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The Environmental Stress Rises of the Dynamic Linkages between Green Bonds and Stock, Bonds and Oil Indexes: Evidence from the DECO-GARCH Model

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ABSTRACT

This study investigates the dynamic interlinkages and volatility spillovers between green bonds and traditional financial assets (stocks, bonds, oil, and gold indexes), particularly during periods of environmental stress. We employ the DECO-GARCH model using daily data from 2009 to 2023, segmented around major events such as COVID-19 and the Russia-Ukraine conflict, to estimate time-varying equicorrelations. The findings of this study indicate that green bonds exhibit significant volatility connections with conventional assets, particularly during periods of crisis. The DECO-GARCH model underscores their potential role as safe-haven assets, revealing dynamic interconnectedness. This paper provides novel insights into the response of green bonds to systemic shocks, thereby enhancing the understanding of their diversification benefits. It contributes to portfolio management literature by demonstrating the resilience of green bonds during turbulent periods.

INTRODUCTION

In light of the unprecedented heatwaves experienced globally over the past two years, the objectives of the Paris Agreement, which aim to curtail greenhouse gas emissions and restrict the increase in global average temperature to 2°C above pre-industrial levels have assumed heightened urgency. Additionally, Russia's invasion of Ukraine has underscored the critical importance of energy security and emphasized the necessity of significantly reducing reliance on fossil fuels.

Supporting the energy transition to a low-carbon global environment has become a priority for governments and societies worldwide. The International Energy Agency (IEA) estimates that $4 trillion in annual investments in clean energy will be required worldwide to achieve “net zero emissions” by 2030. With a focus on sustainable finance to provide solutions that accelerate the energy transition, green bonds have emerged as a key investment vehicle to help finance a radical transformation of the energy mix (Arif et al., 2021). Green bonds are increasingly recognized as viable options for investing in sustainable projects (Ferrat et al., 2022). They allow investors to support initiatives that contribute to a more sustainable future while benefiting from financial returns. Additionally, green bonds assist companies in financing their environmental goals and enhancing their standing as sustainability leaders (Reboredo et al., 2020).

Arguably, green bonds are among the best fixed-income instruments available for accelerating the transition to a low-carbon economy (Monasterolo and Raberto, 2018). With interest rates at their highest levels in over a decade, the bond market now presents an attractive investment alternative for those seeking new opportunities amid macroeconomic slowdown and record-high equity valuations. Comprising issuers with strong fundamentals and an average rating of AA-, green bonds are well-positioned to meet this new demand while providing a real and measurable environmental benefit.

The development of green bonds has prompted studies on the connectivity and shock transmission between conventional non-environmental financial markets and green bond markets. Green bonds, a financial instrument recently introduced in sustainable finance, aim to support the transition to a low-carbon economy (Monasterolo and Raberto, 2018) while distributing the costs of combating climate change across current and future generations (Flaherty et al., 2017). First launched in 2007 by the European Investment Bank to finance renewable energy and energy efficiency projects, green bonds have since gained increasing attention. Currently, they are primarily issued by companies, municipalities, public sector entities, and supranational institutions, sharing characteristics similar to those of traditional fixed-income bonds. The proceeds are dedicated to environmental projects, such as green buildings, renewable energy, and waste and pollution management.

The ongoing evolution of green bonds as sophisticated and sustainable financial instruments presents significant investment opportunities for environmentally conscious individuals and institutions, enabling portfolio diversification beyond conventional assets. However, uncertainty persists regarding the financial performance of green bonds, especially amid volatility and fluctuations in broader financial markets. Understanding the transmission mechanism between green bonds and other financial markets is crucial for assessing their potential role in hedging and managing portfolio risk (Reboredo et al., 2018).
When the value of a specific financial market fluctuates, associated risks can accumulate and transfer to other markets as investors adjust their portfolio management strategies, potentially leading to capital movements that trigger a “butterfly effect” (Gao et al., 2021). Conversely, as investment and hedging assets, green bonds share similar pricing factors with other financial instruments (Reboredo and Ugolini, 2020; Reboredo et al., 2020), resulting in co-evolution between these assets. Specifically, green bonds are considered substitutes for fixed-income assets, such as treasury and corporate bonds, sharing similar characteristics except for their inherent greenness of green bonds (Reboredo et al., 2018). This interrelationship underscores the importance of understanding how variations in the green bond market can influence and be influenced by other segments of financial markets.

Using the DECO-GARCH model, this study provides an in-depth analysis of the interrelationships between green bonds and other financial assets, such as equities, conventional bonds, and oil indices. This provides a better understanding of how market fluctuations can influence the green bond sector in the context of environmental stress. This contribution is essential for investors seeking to assess the risks associated with investments in environmentally related assets.

This study analyzes the role of green bonds in the transition to a low-carbon economy by examining their interconnection with traditional financial markets and their capacity to manage portfolio risks, particularly during times of economic volatility.

To achieve this goal, the remainder of this paper is organized as follows: the next section provides a concise literature review, the third section introduces the methodology, the fourth section presents the results and discussions, and the final section outlines the main conclusions.

1. LITERATURE REVIEW

Prior research has primarily investigated the benefits and returns associated with green assets compared with other asset classes. Kanamura (2020) and Karpf and Mandel (2017) found a positive excess return for green assets, while Flammer (2021) and Larcker and Watts (2020) reported a largely insignificant premium on green investments. In contrast, a distinct branch of the literature, represented by studies made by Wang et al. (2020) and Tang and Zhang (2020), concluded that both investors and issuers could benefit from issuing green assets.

The strong interest and increased attention from researchers in understanding the nature and characteristics of green assets relative to conventional assets reflect a growing awareness among academics and practitioners. Similarly, Russo et al. (2021) analyzed the determinants of green bond performance to identify sustainable strategies and policy. Iqbal et al. (2021) adopted a time-frequency approach to examine the asymmetry of sustainable investments. However, the study of shock transmission has rarely been addressed, which provides an opportunity to examine the impact of shock transmission from financial asset indices to the green bond index.

Ngo Thai Hung (2021) adopted a novel approach to analyze the causal links between green bonds and various conventional assets, such as clean energy, the price of CO2 emission allowances, Bitcoin, and the S&P 500 stock market, over the period from January 2013 to March 2019. His results revealed a reciprocal relationship between the green bond market, the S&P 500, and Bitcoin, whereas a unidirectional relationship was observed between green bonds and the price of CO2 emission allowances. In summary, this study concluded that the influence of clean energy on green bonds, and vice versa, was significant throughout the observation period.

Yadav et al. (2023) investigated the impact of green bond volatility on the renewable energy and cryptocurrency sectors using daily data from October 1, 2015, to February 24, 2022. The results highlight the long-term impact of green bonds on both sectors. Furthermore, the B&K test results suggest that the effects on all analyzed series are more muted in the short term than in the medium and long term, thus providing increased opportunities for portfolio diversification in the short terms.

In the same context, Naeem et al. (2022) sought to assess the potential benefits for investors arising from the risk diversification properties associated with the inclusion of green bonds among other assets, particularly during the COVID-19 pandemic. Their approach relied on the use of a quantile connectivity methodology to analyze a set of assets, both green and traditional, such as commodities, stocks, and bonds, from 2008 to 2020. The results highlighted an increase in total variable risk spillovers over time, particularly during periods of extremely high volatility compared to those characterized by medium or low volatility. Regarding pairwise risk spillovers, green bonds present more diversification opportunities when volatility is very low. However, diversification benefits increased during the COVID-19 pandemic. The significant and bidirectional risk spillovers between green and conventional bonds suggest that green bonds could be considered an attractive alternative to conventional bonds, capitalizing on their diversification potential, particularly in the energy and agriculture sectors.

Yadav et al. (2023) explored the co-evolution of green bonds, energy commodities, and equities to determine the benefits of adding green bonds to a diversified portfolio. Using the Granger causality test, wavelet analysis, and network analysis, they examined daily prices for selected markets from August 26, 2014, to March 30, 2021. Their findings from the Granger causality test indicate no causality between pairs of variables, while the cross-wavelet transform and wavelet coherence analysis confirm strong large-scale coherence during the pandemic, thereby validating the co-evolution between the three asset classes.

Furthermore, network analysis corroborates this connectivity, implying a strong association between the stock markets and energy commodity markets.

Zhang and Umair (2023) studied the interconnectivity of green finance by analyzing the dynamic spillover effects between green bonds, renewable energy stocks, and carbon markets. Using daily data from January 2010 to December 2020, they applied vector autoregressive models and time-varying parameter models to examine the shock transmission channels between these different assets. The results highlight significant dynamic spillover effects between green bonds and renewable energy stocks and between carbon markets and renewable energy stocks. Moreover, the findings suggest a complementary relationship between green bonds and carbon markets, providing insights into the interdependence of various green financial instruments and their role in promoting sustainable development.

This study hypothesizes that there is significant risk transmission between green assets and other asset classes. To explore this hypothesis, this study examines the risk transmission mechanism between green assets and other asset classes. This analysis is based on a unique set of methodologies, which are detailed in the following sections.

2. METHODOLOGY AND DATA

To analyze the risk transmission between green and conventional assets, we adopted a specific methodological approach. Initially, the BEKK model, as defined by Baba, Engle, Kraft, and Kroner (1990) was implemented. Subsequently, the multivariate DECO-GARCH model was employed to estimate dynamic equicorrelation. The following subsections deals with the advantages of each of these models, along with their methodological approaches, thereby providing a comprehensive overview of analysis methodology employed.

2.1 ARCH and GARCH models

The ARCH model, initially presented by Engle (1982), and the GARCH model, developed by Bollerslev (1986), are among the most widely used frameworks for modeling stock return volatility. However, when analyzing volatility links across countries, a multivariate GARCH approach is preferable to univariate models. Unfortunately, these models cannot be estimated by imposing specific restrictions on the conditional variance-covariance matrix. The model proposed by Bollerslev et al. (1988) does not guarantee the positivity of the conditional variance matrix and does not allow the conditional variance and covariance equations to influence each other because of oversimplified restrictions.

These issues have been largely addressed in the BEKK model (Baba, Engle, Kraft, and Kroner) proposed by Engle and Kroner (1995). The use of quadratic forms in this model ensures positivity while being consistent with the constant correlation assumption, allowing for effective modeling of market volatility. However, this presents a trade-off between the generality of the model and the increasing complexity of computations with higher-dimensional systems. For a plausibly estimated multivariate GARCH model, the matrix $\sum_t$ must be positive-definite for all values of the disturbances. Verifying this condition is a non-trivial task, even for moderately sized VEC or diagonal VEC models.

To overcome this challenge, Engle and Kroner (1995) proposed a quadratic formulation for the parameters to ensure that they remain positive definite. This formulation is known as the BEKK model (Brooks et al., 2003). The number of parameters in this model increases linearly with the number of assets, making it relatively suitable for large asset sets (De Goeij et al., 2004). The BEKK model is formulated as follows:

$$\Sigma_t = C_0 C_0' + \sum_{k=1}^{k} \sum_{i=1}^{q} A_{ki}' \, \varepsilon_{t-1} \varepsilon_{t-1}' A_{ki} + \sum_{k=1}^{k} \sum_{i=1}^{p} B_{ki}' \, \Sigma_{t-i} B_{ki} \tag{1}$$

Where C_0 is a lower triangular matrix, Aki and Bki are N x N parameter matrices of size N x N. Based on the parameterization of the symmetric model, Σt is almost surely positive definite provided that Σ0Σ0 is positive definite (Tsay, 2005).

Engle and Kroner (1995) demonstrated that a necessary condition for the covariance stationarity of the BEKK model is that the eigenvalues (characteristic roots) of ΣΣ must be less than one in absolute value. Thus, the process can remain stationary even if there is an element in the matrix with a value greater than one. This condition differs from that required by the univariate GARCH model, i the sum of the ARCH and GARCH terms must be less than one (Pang et al., 2002). The BEKK (1,1 K) model is defined as follows:

$$\Sigma_t = C_0 C_0' + \sum_{k=1}^{k} A_k' \, \varepsilon_{t-1}\varepsilon_{t-1}' A_k + \sum_{k=1}^{k} B_k' \, \Sigma_{t-i} B_k \tag{2}$$

Where C_0, Ak and Bk are parameter matrices of size N x N, but C0 is upper triangular. Alternatively, C_0 × C = Ω > 0. The positivity of ∑t is guaranteed if ∑0 ≥ 0. The positivity of ∑∑t is guaranteed if Σ0≥0Σ0≥0. This model has 11 parameters, compared to the 21 of the VEC model (Bauwens, 2005), and allows for dynamic dependence between volatility series (Tsay, 2005).

2.2 DECO-GARCH estimation

DECO-GARCH estimation is crucial because multivariate GARCH (MGARCH) models face methodological constraints. DECO-GARCH addresses these limitations by enabling the efficient computation and visualization of high-dimensional systems, as noted by Engle and Kelly (2012). The DECO technique is a component of the DCC model, where all variables are uniformly associated, but their adjacent equicorrelations vary over time. A significant strength of this approach lies in its ability to provide robust forecasts, particularly when economic conditions are unfavorable and exposed to tail risks, as highlighted by Clements et al. (2015). Therefore, the DECO-GARCH model is particularly suitable for revealing the relationships between green assets and other categories. In line with Kang et al. (2017), t the average equation for a series of vector returns is set as follows:

$$r_t = \vartheta_t + \theta r_{t-1} + \varepsilon_t \tag{3}$$

Where, ϑ represents the vector constant and εt denotes the vector consisting of the error terms.

Subsequently, by applying the univariate GARCH model (1,1), the conditional volatilities is evaluated as follows:

$$f_{i,t}^2 = \omega + \gamma \varepsilon_{i,t-1}^2 \tau f_{i,t-1}^2 \tag{4}$$

When ω > 0, γ ≥ 0 and τ ≥ 0, with γ + τ < 1, the DCC model of Engle (2002) is employed to analyze the dynamic correlations between green and other asset classes. Indeed, the conditional variance-covariance matrix, Ht, can be presented as follows:

$$F_t = D_t^{1/2} R_t D_t^{1/2} \tag{5}$$

The conditional correlation matrix is represented by Rt = [ρi j, t], while Dt = diag (f i, t, · · ·, h n, t) constitutes the diagonal matrix of conditional variances. The characterization of H t, resulting from dynamic correlations, is formulated as follows:

$$R_t = \{Z_t^*\}^{-1/2} Z_t (Z_t^*)^{-1/2} \tag{6}$$

$$Z_t^* = diag[Z_t] \tag{7}$$

$$Z_t^* = [z_{i,it}] = (1 - a - b)S + \alpha\mu_{t-1}\mu'_{t-1} + bZ_{t-1} \tag{8}$$

The term u_t represents the standardized residuals, while, a and b are non-negative scalars adjusted so that, a+b <1, and the method employed is the DCC approach. An observation made by Aielli (2013) indicates that estimating the covariance matrix Qt using this method leads to inconsistent results. Therefore, it is recommended to opt for a consistent DCC model for the correlation steering process, which can be described as follows:

$$Z_t = (1 - 1 - b)S^* a \left(Z_{t-1}^{*\frac{1}{2}} \mu_{t-1}\mu'_{t-1} Z_{t-1}^{*\frac{1}{2}} \right) + bZ_{t-1} \tag{9}$$

The S* matrix symbolizes the unconditional covariance of $Z_{t-1}^{*\frac{1}{2}}\mu_t$. The DECO approach results from using a correlation matrix (Zt) and taking an average of the off-diagonal elements, where ρt is derived from the DCC process (Engle & Kelly, 2012). Thus, the scalar equicorrelation is expressed as follows:

$$\rho_n^{DECO} = \frac{1}{n(n-1)}\left(f_n' R_t^{cDCC} f_n - n\right) = \frac{2}{n(n-1)} \sum_{i=1}^{n-1} \sum_{j=2}^{n} \frac{z_{i,j,t}}{\sqrt{z_{ii,t} z_{jj,t}}} \tag{10}$$

In order to estimate the conditional correlation matrix, scalar equicorrelation is used as follows:

$$R_t = (1 - \varphi_t)I_n + \varphi_t I f_n \tag{11}$$

By following these steps, the extent of tail risk transmission between green assets and other asset classes can be formulated using a single time-varying correlation coefficient.

2.3 Data

Daily price data for all indices, from January 1, 2009, to October 23, 2023 have been analyzed. This period provides a unique opportunity to study the impact of events such as the COVID-19 pandemic and the Russo-Ukrainian conflict on the interactions and evolution of different indices. To facilitate this analysis, the study period is divided into two distinct sub-periods: the pre-COVID-19 period (January 2009 to December 2019) and the post-COVID-19 period (January 2020 to October 2023). To ensure the robustness of our work, we calculated the returns for each index by using the following formula: ((Pt-Pt-1)/Pt-1). All data was extracted from the Datastream database. These data include the Global Equity Index, the Gold Index, the Crude Oil Spot Index, the Global Government Bond Index, and the Green Bond Index. The data and their sources are listed in Table 1.

Table 1. Data sources

Data	Sources
MLCX Crude Oil (WTI) Spot Index - PRICE INDEX	DataStream https://www.lseg.com/en/data-analytics/products/datastream-macroeconomic-analysis

FTSE World Government Bond Index	DataStream https://www.lseg.com/en/data-analytics/products/datastream-macroeconomic-analysis
S&P GREEN BOND INDEX - PRICE INDEX	DataStream https://www.lseg.com/en/data-analytics/products/datastream-macroeconomic-analysis
S&P GLOBAL 1200 GOLD - PRICE INDEX	DataStream https://www.lseg.com/en/data-analytics/products/datastream-macroeconomic-analysis
S&P GLOBAL BMI U$ - PRICE INDEX	DataStream https://www.lseg.com/en/data-analytics/products/datastream-macroeconomic-analysis

Source : own

2.4 Descriptive statistics

The statistical descriptions provided in table 2 show the characteristics of five different financial variables: GBI, CBI, GOLD, WTI and STI.

Table 2. Descriptive statistics

	WGBI	CBI	GOLD	WTI	STI
Mean	5.50E-05	-6.02E-05	8.34E-05	0.000508	0.000319
Median	0.000124	-1.09E-05	-1.63E-05	0.001255	0.000660
Maximum	0.012557	0.056660	0.125425	0.227144	0.082795
Minimum	-0.014421	-0.030436	-0.299740	-0.285675	-0.095404
Std. Dev.	0.002051	0.004856	0.021116	0.024289	0.009620
Skewness	0.012881	0.281558	-0.636091	-0.505196	-0.621221
Kurtosis	7.152950	12.36126	15.52490	17.88964	13.01720
Jarque-Bera	2773.998	14145.34	25490.72	35821.18	16386.99
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	0.212318	-0.232477	0.321892	1.961472	1.232976
Sum Sq. Dev.	0.016228	0.090989	1.720672	2.276618	0.357158
Observations	3860	3860	3860	3860	3860

Source: own

The mean of the GBI variable is 5.50E-05, with a higher median of 0.000124. The CBI variable has a slightly negative mean of -6.02E-05, with a median close to zero at -1.09E-05. For the GOLD variable, the mean is 8.34E-05, with a negative median of -1.63E-05, suggesting negative skewness in the data distribution. The WTI variable has a higher mean of 0.000508 and a median of 0.001255, indicating a possible presence of extreme values in the distribution. Finally, the STI variable has a mean of 0.000319 and a median of 0.000660. The standard deviations for each variable vary, ranging from 0.002051 to

0.024289, suggesting different levels of dispersion across the data. Skewness and kurtosis measures indicate skewed distributions for some variables, with higher values for GOLD, WTI, and STI. Jarque-Bera tests show very low probabilities, suggesting that the data distributions do not follow a normal distribution. These statistical descriptions provide a detailed view of the characteristics of the financial data analyzed, which can be useful for investment and portfolio management decisions.

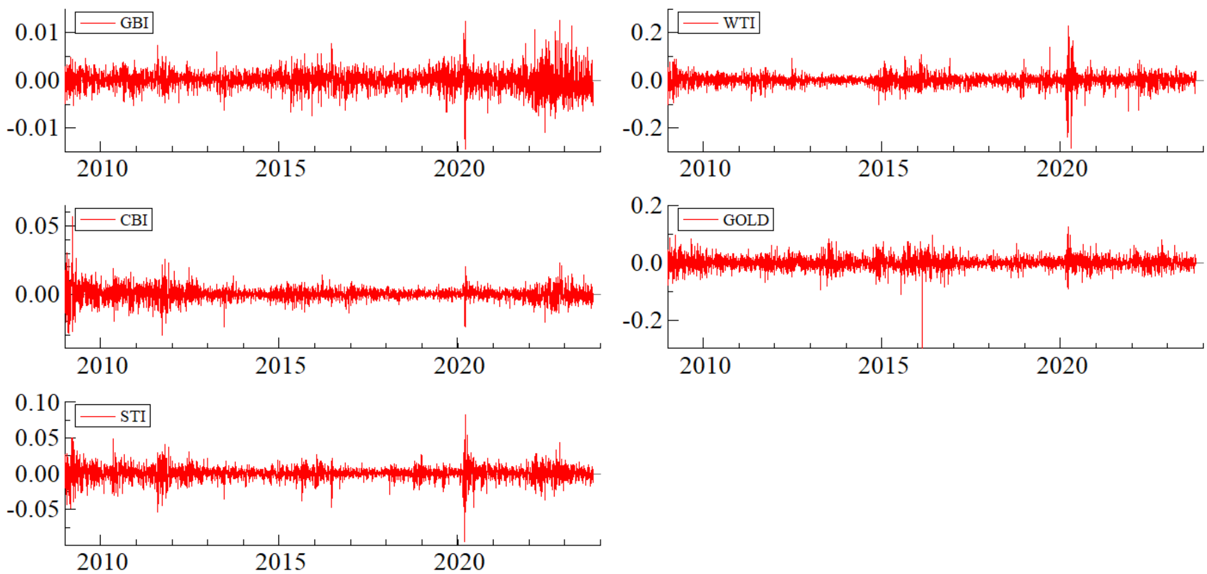

Figure 1. Indices returns

Figure 1 displays the index returns used in this study. It demonstrates that during the pandemic, high volatility and a decline in index returns were observed, reflecting the uncertainty and economic disruptions caused by the health crisis. Some indices recorded negative or stable performances, while others benefited from economic stimulus measures and support from financial markets. In relation to the Russia-Ukraine conflict, additional fluctuations in index returns were also noted, particularly for those associated with the affected region or for sectors especially sensitive to geopolitical tensions.

2.4.1 Stationarity test

The results of the ADF and PP tests are presented for the levels and differences in the GBI, CBI, STI, WTI, and GOLD series. Values marked with "***" indicate statistical significance at a very high level (p-value < 0.01), leading us to reject the null hypothesis of the presence of a unit root. Indeed, all series GBI, CBI, STI, WTI, and GOLD—are significantly stationary at the level. The very negative values of the test statistics and high significance indicate that the null hypothesis of non-stationarity is rejected. This means that these series do not require differentiation for use in econometric models (Table 3).

Table 3. Stationarity test

	ADF test in level	ADF test in difference	PP test in level	PP test in difference
GBI	-55.34190***	-25.02335***	-55.30375***	-819.3580***
CBI	-60.50914***	-21.38572***	-60.52989***	-575.0194***
STI	-19.84339***	-23.82725***	-56.55635***	-565.5748***
WTI	-65.51463***	-21.13089***	-65.52500***	-1040.144***
GOLD	-58.88210***	-22.12308***	-58.81958***	-1365.832***

Note(s): ***, **, * statistical significance at 1%, 5% and 10% levels, respectively
Source: own

Difference tests are generally unnecessary here, as the level tests already demonstrate that the series are stationary. However, the results of the difference tests remain highly significant, further supporting the conclusion that these series are stationary. The agreement between the ADF and PP test results strengthens confidence in this interpretation. While treating autocorrelation differently, both tests, conclude that the series are stationary.

3. RESULTS AND DISCUSSIONS

These results are crucial for understanding the volatility dynamics between green bonds and conventional assets, which is essential for investors and policymakers seeking to navigate a financial landscape increasingly influenced by environmental considerations as shown in the following table.

Table 4. Results of the volatility transmission between green bond index and conventionnel index using DECO-GARCH model total period

	CBI	STI	WTI	GOLD
		Univariate GARCH model		
Constant	(0.0001043) 0.0032**	(0.000157) 0.00212**	(0.0001253) 0.0004***	(0.000118) 0.0002***
ARCH	(0.056128) 0.7292	(-0.139127) 0.023545**	(-0.112518) 0.3680	(-0.088679) 0.25687
GARCH	(0.998803) 0.0000***	(0.998415) 0.0000***	(0.998650) 0.0000***	(0.998680) 0.0000***
		DECO model		
A_{DECO}	(0.035535) 0.0000***	(0.060105) 0.0000***	(0.033491) 0.0130**	(0.014732) 0.0005***
B_{DECO}	(0.960227) 0.0000***	(0.903955) 0.0000***	(0.853860) 0.0000***	(0.979492) 0.0000***
		Multivariate diagnostic tests		
Normality test	661.15 [0.0000] **	565.92 [0.0000] **	955.50 [0.0000] **	1126.7 [0.0000] **
Hosking (10)	88.9743 [0.0000057]	75.5963 [0.0002733]	77.8861 [0.0001455]	71.8224 [0.0007480]
Li-McLeod (10)	88.9404 [0.0000058]	75.5924 [0.0002736]	77.8757 [0.0001459]	71.8002 [0.0007523]

Note: Hosking (10) and McLeod-Li (10) multivariate Portmanteau statistics test the null hypothesis of no serial correlation in squared standardized residuals (10 lags). P-values are shown in brackets. ***,**,* represent 1%, 5%, and 10% significance level, respectively.
Source: own

The analysis of the results in Table 4 from the DECO-GARCH model for the transmission of volatility between the green bond index and the conventional index over the full period reveals several important aspects. First, examining the results of the univariate GARCH model, it is found that for the CBI index, the constant is very small at 0.0001043. The coefficients of the ARCH and GARCH terms indicate a weak influence of both the ARCH and GARCH effects on the volatility of the index. Similar results are observed for the STI, WTI, and GOLD indices, which show significant coefficient values for the constant and ARCH terms, but weaker values for the GARCH terms.

Turning to the DECO model, it is observed that, for ADECO, the coefficients of the terms are significant and indicate a considerable influence of past values on current volatility, particularly for the GOLD index. For BDECO, the coefficients also demonstrate a significant influence of past values on current volatility, albeit in a more attenuated manner than ADECO.

Regarding the multivariate diagnostic tests, the results of the normality tests reveal significant statistical values for all indices, indicating deviations from the normal distribution. The Hosking and Li-McLeod tests with a lag of 10 periods also show significant statistical values for all indices, suggesting that the models may not fully capture the volatility structure of the data.

Table 5. Results of the volatility transmission between green bond index and conventionnel index using the DECO-GARCH model in pre-COVID 19 period

	CBI	STI	WTI	GOLD
		Univariate GARCH model		
Constant	(0.000150) 0.0002***	(0.000177) 0.00509**	(0.000173) 0.0013***	(0.000146) 0.00035***
ARCH	(-0.027203) 0.2195	-0.158217) 0.13365	(-0.125719) 0.4563	(-0.094123) 0.36159
GARCH	(0.998476) 0.0000***	(0.998092) 0.0000***	(0.998337) 0.0000***	(0.998432) 0.0000***
		DECO model		
A_{DECO}	(0.041117) 0.0000***	(0.056409) 0.0000***	(0.022464) 0.3088	(0.015835) 0.0012***
B_{DECO}	(0.951475) 0.0000***	(0.899236) 0.0000***	(0.937129) 0.0000***	(0.979759) 0.0000***
		Multivariate diagnostic tests		
Normality test	447.15 [0.0000]**	433.48 [0.0000]**	578.30 [0.0000]**	1043.4 [0.0000]**
Hosking (10)	52.1294 [0.0631217]	50.9905 [0.0774603]	49.7943 [0.0953342]	47.4636 [0.1396892]
Li-McLeod (10)	52.1604 [0.0627655]	51.0180 [0.0770835]	49.8079 [0.0951134]	47.4625 [0.1397151]

Note: Hosking (10) and McLeod-Li (10) multivariate Portmanteau statistics test the null hypothesis of no serial correlation in squared standardized residuals (10 lags). P-values are shown in brackets. ***,**,* represent 1%, 5%, and 10% significance level, respectively.
Source: own

The results of the volatility transmission between the green bond index and the conventional index using the DECO-GARCH model during the pre-COVID-19 period reveal several important insights (see Table 5).

First, an examination of the univariate GARCH model results reveals that the coefficients of the constant terms, ARCH, and GARCH vary across indices. For the CBI index, the coefficients are generally low, suggesting relatively stable volatility. In contrast, the STI, WTI, and GOLD indices show higher coefficients, indicating increased volatility in these markets.

Regarding the DECO model, the coefficients for ADECO and BDECO demonstrate a significant influence of past values on current volatility, particularly for the GOLD index. This suggests persistence in the volatility of this index, which may have important implications for investment strategies.

Multivariate diagnostic tests reveal significant values for normality tests, indicating deviations from the normal distribution for all indices. The Hosking and Li-McLeod tests with a 10-period lag show statistically significant values for some indices, suggesting that the models could be improved to better capture the volatility structure of the data.

Table 6. Results of the volatility transmission between green bond index and conventionnel index using the DECO-GARCH model COVID 19 and conflict between Russia and Ukraine period

	CBI	STI	WTI	GOLD
		Univariate GARCH model		
Constant	(-0.000038)	(-0.000135)	(-0.000233)	(-0.000158)
	0.0034***	0.00236**	0.0286**	0.2468
ARCH	(0.507369)	(0.454035)	(1.665538)	(0.725641)
	0.0295**	0.00238***	0.0939*	0.1305
GARCH	(0.995214)	(0.993820)	(0.994869)	(0.994898)
	0.0000***	0.0000***	0.0000***	0.0000***
		DECO model		
A_{DECO}	(0.027336)	(0.055825)	(0.074011)	(0.0000003)
	0.1862	0.0155**	0.0921*	0.9972
B_{DECO}	(0.959980)	(0.889515)	(0.579459)	(0.821565)
	0.0000***	0.0000***	0.0000***	0.8569
		Multivariate diagnostic tests		

Normality test	121.16 [0.0000]**	109.79 [0.0000]**	161.81 [0.0000]**	61.740 [0.0000]**
Hosking (10)	70.3699 [0.0010894]	31.4709 [0.7639324]	15.9109 [0.9993905]	59.3190 [0.0149974]
Li-McLeod (10)	70.0204 [0.0011914]	31.5922 [0.7590534]	16.2045 [0.9992467]	59.1447 [0.0155719]

Note: Hosking (10) and McLeod-Li (10) multivariate Portmanteau statistics test the null hypothesis of no serial correlation in squared standardized residuals (10 lags). P-values are shown in brackets. ***,**,* represent 1%, 5%, and 10% significance level, respectively.
Source: own

The results of the volatility transmission between the green bond index and the conventional index using the DECO-GARCH model during the COVID-19 period and the conflict between Russia and Ukraine reveal interesting dynamics (see Table 6).

Examining the coefficients of the univariate GARCH model, we observed significant variations in volatility levels among the different indices. For the CBI index, the coefficients of the constant and ARCH terms are relatively low, suggesting a stability in volatility. In contrast, the STI, WTI, and GOLD indices exhibit higher coefficients, indicating more pronounced volatility in these markets, potentially influenced by the disruptions related to COVID-19 and the conflict in Eastern Europe.

Focusing on the DECO model, the coefficients for the ADECO and BDECO terms reveal the influence of past values on the current volatility of the indices, particularly for the GOLD index. This suggests some persistence in the volatility of this index, which can be attributed to the economic and geopolitical uncertainty surrounding the COVID-19 period and the Russian-Ukrainian conflict.

Multivariate diagnostic tests indicate significant deviations from the normal distribution for all indices, highlighting the impact of recent events on market volatility. The Hosking and Li-McLeod tests show statistically significant values, particularly for the CBI index, suggesting potential challenges in modeling the volatility of this index, due to the disruptions caused by the COVID-19 pandemic and the ongoing conflict.

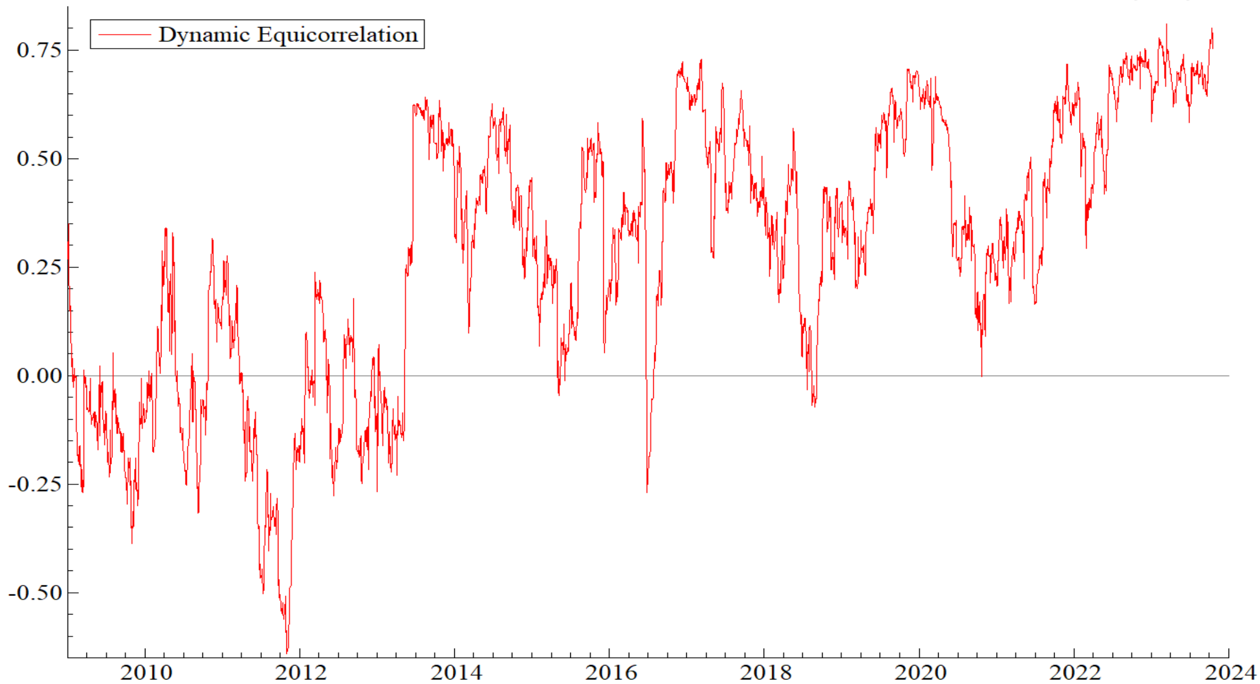

Figure 2. Dynamic equicorrelation between green bond index and conventional bond index

Figure 2 illustrates the dynamics of the equicorrelation between the global green bond and conventional bond indices. This equicorrelation is important because it helps us understand how these two indices move together and how external events can influence them.

During the COVID-19 period, an increase in the correlation between the two indices is observed, indicating greater synchronization in their movements. This rise in equicorrelation may be attributed to the widespread impact of the pandemic on global financial markets, leading to similar fluctuations in both green and conventional bonds in response to economic uncertainties and stimulus policies implemented during this time. Additionally, investor reactions to the crisis may further influence the correlation; during this period, investors might have favored green bonds because of their sustainability and perceived stability, resulting in a stronger correlation between the two indices.

In the context of the Russia – Ukraine conflict, spikes in correlation between the two indices are observed, suggesting a joint reaction to geopolitical instability. Political tensions and geopolitical risks can increase the equicorrelation between green and conventional bonds, reflecting heightened volatility and sensitivity to geopolitical events. Indeed, geopolitical tensions can lead to increased volatility in financial markets, which may be reflected in the equicorrelation between green and conventional bonds.

Investor behavior is a key element to consider, as it can influence the demand for green bonds relative to conventional bonds, thereby affecting the equicorrelation between the two indices. Investors may adopt more defensive positions or seek safer assets, which can further impact correlation dynamics.

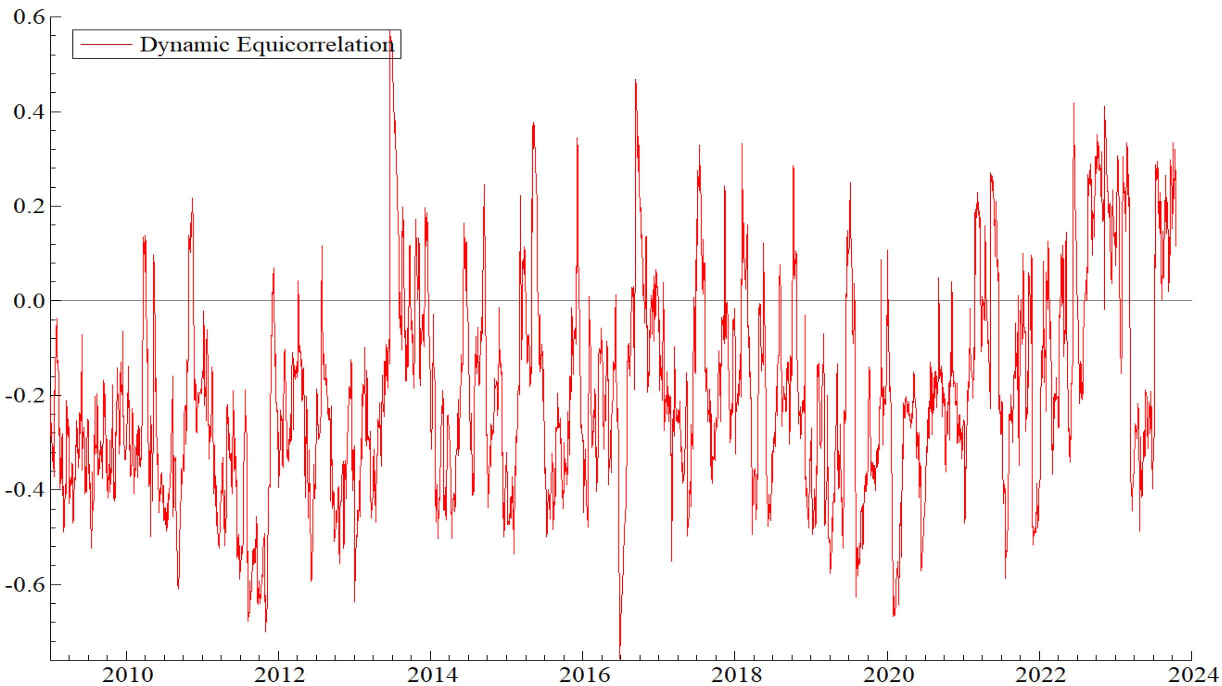

Figure 3. Dynamic equicorrelation between green bond index and stock index

Figure 3 illustrates the dynamics of the equicorrelation between the global green bond index and the stock index, particularly during the COVID-19 period and the conflict between Russia and Ukraine. During the COVID-19 period, financial markets were significantly affected by economic uncertainty and volatility. Investors may have responded by adjusting their portfolios, possibly favoring green bonds because of their sustainable and responsible nature.

The geopolitical situation between Russia and Ukraine may have also influenced the correlation between the green bond and stock indices. Political tensions can create instability in financial markets, prompting investors to shift towards assets considered safer, such as green bonds, at the expense of the stock index.

Understanding how these external events can impact the correlation between different indices is crucial, as is recognizing how these factors shape investor behavior. During periods of crisis and geopolitical tensions, investor reactions often play a decisive role in the dynamics of financial markets and the correlation between various asset types.

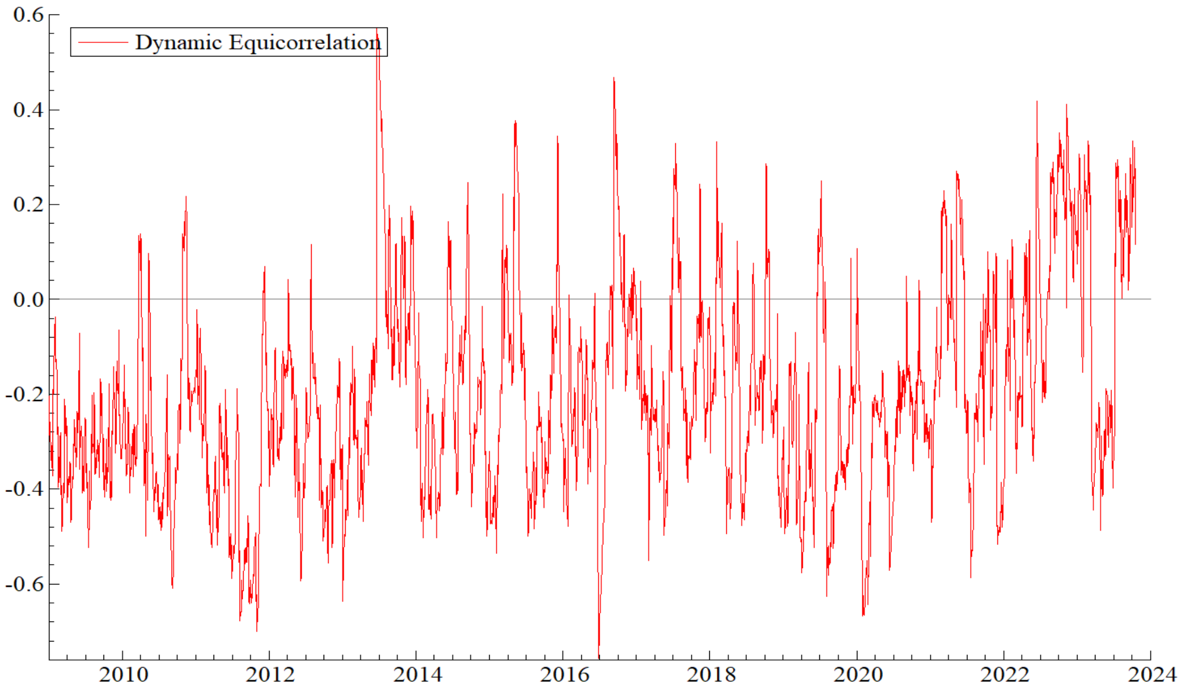

Figure 4. Dynamic equicorrelation between green bond index and crude oil index

Analyzing figure 4 showing the dynamics of the equicorrelation between the global green bond and oil indices reveals several important elements. First, it is evident that the two indices exhibit joint fluctuations over time. A high equicorrelation suggests a strong linkage between their movements, indicating some dependence between the green bond market and the oil market.

By examining the variations in equicorrelation over time, periods when the correlation between the two indices is stronger or weaker can be identified. These fluctuations may result from economic, political, or external factors that impact the two markets differently. Additionally, a deeper analysis of the dynamics of equicorrelation can contributes to a better understanding of the relationships between green bonds and the oil market, as well as help anticipate possible future trends. The chart indicates that the COVID-19 pandemic led to significant market volatility, characterized by sudden declines followed by rapid rebounds. The lockdown measures and economic disruptions caused by the pandemic affected markets broadly, including both green bonds and oil. Investors had to adapt to an uncertain and constantly changing economic environment.

Similarly, the conflict between Russia and Ukraine has also affected financial markets, particularly the energy sector. Geopolitical tensions and risks associated with potential armed conflict have influenced oil and other commodity prices, affecting the balance between supply and demand in the market. Thus, the combination of these events has created a complex and volatile environment for investors, necessitating in-depth analysis and prudent risk management. It is essential to closely monitor the evolution of the situation and adjust investment strategies accordingly to navigate these uncertain times effectively.

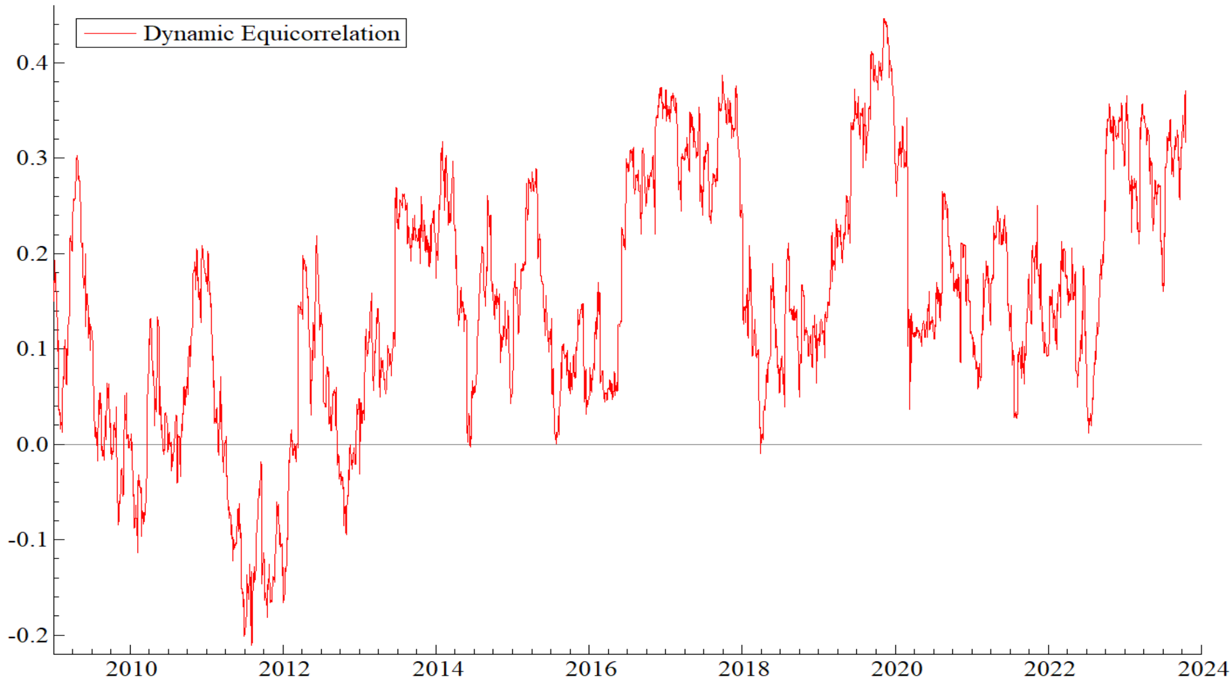

Figure 5. Dynamic equicorrelation between green bond index and gold index

The chart illustrates the dynamics of the equicorrelation between the global green bond index and the gold index. It is important to note that gold is often regarded as a safe haven during times of economic and geopolitical uncertainty, while green bonds are generally associated with sustainable and responsible investments (see figure 5).

During the COVID-19 period, investors may have shifted towards assets considered safer and more stable, such as gold because of global economic uncertainty caused by the pandemic. This shift could lead to a stronger correlation between the gold index and the global green bond index, as both assets may be perceived as safe havens in times of crisis. Indeed, the investment decisions of market participants can be influenced by various factors, including economic conditions, geopolitical events, and prevailing market trends.

Regarding the conflict in Russia Russia-Ukraine Conflict), geopolitical tensions can also affect the correlation between gold and green bonds. During periods of political unrest, investors may seek protection by investing in tangible assets like gold, which could impact the correlation with green bonds, which are more closely tied to environmental and social concerns. In the face of geopolitical conflicts, investors may adjust their portfolios to mitigate potential risks associated with these events. This response may result in increased demand for safe-haven assets, such as gold, often at the expense of other, riskier asset classes. During such times, investors might seek to protect themselves against potential risks by gravitating towards safer assets. Demand for gold, as a traditional safe haven, may rise during periods of uncertainty, thereby influencing the correlation between the gold index and the green bond index. Additionally, investors may consider the environmental and sustainability aspects of their investments, which could further affect the dynamics of the equicorrelation between green bonds and gold.

CONCLUSION

The analysis of dynamic linkages between green bonds and other conventional assets using the DECO-GARCH model, while considering the effects of the COVID-19 pandemic and the war between Russia and Ukraine, revealed significant results and profound implications. The study uses daily data, covering the period from 2009 to 2023, extracted from the DataStream database and includes various indices such as the S&P Green Bond and the FTSE World Government Bond indices.

The COVID-19 pandemic caused unprecedented fluctuations in financial markets, increasing volatility and altering correlations between assets. Green bonds demonstrated relative resilience, acting as safe-haven assets during periods of uncertainty. Similarly, the war in Ukraine exacerbated geopolitical and economic tensions, influencing investment flows. Investors responded by reassessing their portfolios, leading to shifts in correlations, including a heightened interest in sustainable assets.

The findings indicate that correlations between green bonds and conventional assets increased during crisis periods, reflecting a tendency for investors to gravitate toward assets perceived as safer, including green bonds. These dynamics highlight the importance of analytical models that account for the variability of correlations in crisis contexts, enabling investors to manage risks more effectively. Moreover, the growing awareness of environmental issues, amplified by health and geopolitical crises, has reinforced the appeal of green bonds. Investors are increasingly seeking not only to protect their capital but also to align their investments with sustainable values.

Using the DECO-GARCH model, this study provides an in-depth analysis of the interrelationships between green bonds and other financial assets, such as equities, conventional bonds and oil indices. This provides a better understanding of how market fluctuations can influence the green bond sector in the context of environmental stress. The paper sheds light on how increasing environmental stress affects the relationships between different types of assets. This contribution is essential for investors seeking to assess the risks associated with investments in environmentally related assets. By identifying the links between green bonds and other asset classes, the paper contributes to more informed diversification strategies, allowing investors to better manage climate change risks. Similarly, by demonstrating the resilience of green bonds in an environment of increasing stress, the study strengthens the case for green bonds as an effective way to channel investments into sustainable projects, thereby supporting sustainable finance initiatives.

Moving forward, it will be essential to continue monitoring the evolution of asset correlations in the context of ongoing global crises. Future research could explore the impact of new crises or political changes on the connectivity between green bonds and traditional assets. The application of the DECO-GARCH model could be extended to other asset classes, allowing for a more comprehensive analysis of interrelationships in financial markets.

In conclusion, the dynamic links between green bonds and conventional assets, considering the effects of COVID-19 and the war in Ukraine, underscore the importance of environmental and strategic considerations in a rapidly changing economic landscape.

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