Corporate Social Responsibility and Environmental Management

WILEY

Corporate Social Responsibility and Environmental Management

RESEARCH ARTICLE OPEN ACCESS

Tracking Climate and Environmental Attention: A News-Based Composite Index

Gianna Figà-Talamanca[1] | Andrea Fronzetti Colladon[2] | Barbara Guardabascio[1] | Ludovica Segneri[3]

[1]Department of Economics, University of Perugia, Italy | [2]Department of Civil, Computer Science and Aeronautical Technologies Engineering, Roma Tre University, Italy | [3]Department of Economics, Society and Politics, University of Urbino, Italy

Correspondence: Gianna Figà-Talamanca (gianna.figatalamanca@unipg.it)

Received: 15 September 2025 | **Revised:** 24 January 2026 | **Accepted:** 22 February 2026

Keywords: climate attention | composite index | text analysis

ABSTRACT

This study introduces the Climate and Environmental Attention Index, a composite indicator that tracks media attention to climate and environmental issues. Based on the Semantic Brand Score, the proposed index extracts significant signals from unstructured text, going beyond traditional measures of word frequency and sentiment. By aggregating semantic scores for keywords related to the green transition, climate impacts, and environmental opportunities, we develop a set of indices suitable to help assess the dynamic relationship between climate-related media attention and economic and financial conditions, providing a useful input for policy analysis.

JEL Classification: Q58, E37, O44

1 | Introduction

Climate change has become a central issue that shapes policy, business, and society. Recent evidence shows that macro-level climate policies influence corporate financial structure, as firms adjust leverage in response to climate adaptation plans. In addition, regulatory bodies respond to the increased perception of climate change by imposing stricter regulations. For example, carbon pricing mechanisms, emissions trading systems, and stringent environmental standards are being implemented worldwide. These regulations not only affect the cost structure of companies, but also influence consumer behavior, as eco-conscious consumers increasingly prefer sustainable products (Herweg and Schmidt 2022; De Marchi et al. 2022).

Firms lagging in climate adaptation and mitigation are increasingly facing higher financing premia (Wang et al. 2024), while investors are progressively incorporating climate risk into their strategies (Ameli et al. 2020).

Although measuring environmental and climate risk is challenging (e.g., Fliegel 2025), several studies have attempted to define a suitable index. Traditional environmental indices, including the *Environmental Performance Index (EPI)* (Block et al. 2024; Yale Center for Environmental Law and Policy 2024), usually refer to physical measures of emissions, biodiversity, or waste management. Others, such as the *Sustainable Society Index* (Van de Kerk and Manuel 2008) and the *Composite Index of Environmental Performance* (García-Sánchez et al. 2015), incorporate economic or social dimensions, providing a broader perspective. In addition, more targeted indices, such as the *Living Planet Index* (Living Planet Index 2024) and the *Ecological Footprint* (Global Footprint Network 2024), focus on biodiversity or emissions, respectively. Although valuable, these indicators are typically available at a low frequency and therefore do not capture real-time changes in climate attention. Previous studies have documented the increasing economic and financial relevance of climate and physical environmental risks (Boykoff 2011; Malik et al. 2022; Jia et al. 2023; Cevik and Gwon 2024; Cisagara 2024; Vestrelli et al. 2024). Their findings reinforce the need for market participants to integrate climate considerations into investment decisions, as climate-related uncertainties continue to shape market dynamics. See Giglio et al. (2021) for a more comprehensive review.

Recent literature suggests that the way investors and economic agents process information is shaped by attention constraints and narrative relevance. Shiller (2020) argues that economic fluctuations are often driven by popular narratives that influence collective behavior. In financial markets, attention to relevant topics, especially when amplified by news coverage, can affect trading volume, asset prices, and volatility (Da et al. 2011; Barber and Odean 2008).

The *Economic Policy Uncertainty* (EPU) pioneered the analysis of newspaper coverage to quantify economic uncertainty (Baker et al. 2016), and is currently the most influential economic index based on media coverage (Gentzkow et al. 2019). In the context of climate change, increased media attention signals shifts regarding policy, regulation, and transition pathways, which are relevant to pricing long-term risks (Pástor et al. 2022; Engle et al. 2020; Giglio et al. 2021). In fact, the news media plays a fundamental role in shaping perceptions of climate change, influencing investor behavior, regulatory responses, and public opinion. Indices like the *Climate Policy Uncertainty (CPU)* (Gavriilidis 2021) and the *ESG-Related Uncertainty Index (ESGUI)* (Ongan et al. 2025) extend the text-based approach to the climate and environmental domains. However, these indices are based only on keyword frequency, with limited attention to the contextual meaning or importance of terms within the broader discourse. Finally, the *Media Climate Change Concern Index (MCCC)*, introduced in Ardia et al. (2023), is designed to proxy unexpected dynamics in climate change concerns.

Contributing to this emerging literature, the present study introduces the *Climate and Environmental Attention Index (CEAI)*, a media-based metric of climate attention derived from news content. The CEAI differs from existing media-based indicators by combining a higher-frequency weekly construction and the semantic centrality of selected keywords rather than solely their frequency, capturing how climate-related themes are positioned and interconnected within public narratives.

We construct clusters of words reflecting three core themes: regulatory challenges (Transition Pillar), physical environmental events (Physical Pillar), and opportunities associated with the green energy transition (Opportunity Pillar). The semantic importance of each word cluster is aggregated through a data-driven weighting scheme based on data envelope analysis (DEA) to effectively measure the depth of climate-related discussions and their time dynamics (Greco et al. 2019; Zhou et al. 2017).

Another feature of our methodology is the distinction between generalist and specialized financial media, as we believe the way news is framed across these outlets can influence individual perceptions and awareness of environmental and climate concerns, according to the theory of Chong and Druckman (2007).

Using vector autoregression models and impulse response functions, we explore the dynamic impact of CEAI metrics on US macroeconomic variables, financial markets, and market volatility and find that they have a significant, albeit sometimes nuanced and short-lived effect, especially when sourced from financial news. An interesting future development of this research is the construction of hedging strategies, based on CEAI, to mitigate the exposure of financial assets to climate events in line with Engle et al. (2020), Giglio et al. (2021).

The paper is structured as follows. Section 2 describes the methodology underlying the proposed index; Section 3 introduces the Climate and Environmental Attention Index, identifying the data sources, explaining the keyword selection process, and providing evidence on the time-varying weighting structure. Section 4 investigates the impact of the index on economic and financial variables using impulse response functions and variance decomposition. Finally, Section 5 summarizes the main findings, discusses policy implications, and suggests directions for future research.

2 | Methodology

Natural Language Processing (NLP) algorithms are traditionally based on dictionaries, frequency measures, and word embeddings (e.g., Hutto and Gilbert 2014; Loughran and McDonald 2011; Mikolov et al. 2013; Pennington et al. 2014). Maibaum et al. (2024) demonstrates, in a recent review, that the above methodologies have been surpassed by topic-modeling algorithms (e.g., Meijer et al. 2014; Li et al. 2021; Frankel et al. 2022). Topic modeling is mostly effective in identifying thematic clusters by assuming a latent probabilistic distribution over documents and words. However, it often overlooks the centrality and relevance of terms within the discourse. Our approach, instead, employs graph-based metrics to assess semantic importance, providing a more nuanced analysis of topic positioning across various media content.

2.1 | Assessing Semantic Importance

We assess the semantic importance of word clusters by applying the Semantic Brand Score (SBS). The SBS is a comprehensive metric that aggregates standardized scores of three core dimensions (*prevalence*, *diversity*, and *connectivity*) to capture the multifaceted role of a term within a discourse network (Colladon 2018), successfully applied in various research fields (Colladon et al. 2019, 2025). Its calculation begins with cleaning unstructured text with standard preprocessing techniques (Porter 2006). The processed corpus of on-line news articles from a specific time frame is then converted into a semantic network G whose nodes N represent words and edges E represent word co-occurrences. This network is used to calculate *diversity* and *connectivity*, while *prevalence* is simply the frequency of a term in the corpus.

Diversity is measured using the distinctiveness centrality (Colladon and Naldi 2020) metric, which captures the extent to which a network node (word) is connected to less connected and therefore more distinctive terms. Its formula is the following:

$$\mathrm{DI}(i) = \sum_{\substack{j=1 \\ j \neq i}}^{N} \log_{10}\left(\frac{N-1}{\deg(j)}\right) I\left(w_{ij} > 0\right) \tag{1}$$

where i is a node (word) in the network, $\deg(j)$ is the number of edges connected to each node (word) adjacent to i, and $I(w_{ij} > 0)$ is an indicator function equal to 1 if an edge exists between nodes i and j and 0 otherwise. This centrality metric is not simply about how well-connected a node is overall, but rather how connected it is to nodes that are not highly connected. In other terms, distinctiveness centrality reflects how much a word co-occurs with less common, more distinctive ones.

Connectivity is calculated through weighted betweenness centrality (Brandes 2001), which measures the extent to which a word acts as a bridge between other ones and is given by the formula:

$$\mathrm{CO}(i) = \sum_{j<k} \frac{s_{jk}(i)}{s_{jk}} \tag{2}$$

where s_{jk} is equal to the number of shortest paths linking the generic pair of words (nodes j and k) and $s_{jk}(i)$ is equal to the number of those paths that contain the node i. This centrality metric quantifies how often a node appears on the shortest path between other pairs of nodes. In the context of word networks, betweenness centrality can be used to measure a term's *connectivity* by indicating how central it is inconnecting different words.

2.2 | Constructing the Composite Index

Once SBS scores have been computed for groups of thematically related word clusters (detailed in Section 3.1), the next step is to aggregate these scores into a composite indicator representing media attention to climate and environmental themes.

Our work builds on the literature defining composite indicators to quantify complex and multidimensional phenomena that are not directly observable by breaking them down into measurable components. This approach assumes that the phenomenon can be represented by a set of informative variables, denoted as $X_1, \dots, X_K$. The process of creating a composite indicator typically involves transformation of the components, such as normalization and standardization, to allow comparability ($T_j(X_j)$, $j = 1, \dots, K$) and then aggregation of transformed variables through a suitable function $\Psi[T_1(X_1), \dots, T_k(X_k);\ w_1, \dots, w_k]$, with $w_1, \dots, w_k$ being suitable weights representing the degree of relevance of the components. We favor standardization over normalization, as the latter can distort indicator significance, especially in the presence of outliers or variable range fluctuations. Standardization, instead, removes scale differences but preserves relationships and correlations among variables (Hair et al. 2019), ensuring that each variable contributes equally to the analysis.

In a well-defined mathematical context, a composite indicator loses its significance when the applied transformation and aggregation scheme modify the original data structure and the information it contains.

Research has shown that experts tend to interpret weights as indicators of importance rather than as trade-offs between their components (Munda and Nardo 2003). As noted by Freudenberg (2003), "Greater weight should be assigned to components that are deemed more significant within the specific context of the composite indicator". In accordance, Lovell et al. (1995) point out that treating all components and time periods equally is too restrictive. In particular, equal-weighted or variance-maximizing schemes may fail to reflect the time-varying relevance of the underlying components and may reduce the interpretability of the resulting index.

To overcome these issues, new aggregation methodologies have been introduced, such as the *Benefit of the Doubt* (BoD) based on *Data Envelopment Analysis* (DEA). This approach builds on the principle that weights must be non-negative, can fluctuate over time ($t = 1, 2, \dots, T$) within a specified range, and must adhere to an ordinal ranking determined by relative efficiency.

Precisely, the BoD aggregation scheme selects endogenously at each time $t = 1, 2, \dots, T$ the optimal weights $\left(w^*_{1,t}, \dots, w^*_{K,t}\right)$ for the full set of components by solving a constrained optimization problem to maximize the (relative) efficiency score defined as

$$\mathcal{E}_t\left(w_{1,t}, \dots, w_{K,t}\right) := \frac{\sum_{j=1}^{K} w_{j,t} X_{j,t}}{\max_{u=1,2,\dots,T} \sum_{j=1}^{K} w_{j,u} X_{j,u}} \tag{3}$$

where $X_{1,t}, X_{2,t}, \dots, X_{K,t}$ are the values of the K components observed at time t. Finally, the optimal weights are formally given by:

$$\left(w^*_{1,t}, \dots, w^*_{K,t}\right) := \underset{(w_{1,t},\dots,w_{K,t}) \in \mathcal{W}}{\operatorname{argmax}} \ \mathcal{E}_t\left(w_{1,t}, \dots, w_{K,t}\right) \tag{4}$$

with $\mathcal{W}$ representing the set of weight restrictions that ensure that the weights are non-negative and sum to 1.

According to Vidoli et al. (2015), BoD is an extremely parsimonious data-driven methodology that proves useful when there is uncertainty or no consensus on the weighting scheme to be adopted. This should be interpreted as responsiveness to news rather than an instability drawback. We refer the reader to Greco et al. (2019) and OECD (2008) for more details on the methodological construction of composite indices and related properties.

3 | The Climate and Environmental Attention Index

We define CEAI as a high-frequency, media-based composite indicator that measures the intensity and semantic prominence of climate and environmental themes within public narratives at a given point in time.

The conceptual structure of the index explicitly accounts for two distinct and complementary domains commonly recognized in the sustainability literature: climate and environment. The former captures attention on themes directly related to weather variables and the climate system (e.g., greenhouse gas emissions, mitigation and adaptation strategies, physical and socio-economic effects of climate change),[1] while the latter relates to broader ecological and governance issues such as pollution, waste management, environmental regulation, transparency, and the green economy[2] (Barnett et al. 2020; Giglio et al. 2021).

3.1 | Input Data and News Corpus

We gather articles published between 2014 and 2022 by the main US generalist newspapers[3] (*USA Today*, *New York Times*, *Los Angeles Times*) and by the *Wall Street Journal* and *Financial Times*, specialized in global financial markets. Online articles are collected from Event Registry, an AI-powered media monitoring platform, on a weekly time-frame to provide a high level of information granularity and ensure a comprehensive corpus of news for each period.

Focusing on this set of high-impact outlets follows established media-research practices, as they define the dominant frames in the broader public sphere; see Boykoff and Roberts (2007), Ardia et al. (2023) among others. Overall, our sample includes more than 700,000 articles with an average of 1584 documents per week, ensuring that the news corpus is both representative and sufficiently rich for robust analyses.

We clean the news corpus using standard preprocessing techniques, including tokenization, which segments text into individual words or tokens; lowercasing, which standardizes text by converting all characters to lowercase; stopword removal, which eliminates common but semantically uninformative words (e.g., "the," "and," "of"); and stemming with the Porter stemmer (Porter 2006), which reduces words to their root forms to unify morphological variants. To create word clusters, relevant keywords are extracted with the SBS BI app (Colladon and Grippa 2020) using TF-IDF logic (Roelleke and Wang 2008), filtered for climate and environmental issues and expanded through the Lexicon Augmenter tool, which uses WordNet (1998) and pre-trained word embeddings such as Word2Vec (Church 2017) and Glove (Pennington et al. 2014) to identify synonyms, hyponyms, hypernyms, and related terms.

To further avoid omissions and strengthen conceptual validity, we triangulated the automatically generated terms with authoritative external sources, including academic research that develops or analyzes glossaries and taxonomies related to climate and environmental topics (Engle et al. 2020; Li and Yu 2022); policy reference documents, most notably the Intergovernmental Panel on Climate Change (IPCC) and major reporting and disclosure frameworks, including the Global Reporting Initiative (GRI) Standards the Task Force on Climate-related Financial Disclosures (TCFD) Recommendations and the EU Taxonomy for Sustainable Activities.[4] Subsequently, with the support of two experts, we organized these keywords (823 terms) into 22 word clusters, with an average of 37 items per cluster. Finally, in accordance with the guidelines of the U.S. Environmental Protection Agency (EPA), we grouped these clusters into three principal macro-pillars. Table 1 describes each macro-pillar and related word clusters (labels for each cluster are provided in parentheses), along with representative examples of keywords selected for their informativeness and coverage. Specifically, the Transition Pillar encompasses regulatory, policy, educational, legal, and governance transformations that are fundamental to enabling the transition to climate mitigation and adaptation (Fliegel 2025). The Physical Pillar represents the biophysical impacts, risks, and consequences of climate change, focusing on environmental stressors and outcomes. Covers both the drivers and the direct effects of climate dynamics. The Opportunities Pillar, related to innovation, positive practices, and sectoral opportunities to advance climate resilience, sustainable growth, and environmental stewardship. The SBS methodology is finally applied to compute the semantic importance of each word cluster, following the procedure described in Section 2.1.

Building on the thematic coverage of the keyword clusters reported in Table 1, we label our composite measure the Climate & Environmental Attention Index to reflect the dual structure of the themes it captures. Specifically, clusters related to emissions, climate impacts, climate action, energy transition, and resilience constitute the climate dimension of the index, whereas clusters referring to environmental law, education, waste, green economy, transparency, and greenwashing map onto its environmental dimension.

3.2 | Time Varying Weighting Structure

We aggregate the SBS scores of each word cluster in the CEAI through the Benefit-of-Doubt (BoD) aggregation scheme, capturing the overall media attention and the three thematic pillars defined in Section 3.1: transition, physical, and opportunity. We compute the time-varying weights and evidence the responsiveness of the CEAI index to changes in topic prominence. We end up with a full index, pillar-specific subindices, and distinguished metrics for generalist and financial newspapers.

In what follows, we evidence how the time-varying weight structure highlights moments of increased or decreased importance for specific discourse components for either financial or generalist outlets.

3.2.1 | Financial Newspapers

Financial newspapers provide detailed analysis and expert opinions on business, finance, and economic news for professionals, investors, and business leaders. They explore topics such as stock markets, corporate earnings, and macroeconomic trends, using technical language tailored to their specialized audience. The heatmap in Figure 1 shows the structural weights of the Full Composite Index from 2014 to 2022, illustrating how the importance of each component changes over time. A color gradient represents relative weights: blue (0) indicates no influence, red (1) the highest impact, and intermediate shades (0.2–0.8) varying contributions.

Figure 1 shows that some components, such as Green Financial Products (GFPROD) and Renewable Energy (RNWENG), remain fairly steady in importance over time, while others, such as Energy Efficiency (ENGEFF) and Green Mobility (GRNMOB), present intermittent peaks. Notable waves of increased weighting occur in 2017–2018 and again in 2021–2022, reflecting increased media attention and changes in discourse. After 2019, the weight pattern

TABLE 1 | Summary of the climate and environmental related word clusters.

Theme	Word cluster (LABEL)	Description	Keyword examples
Transition pillar	1. Energy Regulation (ENGREG)	Considers terms associated with policy frameworks in energy governance, regulatory changes and governance strategies to support the energy transition.	Climate finance governance, energy policy, energy regulation, energy trade, marine policy framework
	2. Environment & Education (ENVEDU)	Includes terms on environmental education and awareness.	Environmental education, sustainability education, green skills, biodiversity education, climate change education
	3. Environmental Law (ENVLAW)	Includes terms related to standards and laws for waste management and environmental protection.	Basel Convention, Stockholm Convention, Clean Air Act, Montreal Protocol, Paris Agreement
	4. Greenwashing (GRNWSH)	Terms related to misleading environmental claims by corporations.	Greenwashing, blue washing, environmental disinformation, environmental whitewashing, misleading packaging
	5. Transparency (TRANSP)	A set of terms associated with the concept of transparency in corporate sustainability practices, highlighting its influence on accountability, trust, and ethical performance.	Company transparency, ethical company, fair trade, firm integrity
	6. Net Zero Emissions (NETZEM)	Terms related to the balance between emitted and removed greenhouse gases.	Carbon neutrality, climate neutrality, zero emission, net-zero emission, carbon balance
Physical pillar	7. Climate Human Effects (CLHEFF)	Terms related to the human-driven effects of climate change.	Climate change, global warming, heatwave, drought, flood
	8. Direct Climate Change Effects (DCCEFF)	Terms to measure the general impact of climate change.	Climate change, global warming, heatwave, drought, flood
	9. Gas Emission (GASEMS)	Terms related to emissions and the global warming.	Carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), fluorinated gases, carbon emissions
	10. Sustainability General (SUSGEN)	Terms referring to sustainability.	Climate action, sustainability, green energy transition, climate action plans, energy transition
	11. Waste Negative (WSTNEG)	Terms related to dangerous waste practices.	Chemical waste, discarded plastic, electronic waste (e-waste), hazardous waste, landfill
	12. Waste Positive (WSTPOS)	Terms related to effective waste management solutions.	Biodegradable waste, composting, recycling, material recovery, resource recovery
Opportunities pillar	13. Climate Action (CLMACT)	Terms related to proactive strategies for mitigating climate change.	Afforestation, biodiversity conservation, carbon capture, carbon mitigation, climate-smart agriculture
	14. Climate Resilience (CLMRES)	Terms that capture adaptation strategies in response to climate change.	Climate adaptation, climate resilience, climate resilient cities, drought resilience, energy resilience
	15. Energy Efficient (ENGEFF)	Terms related to strategies for reducing energy consumption.	Eco-efficiency, energy conservation, energy efficient, energy saving, resource efficiency

(Continues)

TABLE 1 | (Continued)

Theme	Word cluster (LABEL)	Description	Keyword examples
	16. Energy Collaboration (ENGCOL)	Collaborative approaches to sustainable energy.	Climate cooperation, climate diplomacy, climate partnerships, energy collaboration, energy diplomacy
	17. Energy Community (ENGCOM)	Terms related to energy communities.	Community energy, decentralized energy system, energy community, energy co-ops, smart grid
	18. Green Economy (GRNECM)	Terms related to economic opportunities in sustainability, including synonyms of green industries.	Green economy, circular economy, blue economy, clean economy, low-carbon economy
	19. Green Financial Products (GFPROD)	Terms encompassing green financial products.	Green bond, carbon credit, climate finance, green investment, sustainability bond
	20. Green Jobs (GRNJOB)	Terms associated with green jobs and sustainable employment opportunities.	Green jobs, clean energy jobs, renewable energy jobs, environmental jobs, green work
	21. Green Mobility (GRNMOB)	Terms related to sustainable transportation solutions and clean mobility.	Bike lanes, car-free cities, electric vehicles, green transportation, public transportation
	22. Renewable Energy (RNWENG)	Terms related to clean and renewable energy sources.	Bioenergy, solar energy, wind energy, hydropower, geothermal energy

becomes more volatile, with the latter years marked by sudden jumps in relevance for several clusters, indicated by intensified colors in the lower part of the chart. Climate Action (CLMACT) and Energy Community (ENGCOM) show frequent and significant fluctuations over multiple years, likely mirroring global changes in attention to these themes. In recent years, Green Economy (GRNECM) and Green Jobs (GRNJOB) have gained prominence, highlighting the growing focus on sustainable economic development and employment in the news corpus. The heatmaps for the subindices: Physical, Transition and Opportunity pillars are provided in Appendix A (Figures A.1, A.3, and A.5).

Table 2 summarizes the weight structure for the CEAI and reports in the last column the weights assigned to each word cluster by the first component (PC_1) of the system obtained through dimensionality-reduction techniques such as principal component analysis (PCA), a common benchmark for aggregation. The displayed values evidence the BoD aggregation scheme's higher flexibility; for example, transparency (TRANSP) shows a relative importance of 0.147 in the construction of the PC_1 of the Transition pillar, fixed for the whole period under analysis, while it ranges from 0 to 0.192 in the BoD weighting scheme and is positive only in 157 out of 463 weeks. Similarly, the Direct Climate Effect cluster (DCCEFF) accounts for 0.066 of the PC_1 index for the Physical pillar, while it ranges from 0 to 0.116 in the BoD, being positive only 89 times.

3.2.2 | Generalist Newspapers

In contrast to more specialized financial newspapers, generalist newspapers provide coverage on a wide range of topics such as politics, sports, entertainment, and culture. These publications are designed for a broad audience, using clear and accessible language with less specialized content. In this section, we report the results on the weight structure of the proposed indices when focusing on generalist newspapers and highlight the main differences with respect to the evidence for financial outlets.

In Figure 2 we plot the heatmap for the time-varying weights of BoD within the generalist news corpus. There is a clear divergence when comparing the weight distributions for generalist newspapers and financial newspapers. While financial news tends to focus more on market-sensitive topics such as *Net Zero Emissions*, *Gas Emissions*, and regulatory frameworks, reflecting their business-oriented readership, generalist news coverage yields a more evenly distributed weighting structure across topics. In particular, themes such as *Waste Management* (both positive and negative), *Climate Resilience*, and *Sustainability* are relatively more relevant for generalist sources compared to financial ones. This outcome suggests a more stable engagement with climate-related topics for the generalist news narrative that integrates long-term environmental concerns rather than focusing on events with a potential immediate market reaction; see Figure 2.

In summary, financial news shows sharper fluctuations and focuses on immediate economic issues, while generalist news offers a broader, more stable view of environmental discourse. This divergence has important implications for interpreting composite indices based on media content, particularly when evaluating their responsiveness to different facets of climate change narratives. The heatmaps illustrating the time-varying weights for the Physical, Transition, and Opportunity sub-indices, based on generalist newspaper coverage, are provided in Appendix A (Figures A.2, A.4, and A.6).

In line with the analysis for financial newspapers, we summarize in Table 3 the weight characteristics for the CEAI index; for the sake of comparison, the last column displays the weights of the alternative PC_1 aggregation. Again, the time-varying weights of the BoD allow for greater flexibility in the relative importance of the cluster. For example, the weight for the Green Mobility cluster (GRNMOB) is fixed at 0.212 in the PC_1 Opportunity index, while it ranges from 0 to 0.249 for the BoD with an overall mean of 0.037 over the full sample and 0.153 over the 111 weeks when it is deemed relevant. In contrast, the simple average accounts for a weight of 0.1.

3.3 | Validation and Robustness

The construction of a composite index follows specific methodological rules and a proper validation procedure (OECD 2008). Since there is no observable benchmark or target variable to validate the effectiveness of CEAI, we provide here evidence that the index captures salient events within the climate and environmental framework and addresses the validity and reliability of the CEAI by leveraging the multiple design features already embedded in its construction. Together, these elements provide a comprehensive internal validation framework, ensuring that the CEAI captures a stable and meaningful signal of climate and environmental attention rather than artifacts driven by specific modeling assumptions.

Figure 3 reports the time series of the CEAI index for generalist and financial newspapers, together with selected climate-related event windows including the Paris Agreement, the Fridays for Future movement, COP26 in Glasgow, and the U.S. Inflation Reduction Act, which has introduced numerous incentives to the green transition. To highlight medium-term dynamics and regime shifts in climate attention, we overlay the 8-week moving average of the CEAI index (solid black line). In particular, both the raw index and the moving average assume high values corresponding to the selected events. The temporal evolution of CEAI aligns with major developments in the climate and environmental debate. In particular, the rise in both the level and volatility of the index after 2020 is consistent with the intensification of climate-related discourse observed globally. This temporal coherence provides an additional layer of validity, suggesting that the CEAI responds to real-world developments in a plausible and interpretable manner.

Interestingly, the index based on generalist newspapers peaked during the Paris Agreement, whereas the one constructed from financial newspapers shows only a limited response. This divergence reflects the different informational roles of the two media types: generalist outlets tend to amplify major symbolic, political, and societal climate events that shape public awareness and public discourse, while financial newspapers primarily emphasize developments with direct and clearly identifiable implications for firms, markets, and regulation. Since the Paris Agreement initially represented a broad, forward-looking global commitment rather than an immediate set of binding corporate constraints, its relevance is more strongly captured by generalist media attention.

As discussed in Section 3.2, we compute CEAI using the BoD approach based on Data Envelopment Analysis and providing data-driven, time-varying weights. To check the robustness of our index, we compare the CEAI index with variants where alternative approaches are considered, from equal and time-invariant weights (mean) to fixed weights maximizing variance (PC_1).

Figure 4 shows the CEAI index time series, scaled to 0–1, for the three alternative aggregation approaches: the mean indices (blue) and PC_1 (orange) follow closely aligned paths, following the major exogenous shocks. The BoD approach (green) is characterized by greater variability over time, since DEA methods emphasize extremes in efficiency scores (Bauer 1990). Indeed, this variability should be interpreted as enhanced responsiveness to changes in thematic prominence in media narratives, allowing the index to dynamically adjust not only in the wake of significant events but also to changes in thematic focus over time.

Since 2020, all three indices show an increasing trend. This effect coincides with major environmental events, the renewed focus during the pandemic (Usman et al. 2021), international climate agreements, and severe environmental disasters, which increased media attention and broadened the climate discourse. In this period, the Paris Agreement's 5-year cycle also came into play, with countries submitting increasingly ambitious Nationally Determined Contributions (NDCs), further intensifying global discussions on sustainability.

An additional robustness dimension is provided by the distinction between generalist and financial newspapers. Rather than pooling all media sources, we construct separate CEAI variants for each category, allowing us to examine whether the index behaves consistently across different informational environments.

Table 4 displays the correlation values between CEAI variants, which provides interesting information on the internal consistency of the index. First, a very high correlation is evidenced among the different aggregation schemes, both within the financial and generalist news, confirming that all composition approaches, Mean, PC_1, and BoD, effectively capture a common core of the climate-related discourse. Second, a much lower correlation is observed between generalist and financial-based indicators, suggesting that the two categories of media correctly emphasize different narratives. This evidence highlights the advantage of disaggregating news sources and further supports the choice of semantic importance as a robust approach in the construction of our index. Moreover, the BoD aggregation scheme provides the lowest correlation (0.45) across the two information sources. Together, these elements indicate that the CEAI exhibits strong internal consistency and robustness across aggregation methods and data sources.

3.3.1 | Informative Power

To further strengthen the validation of the CEAI index, we analyze its association with a set of existing benchmarks, that is, news-based indices which are widely recognized in the

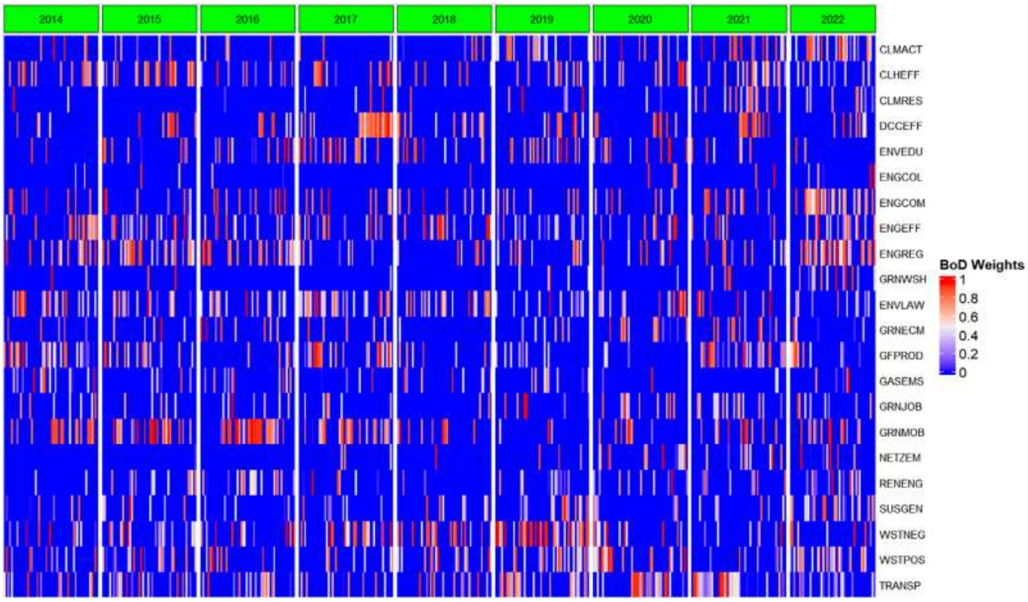

FIGURE 1 | Weight structure of BoD components (labeled on the right), based on financial newspapers, within the period 2014–2022. The changes over time are mapped through color gradient (heatmap legend): blue (0), red (1); intermediate shades (0.2–0.8) indicate varying degrees of weights.

literature: (1) the Economic Policy Uncertainty Index; (2) the Climate Policy Uncertainty Index; (3) the US Climate Risk Index; (4) the ESG-Related Uncertainty Index, also known as the Sustainability Uncertainty Index, computed for the US; (5) the Media Climate Change Concerns Index. We do not consider the WSJ and CH measures suggested in Engle et al. (2020) since the overlapping period with our indicator only includes a few monthly observations. The EPU index tracks the frequency of articles discussing economic policy uncertainty (Baker et al. 2016)[5] and is calculated by examining articles from 10 prominent newspapers that mention terms related to the economy, uncertainty, and specific policy topics such as "Congress", "deficit", and "the Federal Reserve".

The CPU, developed by Gavriilidis (2021), adapts the EPU methodology to specifically capture uncertainty in US climate policy. It is constructed using textual data from eight major US newspapers and exhibits sensitivity to policy-relevant events such as emission regulation announcements, presidential climate statements, and major environmental protests.[6] Recent studies indicate that the CPU exhibits heterogeneous effects on corporate behavior (Hoang 2022; Liu and Xiang 2025). However, it remains policy-oriented and does not fully reflect the evolving public discourse on climate and environmental issues. Our CEAI complements this line of research by capturing attention dynamics in news narratives that can anticipate both policy adjustments and corporate reactions.

The *US Climate Risk Index* (USCRISK), compiled by the Volatility Laboratory (V-Lab) at NYU Stern, quantifies the expected capital shortfall for US financial firms under a severe climate crisis scenario. Specifically, it models systemic risk that results from a sharp depreciation (more than 50%) in the valuation of stranded asset portfolios over a 6-month period.[7]

The ESGUI, proposed by Ongan et al. (2025), is a textual metric derived from the frequency of ESG-related terms in the Economist Intelligence Unit's monthly country reports. It is designed to reflect ambiguity and unpredictability in the sustainability discourse at the national level for several countries.[8]

Finally, the MCCCI, introduced in Ardia et al. (2023), is obtained as a combination of the attention (based on frequency) and the sentiment polarity of the news articles. Although the above-mentioned measures are available monthly, the MCCC index is calculated at a daily frequency.[9]

The CEAI differs from other uncertainty indices in some main features: its thematic focus, data source, aggregation method, and most notably its observation frequency. In fact, most of the existing indicators are updated monthly, while the CEAI is calculated from the text of news articles within a weekly time frame. This higher frequency is essential when it comes to capturing rapid dynamics in climate-related texts triggered by breaking news, political announcements, or significant market events. This reflects more timely information integrated in the CEAI, making it especially useful for shaping policies or making investment decisions in high-volatility settings, such as financial markets or political debates.

Concerning the thematic focus, the EPU index primarily tracks macroeconomic and fiscal uncertainty, which is distinct from the specialized domain of environmental discourse. However, the USCRISK index is based on financial systemic risk modeling from balance sheet data under climate stress scenarios. Instead, among the indices mentioned, CPU, ESGUI, and MCCC partially share the thematic focus on news about climate and the environment. The ESGUI relies on the Economist Intelligence Unit (EIU) monthly country reports, which are structured and analyst-written documents, while the CEAI is based on media coverage from financial or generalist newspapers, reflecting public and investor attention rather than curated expert assessments. The MCCC, instead, is based on news tagged as "climate change" by the publisher

TABLE 2 | Structure of index weights based on financial news.

Variable	Freq.	Min	Max	Mean—pos	Mean	St. Dev.	PC_1
Transition pillar							
ENVEDU	81	0.000	0.124	0.090	0.015	0.036	0.099
ENVLAW	132	0.000	0.096	0.058	0.016	0.029	0.143
ENGREG	120	0.000	0.187	0.133	0.034	0.062	0.120
GRNWSH	30	0.000	0.062	0.090	0.002	0.010	0.163
NETZEM	37	0.000	0.107	0.063	0.005	0.019	0.332
TRANSP	157	0.000	0.192	0.096	0.032	0.056	0.147
Physical pillar							
CLHEFF	114	0.000	0.135	0.093	0.023	0.042	0.234
DCCEFF	89	0.000	0.116	0.092	0.002	0.037	0.066
GASEMS	59	0.000	0.134	0.069	0.009	0.027	0.398
SUSGEN	80	0.000	0.174	0.089	0.015	0.038	0.385
WSTNEG	132	0.000	0.271	0.178	0.050	0.090	0.105
WSTPOS	126	0.000	0.152	0.087	0.023	0.044	0.124
Opportunity pillar							
CLMACT	85	0.000	0.122	0.081	0.014	0.035	0.280
CLMRES	38	0.000	0.066	0.041	0.003	0.012	0.189
ENGCOL	18	0.000	0.114	0.079	0.003	0.016	0.236
ENGCOM	92	0.000	0.106	0.078	0.015	0.032	0.174
ENGEFF	121	0.000	0.141	0.086	0.022	0.043	0.157
GRNECM	60	0.000	0.142	0.089	0.011	0.033	0.130
GFPROD	115	0.000	0.206	0.119	0.029	0.059	0.143
GRNJOB	67	0.000	0.118	0.069	0.009	0.026	0.092
GRNMOB	129	0.000	0.220	0.165	0.046	0.079	0.091
RNWENG	78	0.000	0.217	0.102	0.017	0.045	0.365

Note: The first and second columns represent the cluster labels and their absolute frequency as a component of the BoD index, respectively. Columns from 3 to 7 show the main descriptive figures of the labels' weight distribution in the composition of the BoD index, where Mean—pos (column 5) computes the average value of the positive weights only. The last column reports the weights of each label in the first principal component aggregation scheme.

of major US newspapers. Similarly, the CPU is based on a predefined keyword search, but focuses more narrowly on policy uncertainty. With our indices, we distinguish between financial-oriented and generalist news sources. Furthermore, the structure of the CEAI sub-indices allows us to capture physical events, transition rules, and climate-related opportunities as distinct components, providing a level of thematic granularity absent in the other indices.

Moreover, the CEAI differs from the aforementioned indices since it employs the SBS score, an advanced natural language processing technique, to identify the semantic relevance of climate-related events and opportunities. Furthermore, the use of a time-varying weighting scheme based on the BoD approach makes the CEAI index more responsive to changes in the news narrative. In contrast, the ESGUI relies on a simple arithmetic average of normalized keyword frequencies, assigning equal weight to environmental, social, governance, and uncertainty terms. This approach lacks the dynamic adaptability of the CEAI's BoD aggregation, particularly during periods of thematic imbalance. To evaluate the informative power of our indices in relation to the benchmarks, we compute the correlations between the CEAI variants (mean, PC_1, and BoD) and the established indices. The temporal alignment with monthly indices (EPU, CPU, USCRISK, ESGUI) is achieved by aggregating our weekly data to match the lower frequency[10]; in contrast, the daily values of the MCCC index were aggregated to the weekly level.

Figure 5 displays the correlation matrices between the CEAI index variants according to alternative composition approaches and the benchmark indices considered.

The monthly CEAI indices (Figure 5, left side) show negligible correlations with EPU and USCRISK. In fact, the CEAI index,

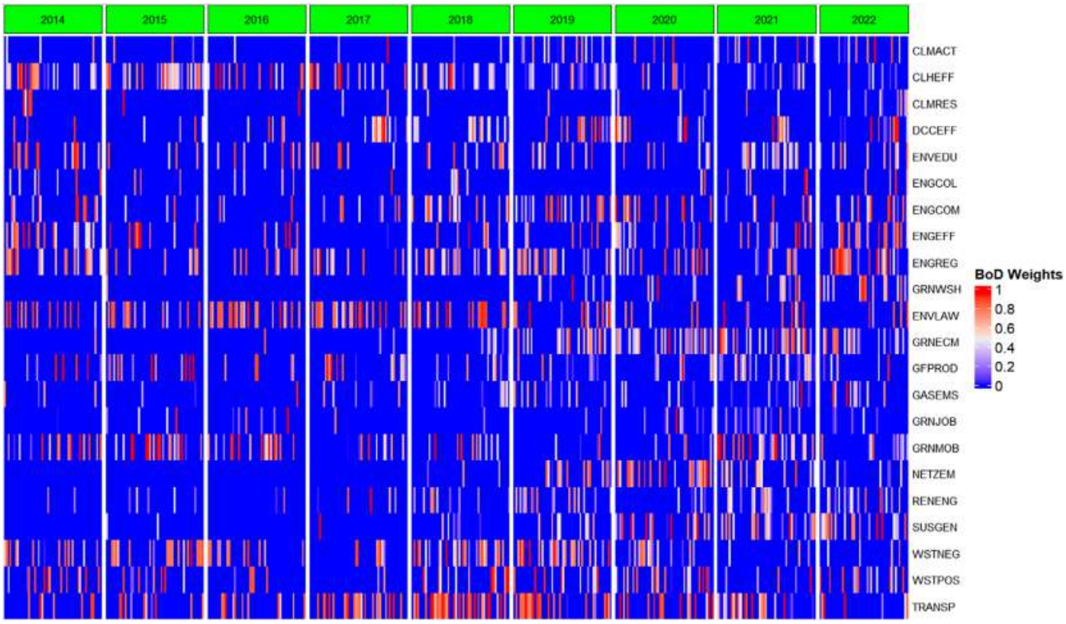

FIGURE 2 | Weight structure of BoD components (labeled on the right), based on generalist newspapers, within the period 2014–2022. The changes over time are mapped through color gradient (heatmap legend): blue (0), red (1); intermediate shades (0.2–0.8) indicate varying degrees of weights.

with its semantic-based and high-frequency media foundation, captures a distinct type of climate-related information that differs from the structural or policy-driven content emphasized by EPU and the financial risk exposure modeled in USCRISK. Even the CPU, which is thematically closer, exhibits only weak positive correlations with CEAI. This likely reflects its narrower focus on climate policy-related uncertainty, without accounting for the broader and more nuanced narrative layers captured by CEAI across transition, physical, and opportunity pillars. The negative correlations between ESGUI and CEAI indicators derived from financial newspapers, particularly BoD_Fin, suggest opposite informational content. ESGUI is higher during periods of general uncertainty about the ESG, such as policy ambiguity or reputational risk. On the other hand, CEAI tends to increase when climate discourse is outstanding, often due to positive attention like innovation and investment. Furthermore, CEAI based on generalist sources shows only weak or insignificant correlations with ESGUI. This is likely because ESGUI, based on EIU reports, mirrors structured analysis, while CEAI is informed by the narrative of the media. This distinction promotes the value of CEAI, as it offers a high-frequency signal that responds to the dynamics of climate discussions, unlike the planned monthly ESG assessments.

The correlation with the weekly MCCC index (Figure 5, right side) is also very low. Taking into account generalist news sources, this value is 18%, while the correlation achieves its highest value of 30% for financial news, with the BoD aggregation providing the lowest value of 17%. Rather than replacing existing measures, these findings demonstrate that the CEAI provides complementary information content that adds interpretive depth to the landscape of climate-related attention indices, particularly by focusing on financial media as a conduit of climate narratives to investors. The weekly frequency, thematic granularity, and semantic approach of CEAI make it particularly well-suited to capture rapid developments in climate discourse, offering significant value for financial market analysis, macroeconomic forecasting, and climate policy assessment.

The CEAI indices obtained through the BoD aggregation scheme are especially notable for their relatively low correlation with all benchmark indices, confirming their higher temporal responsiveness and ability to detect distinct phases of climate discourse. This further supports the adoption of BoD as the selected aggregation scheme to define the CEAI.

4 | The Impact of Climate Attention: Impulse Response Functions and Variance Decomposition

The primary objective of this analysis is to assess how climate attention, measured through climate news indices, affects some key macroeconomic indicators, financial market volatility, and financial uncertainty and distress. Following the validation approach of Caldara and Iacoviello (2022), who introduce a text-based geopolitical risk measure, we examine the response of these variables to climate shocks using Impulse Response Functions (IRFs) by estimating a sequence of bivariate Vector AutoRegressive (VAR) models.

In line also with standard practice in the text-based index literature (Barsky and Sims 2012; Beaudry and Portier 2006), we estimate a sequence of bivariate VARs. This parsimonious specification suits the weekly frequency and relatively short sample, prevents overparameterization in higher-dimensional systems, and allows for transparent identification of climate-attention shocks without relying on arbitrary ordering assumptions. This approach is particularly well suited to our analysis because it captures the dynamic and potentially bidirectional interactions between climate attention and economic or financial variables, allowing each to evolve over time as a function of its own history and that of the other variable in the system.

TABLE 3 | Structure of BoD and PC_1 index weights based on generalist news.

Variable	Freq.	Min	Max	Mean—pos	Mean	St. Dev.	PC_1
Transition pillar							
ENVEDU	87	0.000	0.135	0.090	0.017	0.037	0.020
ENVLAW	116	0.000	0.113	0.088	0.022	0.039	0.015
ENGREG	127	0.000	0.155	0.101	0.028	0.049	0.149
GRNWSH	39	0.000	0.089	0.049	0.004	0.015	0.234
NETZEM	59	0.000	0.153	0.094	0.012	0.034	0.331
TRANSP	144	0.000	0.253	0.195	0.061	0.095	0.110
Physical pillar							
CLHEFF	138	0.000	0.150	0.076	0.023	0.042	0.111
DCCEFF	80	0.000	0.173	0.109	0.019	0.045	0.210
GASEMS	111	0.000	0.249	0.153	0.037	0.075	0.347
SUSGEN	71	0.000	0.237	0.134	0.021	0.055	0.359
WSTNEG	119	0.000	0.203	0.133	0.034	0.063	0.108
WSTPOS	88	0.000	0.169	0.111	0.021	0.048	0.150
Opportunity pillar							
CLMACT	46	0.000	0.150	0.080	0.008	0.028	0.336
CLMRES	25	0.000	0.079	0.044	0.002	0.011	0.095
ENGCOL	32	0.000	0.113	0.076	0.005	0.020	−0.014
ENGCOM	94	0.000	0.151	0.102	0.021	0.044	0.178
ENGEFF	87	0.000	0.135	0.093	0.018	0.039	0.157
GRNECM	98	0.000	0.071	0.036	0.008	0.017	0.211
GFPROD	86	0.000	0.210	0.108	0.020	0.050	0.233
GRNJOB	42	0.000	0.117	0.038	0.003	0.015	0.127
GRNMOB	111	0.000	0.249	0.153	0.037	0.075	0.212
RNWENG	74	0.000	0.207	0.088	0.014	0.039	0.349

Note: The first and second columns represent the cluster labels and their absolute frequency as a component of the BoD index, respectively. Columns from 3 to 7 show the main descriptive figures of the labels' weight distribution in the composition of the BoD index, where Mean—pos (column 5) computes the average value of the positive weights only. The last column reports the weights of each label in the first principal component aggregation scheme.

4.1 | VAR Model

A VAR(p) model with k endogenous variables can be represented as:

$$Y_t = A_0 + A_{t-1}Y_{t-1} + \cdots + A_{t-p}Y_{t-p} + \varepsilon_t \quad (5)$$

where $Y_t \in \mathbb{R}^k$ is the response vector, A_0 is a $k \times 1$ vector of intercept terms, A_i are $k \times k$ coefficient matrices that capture lagged relationships up to order p, $\varepsilon_t \sim WN(0, \Sigma)$ is a $k \times 1$ vector of white noise residuals with zero mean and variance–covariance $k \times k$ matrix Σ. In this framework, impulse response functions (IRFs) allow to trace the dynamic response of one variable (target) to exogenous shocks in other variables (explanatory). Formally, the IRF measures the effect of a one-unit change on a variable of interest and can be used to understand the relationship between variables. Observing how the output of the system changes after the impulse, it is possible to infer the influence of that impulse on the target.

To derive the IRF, we first rewrite the VAR model in its vector moving average (VMA) representation:

$$Y_t = \mu + \sum_{i=0}^{\infty} \Phi_i + \varepsilon_{t-i} \quad (6)$$

where μ is the deterministic component of the system and Φ_i are the impulse response matrices that capture the effect of past shocks on Y_t.

The matrix Φ_i is computed recursively from the VAR coefficients:

$$\Phi_i = A_1\Phi_{i-1} + A_2\Phi_{i-2} + \cdots + A_p\Phi_{i-p} \quad (7)$$

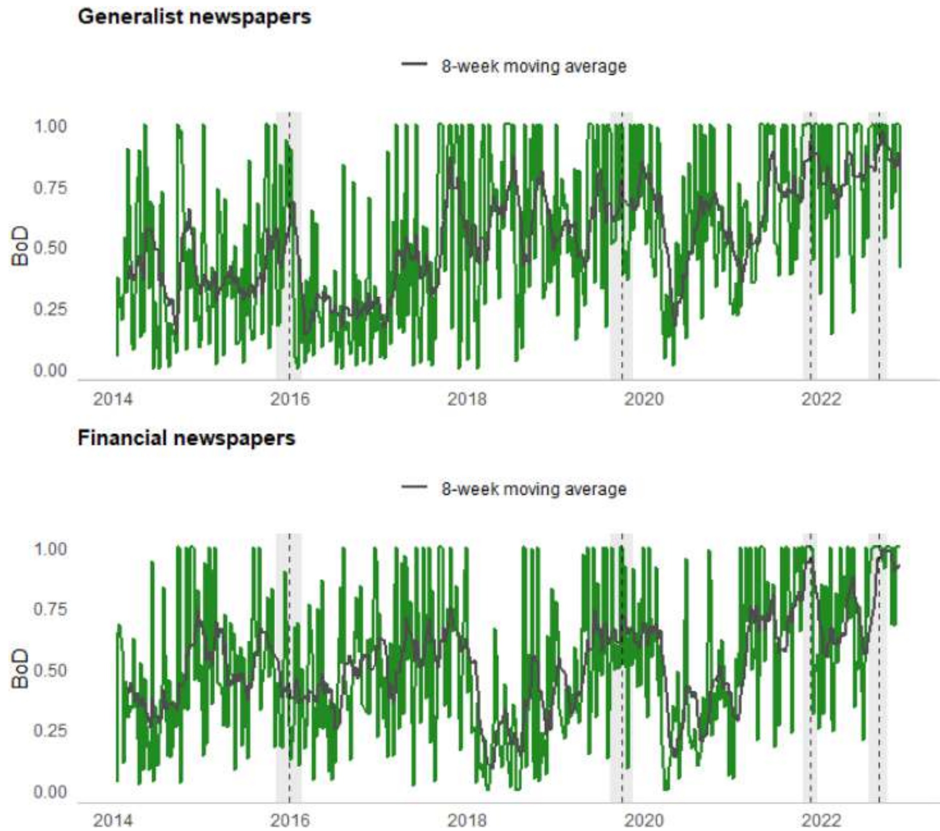

FIGURE 3 | Climate and Environmental Attention Index (BoD). The green line reports the weekly BoD-based CEAI, while the gray line shows an 8-week moving average. Shaded areas denote selected climate-related event windows, including the Paris Agreement (December 2015), the Fridays for Future movement (August 2019), COP26 in Glasgow (November 2021), and the U.S. Inflation Reduction Act (August 2022). The top panel refers to generalist newspapers, the bottom panel to financial newspapers.

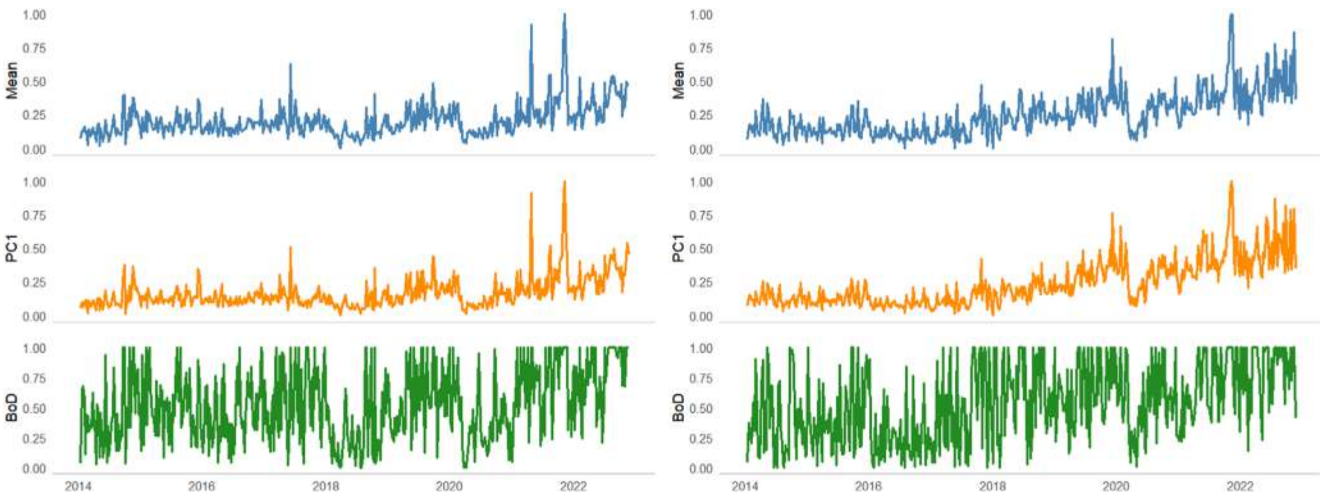

FIGURE 4 | Time series from January 2014 to November 2022 of the (scaled) CEAI variants with different aggregation rules: financial (left) and generalist (right) news sources.

with initial condition: $\Phi_0 = I_k$ where I_k is the $k \times k$ identity matrix.

In order to obtain meaningful IRFs, it is essential to orthogonalize the estimated VAR residuals ε_t. This process is achieved through structural decomposition methods, with Cholesky decomposition being the primary technique utilized in our analysis.

The Cholesky decomposition assumes a recursive causal ordering of variables. The reduced-form error term ε_t is decomposed into a set of mutually uncorrelated structural shocks u_t as follows:

$$\varepsilon_t = Su_t \tag{8}$$

where S is a lower triangular matrix obtained from the Cholesky decomposition of Σ (i.e., $\Sigma = SS'$).

In order to quantify the impact of CEAI on economic activity and financial stability, we examine a set of weekly target variables, as described in Table 5, categorized into three groups: macroeconomic indicators, financial stock indices and market volatility.

In fact, climate-related events and policy changes have been shown to influence macroeconomic fundamentals such as inflation, employment, and overall economic growth, represented in our analysis through the Consumer Price Index (CPI), the Unemployment Rate (UR), and the Weekly Economic Index (WEI), respectively. In addition, financial markets are known to respond quickly to emergences and opportunities, making stock indices and volatility measures essential to capture investor reactions. The effect on the S&P 500 provides a comprehensive measure of market-wide reactions, while the impact on the Nasdaq 100 provides a focus on technology- and innovation-driven companies. In contrast, the DJIA, composed of blue-chip industrial firms, offers insight into how traditional industries respond to climate-related narratives and policy changes. Beyond stock market performance, market volatility plays a crucial role in understanding uncertainty related to climate attention. Our analysis on the VIX, often referred to as the “fear gauge”, helps to determine whether increased media coverage of climate issues contributes to greater investor uncertainty. Similarly, the impact on OVX estimates the reaction of the energy sector to climate-related developments, given that fossil fuel markets are highly sensitive to policy changes, technological changes, and investor sentiment regarding sustainability.

4.2 | Model Estimation and Empirical Results

Prior to estimation, we test each series for stationarity using the Augmented Dickey-Fuller (ADF) test. When necessary, we apply first or second differencing to ensure stationarity, removing non-stationary trends that could bias the VAR results.[11] We define $Y := (\mathrm{CEAI}, X)$, where X is the selected target variable, and estimate the bivariate model in (5) where we fix the lag order $p = 13$, corresponding to roughly one quarter of weekly observations. This choice balances the need to capture short-term dynamics while avoiding overfitting in a small-sample bivariate setting. Following Lütkepohl (2005), this fixed lag structure is consistent with standard practice in time series analysis, where approximately one quarter's worth of lags is used to account for cyclical adjustment. Moreover, recent methodological work demonstrates that impulse response estimates from VAR models with fixed lags closely match those obtained via local projections, validating their use even in high-frequency bivariate applications (Plagborg-Møller and Wolf 2021).

In all models, we treat CEAI as the shock variable of interest and examine how each target variable X individually responds to its changes. This setup reflects our interest in understanding how fluctuations in environmental attention, measured

TABLE 4 | Correlation matrix between CEAI variants.

	BoD_ Fin	Mean_ Fin	PC_ Fin	BoD_ Gen	Mean_ Gen	PC_ Gen
BoD_Fin	1.00	0.85	0.78	0.45	0.54	0.56
Mean_Fin	0.85	1.00	0.98	0.53	0.72	0.72
PC_Fin	0.78	0.98	1.00	0.55	0.78	0.78
BoD_Gen	0.45	0.53	0.55	1	0.84	0.79
Mean_Gen	0.54	0.72	0.78	0.84	1.00	0.98
PC_Gen	0.56	0.72	0.78	0.79	0.98	1.00

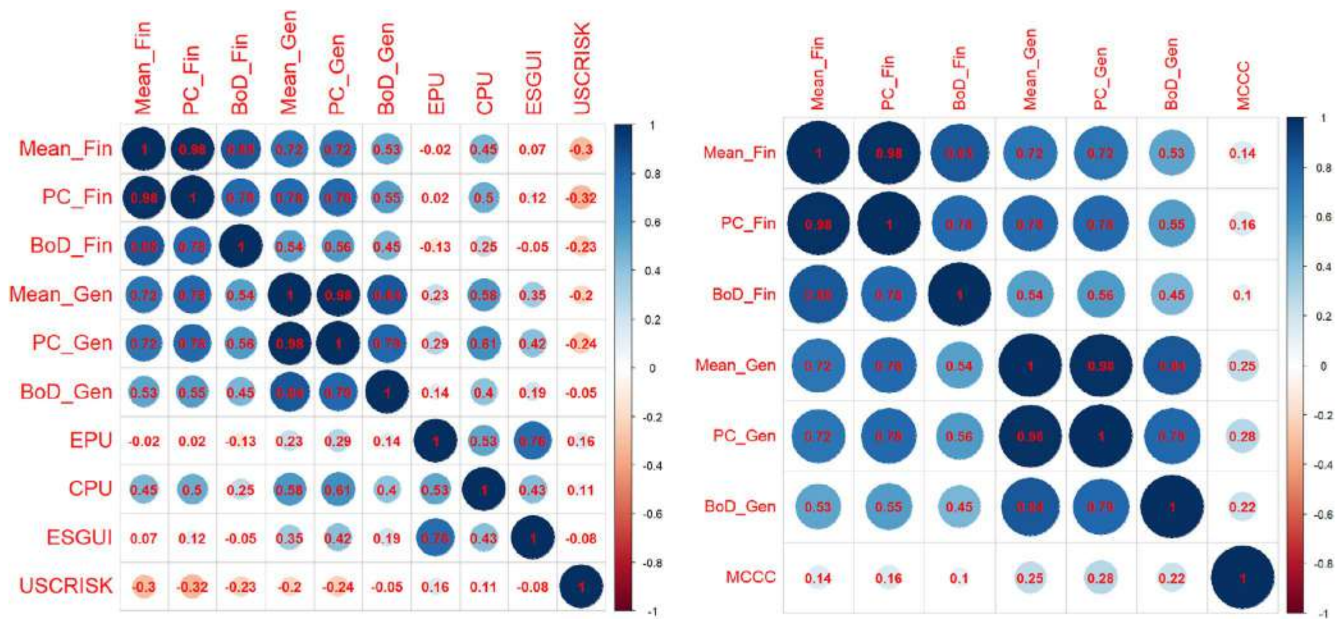

FIGURE 5 | Correlation matrices of the CEAI variants with benchmarks: monthly news-based attention indices (left) and the weekly MCCC index (right).

TABLE 5 | Target variables in the IRF exercise.

Label	Definition
Macroeconomic indicators	
WEI	Weekly Economic Index: index of US real economic activity aligned to the yearly GDP growth rate
CPI	Consumer Price Index: index measuring changes in the prices of goods and services
UR	Unemployment rate: number of unemployed as a percentage of labor force
Financial markets: stock indices and volatility measures	
SPX	S&P 500 stock market index tracking the performance of the 500 largest companies by market capitalization
NASDAQ100	Stock market index tracking the performance of the 100 largest companies by modified market capitalization on NASDAQ exchanges
DJIA	Stock market index tracking the performance of the 30 largest publicly owned blue-chip companies traded on the New York and NASDAQ exchanges
VIX	CBOE Market Volatility: index representing the market expectations for 1-month ahead price changes of the S&P 500 Index
OVX	CBOE Oil Volatility: index representing the market expectations for one-month ahead price changes of crude oil as prices by the United Stated Oil Funds (USO)

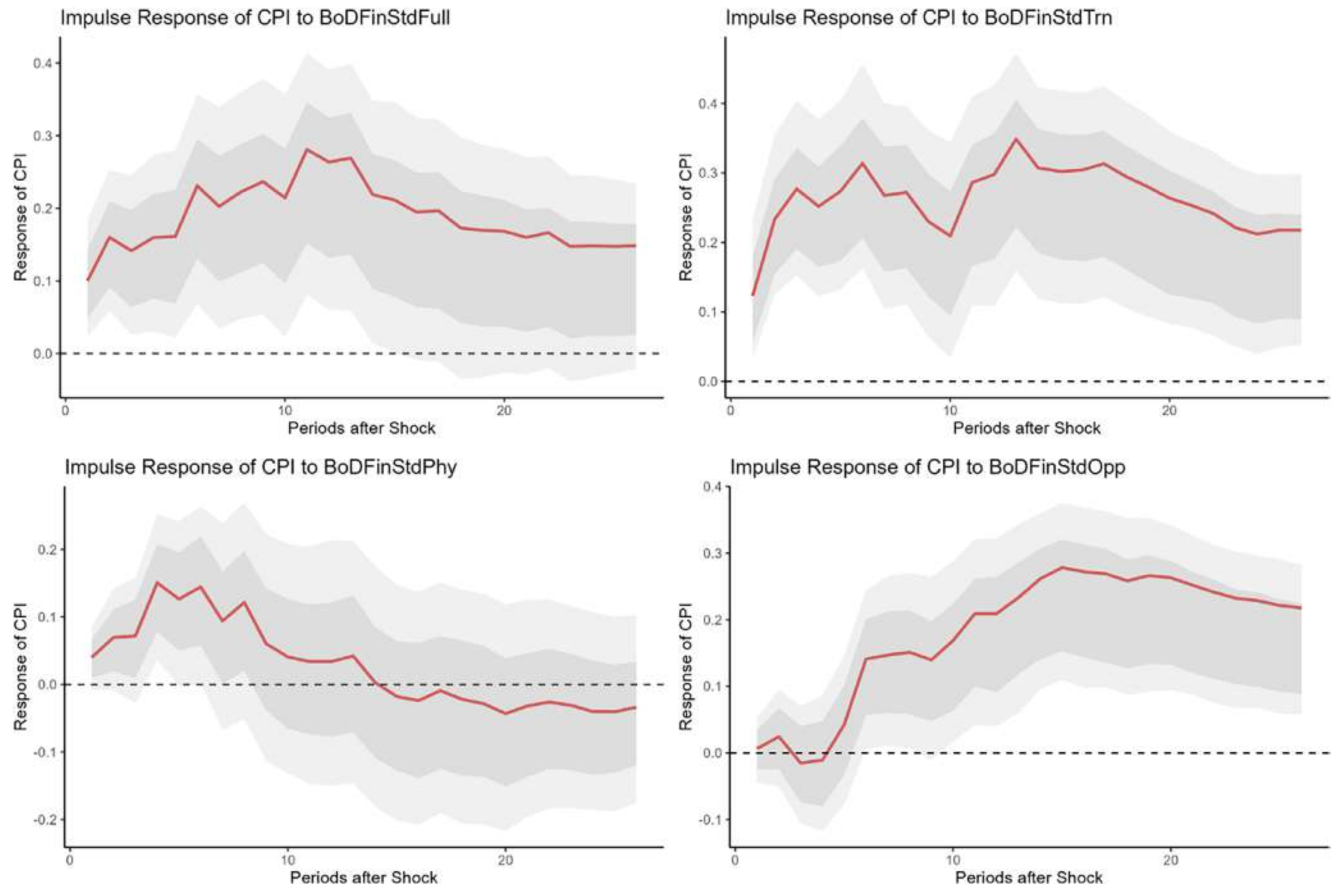

FIGURE 6 | IRF of Climate and Environmental Attention on the Consumer Price Index (CPI): full (top left), transition (top right), physical (bottom left) and opportunity (bottom right) attention measured on financial newspapers. The shaded regions represent the bootstrap intervals with 68% and 90% confidence levels.

through news discourse, may shape economic and market variables. Given the weekly frequency of our data and the nature of news-driven indices, it is reasonable to assume that CEAI may influence selected target variables within the same period, while it is less likely that they can impact CEAI. In this sense, we interpret IRFs as descriptive tools to explore potential information

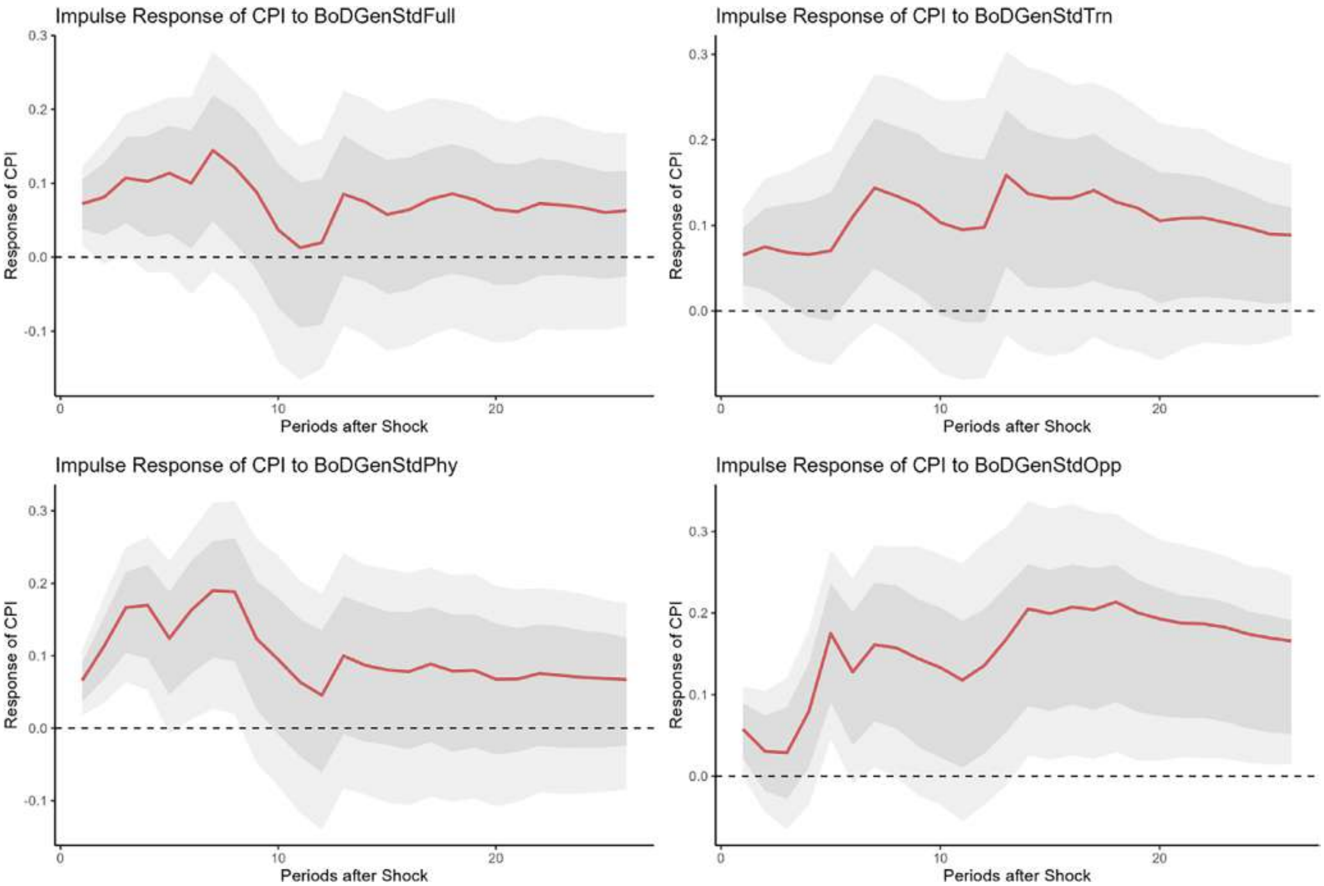

FIGURE 7 | IRF of Climate and Environmental Attention on the Consumer Price Index (CPI): full (top left), transition (top right), physical (bottom left) and opportunity (bottom right) attention measured on generalist newspapers. The shaded regions represent the bootstrap intervals with 68% and 90% confidence levels.

transmission patterns from climate discourse to economic and market-relevant outcomes, consistent with other work using narrative or sentiment indicators as impulse variables in VAR frameworks (Barsky and Sims 2012; Beaudry and Portier 2006).

Precisely, we define an exogenous climate attention shock as a sudden and unexpected increase in one of the climate attention indices introduced above, based on general discourses (Full) or specific themes (TRN, PHY, OPP) and reported either in financial or generalist journals. A one-standard-deviation shock is typically used for clarity and interpretation. It is worth noticing that, since only two variables are included in each model, concerns about variable ordering in larger systems are not relevant in this application. The IRFs demonstrate how the target variables respond over time to this shock. To assess economic and statistical significance, we construct 68% and 90% bootstrap confidence intervals using Monte Carlo simulations. The 68% interval, equivalent to $\pm$ 1 standard deviation, is commonly reported in macroeconomic analyses of impulse responses (e.g., Inoue and Kilian 2013), while the 90% interval serves as a standard threshold for statistical inference.

4.3 | Empirical Results

In what follows, we report the results of the impulse response analysis, focusing on the target variables that evidenced a significant response to shocks in some of the CEAI indicators. The complete set of results is summarized in Appendix B.

4.3.1 | Economics Indicators

The response of WEI to climate attention shocks is relatively mild and short-lived (Figures B.1 and B.2 in Appendix B). In contrast, the response of the CPI to climate attention shocks is mostly positive, indicating that increased coverage of climate-related news (in financial and generalist newspapers) is associated with an increase in the CPI, as evidenced in Figures 6 and 7. Moreover, the response tends to accumulate over time, also suggesting a long-term impact of climate attention on inflation rather than a short-term fluctuation. The confidence bands show statistical significance in several cases, despite some uncertainty.

Delving into the thematic sub-indices, note that the positive impact is particularly evident for the opportunity-based climate attention index that leads to a steady increase in CPI over time; this outcome suggests that discussions about climate-related economic opportunities (climate transition investments, green economic shifts, etc.) appear to fuel expectations of rising prices and may contribute to inflationary pressures. Similarly, policy-related and physics-based indices also contribute to CPI growth, possibly reflecting expectations of regulatory costs, supply chain disruptions, and increased production expenses due to climate

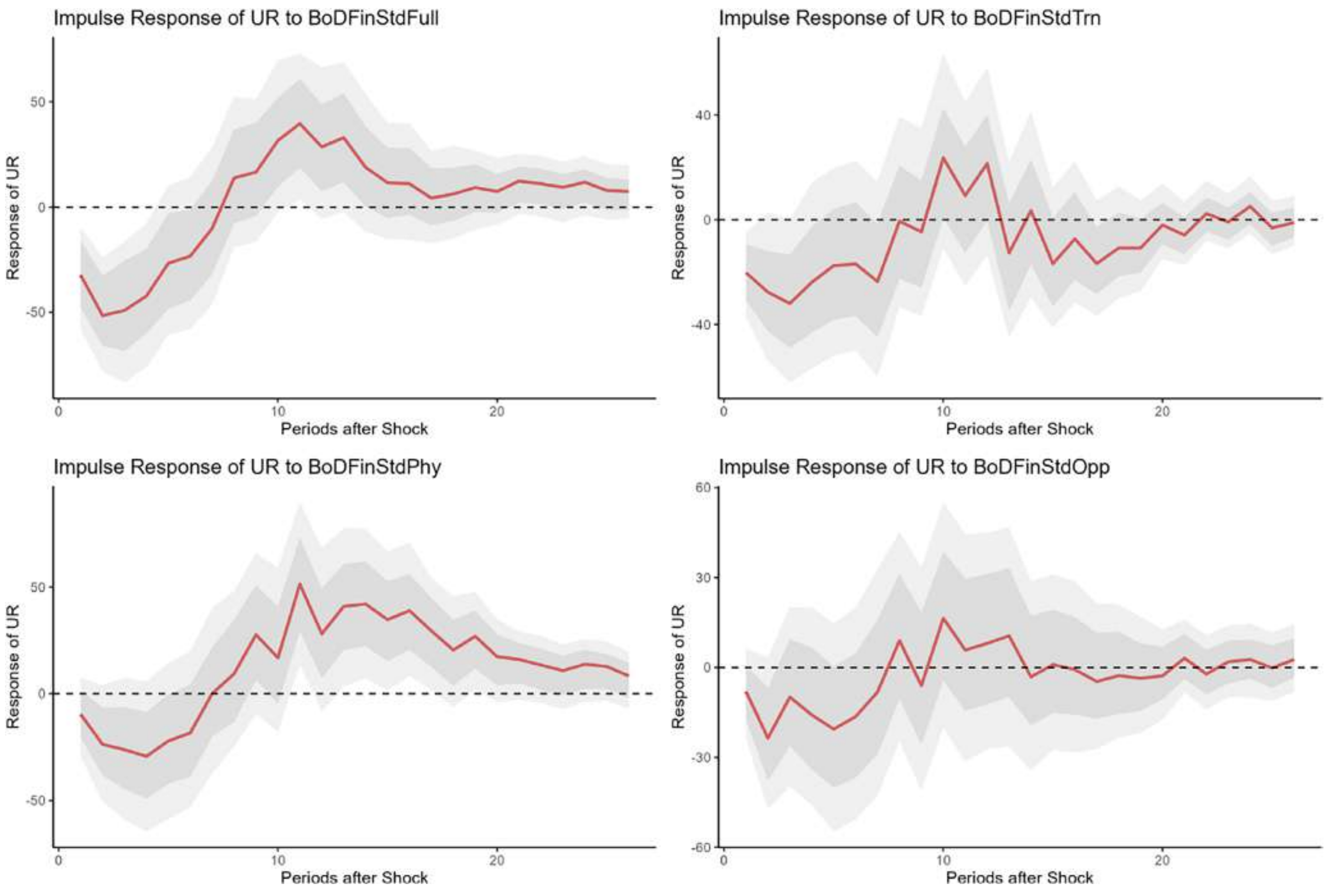

FIGURE 8 | IRF of Climate and Environmental Attention on the Unemployment Rate: full (top left), transition (top right), physical (bottom left), and opportunity (bottom right) attention measured on financial newspapers. The shaded regions represent the bootstrap intervals with 68% and 90% confidence levels.

adaptation measures. It is worth noticing that the response to physical-based news starts positive but gradually declines, indicating that CPI reacts to initial concerns about physical climate events but does not sustain an inflationary effect over time. In particular, financial newspapers exhibit a stronger and more significant response compared to generalist newspapers, showing a more decisive reaction of market participants and businesses to climate-related financial reporting. It is worth noticing that our results are in line with Qi et al. (2025) where climate change is shown to significantly increase the inflation rate.[12] In the quoted article, the main explanatory variable considered to assess the impact on inflation is the Climate Change Performance Index (CCPI), which tracks the actions to cope with climate change and has been computed annually since 2005. This index is provided by Germanwatch[13] and ranks the performance of several countries based on four categories of actions: GHG Emissions, Renewable Energy, Energy Use, and Climate Policy.

The IRF for the Unemployment Rate indicator shows an interesting dynamic in which CEAI initially reduces unemployment before leading to higher unemployment over time; see Figures 8 and 9. This suggests that climate-related changes may create short-term green jobs but lead to longer-term disruption as traditional industries decline. The impact is particularly strong in financial newspapers, where climate policy-related and physics-based news tend to show the most pronounced fluctuations in UR. Later increases in unemployment suggest structural labor shifts driven by regulation, capital reallocation, or job mismatches. However, some responses show high uncertainty (wide confidence bands), especially for policy-based climate attention, indicating that the effects may not be statistically significant. The same assessments are evidenced from the results of Fankhaeser et al. (2008) in which the authors argue that climate change policy can have positive effects on employment in the short term, particularly by creating green jobs, while the medium- and long-term effects are more nuanced. Similarly, Dell'Anna (2021) finds that investments in renewable energy generate significant direct and indirect jobs. Marin and Vona (2019) examine how climate policies affect employment across different skill levels in the EU and find that such policies have a skill-biased impact favoring technicians and disadvantaging manual workers, with no strong long-term effect on overall employment levels. This indicates that climate policy reinforces the broader trend of skill upgrades in labor markets and suggests that policy support for reskilling will be essential for the green transition.

4.3.2 | Financial Markets: Stock Indices and Volatility Measures

The magnitude and significance of the responses are very small for all considered stock indices (see Figures B.3–B.8 in Appendix B). In contrast, as shown in Figures 10 and 11, a generally positive response is evident for the VIX index, across

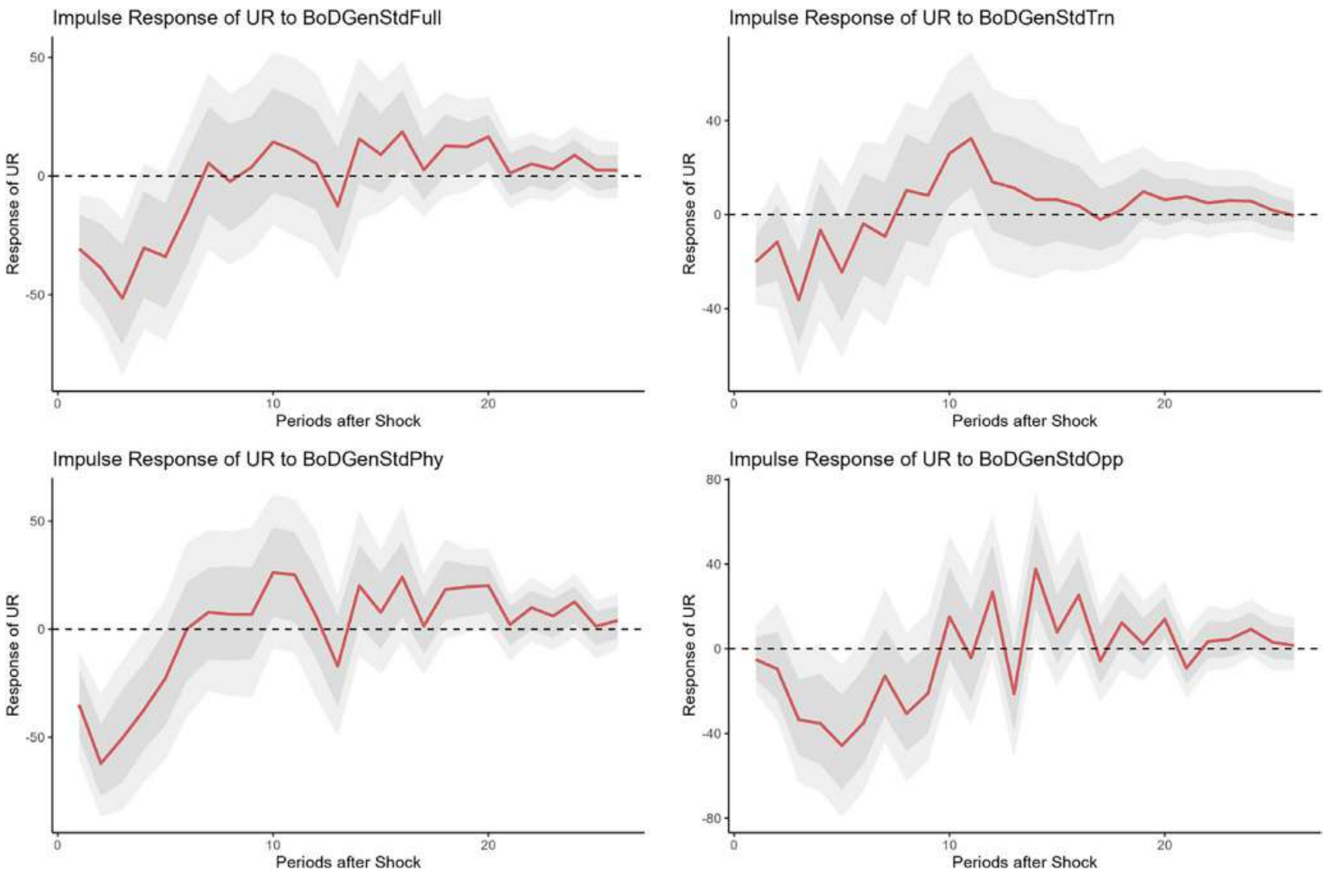

FIGURE 9 | IRF of Climate and Environmental Attention on the Unemployment Rate: full (top left), transition (top right), physical (bottom left), and opportunity (bottom right) attention measured on generalist newspapers. The shaded regions represent the bootstrap intervals with 68% and 90% confidence levels.

all specifications of CEAI measures (Physical, Transition, and Opportunity), indicating that markets interpret climate-related developments as potential sources of uncertainty and suggesting the CEAI indices as information signals to anticipate changes in market uncertainty. However, confidence intervals show variability in both the statistical significance and persistence of these effects, related to the specific nature of the climate news considered. An in-depth analysis of the figures evidences that shocks on the full CEAI index generate an increase in the VIX, which is highest 10–15 weeks after the shock. The persistent effect demonstrates a long-term adjustment of the market to climate-related discourse. Shocks of the transition pillar (TRN) CEAI generate notable but somewhat volatile responses. In fact, the transition involves regulatory changes, technological adaptation, and changes in consumer behavior, and markets may react with increased uncertainty as firms navigate these structural changes. Finally, opportunity-related shocks exhibit a relatively moderate impact on VIX. Although there is an initial increase in volatility, the effect diminishes over time. This is possibly due to investors' perception of discussions around climate-related opportunities as less disruptive compared to those on risks and compliance.

The results also show that climate attention on specialized financial news tends to have a more pronounced impact (Figure 10) compared to generalist newspapers (Figure 11). This effect is particularly evident for physical-related discourses, where the response is both stronger and more persistent and suggests that market participants view physical climate events as a major uncertainty factor that could affect asset valuations and financial stability.

The OVX also exhibits a positive and significant response to climate attention shocks, as evidenced in Figures 12 and 13, indicating that greater climate attention increases oil price volatility. The effect holds for both generalist and financial discourses and does not dissipate quickly (persists beyond 20 periods), suggesting a prolonged market adjustment to climate-related oil price uncertainty. Attention to physical events generates the strongest reaction, aligning with the notion that physical climate events (hurricanes, droughts, and extreme weather) affect oil supply chains, production, and market expectations.

5 | Concluding Remarks

In this study, we develop the CEAI, a high-frequency composite indicator designed to capture changes in public discourse across climate-related discourse, and variants based on either financial or generalist news sources or focused on specific subthemes (transition, physical, and opportunity pillars).

Unstructured text data are transformed into structured and semantically grounded indicators by applying the Semantic

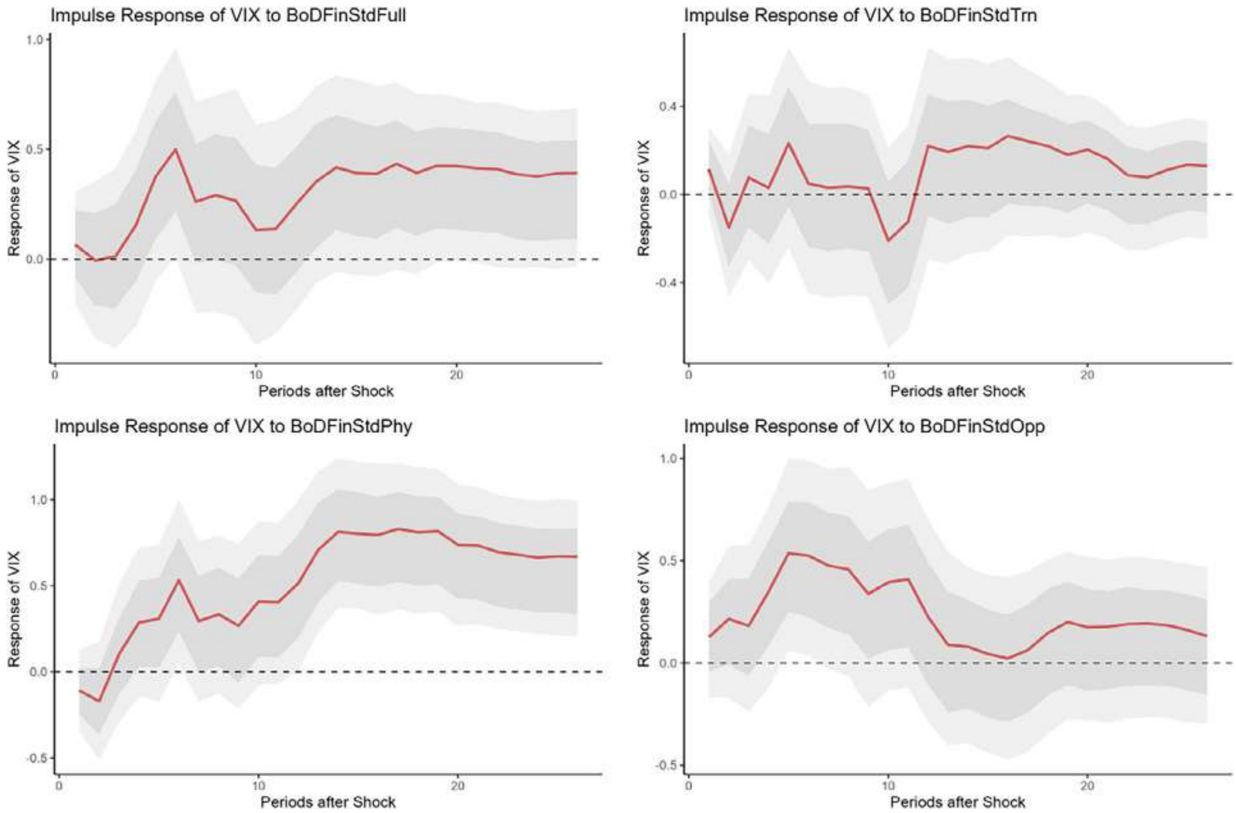

FIGURE 10 | IRF of Climate and Environmental Attention on the VIX volatility index: full (top left), transition (top right), physical (bottom left) and opportunity (bottom right) attention measured on financial newspapers. The shaded regions represent the bootstrap intervals with 68% and 90% confidence levels.

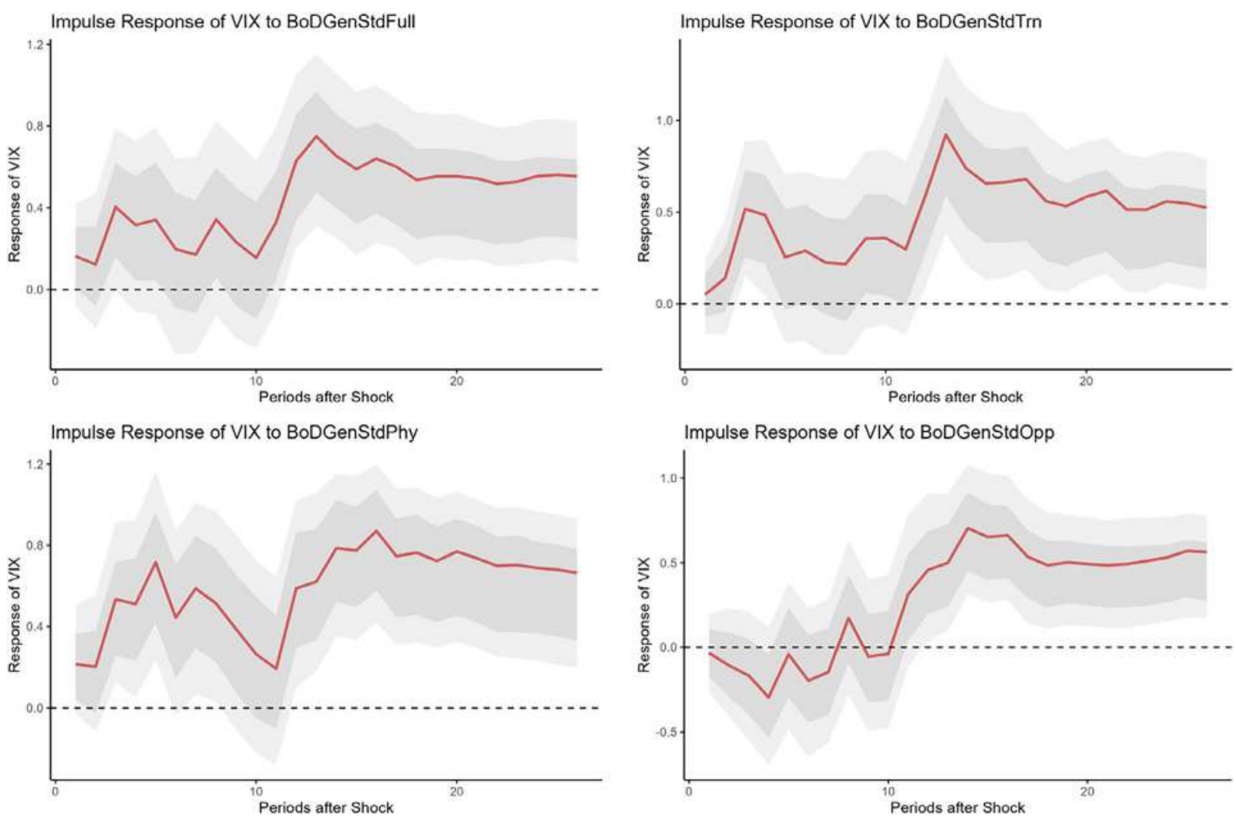

FIGURE 11 | IRF of Climate Attention and Environmental Attention on the VIX volatility index: full (top left), transition (top right), physical (bottom left), and opportunity (bottom right) attention measured on generalist newspapers. The shaded regions represent the bootstrap intervals with 68% and 90% confidence levels.

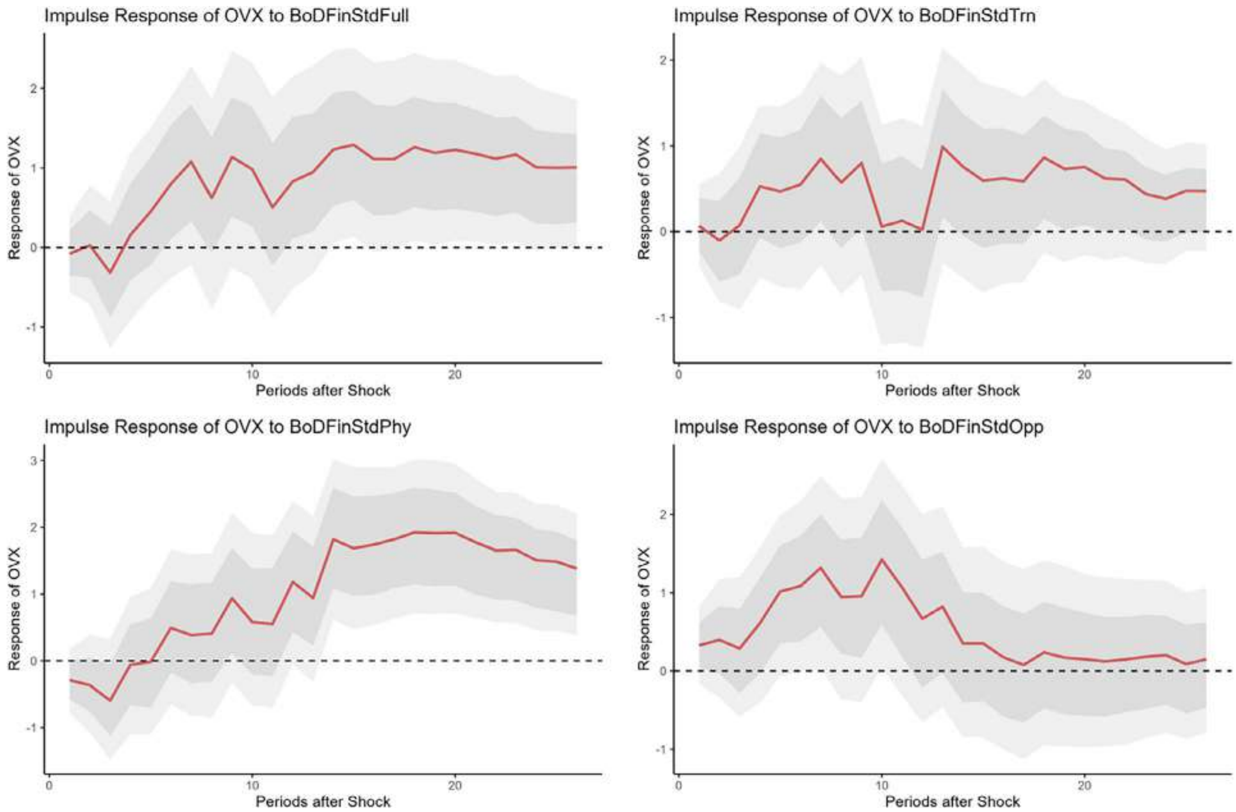

FIGURE 12 | IRF of Climate and Environmental Attention on the OVX volatility index: full (top left), transition (top right), physical (bottom left) and opportunity (bottom right) attention measured on financial newspapers. The shaded regions represent the bootstrap intervals with 68% and 90% confidence levels.

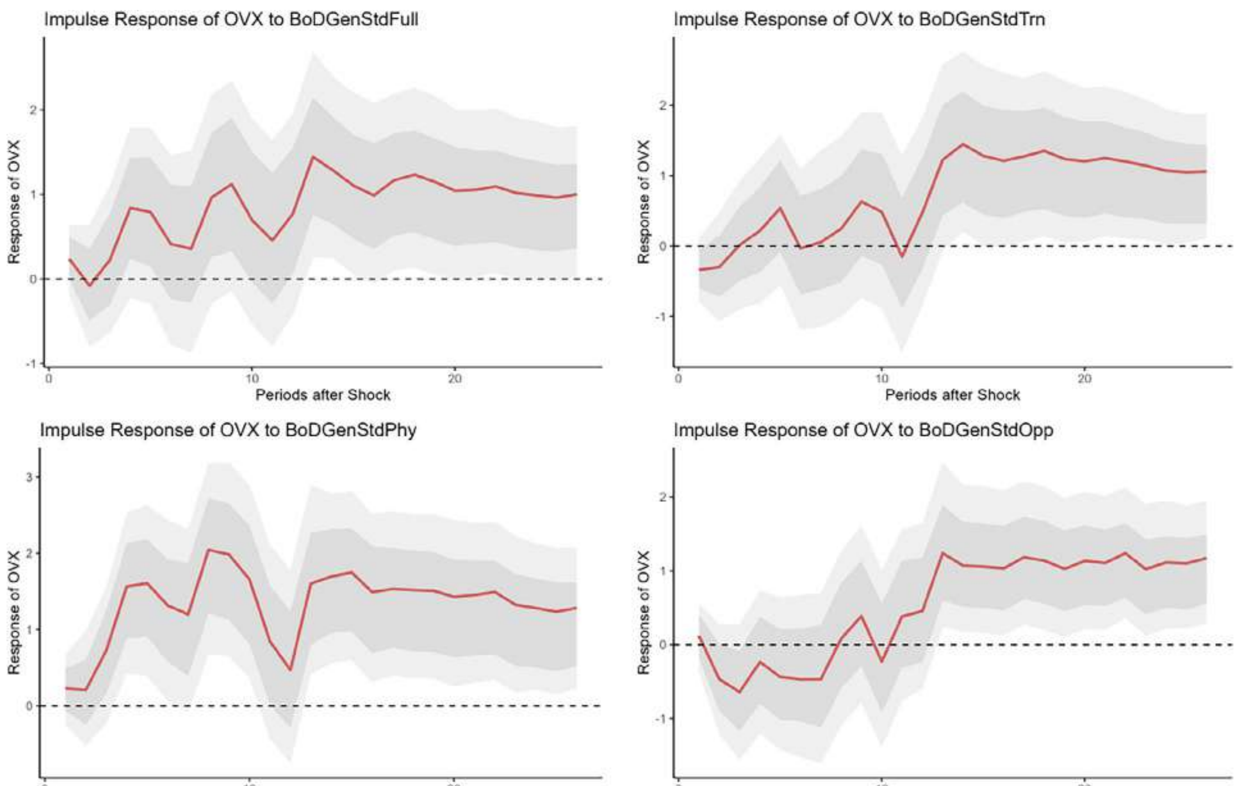

FIGURE 13 | IRF of Climate Attention on the OVX volatility index: full (top left), transition (top right), physical (bottom left), and opportunity (bottom right) attention measured on generalist newspapers. The shaded regions represent the bootstrap intervals with 68% and 90% confidence levels.

Brand Score (SBS) methodology to climate and environment-related news content from 2014 to 2022. The CEAI contributes a complementary information signal to the landscape of climate-related metrics, offering thematic disaggregation, adaptability through time-varying weighting schemes, and responsiveness to evolving narratives. Its limited correlation with existing uncertainty indices confirms its distinctiveness as a decision-support input. Unlike traditional sentiment or keyword count measures, the CEAI leverages network-based semantic analysis, allowing deeper interpretability of media discourse. The empirical evidence, based on vector autoregression models and impulse response functions, reveals that climate attention, particularly when opportunity-oriented, has modest but meaningful short-term effects on inflation and labor markets, whereas physical event narratives induce a stronger influence on financial market volatility. These findings highlight the potential for climate discourse to serve as a forward-looking signal for monetary and employment policy considerations. In addition, market volatility indicators such as VIX and OVX respond strongly to concerns about the physical climate, underscoring investor sensitivity to the matter. CEAI offers a valuable addition to real-time monitoring frameworks. It can be integrated into dashboards, early warning systems, or automated policy support tools used by institutions to track climate attention and assess readiness for transition. The adaptability of the methodology has been demonstrated through media-type customization, distinguishing between generalist and financial news sources; this enhances its applicability in diverse decision-making contexts, including central banking, financial supervision, ESG investment analysis, and workforce planning. Looking ahead, further development may analyze the effect of CEAI in different industries. In addition, integration of real-time data streams, including social networks and the international press, can enhance the granularity and reactivity of the proposed indices. In conclusion, this study highlights the value of semantically enriched media analytics in the architecture of data-driven decision support. As the climate transition accelerates, tools like the CEAI can help bridge the gap between public discourse, market perception, and policy action, supporting more informed, adaptive, and resilient decision making.

Acknowledgements

This research has been partially funded by the University of Perugia through the FRB21 and FRB22 funding campaigns and by the Italian Ministry of University and Research through the PRIN2022, grant no. 2022FPLY97. Open access publishing facilitated by Universita degli Studi di Perugia, as part of the Wiley - CRUI-CARE agreement.

Funding

This work was supported by Università degli Studi di Perugia, FRB2021, FRB2022; Ministero dell'Università e della Ricerca, PRIN2022-2022FPLY97.

Endnotes

[1] See https://www.ipcc.ch/site/assets/uploads/2018/03/wg2TARannexB.pdf.

[2] See https://wesr-staging.azurewebsites.net/glossary/. By construction, the index aggregates semantically weighted signals extracted from news articles, allowing it to track shifts in attention across both climate and environmental themes, offering a distinct perspective from traditional indicators focused on physical variables such as temperature or emissions.

[3] See journal ranking https://www.refdesk.com/top100pap2007.html.

[4] *Sources*: https://www.ipcc.ch/site/assets/uploads/2018/03/wg2TARannexB.pdf, https://www.globalreporting.org/pdf.ashx?id=12,732&page=1, https://assets.bbhub.io/company/sites/60/2020/10/FINAL-2017-TCFD-Report-11,052,018.pdf, https://finance.ec.europa.eu/sustainable-finance/tools-and-standards/eu-taxonomy-sustainable-activities_en.

[5] *Source*: https://www.policyuncertainty.com/us_monthly.html.

[6] *Source*: https://www.policyuncertainty.com/climate_uncertainty.html.

[7] *Source*: https://vlab.stern.nyu.edu/climate.

[8] *Source*: https://www.policyuncertainty.com/sustainability_index.html.

[9] The index data is available in the supplementary material of the cited paper: https://pubsonline.informs.org/doi/suppl/10.1287/mnsc.2022.4636.

[10] The monthly values of the CEAI index were obtained by averaging the weekly observations in each month.

[11] ADF test results and transformation steps for each series are available upon request.

[12] The authors in Qi et al. (2025) claim that the impact is only in the short term, which, given the yearly frequency of their time series, corresponds to a few years. This is confirmed by our results where there is a persistent impact over 6 months.

[13] *Source*: https://www.germanwatch.org/en/CCPI.

References

Ameli, N., P. Drummond, A. Bisaro, M. Grubb, and H. Chenet. 2020. "Climate Finance and Disclosure for Institutional Investors: Why Transparency Is Not Enough." *Climatic Change* 160: 565–589.

Ardia, D., K. Bluteau, K. Boudt, and K. Inghelbrecht. 2023. "Climate Change Concerns and the Performance of Green Vs. Brown Stocks." *Management Science* 69, no. 12: 7607–7632.

Baker, S. R., N. Bloom, and S. J. Davis. 2016. "Measuring Economic Policy Uncertainty." *Quarterly Journal of Economics* 131, no. 4: 1593–1636.

Barber, B. M., and T. Odean. 2008. "All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors." *Review of Financial Studies* 21, no. 2: 785–818.

Barnett, M., W. Brock, and L. P. Hansen. 2020. "Pricing Uncertainty Induced by Climate Change." *Review of Financial Studies* 33, no. 3: 1024–1066.

Barsky, R. B., and E. R. Sims. 2012. "Information, Animal Spirits, and the Meaning of Innovations in Consumer Confidence." *American Economic Review* 102, no. 4: 1343–1377.

Bauer, P. W. 1990. "Recent Developments in the Econometric Estimation of Frontiers." *Journal of Econometrics* 46, no. 1: 39–56.

Beaudry, P., and F. Portier. 2006. "Stock Prices, News, and Economic Fluctuations." *American Economic Review* 96, no. 4: 1293–1307.

Block, S., J. W. Emerson, D. C. Esty, et al. 2024. *2024 Environmental Performance Index*. Yale Center for Environmental Law & Policy. https://epi.yale.edu.

Boykoff, M. T. 2011. *Who Speaks for the Climate?: Making Sense of Media Reporting on Climate Change*. Cambridge University Press.

Boykoff, M. T., and J. T. Roberts. 2007. "Media Coverage of Climate Change: Current Trends, Strengths, Weaknesses." *Human Development Report* 2008, no. 3: 1–53.

Brandes, U. 2001. "A Faster Algorithm for Betweenness Centrality." *Journal of Mathematical Sociology* 25, no. 2: 163–177.

Caldara, D., and M. Iacoviello. 2022. "Measuring Geopolitical Risk." *American Economic Review* 112, no. 4: 1194–1225.

Cevik, S., and G. Gwon. 2024. "This Is Going to Hurt: Weather Anomalies, Supply Chain Pressures and Inflation." *International Economics* 180: 100560.

Chong, D., and J. N. Druckman. 2007. "Framing Theory." *Annual Review of Political Science* 10, no. 1: 103–126.

Church, K. W. 2017. "Word2vec." *Natural Language Engineering* 23, no. 1: 155–162.

Cisagara, B. 2024. "Finance and Climate Change: Assessing the Impact of Physical, Transition, and Regulation Risks on Asset Pricing Valuation." *Journal of Asset Management* 25: 1–23.

Colladon, A. F. 2018. "The Semantic Brand Score." *Journal of Business Research* 88: 150–160.

Colladon, A. F., and F. Grippa. 2020. "Brand Intelligence Analytics." In *Digital Transformation of Collaboration*, edited by A. Przegalinska, F. Grippa, and P. A. Gloor. Springer Nature Switzerland.

Colladon, A. F., B. Guardabascio, and R. Innarella. 2019. "Using Social Network and Semantic Analysis to Analyze Online Travel Forums and Forecast Tourism Demand." *Decision Support Systems* 123: 113075.

Colladon, A. F., B. Guardabascio, and F. Venturini. 2025. "A New Mapping of Technological Interdependence." *Research Policy* 54, no. 1: 105126.

Colladon, A. F., and M. Naldi. 2020. "Distinctiveness Centrality in Social Networks." *PLoS One* 15, no. 5: e0233276.

Da, Z., J. Engelberg, and P. Gao. 2011. "In Search of Attention." *Journal of Finance* 66, no. 5: 1461–1499.

De Marchi, E., A. Cavaliere, and A. Banterle. 2022. "Climate Change and Consumer Behavior." In *Interdisciplinary Approaches to Climate Change for Sustainable Growth*, 315–331. Springer.

Dell'Anna, F. 2021. "Green Jobs and Energy Efficiency as Strategies for Economic Growth and the Reduction of Environmental Impacts." *Energy Policy* 149: 112031.

Engle, R. F., S. Giglio, B. Kelly, H. Lee, and J. Stroebel. 2020. "Hedging Climate Change News." *Review of Financial Studies* 33, no. 3: 1184–1216.

Fankhaeser, S., F. Sehlleier, and N. Stern. 2008. "Climate Change, Innovation and Jobs." *Climate Policy* 8, no. 4: 421–429.

Fliegel, P. 2025. "How (Not) to Measure Companies' Climate Transition Risk: A Framework and Categorized Literature Review." *Corporate Social Responsibility and Environmental Management* 32, no. 3: 3049–3077.

Frankel, R., J. Jennings, and J. Lee. 2022. "Disclosure Sentiment: Machine Learning Vs. Dictionary Methods." *Management Science* 68, no. 7: 5514–5532.

Freudenberg, M. 2003. *Composite Indicators of Country Performance: A Critical Assessment. OECD Science, Technology and Industry Working Papers.*

García-Sánchez, I.-M., T. Alexandre, N. das Almeida, and R. P. de Barros Camara. 2015. "A Proposal for a Composite Index of Environmental Performance (CIEP) for Countries." *Ecological Indicators* 48: 171–188.

Gavriilidis, K. 2021. Measuring Climate Policy Uncertainty.

Gentzkow, M., B. Kelly, and M. Taddy. 2019. "Text as Data." *Journal of Economic Literature* 57, no. 3: 535–574.

Giglio, S., B. Kelly, and J. Stroebel. 2021. "Climate Finance." *Annual Review of Financial Economics* 13, no. 1: 15–36.

Global Footprint Network. 2024. Ecological Footprint—Our Work Accessed: March 12, 2025. https://www.footprintnetwork.org/ourwork/ecological-footprint/.

Greco, S., A. Ishizaka, M. Tasiou, and G. Torrisi. 2019. "On the Methodological Framework of Composite Indices: A Review of the Issues of Weighting, Aggregation, and Robustness." *Social Indicators Research* 141: 61–94.

Hair, J. F., W. C. Black, B. J. Babin, and R. E. Anderson. 2019. Multivariate Data Analysis.

Herweg, F., and K. M. Schmidt. 2022. "How to Regulate Carbon Emissions With Climate-Conscious Consumers." *Economic Journal* 132, no. 648: 2992–3019.

Hoang, K. 2022. "How Does Corporate R&D Investment Respond to Climate Policy Uncertainty? Evidence From Heavy Emitter Firms in the United States." *Corporate Social Responsibility and Environmental Management* 29, no. 4: 936–949.

Hutto, H. C., and E. E. Gilbert. 2014. "Vader: A Parsimonious Rule-Based Model for Sentiment Analysis of Social Media Text." In *Proceedings of the International AAAI Conference on Web and Social Media*, vol. 8, 216–225. PKP Publishing Services Network.

Inoue, A., and L. Kilian. 2013. "Inference on Impulse Response Functions in Structural Var. Models." *Journal of Econometrics* 177, no. 1: 1–13.

Jia, S., X. Chen, L. Han, and J. Jin. 2023. "Global Climate Change and Commodity Markets: A Hedging Perspective." *Journal of Futures Markets* 43, no. 10: 1393–1422.

Li, K., F. Mai, R. Shen, and X. Yan. 2021. "Measuring Corporate Culture Using Machine Learning." *Review of Financial Studies* 34, no. 7: 3265–3315.

Li, K., and T. Yu. 2022. "A Machine Learning-Based Anatomy of Firm-Level Climate Risk Exposure." In *A Machine Learning-Based Anatomy of Firm-Level Climate Risk Exposure*.

Liu, X., and Y. Xiang. 2025. "Climate Policy Uncertainty and Corporate Sustainability Capability: Evidence From Esg Performance." *Corporate Social Responsibility and Environmental Management* 32, no. 4: 5302–5322.

Living Planet Index. 2024. About the Living Planet Index Accessed: March 12, 2025. https://livingplanetindex.org/about_index.

Loughran, T., and B. McDonald. 2011. "When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-ks." *Journal of Finance* 66, no. 1: 35–65.

Lovell, C. A. K., J. T. Pastor, and J. A. Turner. 1995. "Measuring Macroeconomic Performance in the OECD: A Comparison of European and Non-European Countries." *European Journal of Operational Research* 87, no. 3: 507–518.

Lütkepohl, H. 2005. *New Introduction to Multiple Time Series Analysis*. Springer Science & Business Media.

Maibaum, F., J. Kriebel, and J. N. Foege. 2024. "Selecting Textual Analysis Tools to Classify Sustainability Information in Corporate Reporting." *Decision Support Systems* 183: 114269.

Malik, A., M. Li, M. Lenzen, et al. 2022. "Impacts of Climate Change and Extreme Weather on Food Supply Chains Cascade Across Sectors and Regions in Australia." *Nature Food* 3, no. 8: 631–643.

Marin, G., and F. Vona. 2019. "Climate Policies and Skill-Biased Employment Dynamics: Evidence From EU Countries." *Journal of Environmental Economics and Management* 98: 102253.

Meijer, K., F. Frasincar, and F. Hogenboom. 2014. "A Semantic Approach for Extracting Domain Taxonomies From Text." *Decision Support Systems* 62: 78–93.

Mikolov, T., K. Chen, G. Corrado, and J. Dean. 2013. "Efficient Estimation of Word Representations in Vector Space." *arXiv Preprint*: arXiv:1301.3781.

Munda, G., and M. Nardo. 2003. *On the Methodological Foundations of Composite Indicators Used for Ranking Countries*, 1–19. Joint Research Centre of the European Communities.

OECD. 2008. *Handbook on Constructing Composite Indicators: Methodology and User Guide*. Organisation for Economic Co-Operation and Development.

Ongan, S., I. Gocer, and C. Işık. 2025. "Introducing the New ESG-Based Sustainability Uncertainty Index (ESGUI)." *Sustainable Development* 33, no. 3: 4457–4467.

Pástor, L'u., R. F. Stambaugh, and L. A. Taylor. 2022. "Dissecting Green Returns." *Journal of Financial Economics* 146, no. 2: 403–424.

Pennington, J., R. Socher, and C. D Manning. 2014. "Glove: Global Vectors for Word Representation." In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, 1532–1543. Association for Computational Lingustics.

Plagborg-Møller, M., and C. K. Wolf. 2021. "Local Projections and Vars Estimate the Same Impulse Responses." *Econometrica* 89, no. 2: 955–980.

Porter, M. F. 2006. Stemming Algorithms for Various European Languages. http://snowball.tartarus.org/texts/stemmersoverview.html.

Qi, C., Y. Ma, M. Du, X. Ma, Y. Xu, and X. Zhou. 2025. "Impacts of Climate Change on Inflation: An Analysis Based on Long and Short Term Effects and Pass-Through Mechanisms." *International Review of Economics and Finance* 98: 103846.

Roelleke, T., and J. Wang. 2008. "TF-IDF Uncovered." In *Proceedings of the 31st Annual International ACM SIGIR Conference on Research and Development in Information Retrieval—SIGIR '08*, 435–442. ACM Press.

Shiller, R. J. 2020. *Narrative Economics: How Stories Go Viral and Drive Major Economic Events*. Princeton University Press.

Usman, M., M. Husnain, A. Riaz, A. Riaz, and Y. Ali. 2021. "Climate Change During the COVID-19 Outbreak: Scoping Future Perspectives." *Environmental Science and Pollution Research* 28, no. 35: 49302–49313.

Van de Kerk, G., and A. R. Manuel. 2008. "A Comprehensive Index for a Sustainable Society: The SSI—The Sustainable Society Index." *Ecological Economics* 66, no. 2–3: 228–242.

Vestrelli, R., A. F. Colladon, and A. L. Pisello. 2024. "When Attention to Climate Change Matters: The Impact of Climate Risk Disclosure on Firm Market Value." *Energy Policy* 185: 113938.

Vidoli, F., E. Fusco, and C. Mazziotta. 2015. "Non-Compensability in Composite Indicators: A Robust Directional Frontier Method." *Social Indicators Research* 122: 635–652.

Wang, Y., S. Shen, J. Xie, H. Fujii, A. R. Keeley, and S. Managi. 2024. "How Corporate Climate Change Mitigation Actions Affect the Cost of Capital." *Corporate Social Responsibility and Environmental Management* 31, no. 6: 5139–5154.

Yale Center for Environmental Law & Policy. 2024. Environmental Performance Index 2024 Accessed March 12, 2025. https://epi.yale.edu/.

Zhou, P., M. A. Delmas, and A. Kohli. 2017. "Constructing Meaningful Environmental Indices: A Nonparametric Frontier Approach." *Journal of Environmental Economics and Management* 85: 21–34.

Appendix A

Time-Varying Weights Within Sub-Indices

We report here the time-varying BoD weights for the three sub-indices proposed in the paper: transition (Figures A.1 and A.2), physical (Figures A.3 and A.4), and opportunity (Figures A.5 and A.6). For all the sub-indices, the components are tracked over the years from 2014 to 2022, showing how their relative importance (weight) changes over time. In all the reported heatmaps, the color gradient is given by: Blue is assigned to lowest weights (0–0.2), Red is linked to highest weights (0.8–1), and intermediate shades indicate varying degrees of weight within the 0.2–0.8 range.

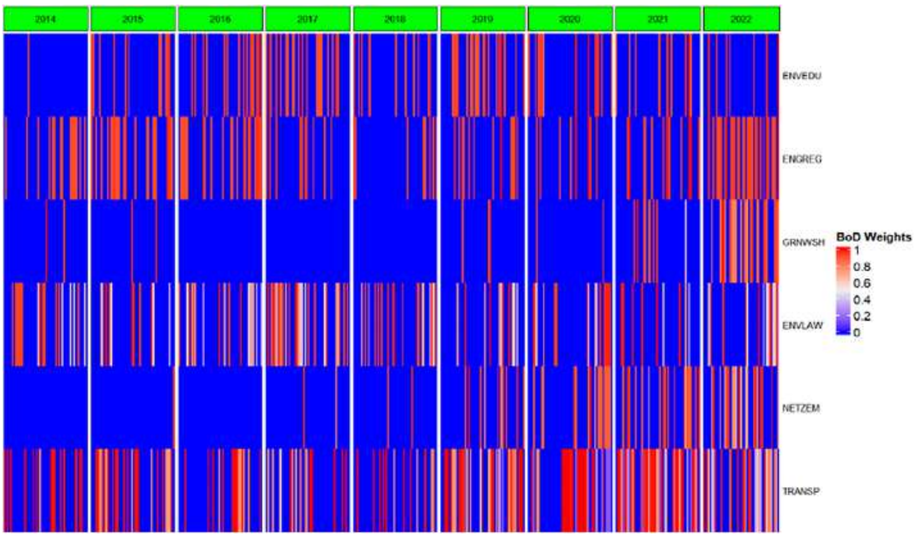

FIGURE A.1 | Weight structure of BoD based on financial newspapers for the transition index components.

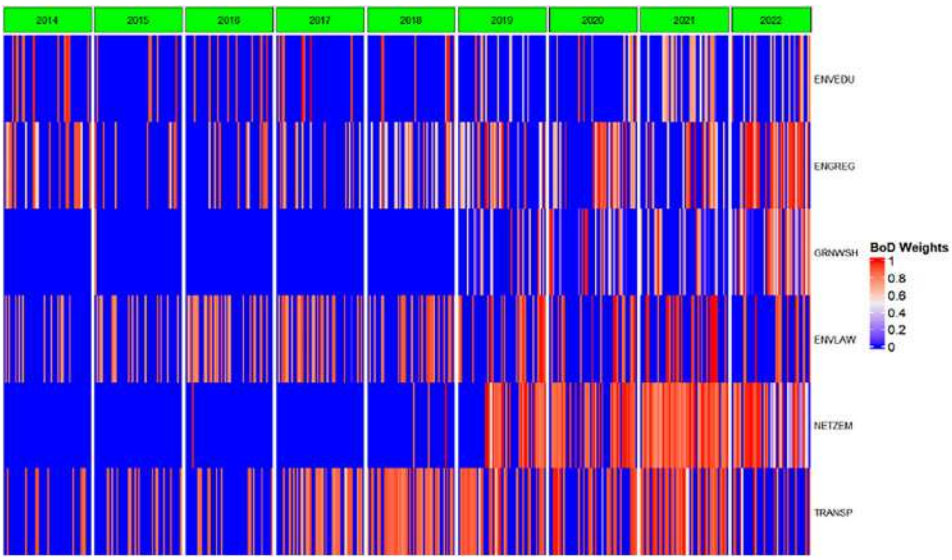

FIGURE A.2 | Weight structure of BoD based on generalist newspapers for the transition index components.

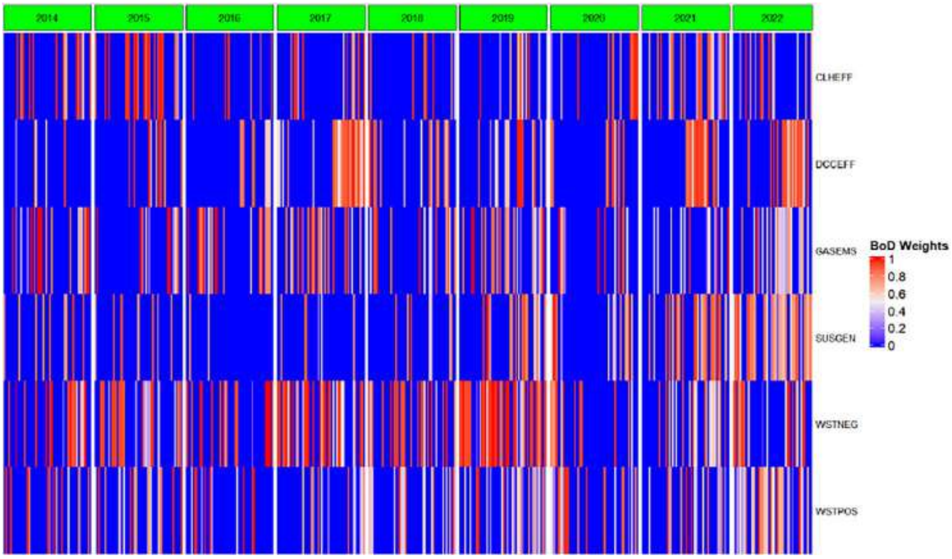

FIGURE A.3 | Weight structure of BoD based on financial newspapers for the physical index components.

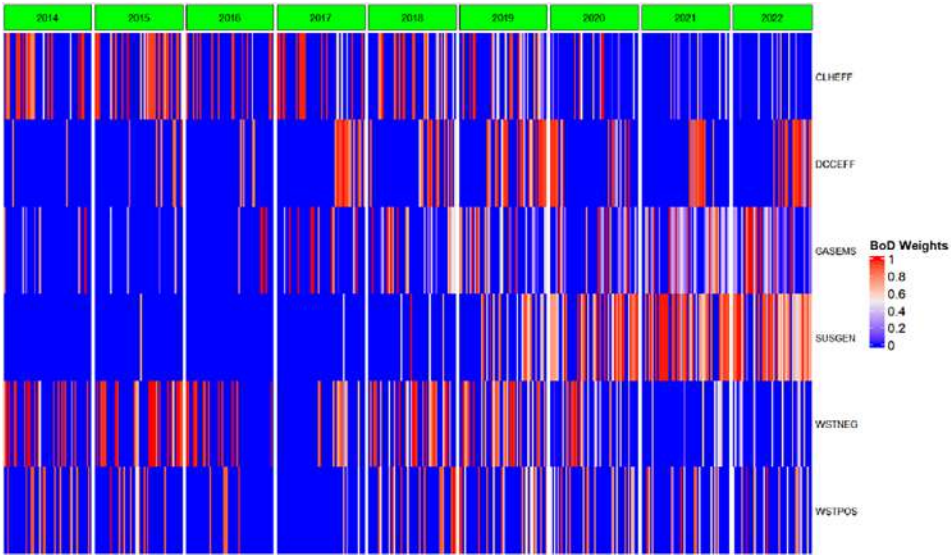

FIGURE A.4 | Weight structure of BoD based on generalist newspapers the physical index components.

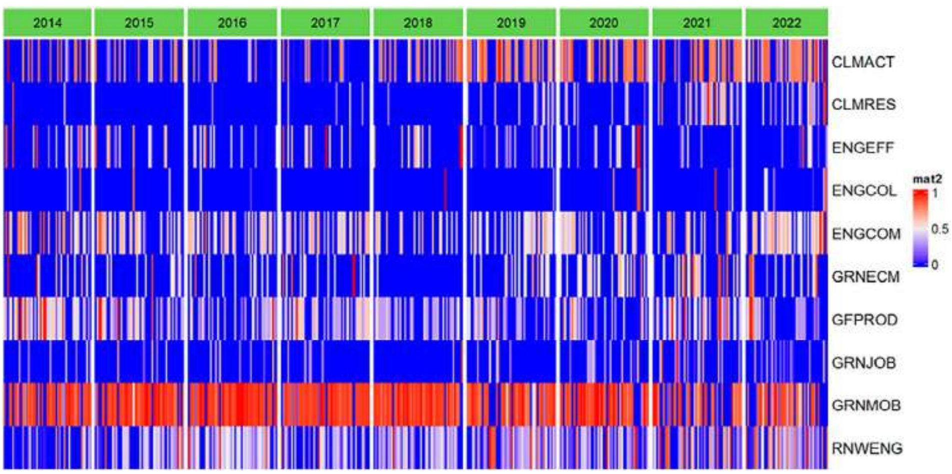

FIGURE A.5 | Weight structure of BoD based on financial newspapers for the opportunity index components.

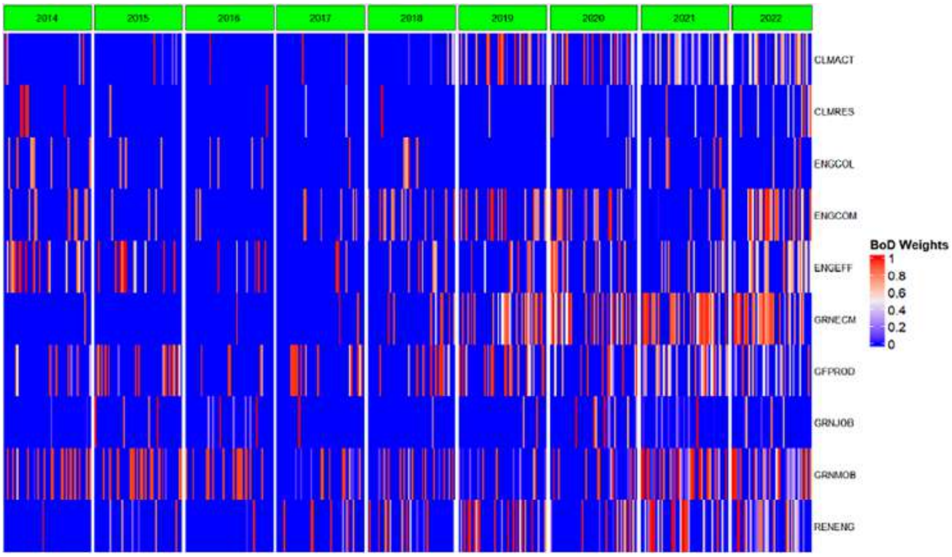

FIGURE A.6 | Weight structure of BoD based on generalist newspapers for the opportunity index components.

Appendix B

Impulse Response Functions Additional Outcomes

In this section, we summarize the impulse response outcomes for the target variables that do not show a significant reaction to shocks in the proposed climate attention indices. We plot the impulse response function of the considered target variable to the full (top left), transition (top right), physical (bottom left) and opportunity (bottom right) attention measures, based on either financial or generalist newspapers. The shaded regions represent the bootstrap intervals with 68% and 90% confidence levels.

The response of WEI to climate attention shocks is relatively weak and short-lived, as shown in Figures B.1 and B.2.

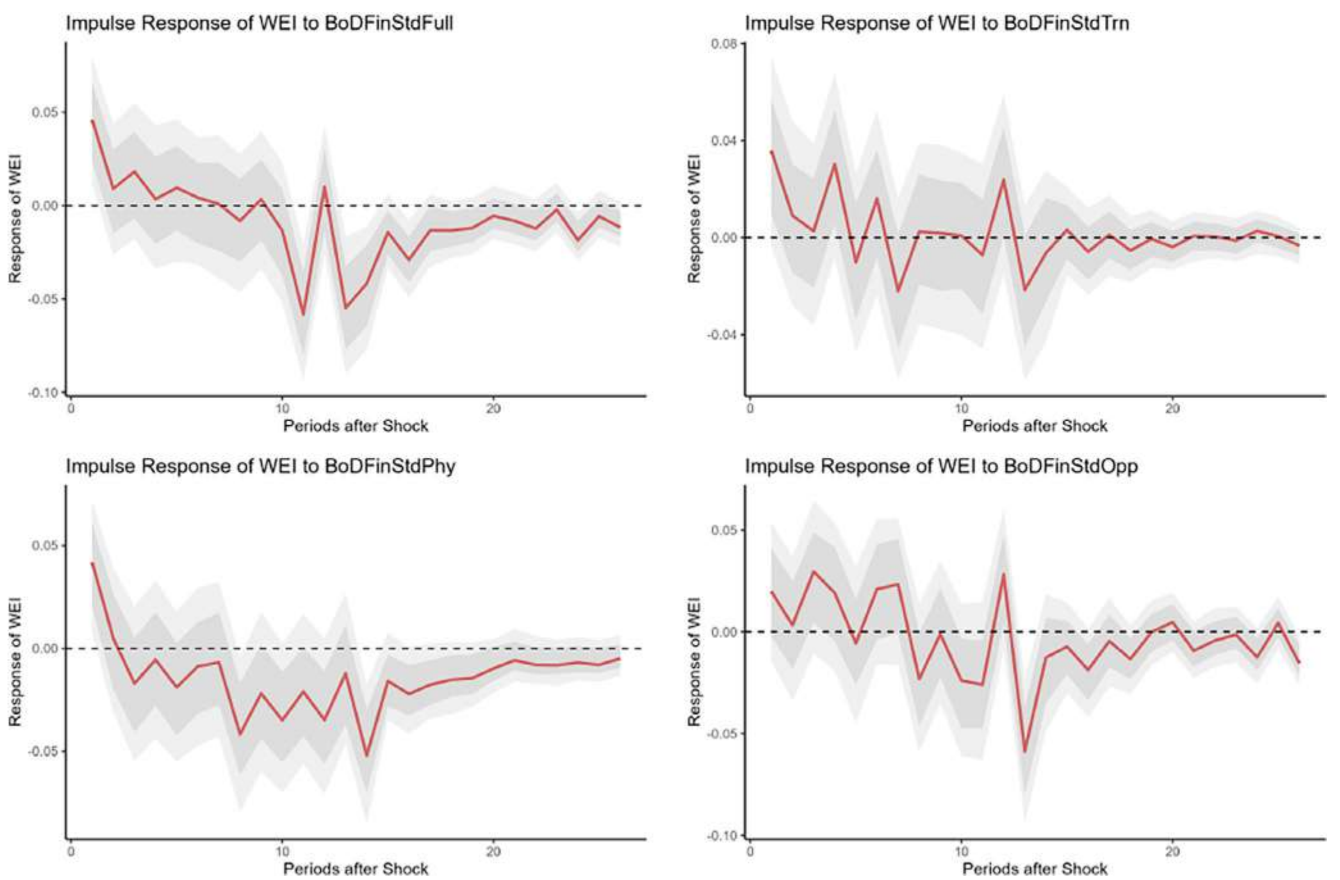

FIGURE B.1 | IRF of climate and environmental attention (financial newspapers) on the Weekly Economic Index (WEI).

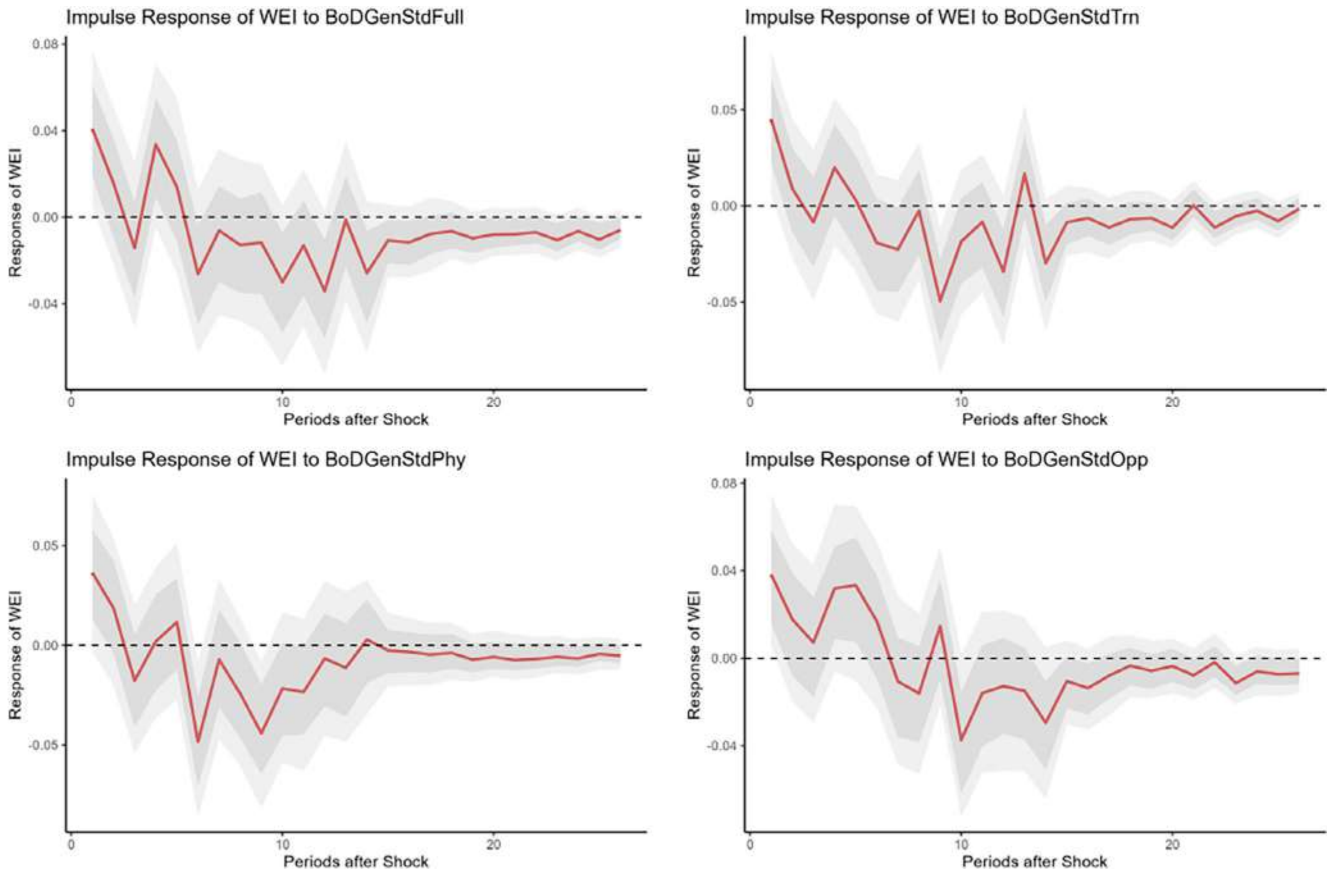

FIGURE B.2 | IRF of climate and environmental attention (generalist newspapers) on the Weekly Economic Index (WEI).

The opportunity-based and full indices exhibit a temporary positive effect on WEI, likely reflecting optimism about climate-related economic opportunities such as green investment and innovation; physics-based and regulation-based indices have weaker and sometimes negative effects, indicating that concerns about physical climate events and regulatory uncertainty may weigh on economic confidence. However, the confidence intervals suggest that in most cases none of the responses is statistically significant, reinforcing the notion that climate attention alone is not a primary driver of short-term economic activity.

The response of the three considered stock market indices is also nonsignificant, as evidenced in Figures B.3–B.8, suggesting that the attention of climate-related news does not strongly influence market prices and returns. The results also suggest that investors in traditional industries (DJIA) might be slightly more concerned about climate regulation, while investors in tech assets (Nasdaq 100) appear indifferent to climate-related news. The S&P 500 evidences some fluctuations in response to financial news categories but no sustained effect. In fact, since this market index covers a mix of sectors, the mild response could stem from energy-heavy components being more exposed to climate concerns, while the presence of resilient sectors like tech and healthcare dampens the impact. A sector-specific analysis is on our research agenda in order to reveal possible stronger responses that are masked at the index level.

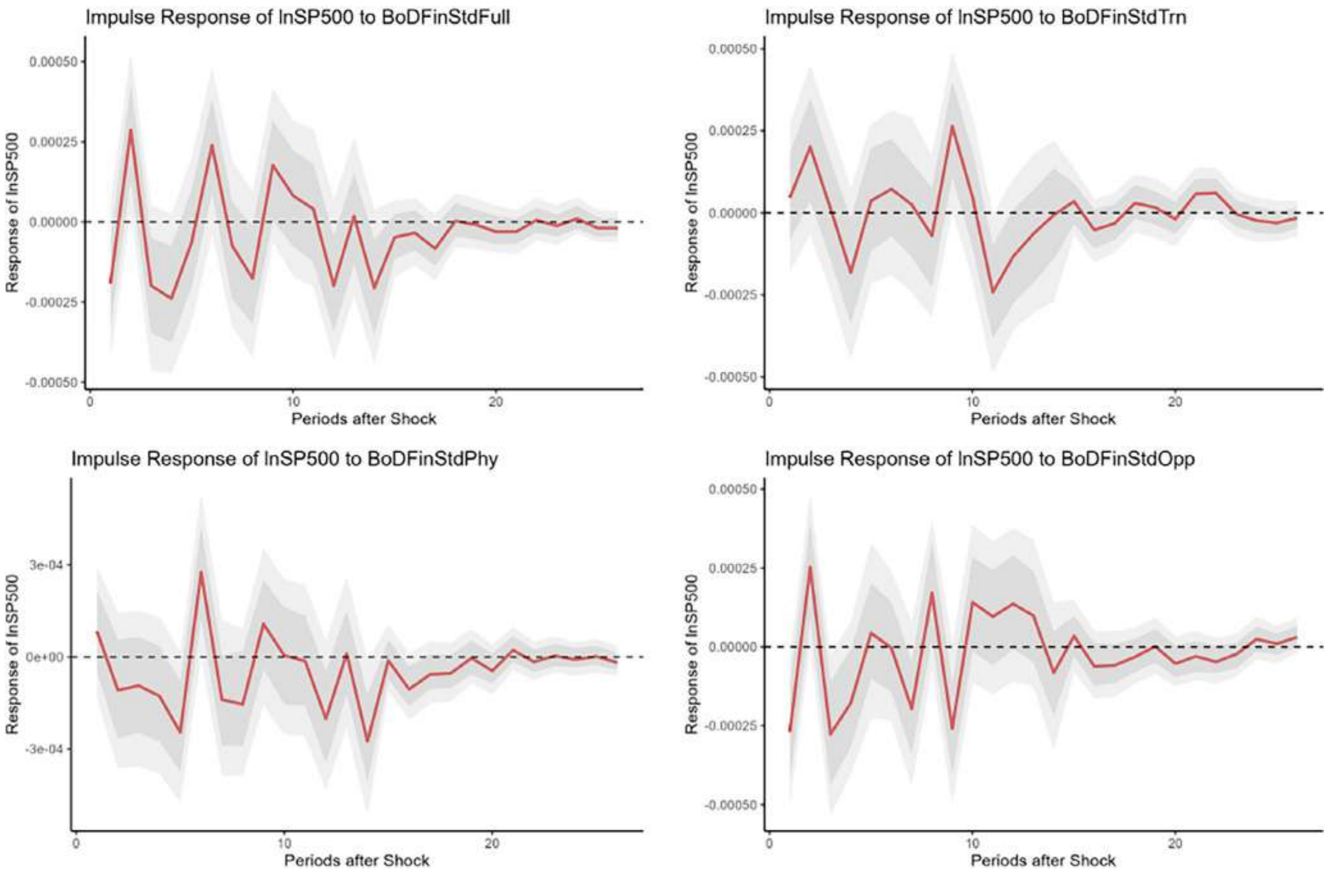

FIGURE B.3 | IRF of climate and environmental attention (financial newspapers) on the S&P 500 market index.

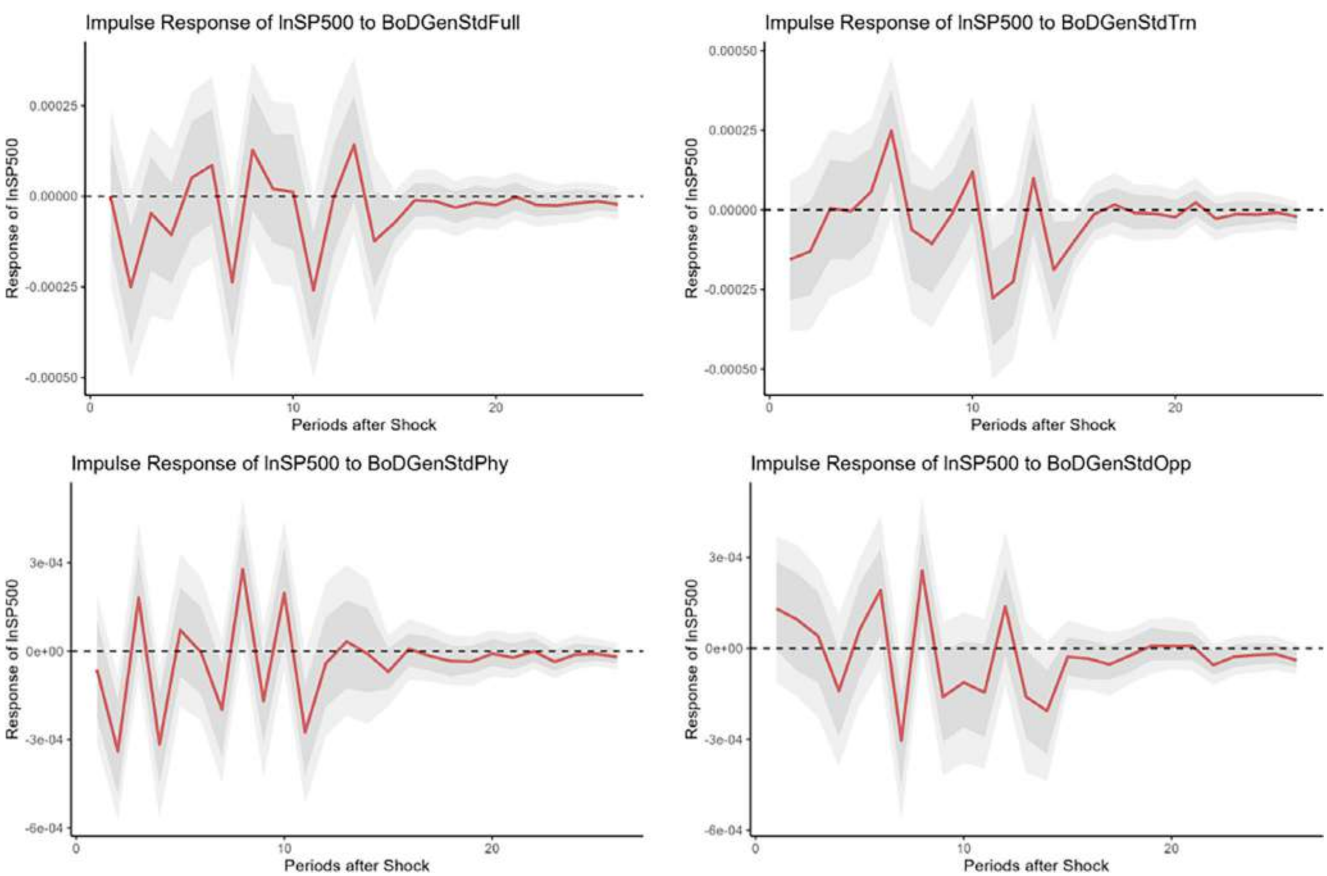

FIGURE B.4 | IRF of climate and environmental attention (generalist newspapers) on the S&P 500 market index.

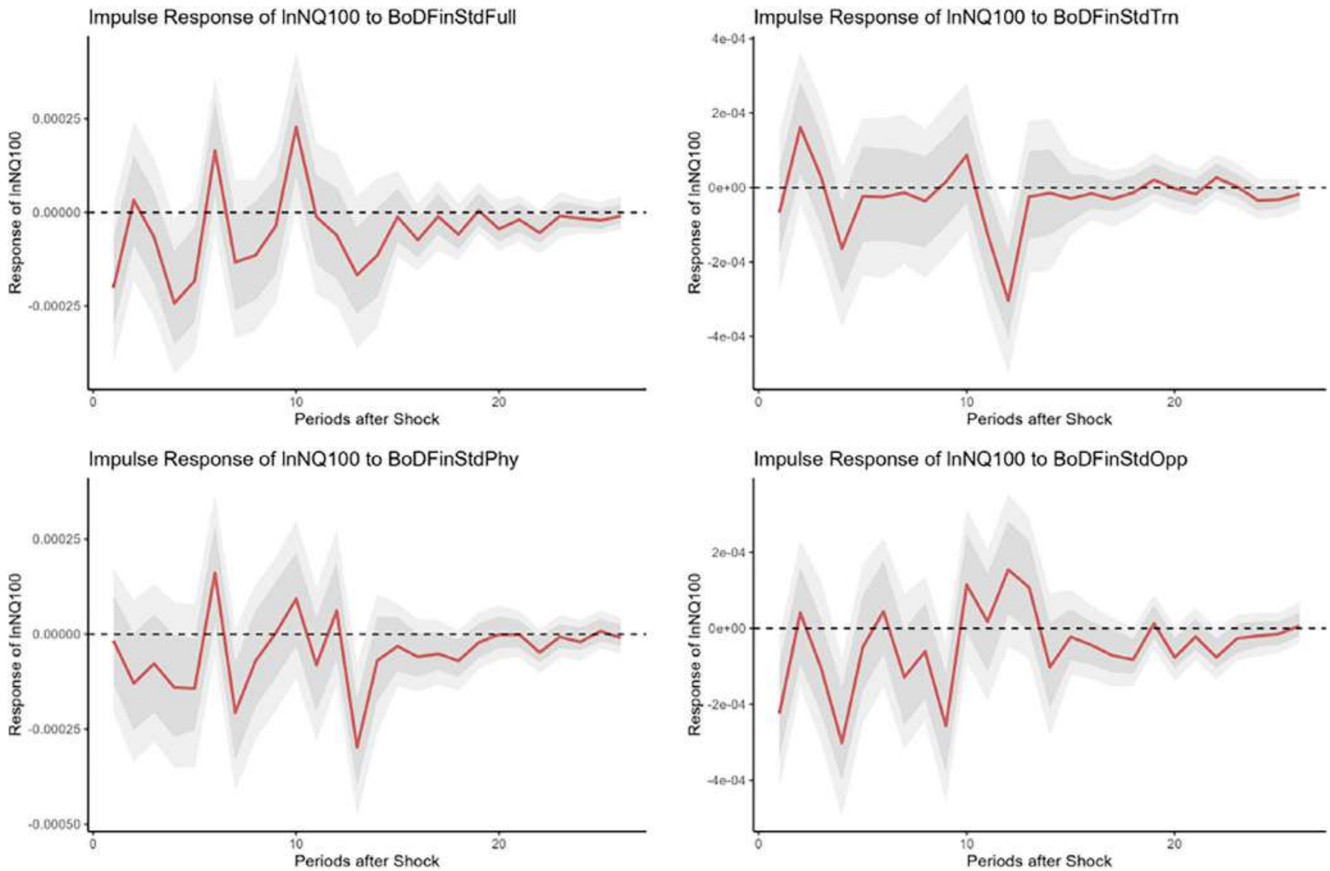

FIGURE B.5 | IRF of climate and environmental attention (financial newspapers) on the NASDAQ 100 market index.

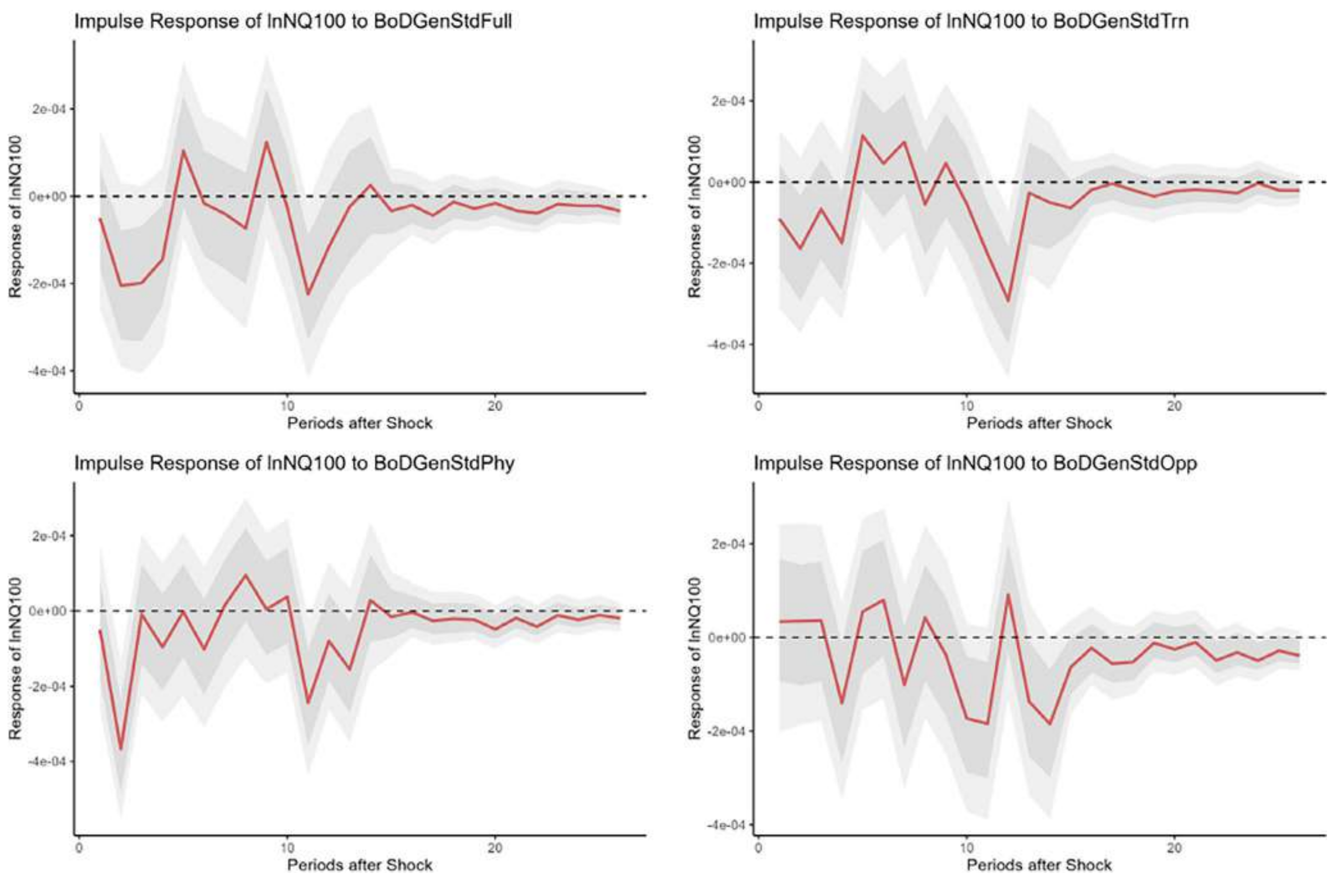

FIGURE B.6 | IRF of climate and environmental attention (generalist newspapers) on the NASDAQ 100 market index.

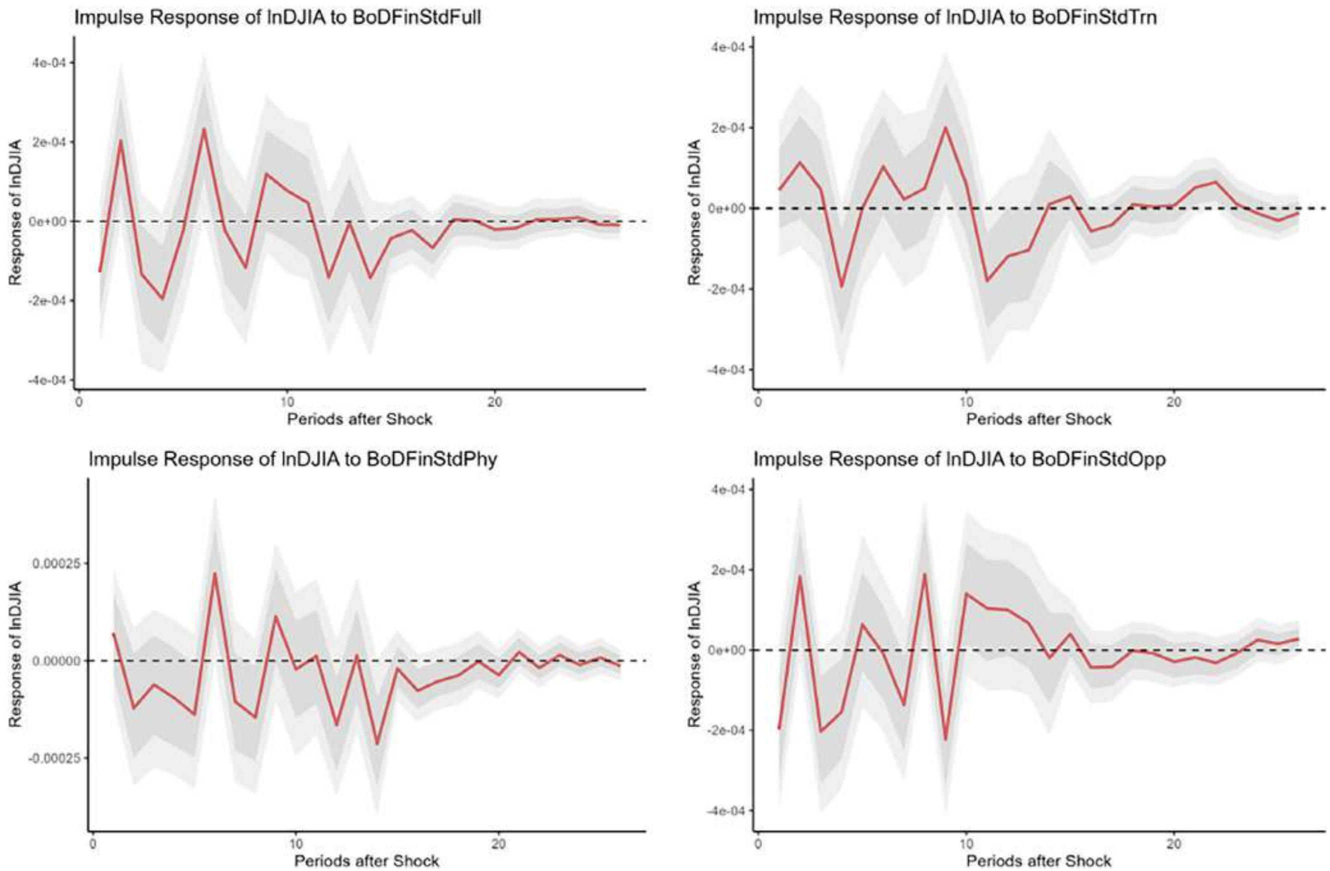

FIGURE B.7 | IRF of climate and environmental attention (financial newspapers) on the DJIA market index.

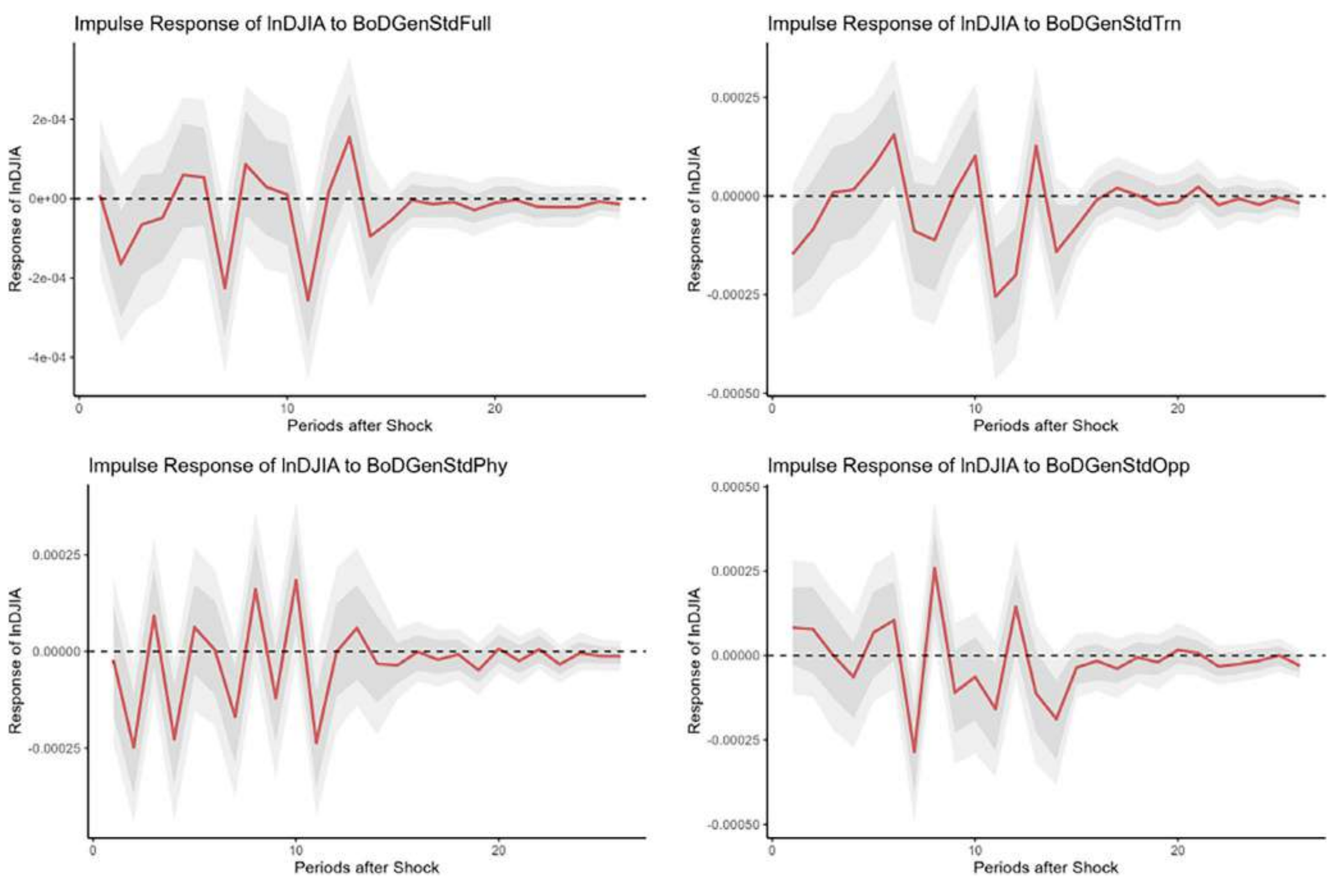

FIGURE B.8 | IRF of climate and environmental attention (generalist newspapers) on the DJIA market index.