finally, Wang et al. (2023) used quantile ARDL models to estimate the influence of China's EPU on the GB market. Their results showed that EPU has a negative and significant long-run effect on the GB market in most quantiles, whereas the short-run effects are positive and significant only in high quantiles.

Several studies in the literature investigate the impact of EPU on both GB and GS markets. Haq et al. (2021) employed DCC-MGARCH models to examine the dynamic relationship between EPU, GBs, and clean energy stocks, finding that GBs provide protection against EPU, while clean energy stocks and rare earths exhibit safe-haven characteristics. Urom et al. (2022) applied wavelets, cross-quantilogram techniques, and TVP-VAR models to explore sector-specific responses of clean investments to EPU, revealing that these responses vary by sector, market conditions, and time horizons.

Wang et al. (2022) applied time-varying causality analysis to explore the interaction between green market returns and EPU, finding a bidirectional and time-varying causality, with green markets serving as risk transmitters. Su et al. (2023) examined the relationship between GB and GS markets in China, using cross-quantilogram methods. They concluded that EPU does not significantly influence the interrelationships between these assets. Using quantile-quantile regression, Xi et al. (2023) discovered that EPU negatively impacts green financial markets, with GSs showing stronger reactions than GBs. Xia et al. (2023) used asymmetric TVP-VAR and EGARCH models to show that GBs, CEAs, and GSs serve as hedges against EPU, even when alternative EPU measures are applied. Adetokunbo and Mevhare (2024), using a TVP-VAR framework, highlighted that global EPU, linked to Brent oil prices, has a more pronounced volatility effect on green stocks, with the US EPU serving as a net volatility transmitter. Adebayo et al. (2024) employed wavelet quantile causality to demonstrate that time, frequency, and quantile significantly influence financial asset returns, including clean energy stocks and GBs.

Aloui et al. (2024) investigated the potential of clean energy stocks and GBs as safe havens in the face of global uncertainties using quintile wavelet models. Their findings revealed that the safe-haven activities of these assets fluctuate in terms of time horizons and risk conditions. Wang et al. (2024) explored the nexus between GBs, GSs, and EPU in China, employing nonparametric quantile methods. They discovered that the adverse predictive effects of EPU are more significant in extreme quantiles.

The existing literature underlines that the influence of EPU on green assets is usually measured by the EPU indicator introduced by Baker et al. (2016), whereas the number of papers utilising TVEPU is entirely restricted (Adebayo et al., 2024). Therefore, this paper is projected to contribute to filling a critical research gap in the literature.

3. DATA AND METHODOLOGY

This research intends to determine the time-varying connectivity between TVEPU and green asset returns for 01.10.2014-30.09.2024. The TVEPU index is an AI-based index developed by Hong et al. (2021) and Bergbrant and Bradley (2022) to construct EPU from major US cable news networks. In addition, following the existing literature (Syed et al., 2022; Wang et al., 2022; Adebayo et al., 2024; Aloui et al., 2024), this research considers GB and GS market indices to represent green assets. Meanwhile, the series of changes in TVEPU are obtained from the formula $TVEPUC_t = \ln(Y_t) - \ln(Y_{t-1})$, and the green asset returns are estimated by the formula $r_t = \ln(p_t) - \ln(p_{t-1})$. Table 1 provides detailed information about the data set. Table 2 contains descriptive statistics and stationarity results for the data.

Table 1: Data set Informations

Variables	Description	Data Sources
Green Assets		
Green Stock Markets		
SPXESRP	S&P 500 Environmental and Socially Responsible Index	www.spglobal.com
SPGSCEE	S&P GSCI Carbon Emission Allowances Index	
TXCT	S&P/TSX Renewable Energy and Clean Technology Index	
W1SGI	Dow Jones Sustainability World Index	
SP5F3UP	S&P 500 Fossil Fuel Reserves Free Index	
SPGTCED	S&P Global Clean Energy Index	
Green Bond Market		
SPGBI	S&P Green Bond Index	www.spglobal.com
RTVEPU	Cable News-based Economic Policy Uncertainty Index	www.policyuncertainty.com

According to Table 2, excluding SPGBI and TXCT, the sample mean of all other variables is positive and very close to zero. However, there is a significant difference between the minimum and maximum values of the dependent and independent indicators, showing potential fluctuation levels. Standard deviation values state that the volatility of the RTVEPU variable is higher than the volatility of other indicators. The positive skewness values of the RTVEPU variable suggest that the variable shows positive asymmetry and exhibits a right-skewed distribution. The negative skewness values of all other variables demonstrate that they are characterised by negative asymmetry and a left-skewed distribution. The kurtosis coefficients state that the distribution curves of all variables are characterised by leptokurtic to a large extent, and this pressure is more intense in all variables except SPGBI and SPGSCEE variables. In addition, according to Jarque-Bera statistics, the p-probability values of all variables are 0.0000, confirming that the indicators are not normally distributed. Ljung Box Q and Q^2 and ARCH statistics reveal a serious autocorrelation problem and autoregressive conditional heteroscedasticity effect at lag 20. Lastly, the significance level of ADF test statistics means that all variables are stationary. The time series graphs in Figure 1 also suggest that the variables do not exhibit a normal distribution and suffer from autocorrelation problems. The time series in Figure 1 also suggests that the indicators suffer from autocorrelation problems and are not normally distributed.

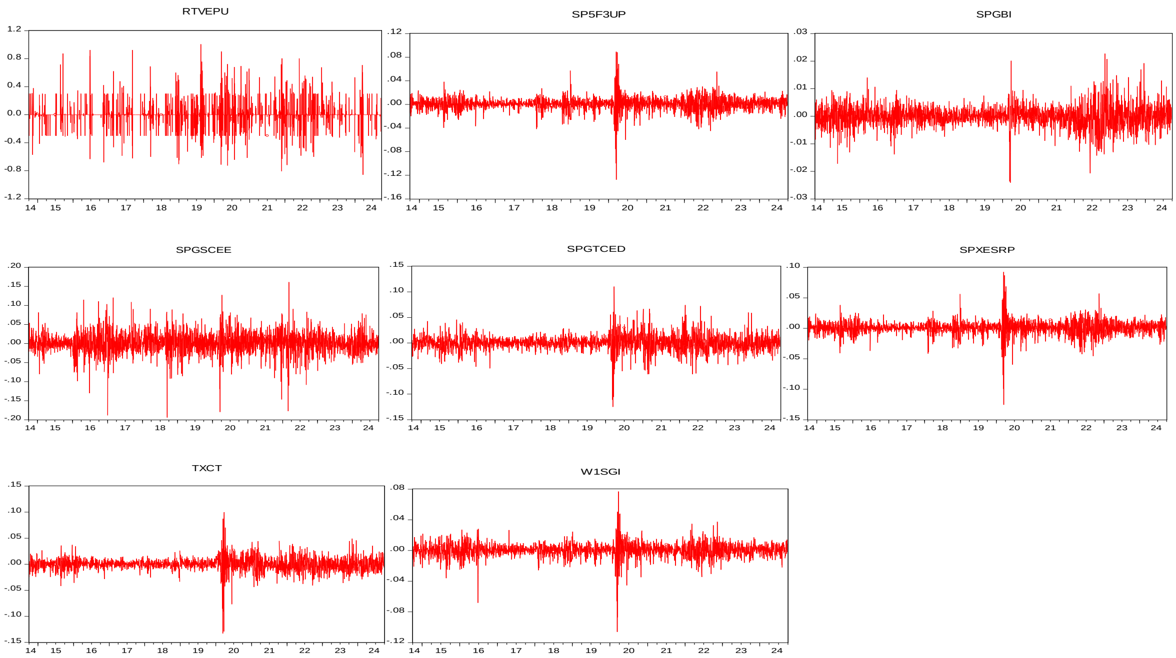
Table 2: Descriptive and Unit Root Statistics

	RTVEPU	SP5F3UP	SPGBI	SPGSCEE	SPGTCED	SPXESRP	TXCT	W1SGI
Mean	0.002951	0.000456	-8.15E-06	0.001018	0.000125	0.000457	-1.22E-05	0.000276
Median	0.000000	0.000572	6.73E-05	0.001344	0.000281	0.000557	0.000195	0.000620
Max.	1.007108	0.089156	0.022717	0.161353	0.110330	0.092403	0.099901	0.076939
Min.	-0.857617	-0.127369	-0.024099	-0.194283	-0.124971	-0.125476	-0.132895	-0.106051
Std. Dev.	0.165187	0.011392	0.003910	0.028634	0.015486	0.011508	0.013018	0.009314
Skewness	0.451526	-0.751778	-0.124729	-0.437145	-0.292673	-0.689355	-0.800649	-1.114701
Kurtosis	10.46194	18.12700	6.834301	7.558726	10.23389	17.41543	17.79518	18.66001
Jarque-Bera	5800.259***	23724.90***	1515.781***	2212.094***	5407.637***	21529.77***	22736.73***	25687.82***
Q(20)	315.414*** [0.0000]	323.544*** [0.0000]	53.2359*** [0.0000]	29.8782*** [0.0071]	121.008*** [0.0000]	325.384*** [0.0000]	95.9860*** [0.0000]	161.671*** [0.0000]
Q^2(20)	667.709*** [0.0000]	3571.33*** [0.0000]	761.818*** [0.0000]	327.844*** [0.0000]	1870.18*** [0.0000]	3672.71*** [0.0000]	3887.83*** [0.0000]	2057.01*** [0.0000]
ARCH(20)	22.688*** [0.0000]	80.288*** [0.0000]	16.024*** [0.0000]	8.7717*** [0.0000]	37.697*** [0.0000]	80.264*** [0.0000]	98.017*** [0.0000]	49.679*** [0.0000]
ADF	-37.36071***	-15.87911***	-44.23193***	-51.81583***	-17.15008***	-15.83130***	-17.74388***	-16.12591***

Note: *** demonstrates statistical significance at the 1% level.

Additionally, Figure 1 shows that small changes follow small changes in variables. Similarly, large changes follow large changes. This fact indicates that volatility clustering is experienced in all variables.

Figure 1: Time Series Graphs of Indicators for the Period 01.10.2014-30.09.2024



This research utilises the TVP-VAR connectedness approach to investigate the time-varying dependence structure between TVEPU and green assets. The TVP-VAR provides more flexibility and robustness compared to conventional VAR models. The lower triangular matrix assumption performs the iterative identification task for the VAR system. Since many parameters are estimated in the TVP-VAR, researchers propose to reduce the number of parameters by assuming a random walk process for parameter innovation. Furthermore, this model shows that the extension of the forecasting algorithm to include a stationary process can be easily achieved (Nakajima, 2011). A classical TVP-VAR procedure can be constructed as in equation (1):

$$y_t = B_{1t}y_{t-1} + \cdots + B_{kt}y_{t-k} + u_t, \qquad u_t \sim N\left(0, A_t^{-1}\sum_t \varepsilon_t\right), t = 1, \ldots, T \tag{1}$$

where y_t indicates $nx1$ vector of variables. $B_{it}, i = 1, \ldots, k$ shows nxn time-varying coefficient matrices. Moreover, u_t represents $nx1$ vector of structural shocks which have a lower triangular matrix A_t and diagonal matrix $\sum_t$. $\varepsilon_t \sim N(0,1)$.

The TVP-VAR connectedness technique builds upon the spillover index derived by Diebold and Yilmaz (2014). They used this method to estimate the generalized association procedure from variance-covariance matrices and time-varying coefficients. This approach calculates GIRF and GFEVD considering the method of Koop et al. (1996). It also converts the TVP-VAR procedure to a vector moving average (VMA) representation using the Wold representation theorem to calculate GIRF and GFEVD. The process of obtaining the VMA reproduction involves recursive displacement. The VMA reproduction is displayed as $\sum_{j=0}^{\infty} A_{jt}\varepsilon_{t-j}$, A_{jt} is the nxn matrix. Assuming that $|\beta_{(z)}|$ is outside the unit circle, the MA(∞) process as $y_t = \Psi(L)\varepsilon_t$, traditionally depicts the VAR process, representing a fundamental aspect of time-varying relationship modelling in empirical macroeconomics. Where, $\Psi(L)$ refers to a matrix of polynomials with infinite lags (Koop and Korobilis, 2013). In such a system, the relationships between variables are usually stated employing estimation error variance decomposition because shocks in one variable may affect others as well as itself. Since these shocks may not occur independently, the standard Cholesky decomposition based on ranking the variables according to the expected propagation of the shocks may not be appropriate. Therefore, we utilise the GFEVD methodology proposed by Koop and Korobilis (2014) to assess the pairwise link from variable (j) to variable (i). This approach effectively recognises the influence of indicator (j) on indicator (i) concerning the estimation variance margin. GFEVD can be expressed as follows:

$$\Gamma_{ij,t}(K) = \frac{\sum_{t=1}^{K-1}\omega_{ij,t}^2}{\sum_{j=1}^{n}\sum_{t=1}^{K-1}\omega_{ij,t}^2} \tag{2}$$

$\sum_{j=1}^{n}\Gamma_{ij,t}(K) = 1$ and $\sum_{ij=1}^{n}\Gamma_{ij,t}(K) = n$. H is the number of forecast horizons. $GIRF\left(\Psi_{ij,t}(K)\right)$ can be calculated as follows:

$$GIRF_t(H, p_{j,t}, \Omega_{t-1}) = E(y_t + H|e_j = p_{j,t}, \Omega_{t-1}) - E(y_{t+j}|\Omega_{t-1}) \tag{3}$$

$$\Psi_{ij}(K) = \frac{A_{H,t}\sum_t e_j}{\sqrt{\sum_{jj,t}}}\frac{p_{j,t}}{\sqrt{\sum_{jj,t}}}p_{j,t} = \sqrt{\sum_{jj,t}} \tag{4}$$

$$\Psi_{ij}(K) = \sum_{jj,t}^{-1/2} A_{H,t}\sum_t e_j \tag{5}$$

e_j shows an nx1 vector, whose jth element equals 1.

One of the primary conditions for understanding financial markets is to analyse networks. The Total Connectedness Index (TCI) captures how a shock in one variable measures the transmission effect of a shock to others. According to Monte Carlo simulations, the individual variance shares are always more outstanding than or equal to the cross variance shares. This case limits the TCI to be in the range of $\left[0, \frac{k-1}{k}\right]$. In order to determine the average level of co-movement between networks as a percentage, the TCI needs to be adjusted slightly. TCI can be calculated as follows (Broadstock et al., 2022):

$$TCI_t^g(K) = \frac{\sum_{i,j=1,i\neq j}^{m}\vartheta_{ij,t}^q(K)}{k-1}, \qquad 0 \leq TCI_t^g(K) \leq 1 \tag{6}$$

To compute the pairwise connectivity index (PCI) between assets i and j, the TCI index can be constructed as follows:

$$PCI_{ijt}(K) = 2\left(\frac{\vartheta_{ij,t}^q(K) + \vartheta_{ji,t}^q(K)}{\vartheta_{ii,t}^q(K) + \vartheta_{ij,t}^q(K) + \vartheta_{ji,t}^q(K) + \vartheta_{jj,t}^q(K)}\right), \qquad 0 \leq PCI_{ijt}^g(K) \leq 1 \tag{7}$$

Total directional connectivity index (TDCI) from others can be calculated as follows:

$$\Gamma_{i\leftarrow j,t}(K) = \frac{\sum_{j=1,i\neq j}^{m}\vartheta_{ij,t}(K)}{\sum_{i=1}^{m}\vartheta_{ij,t}(K)} * 100 \tag{8}$$

As the impact of indicator i on itself is eliminated, the TDCI of all other variables on variable i must be strictly less than 100 per cent. Considering GFEVD, TDCI to others is measured as follows:

$$\Gamma_{i\to j,t}(K) = \frac{\sum_{j=1,i\neq j}^{n} \vartheta_{ji,t}(K)}{\sum_{j=1}^{n} \vartheta_{ji,t}(K)} * 100 \tag{9}$$

This measure computes the effect of indicator i on all other indicators j in the system by summing the influence of indicator i on the forecast error variance of each of the other indicators. It is also beneficial to acknowledge that measures of TDCI can take values below, equal to or above 100 per cent. Net total directional connectivity index (NTDCI) describes the comprehensive impact of a variable i on the entire network. This measure considers the cumulative effect of the prediction error variance of indicator i on each of the other indicators in the system. It provides valuable insight into the overall importance of the indicator in the network. NTDCI is computed as follows:

$$\Gamma_{i,t} = \Gamma_{i\to j,t}(K) - \Gamma_{i\leftarrow j,t}(K) \tag{10}$$

If $\Gamma_{i,t} > 0$, variable i has a significant impact on the network. Conversely, if $\Gamma_{i,t} < 0$, variable i is being effected by the network. Net pairwise directional connectivity index (NPDCI) is a powerful instrument for examining the bidirectional nexus between indicator i and indicator j:

$$NPDCI_{ij}(K) = \left(\vartheta_{ji,t}(K) - \vartheta_{ij,t}(K)\right) * 100 \tag{11}$$

NPDCI estimates the dominance between indicators i and j. NPDCI greater than 0 means that i dominates j. Conversely, an NPDCI less than 0 states that j is dominant over i. This captures the difference between the gross shocks transmitted from i to j and vice versa, measuring the net influence of directional connectivity (Antonakakis et al., 2020).

4. FINDINGS AND DISCUSSIONS

Firstly, we approach the analyses from a linear perspective. However, since the presence of features such as leptokurtic, excessive kurtosis, non-normal distribution, autocorrelation, and heteroscedasticity in the variables strengthens the possibility of non-linearity of the variables, we investigate whether the variables are linear or not with the BDS non-linearity test and present the findings obtained in Table 3.

Table 3: BDS (Non)linearity Estimate Results

	λ =2	λ =3	λ =4	λ =5	λ =6
SP5F3UP	0.028920***	0.062702***	0.088105***	0.104058***	0.112714***
SPGBI	0.018524***	0.034281***	0.045792***	0.053551***	0.057043***
SPGSCEE	0.013698***	0.026450***	0.036132***	0.041277***	0.042647***
SPGTCED	0.018963***	0.040975***	0.057020***	0.069066***	0.075527***
SPXESRP	0.028287***	0.061740***	0.086835***	0.102719***	0.111296***
TXCT	0.024248***	0.051454***	0.072848***	0.086483***	0.093829***
W1SGI	0.020415***	0.041965***	0.060033***	0.070676***	0.075034***

Note: We applied the BDS test to the residuals of the VAR(1) models. λ represents to the embedding dimensions. *** demonstrates statistical significance at the 1% level.

According to the BDS test results, the fact that the probability values of all variables are less than 1% significance level for all dimensions confirms that the probability distributions of the error terms obtained from the linear model are not independent and that there is a non-linear relationship between the indicators. Therefore, the research should be carried out using non-linear models. Accordingly, we apply the TVP-VAR connectedness technique to the analyses and display the results on the total connectedness between TVEPU and green assets in Table 4.

Table 4: Total Connectedness between TVEPU and Green Assets

	SPGBI	W1SGI	SPXESRP	SP5F3UP	SPGSCEE	TXCT	SPGTCED	RTVEPU	FROM
SPGBI	66.25	8.33	4.84	4.95	2.44	4.31	6.67	2.21	33.75
W1SGI	3.9	30.52	21.64	21.71	1.89	7.72	11.73	0.89	69.48
SPXESRP	1.93	20.33	29.43	29.19	1.42	7.98	8.84	0.88	70.57
SP5F3UP	1.94	20.19	29	29.23	1.45	8.23	9.08	0.86	70.77
SPGSCEE	2.49	4.28	3.42	3.5	78.74	2.65	2.86	2.06	21.26
TXCT	2.58	10.04	11.48	11.92	1.71	46.09	15.02	1.16	53.91

SPGTCED	3.95	14.54	11.93	12.35	1.6	14.49	40.21	0.92	59.79
RTVEPU	2.48	1.91	1.83	1.81	1.9	1.9	1.67	86.5	13.5
TO	19.27	79.63	84.14	85.42	12.42	47.29	55.89	8.98	393.03
Inc.Own	85.52	110.15	113.57	114.65	91.16	93.37	96.09	95.48	cTCI/TCI
NET	-14.48	10.15	13.57	14.65	-8.84	-6.63	-3.91	-4.52	56.15/49.13

According to Table 4, the TCI is 49.13. This result demonstrates that the spillover effect between markets is moderate. The spillover contribution of TVEPU to other markets is 8.98%. Therefore, the power of this index to affect other indices is at the lowest level. The 85.42% spillover contribution of the fossil fuel reserves free index to other indices emphasises that this market has the most influence on other markets. In addition, according to the net spillover index values, the net spillover indices for Fossil Fuel Reserves Free (SP5F3UP), Environmental and Social Responsibility (SPXESRP) and Dow Jones Sustainability (W1SGI) indices have positive values with 14.65%, 13.57% and 10.15%, respectively. This result implies that these markets are net transmitters of systematic shocks. The GB index (SPGBI) also received the most shocks from other markets, with a net spillover index of -14.48. This market is followed by CEAs (SPGSCEE), Renewable Energy and Clean Technology (TXCT), TVEPU and Global Clean Energy (SPGTCED) markets with net spillover indices of -8.84, -6.63, -4.52 and -3.91, respectively. In other words, these markets are most exposed to other markets and are net receivers of systematic shocks. Figure 2 is a graphical illustration of the dynamic TCI.

Figure 2: Dynamic Total Connectedness Index

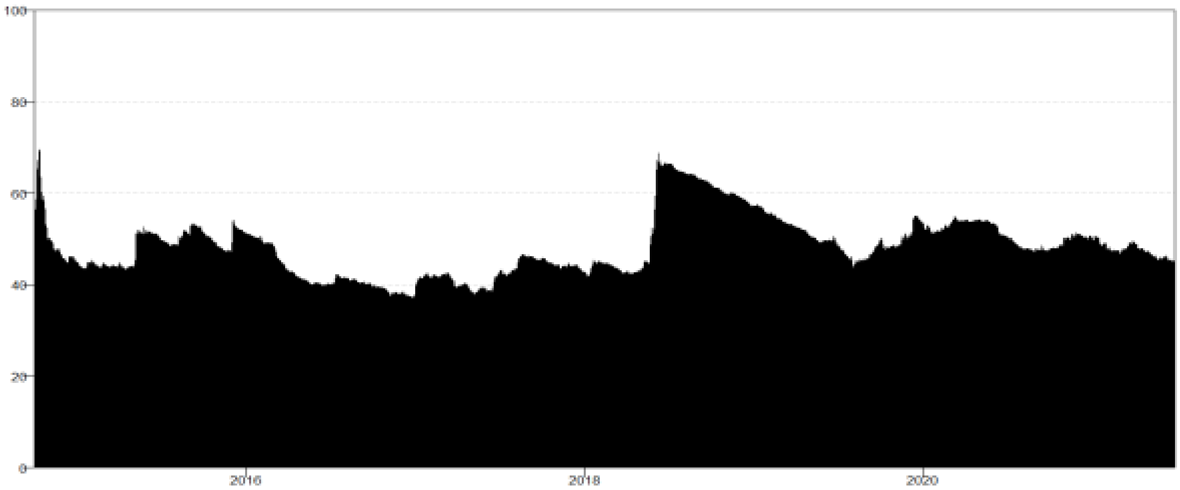
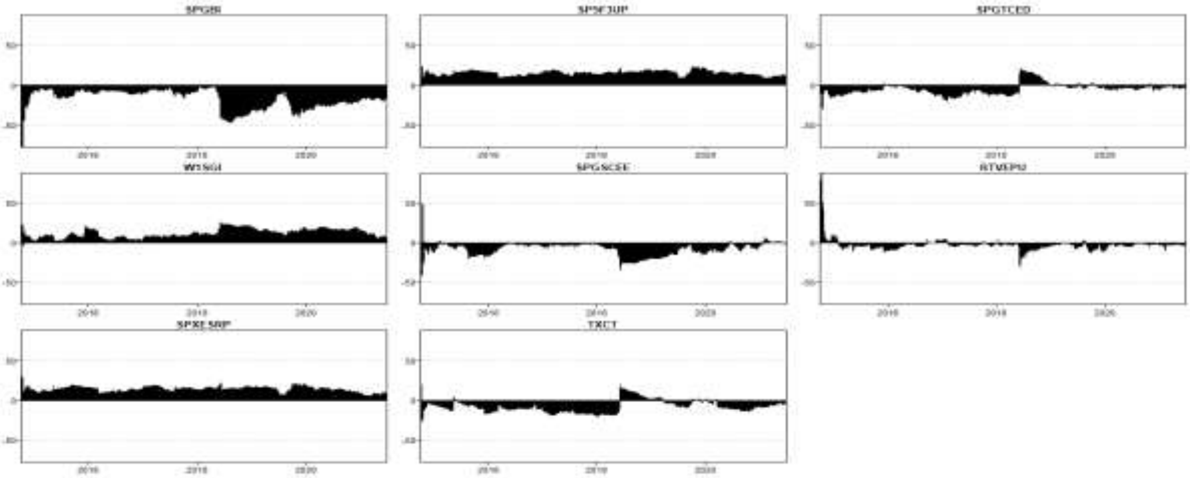


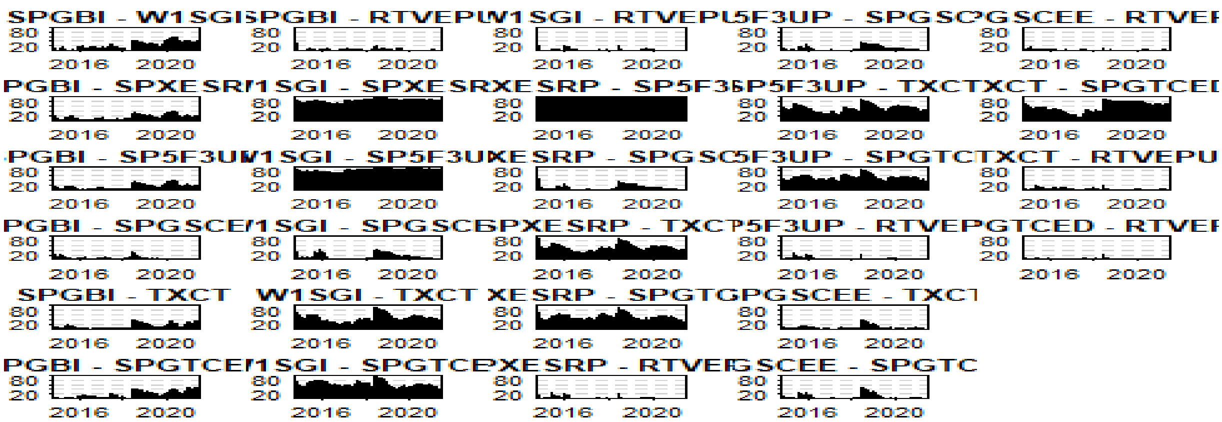
Figure 2 demonstrates that the sensitivity of the spillover effects between green equity markets, GB markets and TVEPU increases significantly under extreme positive and extreme adverse shocks. At the same time, extreme spillover effects between these markets are significantly amplified by major international events and news, such as the civil war in Syria, the annexation of Crimea to Russia, the US-China trade war, the Ferguson events, the election of Donald Trump as US president, the Ebola and COVID-19 outbreaks, and the Russia-Ukraine war. This is because crises affect socio-economic conditions, which in turn affect financial markets. Figure 3 visualises the results of the NTDCI.

Figure 3: Time-Varying Net Total Directional Interconnectedness Index



In the NTDC Index graph, the coloured areas above the zero point indicate the shocks transmitted at the relevant date or period, in contrast to the coloured areas below zero, which represent the shocks received at the relevant date or period. According to Figure 3, SP5F3UP, W1SGI and SPXESRP variables are positive for almost the entire sample period, whereas the SPGBI variable follows a negative path. These findings mean that the GB market is a net shock receiver, in contrast to the Fossil Fuel Reserves Free, Dow Jones Sustainability and Environmental and Social Responsibility markets, which are net shock transmitters. The net spillovers of SPGTCED, RTVEPU, SPGSCEE and TCXT change over time. Indeed, Renewable Energy and Clean Technology and Global Clean Energy markets have been net shock receivers until 2019. However, they acted as net shock transmitters until the second half of 2019, with positive shocks arising from global events and news, such as the trade wars between the China and US and returned to the net shock receiver position with the influence of global news and events like the COVID-19 outbreak. Similarly, TVEPU reacted positively to events and developments such as the civil war in Syria and the annexation of Crimea to Russia and continued as a shock transmitter in the first quarter of 2015. It has been a shock receiver since the second quarter of 2015 with the impact of news and developments such as the Ferguson events and the migrant crisis. Lastly, although the CEAs market was a shock receiver until 2023, it became a shock transmitter by reacting positively to events and news, such as the FED's interest rate hike. Figure 4 contains the results of the NPDCI.

Figure 4: Net Pairwise Directional Interconnectedness Index

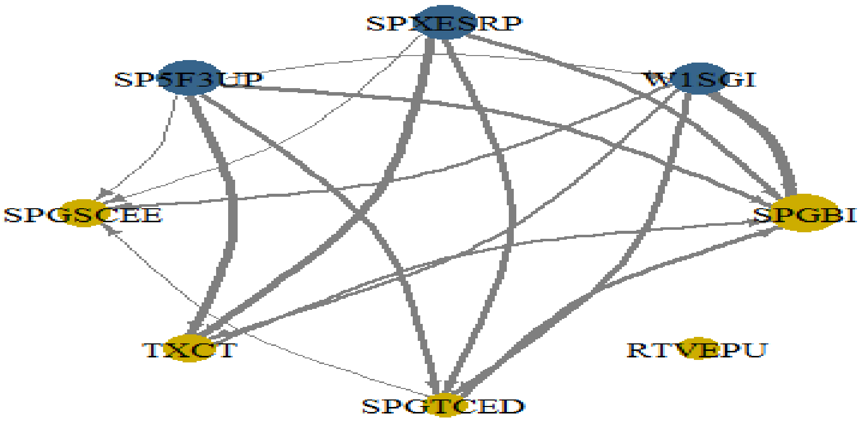


The NPDC Index plots show a low nexus level between the TVEPU index and GSs and GBs in the period under consideration. In other words, there is a shallow connection between the change in the TVEPU index and GB, Sustainability World, CEAs, Renewable Energy and Clean Technology, Fossil Fuel Reserves Free, Environmental and Social Responsibility and Global Clean Energy indices returns over the entire period considered. This result implies that GSs and GBs returns are only marginally affected by the change in the TVEPU index over the sample period.

There is a strong dependence between the returns of all other green assets except the GB index. In addition, the correlation level between these index returns is also quite high. However, although there is a low correlation between GS returns and

GB returns, this relationship has increased with the COVID-19 pandemic period. Lastly, Figure 5 reports the network connectedness index results between variables.

Figure 5: Network Connectedness Index



Graph 5 represents the connectedness between TVEPU and green market assets through network plots. The blue dots in the graph indicate the variables that transmit shocks, while the yellow dots refer to the variables that receive shocks. Moreover, the dots' sizes show the spillover effects' size. In the graph, the arrows outside the dots define the direction of the connectedness, and the thickness of the lines, along with the arrows, define the magnitude of the connectedness. Network plots also confirm that the interaction between TVEPU and green market assets is not remarkable. Figure 5 demonstrates a substantial shock transmission from the Fossil Fuel Reserves Free and Environmental and Social Responsibility indices to the Renewable Energy and Clean Technology, GBs and Global Clean Energy indices. However, the magnitude of the shock transmitted to the CEAs index is smaller than the others.

Similarly, while there is a robust shock transmission from the Dow Jones Sustainability indices to the GB and Global Clean Energy indices, the transmission of shocks to the CEAs and Renewable Energy and Clean Technology indices is relatively tiny. Additionally, medium-sized shocks from the Renewable Energy and Clean Technology and Global Clean Energy indices impact the GB index during specific periods. Finally, the Global Clean Energy index influences the CEAs index through relatively low-magnitude shocks during specific periods.

5. CONCLUSION AND IMPLICATIONS

Recently, interest in green investment assets such as GS and GB has increased intensively. Despite this, there are ongoing discussions in the economics and finance literature on their effectiveness in risk management, especially as a protection, safe-haven, and diversification strategy against EPU. This research seeks to examine the dynamic nexus between TVEPU and the returns of green assets, specifically focusing on their potential as hedges and safe havens. In doing so, this paper investigates the existence of a dynamic connectivity between changes in the TVEPU index and the returns of various indices, including GB, CEAs, Environmental and Social Responsibility, Renewable Energy and Clean Technology, Fossil Fuel Reserves Free and Global Clean Energy, for the period from October 1, 2014, to September 30, 2024, utilised TVP-VAR models.

The major findings of this research can be listed as follows. First, the Fossil Fuel Reserves Free index exerts the most significant influence on other indices, while the TVEPU index has the least impact. Second, exceptionally optimistic and pessimistic shocks from international events and news significantly heighten the sensitivity of spillover effects between green asset returns and TVEPU. Third, the GB market is a net shock receiver, while the Fossil Fuel Reserves Free, Sustainability World, and Environmental and Social Responsibility indices function as net shock transmitters. The net spillovers of the TVEPU, Global Clean Energy, CEAs and Renewable Energy and Clean Technology indices fluctuate over time. Fourth, GS and GB returns are only mildly influenced by changes in the TVEPU index. Finally, at the time-varying level, the GBs, Global Clean Energy, CEAs and Renewable Energy and Clean Technology indices are the most affected by shocks from other indices. These results align with the results of Haq et al. (2021), Su et al. (2023), Aloui et al. (2024), and Wang et al. (2024).

Empirical results provide many noteworthy suggestions for investors and policymakers: First, the results suggest that investors with a strong focus on environmental factors can enhance their diversification benefits by including GBs and GSs in their portfolios. This diversification advantage also strengthens policymakers' confidence in scaling the GB market to promote environmental responsibility. Second, when EPU is high, GSs tend to react more strongly than GBs. In such scenarios, investors need to use the safe-haven nature of GBs to protect themselves from the volatility of GSs. Since GBs are typically long-run investments that do not respond immediately to policy changes, EPU has less impact on their short-run returns. This fact makes it a good investment tool for managing assets and more stable due to its long-term sustainability objectives. Moreover, the hedging ability of GBs over green GSs is revealed when the green stock market experiences an extreme decline due to a rise in EPU. Third, the findings may guide market actors to optimise their portfolios promptly during extreme shocks. Additionally, as market uncertainty can help governments predict future economic fluctuations effectively, governments can achieve win-win objectives such as green and low-carbon development. Finally, due to the notable influence of the EPU on renewable energy stocks, policymakers should increase the degree of clarity and transparency in policy decisions to reduce potential adverse effects on the green investment sector.

This paper has some limitations that could benefit future research. For example, while this research confirms the time-varying dynamic connectivity between TVEPU and selected green assets, it does not examine the interaction across different frequencies and quantiles. These aspects could offer valuable insights and serve as a direction for future studies.

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