Scientific Annals of Economics and Business
72 (3), 2025, 353-374
DOI: 10.47743/saeb-2025-0025

Do the Green Bonds Markets React to Political Uncertainty and Financial Stress Alike?

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Abstract: This study investigates the dynamic relationship between political uncertainty (EPU), financial stress, and green bond returns, utilizing the Range-DCC GARCH model and wavelet coherence analysis. The primary objective is to assess how these factors interact during periods of economic and geopolitical turmoil, specifically the 2014-2016 oil crisis and the COVID-19 pandemic. Our findings reveal a positive correlation between political uncertainty and green bond returns during these crisis periods, suggesting that green bonds act as a safe haven or diversification tool when facing heightened uncertainty. The Range-DCC GARCH model confirms that EPU significantly impacts green bond returns in times of crisis, while the wavelet coherence analysis uncovers a time-frequency co-movement between financial stress, political uncertainty, and green bond performance, particularly during major disruptions. These results contribute to the understanding of green bonds' role as a resilient investment asset during times of volatility. From a practical perspective, these findings offer valuable insights for investors and policymakers seeking to enhance risk management and sustainable investment strategies amid growing uncertainties. Future research could build on these insights by incorporating additional dimensions of uncertainty such as climate risk and environmental policy uncertainty to better understand their differentiated impacts on green bond market behavior and resilience.

Keywords: green bonds; policy uncertainty; Wavelet Coherence; range-DCC-GARCH; financial stress.

JEL classification: G0; G1.

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Article history: Received 19 October 2024 | Accepted 3 July 2025 | Published online 30 July 2025

To cite this article: Trichilli, Y., Boujelbène, M., Abbes, M. B. (2025). Do the Green Bonds Markets React to Political Uncertainty and Financial Stress Alike?. *Scientific Annals of Economics and Business*, 72(3), 353-374. https://doi.org/10.47743/saeb-2025-0025.

1. INTRODUCTION

Political instability or risk is a complex concept that presents difficulties in its definition, capture, and quantification across various dimensions (Burger *et al.*, 2016). Within economic literature, it is associated with political turmoil, abrupt shifts in political authority, and alterations in executive power through both violent and constitutional means (constitutional) (Barro, 1991; Fosu, 1992; Alesina *et al.*, 1996).

In accordance with Lipset (1959), political instability can be understood as the antithesis of political stability. A transition in government is characterized by Miljkovic and Rimal (2008) as an indication of political instability, implying a disruption in governance structures regardless of their nature. Butkiewicz and Yanikkaya (2006) categorize the main metrics for assessing the political ramifications of instability into 3 groups: political violence, government stability and social unrest/stability.

Political risk pertains to the uncertainty stemming from governmental actions and political dynamics within and across nations. This form of risk underscores the unpredictability surrounding potential shifts in government policies and their repercussions on the future economic landscape. Extensive research has established a strong correlation between political risk and the valuation of a country's sovereign bonds, with several studies proposing a direct influence of political risk on sovereign debt returns (Bekaert *et al.*, 2016).

In recent times, financial strategies like green finance, environmental finance, and sustainable finance, which prioritize environmental conservation and sustainable progress, have garnered increased attention and significance (Zhang *et al.*, 2021; Wei *et al.*, 2022; Yu *et al.*, 2022; Wang *et al.*, 2024).

Securing funding for environmentally conscious projects presents challenges despite the crucial role financing plays in advancing sustainable development. Green bonds serve as a financial tool enabling the financing of such initiatives, offering capital for enduring projects. We contend that fostering a conducive regulatory framework and enhancing transparency in disclosures are pivotal elements for the expansion of green bonds.

Inspired by the complex interconnections between political uncertainty, financial stress, and stock market returns, our study shifts the focus to green bond markets, an area that remains largely unexplored. While existing research has extensively analyzed the effects of political uncertainty and financial stress on traditional financial markets, little is known about their influence on green bonds. Understanding these interactions is crucial, as green bonds play an increasing role in sustainable finance and global investment strategies.

To address this gap, we adopt a dual-method approach, combining Wavelet analysis and Range-DCC-GARCH modeling. The Wavelet approach allows us to examine how these interactions evolve over time and across different frequencies, capturing both short-term fluctuations and long-term dependencies. At the same time, the Range-DCC-GARCH model, which integrates high, low, and closing prices rather than relying solely on closing prices, provides a more refined measure of volatility dynamics and time-varying correlations. This allows for a deeper understanding of how political uncertainty and financial stress impact green bond markets, beyond what traditional models can reveal.

By integrating these advanced analytical techniques, our study provides new empirical insights into the evolving relationship between political uncertainty, financial stress, and green bonds. To the best of our knowledge, this is the first study to apply Wavelet and Range-DCC-GARCH methodologies in this context, addressing a critical gap in the literature. Our findings offer valuable implications for policymakers, investors, and market participants navigating the green finance landscape.

This study makes several significant contributions to the literature on the interplay between political uncertainty, financial stress, and green bonds.

First, we employ wavelet coherence analysis to examine the dynamic relationships between political uncertainty, financial stress, and green bonds within the time-frequency domain. This approach uncovers significant correlations that vary across different time periods and frequencies, offering a nuanced understanding of how these factors interact over time. Unlike traditional econometric methods, which typically assume static relationships, this technique reveals the temporal complexity of these interactions. This insight is particularly valuable for policymakers, as it enables them to assess the resilience of green finance in response to macroeconomic shocks and identify the timescales during which these interactions are most pronounced, thereby aiding the development of more robust climate finance policies.

Second, we introduce the Range-DCC GARCH model to analyze the time-varying correlations and mean-reverting behavior of these financial variables. By integrating Engle's DCC model with Molnár's Range-GARCH framework (2016), our methodology enhances volatility estimation with a superior daily price range-based estimator. This advanced approach significantly contributes to understanding the stability and predictability of the relationship between political uncertainty, financial stress, and green bonds. These insights are crucial for financial regulators tasked with assessing and mitigating systemic risks, and they underscore the role of green bonds as potential stabilizing assets during volatile market conditions. Furthermore, this methodology provides actionable tools for stakeholders looking to assess risk and stability in green bond markets.

Third, this study addresses a critical gap by analyzing the co-movement and volatility spillovers between political uncertainty, financial stress, and green bonds from a time-series perspective. In contrast to prior studies focused on traditional financial assets such as government bonds and cryptocurrencies, the exploration of green bonds as a distinct asset class adds a fresh dimension to the field. This perspective is particularly relevant for investors, as it offers new insights into potential hedging and diversification strategies during periods of heightened political and financial instability. By understanding the volatility spillovers between these factors, investors can better manage portfolio risks and enhance the resilience of their green bond investments.

Moreover, our findings hold important implications for policymakers involved in developing frameworks to support the stability and growth of green finance markets. We will expand the discussion in the revised version to highlight how these insights could be used to design policies that support the integration of green bonds into broader financial markets. For example, policymakers could leverage our findings to develop strategies that enhance the liquidity and stability of green finance markets during times of political uncertainty and financial stress.

By integrating both theoretical and practical aspects, this study not only fills a significant gap in the literature but also provides actionable insights that can help policymakers, investors, and financial regulators navigate the complexities of green finance during times of crisis.

In our study, Section 2 provides an extensive review of the literature. Section 3 delves into the methodology utilized, covering aspects such as data collection and its attributes. The analysis of the results is outlined in Section 4 and the robustness checks in Section 5. Lastly, Section 6 concludes the article by summarizing the findings obtained.

2. LITERATURE REVIEW

Political risk plays a crucial role in shaping country risk, with a significant impact on stock market behavior. The association between political instability and stock markets has been extensively studied, particularly following the recent financial crisis. A range of research explores the intricate relationship between financial markets and green bonds, providing insights into how these financial instruments interact with various forms of uncertainty. For instance, Mohammed *et al.* (2024) examine the effect of green bonds on climate risk indices, focusing on Economic Policy Uncertainty (EPU) and climate summit indices. Their findings indicate that green bonds have significant potential to mitigate climate risk, even amid economic and environmental policy uncertainty.

Building on this, Wang *et al.* (2024) explore the relationships between green bonds (GB), green stocks (GS), EPU, and Climate Policy Uncertainty (CPU) in China. Their results show that the negative predictive effects of EPU and CPU on the green finance market are primarily concentrated at extreme quantiles. They also find an interaction between CPU and EPU, suggesting that these two factors influence the green financial market in complex ways. Furthermore, a negative correlation between the GB and GS markets is observed in the short term, indicating that investors may be able to hedge risk and diversify their portfolios by investing in both green bonds and green stocks.

In a similar vein, Wei *et al.* (2022) investigate the wavelet-based quantile dependence between EPU and green bond markets over the period 2014–2021. Their findings reveal that the Granger causality from EPU to the green bond market is non-linear and varies across different time scales, which adds depth to our understanding of how economic uncertainty affects the green finance sector. Chau *et al.* (2014) also examined political uncertainty stemming from the "Arab Spring" and its impact on stock market volatility in MENA financial markets. They found a significant rise in the volatility of Islamic indices during periods of political turmoil, while conventional index volatility was largely unaffected by uprisings or exhibited minimal impact.

More recently, Moalla (2021) studied the effect of electoral uncertainty on the Canadian stock market, covering 13 federal elections from 1975 to 2019. His research concluded that electoral uncertainty affects market volatility differently depending on the composition of the market portfolio. For instance, it decreased the conditional variance of the equal-weighted portfolio (small caps) but had no effect on its average return. In contrast, electoral uncertainty reduced the return on the weighted portfolio (large caps) without significantly affecting its volatility. This highlights the complex ways in which political events can influence financial markets.

Batrancea (2021a) investigated the impact of financial performance on the assets and liabilities of 45 major banks across Europe, Israel, the United States, and Canada from 2006 to 2020. Using a panel generalized method of moments approach, the study revealed that asset and liability ratios significantly influence financial performance indicators. This underscores the broader impact of financial performance on market behavior, particularly during times of economic and political uncertainty. Similarly, Batrancea (2021b) examined how financial performance influences long-term financial equilibrium, analyzing data from 34 major companies listed on the New York Stock Exchange. His findings demonstrated that the short-term and long-term financial equilibria of these public companies, measured by indicators such as the current ratio, quick ratio, and debt-to-equity ratio, were significantly affected by various financial performance indicators, particularly during crises like the 2008 financial collapse and the COVID-19 pandemic.

In the broader context of market diversification and risk hedging, Haq *et al.* (2021) explored the dynamic relationship between economic policy uncertainty, green bonds, clean energy stocks, and rare earth elements. They found that green bonds act more as a hedge than a safe haven during periods of economic uncertainty. Moreover, during crises such as COVID-19, green bonds served as diversifiers alongside clean energy stocks and rare earth elements, demonstrating their value in risk management. This aligns with the broader findings in the literature that show green bonds can offer diversification benefits, especially in uncertain times.

Moreover, limited research has examined the correlation between green bonds and various sources of uncertainty, as well as how these uncertainties impact green bond returns. For instance, Pham and Nguyen (2022) analyzed the impact of stock and oil volatilities, as well as EPU, on green bond returns. Their study revealed a dynamic and regime-dependent relationship, with varying impacts depending on market conditions. Similarly, Li *et al.* (2024) explored the asymmetric effects of U.S. EPU, geopolitical risks, and crude oil prices on green bond returns, demonstrating differing effects over the short and long term. These studies emphasize the multifaceted nature of green bond performance in response to global uncertainties.

Finally, Doğan *et al.* (2023) highlighted the role of green bonds as a safe haven asset during uncertain periods. Their research underscores the importance of green bonds in portfolio diversification and risk management, especially during times of economic distress. Si Mohammed *et al.* (2024) also supported the potential of green bonds in mitigating climate risk despite uncertainties in both economic and environmental policies. These findings advocate for an incentivizing framework to enhance the growth of green bonds and to support advancements toward Sustainable Development Goal 13, which focuses on climate action.

Batrancea *et al.* (2023) further contribute to the understanding of economic growth by exploring the relationship between well-being-related infrastructure and economic growth across 212 NUTS 2 regional subdivisions in the EU-28 from 2001 to 2020. Their study, which analyzed data from 151 regions in Western Europe and 61 regions in Central and Eastern Europe, utilized a panel data approach with the first difference generalized method of moments estimator. The results demonstrated how regional responses in Western Europe were influenced by factors such as disposable household income, inter-regional mobility, housing indicators, labor force participation, while in Central and Eastern Europe, factors like housing indicators, internet broadband access, and air pollution were more significant. This regional divergence highlights the varying factors that influence economic growth and stability, providing further insight into the complex dynamics of financial markets during uncertain periods.

The underlying hypotheses guiding this research are formulated as follows:

H1*: Political uncertainty influences green bonds.*

H2*: Financial stress influences green bonds.*

3. DATA AND METHODOLOGY

3.1 Data

We have utilized monthly closing prices for the following green bonds: S&P GREEN BOND INDEX, S&P GREEN BND SELECT IN, and S&P MUNI GREEN BOND. Their monthly returns are calculated by using the following equation:

$$R_t = In(\frac{P_t}{P_{t-1}}) \qquad (1)$$

where P_t denotes the closing index price for month t and P_{t-1} represents the closing index price for the preceding month.

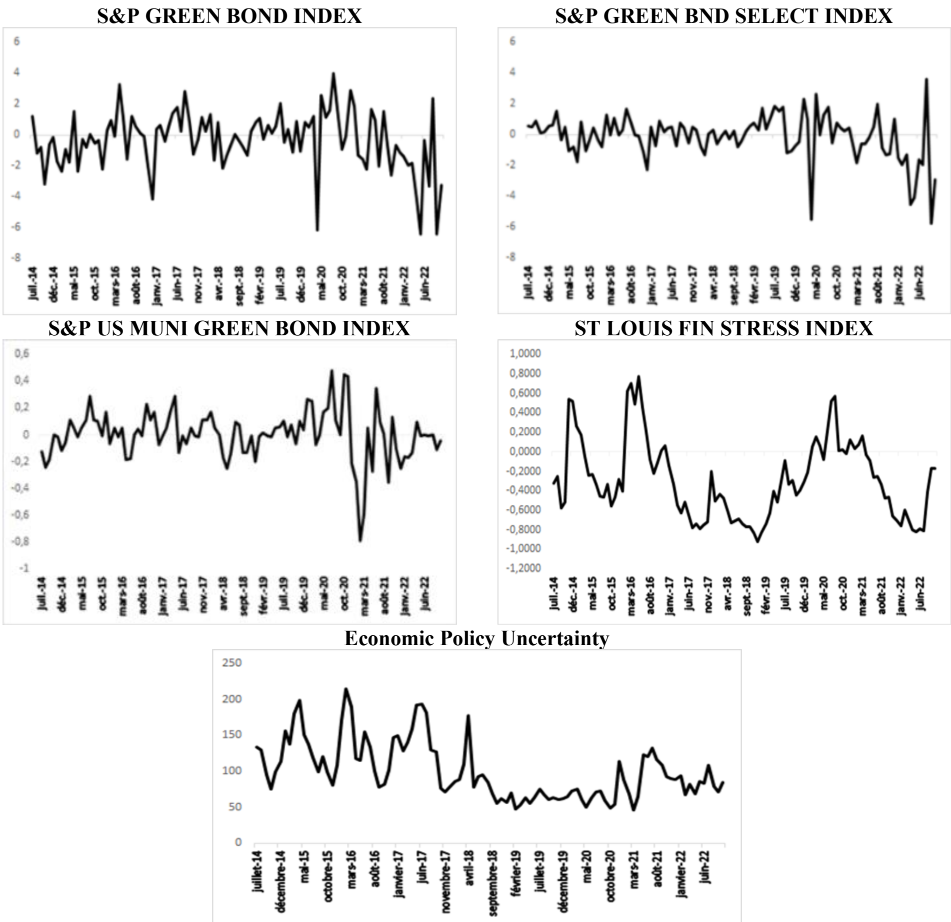

Figure no. 1 – The dynamics of green bond returns in relation to Political uncertainty and financial stress

For the Range-based DCC models, we specifically utilize the highest, lowest, opening, and closing prices of each month.We also incorporated policy uncertainty variables: ST LOUIS FIN STRESS INDEX (FSI) and Economic Policy Uncertainty (EPU). These data were obtained from the DataStream database for the period 2014-2022.

The examination of green bond returns, political uncertainty, and financial stress, as depicted in Figure no. 1, unveils intriguing patterns. In 2020, amid the pandemic crisis, green bonds experienced a notable decline, reflecting the market's response to the economic challenges posed by the global health emergency. Conversely, Economic Policy Uncertainty and the ST LOUIS FIN STRESS INDEX saw a surge during the oil crisis, indicating heightened geopolitical tensions, followed by a sharp decrease in response to the COVID-19 health crisis as governments focused on managing the pandemic. Fast forward to 2022, a discernible downward trend is observed in the curves, attributed to the ongoing conflict between Ukraine and Russia, underscoring how geopolitical events can impact financial markets and investment instruments such as green bonds.

3.2 Methodology

The methodology of our study is designed to provide comprehensive insights. Firstly, we utilize the Range-DCC GARCH to assess the effect of political uncertainty, financial stress on the dynamic of green bond market. This model introduces a novel approach, departing from conventional GARCH models by utilizing the intraday price range between peak and trough to capture volatility dynamics. Additionally, we employ the wavelet coherence model to investigate co-movements over time and frequency, enriching our comprehension of the connection between green bond yields and political uncertainty.

3.2.1 The Range-DCC GARCH

Integrating Molnár's (2016) Range-GARCH model into the DCC-GARCH model marks a notable progress. The RGARCH(p,q) model, with its precise formulation tailored to depict the range dynamics of the data, stands out as a sophisticated tool. By harnessing Molnár's novel methodology, this model excels in managing the complex interconnections and patterns inherent in financial or time series data.

By incorporating range dynamics, this specification provides a more sophisticated understanding of volatility, greatly enhancing the modeling capabilities. The comprehensive structure of the RGARCH(p,q) formulation allows for a detailed exploration of volatility patterns, resulting in more accurate forecasts and risk assessments. This integration of methodologies not only broadens the model's capabilities but also boosts its predictive precision, establishing a robust framework for analyzing complex financial data.

Thus, the RGARCH(p,q) model is formulated as the following specification:

$$\varepsilon_t \mid |\psi_{t-1} \sim Normal\ (0, h_t) \tag{2}$$

where $h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \sigma_{p_{t-i}}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}$

$\sigma^2_{p_t}$ represents the Parkinson (1980) estimator calculated using the low high opening and closing prices expressed as $\sigma^2_{p_{t-i}} = \frac{[\ln {(H_t)}/_{L_t}]^2}{4ln2}$

In order to preserve the positivity of h_t in the RGARCH model, similar to the GARCH model, certain parameter requirements must be met. Guaranteeing the stability and dependability of the RGARCH process entails satisfying specific criteria. One critical condition is that the sum of the squares of the parameters in the model must be less than one. This condition can be represented as:

$$\sum_{i=1}^{q} \alpha_i = \sum_{j=1}^{p} \beta_j < 1 \tag{3}$$

When the total sum of the squares of the parameters (α_i and β_j) is below one, it ensures the covariance stationarity of the RGARCH process. This criterion is essential for upholding stability within the model, enabling a thorough and dependable analysis of volatility dynamics in financial or time series data.

Adhering to this requirement not only ensures the covariance stationarity of the RGARCH process but also establishes a critical groundwork for precise volatility modeling and forecasting in diverse analytical scenarios. By meeting this inequality, the RGARCH model can adeptly capture and describe the underlying dynamics of data volatility, creating a more resilient and precise framework for risk evaluation and predictions.

Specifically, this enables us to concentrate on developing the new DCC-Range-GARCH model (DCC-RGARCH). The formulation of the $DCC(P\,,Q) - RGARCH(p,q)$model is as follows:

$$\begin{gathered} \varepsilon_t \mid |\psi_{t-1} \sim \; Normal\;(0, cov_t\,), \\ cov_t \;=\; D_t\; cor_t D_t\;, \\ cor_t \;=\; Q_t^{*-1}\; Q_t Q_t^{*-1}\;, \end{gathered} \tag{4}$$

$$Q_t \;=\; \left(1 - \sum_{i=1}^{Q} \varepsilon_i - \sum_{j=1}^{P} \theta_j\right) s + \sum_{j=1}^{P} \varepsilon_i (Z_{t-i}^{RGARCH} (Z_{t-i}^{RGARCH})') + \sum_{j=1}^{P} \theta_j\, Q_{t-j} \tag{5}$$

Here $D_t = diag\left((h_{1t}^{RGARCH})^{1/2}, (h_{2t}^{RGARCH})^{1/2}, \dots \dots \dots, (h_{Nt}^{RGARCH})\right)$ represents the diagonal matrix of conditional variances h_{kt}^{RGARCH} where $k = 1{,}2 \dots \dots, N$. Additionally, Z_t^{RGARCH} denotes the standardized $N \times 1$ residual vector containing the standardized residuals Z_{kt}^{RGARCH} computed from the RGARCH model $Z_{kt}^{RGARCH} = {}^{\varepsilon_{kt}}/_{(h_{kt}^{RGARCH})^{1/2}}$.

The parameter estimation process for the DCC-R-GARCH model employs an advanced two-stage approach, utilizing the quasi-maximum likelihood method. This method entails optimizing the log-likelihood function, which can be split into 2 essential components: the volatility component and the correlation component.

The total log-likelihood function, presented as $L^{DCC-RGARCH}$included the sum of these two distinct parts, namely $L_{Vol}^{DCC-RGARCH}$ and $L_{Corr}^{DCC-RGARCH}$.

$$L^{DCC-RGARCH}_{=L_{Vol}^{DCC-RGARCH}} + L_{Corr}^{DCC-RGARCH} \tag{6}$$

The initial element, $L_{Vol}^{DCC-RGARCH}$ concerns the volatility component and is articulated as follows:

$$L_{Vol}^{DCC-RGARCH} = -\frac{1}{2}\sum_{k=1}^{n}\left(n\, ln(2\pi) + \sum_{t=1}^{n}\left(ln(h_{kt}) + \frac{\varepsilon_{kt}^2}{h_{kt}}\right)\right) \tag{7}$$

This segment of the log-likelihood function captures the intricacies of volatility dynamics by incorporating the logarithm of the conditional variances (h_{kt}) and the standardized residuals (ε_{kt}). It holds a crucial position in modeling the volatility of asset returns across time, making a substantial contribution to comprehending and predicting fluctuations in financial markets.

Conversely, $L_{corr}^{DCC-RGARCH}$ signifies the correlation component, as depicted by the subsequent equation:

$$L_{corr}^{DCC-RGARCH} = -\frac{1}{2}\sum_{k=1}^{n}(n\, ln|cor_t| + (z_t^{RGARCH})' cor_t^{-1} z_t^{RGARCH} - (z_t^{RGARCH})' z_t^{RGARCH}) \tag{8}$$

This section delves into the fluctuations of the conditional correlation matrix (cor_t) and the corresponding vectors (z_t^{RGARCH}). It encompasses terms involving the logarithm of the determinant of the correlation matrix and the quadratic form of the standardized residuals in the inverted correlation matrix. This crucial part aims to capture the interdependencies and connections among assets or variables, offering valuable insights into the co-movements and relationships within the dataset.

By optimizing these intertwined components employing the quasi-maximum likelihood model, the DCC-R-GARCH model can estimate parameters effectively, enhancing the understanding of both volatility and correlation dynamics in financial or time series datasets. The intricate and refined nature of these elements elevates the model's precision and efficiency in capturing the intricate structures inherent in market fluctuations and asset interrelations.

3.2.2 Wavelet Coherence

The wavelet coherence method integrates both the temporal and frequency dimensions of a time series, with the goal of evaluating the correlation between pair of temporal datasets across various time and frequency intervals. We utilize the wavelet coherence technique in accordance with the definition provided by implementing smoothing techniques in the time and frequency domains. Cross-wavelet examination is employed to explore the relationship between two signals within a common power spectrum. The cross-wavelet analysis of two signals $x = x\,(tn)$ and $y = y\,(tn)$ is characterized by:

$$\mathrm{W}^{\mathrm{xy}}(\mathrm{t},\mathrm{s})=\mathrm{W}^{\mathrm{X}}(\mathrm{t},\mathrm{s})\mathrm{W}^{\mathrm{y}*}(\mathrm{t},\mathrm{s}) \tag{9}$$

with $\mathrm{W}^{\mathrm{y}*}(\mathrm{t},\mathrm{s})$ presents the conjugate complex of $\mathrm{W}^{\mathrm{y}}(\mathrm{t},\mathrm{s})$.

In Equation (7), the variables 's' and 't' refer to the scale and position indices, respectively. The continuous wavelet transform for any given pair of time series 'x' and 'y' can be expressed as $\mathrm{W}^{\mathrm{X}}(t,s)$ and $\mathrm{W}^{\mathrm{y}*}(t,s)$ where the symbol '*' denotes the complex conjugate operation applied to the series 'y'. Hence, the wavelet transform aims to examine the association between the two time series 'x' and 'y'.

Torrence and Compo (1998) proposed a wavelet coherence method for estimating cross-wavelet power, aiming to identify significant covariance between each two time points across the cross-wavelet power series per scale. While the objective of wavelet coherence aligns closely with that of cross-wavelet power, it might not exhibit high wavelet power. Hence, this paper adopts Torrence and Webster (1999) approach for calculating squared wavelet coherence between pairs, extending the original method by Torrence and Compo (1998). Consequently, the squared wavelet coherence in equation (10) can be expressed as outlined:

$$\mathrm{R}^2(\mathrm{t},\mathrm{s})=\frac{|\mathrm{S}[\mathrm{S}^{-1}\mathrm{W}^{\mathrm{Xy}}(\mathrm{t},\mathrm{s})]|^2}{\mathrm{S}[\mathrm{S}^{-1}|\mathrm{W}^{\mathrm{X}}(\mathrm{t},\mathrm{s})|^2\mathrm{S}\mathrm{S}^{-1}|\mathrm{W}^{\mathrm{y}}(\mathrm{t},\mathrm{s})|^2]} \tag{10}$$

In equation (10), the smoothing operator 's' functions across both temporal and spatial dimensions, with $\mathrm{R}^2(\mathrm{t},\mathrm{s})$ representing the localized squared correlation across time and frequency domains. Furthermore, the squared correlation coefficient varies from $0 \leq \mathrm{R}^2(\mathrm{t},\mathrm{s}) \leq 1$.

The value of $\mathrm{R}^2(\mathrm{t},\mathrm{s})$ establishes the correlation between two time series, and a high (low) value of $\mathrm{R}^2(\mathrm{t},\mathrm{s})$ indicates a high (low) co-movement.

4. EMPIRICAL RESULTS

4.1 Multicollinearity and descriptive statistics

We tested for multicollinearity using both the correlation matrix and the Variance Inflation Factors (VIF), as shown in Table no. 1.

The correlation matrix provides valuable insights into the relationships between the green bond indices (S&P Green Bond Index, S&P Green Bond Select Index, and S&P US Muni Green Bond Index) and key financial stress and uncertainty indicators (St. Louis Financial Stress Index - FSI and Economic Policy Uncertainty - EPU). The results reveal a strong positive correlation between the green bond indices, particularly between the S&P Green Bond Index and the S&P Green Bond Select Index (0.71), suggesting that these indices display similar market dynamics. Additionally, there is a significant positive correlation between the EPU and the green bond indices, with a high value of 0.93 for the S&P Green Bond Index. This highlights the sensitivity of green bonds to economic policy uncertainty and supports the idea that investors may view green bonds as a safe-haven asset during periods of heightened political and economic uncertainty. In contrast, the FSI shows a weaker, and in some cases, negative correlation with the green bond indices, such as the -0.19 correlation with the S&P Green Bond Select Index. This indicates that financial stress has a more ambiguous effect on green bond performance, possibly due to differing investor sentiment and market conditions.

Overall, these findings underscore the role of green bonds in portfolio diversification and their responsiveness to macroeconomic uncertainty.

Additionally, as shown in Table no. 1, no correlation value exceeds 0.8, and no VIF value is close to 10. Therefore, we can conclude that the model does not exhibit multicollinearity.

Table no. 1 – Correlation Matrix and Variance Inflation Factor

	(1)	(2)	(3)	(4)	(5)
(1)	1				
(2)	0.710603820449917	1			
(3)	0.1121243177912375	0.1526506001985651	1		
(4)	-0.1914011127883334	-0.19969741407459	-0.04746034473441598	1	
(5)	0.9935213829956638	0.9026059291832366	0.7473757627783605	0.1722443390906292	1
(6)	2.093447	2.076348	1.023458	1.393482	1.326233

Note: (1) S&P GREEN BOND INDEX; (2) S&P GREEN BND SELECT INDEX; (3) S&P US MUNI GREEN BOND INDEX; (4) ST LOUIS FIN STRESS INDEX; (5) Economic Policy Uncertainty; (6) Variance Inflation Factors (VIF)

Table no. 2 presents summary statistics of monthly returns based on bond indices, political uncertainty and financial stress. The S&P US MUNI GREEN BOND index outperforms other green bonds. As for the kurtosis coefficient, the values are higher than 3 for all green bond markets, suggesting leptokurtic distributions. Furthermore, the skewness coefficient is negative for all the variables studied, indicating leftward asymmetry in the distribution. Therefore, normality is rejected. This result is further supported by the J-B statistic, which rejects normality at the 1% threshold for all distributions.

We also report the ARCH test in the last line of Table no. 2, which demonstrates the presence of autocorrelation and heteroskedasticity issues in the data. They are thus suitable for further statistical analysis.

Table no. 2 – descriptive statistics of green bonds return, Political uncertainty and financial stress

	S&P GREEN BOND INDEX	***S&P GREEN BND SELECT INDEX***	***S&P US MUNI GREEN BOND INDEX***	***ST LOUIS FIN STRESS INDEX***	***Economic Policy Uncertainty***
Mean	-0.355039	-0.136815	0.001297	-0.287532	100.5773
Std. Dev.	1.890016	1.483209	0.184921	0.404669	40.03594
Skewness	-0.824153	-1.214893	-0.722996	0.665643	0.908988
Kurtosis	4.556033	6.358660	6.439488	2.771542	3.058350
Jarque-Bera	21.40896	71.60191	58.00403	7.602146	13.78517
Probability	0.000022	0.000000	0.000000	0.022347	0.001015
ARCH	0.667573***	0.692523***	0.540746***	0.7068***	0.8974***

4.2 Range DCC- GARCH model: Dynamic correlation between Political uncertainty, financial stress and green bonds

In this section, we explore the dynamic correlation between green bond returns, political uncertainty, and financial stress using the Range DCC-GARCH model proposed by Engle (2002). Figure no. 1 illustrates these relationships, focusing on key economic indicators such as the St. Louis Financial Stress Index (FSI) and Economic Policy Uncertainty (EPU), in relation to the S&P Green Bond Index, S&P Green Bond Select Index, and S&P Muni Green Bond Index.

Our results reveal a strong correlation between EPU and green bonds in 2015, with the exception of the S&P Green Bond Select Index. This can be attributed to the oil crisis, which positively influenced the co-movement between EPU and green bonds. Despite economic challenges during this period, interest in green bonds remained strong, underscoring the growing emphasis on sustainable investments even amidst financial turbulence. These findings contrast with those of Pham and Nguyen (2022), who suggest that during periods of low uncertainty, green bonds and EPU exhibit only a weak connection, implying that green bonds can serve as a hedge against uncertainty in such contexts. Similarly, Si Mohammed *et al.* (2024) highlight that, green bonds hold significant potential in mitigating climate risk, even in the face of uncertain economic and environmental policies.

However, the weak correlation during periods of low political uncertainty, as observed in our study, indicates that the relationship between political uncertainty and green bonds is not always consistent. These finding challenges hypothesis H1, suggesting that while political uncertainty can influence green bond returns in some contexts, it does not always lead to a clear or strong connection, especially when uncertainty levels are moderate or low.

During oil crises, we observe a negative correlation between the FSI and green bonds, suggesting that declining oil prices exert a non-economic financial impact on green bonds. This implies that investors tend to shift away from green bonds in favor of more traditional financial assets when uncertainty in the oil market rises.

In the context of financial stress, while our hypothesis H2 predicts a consistent influence of financial stress on green bonds, we find that financial stress does not always correlate positively with green bond returns. The negative correlation observed during the oil crisis and some periods of the COVID-19 pandemic suggests that financial stress can sometimes lead investors to move away from green bonds, questioning the stability of the relationship proposed in hypothesis H2.

In the context of health crises, particularly during the COVID-19 pandemic, the data indicates a positive relationship between EPU and green bonds. However, an exception is noted for the S&P Green Bond Index, which exhibits a negative correlation. This divergence highlights the complexity of interactions between economic and environmental factors during times of disruption. Conversely, the negative correlation between FSI and green bonds suggests that the pandemic significantly influenced investor behavior, reinforcing the perception of green bonds as a relatively stable investment during financial turmoil. The dynamic contagion effect observed in this study appears to be strongly shaped by pivotal events such as the oil crises of 2014–2016 and the COVID-19 outbreak. These findings contrast with those of Mohammed *et al.* (2024), who argue that financial stress positively impacts the middle quantiles of both conventional and green equities, while financial uncertainty negatively affects the upper quantiles. Additionally, Tsagkanos *et al.* (2022) challenge conventional financial stress theory by establishing a causal relationship from green bonds to financial stress, rather than the reverse.

Moreover, the positive correlation between EPU and green bonds supports the idea that green bonds play a diversification role in bond returns during global financial crises and the COVID-19 pandemic. This aligns with the findings of Pham and Nguyen (2022), which emphasize green bonds' potential as diversifying assets across different time horizons. In contrast, the negative correlation between FSI and green bonds reinforces their role as a safe-haven asset, except for the S&P Green Bond Select Index. This result is consistent with Naeem *et al.* (2023), who argue that green bonds exhibit strong safe-haven characteristics, offering investors valuable diversification opportunities in uncertain economic environments.

Nevertheless, the periods of negative or weak correlation during certain crises challenge the uniformity of green bonds as a safe-haven asset, particularly in the case of financial stress and political uncertainty.

Furthermore, Dong *et al.* (2023) demonstrate that both conventional and green bonds serve as safe havens during periods of heightened geopolitical risk (GPR), with green bonds outperforming their conventional counterparts under increased EPU and CPU levels. Syed *et al.* (2022) also show that positive EPU shocks negatively impact green bonds, whereas negative shocks enhance green bond performance, as evidenced by their NARDL estimation. Additionally, Saud *et al.* (2023) highlight that political and regulatory uncertainties extend their influence to commodity markets, affecting oil and gasoline prices and potentially shaping the evolution of the cryptocurrency market. The persistent correlation between green bond returns and political uncertainty variables over the observed period further underscores these dynamics.

4.3 Relationship between Political Uncertainty, financial stress and Green Bonds: Wavelet Coherence

Wavelet coherence serves as a potent tool for visualizing the simultaneous movement in space-time frequency between policy uncertainty variables and green bond returns. Figure no. 2 illustrates the estimated wavelet coherence between political uncertainty, financial stress and green bond returns, with the horizontal axis representing time and the vertical axis denoting the period. The color code, displayed to the right of each figure, suggests performance levels, with blue representing low performance and red indicating high performance. Inter-wavelet coherence allows for the examination of distinct characteristics in the co-movement between uncertainty variables and green bond performance within the time-frequency domain. Additionally, dotted arrows depict the phase difference of the wavelets, offering insights into the lead-lag structure in the time-frequency domain.

The wavelet co-movement between political uncertainty, financial stress and green bond returns highlights a notable correlation during the periods 2014-2016, coinciding to the oil crisis, and the period of the COVID-19 health crisis. Moreover, black contours on the left and right sides of several scales reveal a positive co-movement at the 5% significance level in both the long run and the short run. This suggests that during crisis periods, political uncertainty and financial stress have a positive co-movement with green bonds, reinforcing hypothesis H1 and H2 during times of high uncertainty. However, the wavelet coherence analysis also indicates that the strength of these correlations weakens during low-uncertainty periods. This contrasts with hypothesis H1, which suggests that political uncertainty continuously impacts green bonds, and hypothesis H2, which assumes a consistent link between financial stress and green bonds. However, the wavelet coherence analysis also indicates that the strength of these correlations weakens during low-uncertainty periods. This contrasts with hypothesis H1, which suggests that political uncertainty continuously impacts green bonds, and hypothesis H2, which assumes a consistent link between financial stress and green bonds.

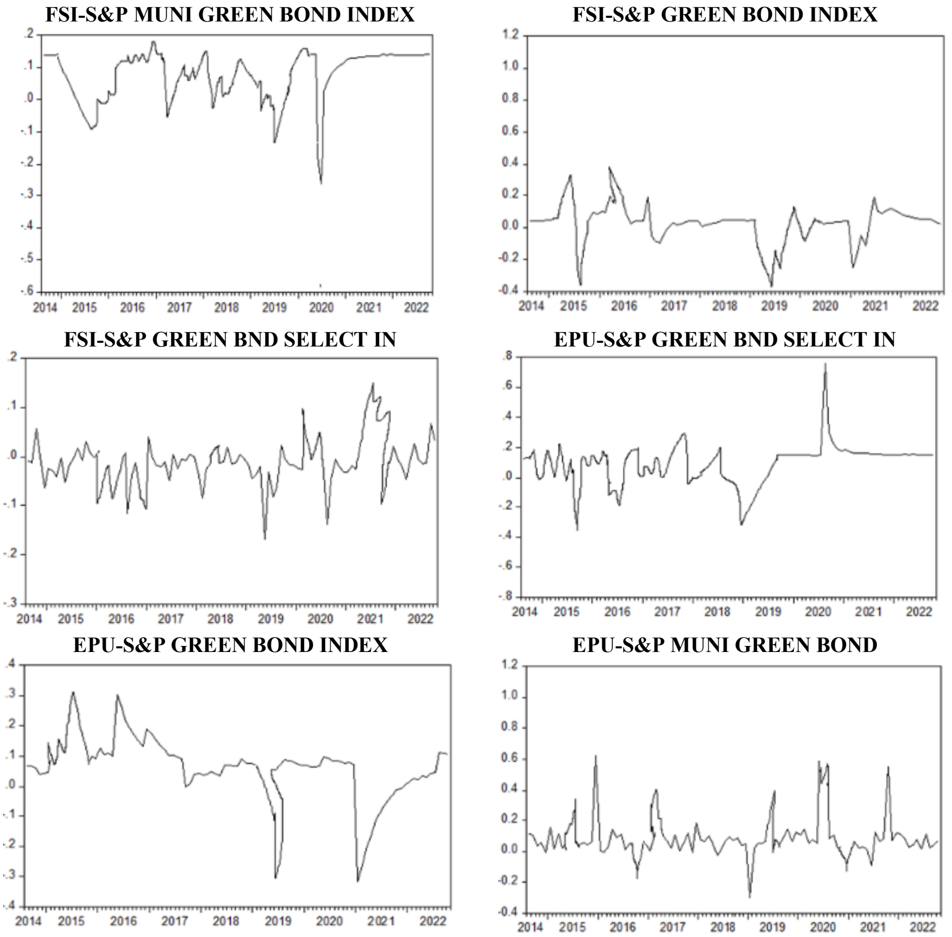

Figure no. 2 – The dynamic correlation between green bond's return, Political uncertainty and financial stress: Range DCC- GARCH model

This indicates that political uncertainty and financial stress have a positive co-movement on green bonds during crisis periods. The significant correlation underscores the influence of the oil crisis on green bonds, suggesting a shock transmission between financial stress, economy policy uncertainty and green bonds. These findings are consistent with the study by (2015), which revealed a positive correlation between government bond yields and international political risk. However, they contrast with the research of Arif *et al.* (2022), who proposed that the green bond index offers substantial hedging and safe-haven opportunities for long-term investors in traditional financial instruments.

Moreover, the wavelet analysis results support the Range-DCC GARCH outcomes, highlighting a notable positive correlation between Economic Policy Uncertainty and green bond returns during crises. This result contradicts the findings of Haq *et al.* (2021), who suggested that green bonds act more as a hedge than a safe haven in the face of EPU.

Conversely, the Range-DCC GARCH model's results indicate a negative correlation between the financial stress index and green bonds. These findings further contribute to the mixed evidence on the role of green bonds in periods of financial stress, especially when examining them across different time periods.

Additionally, in low-uncertainty periods like the COVID-19 pandemic, the connection between green bonds, financial stress, and political uncertainty weakens. This suggests that green bonds could potentially serve as a hedge contrary to uncertainty during such times (Pham and Nguyen, 2022) As emphasized by Guo and Zhou (2021), green bonds are purposefully crafted to emphasize long-term sustainable investments, positioning them as a crucial hedging tool against climate risks, financial uncertainties, and unforeseen events like the COVID-19 epidemic.

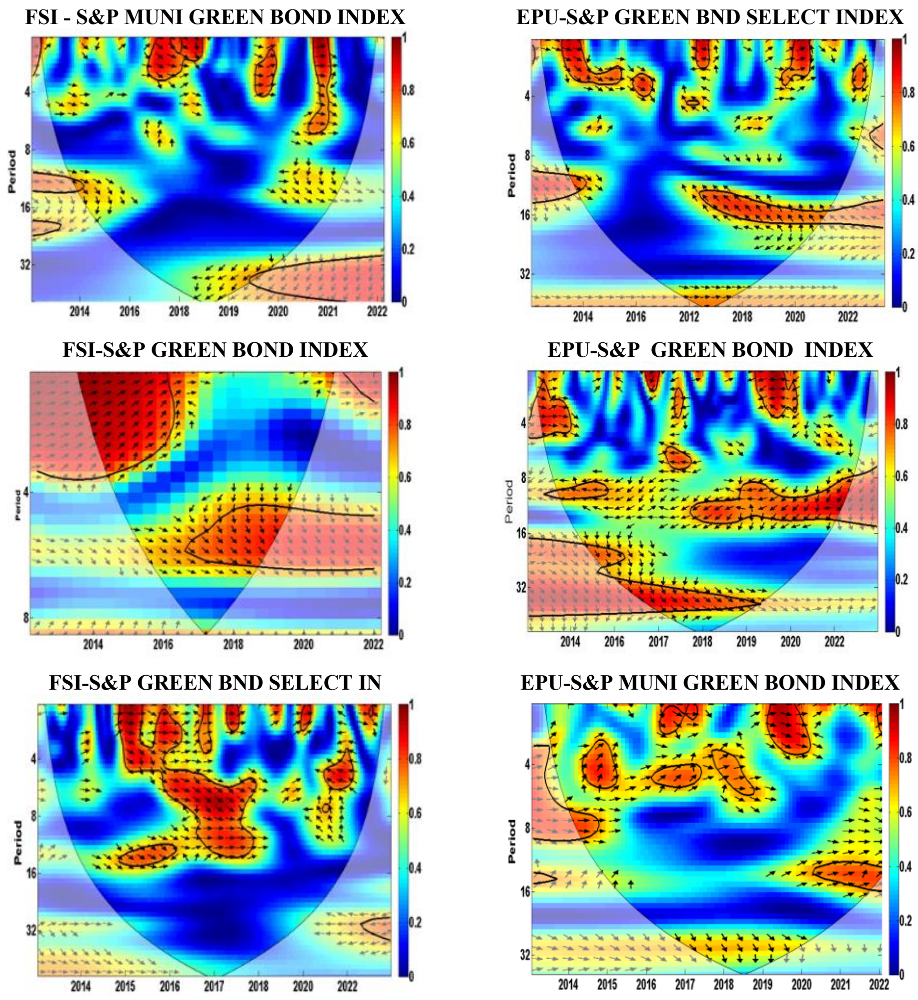

Figure no. 3 – Wavelet coherence between political uncertainty, financial stress and green bond returns

5. ROBUSTNESS CHECK

5.1 Unit Root test

Table no. 3 presents the results of the Augmented Dickey-Fuller (ADF) unit root test for various green bond indices, financial stress indices, and economic policy uncertainty. The ADF test examines whether the time series are stationary by testing the null hypothesis of the presence of a unit root against the alternative hypothesis of stationarity. The reported test statistics are compared to the critical values at the 1%, 5%, and 10% significance levels. Since the test statistics for all variables are lower than the critical values at conventional significance levels and the corresponding p-values are close to zero, the null hypothesis of a unit root is strongly rejected. These results indicate that all series are stationary, implying that they do not require further differencing to achieve stationarity.

Table no. 3 – ADF Unit root test

Variables	Augmented Dickey-Fuller	Critical values 1% level	5% level	10% level	Prob
S&P GREEN BOND INDEX	-8.183837	-3.501445	-2.892536	-2.583371	0.0000
S&P GREEN BND SELECT INDEX	-8.821770	-3.500669	-2.892200	-2.583192	0.0000
S&P US MUNI GREEN BOND INDEX	-13.16217	-3.498439	-2.891234	-2.582678	0.0001
ST LOUIS FIN STRESS INDEX	-9.621204	-3.498439	-2.891234	-2.582678	0.0000
Economic Policy Uncertainty	-7.838345	-3.499910	-2.891871	-2.583017	0.0001

5.2 Cointegration Analysis of Green Bonds, Financial Stress, and Economic Policy Uncertainty

In this section, we examine the long-term cointegration between green bond indices, financial stress, and economic policy uncertainty (EPU). The optimal lag length for the vector autoregression (VAR) model is set to one ($p = 1$), as determined by the Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC), both of which reach their minimum values at $p = 1$.

Table no. 3 presents the results of the Johansen cointegration test, which assesses the presence of long-term relationships between green bond indices, financial stress, and economic policy uncertainty (EPU). The trace and max statistics indicate that, in most cases, at least one cointegrating relationship exists, as the test statistics exceed the corresponding critical values. This suggests that these variables are not entirely independent in the long run, meaning that financial stress and economic policy uncertainty influence the movement of green bond indices over time.

The presence of cointegration between financial stress and green bonds implies that fluctuations in financial stability have persistent effects on the valuation of green bonds. This can be explained by shifts in investor sentiment and liquidity constraints during periods of financial distress, which may reduce demand for green assets. The long-term relationship also suggests that green bonds are not completely insulated from broader financial market stress, challenging their potential role as a safe-haven asset. This dynamic is supported by the Range DCC-GARCH model's findings, which show how financial stress influences the returns of green bonds over time.

Similarly, the cointegration between economic policy uncertainty (EPU) and green bond indices highlights the sensitivity of the green bond market to regulatory and macroeconomic uncertainties. Given that green investments are often influenced by policy incentives and climate regulations, uncertainty in these areas can create sustained volatility in green bond prices. The existence of a long-term relationship suggests that investors adjust their expectations based on evolving policy frameworks, reinforcing the importance of regulatory stability for green finance. The Range DCC-GARCH model further confirms this by showing the changing correlation between EPU and green bond returns throughout different periods of uncertainty. These results are also validated by Wei *et al.* (2022), who propose a quantile-based framework to analyze the dependence between EPU and green bond markets under various market conditions. Their findings reveal that the Granger causality from EPU to the green bond market is nonlinear and varies across time scales. These insights provide policymakers with valuable guidance in designing strategies to mitigate systemic volatility caused by external shocks in the green bond market.

From a portfolio optimization and hedging perspective, these findings emphasize the need to account for financial stress and policy uncertainty when constructing green investment strategies. Given that green bonds exhibit a long-term dependence on these factors, diversification into assets less sensitive to financial turbulence and regulatory shifts may be necessary to enhance portfolio resilience. These results are further validated by Syed *et al.* (2022), who provide insights into the hedging and diversification properties of Bitcoin and the influence of U.S. economic policy uncertainty on green bonds. Additionally, Broadstock and Broadstock and Cheng (2019) present evidence that the relationship between green and black bonds is highly sensitive to fluctuations in financial market volatility, economic policy uncertainty, daily economic activity, oil prices, and uniquely constructed sentiment indicators reflecting positive and negative news on green bonds.

Table no. 4 – Cointegration test

		Eigenvalue	**Trace Statistic**	**Critical Value**	**Max-Statistic**	**Critical Value**
S&P GREEN BOND INDEX-ST LOUIS FIN STRESS INDEX	None *	0.156045	23.85807	15.49471	16.45663	14.26460
	At most 1 *	0.073465	7.401447	3.841465	7.401447	3.841465
S&P GREEN BOND INDEX-Economic Policy Uncertainty	None *	0.169151	26.49542	15.49471	17.97486	14.26460
	At most 1 *	0.084093	8.520562	3.841465	8.520562	3.841465
S&P GREEN BND SELECT INDEX -ST LOUIS FIN STRESS INDEX	None *	0.154793	23.70789	15.49471	16.31289	14.26460
	At most 1 *	0.073403	7.394994	3.841465	7.394994	3.841465
S&P GREEN BND SELECT INDEX -Economic Policy Uncertainty	None *	0.136791	23.31707	15.49471	14.26855	14.26460
	At most 1 *	0.089065	9.048519	3.841465	9.048519	3.841465
S&P US MUNI GREEN BOND INDEX - ST LOUIS FIN STRESS INDEX	None *	0.242810	34.13022	15.49471	26.97966	14.26460
	At most 1 *	0.071066	7.150555	3.841465	7.150555	3.841465
S&P US MUNI GREEN BOND INDEX - Economic Policy Uncertainty	None *	0.215888	32.37600	15.49471	23.59075	14.26460
	At most 1 *	0.086589	8.785249	3.841465	8.785249	3.841465

5.3. VECM Analysis of Green Bonds, Financial Stress, and Policy Uncertainty

The VECM estimation results provide valuable insights into the relationship between green bonds, financial stress (S&P US Financial Stress Index), and economic policy uncertainty (EPU). The presence of a negative and significant error correction term (ECT) confirms the existence of a long-term equilibrium among these variables, indicating that any short-term deviations due to external shocks will gradually correct themselves over time. The impact of financial stress on green bonds is particularly revealing. A negative coefficient on financial stress suggests that increased market instability leads to a decline in green bond prices, as risk-averse investors shift away from relatively volatile assets. This aligns with traditional flight-to-safety behavior, where capital moves towards more stable investment options during periods of financial turmoil. However, a positive coefficient would imply that green bonds are perceived as a safe-haven asset, attracting investors seeking stability in uncertain financial conditions. This result is further confirmed by the Range DCC-GARCH model, which highlights the negative correlation between financial stress and green bonds, especially during economic crises such as the oil crisis and COVID-19 pandemic, reinforcing their role as a hedge in uncertain times.

Similarly, the effect of EPU on green bonds varies depending on investor sentiment. A negative coefficient indicates that rising economic uncertainty discourages investment in green bonds, as investors prioritize liquidity and opt for more traditional safe assets, such as government bonds or cash reserves. Conversely, a positive coefficient would suggest that green bonds are regarded as resilient, potentially benefiting from their long-term sustainability appeal, which aligns with investor preferences for stable, socially responsible investments during uncertain times. This finding is consistent with the dynamic correlations observed in the Range DCC-GARCH model, which shows that EPU positively correlates with green bonds in certain periods, such as the COVID-19 crisis, confirming that green bonds can serve as a diversification tool in times of high uncertainty.

In the short run, the lagged effects of financial stress and EPU demonstrate that past fluctuations in these variables significantly shape present green bond valuations. The speed and magnitude of these adjustments depend on the estimated coefficients, shedding light on how quickly investors react to macroeconomic instability and policy shifts. The results suggest that both financial stress and economic policy uncertainty play a crucial role in shaping the green bond market. While financial stress generally reduces green bond investment, EPU can have mixed effects depending on investor perceptions. These findings, confirmed by the time-varying correlations of the Range DCC-GARCH model, underscore the importance of macroeconomic conditions and investor sentiment in determining the behavior of green bonds in both stable and volatile environments.

Table 5. Vector Error Correction Model (VECM)

Error Correction	D(S&P GREEN BOND INDEX)	D(S&P GREEN BND SELECT INDEX)	D(S&P US MUNI GREEN BOND INDEX)	D(ST LOUIS FIN STRESS INDEX)	D(Economic Policy Uncertainty)
	-0.425781	0.326015	-0.032261	-0.030971	-5.145087
COINTEQ1	(0.21838)	(0.18468)	(0.02273)	(0.02799)	(3.14705)
	[-1.94974]	[1.76531]	[-1.41912]	[-1.10658]	[-1.63489]
D(S&P GREEN	-0.357712	-0.217101	0.027881	0.025955	3.638346
BOND INDEX (-1))	(0.19651)	(0.16619)	(0.02046)	(0.02519)	(2.83194)

Error Correction	D(S&P GREEN BOND INDEX)	D(S&P GREEN BND SELECT INDEX)	D(S&P US MUNI GREEN BOND INDEX)	D(ST LOUIS FIN STRESS INDEX)	D(Economic Policy Uncertainty)
	[-1.82030]	[-1.30636]	[1.36294]	[1.03053]	[1.28475]
D(S&P GREEN BOND INDEX (-2))	0.074159 (0.14342) [0.51709]	0.038930 (0.12128) [0.32098]	0.030015 (0.01493) [2.01044]	0.021235 (0.01838) [1.15531]	2.819347 (2.06676) [1.36414]
D(S&P GREEN BND SELECT INDEX (-1))	-0.393431 (0.21528) [-1.82757]	-0.537462 (0.18205) [-2.95221]	-0.038485 (0.02241) [-1.71733]	-0.012439 (0.02759) [-0.45083]	-3.980938 (3.10232) [-1.28321]
D(S&P GREEN BND SELECT INDEX (-2))	-0.558579 (0.18023) [-3.09932]	-0.376251 (0.15241) [-2.46861]	-0.026711 (0.01876) [-1.42372]	-0.011340 (0.02310) [-0.49094]	-3.645915 (2.59724) [-1.40376]
D(S&P US MUNI GREEN BOND INDEX(-1))	2.120774 (0.99646) [2.12831]	1.945139 (0.84269) [2.30826]	-0.321279 (0.10373) [-3.09725]	0.157553 (0.12771) [1.23368]	33.21446 (14.3600) [2.31299]
D(S&P US MUNI GREEN BOND INDEX(-2))	3.901357 (1.02354) [3.81165]	1.836151 (0.86558) [2.12129]	-0.135933 (0.10655) [-1.27578]	-0.013961 (0.13118) [-0.10642]	17.32263 (14.7501) [1.17441]
D(ST LOUIS FIN STRESS INDEX (-1))	-0.671866 (0.84007) [-0.79977]	-0.734817 (0.71043) [-1.03432]	-0.103615 (0.08745) [-1.18484]	0.011585 (0.10767) [0.10760]	13.05820 (12.1062) [1.07863]
D(ST LOUIS FIN STRESS INDEX (-2))	0.584866 (0.85280) [0.68582]	-0.056024 (0.72119) [-0.07768]	-0.127473 (0.08878) [-1.43591]	-0.082955 (0.10930) [-0.75899]	-1.292261 (12.2896) [-0.10515]
D(Economic Policy Uncertainty(-1))	0.017647 (0.00726) [2.42963]	0.013228 (0.00614) [2.15355]	-5.73E-05 (0.00076) [-0.07572]	-0.000111 (0.00093) [-0.11923]	6.59E-05 (0.10467) [0.00063]
D(Economic Policy Uncertainty(-2))	0.004873 (0.00745) [0.65430]	0.003078 (0.00630) [0.48869]	-0.001543 (0.00078) [-1.99102]	-0.001131 (0.00095) [-1.18450]	-0.153687 (0.10732) [-1.43206]
C	-0.047285 (0.18263) [-0.25892]	-0.069410 (0.15444) [-0.44942]	0.000540 (0.01901) [0.02843]	0.003929 (0.02341) [0.16786]	-0.260299 (2.63181) [-0.09891]
R-squared	0.641541	0.581072	0.731158	0.667989	0.545749
Adj. R-squared	0.582211	0.413917	0.531661	0.552624	0.535199
Sum sq. resids	274.3513	196.2094	2.973036	4.506458	56976.20
S.E. equation	1.796570	1.519324	0.187021	0.230255	25.89031
F-statistic	9.127604	7.163574	2.323268	0.563699	1.318402
Log likelihood	-188.0624	-171.8039	31.39165	11.21914	-446.8574
Akaike AIC	4.124998	3.789771	-0.399828	0.016100	9.460978
Schwarz SC	4.443519	4.108292	-0.081307	0.334621	9.779499
Mean dependent	-0.025667	-0.039465	0.001374	0.004207	-0.116428
S.D. dependent	2.496707	1.984590	0.200699	0.224425	26.35837
Determinant resid covariance (dof adj.)		4.343460			
Determinant resid covariance		2.244253			
Log likelihood		-727.3913			
Akaike information criterion		16.33796			
Schwarz criterion		18.06329			
No. of coefficients		65			

6. CONCLUSION

In conclusion, this study offers valuable empirical insights into the transmission of volatility within the green bond markets, using both the Range-DCC GARCH model and wavelet coherence analysis. Our results demonstrate the significant impact of political uncertainty and financial stress on green bond performance, particularly during crisis periods. The Range-DCC GARCH model highlights a strong correlation between Economic Policy Uncertainty (EPU) and green bonds during the 2015 oil crisis, while a negative correlation is observed between the Financial Stress Index (FSI) and green bonds during oil price declines. Additionally, during the COVID-19 pandemic, a positive relationship between EPU and green bonds is evident, although exceptions such as the S&P Green Bond Index illustrate the complexity of the observed dynamics. Wavelet coherence analysis further corroborates these findings, showing significant correlations between political uncertainty, financial stress, and green bond returns during both the oil crisis and the COVID-19 pandemic.

However, the results of this study should be interpreted in light of certain limitations. The reliance on specific indices, particularly those from certain geographic regions, may limit the generalizability of the conclusions to a broader range of global economic contexts. This suggests that future studies could expand the geographical scope to better understand the global relevance of the observed relationships. Moreover, while this paper has suggested that green bonds can serve as a hedge against financial uncertainties, the results also indicate periods of negative correlation, particularly during financial stress. This observation highlights that the hedging function of green bonds is context-dependent and may not be uniformly evident across all crisis scenarios.

It is therefore essential to adopt a nuanced perspective regarding the role of green bonds as a hedging instrument, taking into account the specific contexts of different crises. Wavelet coherence analysis provides additional insights into the dynamic evolution of the relationships between green bonds and uncertainty variables, offering avenues for investment strategies tailored to periods of high or low uncertainty.

This study contributes to the literature by highlighting the dynamic interaction between green bonds, political uncertainty, and financial stress during crisis periods. Future research could extend this analysis by incorporating other dimensions of uncertainty, such as climate-related or environmental policy risks, to further understand their influence on green bond dynamics and resilience.

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