

Asymmetric bidirectional relationships between green attention index, green and conventional bonds in a regime-switching environment: evidence from N-ARDL approach

Yousra Trichilli, Moez Boujelbène and Mouna Boujelbène-Abbes
*Faculty of Economics and Management of Sfax, University of Sfax,
Sfax, Tunisia*

Abstract

Purpose – This study initially constructs a monthly green attention index using Google Trends and subsequently investigates the bidirectional asymmetric relationship between this index and green and conventional bond returns in the bull and bear regimes.

Design/methodology/approach – This study builds upon Da *et al.* (2015) methodology to establish a monthly green attention index for the United States of America. Secondly, we introduce an innovative methodology using the non-linear autoregressive distributed lag (ARDL) model to detect both short-term and long-term relationships within this index, considering green and conventional bond returns, while distinguishing between bull and bear regimes through a switching model to enhance the understanding of market dynamics.

Findings – In the long run, our results revealed that during bullish markets, there's a positive asymmetric association between the green attention index and both types of bonds, implying a diversifying role in bond returns. However, in bearish markets, both green and conventional bonds showcase a long-term safe haven role. While the green attention index acts as a safe haven for both bonds, its impact is notably more negative during bearish phases, emphasizing its significant safe-haven characteristic. On the other hand, in the short run, the study suggests that the green attention index acts as a robust safe haven, whereas conventional bonds may not effectively hedge or serve as safe-haven assets for the green attention index. Conversely, in bearish markets, both green and conventional bonds serve as strong safe havens in the long term. Overall, the green attention index might not effectively operate as hedging or safe-haven assets for either conventional or green bonds in both short- and long-run scenarios. Finally, while examining the variation of dynamic multiplier adjustments for the green attention index and green and conventional bonds, we concluded that the effect of a negative shock in green and conventional bonds dominates that of a positive shock in the short run.

Practical implications – Understanding the changing roles of green and conventional bonds as diversifiers or safe havens extends implications to financial institutions, market participants and portfolio managers, emphasizing the need to shape robust investment strategies, optimize asset allocation across different market conditions and reconsider risk mitigation strategies to enhance resilience against market volatilities.

Originality/value – This paper makes dual contributions to the burgeoning field of green finance. Firstly, it draws upon the methodology established by Da *et al.* (2015) as a foundational framework to create the monthly green attention index specifically tailored for the United States of America. Secondly, our research adds a distinctive layer to the existing empirical knowledge by introducing a pioneering model that effectively oversees both short- and long-term interactions while accounting for potential asymmetries within these relationships. To achieve this objective, we employ the nonlinear autoregressive distributed lag model. These contributions collectively enrich the understanding and practical application of green finance methodologies, laying a stronger foundation for future research and financial decision-making within sustainability frameworks. Thirdly, this research identifies a specific contribution of notable interest to portfolio managers and investors, enabling them to tailor their portfolio strategies accordingly in response



to different market conditions. Such insights hold the potential to profoundly impact investment decisions within diverse market regimes.

Keywords Green attention index, N-ARDL, Conventional bonds, Green bonds, Bidirectional relationship, Regime switching

Paper type Research article

1. Introduction

The concept of green finance has developed in the context of increasing ecosystem imbalances caused by human activities. Green finance facilitates the mobilization of funds and investments to implement sustainable economic, social and environmental projects in countries around the world (Zhang and Wang, 2019). It is seen as the corporate social responsibility of financial institutions to finance environmentally friendly business projects and social activities (Bert, 2006; Koo, 2010). However, GF aims to balance the progress of monetary events, environmental stability and ecological protection to achieve long-term development (Zhou et al. (2020)). It considers environmental outcomes when financing a project and prioritizes investments in various environmentally friendly activities such as renewable energy, waste management (solid and liquid), clean energy, climate change mitigation and adaptation strategies, alternative energy, green brick production, green industry development, paper waste recycling, energy efficient technology, biodiversity protection and so on. Green finance could benefit from adjustments to national regulatory frameworks, the harmonization of public financial incentives, an increase in green finance from various sectors, the alignment of public sector financing decisions with the environmental dimension of the Sustainable Development Goals (SDGs), greater investment into clean and green technologies, financing towards a sustainable natural resource-based and climate-friendly green economy, and an increased use of green bonds.

Investment in green assets is growing in importance and represents a new category of capital for investors. Green bonds offer comparable features and mechanisms to conventional fixed income corporate bonds (Reboredo and Ugolini, 2020). They are one of the significant instruments of green finance and have received extensive research from scholars (Huang et al., 2023; Li et al., 2022).

The ESG principle is a framework that encompasses environmental (E), social (S) and governance (G) factors. The Principles for Responsible Investment (PRI) define responsible investment as “a strategy and practice for integrating environmental, social and governance (ESG) factors into investment decisions and active ownership” (PRI, 2021). As such, ESG is typically a standard and strategy used by investors to assess corporate behavior and future financial performance.

Researchers have also paid considerable attention to ESG as an asset class. In recent years, many studies have explored the links between the ESG index and other conventional asset classes traded on the stock market. Andersson et al. (2020) examine the causal relationship between the World ESG Index and currency, commodity and equity markets. They find that ESG portfolio returns influence currency and commodity returns. Plastun et al. (2022) find that the price effects of one-day abnormal returns are not significantly different for conventional and ESG indices in developed and emerging markets. Examining the volatility risk spillover between the world's leading ESG equity markets, Chen et al. (2023) find that the North American (NA) and EU markets are the main risk transmitters to the global ESG investment market. Kilic et al. (2022) examine the interdependence between conventional and ESG stocks for thirty-eight developing and developed countries and find positive (negative) co-movements of ESG returns with conventional stock returns for developing (developed) countries.

Despite the fact that a variety of studies have looked into the linkages between the same classes of assets (Tiwari et al., 2018) and the connectedness between different asset classes (Corbet et al., 2018), there has been little empirical work on connectedness between ESG and other asset classes while most of the studies do not account for the asymmetric effects. Therefore, in this paper, we examine the bidirectional asymmetric relationship between green

attention index, green and conventional bonds return in the bull and bear regimes. To do so, we used the NARDL model and checked the long and short-run asymmetry effects.

From a theoretical perspective, the relationship between green attention and bond markets can be explained through three main transmission channels. First, the information channel suggests that increased environmental attention reduces information asymmetry and enhances transparency regarding sustainable financial instruments. Second, the behavioral channel implies that heightened green awareness may alter investor sentiment and preferences, leading to portfolio reallocation toward environmentally responsible assets. Third, the risk-hedging channel posits that during periods of financial instability, green assets may be perceived as relatively resilient, thereby strengthening their safe-haven or hedging characteristics. These mechanisms justify the need to explore asymmetric and regime-dependent effects in bond markets.

This paper makes dual contributions to the burgeoning field of green finance. Firstly, it draws upon the methodology established by [Da et al. \(2015\)](#) as a foundational framework to create the monthly green attention index specifically tailored for the United States. In addition, the GAI is constructed by selecting relevant environmental keywords from Google Trends, aggregated monthly, and validated for reproducibility by checking its correlation with green bond market activity. Secondly, our research adds a distinctive layer to the existing empirical knowledge by introducing a pioneering model that effectively oversees both short-term and long-term relationships while accounting for potential asymmetries within these relationships. Achieving this objective, we employ the non-linear Autoregressive Distributed Lag (ARDL) model. These contributions collectively enrich the understanding and practical application of green finance methodologies, laying a stronger foundation for future research and financial decision-making within sustainability frameworks.

The non-linear ARDL model, as recently formulated by [Shin et al. in 2014](#), is equipped with positive and negative partial sum decompositions, enabling the detection of asymmetric effects in both the short and long terms. When compared to conventional cointegration models, the NARDL models offer several advantages. Firstly, they demonstrate superior performance in identifying cointegration relationships, particularly when working with small sample sizes ([Romilly et al., 2001](#)). Secondly, they can be applied regardless of whether the regressors are stationary at the level or at the first difference (i.e. $I(0)$ or $I(1)$). However, it's worth noting that they cannot be applied if the regressors are $I(2)$. Thirdly, this research identifies a specific contribution of notable interest to portfolio managers and investors, enabling them to tailor their portfolio strategies accordingly in response to different market conditions. Such insights hold the potential to profoundly impact investment decisions within diverse market regimes.

Although there is an abundance of research on green finance, green bonds and ESG indices, the current literature nevertheless has several notable limitations. First, few studies explicitly examine the influence of investor attention on bond market dynamics, particularly from an asymmetric perspective. Second, most current research uses linear models that fail to capture behavioral differences between bull and bear market phases. Third, the dynamic interactions between green attention, green bonds and traditional bonds remain largely unexplored. This research seeks to address these gaps by suggesting an innovative method that combines a regime-switching Markov model with a non-linear NARDL model. This approach allows for the simultaneous examination of (1) asymmetric impacts, (2) market regime dependence, and (3) short- and long-term adjustments between the green attention index and the bond market.

Accordingly, this study addresses the following research questions:

- (1) Does green attention exert asymmetric effects on green and conventional bond returns?
- (2) Do these effects differ across bullish and bearish market regimes?
- (3) Do green bonds provide stronger hedging and safe-haven properties compared to conventional bonds in response to green attention shocks?

This research makes three main contributions. First, it provides an operational framework for environmental attention based on Google Trends data. Second, it highlights the asymmetric and systematic nature of the relationship between green attention index, green bonds and conventional bonds. Third, it offers new insights into diversification, risk management and financial stability in the context of climate transition.

The study has three main objectives, to verify whether there is an asymmetric link between attention to environmental issues and bond yields, and whether this relationship varies depending on market conditions (bullish or bearish). To examine the role of green and traditional bonds as hedging instruments or safe havens in the face of fluctuations in investor interest.

Based on these objectives, the following hypotheses are established:

- H1. The effect of green attention on bond returns is asymmetric.
- H2. The relationship between green attention and bonds varies depending on market regime.
- H3. Green bonds offer better hedging and safe-haven characteristics than traditional bonds, especially during periods of financial stress.

The results indicate, in particular, that green bonds play a more pronounced safe-haven role during bearish market, while their function is closer to that of a diversification asset during periods of bull market. Overall, the findings confirm the presence of asymmetric and regime-dependent dynamics between green attention and bond markets, underscoring the importance of incorporating nonlinearity and market states when evaluating sustainable financial assets. These findings constitute an innovative empirical contribution to the field of sustainable finance and investor interest.

The remainder of this paper follows this structure: [Section 2](#) outlines the literature review. [Section 3](#) provides an overview of the data, followed and the methodology used in the analysis. [Section 4](#) presents the empirical findings and Hypotheses Validation, and finally, [Section 5](#) concludes the study, addressing its implications.

2. Literature review

Over the past decade, there has been a growing body of research on the link between ESG characteristics and multiple dimensions of financial performance, including but not limited to equity returns, bond returns, and access to credit markets ([Brooks and Oikonomou, 2018](#); [Matos, 2020](#); [Gillan et al., 2021](#)). This area of research has been extended to green bonds as a key instrument of sustainable finance. For instance, [Wang and Wang \(2022\)](#) find that good ESG practices not only increase listed companies' willingness to issue green bonds but also help them in doing so. Moreover, [Immel et al. \(2022\)](#) find a statistically significant impact of ESG ratings on bond spreads. A one-point increase in the weighted average ESG score is associated with a spread reduction of between 6 and 13 basis points. The evolution of green bonds during times of crisis has also attracted attention. For their part, the pandemic progress has a non-linear impact on green bonds and ESG markets [Perote et al. \(2023\)](#), while, [Bokhtiar Hasan et al. \(2023\)](#) observe the lower volatility spillover between green bonds and ESG stocks is evident during calm and turbulent periods (e.g. COVID-19 and the Russia-Ukraine war), suggesting potential hedging benefits.

Alongside ESG exploration, assessments of investor attention and sentiment have highlighted the critical importance of information seeking in asset valuation. The attention index, based on Google search data and developed through the innovative research of [Da et al. in 2015](#), has proven effective in anticipating stock market performance. This method has been extended to sustainable finance, forming the basis for our Green Attention Index (GAI), which quantifies investor interest in environmental and sustainability issues. Despite its relevance, the dynamic interaction between these "green attention" indicators and bond markets remains underexplored, particularly regarding asymmetric and bidirectional effects between green and conventional bonds.

A significant theoretical and practical shortcoming in current research studies concerns the asymmetric and system-dependent nature of financial relationships. Traditional linear models frequently fail to capture how relationships between variables change in rising or falling markets, or in response to positive or negative shocks. To address this, we build on a crucial framework developed through the fundamental research of Robert Engle and collaborators on asymmetric dynamics, conditional correlations, and climate risk. For example, the A-DCC (Asymmetric Dynamic Conditional Correlation) model (Cappiello *et al.*, 2006) illustrates how correlations between global asset returns can fluctuate significantly during periods of market stress. Engle's recent work on climate-related financial risks, such as CRISK and climate stress tests (Jung *et al.*, 2021; Acharya *et al.*, 2023), provides a rigorous foundation for analyzing regime-dependent safe haven properties of green bonds. Furthermore, Engle *et al.* (2019) demonstrate how media coverage of climate change impacts market risk, paralleling the conceptual basis of the GAI as an attention-driven risk measure.

The study by Zhang *et al.* (2021) investigated the time-varying relationships among major sustainable investment indices using the asymmetric dynamic conditional correlation (A-DCC) model. Their study provides essential insights into how correlations between ESG stocks, renewable energy stocks, green bonds, and broad sustainability indices change under different market conditions. While previous studies have examined links within the same asset class (such as Tiwari *et al.*, 2018) or between different conventional categories (Corbet *et al.*, 2018), there is a clear gap in empirical research examining the bidirectional and asymmetric relationship between investor interest in environmental issues (green attention index) and the bond market, with a specific focus on the differentiation between green bonds and conventional bonds under different market regimes.

This study seeks to fill these gaps by incorporating a green attention index derived from Google Trends into a nonlinear autoregressive distributed lag regime-switching (NARDL + Markov switching) model. This approach allows us to capture asymmetric impacts in both the short and long term, account for market regime dependence (bull vs bear markets), and examine the reciprocal causality between environmental interest and bond yields. It offers a new perspective on how GAI affects bond market dynamics and, conversely, how bond market performance influences investor attention to sustainability at various stages of the financial cycle.

In doing so, this study contributes both theoretically and empirically to the literature. Theoretically, it extends asymmetric finance theories by integrating investor attention dynamics into sustainable bond market analysis, linking information-based asset pricing models with regime-dependent financial behavior. Empirically, it advances prior research by explicitly modeling positive and negative shocks via a nonlinear framework (NARDL), incorporating Markov regime-switching to capture structural market changes, and analyzing short- and long-run dynamics simultaneously. Consequently, the study positions itself at the intersection of sustainable finance, asymmetric modeling, and regime-dependent asset pricing, thereby strengthening its relevance within the evolving body of literature and directly addressing gaps identified in previous studies.

3. Data and methodology

3.1 Data description

3.1.1 Green and conventional bond returns. In this paper we examine the asymmetric relationship between Green attention index, green and conventional bonds. We used monthly close prices of the following green bonds: S&P GREEN BOND INDEX, S&P GREEN BOND SELECT IN, S&P MUNI GREEN BOND, alongside conventional bonds, namely S&P 500 COMPOSITE, S&P 500 FINANCIALS BOND INDEX, S&P 500 BOND INDEX.

The sample period spans from August 2014 to February 2023 providing sufficient observations to capture different market conditions, including crisis and expansion phases. Monthly frequency is adopted to ensure consistency with the construction of the Green

Attention Index (based on monthly Google Trends data) and to reduce excessive short-term noise typically observed in daily data. This frequency is particularly suitable for capturing medium-term adjustment dynamics within the NARDL framework.

The monthly bond return is calculated as follows:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

Where P_t is the closing index price on month t and P_{t-1} is the closing index price on month $t - 1$.

The evolutions of returns for green and conventional bonds are illustrated in Figure 1. It is noticeable that there was a sharp decline in both green and conventional bonds during the pandemic crisis in 2020. Additionally, fluctuations, both positive and negative, can be observed in the performance of green and conventional bonds during the period of the Russian-Ukrainian conflict in 2022.

3.1.2 Green attention index constructions. We adopt the methodology outlined by Da et al. (2015) as a framework to craft the monthly green attention index within the United States. Subsequently, we elucidate the fundamental construction steps articulated in their study and emphasize the variances in our approach when applied to this global context.

Our primary data source, Google Trends (accessible at <https://www.google.com/trends/>), supplies the Search Volume Index (SVI) for any search query across multiple countries, in diverse languages, and over specific time frames. This information facilitates a comprehensive view of search activity, contributing to the development of our international green attention index.

The following steps summarize the construction of this proxy (Trichilli et al., 2018).

Step 1: We have selected words related to ESG such as environment, sustainability, social, etc. These words indicate positive or negative sentiment. Positive words refer to an action, solution or good practice, while negative words refer to risk, pollution, impact or a problem.

The full list of keywords used in the construction of the Green Attention Index is explicitly reported in Table 1 above to ensure full reproducibility. The classification into positive and negative terms follows a semantic and economic rationale: positive terms reflect sustainable practices, environmental solutions, governance quality, and social responsibility, whereas negative terms capture environmental degradation, social risks, pollution, and governance concerns. This classification is consistent with prior ESG attention literature and ensures conceptual coherence.

Step 2: We use the English language for all studies conducted in the United States, and we also use the finance field in Google Trends to wait for financial data.

Step 3: We download the monthly search volume index for each term from Google Trends. Only search terms with positive or negative frequencies are included to obtain an accurate baseline. To ensure robustness, we exclude keywords with insufficient or unstable search intensity over time. This filtering procedure guarantees that the index reflects meaningful variations in public environmental attention rather than sporadic search activity.

Step 4: We calculate the monthly change in SVI (ΔSVI) for every search term. After this, we finally obtain the adjusted monthly change in search volume $\Delta ASVI$.

Step 5: Using positive and negative terms in forming our measure of Green Attention Index (GAI), we averaging $\Delta ASVI$ the top positive and the top negative search terms for every month and we calculate the difference between them to obtain the green attention index.

The measure of green attention index is displayed as follows:

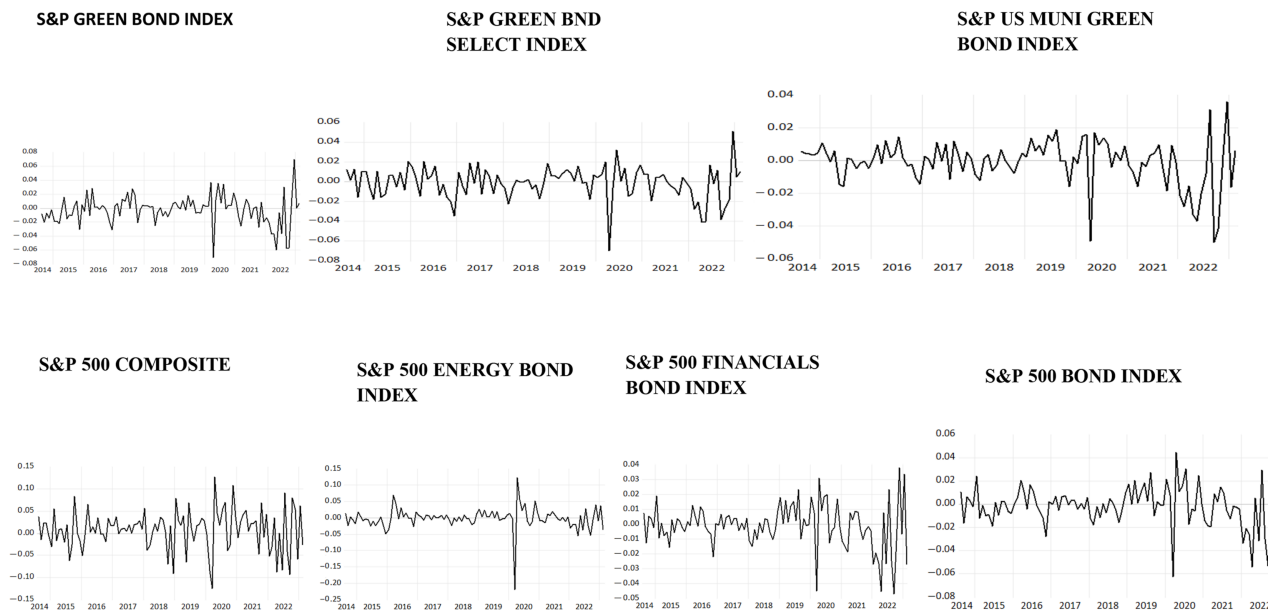


Figure 1. Evolution of green and conventional bond returns

Table 1. List and classification of ESG-related search terms (positive vs. negative) for green attention index construction

● Positifs	● Négatifs
Waste management	Greenhouse gases
Water management	Greenhouse gas emission
Biodiversity	Carbon dioxide
Renewable energy	Carbon emission
Environmentally friendly	CO2 emission
Transparency	Carbon footprint
Environment	Footprint
Governance	Climate change
Social	Air pollution
Community	Pollution
Leadership	Environmental factors
Social impact	Social problems
Recycling	Social risk
Natural resources	Executive compensation
Corporate Responsibility	
ESG	
SRI	
Human rights	
Diversity	
Business ethics	
Green finance	
Energy transition	
Sustainability	
Green products	
Stakeholders	
Green construction	
Green energy	
Social performance	
Internal audit	

$$\text{Green attention index} = \sum R_+(\Delta \text{ASVI}) - \sum R_-(\Delta \text{ASVI})$$

Where ΔASVI is the adjusted monthly change in search volume of positive (negative) searched terms. Thus, Green Attention Index (GAI) is calculated by subtracting the t-statistic-weighted average of the top positive searched terms and the t-statistic-weighted average of the top negative searched terms. This weighting scheme ensures that more statistically relevant search terms contribute proportionally to the index construction, thereby improving measurement precision and reducing noise bias.

The GAI's progression is depicted in [Figure 2](#), illustrating both positive and negative peaks. These fluctuations can be attributed to various natural and man-made occurrences influencing the green attention index. Notably, between 2019 and 2020, there was a substantial surge in the green attention index, attributed to the widespread effects of the COVID-19 pandemic. Conversely, in 2022, a significant decline is evident, underscoring the environmental, social, and governance repercussions of the Ukraine-Russia war during that period.

3.2 Methodology

The methodology employed in this study comprises two distinct stages. The initial phase involves the application of a regime-switching model to discern between low and high financial market states. Subsequently, we undertake the estimation of the long and short-run

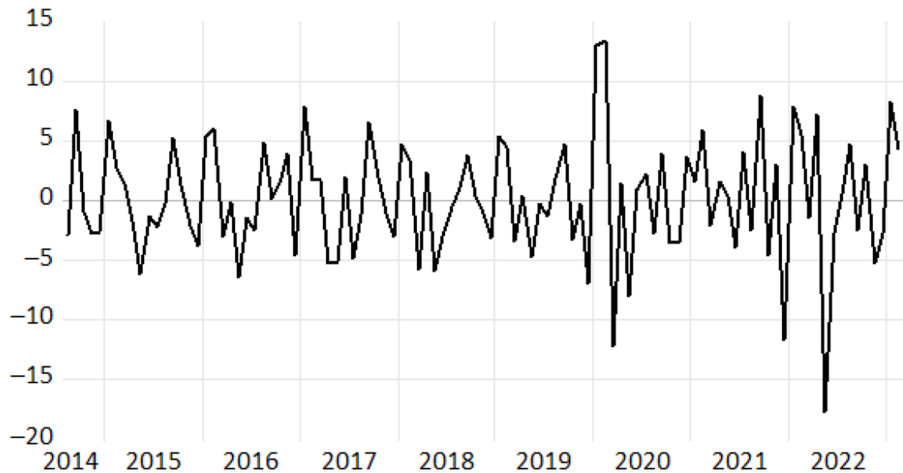


Figure 2. Evolution of green attention index (GAI)

asymmetrical relationships between returns on green attention index, green, and conventional bonds in diverse market states utilizing the N-ARDL model.

This two-step strategy is directly aligned with the study's hypotheses. While the regime-switching model captures structural changes across different market conditions (bull and bear regimes), the NARDL framework allows for the identification of asymmetric responses to positive and negative shocks. Therefore, the two approaches are complementary: the first accounts for regime dependence, and the second captures shock-based asymmetry in both the short and long run.

3.2.1 Nonlinearity diagnostic test (BDS test). Prior to the estimation of the linear ARDL model, the Brock–Dechert–Scheinkman (BDS) test is applied to the residuals obtained from the NARDL specification in order to examine whether the underlying data-generating process follows an independent and identically distributed (i.i.d.) structure. The BDS test is a non-parametric tool designed to detect hidden nonlinear dependence in time series data. Rejection of the null hypothesis provides empirical justification for the adoption of nonlinear econometric models such as the NARDL framework. Following Brock *et al.* (1996), the test is conducted for embedding dimensions ranging from 2 to 5 and for distance parameters set at 0.5σ , 1σ , and 1.5σ of the residuals' standard deviation.

Table 2 reports the results of the BDS test applied to the residuals of the baseline linear model. The null hypothesis of independent and identically distributed residuals is rejected at the 1% significance level for most embedding dimensions and distance parameters, indicating potential nonlinear dependence in the residual series. However, given that significance is only observed at the 1% level, these results should be interpreted with caution. They suggest that nonlinear modeling approaches like the NARDL framework may better capture asymmetric dynamics between the green attention index and green and conventional bonds, but additional robustness checks are recommended.

The consistency of rejection across several embedding dimensions strengthens the empirical support for departing from a purely linear specification and justifies the implementation of an asymmetric modeling strategy.

3.2.2 Regime switching model. This study employs the Markov Switching – Auto Regressive (MS-AR) method, an extension of the $AR()$ model tailored for nonlinear scenarios. It postulates a finite set of states, each defined by an $AR()$ model. The essence of the Markov switching model lies in acknowledging that time series can exhibit periodic shifts in

Table 2. BDS test results on NARDL residuals

Embedding dimension (m)	$\varepsilon = 0.5\sigma$	$\varepsilon = 1\sigma$	$\varepsilon = 1.5\sigma$
2	5.41***	4.87***	3.92***
3	6.02***	5.31**	4.28***
4	6.74***	5.98***	4.91***
5	7.15***	6.42***	5.33***

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

their behavior. These shifts occur via state switches, wherein both the process generating the data and the typical duration of each state may vary. This framework is particularly suitable for financial time series, which often experience structural changes associated with market stress, crises, or expansion periods. By allowing parameters to vary across regimes, the model captures differences in mean and volatility between high- and low-volatility states without imposing exogenous break dates.

Consider r_t as a time-series stemming from an autoregressive model of order p , incorporating regime shifts affecting both mean and variance.

$$r_t - \mu(S_t) = \sum_{i=1}^p \phi_i(r_{t-1} - \mu(S_{t-1})) + \sigma^2(S_t)\varepsilon_t \quad (1)$$

With mean μ and variance σ^2 of the process depend on the regime at time t , indexed by S_t a discrete variable. ϕ_i is the model parameter and ε_t is an i.i.d $N(0,1)$ random variable. S_t is assumed to be a n -state, first order Markov process, taking the values $1 \dots \dots n$ with transition probability matrix:

$$P = \{P_{ij}\} \text{ i,j} = 1 \dots n;$$

$$\text{Where, } p_{ij} = \Pr[S_t = j | S_{t-1} = i] \text{ with } \sum_{j=1}^n P_{ij} = 1 \text{ for all } i \quad (2)$$

The state dependent mean and variances are specified as;

$$\mu(S_t) = \mu_1 S_{1t} + \dots + \mu_n S_{nt} \quad (3)$$

$$\sigma^2(S_t) = \sigma_1^2 S_{1t} + \dots + \sigma_n^2 S_{nt} \quad (4)$$

Where S_{it} it takes the value of one when S_t is equal to i and two otherwise. Then [equation \(1\)](#) can then be written as $r_t = \mu_1 S_{1t} + \dots + \mu_n S_{nt} + \gamma_t$ (5)

$$\gamma_t = \sum_{i=1}^p \phi_i \gamma_{t-1} + (\sigma_1^2 S_{1t} + \dots + \sigma_n^2 S_{nt})\varepsilon_t \quad (6)$$

Using [equation \(2\)](#) as a foundation, a pair of matrices governing state transitions can be constructed, employing a first-order Markov process.

$$\text{Prob}[S_t = 1 | S_{t-1} = 1] = p_{11}$$

$$\text{Prob}[S_t = 2 | S_{t-1} = 1] = 1 - p_{11} = p_{12}$$

$$\text{Prob}[S_t = 2 | S_{t-1} = 2] = p_{22}$$

$$\text{Prob}[S_t = 2 | S_{t-1} = 1] = 1 - p_{22} = p_{21}$$

$$\text{With } p_{11} + p_{12} + p_{22} + p_{21} = 1$$

Within the algorithm mentioned earlier, p_{11} and p_{22} represent the likelihood of the system being in regime one or regime two, respectively, considering its state in the previous period.

Thus $1 - p_{11}$ defines the probability that y_t will change from state 1 in period $t - 1$ to state 2 in period t , and $1 - p_{22}$ defines the probability of shift from state 2 to state 1 between times $t-1$ and t . Thus p_{12} is the probability of going from state 1 to state 2.

3.2.3 N-ARDL bound-testing approach. We employ the Non-linear Autoregressive Distributed Lag Model (NARDL), which accommodates data series exhibiting mixed integration orders. This model uniquely enables the distinct modeling of short-term and long-term impacts of explanatory variables.

This model framework accommodates the analysis of bidirectional effects. It explores how changes in the green attention index not only impact bond returns but also how fluctuations in the bond's returns can influence the observed levels of the green attention index. By allowing for the consideration of both positive and negative effects, this approach aims to unravel the intricate interplay between the attention index and the returns of these bonds within the market, capturing the nuanced dynamics governing their relationship.

$$y_t = f(X_t) \quad (7)$$

Where y_t represent the dependent variable and X_t represents the independent variable.

The NARDL model, as proposed by [Pesaran et al. \(2001\)](#), enables the consideration of both positive and negative effects of the explanatory variables. The formulation is presented below

$$\Delta y_t = \alpha_0 + \sum_{i=0}^p \alpha_1 \Delta y_{t-i} + \sum_{i=0}^q \alpha_2 \Delta X_{t-i}^+ + \sum_{i=0}^q \alpha_3 \Delta X_{t-i}^- + \rho y_{t-1} + \varphi_1^+ X_{t-1}^+ + \varphi_2^- X_{t-1}^- + \mu_t \quad (8)$$

The key question to address is whether the impact of explanatory variables on the dependent variable exhibits similar magnitudes of changes in both instances (positive and negative). If the impact consistently demonstrates similar magnitudes of changes, it implies a symmetric relationship. Conversely, if the magnitudes of changes differ, it suggests an asymmetric relationship. In the NARDL model, the positive partial sum of changes in X is denoted as X^+ , and the negative partial sum of changes as X^- . The representation of partial sums for increases and decreases can be articulated as follows:

$$X_t^+ = \sum_{j=1}^t \Delta X_j^+ = \sum_{j=1}^t \max(\Delta X_j, 0)$$

$$X_t^- = \sum_{j=1}^t \Delta X_j^- = \sum_{j=1}^t \min(\Delta X_j, 0) \quad (9)$$

The form of our practical model, integrating asymmetric error correction according to the proposals of [Pesaran et al. \(2001\)](#) and [Shin et al. \(2014\)](#), is outlined as:

$$\begin{aligned}\Delta y_t = & \alpha_0 + \sum_{i=1}^p \alpha_1 \Delta y_{t-i} + \sum_{i=0}^q \alpha_{21} \Delta X_{t-i}^+ + \sum_{i=0}^q \alpha_{22} X_{t-i}^- + \sum_{i=0}^q \alpha_{31} \Delta Z_{t-i}^+ \\ & + \sum_{i=0}^q \alpha_{32} \Delta Z_{t-i}^- (\phi_{11}^+ X_{t-i}^+ + \phi_{12}^- X_{t-i}^-) + (\phi_{21}^+ Z_{t-i}^+ + \phi_{22}^- Z_{t-i}^-) + \rho y_{t-1} + \mu_t \quad (10)\end{aligned}$$

Identifying asymmetry in both short and long-run dynamics can be achieved through the application of the Wald test. The Wald F-statistics operate under the assumption of a hypothesis test assessing joint significance, wherein:

$$\begin{cases} H_0: \rho = \phi_{11}^+ = \phi_{12}^- = \phi_{21}^+ = \phi_{22}^- = 0 \\ H_a: \rho \neq \phi_{11}^+ \neq \phi_{12}^- \neq \phi_{21}^+ \neq \phi_{22}^- \neq 0 \end{cases}$$

If the F-statistics surpass the critical values, following the criteria set by [Pesaran et al. \(2001\)](#), the null hypothesis is rejected. This signifies the potential establishment of a long-term relationship.

$$\begin{cases} H_0: \rho = 0 \\ H_a: \rho < 0 \end{cases}$$

As per [Banerjee et al. \(1998\)](#), the rejection of the null hypothesis suggests the potential existence of a long-term relationship, particularly in the presence of an asymmetric effect. Wald introduced a hypothesis test for discerning symmetric or asymmetric effects, which involves the computation of the coefficient of long-run asymmetry:

$$\begin{cases} \frac{-\phi_{12}^+}{\rho} = L_{M_1^+} \\ \frac{-\phi_{22}^-}{\rho} = L_{M_1^-} \end{cases}$$

The test examining the long-run effect hypothesis is as follows:

$$\begin{cases} H_0: \frac{-\phi_{11}^+}{\rho} = \frac{-\phi_{12}^-}{\rho} \rightarrow \text{symmetric effect of } X_{t-1} \text{ on } y_t \text{ in long-run} \\ H_a: \frac{-\phi_{11}^+}{\rho} \neq \frac{-\phi_{12}^-}{\rho} \rightarrow \text{asymmetric effect of } X_{t-1} \text{ on } y_t \text{ in long-run} \end{cases}$$

The test examining the short-run effect hypothesis is as follows:

$$\begin{cases} H_0: \frac{-\alpha_{21}^+}{\alpha_1} = \frac{-\alpha_{22}^-}{\alpha_1} \rightarrow \text{symmetric effect of } X_{t-1} \text{ on } y_t \text{ in short-run} \\ H_a: \frac{-\alpha_{21}^+}{\alpha_1} \neq \frac{-\alpha_{22}^-}{\alpha_1} \rightarrow \text{asymmetric effect of } X_{t-1} \text{ on } y_t \text{ in short-run} \end{cases}$$

4. Empirical results and Hypotheses Validation

4.1 Descriptive statistics

[Table 3](#) presents the descriptive statistics of the green attention index, green and conventional bonds.

Table 3. Descriptive statistics of green and conventional bonds returns and green attention index

		Mean	Median	Maximum	Minimum	Std. dev.	Skewness	Kurtosis	Jarque-Bera	Probability
Green Bonds	S&P GREEN BOND INDEX	-0.002758	-4.22E-05	0.069538	-0.070821	0.020751	-0.361438	5.150804	22.09568	0.000016
	S&P GREEN BND SELECT INDEX	-0.001180	0.000888	0.035667	-0.050221	0.013909	-1.109665	5.799734	54.77857	0.000000
	S&P US MUNI GREEN BOND INDEX	-0.001159	0.000924	0.050657	-0.069842	0.016549	-0.788522	5.703776	42.04750	0.000000
Conventional Bonds	S&P 500 COMPOSITE	0.008035	0.013128	0.126844	-0.125119	0.045059	-0.362364	3.481352	3.248492	0.197060
	S&P 500 ENERGY BOND INDEX	-0.002133	0.054671	3.154193	-3.081910	0.986824	-0.079753	3.535607	0.054671	3.154193
	S&P 500 FINANCIALS BOND INDEX	-0.001273	-0.000667	0.037932	-0.047004	0.014600	-0.478786	4.650345	15.62416	0.000405
Green attention index	S&P 500 BOND INDEX	-0.001297	-0.000256	0.044603	-0.062587	0.017916	-0.495380	4.804873	18.19311	0.000112
		1.379365	-0.080377	138.3419	-17.69449	14.45072	8.341759	79.95138	26607.71	0.000000

From [Table 3](#), the results indicate that all series exhibit a negative mean value, except for S&P 500 COMPOSITE and Green Attention Index (GAI). Among these, the highest mean value is observed in GAI, while the lowest is seen in the S&P GREEN BOND INDEX. The skewness statistic is negative for both green and conventional bonds, suggesting left-tailed return distributions. However, for GAI, the skewness statistic is positive, indicating a longer right tail in its distribution. All variables display positive kurtosis, indicating a leptokurtic distribution. This phenomenon is particularly prominent in the green attention index, where the tails of the distribution are thicker compared to a normal distribution, leading to the frequent occurrence of extreme values. Contrastingly, among all bonds, the S&P 500 ENERGY BOND INDEX exhibits lower stability, as evidenced by its higher kurtosis value compared to other bonds. Consequently, the Jarque–Bera normality test confirms that all bonds and green attention index deviate significantly from a normal distribution. These findings highlight the suitability of nonlinear models, such as the NARDL framework, to capture asymmetric and extreme movements in both green and conventional bond returns.

[Table 4](#) displays the correlation matrix depicting the relationships among variables during the bull regime (Panel A) and the bear regime (Panel B).

The findings unveil that conventional bonds showcase a weak, negative correlation with the green attention index in both bullish and bearish market phases. This contradicts [Kamal and Hassan's \(2022\)](#) findings, which suggest a positive relationship between S&P500 stocks and the ICEA in both market conditions. In contrast, green bonds display a weak, positive correlation with the green attention index across both market regimes. This diverges from the conclusions drawn by [Kamal and Hassan \(2022\)](#), who found an insignificant relationship between green bonds and the ICEA in both regimes. This suggests that green bonds may provide limited but positive diversification benefits, while conventional bonds do not consistently align with shifts in green attention.

[Table 5](#) presents unit root tests conducted in the bull (Panel A) and bear (Panel B) regimes. The analysis indicates that certain variables exhibit stationarity at their levels, while others show stationarity in their differences. This signifies a combination of $I(1)$ and $I(0)$ characteristics within the underlying regressions. In the bull regime, the S&P GREEN BND SELECT INDEX, S&P 500 FINANCIALS BOND INDEX, and S&P 500 BOND INDEX are stationary at their levels, while the remaining bonds and the green attention index display stationarity in differences ($I(1)$). However, in the bear regime, all bonds exhibit stationarity, regardless of being at level or in difference. These mixed properties justify the use of NARDL, which accommodates variables with different integration orders and enables the estimation of long- and short-term asymmetric effects.

4.2 N-ARDL estimation results

4.2.1 The long-term relationship between green attention index on green and conventional bonds. [Table 6](#) illustrates the long-run asymmetric Effects of Green and Conventional Bonds on the Green Attention Index for the bull (Panel A) and bear (Panel B) regimes.

We can see from [Table 6](#) that, during a bullish market phase, conventional and green bonds exhibit a notable positive asymmetric impact on GAI. This indicates that the Green Attention Index responds more strongly to increases in bond returns than to decreases, confirming [H1](#): GAI reacts asymmetrically to bond market changes. This result implies that, in the long run, green attention index responds more to the increasing movements of green and conventional index than to the decreasing ones. For example, when the S&P Green Bond Index rises by 1%, the GAI rises by approximately 0.35%, while a decline of the same magnitude has a very limited effect. This asymmetry indicates that the development of bond markets is increasing the appeal of environmental issues for investors, perhaps through wealth effects or an increase in risk appetite. This result is in line with that of [Naeem et al. \(2021\)](#), who suggested that the green bond index might be used as a diversifier in a stock portfolio. This result is therefore

Table 4. Correlation matrix between green and conventional bonds returns and ESG index in the bull and bear regimes

		Green bonds			Conventional bonds				
		S&P GREEN BOND INDEX	S&P GREEN BND SELECT INDEX	S&P US MUNI GREEN BOND INDEX	S&P 500 COMPOSITE	S&P 500 ENERGY BOND INDEX	S&P 500 FINANCIALS BOND INDEX	S&P 500 BOND INDEX	Green attention index
<i>Panel A: bull regime</i>									
Green bonds	S&P GREEN BOND INDEX	1.0000	0.0097	−0.2026	−0.1379	−0.0894	0.0524	0.0010	0.0427
	S&P GREEN BND SELECT INDEX	0.0097	1.0000	−0.0616	−0.0257	−0.1631	−0.0064	−0.0892	0.1294
	S&P US MUNI GREEN BOND INDEX	−0.2026	−0.0616	1.0000	0.1206	0.1790	−0.2327	−0.0003	0.0230
Conventional bonds	S&P 500 COMPOSITE	−0.1379	−0.0257	0.1206	1.0000	0.0120	−0.0350	−0.0034	−0.1843
	S&P 500 ENERGY BOND INDEX	−0.0894	−0.1631	0.1790	0.0120	1.0000	−0.0972	−0.0202	−0.0369
	S&P 500 FINANCIALS BOND INDEX	0.0524	−0.0064	−0.2327	−0.0350	−0.0972	1.0000	0.0758	−0.2152
	S&P 500 BOND INDEX	0.0010	−0.0892	−0.0003	−0.0034	−0.0202	0.0758	1.0000	−0.0513
	Googling ESG index	0.0427	0.1294	0.0230	−0.1843	−0.0369	−0.2152	−0.0513	1.0000
<i>Panel B: bear regime</i>									
Green bonds	S&P GREEN BOND INDEX	1.0000	−0.2164	−0.0570	−0.0130	0.0022	−0.0733	0.0050	0.0055
	S&P GREEN BND SELECT INDEX	−0.2164	1.0000	−0.0123	0.0407	−0.0548	0.0633	−0.1099	0.0202
	S&P US MUNI GREEN BOND INDEX	−0.0570	−0.0123	1.0000	−0.0598	−0.0185	−0.1102	−0.1082	0.0552
Conventional bonds	S&P 500 COMPOSITE	−0.0130	0.0407	−0.0598	1.0000	0.1127	−0.0074	−0.0292	−0.0682
	S&P 500 ENERGY BOND INDEX	0.0022	−0.0548	−0.0185	0.1127	1.0000	0.0754	0.0826	−0.0909
	S&P 500 FINANCIALS BOND INDEX	−0.0733	0.0633	−0.1102	−0.0074	0.0754	1.0000	−0.0493	−0.2765
	S&P 500 BOND INDEX	0.0050	−0.1099	−0.1082	−0.0292	0.0826	−0.0493	1.0000	−0.0488
Green attention index		0.0055	0.0202	0.0552	−0.0682	−0.0909	−0.2765	−0.0488	1.0000

Table 5. Break point unit root test in the bull and bear regimes

		In level	<i>p</i> -value	In difference	<i>p</i> -value	Integration order
<i>Panel A: Bull regime</i>						
Green Bonds	S&P GREEN BOND INDEX	−4.3558	0.5329	−22.1756**	<0.05	I(1)
	S&P GREEN BND SELECT INDEX	−4.3530**	<0.05	−22.1540	0.9112	I(0)
	S&P US MUNI GREEN BOND INDEX	−2.1869	0.2167	−20.8581*	<0.01	I(1)
	S&P 500 COMPOSITE	−1.1183	0.2568	−26.6339*	<0.01	I(1)
Conventional Bonds	S&P 500 ENERGY BOND INDEX	−5.0634	0.8778	20.4822**	<0.05	I(1)
	S&P 500 FINANCIALS BOND INDEX	−4.4730*	<0.01	−20.1942	0.2346	I(0)
	S&P 500 BOND INDEX	−5.7555*	<0.01	−21.3185	0.3115	I(0)
	Green attention index	−4.5964	0.3041	−0.7546**	<0.05	I(1)
<i>Panel B: Bear regime</i>						
Green Bonds	S&P GREEN BOND INDEX	−5.1161*	<0.01	−20.0092	0.4993	I(0)
	S&P GREEN BND SELECT INDEX	−2.2172	0.8057	−31.0701*	<0.01	I(1)
	S&P US MUNI GREEN BOND INDEX	−7.1502*	<0.01	−22.0811	0.5182	I(0)
	S&P 500 COMPOSITE	−3.6249*	<0.01	−31.9306	2.0021	I(0)
Conventional Bonds	S&P 500 ENERGY BOND INDEX	−4.6668	0.3258	−30.8677*	<0.01	I(1)
	S&P 500 FINANCIALS BOND INDEX	−5.6041	1.5233	−30.5243*	<0.01	I(1)
	S&P 500 BOND INDEX	−3.6387	2.8011	−20.5919*	<0.01	I(1)
	Green attention index	−3.6798	0.8896	−33.1258**	<0.05	I(1)

Note(s): *,**respective significances at the 1%, 5%

aligned with that of [Wei \(2021\)](#), who indicated that both green bonds and clean energy stocks provide risk diversification benefits for investors with dirty energy stocks.

In examining the bear regime, our analysis revealed the negative effect of both green and conventional bonds is higher than the positive one. This result means that green attention index responds more to the decreasing movements of both green and conventional bonds in the long run. For example, 1% decline in conventional bond yields (S&P 500 Composite) increases the GAI by approximately 0.86%, while a comparable increase has a negligible effect. This supports [H2](#): the impact of GAI on bond markets is regime-dependent, with stronger responses observed during bearish periods. This pattern reflects a shift in investor preferences towards sustainable and socially responsible investments in times of heightened market stress. This phenomenon reinforces the perception that green attention measures play a crucial role not only in sustainable investing but also as a refuge during market downturns, positioning them as a valuable risk management tool for investors seeking stability and sustainability within their portfolios. This result is therefore aligned with that of [Arif et al. \(2022\)](#), who suggested that the green bond index emerges as a significant hedging and safe-haven asset for long-term

Table 6. The long-run asymmetric effects of green and conventional bonds on the green attention index for the bull and bear regimes

Green attention index		
<i>Panel A: Bull regime</i>		
Green Bonds	S&P GREEN BOND INDEX	
	+	0.3529 (0.0344)
	–	0.1869 (0.3935)
	S&P GREEN BND SELECT INDEX	
	+	0.2743 (0.8466)
	–	0.0634 (0.0913)
	S&P US MUNI GREEN BOND INDEX	
	+	0.4729 (0.4528)
	–	–0.7555 (0.0572)
	S&P 500 COMPOSITE	
Conventional Bonds	+	0.1183 (0.0000)
	–	–0.3557 (0.0327)
	S&P 500 ENERGY BOND INDEX	
	+	0.0010 (0.0408)
	–	–0.3727 (0.5277)
	S&P 500 FINANCIALS BOND INDEX	
	+	0.4746 (0.3882)
	–	0.0854 (0.6015)
	S&P 500 BOND INDEX	
	+	0.4463 (0.5557)
	–	–0.8411 (0.0025)
<i>Panel B: Bear regime</i>		
Green Bonds	S&P GREEN BOND INDEX	
	+	–0.8497 (0.0549)
	–	0.2127 (0.6754)
	S&P GREEN BND SELECT INDEX	
	+	0.2384 (0.5719)
	–	0.4287 (0.0879)
	S&P US MUNI GREEN BOND INDEX	
	+	–0.5138 (0.2292)
	–	0.4173 (0.0188)
	S&P 500 COMPOSITE	
Conventional Bonds	+	–0.0493 (0.0000)
	–	0.8567 (0.0537)
	S&P 500 ENERGY BOND INDEX	
	+	0.0725 (0.0825)
	–	0.3727 (0.5287)
	S&P 500 FINANCIALS BOND INDEX	
	+	–0.5379 (0.2473)
	–	0.0575 (0.0753)
	S&P 500 BOND INDEX	
	+	0.1213 (0.0996)
	–	0.2455 (0.4021)

investors of conventional financial assets. It also contradicts the results of [Boujelbène-Abbes et al. \(2023\)](#) who found that green bonds may serve as a potential diversifier asset at different time horizons.

Before delving deeper into the analysis, the goal is to understand the bidirectional relationship between the green attention index and both green and conventional bonds, [Table 5](#) explores the long-run asymmetric Effects of Green Attention Index on the Green and Conventional Bonds for the bull and bear regimes.

From [Table 7](#), we can conclude that in a bullish market, the green attention index notably influences green and conventional bonds. For example, a 1% rise in GAI increases the yield on green bonds by 0.5% and the yield on conventional bonds by between 0.13% and 0.78%, depending on the index. This indicates that emphasizing sustainability as a positive signal for bond markets during optimistic periods, potentially due to investor confidence or perceived lower risk profiles. In bear markets, declines in GAI trigger larger negative responses in bond returns, emphasizing its market-sensitive and informational function. [H3](#) is partially confirmed, as green bonds demonstrate conditional hedging and safe-haven properties primarily in bearish periods.

During the analysis of the bear market phase, our findings highlight a more substantial negative impact from green attention index compared to their positive influence. This indicates that the green and conventional bonds demonstrate a stronger response to the declining trends of the green index attention over the long term. In this context, a reduction in the green attention index is considered an aggravating negative signal, which could reflect a more general loss of confidence or extreme risk aversion affecting all asset classes.

Overall, these findings highlight the bidirectional and regime-dependent relationship between GAI and green/conventional bonds. [Tables 6](#) and [7](#) confirm [H1](#) (asymmetric reactions), [H2](#) (regime dependence), and partially confirm [H3](#) (conditional safe-haven role of green bonds), while emphasizing that GAI serves mainly as an environmental information signal rather than a hedging tool.

4.2.2 The short-run effect between green attention index on green and conventional bonds. [Table 8](#) displays the results regarding the Short-run asymmetric Effects of Green and Conventional Bonds on the Green Attention Index during both bullish (Panel A) and bearish (Panel B) market conditions. Meanwhile, [Table 9](#) illustrates the Short-run asymmetric Effects of Green Attention Index Green on the Conventional Bonds during both bullish (Panel A) and bearish (Panel B) market scenarios.

From [Table 8](#) and [Table 9](#), we can infer that the coefficient in the co-integration equation signifies the presence of a long-term or equilibrium relationship between the variables. The error correction term pertains to the impact of the previous period's deviation from the long-term equilibrium, known as the error, on its short-term dynamics of the dependent variable. Notably, all error correction terms whether for the bull or bear regime exhibit a statistically significant negative correlation.

The short-term results ([Table 8](#)) show that negative shocks on green and conventional bonds have a statistically significant impact on the Green Attention index, while positive shocks produce a weaker or insignificant effect. This finding confirms [H1](#) in the short run, as the response of the Green Attention Index to bond market movements is clearly asymmetric. This asymmetry is observed in both market regimes (higher coefficients in absolute terms during bearish phases), confirming the presence of marked non-linearity and regime dependence. This provides additional confirmation of [H2](#), demonstrating that the GAI-bond nexus is regime-dependent even in the short term.

From an economic perspective, these results indicate that bonds, in particular green bonds, play an effective hedging role against fluctuations in environmental awareness. The stronger reaction of the Green Attention Index to negative shocks suggests that when bond yields deteriorate, investors place greater importance on environmental considerations, thereby reinforcing the safe-haven role of bonds in times of uncertainty, particularly during bear markets. These results support [H3](#), confirming the conditional hedging and safe-haven role of green bonds during periods of market stress. This interpretation is consistent with the work of [Reboredo \(2018\)](#) and [Broadstock and Cheng \(2019\)](#), which highlight the diversification and safe-haven benefits of green bonds, as well as with [Imran and Ahad \(2023\)](#), who show that these properties persist in both normal and crisis periods.

The analysis in [Table 9](#) suggests that in the short term and in bullish or bearish market conditions, the Green Attention Index has a positive asymmetric impact on conventional bonds and green bonds. This implies increased responsiveness of both bond types to short-

Table 7. The Long-run asymmetric effects of green attention index green on the conventional bonds for the bull and bear regimes

		Green bonds						Conventional bonds							
		S&P GREEN BOND INDEX		S&P GREEN BND SELECT INDEX		S&P US MUNI GREEN BOND INDEX		S&P 500 COMPOSITE		S&P 500 ENERGY BOND INDEX		S&P 500 FINANCIALS BOND INDEX		S&P 500 BOND INDEX	
<i>Panel A: Bull regime</i>															
Green attention index	+	0.4968	(0.000)	0.3699	(0.9536)	0.7821	(0.4698)	0.1288	(0.0000)	0.0028	(0.0966)	0.4861	(0.0012)	0.7712	(0.0055)
	−	0.2234	(0.5964)	0.089	(0.5238)	0.4888	(0.0332)	0.6987	(0.0247)	0.8636	(0.5332)	0.0955	(0.7018)	0.8957	(0.0057)
<i>Panel B: Bear regime</i>															
Green attention index	+	−0.8955	(0.0625)	−0.8102	(0.5025)	−0.2151	(0.0002)	−0.0335	(0.0000)	−0.0825	(0.0025)	−0.6352	(0.2666)	−0.3318	(0.0002)
	−	0.3313	(0.8150)	0.4025	(0.0869)	0.1298	(0.0254)	−0.7798	(0.0002)	−0.2144	(0.5874)	−0.0858	(0.0000)	0.6436	(0.4205)

Table 8. The Short-run asymmetric effects of green and conventional bonds on the green attention index for the bull and bear regimes

	Green bonds				Conventional bonds				X = S&P 500					
	X = S&P GREEN BOND INDEX		X = S&P GREEN BND SELECT INDEX		X = S&P US MUNI GREEN BOND INDEX		X = S&P 500 composite		X = S&P 500 ENERGY BOND INDEX		FINANCIALS BOND INDEX		X = S&P 500 BOND INDEX	
Panel A: Bull Regime														
ARDL model	(1,0,0,0,0)		(1,0,0,0,0)		(1,0,0,0,0)		(1,0,0,0,0)		(1,0,0,0,0)		(1,0,0,0,0)		(1,0,0,0,0)	
cointEq(−1)	−0.061681	(0.0000)	−0.074437	(0.0002)	−0.0128745	(0.0000)	−0.0774544	(0.0000)	−0.0990213	(0.0003)	−0.0118335	(0.0000)	−0.0844719	(0.0000)
dy(−1)	0.040680	(0.0396)	0.0156007	(0.04284)	0.0184190	(0.09406)	0.013618	(0.0917)	0.0196327	(0.02396)	0.055795	(0.0327)	0.011396	(0.09385)
dx1p	0.0317375	(0.2135)	0.0163370	(0.2712)	−0.037389	(0.05121)	−0.009700	(0.09416)	−0.206382	(0.02135)	−0.0435296	(0.0344)	0.007748	(0.9583)
dx1p(−1)	0.036634	(0.7687)	0.0164171	(0.03131)	−0.310292	(0.08919)	−0.107860	(0.03074)	−0.029088	(0.07687)	−0.186925	(0.03935)	0.080701	(0.04264)
Dx1n	0.034499	(0.0736)	0.005195	(0.1541)	−0.047020	(0.01308)	0.009802	(0.108694)	−0.002634	(0.08489)	0.076045	(0.05379)	−0.076432	(0.08240)
DW statistic	1.940574		1.952309		1.957862		1.981710		1.967857		2.123096		2.085626	
AIC	8.253857		2.840323		8.367055		2.939304		3.138455	3.138455	8.350856		2.883741	
SIC	8.486888		3.202815		8.729547		3.198227		3.425024	3.425024	8.950045		3.142664	
F- statistic	14.88488**		10.19312**		8.445797*		8.407269*		11.50571*		6.240168**		8.358927*	
Panel B: Bear Regime														
ARDL model	(1,0,0,0,0)		(1,0,0,0,0)		(1,0,0,0,0)		(1,0,0,0,0)		(1,0,0,0,0)		(1,0,0,0,0)		(1,0,0,0,0)	
cointEq(−1)	−0.081437	(0.0000)	−0.00882	(0.0000)	−0.079230	(0.0000)	−0.046820	(0.0000)	−0.0987900	(0.0000)	−0.0134983	(0.0000)	−0.053042	(0.0000)
dy(−1)	0.0216149	(0.0928)	0.0243590	(0.01539)	0.061609	(0.05724)	0.091812	(0.0525)	0.003385	(0.09816)	0.0266955	(0.0963)	0.017176	(0.09138)
dx1p	0.0215416	(0.0903)	−0.0230955	(0.01750)	−0.059639	(0.05891)	0.0101189	(0.04832)	−0.001015	(0.09945)	0.0262567	(0.0986)	−0.007357	(0.09629)
dx1p(−1)	0.020384	(0.0840)	0.094709	(0.03572)	−0.187875	(0.0685)	−0.015388	(0.08826)	−0.007006	(0.09474)	0.0143058	(0.1552)	−0.017568	(0.08665v
Dx1n	0.058864	(0.0818)	0.672198	(0.6255)	−0.000117	(0.04194)	0.079522	(0.05033)	−0.509950	(0.534347)	0.065901	(0.07503)	−0.086517	(0.067863)
DW statistic	2.001148		2.010716		1.878878		1.944138		2.013460		2.039852		1.977552	
AIC	5.933524		6.115115		5.802516		6.144084		6.206376		6.468305		6.147157	
SIC	6.192447		6.348145		6.061439		6.403006		6.465299		6.314202		6.406080	
F- statistic	9.095972**		11.03510*		12.78988*		14.46889**		10.27147*		12.32057*		14.39345**	
Note(s): The probability values given in parentheses () ; y presents the green attention index; *, and ** indicates that the model is globally significant in 10% and 5% level														

Table 9. The short-run asymmetric effects of green attention index green on the conventional bonds for the bull and bear regimes

X = green attention index		
<i>Panel A: Bull Regime</i>		
ARDL model	(1,0,0,0,0)	
cointEq(−1)	−0.033926	(0.0000)
y ₁ (−1)	0.075616	(0.0327)
y ₂ (−1)	0.154014	(0.0344)
y ₃ (−1)	0.058089	(0.3935)
y ₄ (−1)	0.079776	(0.2836)
y ₅ (−1)	0.482226	(0.6310)
y ₆ (−1)	−0.094152	(0.8466)
y ₇ (−1)	−0.0318472	(0.1913)
dx1p	0.054555	(0.4528)
dx1p(−1)	0.930623	(0.0572)
Dx1n	0.006409	(0.2223)
DW statistic	2.239164	
AIC	8.070130	
SIC	7.081058	
F- statistic	12.634452*	
<i>Panel B: Bear Regime</i>		
ARDL model	(1,0,0,0,0)	
cointEq(−1)	−0.067740	(0.9927)
dy(−1)	−0.024344	(0.2879)
y ₁ (−1)	0.091874	(0.0408)
y ₂ (−1)	0.025836	(0.5277)
y ₃ (−1)	−0.004344	(0.3882)
y ₄ (−1)	0.078723	(0.6015)
y ₅ (−1)	−0.050582	(0.5557)
y ₆ (−1)	−0.015224	(0.0025)
y ₇ (−1)	0.047335	(0.8386)
dx1p(−1)	0.077709	(0.5645)
Dx1n	0.006930	(0.3909)
DW statistic	2.309854	
AIC	9.558324	
SIC	6.226536	
F- statistic	14.679811**	
Note(s): The probability values given in parentheses () ; y ₁ = S&P GREEN BOND INDEX; y ₂ = S&P GREEN BND SELECT INDEX; y ₃ = S&P US MUNI GREEN BOND INDEX; y ₄ = S&P 500 composite; y ₅ = S S&P 500 ENERGY BOND INDEX; y ₆ = S&P 500 FINANCIALS BOND INDEX; y ₇ = S&P 500 BOND INDEX; *, and ** indicates that the model is globally significant in 10% and 5% level		

term increases in the Green Attention Index, as indicated in particular by the consistently negative significance of all error correction terms. Consequently, these results suggest that the GAI’s influence on bond markets is predominantly transitory. From an economic perspective, these results show that the Green Attention Index functions primarily as a means of disseminating environmental information, rather than as a hedging or safe-haven asset for bonds. Therefore, while H2 remains confirmed due to regime-sensitive reactions, H3 is only partially supported in the short run, since GAI itself does not function as a stable safe-haven asset for bonds but rather as a short-term informational driver.

In the subsequent estimation phase, Brown *et al.*’s work (1975) is utilized to assess parameter and variance stability within the specified model. The findings presented in Figure 3 for the bull regime and Figure 4 for the bear regime reveal consistent parameter stability under cumulative sum (CUSUM) testing at a 5% significance level. These results are corroborated

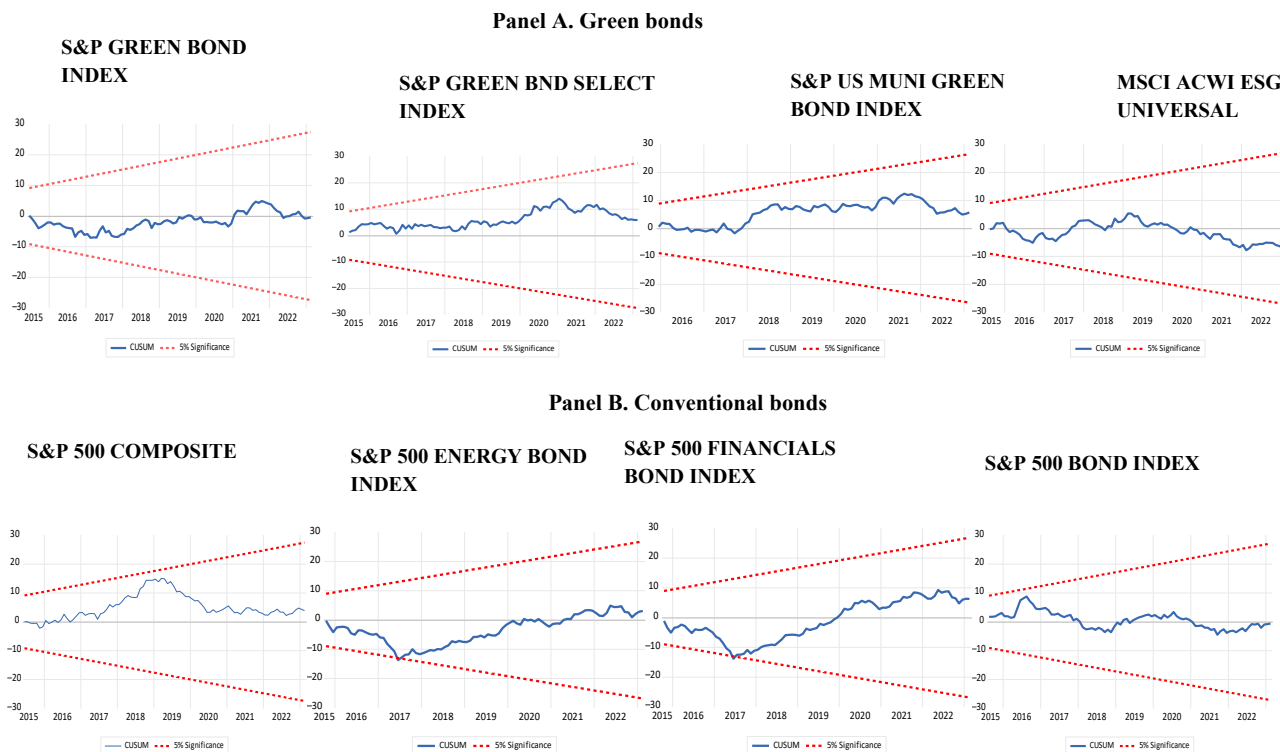


Figure 3. Cumulative sum of recursive residuals in the bull regime

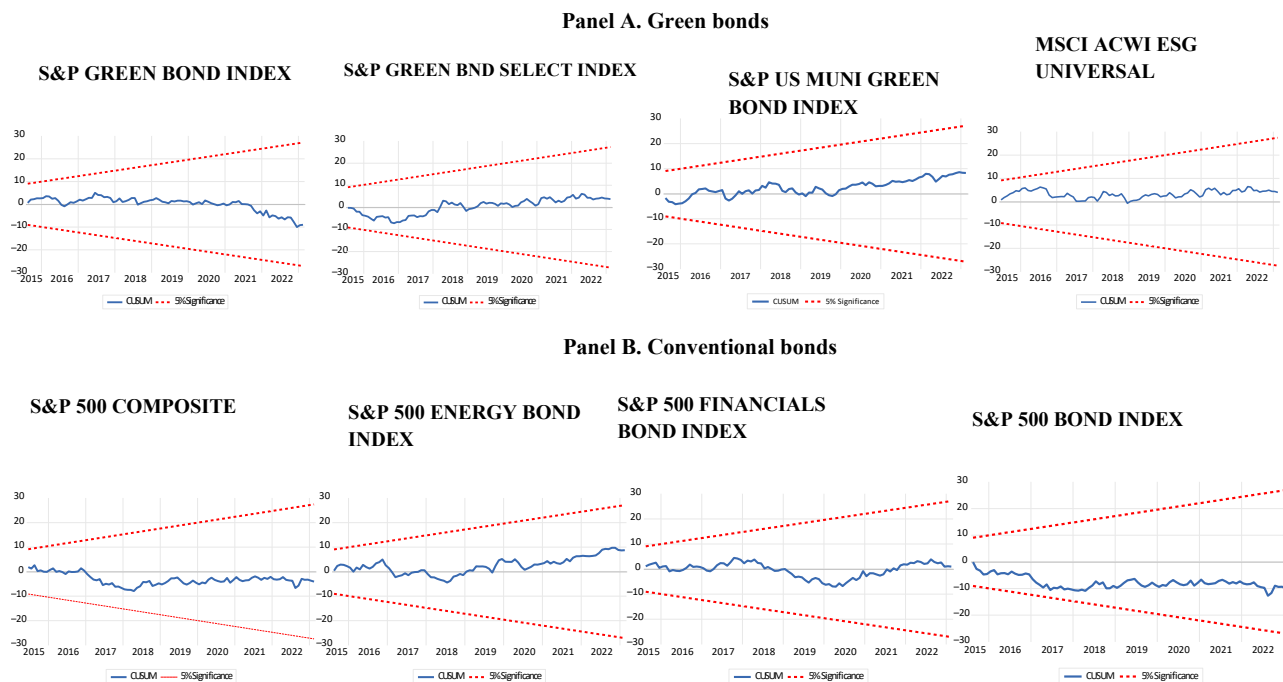


Figure 4. CUSUM in the bear regime

by the observed stability of the estimated parameters across both [Figures 3](#) and [4](#). This is because the individual Cusums do not cross the intervals. Notably, the NARDL model (1, 0, 0, 0, 0) demonstrates overall stability, with the estimated lines consistently within the critical boundaries at a 5% significance level. This stability analysis further reinforces [H1](#) and [H2](#), as the asymmetric and regime-dependent relationships identified in the short-run estimations are not driven by structural instability or model misspecification.

4.2.3 Dynamic green attention index adjustments to green bonds and conventional bonds variations. [Figure 5](#) depicts the variation of dynamic multiplier adjustments for the green attention index, green and conventional bonds to balance long-term positive and negative shocks in the bull regime. Similarly, [Figure 6](#) illustrates these adjustments in the bear scenario.

These multipliers demonstrate how both green and conventional returns adjust symmetrically or asymmetrically towards their new long-term equilibrium after a positive or negative unitary variation in the green attention index. The positive and negative change curves illustrate how the green attention index adapts to fluctuations in green and conventional bonds over a specific forecasted period within both bullish and bearish market conditions. Meanwhile, the asymmetry curve represents the combined linear effect of dynamic multipliers associated with positive and negative variations in the green attention index.

The positive curve (blue line) and the dashed black line indicate how adjustments to positive and negative shocks differ at a specific forecast horizon. The dashed blue line, representing the asymmetry curve, shows the variance between the dynamic multipliers linked to positive and negative shocks for both green and conventional returns. Additionally, the 95% confidence interval is depicted by the lower (red line) and upper (black line) bands, offering a gauge of the statistical significance of asymmetry across horizons. When the zero line falls between the lower and upper bands, it suggests that the asymmetric effects of green and conventional returns on the green attention index lack significance at the 5% level.

[Figures 5](#) and [6](#) illustrate the adjustment pattern of the green attention index to positive and negative unitary shocks of both green and conventional bonds in the bull and bear regimes. The graphs in these figures confirm the existence of the negative impacts of green and conventional bonds on the green attention index. More specifically, the dynamic multipliers converge toward the long-term equilibrium after a short adjustment phase, indicating a stable asymmetric correction mechanism in both regimes. In fact, *Haut du formulaire* the asymmetric path shows that the effect of a negative shock in green and conventional bonds dominates that of a positive shock in the short run, thus confirming previous results about the greater short-run effect coefficients of green and conventional bonds, as indicated in [Table 5](#). This dominance of negative shocks is more pronounced in the bear regime, highlighting stronger regime dependence and reinforcing the non-linear nature of the relationship. Moreover, this negative asymmetric relationship between green and conventional bonds and green attention index leads to the conclusion that green and conventional bonds can act as a good hedging instrument or a safe haven against the stock markets. This similarity aligns with the conclusions drawn by [Huang et al. \(2022\)](#), who found that the green bonds function as both a strong safe haven and a strong hedge for the crude oil market. Additionally, [Dong et al. \(2023\)](#) concluded that both conventional and green bonds exhibit a safe-haven function when GPR levels are high, while green bonds outperform conventional bonds as a safe haven when EPU and CPU levels are high.

The adjustment patterns further reinforce that green and conventional bonds can act as hedges or safe havens against market fluctuations, particularly under bearish conditions. Therefore, Hypothesis [H1](#), which posits the existence of asymmetric long- and short-run effects between bonds and the Green Attention Index, is confirmed. Similarly, Hypothesis [H3](#), which states that green and conventional bonds serve as hedging and safe-haven instruments, is also confirmed, especially under bearish market conditions where negative shocks dominate.

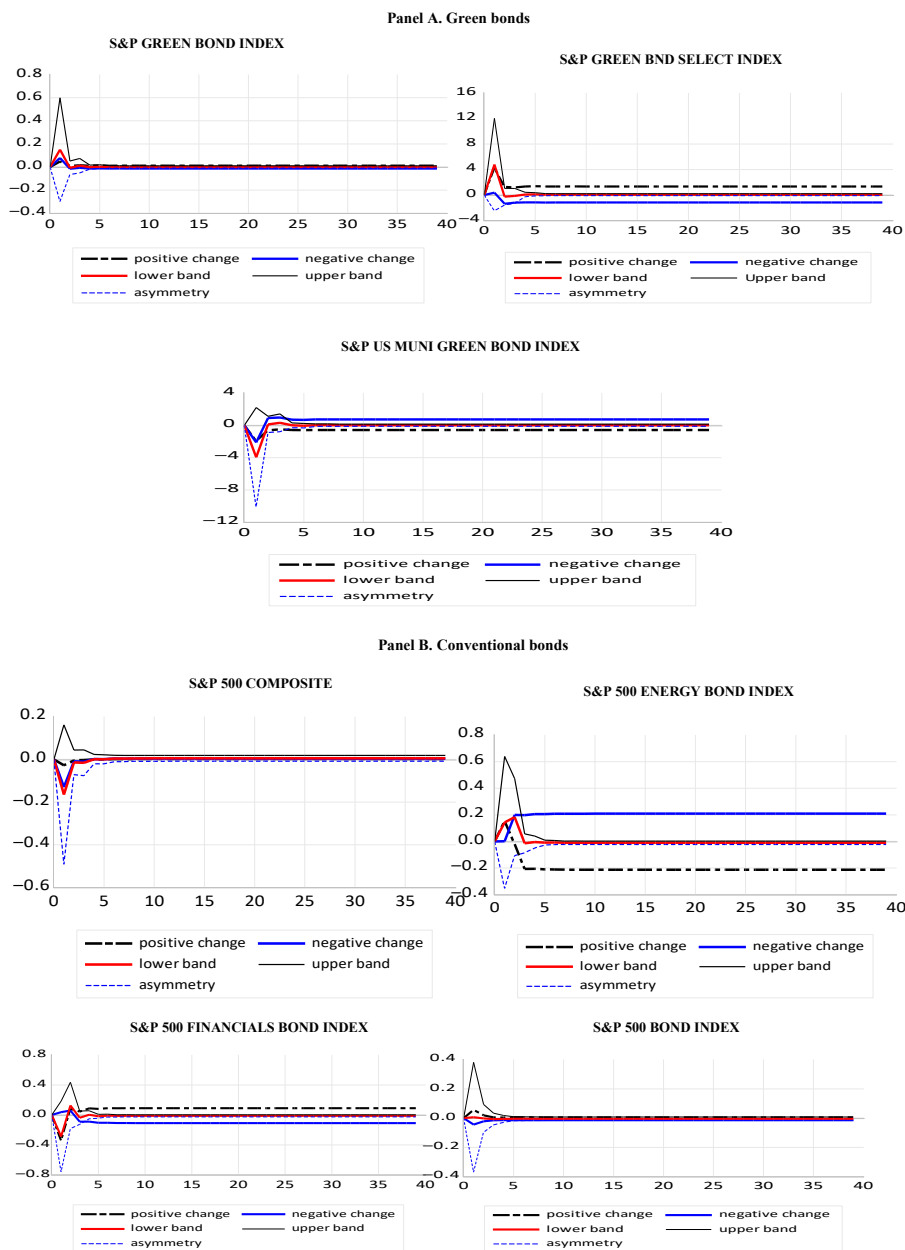


Figure 5. Dynamic green attention index adjustments to green bonds and conventional bonds variations in the bull regime

4.3 Diagnostic and stability tests

To validate the robustness of the NARDL estimations, we report the results of residual diagnostic and stability tests in [Table 10](#).

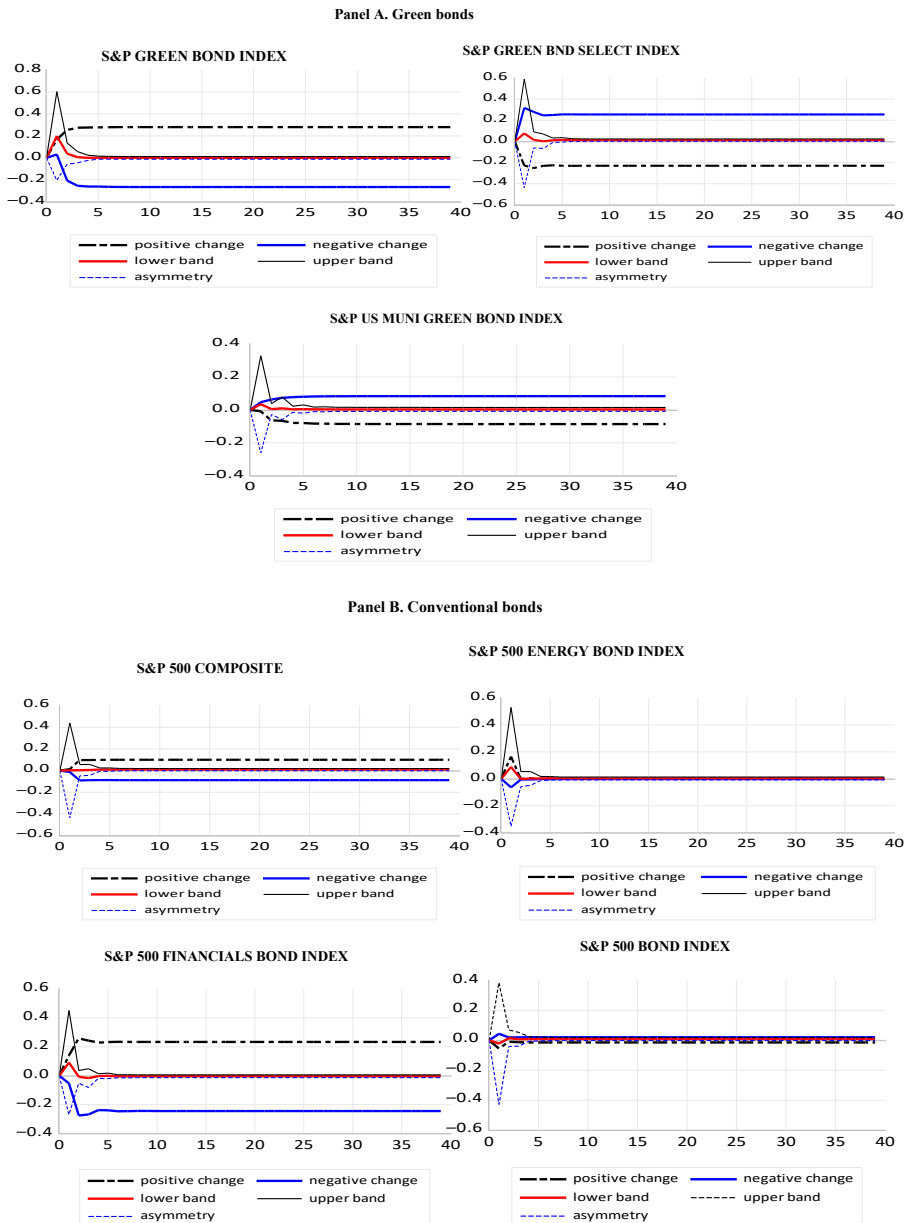


Figure 6. Dynamic green attention index adjustments to green bonds and conventional bonds variations in the bear regime

The results strongly support the adequacy and robustness of the estimated model. Regarding serial correlation, the Breusch–Godfrey LM statistic (1.842; p -value = 0.168) indicates that the null hypothesis of no serial correlation cannot be rejected at conventional significance levels. This confirms that the residuals are not autocorrelated, ensuring that the

Table 10. Post-estimation diagnostic and stability tests for the NARDL model

Diagnostic test	Statistic	<i>p</i> -value	Inference
<i>Breusch–Godfrey LM Test</i> (Serial Correlation)	1.842	0.168	Fail to reject $H_0 \rightarrow$ No serial correlation
<i>ARCH Test</i> (Heteroskedasticity)	1.276	0.243	Fail to reject $H_0 \rightarrow$ No ARCH effects
<i>Ramsey RESET Test</i> (Functional Form)	0.954	0.331	Fail to reject $H_0 \rightarrow$ Model correctly specified
<i>CUSUM Stability Test</i>	–	–	Parameters stable (within 5% bounds)
<i>CUSUMSQ Stability Test</i>	–	–	Variance stable (within 5% bounds)
Note(s): H_0 for Breusch–Godfrey: no serial correlation. • H_0 for ARCH: homoskedastic residuals. • H_0 for RESET: correct model specification			

estimated coefficients are efficient and unbiased. Concerning heteroskedasticity, the ARCH test statistic (1.276; p -value = 0.243) fails to reject the null hypothesis of homoskedasticity. This suggests that the variance of the residuals remains stable over time, reinforcing the reliability of the estimated standard errors and test statistics.

The Ramsey RESET test statistic (0.954; p -value = 0.331) also fails to reject the null hypothesis of correct model specification. This finding indicates that the functional form of the model is appropriate and that no major nonlinearities or omitted variables distort the estimated relationships.

Finally, the CUSUM and CUSUMSQ tests confirm parameter and variance stability throughout the sample period. Since the recursive residuals remain within the 5% critical bounds, there is no evidence of structural instability. This suggests that the estimated asymmetric relationships remain stable across different market conditions.

Overall, these diagnostic results confirm that the model is econometrically sound and that the empirical findings can be interpreted with confidence.

5. Conclusion and implications

This study constructs a monthly Green Attention Index (GAI) using Google Trends data and investigates its bidirectional asymmetric relationship with green and conventional bond returns within a nonlinear ARDL framework under distinct bullish and bearish regimes. By combining asymmetry and regime dependence, the analysis provides a more nuanced understanding of how environmental attention interacts with fixed-income markets.

The empirical findings reveal that the relationship between the GAI and bond markets is both asymmetric and state-dependent. In the long run, during bullish market conditions, positive shocks in green and conventional bonds exert stronger effects on the GAI, suggesting that bond market optimism reinforces environmental attention dynamics. In contrast, during bearish phases, negative shocks dominate, indicating that the GAI responds more strongly to adverse bond market movements. These results imply that both green and conventional bonds may exhibit safe-haven characteristics under prolonged market stress, with green bonds demonstrating comparatively stronger defensive properties. In the short run, however, the GAI primarily functions as an informational transmission channel rather than a consistent hedging instrument, as negative shocks from bond markets generate more pronounced immediate responses. Overall, the findings confirm a bidirectional and nonlinear interaction that varies across market regimes.

Beyond the empirical results, this study contributes to the sustainable finance literature by extending attention-based asset pricing theory to fixed-income markets. While most previous research has focused on equity markets, this analysis demonstrates that environmental attention also plays a significant role in shaping bond market dynamics. Moreover, the evidence of asymmetric and regime-dependent effects highlights the importance of adopting

nonlinear frameworks when examining sustainability-driven financial relationships. Ignoring structural market states or shock direction may lead to incomplete interpretations of green asset behavior.

The findings also carry important practical and policy implications. For portfolio managers, recognizing that green bonds display stronger safe-haven characteristics during bearish regimes can improve risk diversification strategies. Investors should therefore incorporate regime-specific dynamics into asset allocation decisions rather than assuming stable hedging properties over time. For policymakers and regulators, the sensitivity of environmental attention to market downturns underscores the importance of transparency, standardized ESG disclosures, and credible green bond certification mechanisms. Strengthening regulatory frameworks may help stabilize investor expectations and reduce informational volatility linked to sustainability concerns. Financial institutions may also benefit from integrating attention-based indicators into their risk management models, particularly during periods of heightened market uncertainty.

Despite these contributions, the study has certain limitations. The Green Attention Index, constructed from Google Trends data, may not fully capture institutional investor sentiment or deeper structural climate risk perceptions. In addition, the analysis relies on aggregate bond indices, which may conceal heterogeneity across maturities, regions, or credit qualities. Finally, although the nonlinear ARDL framework captures asymmetry and regime shifts, it may not fully account for abrupt structural breaks associated with major policy interventions or global crises.

Future research could extend this analysis by incorporating alternative attention proxies such as news-based climate indices or social media sentiment measures. Cross-country comparisons and maturity-specific bond analyses would further enhance understanding of heterogeneous market responses. Moreover, integrating macroeconomic uncertainty indicators or climate policy shocks into a multivariate nonlinear framework could provide deeper insights into the transmission mechanisms between environmental attention and financial markets.

In sum, this study demonstrates that environmental attention and bond markets are linked through complex, asymmetric, and regime-sensitive dynamics. Recognizing these nonlinear interactions is essential for advancing sustainable finance research and for designing more resilient investment and regulatory strategies in an era of increasing climate-related financial risk.

References

- Acharya, V.V., Berner, R., Engle, R.F., Jung, H., Stroebe, J., Zeng, X. and Zhao, Y. (2023), "Climate stress testing", (NBER Working Paper No. 31097), National Bureau of Economic Research.
- Andersson, E., Hoque, M., Rahman, M.L., Uddin, G.S. and Jayasekera, R. (2020), "ESG investment: what do we learn from its interaction with stock, currency and commodity markets?", *International Journal of Finance and Economics*, Vol. 27 No. 3, pp. 3623-3639, doi: [10.1002/ijfe.2341](https://doi.org/10.1002/ijfe.2341).
- Arif, M., Naeem, M.A., Farid, S., Nepal, R. and Jamasb, T. (2022), "Diversifier or more? Hedge and safe haven properties of green bonds during COVID-19", *Energy Policy*, Vol. 168, 113102, doi: [10.1016/j.enpol.2022.113102](https://doi.org/10.1016/j.enpol.2022.113102).
- Banerjee, A., Dolado, J.J. and Mestre, R. (1998), "Error-correction mechanism tests for cointegration in a single-equation framework", *Journal of Time Series Analysis*, Vol. 19 No. 3, pp. 267-283, doi: [10.1111/1467-9892.00091](https://doi.org/10.1111/1467-9892.00091).
- Bert, S. (2006), "Finance as a driver of corporate social responsibility", *Journal of Business Ethics*, Vol. 68, pp. 19-33.
- Bokhtiar Hasan, Md., Mamunur Rashid, Md., Naiem Hossain, Md., Rahman, M.M. and Ruhul Amin, Md. (2023), "Using green and ESG assets to achieve post-COVID-19 environmental sustainability", *Fulbright Review of Economics and Policy*, ISSN: 2635-0173.

- Boujelbène-Abbes, M, Mezghani, T. and Ben Hamadou, F. (2023), "Network connectedness and portfolio hedging of green bonds, stock markets and commodities", *International Journal of Emerging Markets*, doi: [10.1108/IJOEM-02-2023-0160](https://doi.org/10.1108/IJOEM-02-2023-0160).
- Broadstock, D.C. and Cheng, L.T.W. (2019), "Time-varying relation between black and green bond price benchmarks: macroeconomic determinants for the first decade", *Finance Research Letters*, Vol. 29, pp. 17-22, doi: [10.1016/j.frl.2019.02.006](https://doi.org/10.1016/j.frl.2019.02.006).
- Brock, W.A., Dechert, W.D., Scheinkman, J.A. and LeBaron, B. (1996), "A test for independence based on the correlation dimension", *Econometric Reviews*, Vol. 15 No. 3, pp. 197-235, doi: [10.1080/07474939608800353](https://doi.org/10.1080/07474939608800353).
- Brooks, C. and Oikonomou, I. (2018), "The effects of environmental, social and governance disclosures and performance on firm value: a review of the literature in accounting and finance", *The British Accounting Review*, Vol. 50 No. Issue 1, pp. 1-15, doi: [10.1016/j.bar.2017.11.005](https://doi.org/10.1016/j.bar.2017.11.005).
- Brown, R.L., Durbin, J. and Evans, J.M. (1975), "Techniques for testing the constancy of regression relationships over time", *Journal of the Royal Statistical Society: Series B*, Vol. 37 No. 2, pp. 149-192.
- Cappiello, L., Engle, R.F. and Sheppard, K. (2006), "Asymmetric dynamics in the correlations of global equity and bond returns", *Journal of Financial Econometrics*, Vol. 4 No. 4, pp. 537-572, doi: [10.1093/jfinec/nbl005](https://doi.org/10.1093/jfinec/nbl005).
- Chen, X., Chen, Y., Xu, L. and Wen, F. (2023), "Green bond issuance and corporate ESG performance: the perspective of internal attention and external supervision", *Humanities and Social Sciences Communications*, Vol. 10, pp. 1-12, doi: [10.1057/s41599-023-01941-2](https://doi.org/10.1057/s41599-023-01941-2).
- Corbet, S., Meegan, A., Larkin, C., Lucey, B. and Yarovaya, L. (2018), "Exploring the dynamic relationships between cryptocurrencies and other financial assets", *Economics Letters*, Vol. 165, pp. 28-34, doi: [10.1016/j.econlet.2018.01.004](https://doi.org/10.1016/j.econlet.2018.01.004).
- Da, Z., Engelberg, J. and Gao, P. (2015), "The sum of all FEARS investor sentiment and asset prices", *Review of Financial Studies*, Vol. 28 No. 1, pp. 1-32, doi: [10.1093/rfs/hhu072](https://doi.org/10.1093/rfs/hhu072).
- Dong, H., Zhang, L. and Zheng, H. (2023), "Green bonds: fueling green innovation or just a fad?", *SSRN Electronic Journal*, doi: [10.2139/ssrn.4635211](https://doi.org/10.2139/ssrn.4635211).
- Engle, R.F., Giglio, S., Kelly, B.T., Lee, H. and Stroebel, J. (2019), "Hedging climate change news", (NBER Working Paper No. 25734), National Bureau of Economic Research.
- Gillan, S.L., Koch, A. and Starks, L.T. (2021), "Firms and social responsibility: a review of ESG and CSR research in corporate finance", *Journal of Corporate Finance*, Vol. 66, 101889, doi: [10.1016/j.jcorpfin.2021.101889](https://doi.org/10.1016/j.jcorpfin.2021.101889).
- Imran, Z.A. and Ahad, M. (2023), "Safe-haven properties of green bonds for industrial sectors (GICS) in the United States: evidence from Covid-19 pandemic and Global Financial Crisis", *Renewable Energy*, Vol. 210, pp. 408-423, doi: [10.1016/j.renene.2023.04.033](https://doi.org/10.1016/j.renene.2023.04.033).
- Jung, H., Engle, R.F. and Berner, R. (2021, revised 2025), "CRISK: measuring the climate risk exposure of the financial system", (Staff Report No. 977), Federal Reserve Bank of New York.
- Kamal, J.B. and Hassan, M.K. (2022), "Asymmetric connectedness between cryptocurrency environment attention index and green assets", *The Journal of Economic Asymmetries*, Vol. 25, e00240, doi: [10.1016/j.jeca.2022.e00240](https://doi.org/10.1016/j.jeca.2022.e00240).
- Kilic, Y., Destek, M.A., Cevik, E.I., Fatih Bugan, M., Korkmaz, O. and Dibooglu, S. (2022), "Return and risk spillovers between the ESG global index and stock markets: evidence from time and frequency analysis", *Borsa Istanbul Review*, Vol. 22 No. Supplement 2, pp. S141-S156, doi: [10.1016/j.bir.2022.11.015](https://doi.org/10.1016/j.bir.2022.11.015).
- Koo, J.H. (2010), "The current status and future of green finance", Finance VIP series 2010-01.
- Li, Q., Zhang, K. and Wang, L. (2022), "Where's the green bond premium? Evidence from China", *Finance Research Letters*, Vol. 48 No. August 2022, 102950, doi: [10.1016/j.frl.2022.102950](https://doi.org/10.1016/j.frl.2022.102950).
- Matos, P. (2020), *ESG and Responsible Institutional Investing Around the World: A Critical Review*, CFA Institute Research Foundation Literature Reviews, 978-1-944960-97-1.

- Huang, J., Cao, Y. and Zhong, P. (2022), "Searching for a safe haven to crude oil: green bond or precious metals?", *Finance Research Letters*, Vol. 50, 103303, doi: [10.1016/j.frl.2022.103303](https://doi.org/10.1016/j.frl.2022.103303).
- Huang, L., Cao, Y. and Zhu, Y. (2023), "Is there any recovery power for economic growth from green finance? Evidence from OECD member countries", *Economic Change and Restructuring*, Vol. 56 No. 6, pp. 3909-3926, doi: [10.1007/s10644-022-09458-5](https://doi.org/10.1007/s10644-022-09458-5).
- Immel, M., Hachenberg, B., Kiesel, F. and Schiereck, D. (2022), "Green bonds: shades of green and Brown", *Risks Related to Environmental, Social and Governmental Issues (ESG)*.
- Naeem, M.A., Nguyen, T.T.H., Nepal, R., Ngo, Q.T. and Taghizadeh-Hesary, F. (2021), "Asymmetric relationship between green bonds and commodities: evidence from extreme quantile approach", *Finance Research Letters*, Vol. 43, 101983, doi: [10.1016/j.frl.2021.101983](https://doi.org/10.1016/j.frl.2021.101983).
- Perote, J., Vicente-Lorente, J.D. and Zuñiga-Vicente, J.A. (2023), "How reactive is investment in US green bonds and ESG-eligible stocks in times of crisis? Exploring the COVID-19 crisis", *Finance Research Letters*, Vol. 53, 103638, doi: [10.1016/j.frl.2023.103638](https://doi.org/10.1016/j.frl.2023.103638).
- Pesaran, M.H., Shin, Y. and Smith, R.J. (2001), "Bounds testing approaches to the analysis of level relationships", *Journal of Applied Econometrics*, Vol. 16 No. 3, pp. 289-326, doi: [10.1002/jae.616](https://doi.org/10.1002/jae.616).
- Plastun, A., Bouri, E., Gupta, R. and Ji, Q. (2022), "Price effects after one-day abnormal returns in developed and emerging markets: ESG versus traditional indices", *The North American Journal of Economics and Finance*, Vol. 59, 101572, doi: [10.1016/j.najef.2021.101572](https://doi.org/10.1016/j.najef.2021.101572).
- PRI (2021), "What is responsible investment?", available at: <https://www.unpri.org/an-introduction-to-responsible-investment/what-is-responsible-investment/4780> (accessed 31 July 2021).
- Reboredo, J.C. (2018), "Green bond and financial markets: co-movement, diversification and price spillovers", *Energy Economics*, Vol. 74, pp. 38-50, doi: [10.1016/j.eneco.2018.05.030](https://doi.org/10.1016/j.eneco.2018.05.030).
- Reboredo, J.C. and Ugolini, A. (2020), "Price connectedness between green bond and financial markets", *Economic Modelling*, Vol. 88, pp. 25-38, doi: [10.1016/j.econmod.2019.09.004](https://doi.org/10.1016/j.econmod.2019.09.004).
- Romilly, P., Song, H. and Liu, X. (2001), "Car ownership and use in Britain: a comparison of the empirical results of alternative cointegration estimation methods and forecasts", *Applied Economics*, Vol. 33 No. 14, pp. 1803-1818, doi: [10.1080/00036840011021708](https://doi.org/10.1080/00036840011021708).
- Shin, Y., Yu, B. and Greenwood-Nimmo, M. (2014), "Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework", in Horrace, W. and Sickles, R. (Eds), *The Festschrift in Honor of Peter Schmidt: Econometric Methods and Applications*, Springer, pp. 281-314, doi: [10.1007/978-1-4899-8008-3_9](https://doi.org/10.1007/978-1-4899-8008-3_9).
- Tiwari, A.K., Cunado, J., Gupta, R. and Wohar, M.E. (2018), "Volatility spillovers across global asset classes: evidence from time and frequency domains", *The Quarterly Review of Economics and Finance*, Vol. 70, pp. 194-202, doi: [10.1016/j.qref.2018.05.001](https://doi.org/10.1016/j.qref.2018.05.001).
- Trichilli, Y., Abdelhédi, M. and Boujelbène Abbes, M. (2018), "Googling investor's sentiment: powerful measure in conventional and Islamic MENA financial markets", *International Economic Journal*, Vol. 32 No. 3, pp. 454-469, doi: [10.1080/10168737.2018.1522055](https://doi.org/10.1080/10168737.2018.1522055).
- Wang, S. and Wang, D. (2022), "Exploring the relationship between ESG performance and green bond issuance", *Frontiers in Public Health*, Vol. 10, 897577, doi: [10.3389/fpubh.2022.897577](https://doi.org/10.3389/fpubh.2022.897577).
- Wei, K. (2021), "The heterogeneity of the diversification effect of sustainable development goals related exchange-traded funds", *Journal of Sustainable Finance & Investment*, Vol. 14 No. 2, pp. 366-387, doi: [10.1080/20430795.2021.1992336](https://doi.org/10.1080/20430795.2021.1992336).
- Zhang, W., Nakajima, T. and Hamori, S. (2021), "Does ESG index have strong conditional correlations with sustainability-related stock indices?", in *ESG Investment in the Global Economy*, Springer, pp. 21-35.
- Zhang, B. and Wang, Y. (2019), "The effect of green finance on energy sustainable development: evidence from China", *Emerging Markets Finance and Trade*, Vol. 55 No. 12, pp. 3435-3454, doi: [10.1080/1540496X.2019.1695595](https://doi.org/10.1080/1540496X.2019.1695595).

Zhou, X., Tang, X. and Zhang, R. (2020), "Impact of green finance on economic development and environmental quality: a study based on provincial panel data from China", *Environmental Science and Pollution Research*, Vol. 27 No. 16, ISSN: 0944-1344.

Further reading

Alex, P.A., Elie, B.B., Rangan, G.C. and Ji, Q. (2022), "Price effects after one-day abnormal returns in developed and emerging markets: ESG versus traditional indices", *The North American Journal of Economics and Finance*, Vol. 59, 101572.

Goldfeld, S.M. and Quandt, R.E. (1973), "A Markov model for switching regressions", *Journal of Econometrics*, Vol. 1 No. 1, pp. 3-15, doi: [10.1016/0304-4076\(73\)90002-x](https://doi.org/10.1016/0304-4076(73)90002-x).

Hamilton, J.D. (1989), "A new approach to the economic analysis of nonstationary time series and the business cycle", *Econometrica*, Vol. 57 No. 2, pp. 357-384, doi: [10.2307/1912559](https://doi.org/10.2307/1912559).

Liu, M., Guo, T., Ping, W. and Luo, L. (2023), "Sustainability and stability: will ESG investment reduce the return and volatility spillover effects across the Chinese financial market?", *Energy Economics*, Vol. 121, 106674, doi: [10.1016/j.eneco.2023.106674](https://doi.org/10.1016/j.eneco.2023.106674).

Yu, C.A. and Lin, B. (2022), "Quantifying the extreme spillovers on worldwide ESG leaders' equity", *International Review of Financial Analysis*, Vol. 84, 102425.

Corresponding author

Yousra Trichilli can be contacted at: yousratrichilli@yahoo.fr