Analysing the Relationship Between Green Bonds and Sustainable Equity Markets: Sustainable Investing in Emerging Global Markets

Huthaifa Sameeh Alqaralleh *

huthaifa89@mutah.edu.jo

Abstract

This research looks at tail risk contagion among environmentally friendly initiatives using data from July 2021 to August 2023. Tail risk is estimated using a novel asymmetric slope Conditional Autoregressive Value-at-Risk (CAViaR) and Time-Varying Parameter Vector Autoregressive (TVP-VAR) connectedness to explore the tail risk spillover. Additionally, the potential drivers of the connectedness network is measured over time. The result demonstrates a considerable degree of interconnection between Green Equities (GEs) and returns connected to sustainability, with sustainability-related indices playing a significant role and non-financial elements undergoing advancements. The level of interconnectedness fluctuates over time, with events such as the Russia-Ukraine War and COVID-19 exerting discernible effects. Investors and governments who are concerned about the environment may benefit greatly from the findings, which demonstrates that green bonds and stocks play distinctive roles and are seen differently in sustainable investing.

Keywords: Green Bonds, Sustainable Equity Markets, Emerging Financial Markets, Environmental Responsibility, Financial Diversification.

* Department of Economics, Business and Finance, Mutah University, Karak, Jordan.
Received: 15/5/2024. Accepted: 12/9/2024.

تحليل العلاقة بين السندات الخضراء وأسواق الأسهم المستدامة: الاستثمار المستدام في الأسواق العالمية الناشئة

حذيفة سميح القراله *

huthaifa89@mutah.edu.jo

ملخص

يهدف هذا البحث إلى دراسة وتحليل آلية انتقال المخاطر بين المبادرات الصديقة للبيئة باستخدام بيانات يومية خلال الفترة 6 :2021 إلى 8 :2023، من خلال تطبيق نموذج قيمة المخاطر الشرطية غير المتماثلة الجديدة (CAViaR) ومتغير المعاملات المتغير مع الوقت (TVP-VAR) المتصل لاستكشاف انتقال مخاطر عبر الكميات الحرجة. توضح النتيجة درجة كبيرة من الترابط بين الأسهم الخضراء (GBs) والعوائد المرتبطة بالاستدامة، حيث تلعب مؤشرات الاستدامة دورًا مهمًا وتشهد العناصر غير المالية تقدمًا. يتقلب مستوى الترابط مع مرور الوقت، حيث تمارس الأحداث مثل الحرب الروسية الأوكرانية وكوفيد –19 تأثيرات ملموسة. وقد يستفيد المستثمرون والحكومات المهتمون بالبيئة بشكل كبير من النتائج، التي توضح أن السندات والأوراق المالية الخضراء تلعب أدوارًا متميزة ويتم النظر إليها بشكل مختلف في الاستثمار المستدام.

الكلمات المفتاحية: السندات الخضراء، أسواق رأس المال المستدامة، الأسواق المالية الصاعدة، المسؤولية البيئية، التنويع المالي.

* قسم اقتصاديات المال والأعمال، كلية الأعمال، جامعة مؤته، الكرك ، الأردن.

تاريخ تقديم البحث: 2024/5/15. تاريخ قبول البحث: 12/ 2024/ .

Introduction:

Environmental degradation and climate change have prompted sustainable activities to promote environmentally responsible and sustainable economic growth (e.g., Wang and Lee, 2022; Lee and Lee, 2022; Liu, 2022). The Copenhagen Accord, which was signed in 2009, highlighted the significance of financial markets in tackling global concerns and emphasised the necessity of utilising these markets in combating against environmental challenges. As a results, over the next thirty years, several influential countries are in the process of migrating towards environmentally responsible economies and enacting climate-related legislation to reach carbon neutrality. They also agree that investing in environmentally friendly stocks and bonds emerged as the most viable means of advancing a sustainable economy as they support a sustainable future with reduced carbon emissions and enhance the economy in the long term (Tiwari et al., 2023; Maltais and Nykvist, 2020).

Less environmentally destructive financialization is not a new concept. Fixed-income bonds with a focus on social responsibility, previously known as "Green Bonds" or "Climate Awareness Bonds," were first introduced by the European Investment Bank (EIB) in 2007. The Green Bond Principles (GBP) were established by The International Capital Market Association in January 2014. Then, the standards for branding green bonds were intended to enhance the quality and liquidity of these bonds.

Green bonds, amongest suitable tools for funding this transition and spreading the bills associated with reducing the effects of climate change across several generations, have had a substantial rise in the global market (Monasterolo and Raberto, 2018). According to the Organisation for Economic Co-operation and Development (2016), the global green bond market grew significantly from $11 billion in 2013 to $36 billion in 2016. In 2018, green bonds reached $167 billion according to the Climate Bonds Initiative (Bonds, 2019), showing a rise of almost 364% in just two years. A new milstone of $550 billion is reached in 2023. To say, the global green bond market has gone through a "budding period" from 2007 to 2012, a "growth period" from 2013 to 2016, and a "maturity period" from 2017 to the present. Moreover, green stocks represent investment in companies that support environmental sustainability. The investment in renewable energy has increased threefold since 2015, demonstrating the increasing importance of these financial instruments in fostering a low-carbon economy.

While green investment models are structurally comparable to traditional ones, the key distinction lies in the limitations imposed on the use of their revenues, which are specifically designated for financing environmentally friendly initiatives. By virtue of this provision, the individuals who own these environmental investment efforts do not instantly subject financial instruments to the risks associated with these projects. This is because the purchasers frequently have access to the whole financial statement of the issuer (Bonds, 2019). The evident advantages of green investing are the reason why they are successfully competing with other forms of financial assets. Under this clause, understanding the interconnections across different sectors of environmentally responsible finance is essential for investors to make rational choices about diversifying their portfolios as environmentally sustainable financial markets continue to grow.

Previous studies explored Green Bond’s (GB) connection to conventional assets, but limited research exists on other aspects of the GB market. We examine how the GB market interacts with sustainability indexes. We assess the strength of these connections, their directional influence, and the impact of market shocks. Questioning this further, we hope to find solutions to these questions: (i) Is there a significant link between GBs and GEs? (ii) How does this connection change over time and in response to market fluctuations? (iii) What are the consequences for eco-conscious investors and policymakers? Asymmetric spillover effects are hypothesized between GBs and sustainability indexes influenced by market conditions.

Recent studies (Pham, 2021; Liu et al., 2021; Tiwari et al., 2022; Lucey and Ren, 2023) have explored aspects of the GB and eco-friendly market* relationship. This study distinguishes itself by investigating this relationship in emerging financial markets (EFM), which include countries that are in the process of rapid industrialization and experiencing significant economic growth. This is crucial because EFMs have been relatively overlooked in the literature despite their pivotal role in global economic growth, diversification opportunities, and risk management challenges. Additionally, the current research is novel as it delves into the connection between GBs and eco-friendly markets, including socially responsible initiatives—a previously unexplored area. I aim to understand how non-financial factors, such as environmental and social responsibility, influence the relationship between GBs and these markets. It is essential as these motives distinguish green assets from traditional financial assets and attract investors. Furthermore, this paper introduces innovative findings using the asymmetric slope Conditional Autoregressive Value-at-Risk (CAViaR) and Time-Varying Parameter Vector Autoregressive (TVP-VAR) connectedness measure (Chatziantoniou et al., 2022b). This method allows us to analyse the dynamic transmission of tail risk, represented by the Value-at-Risk (VaR) measure, among specified sustainable and non-sustainable market variables. Instead of focusing on price returns or overall volatility, it quantifies how extreme losses in one market affect exposure in other markets or the broader financial landscape.

The findings of this study reveal that sustainability-related indexes are similar to traditional non-financial equity investments, whereas GBs stand apart. Investors typically view GBs as fixed-income assets and green equities as equities rather than grouping them. This aligns with earlier research highlighting the impact of fixed-income markets on GBs, as shown by Pham (2021) and Reboredo and Ugolini (2018, 2020). Institutional issuers and investors dominate the GB market, while the GE market attracts a broader range of investors. This research underscores the distinct roles and perceptions of GBs and GEs in sustainable investments.

* Eco-friendly markets here is refer to financial markets that are specifically dedicated to environmentally sustainable and socially responsible investments.

The remaining sections of the paper are listed as follows. Section 2 outlines the data and methods utilised in this study, Section 3 discusses the empirical findings, and Section 4 offers the conclusion.

Literature Review:

Theortically, the connection between environmentally friendly initiatives is influenced by asymmetric price adjustment, news specificity, financial contagion, variations in hedging demand, news decomposition, and asset substitution (Dean et al., 2010). In specific, equities and bonds are seen as competing assets in an asset substitution scenario. Investors engage in buying and selling bonds when there is favourable news about the bond market, and they do the same with stocks when there is great news about the stock market. The latter premise posits that a favourable increase in returns in one market will thereafter result in an adverse decrease in returns in the other market. Hedging demand changes arise once hedgers adjust their portfolio allocation to uphold their desired hedge ratio in reaction to price fluctuations in a particular market. Financial contagion is a situation wherein prices in one market respond to fundamental information and price changes in other markets. Contagion is more probable to occur following highly adverse shocks. The ideas of news specificity and news decomposition suggest that shocks in bond and stock market returns send distinct information to investors, which affects the direction of spillovers between equity and bond markets. Asymmetric price adjustment refers to the phenomenon where positive and negative news affects markets differently, indicating that negative news has a faster influence than favourable news.

The environmentally friendly initiatives can be linked to the spillovers between the bond and stock markets as a whole, and the GB and GEs sub-sectors within it. Beyond monetary considerations, non-financial variables, such as the pro-environmental views of investors, may impact the link between GBs and GE because both types of investments support eco-friendly initiatives. It is expected for GB and GE to have asymmetric spillovers that change depending on the market's normalcy or extremeness.

A significant number of empirical studies have looked at the connection between GBs, GE (shares in environmentally friendly companies), and other conventional assets including equities, bonds, and energy commodities. Ortas and Moneva (2013) find that clean-technology equities indexes outperform traditional stock indices but are riskier. Some previous studies suggest that the prices of renewable energy firms are affected by changes in oil prices. This has been supported by studies conducted by Henriques and Sadorsky (2008), Managi and Okimoto (2013), Kumar et al. (2012), Broadstock et al. (2012, and Inchauspe et al. (2015). Additionally, there is evidence that there is a relationship between the volatility of oil prices and clean energy stock prices, as shown by Sadorsky (2014) and Wen et al. (2018). Furthermore, there is a causal and tail-dependent relationship between oil prices and the prices of renewable energy companies. Additional studies have investigated whether green mutual funds have superior performance compared to conventional ones (Climent and Soriano, 2011; Reboredo et al., 2017).

Another aspect of the growing body of research on GBs is the influence of financial market conditions on the GB market. Reboredo (2018) discovered that the GB market exhibits a strong correlation with both corporate and treasury bond markets. Additionally, it provides investors in stock and energy markets with chances for diversification. Reboredo and Ugolini (2020) indicate that the global GB market has a strong correlation with the global treasury bond and USD currency markets, resulting in significant price spillover effects and little reversal effects. GBs have weak correlations with high-yield corporate bonds, stocks, and energy markets. GBs are a recipient of net price spillovers with insufficient transmission (see also Pham (2016) and Pham and Huynh (2020)). Zerbib (2019) demonstrates that investors' pro-environmental preferences have no substantial impact on bond pricing, since green bonds yield two basis points less than conventional bonds. In their study, Baker et al. (2018) discovered that there is a higher price premium for municipal green bonds, and an even greater premium for externally certified BS in the U.S. GB market.

Broadly, literature has thoroughly examined the mutual reliance between GBs and GE in traditional assets, such as stocks, bonds, and energy commodities. Nevertheless, the correlation between GBs and GE has not been thoroughly investigated. Given the need for substantial financial resources to support environmentally friendly initiatives in the shift towards a low-carbon economy, it is essential for pro-environmental investors and politicians to comprehend the impact of various assets.

A series of recent studies conducted by Liu et al. (2021), Madaleno et al. (2022), and Dogan et al. (2022, 2023) have investigated the relationship between GBs and GE. Positive dependencies are the observed positive connections between the performance of GBs and clean energy (CE) markets. Liu et al. (2021) discovered positive dependencies and emphasised asymmetric risk spillovers, suggesting that the link between global banks (GBNs) and emerging markets in Central and Eastern Europe (CE markets) is not symmetrical in terms of the transmission of risks. This suggests that unforeseen losses in one market might have varying effects on the other. When making judgements, policymakers and GB investors should take into account these subtle distinctions, with a focus on fostering projects that have minimal carbon emissions.

Nguyen et al. (2021) employed the rolling window wavelet methodology to examine the association between GBs and assets, offering a complete perspective on the correlations within the asset market. Chatziantoniou et al. (2022b) conducted a study on the incorporation and transmission of key environmental financial indicators. The study revealed that there are different levels of market risks and overall interconnectedness during extreme occurrences. The Total Connectedness Index (TCI) is a metric used to quantify the extent of interconnectedness between different financial indices (i.e., to assess the level of connectivity among key environmental financial indices). While the TCI exhibited symmetry, indicating balanced connectedness in general, the short-term and long-term TCIs showed asymmetry, with the short-term TCI being higher at lower values. This suggests that short-term risk dynamics may be more pronounced during periods of lower market values.

Data and Methodology

Data and descriptive statistics

For this study and due to data availability, daily data was utilised from July 2021 to August 2023 for emerging market indices that track the performance of a group of stocks from various emerging market countries. These indices serve as benchmarks for investors to gauge the overall performance of these markets. Our dataset comprised four sustainability indexes: the FTSE4Good Emerging Index, MSCI Emerging Markets ESG Index, Dow Jones Sustainability Emerging Markets Index, and Dow Jones Global Select ESG RESI (USD). Additionally, two Social Criteria indexes were included: FTSE4Good Emerging Index Social Criteria and Dow Jones Sustainability Emerging Markets Social Index. Finally, the J.P. Morgan EM GB Diversified Indices was included as a proxy for GBs in Emerging Markets. The data was collected from Bloomberg and Datastream, and our analysis was performed using returns computed by taking the logarithmic difference*.

An overview of the descriptive statistics analysis is provided in panel A of Table 1. It reveals that the stock indices exhibit leptokurtic distributions, indicated by kurtosis values exceeding 3, implying a higher possibility of extreme tail events. The skewness statistics indicate that all of the considered indices are skewed. When we combine these findings with the results of the JB statistic test, it becomes evident that the data series do not conform to a Gaussian distribution. Additionally, the statistically significant results from the ERS unit root test indicate that the return series are stationary. Moreover, all of the series display ARCH errors support the use of the TVP-VAR model, particularly due to the presence of time-varying covariance. Finally, panel B of Table 1 provides the Kendall's Tau a measure of correlation that is robust to outliers and suitable for ordinal data.

For the details of the used variables, see the appendix.*

The Kendall's Tau correlation matrix reveals significant associations among sustainability and social criteria indices in emerging markets. The strongest positive correlation exists between FTSE4Good and FTSE4GoodSC, indicating a shared trend in their rankings. ESG demonstrates notable positive correlations with FTSE4GoodSC, DJSS, and DJESGRESI, suggesting coherence in their movements. Additionally, DJSS and DJESGRESI exhibit a moderate positive correlation, indicating a linked performance. The findings underscore the interconnectedness of sustainability indices and highlight potential synergies between ESG and social criteria indices. Investors and stakeholders in emerging markets can leverage these insights to make informed decisions regarding socially responsible investments, considering the interplay between different sustainability dimensions and the role of social criteria indices in influencing overall market dynamics.

Table (1) Descriptive Statistics

	FTSE4Good	ESG	DJS	FTSE4GoodSC	DJSS	DJESGRESI	GB
Panel A: Descriptive Statistics							
Mean	1.51	1.55	1.52	1.72	1.73	1.81	1.31
Minimum	-0.046	-0.039	-0.117	-0.045	-0.040	-0.045	-0.027
Maximum	0.038	0.050	0.038	0.053	0.0486	0.062	0.045
Variance	0.20	0.15	0.21	0.23	0.16	0.18	0.17
Skewness	1.21	0.89	1.74	1.14	-0.01	1.47	0.34
Ex.Kurtosis	1.96	1.63	5.99	2.28	-0.83	2.59	-0.86
JB	223.27*	134.15*	112.38*	238.53*	15.84*	352.46*	27.55*
ERS	-3.07**	-4.83**	-5.04*	-5.36*	-2.28***	-3.90*	-3.14**
Q(20)	1990.20	1451.33	1708.19	1501.35	4759.87	2124.39	4578.37
Q2(20)	1724.71	1303.91	1199.99	1333.51	4550.11	1956.19	4160.18
Panel B: Kendall's Tau correlation matrix							
FTSE4Good	1.000						
ESG	0.263*	1.000					
DJS	0.104*	0.061*	1.000				
FTSE4GoodSC	0.276*	0.867*	0.052	1.000			
DJSS	0.376*	0.272*	0.206*	0.249*	1.000		
DJESGRESI	0.294*	0.092	0.054	0.091*	0.103*	1.000	
GB	0.215*	0.214*	0.122*	0.231*	0.033	0.350*	1.000

Skewness is tested using the D'Agostino's (1970) test, while kurtosis is tested using Anscombe and Glynn's (1983) test. Jarque and Bera's (1980) test is used to test for normality. Elliott, Rothenberg, and Stock's (1996) test is used to test for unit-root. Fisher and Gallagher's (2012) maintained that portmanteau test is used with a latency of 10. 5 percent. The ERS test has a critical value of 2.97. * Signifcant at 1%; ** signifcant at 5%; *** signifcant at 10%.

Empirical methodology:

In order to investigate how sustainability-related indicators and GBs transmit extreme tail risk, this study follows a three-stage process. In the first step, Value at Risk (VaR) is calculated using the Conditional Autoregressive Value at Risk (CAViaR) method developed by Engle and Manganelli (2004). The negative extreme risk of the considered series is assessed by employing CAViaR, as outlined by Chatziantoniou et al. (2022b). The directly-calculated CAViaR technique is employed, based on the Value-at-Risk (VaR) concept, as introduced by Engle and Manganelli (2004), to account for asymmetric slopes. Prior studies frequently assessed Value-at-Risk (VaR) by indirectly deriving its quantiles following the calculation of the return distribution. Given that the symmetric absolute value approach and the indirect GARCH (1,1) technique do not include asymmetric effects, it is asserted that the slope CAViaR method offers the most flexibility among the three options.

Next, a Time-Varying Parameter Vector Autoregressive (TVP-VAR) model is employed to assess the interconnectedness of risks and identify the channels via which they are transmitted (Antonakakis et al., 2020; Chatziantoniou et al., 2022a). Connectedness measures are used in practical time series analysis because they can effectively capture the direction, non-linearity, and dynamic interactions between variables. They possess a high level of efficacy in delineating intricate patterns and exhibit a wide range of applications in network research, hence uncovering intricate interconnections inside systems. Connectedness measurements also demonstrate enhanced outlier robustness, guaranteeing reliable analysis even in the presence of outliers. Although connectedness measures provide a more adaptable and thorough comprehension of temporal links, classical correlations remain a feasible choice based on the characteristics of the data and the analytical objectives.

Finally, the study employs a dynamic estimating approach, utilising a rolling window of 120 days, to examine the variables that influence the interconnectivity network over time. This analysis takes into account data from major events.

Conditional Autoregressive Value-at-Risk (CAViaR)

As highlighted, the approach used is the CAViaR slope method, which has remarkable adaptability as it can effectively incorporate asymmetric effects, a quality that is lacking in other approaches, such as symmetric absolute value and indirect GARCH (1,1).

The asymmetric slope CAViaR model assumes that the VaR of a certain quantile follows an autoregressive process, which is written as follows (Engle and Manganelli, 2004):

$$f_{\alpha,t}(\beta) = \beta_0 + \beta_1 f_{\alpha,t-1}(\beta) + \beta_2 y_{t-1}^{+} + \beta_3 y_{t-1}^{-} \qquad (1)$$

Where, $f_{\alpha,t}$ is the VaR at the $\alpha = 5\%$ level (downside risk) in period t, β_0 is the constant. The autoregressive terms $\beta_1 f_{\alpha,t-1}(\beta)$ ensure that the quantile changes “smoothly” over time. β_2 and β_3 are the effects of positive (y_{t-1}^{+}) and negative (y_{t-1}^{-}) returns on the VaR, respectively.

For a time series of daily returns $R_{it} \in \{\text{FTSE4Good}, \text{ESG}, \text{DJS}, \text{FTSE4GoodSC}, \text{DJSC}, \text{DJESGRESI}, \text{GB}\}$, the downside VaR ($VaR_{it}^{down}$) can be written as follows:

$$\tau^{\mathrm{down}} = \Pr\{\mathrm{R_{it}} < \mathrm{VaR_{it}^{down}} | \zeta_{i,t-1}\} \qquad (2)$$

where τ represents the quantile of the variables between [0.05 to 0.95]; $\zeta_{i,t-1} = \{y_{is}, s < t\}$ denotes the information up to time t.

Time-Varying Parameter Vector Autoregressive (TVP-VAR) Connectedness

The current analysis involves the estimation of a TVP-VAR (1) model, a choice substantiated by the Bayesian Information Criterion. The model structure is outlined as follows:

$$z_t = \mathrm{B}_t z_{t-1} + \varepsilon_t; \ \ \varepsilon_t \sim N(0, S_t) \qquad (3)$$

$$vec(\mathrm{B}_t) = vec(\mathrm{B}_{t-1}) + \upsilon_t; \ \upsilon_t \sim N(0, R_t) \qquad (4)$$

In Eq. 3, z_t, z_{t-1} and ε_t are k×1 dimensional vectors which represent all tail risk series in $t, t-1$ and the corresponding error term, respectively. B_t and S_t are $k \times k$ dimensional matrices demonstrating the time-varying VAR coefficients and the time-varying variance-covariances. The vector (B_t) and υ_t are $k^2 \times 1$ dimensional vectors and R_t is a $k^2 \times k^2$ dimensional matrix.

The estimated TVP-VAR model then transforms into its Time-Varying Process Moving Average (TVP-VMA) form, facilitated by the foundational principles of the Wold Representation Theorem (Koop et al., 1996; Pesaran and Shin, 1998). This transformation is defined as follows:

$$z_t = \sum_{i=1}^{p} B_{it} z_{t-i} + \varepsilon_t = \sum_{j=0}^{\infty} A_{jt}\, \varepsilon_{t-j} \quad (5)$$

Following Chatziantoniou et al. (2022b) (see also, Diebold and Yilmaz; 2012), the process of normalising the (unscaled) generalized forecast error variance decomposition (GFEVD), signified as $\psi^{g}_{ij,t}(H)$, into its (scaled) form, is such that every row attains a cumulative value of unity. $\tilde{\psi}^{g}_{ij,t}(H)$ embodies the influence exerted by variable j on variable i, expressed through the proportion of their respective forecast error variances. This proportion outlines the bidirectional interconnectedness between variables j and i. The calculation of this metric involves the following steps:

$$\psi^{g}_{ij,t}(H) = \frac{S^{-1}_{ii,t} \sum_{t=1}^{H-1} (\iota'_i A_t S_t \iota_j)^2}{\sum_{t=1}^{H-1} (\iota_i A_t S_t A'_t \iota_i)^2} \text{ and, } \tilde{\psi}^{g}_{ij,t}(H) = \frac{\psi^{g}_{ij,t}(H)}{\sum_{j=1}^{k} \psi^{g}_{ij,t}(H)} \quad (6)$$

Where $\tilde{\psi}^{g}_{ij,t}(H) = 1$, $\sum_{i,j=1}^{k} \tilde{\psi}^{g}_{ij,t}(H) = k$ stands for the forecast horizon, and ι_i corresponds to a selection vector with unity on the i^{th} position and zero otherwise.

To quantify the level of interdependence within the considered series, the TCI is calculated as below:

$$TCI^{g}_{t}(H) = \frac{\sum_{i,j=1, i\neq j}^{k} \tilde{\psi}^{g}_{ij,t}(H)}{k-1}; 0 \leq TCI^{g}_{t}(H) < 1 \quad (7)$$

TCI in Eq. 7 can be then decomposed to the pairwise connectedness index (PCI) measuring the interconnectedness between two variables i and j.

$$PCI^{g}_{ij,t} = 2\left(\frac{\tilde{\psi}^{g}_{ij,t}(H) + \tilde{\psi}^{g}_{ji,t}(H)}{\tilde{\psi}^{g}_{ii,t}(H) + \tilde{\psi}^{g}_{ij,t}(H) + \tilde{\psi}^{g}_{ji,t}(H) + \tilde{\psi}^{g}_{jj,t}(H)}\right); 0 \leq TCI^{g}_{t}(H) < 1 \quad (8)$$

Spanning a range of [0, 1], this PCI effectively portrays the extent of reciprocal interconnection existing between variables i and j—a phenomenon effectively encapsulated within the confines of TCI.

Another important measurement involves the case when variable i and j imparts its shock to every other variable within the system. This is illustrated in Table (2).

Table (2) Connectedness measurements

Measurements	Used to	Formula
TO	when variable i imparts its shock to every other variable j within the system, this condition is denoted as (TO).	$TO^{g}_{i\to j,t}(H) = \sum_{i,j=1,i\neq j}^{k} \tilde{\psi}^{g}_{ij,t}(H)$
FROM	the shock variable i receives from variables j	$FROM^{g}_{i\leftarrow j,t}(H) = \sum_{i,j=1,i\neq j}^{k} \tilde{\psi}^{g}_{ij,t}(H)$
NET	as an indicator of the influence that variable i wields over the analyzed network.	$NET^{g}_{i,t} = TO^{g}_{i\to j,t}(H) - FROM^{g}_{i\leftarrow j,t}(H)$

Drivers of spillovers:

For the potential drivers of the connectedness network over time, the $TCI(H)$ series extracted from Eq. (7) is resorted to a dynamic estimation as below:

$$TCI(H) = \beta_0 + \beta_1 \text{FTSE4Good}_t + \beta_2\, \text{ESG}_t + \beta_3 \text{DJS}_t + \beta_4 \text{FTSE4GoodSC}_t + \beta_5\, \text{DJSC}_t + \beta_6 \text{DJESGRESI}_t + \beta_7 \text{GB}_t + \varepsilon_t \quad (9)$$

Eq. (9) helps in identifying which factors are the most significant in explaining changes in the connectedness network.

Empirical Analysis:

This section is devoted to the presentation and discussion of connectivity results. The implemented methodology enables a comprehensive analysis of the underlying connections, taking into account the dynamics at both the overall and individual levels among the variables contained in the relevant network. It is worth highlighting that in order to ensure the robustness of the findings, a series of rigorous robustness checks were conducted. These checks were designed to scrutinize the stability and reliability of the results under various conditions More precisely, I recalibrate the W-TVP-QVAR model by incorporating 120-, 150-, and 200-step-ahead GFEVD. Additionally, I do the aforementioned studies by employing various levels of CAViaR. For the robustness test, I employ the 1% downside tail risk and the 95% and 99% upside tail risk CAViaR measures. The outcomes derived from the different inputs and model configurations exhibit qualitative similarity and may be obtained upon request.

Averaged connectedness measures:

Commencing with the averaged outcomes spanning the entire duration of the study, the primary focus extends to both the overall averaged results, which are derived from the TCI, and the averaged results about pairwise connections calculated using the PCI.

Table (3) presents the overall results based on the TCI. These findings reveal a moderate level of co-movement within the network of variables. This observation is supported by the Total Connectedness values, which hover around 47%. On average, approximately 47.36% of the variance in forecast errors for each index return can be attributed to changes in all the other indices within the network. Nevertheless, the level of connection among these variables is notably significant. This prompts a thorough exploration of this connectedness, which could significantly enhance our understanding of the complex dynamics in the network among the series of interests. In other words, since this study's connectedness metrics are constructed based on the assessment of tail risk through the asymmetric slope CAViaR method, delving into the analysis of this specific network of variables becomes highly enlightening. This exploration aids in classifying potential sources of uncertainty within these distinct energy markets.

Table (3) also highlights a noticeable distinction between net transmitting and net receiving index returns. Specifically, returns from sustainability-related indexes emerge as the primary contributors, with DJS being the largest receiver (16.39%) followed by ESG, FTSE4Good, and FTSE4GoodSC, with net contributions of 11.07%, 8.00% and 5.42%, respectively. Conversely, non-financial factors, represented by DJESGRESI returns, take the lead as the primary net receivers of innovations within this network of variables, with a net reception of -18.52%, followed by DJSS returns with a net reception of -12.95%. GB also functions as a net reception with a net reception of -9.40%. It is worth noting that the main diagonal of Table 3 corresponds to the shocks of each variable on itself, typically representing the most significant sources of disturbance for the variables within the network.

Table (3) Average total connectedness.

	FTSE4Good	ESG	DJS	DJSS	FTSE4GoodSC	DJESGRESI	GB	FROM
FTSE4Good	51.87	2.17	1.59	1.83	17.77	19.57	5.20	40.13
ESG	5.55	38.75	1.03	39.28	7.28	2.90	5.21	50.18
DJS	2.35	2.48	73.66	2.73	8.76	2.54	7.49	9.95
FTSE4GoodSC	5.54	36.58	0.80	41.41	6.49	3.18	5.99	53.17
DJSS	14.91	3.63	2.76	2.99	67.92	4.41	3.39	45.03
DJESGRESI	6.23	1.51	2.59	1.16	2.74	72.94	12.84	45.58
GB	5.55	3.81	1.18	5.19	2.00	12.98	69.29	40.11
TO	48.13	61.25	26.34	58.59	32.08	27.06	30.71	284.16
NET	8.00	11.07	16.39	5.42	-12.95	-18.52	-9.40	TCI= 47.36
NPT	4.00	1.00	1.00	2.00	4.00	5.00	4.00	

Notes: The estimation results are based on a CAViaR-TVP-VAR model with a lag length of order one (BIC) a 120-days step-ahead generalized forecast error variance decomposition.

Table (4) offers the averaged pairwise results determined by the PCI. It provides insights into the average co-movements, measured as percentages ranging from 0 to 100%, between any two indexes over the entire sample period. An important characteristic of the PCI Table is that all elements along the main diagonal inherently have a value of 1. The significance of the PCI Table lies in its ability to assist in identifying strong co-movements among specific pairs of indexes. For instance, when comparing non-financial factors to sustainability-related indexes, it appears that the former exhibits a relatively high degree of co-movement with the latter compared to its relationship with GB. FTSE4GoodSC demonstrating a substantial co-movement of 97.22% with ESG, while DJESGRESI exhibiting a co-movement of 34.73% with FTSE4Good. GB displays co-movements of 16.68% with FTSE4Good, 15.8% with ESG and 12.76% with DJS.

Table (1) Averaged Pairwise Connectedness

	FTSE4Good	ESG	DJS	FTSE4GoodSC	DJSS	DJESGRESI	GB
FTSE4Good	100.00	15.39	6.24	14.39	42.66	34.73	16.68
ESG	15.39	100.00	6.49	97.22	18.79	7.59	15.80
DJS	6.24	6.49	100.00	6.32	15.37	6.91	12.76
FTSE4GoodSC	14.39	97.22	6.32	100.00	16.20	7.33	18.54
DJSS	42.66	18.79	15.37	16.20	100.00	9.94	7.79
DJESGRESI	34.73	7.59	6.91	7.33	9.94	100.00	31.19
GB	16.68	15.8	12.76	18.54	7.79	31.19	100

Time-varying results:

Figure (1) illustrates the dynamic evolution of total connectedness over time, offering a more comprehensive understanding of transmissions within the system. In addition to the 5% level, CAViaR-based spillovers indicated by the black area, results for the 10% and 2.5% levels have been incorporated, depicted by red and green lines, respectively, to ensure robustness. The dynamic total connectedness plot helps in clarifying our prior findings. The TCI varies throughout the sample period, ranging from 40% to about 65% with relatively high values at certain times. High TCI values typically imply strong spillovers between the relevant indexes.

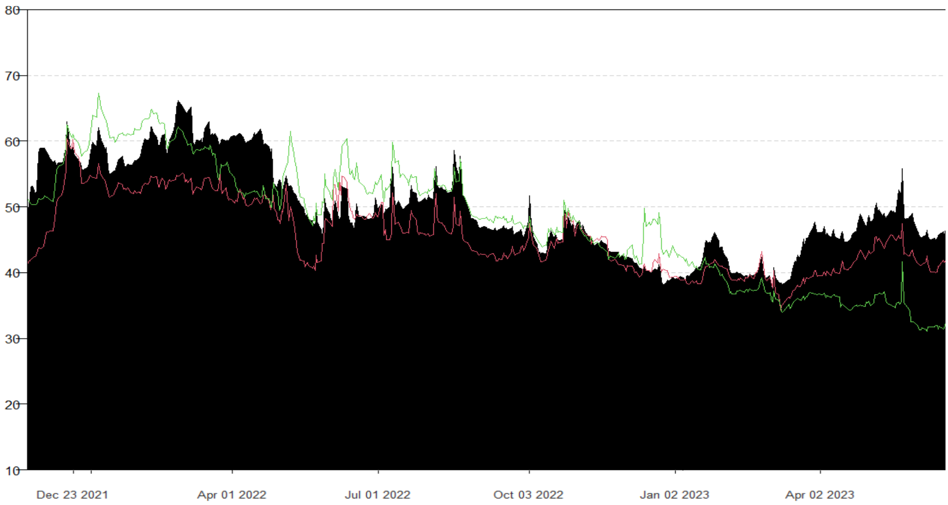

Figure (1): Dynamic total connectedness index (%).

Notes: Black area CAViaR-based spillovers at 5% level; Red line CAViaR-based spillovers at 10% level; Green line CAViaR-based spillovers at 2.5% level.

Drivers of spillover intensity:

Figure (2) illustrates the t-statistics derived from a rolling window regression (Eq. 9). In this figure, one could notice two horizontal red lines positioned above and below the x-axis, which signify the critical values at the 5% significance level as $+1.96$ and -1.96, respectively. As a result, any potential determinants' lines that appear above or below these horizontal lines are indicative of statistically significant estimates. It is worth noting that all the potential driving variables exhibit asymmetric effects on the connectedness network, and these relationships fluctuate over time. Notably, FTSE4Good has the most substantial impact on the connectedness network. Its positive influence on connectedness during the Russia-Ukraine War was significantly higher than that in previous periods. On the other hand, GB does not appear to have a significant impact on connectedness in general. However, during the late stages of the COVID-19 pandemic in 2021 to early 2023, there is an observed trend that higher GB values correspond to increased risk exposure spillovers. This pattern is also evident in FTSE4GoodSC and DJESGRESI. During the second quarter of 2022, DJSS and DJS exhibited relatively high impacts on risk exposure. Interestingly, during this period, DJSS consistently showed a negative and significant effect, while DJS consistently demonstrated a positive and significant effect.

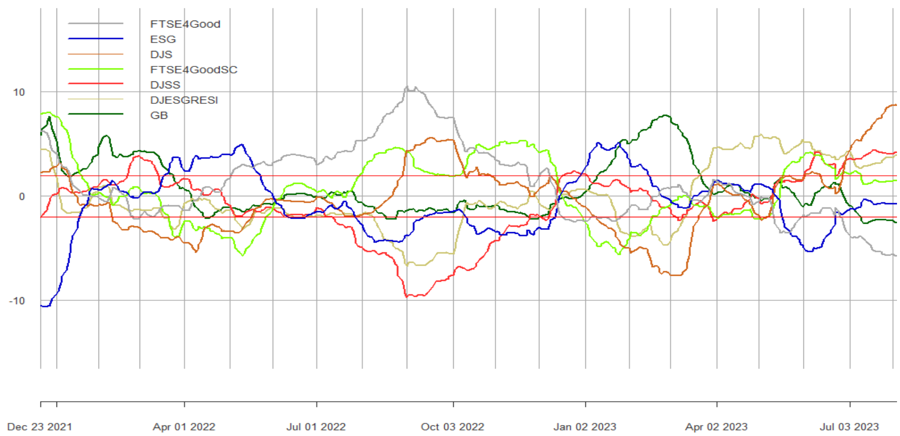

Figure (2): Rolling t-statistic based on a rolling-window (120 observations) regression
Notes: The horizontal red lines indicate 5% critical value of (±1.96)

Discussion and Conclusion:

This study underlines the growing significance of green finance in combating climate change and environmental degradation. It identifies that financial markets have a pivotal role in achieving sustainability objectives, with GBs and green stocks serving as vital funding sources for eco-friendly initiatives. The research delves into the intricate links between GBs and sustainability indexes, emphasising the need for a nuanced comprehension of these relationships, particularly within EFMs. It also explores non-financial aspects, such as environmental and social responsibility, which differentiate green assets and attract distinct investors. This research highlights the significance of green finance in emerging financial markets (EFMs) and the impact of non-financial elements. It emphasises the contribution of financial markets to sustainability initiatives and calls for more investigation by investors and policymakers.

The analysis of the interconnectedness between GBs and sustainability-related returns reveals a moderate yet significant level of interdependence. Sustainability-related indices play a crucial role in increasing connectivity in financial markets, while non-financial elements are subject to innovations. The fluctuating pattern of total connectivity suggests changing dependency among various indices over time, signifying market dynamics. Especially, certain events, such as the Russia-Ukraine War and the COVID-19 pandemic, had distinct impacts on the connectedness network, with FTSE4Good exerting particularly strong influence during the former.

Together, these results designate that sustainability-related indexes share more similarities with other non-financial equity investments, while GBs stand out as distinct. Investors tend to view GBs as fixed-income assets and GEs as equities rather than grouping them. These results align with previous research, which demonstrated how fixed-income markets significantly influence the performance of GBs (as evident by Pham (2021), Reboredo and Ugolini (2018) and (2020). They also align with the observation that institutional issuers and investors dominate the GB market, whereas the GE market includes a broader range of investor groups. This study underscores the unique nature of these two asset classes in the realm of sustainable investments, highlighting the distinct perceptions and roles that investors attribute to GBs and GEs.

Despite these categorisation and perception differences, both GBs and CE investments help reduce emissions. Therefore, it is reasonable to assume that investors may share similar expectations and interests in these low-carbon financial instruments. These findings yield valuable insights into the intricate dynamics of the considered variables, emphasising the importance of accounting for tail risk and interconnections when comprehending the behaviour of financial markets.

1. Compliance with Ethical Standards

Funding: This study received NO funding.

Ethical approval: This article does not contain any studies with human participants performed by any of the authors.

Conflict of Interest: The author declares that he has no conflict of interest.

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Appendix

Index	Appreviation	purpose
FTSE4Good Emerging Index	FTSE4Good	The FTSE4Good Index Series design to helps investors align their portfolios with their values and invest in companies in emerging markets that meet global ESG inclusion standards.
MSCI Emerging Markets ESG Index	ESG	The MSCI Emerging Markets ESG Leaders Index is a weighted index that showcases companies from the MSCI EM Europe Index, chosen based on their adherence to Environmental, Social, and Governance (ESG) criteria.
Dow Jones Sustainability Emerging Markets Index	DJS	The Dow Jones Sustainability Emerging Markets Diversified Index prioritizes sustainability and minimizes regional, industry, and company size biases compared to standard emerging-markets benchmarks. It includes the top 50% of companies from each region and sector within its index universe, selected based on their corporate sustainability scores assessed by S&P Global via the Corporate Sustainability Assessment (CSA).
Dow Jones Global Select ESG RESI (USD).	DJSS	The Dow Jones Global Select ESG Real Estate Securities Index (RESI) is crafted with the aim of gauging the performance of publicly traded real estate securities within the Dow Jones Global Select RESI that conform to sustainability standards. This index seeks to enhance exposure to the GRESB Total ESG score concerning the underlying index. It accomplishes this by giving greater weight to companies with relatively strong GRESB scores and reducing the weight of those with lower or no scores.
FTSE4Good Emerging Index Social Criteria	FTSE4GoodSC	is designed to measure the performance of companies from emerging markets that meet certain environmental, social, and governance (ESG) criteria. The social criteria used for inclusion in this index focus on assessing a company's performance in various social and ethical dimensions.

Dow Jones Sustainability Emerging Markets Social Index.	DJESGRESI	an index that tracks the performance of socially responsible companies in emerging markets. This index is part of the Dow Jones Sustainability Indices (DJSI), which are a series of benchmarks that assess the sustainability performance of companies worldwide.
J.P. Morgan EM Green Bond Diversified Indices	GB	The GENIE EM DIV, an abbreviation for the J.P. Morgan Emerging Markets Green Bond Diversified Index, extends the scope of the primary GENIE index. It offers investors the opportunity to engage with an expansive collection of green bonds that center on emerging markets.