

RESEARCH ARTICLE OPEN ACCESS

Mapping Non-Linear ESG Trajectories in OECD Countries: A Topological Entropy Approach

Sana Gaied Chortane^{1,2}  | Rami Salem^{3,4}  | Salah Ben Hamad⁵

¹ERIC Laboratory, Université Lumière Lyon 2, Lyon, France | ²Laboratoire d'Économie et de Gestion (LEG)LR18ES27, University of Sfax, Sfax, Tunisia | ³College of Business, University of Doha for Science and Technology, Doha, Qatar | ⁴University of Lancashire, Preston, Lancashire, UK | ⁵IFGTLaboratory, Faculty of Economics and Management of Tunis (FSEG), University of Tunis El Manar, Tunisia

Correspondence: Rami Salem (riasalem1@lancashire.ac.uk)

Received: 10 January 2026 | **Revised:** 28 July 2026 | **Accepted:** 18 September 2026

Keywords: change in ESG configuration | ESG performance | OECD countries | sustainability trajectories | topological clustering

ABSTRACT

This study examines the evolution of Environmental, Social and Governance (ESG) performance across 38 OECD countries between 2010 and 2024 using a longitudinal and multi-dimensional analytical framework. Moving beyond static ESG benchmarking approaches, it investigates how sustainability trajectories evolve under changing institutional, economic and governance conditions. The findings reveal that ESG transitions across advanced economies are neither linear nor uniformly convergent. Instead, countries follow differentiated sustainability pathways characterised by persistent trade-offs across ESG dimensions. In particular, improvements in governance and social performance do not necessarily coincide with stronger environmental outcomes, highlighting the complexity of balancing competing sustainability priorities under conditions of uncertainty and external shocks. By integrating Multiple Factor Analysis (MFA), Hierarchical Ascending Classification (HAC) and Topological Local Entropy Clustering (TLEC), the analysis provides a dynamic perspective on ESG evolution across OECD countries. The findings contribute to the sustainability strategy literature by emphasising the importance of adaptive and context-sensitive governance frameworks for managing sustainability transitions. Practical implications are offered for policymakers, firms and investors seeking to strengthen long-term ESG resilience and sustainability integration strategies.

1 | Introduction

Environmental, Social and Governance (ESG) performance has become a central pillar of contemporary sustainability strategy, shaping investment decisions, regulatory frameworks and corporate governance practices across advanced economies (Eccles et al. 2020; Friede et al. 2015). As climate risks, social inequalities and institutional pressures intensify, ESG considerations increasingly influence how firms, investors and governments evaluate long-term resilience and sustainable value creation (Gerged et al. 2023; Ghazwani et al. 2025; Salem et al. 2025). Despite the growing convergence around sustainability principles through international climate agreements and ESG disclosure frameworks, substantial divergence persists in how countries develop and sustain ESG performance over time

(Gerged et al. 2025). While global commitments such as the Sustainable Development Goals (SDGs) have created a shared sustainability agenda, national ESG trajectories remain deeply heterogeneous (Mio et al. 2020). This divergence is particularly visible within OECD countries, whose member states share relatively advanced institutional structures and regulatory capacities, yet exhibit markedly different sustainability pathways (OECD 2022). ESG criteria have therefore become increasingly important tools for guiding investment decisions, public policy and sustainable development strategies (Friede et al. 2015; Eccles et al. 2014). However, behind the growing adoption of ESG frameworks, countries continue to display uneven sustainability transitions shaped by differing institutional structures, economic conditions and governance priorities (Kotsantonis et al. 2016; Khan et al. 2016). Some countries demonstrate

This is an open access article under the terms of the [Creative Commons Attribution](https://creativecommons.org/licenses/by/4.0/) License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

© 2026 The Author(s). *Business Strategy and the Environment* published by ERP Environment and John Wiley & Sons Ltd.

relatively balanced ESG progress, while others experience fragmented transitions characterised by trade-offs between ESG dimensions. These differences suggest that ESG transitions are not linear or universally convergent processes, but rather context-dependent pathways shaped by institutional capacities and adaptive responses to external shocks.

In reality, the OECD represents a highly heterogeneous institutional and economic landscape. Its member states range from nations of fewer than 400,000 inhabitants to economies exceeding 330 million in population, while GDP per capita, industrial structures and economic growth trajectories differ substantially (Capelle-Blancard and Petit 2019; Berg et al. 2022). Such demographic, economic and institutional heterogeneity is not merely contextual; it actively shapes governance capacities, political priorities and national approaches to ESG integration (Kotsantonis et al. 2016; Khan et al. 2016). This tension between shared sustainability ambitions and differentiated national realities raises an important strategic and policy question:

How and why do ESG trajectories diverge across advanced economies despite shared sustainability commitments and institutional convergence pressures?

This question is addressed through a descriptive and interpretive analytical lens, identifying the institutional and economic conditions associated with divergent ESG trajectories rather than estimating causal relationships.

Conventional ESG benchmarking approaches and aggregate rankings often obscure more than they reveal, failing to capture the dynamic trade-offs, discontinuities and context-specific mechanisms that shape national sustainability transitions over time. Understanding these differentiated pathways is increasingly important because ESG transitions now influence economic competitiveness, investment allocation, regulatory exposure and institutional resilience across advanced economies. To address this question, we adopt a dynamic and multidimensional perspective on ESG evolution across OECD countries between 2010 and 2024. Rather than relying on static ESG rankings or cross-sectional comparisons, we examine how sustainability trajectories evolve over time under changing economic, institutional and governance conditions. Specifically, the study pursues three objectives:

1. To analyse the temporal evolution of ESG performance across OECD countries and identify major patterns of convergence, divergence and discontinuity;
2. To develop an empirical typology of national ESG trajectories based on the interaction between ESG dimensions;
3. To interpret differentiated ESG pathways using an integrated framework combining environmental pressures, macroeconomic conditions, institutional governance and cognitive-informational dynamics.

Achieving these objectives requires addressing several important limitations in the existing ESG literature. First, inconsistencies among ESG ratings continue to complicate meaningful cross-country comparisons and longitudinal assessments (Berg et al. 2022). Second, much of the existing literature relies on static or cross-sectional analyses that provide limited insight

into the dynamic and potentially non-linear nature of sustainability transitions over time (Eccles et al. 2020). Third, relatively limited attention has been devoted to the interaction between ESG performance and cognitive-informational dimensions such as investor sentiment, media dynamics and institutional perception, despite their increasing relevance for sustainability strategy and financial decision-making (Bebbington and Unerman 2020; Zeng et al. 2024).

This study addresses these limitations through a longitudinal and multi-dimensional analytical framework. Specifically, we combine sector-disaggregated ESG data with environmental, economic, institutional and informational variables in order to analyse differentiated sustainability trajectories across OECD countries. The empirical analysis integrates multiple factor analysis (MFA), Hierarchical Ascending Classification (HAC) and Topological Local Entropy Clustering (TLEC) to identify heterogeneous ESG pathway patterns and complex transition dynamics. Importantly, the methodological framework is employed as an analytical tool to better understand ESG divergence rather than as an end in itself.

This study contributes to the literature in three important ways. *First*, it provides a longitudinal and sectorally disaggregated analysis of ESG trajectories across OECD countries, thereby moving beyond static benchmarking approaches commonly used in sustainability research. *Second*, it develops an integrated framework linking environmental, economic, governance and cognitive-informational dimensions to characterise differentiated sustainability pathways across advanced economies. *Third*, the study demonstrates how entropy-based analytical approaches can help uncover heterogeneous and context-dependent ESG dynamics, offering additional insights into sustainability strategy, institutional adaptation and policy design. The question of ESG divergence is strategically important because sustainability transitions increasingly shape economic competitiveness, investment allocation, regulatory exposure and institutional resilience. Understanding why countries follow different ESG pathways can therefore provide valuable insights for policymakers, firms, and investors attempting to design adaptive sustainability strategies under conditions of uncertainty and external shocks.

The remainder of our paper is structured as follows. Section 2 reviews the conceptual foundations and key drivers of ESG performance. Section 3 details our data and methodological framework. Section 4 presents the results of our temporal and spatial analyses. Section 5 provides a focused discussion, interpreting the results through our conceptual lens and highlighting the insights from the TLEC approach. Finally, Section 6 concludes with policy implications, limitations and avenues for future research.

2 | Review of the Literature

2.1 | Conceptual Framework: A Multi-Thematic Approach to ESG Dynamics

Understanding the divergent ESG trajectories of OECD countries requires moving beyond monolithic explanations or single-dimension analysis. ESG performance is not

exogenously determined; rather, it is shaped by a complex interplay of structural, institutional and macroeconomic forces, as well as stakeholder perceptions (Gerged et al. 2023). Drawing on established theories and recent empirical evidence, we propose that national sustainability pathways can be understood through four interconnected thematic pillars: (1) Environmental pressures and innovations; (2) Economic & Market structures and cycles; (3) Governance & Institutional quality; and (4) Sentiment & Perception dynamics. This multi-capital framework aligns with the holistic view of value creation promoted by the International Integrated Reporting Council (IIRC) (O'Dwyer et al. 2024) and provides the theoretical scaffolding for our variable selection and subsequent analysis. The following subsections detail the theoretical foundations and empirical relevance of each pillar.

2.2 | The Four Thematic Pillars

2.2.1 | The Environmental Pillar: Ecological Constraints and Innovation

The environmental dimension is foundational to sustainable development. The Natural Resource Based view of the firm (Hart 1995) posits that proactive environmental management constitutes a source of competitive advantage and long-term viability. Similarly, Ecological Modernisation theory (Mol and Spaargaren 2000) argues that technological and institutional innovation can decouple economic growth from environmental degradation. This multidimensional imperative is reflected in contemporary research. Zheng et al. (2025) confirm that green manufacturing reshapes value chains and elevates ESG performance, while Dobre et al. (2025) and Gerged et al. (2023) indicate that transparent environmental disclosure underpins organisational resilience. Crucially, investor pricing of physical and transitional climate risks demonstrates that environmental management is both an ecological and a financial imperative (Al-Shaer et al. 2026; Ben Ameer et al. 2024). Consequently, our framework explicitly incorporates key environmental dimensions including CO₂ emissions, biodiversity, green innovation and climate risk exposure to capture these critical determinants of sustainability performance.

2.2.2 | The Economic and Market Pillar: Macroeconomic Context and Systemic Shocks

ESG trajectories are embedded within and responsive to broader macroeconomic and financial contexts. Stakeholder theory (Freeman 1984) emphasises that sustainable performance is negotiated among various economic actors whose interests are influenced by market conditions. The Adaptive Market Hypothesis (Lo, forthcoming) complements this perspective by suggesting that market behaviour, risk perception and institutional responses evolve with changing economic conditions. This theoretical lens motivates the identification of temporal ESG regimes and guides the inclusion of market volatility, stock-market conditions, economic resilience and systemic-shock indicators in the Economy and Market thematic block.

Modern portfolio theory (Markowitz 1952), extended to include ESG factors, recognises that extra financial risks contribute to overall portfolio volatility. Empirically, the integration of ESG criteria affects market risk premia and investor behaviour, especially during periods of financial stress (Dunbar et al. 2023). Furthermore, macroeconomic instability and exogenous shocks such as pandemics or geopolitical conflicts can create sharp trade-offs between sustainability goals and short-term economic pressures (Wang et al. 2024; Fouejieu et al. 2019). Digital infrastructure and relational governance have also been shown to mediate how economies withstand such disruptions (Liu and Wang 2026). Consequently, this pillar informs our analysis of variables related to GDP growth, inflation, unemployment, market volatility and exposure to systemic crises.

2.2.3 | The Governance and Institutional Pillar: The Framework for Action

Effective institutions provide the essential framework within which environmental and social goals are pursued. Neo-institutional theory (DiMaggio and Powell 1983) highlights isomorphic pressures that drive organisations and nations toward similar structural responses, including the adoption of ESG norms (Luo and Tang 2023). Corporate governance quality is intrinsically linked to firm value and sustainability outcomes (Gompers et al. 2003). Contemporary research supports that robust regulatory frameworks and digital transformation of public institutions enhance transparency, reduce the cost of capital and catalyse green innovation (Jin et al. 2024; Guo and Zhang 2025; Ghazwani et al. 2026). Conversely, corruption undermines profitability and escalates political risk (Hoang et al. 2022; Nguyen 2023), while strong governance can amplify the positive financial impact of ESG performance (Joshi and Joshi 2024). This pillar undergirds our focus on variables measuring corruption perceptions, political stability, digitalisation, human development and collaborative governance.

2.2.4 | The Sentiment and Perception Pillar: The Cognitive Dimension

Beyond tangible metrics, ESG trajectories are increasingly influenced by cognitive and informational dynamics (Xiao et al. 2025). Prospect Theory (Kahneman and Tversky 1979) outlines how cognitive biases shape decision-making under risk, while Agenda-Setting theory (McCombs and Shaw 1972) explains how media frames public and investor priorities. In the ESG domain, investor confidence mediates the link between ESG performance and firm valuation (Tang et al. 2024), and media coverage of ESG incidents directly affects analyst attention and the cost of capital (He and Li 2024). The emergence of Emotional Artificial Intelligence (E-AI) offers new tools to quantify affective valence in large-scale textual data, revealing how sentiment influences market reactions and corporate behaviour (Liu et al. 2024). Furthermore, 'carbon sentiment' derived from alternative data can predict market premiums linked to sustainability (Xie 2024). This evolving pillar justifies the inclusion of novel variables such as investor

confidence indices, media coverage scores and measures derived from emotional AI. Together, Prospect Theory, Agenda-Setting Theory and the behavioural and emotional-finance perspective provide the theoretical basis for the Sentiment and Perception block. These perspectives guide the ex ante selection of investor confidence, media coverage and Emotional AI indicators.

2.3 | Synthesis and Empirical Operationalisation

The theoretical perspectives presented above provide an ex ante framework for variable selection and empirical organisation rather than being used only to label the clusters after their construction. Stakeholder theory motivates the use of the ESG pillar scores as active variables. The Natural Resource-Based View and Ecological Modernisation Theory guide the Environment block. The Adaptive Market Hypothesis supports the temporal-regime approach and the Economy and Market block. Neo-institutional theory provides the foundation for the Governance and Institutions block. Finally, Prospect Theory, Agenda-Setting Theory and behavioural and emotional finance motivate the Sentiment and Perception block.

This framework is operationalised through three consecutive stages. First, the annual ESG scores are used as active variables to identify temporal ESG configurations. Second, within each temporal sub-period, the same active variables are used to construct spatial country typologies. Third, in the MFA-Ward analysis, 25 families of illustrative indicators, measured across six sectors, are organised ex ante into four theoretical themes. These variables do not determine the MFA axes or the Ward cluster membership and are used only to characterise the resulting country profiles. In a separate TLEC analysis, the thematic indicators define a separate contextual space used to examine local similarities and entropy-based configurations. This auxiliary typology is interpreted descriptively and not as a causal explanation of ESG performance. Indicators that conceptually overlap with Refinitiv ESG categories are not treated as independent determinants of ESG performance. Because the study is exploratory and typological, it does not seek to estimate causal effects or test directional causal hypotheses. The theoretical framework instead guides the following research questions:

Research Question 1. What distinct temporal configurations of Environmental, Social and Governance performance emerge across OECD countries between 2010 and 2024?

Research Question 2. How does the spatial composition of OECD country typologies vary across the identified temporal sub-periods?

Research Question 3. How do the four illustrative themes—Environment, Economy and Market, Governance and Institutions and Sentiment and Perception—characterise and differentiate the resulting country classes and help account for their divergence?

Research Question 4. To what extent do the temporal and spatial typologies remain robust to alternative cluster

numbers, time windows, dimensional specifications and clustering methods?

Research Question 1 and Research Question 2 operationalise Objective 1 and the typological aim of Objective 2, respectively. Research Question 3 operationalises the remainder of Objective 2 and the interpretive aim of Objective 3, drawing on the institutional and economic interpretation developed in Section 5.2. Research Question 4 provides a supporting methodological question that underpins the robustness of the typologies used to address Research Questions 1–3, rather than constituting an independent substantive objective; the corresponding analyses are reported in Appendix B and Appendix C. This sequential operationalisation ensures that the theoretical perspectives guide variable selection, thematic organisation and empirical interpretation while the resulting clusters remain data-driven descriptive configurations rather than evidence of causal relationships. To make the link between the theoretical framework and the empirical design explicit, Table 1 summarises how each theoretical perspective guided the selection, thematic organisation and empirical role of the variables used in the analysis.

3 | Data and Methodology

3.1 | Multidimensional Descriptive Analysis

The analysis is carried out in several stages. Figure 1 presents an overview of the conceptual framework of our empirical strategy. More specifically, MFA and HAC, an exploratory phase, are used to establish temporal and spatial typologies of the 38 OECD countries based on ESG scores broken down according to six key sectors (agriculture, automotive, energy, finance, health and technology). This approach is in line with the work of Escofier and Pagès (1998), who highlighted the relevance of factorial methods for thematic classification in high-dimensional ESG data.

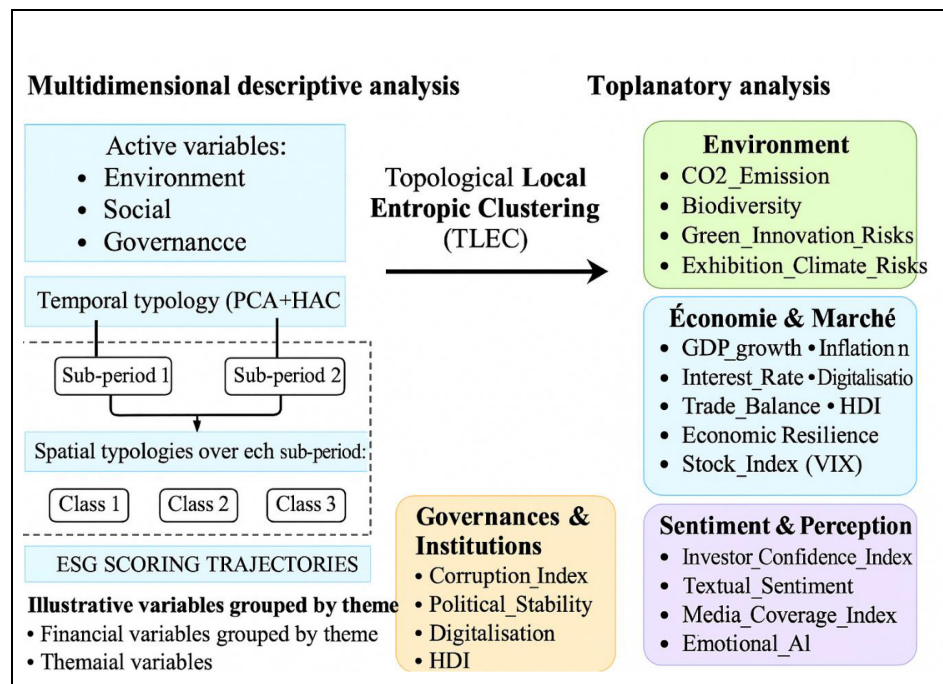
In the next phase, TLEC is used as a complementary topological and descriptive procedure. The method combines k-nearest-neighbour structures with an estimate of local entropy (Kozachenko 1987) and constructs clusters by minimising within-cluster variation in entropy. It is used to identify locally heterogeneous and scale-sensitive configurations in the thematic indicator space. The resulting groups provide a contextual characterisation of countries in terms of environmental exposure, market conditions, institutional characteristics and sentiment indicators. TLEC is therefore interpreted as an auxiliary descriptive typology rather than as an explanatory, confirmatory, predictive or causal model. Drawing on the informational approach to complexity (Shannon 1948), it complements the global Euclidean representation provided by MFA and Ward clustering by examining local neighbourhood and entropy structures. The Adaptive Market Hypothesis (Lo, forthcoming) is subsequently used only as an interpretative framework and does not determine the construction of the TLEC clusters.

The primary aim of these indicators is to monitor how the ESG performance of OECD countries evolves over the period from 2010 to 2024. With these figures, we seek to reflect the evolution of environmental (E), social (S) and governance (G) scores,

TABLE 1 | Theoretical perspectives, empirical mechanisms and the role of variables in the analytical framework.

Theoretical perspective	Empirical mechanism	Corresponding variables	Role in the analysis
Stakeholder theory	Balance among environmental, social and governance expectations	Annual E, S and G scores	Active variables used to construct the temporal and spatial classifications
Natural resource-based view and ecological modernisation	Environmental constraints and green innovation	CO ₂ emissions, biodiversity, green innovation and climate risks	Illustrative environment block
Adaptive market hypothesis	Adaptation to economic cycles and systemic shocks	GDP growth, inflation, unemployment, market volatility and crisis indicators	Illustrative economy and market block
Neo-institutional theory	Institutional capacity and diffusion of ESG norms	Corruption, political stability, digitalisation, HDI and collaborative governance	Illustrative governance and institutions block
Prospect theory, agenda-setting theory and behavioural finance	Effects of confidence, information and perceptions	Investor confidence, media coverage, textual sentiment and Emotional AI	Illustrative sentiment and perception block

Note: This operational structure ensures that the theories guide the analysis ex ante through variable selection and thematic organisation, rather than being used solely as ex post labels for the resulting clusters.

**FIGURE 1** | Overview of the methodology.

in the face of the sustainability challenges encountered over the last 15 years. The three dimensions of ESG performance components make it possible to construct typologies that take into account both time and space, which facilitates a comparative analysis of the trajectories followed by OECD countries between 2010 and 2024.

In addition, we aim to map the performance trajectories of the OECD, the Organisation for Economic Co-operation and

Development, and its 38 member countries. This study uses three variables broken down by sector that are comparable between countries: E score, S score and G score. These variables are detailed in Table 2. The use of disaggregated scores was chosen to allow a more accurate comparison of the ESG performance of nations. Structural heterogeneity among OECD members is extremely significant. In 2024, for example, the United States accounts for around 25% of the OECD population and yet contributes almost 40% of the OECD's total GDP. By contrast,

between 2010 and 2024, Iceland, with a population of just over 370,000, will account for a negligible share in demographic and institutional terms. In the United States in 2010, the population was around 24% and, at the same time, GDP was 35%. The figures show an erosion of the influence of the Member States as time goes by. In addition, there is a degree of inequality between marginalised members and the major economies.

3.1.1 | Data

This study uses annual data for the countries included in the analytical sample over the period 2010–2024. The ESG pillar scores used as active variables were obtained from Refinitiv/LSEG. The cleaned database contains separate pillar scores for each country, economic sector and year. For the multivariate analyses, these scores were aggregated across six sectors: agriculture, automotive, energy, finance, healthcare and technology. The complementary illustrative indicators were obtained from the OECD and the additional sources reported in Table 3. All active variables were standardised before the principal component analysis (PCA), MFA and clustering analyses. Refinitiv constructs its pillar scores by aggregating category-level indicators using provider-defined weights that account for industry materiality. Nevertheless, ESG ratings

remain provider-specific and depend on corporate disclosure, indicator coverage, data availability and the rating methodology. They are therefore treated in this study as comparative proxies rather than fully objective measures of sustainability performance. Standardisation reduces differences in scale but does not eliminate measurement uncertainty or cross-country differences in disclosure practices.

3.1.2 | ESG Measurement Robustness

To assess whether the classifications depend on the construction of the Refinitiv-based ESG measures, the baseline arithmetic-mean specification was compared with three alternative constructions: a 10% trimmed mean, a median-based aggregation and a rank-transformed specification. A leave-one-sector-out analysis was also conducted by successively excluding each of the six economic sectors. The resulting temporal and country partitions were compared using the adjusted Rand index and normalised mutual information, while their internal separation was assessed using the silhouette coefficient. Complete results are reported in Appendix C, Table C1.

Figure 2 shows the temporal trajectories of average ESG scores in OECD countries between 2010 and 2024. Three types of

TABLE 2 | Descriptive statistics for the E, S and G components.

Variables	Frequency	Mean	Minimum	Maximum	Standard deviation	Coefficient of variation (%)
E	38	50.25	44.98	52.86	2.26	4.49
S	38	50.3	48.16	52.34	1.31	2.60
G	38	50.81	46.49	53.04	1.6	3.14

TABLE 3 | Summary of E, S, G profiles of OECD countries by sub-period.

	Period 1	Period 2	Period 3	Period 4	Period 5
Duration	6years	1year	1year	5years	2years
Years	2011,2012, 2015,2018, 2019, 2022	2020	2013	2010,2014,2017,2021,2023	2016,2024
Profile	+S, +G	+E	+S +G	+E	--S --G
Anti-profile	-E	-S -G	- -E	-S -G	-E
Active variables organised by six sectors					
Theme	Variable	Source	Measure	OECD country	Period
Environmental	E	Refinitiv ESG	Score 0–100	38 countries	2010–2024
Social	S	Refinitiv ESG	Score 0–100	38 countries	2010–2024
Governance	G	Refinitiv ESG	Score 0–100	38 countries	2010–2024

Note: The variables shown in the table are significant at the 0.05 level. The signs '+', '–', '–' indicate a level of performance above the OECD average, below the OECD average, and significantly below the OECD average.

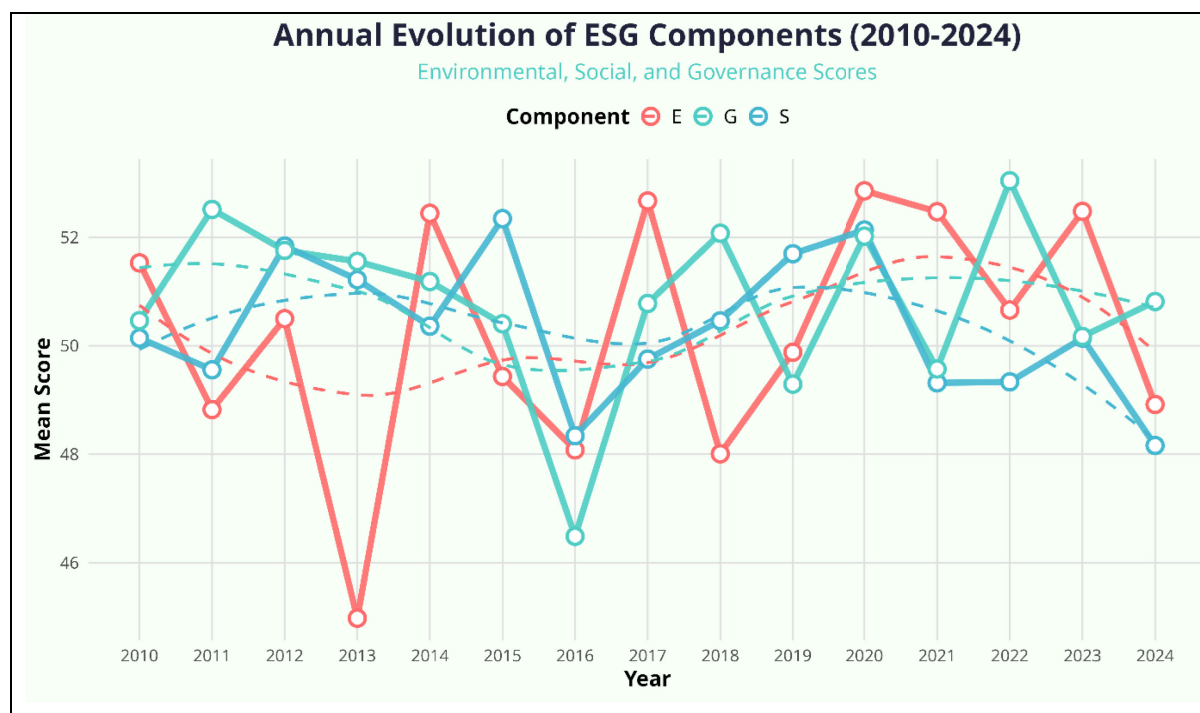


FIGURE 2 | Annual evolution of ESG components (2010–2024).

dynamics can be observed, defined as ‘multidimensional transformation’. The Environmental dimension (E) shows the greatest progress, particularly after 2015, a period marked by the ‘intensification of post-Paris Agreement climate commitments’. The Social (S) component is more stable, reflecting ‘the adaptive resilience of social systems’, while Governance (G) is showing a slower but consistent improvement, linked to “the gradual institutionalisation of ESG practices”. This triple dynamic validates the ‘triple materiality’ theory (Schoenmaker and Schramade 2018, García-Sánchez et al. 2022). The coefficients of variation between countries are respectively of 18.7% for E, 15.4% for S and 12.9% for G, which is in line with the requirement for ‘differentiated convergence’; i.e., national trajectories remain distinct even if they are improving.

The descriptive statistics presented in Table 2 reveal a striking convergence of ESG scores between OECD countries over the period 2010–2024. The average values of the environmental (E), social (S) and governance (G) scores—50.25, 50.3 and 50.81 respectively—suggest a central tendency around the theoretical mid-point of the scale. The limited dispersion, with standard deviations of 2.26 (E), 1.31 (S) and 1.6 (G) and coefficients of variation of 4.50%, 2.60% and 3.15%, respectively, indicates low variability and strong structural alignment of ESG performance among these advanced economies. This empirical observation is consistent with institutionalisation theory (DiMaggio and Powell 1983), which posits that OECD countries converge towards similar ESG standards in the face of global sustainability pressures. Importantly, the slightly higher variability in environmental scores reflects persistent asymmetries in environmental policies and energy dependencies (Sandberg et al. 2023), reinforcing the relevance of sectoral and geographic differentiation in ESG analyses.

3.1.3 | Temporal Typologies of E,S,G Trajectories

We first propose a temporal analysis of the ESG trajectories of OECD countries over the period 2010–2024. We want to study the annual evolution of the three E,S,G components of OECD countries (Table 2) over this period. Since the ‘years’ here are co-occurrences of annual observations of the three annual components, these ‘years’ will in our view be considered as individuals, and the three annual components as variables. We then applied a methodological sequence of two data analysis methods (Tufféry 2005; Escofier and Pagès 1998) to group the 15 ‘years’ into homogeneous classes according to the OECD’s ESG components. More specifically, HAC was used on the significant factors of the PCA of the annual components of ESG trends. This methodological combination of a factorial analysis and a clustering method provides a tool for statistical observation and structural analysis of multidimensional data. Therefore, we can identify the various sub-periods that correspond to different stages of ESG performance.

3.1.4 | Spatial Typologies and ESG Trajectories

To better analyse and understand the evolution of the ESG premium of the 38 OECD countries, we have carried out an analysis of evolutionary data over sub-periods. The approach adopted is based on the combined use of exploratory methods of evolutionary data analysis that consider the characteristics of countries in E, S and G and their evolution in each sub-period. Based on the similarity between the three characteristics, it is possible to draw up a typology of the 38 OECD countries. The evolution of the countries is studied using a MFA, a method based on a weighted analysis of the principal components of all the data. This method enables

several tables of multidimensional data to be explored simultaneously. This method is particularly applicable to time series data. We aim to understand the ESG profiles of countries over time and classify these trajectories to better grasp the dynamics of convergence or divergence in CSG. The illustrative variables used in the figures play an ex-post role, as they are not used in the construction of the main axes. This supplementary status applies specifically to the MFA–Ward classification. The separate role of the thematic indicators in the TLEC contextual space is described in Section 3.2, which are used to measure the degree of covariance with the three components of sustainable governance. To check the validity of

their use, *t*-test was performed to assess the significance of the differences between the means of each illustrative variable within each class and the total observation.

The illustrative variables, as presented in Table 4, are grouped into four key thematic categories: environment, as asserted by Hart (1995) and Mol and Spaargaren (2000), considerations of CO₂ emissions, biodiversity, green innovation and exposure-related climate risks are of paramount importance, and economy and market (stock market index, volatility index, total population, trade balance, GDP growth rate, inflation rate, interest

TABLE 4 | Illustrative variables by theme.

Variable	Abbreviations	Source	Measure	Theme
CO2_emission	CO_Sec	OECD, WB	Tonnes per capital	Environment
Biodiversity	BI_Sec	UNEP-WCMC	Score 0–100	Environment
Green_Innovation	GR_sec	OECD,WIPO	Patents per million	Environment
Exhibition_climate_risk	CL-Sec	OECD_WRI	Risk_score 0–100	Environment
Stock_index	Sk_I_sec	Bloomberg, Yahoo_finance	Index_value	Economy & Market
Volatility_Index	VIX	CBOE, OECD	Score 0–100	Economy & Market
Total_Population	POP	OECD	Total in millions	Economy & Market
Trade_Balance	TB	OECD	Balance in USD	Economy & Market
GDP_Growth	GDP_G	World_Bank	Percentage	Economy & Market
Inflation_Rate	INF	World_Bank	Percentage	Economy & Market
Interest_Rate	INT	IMF	Percentage	Economy & Market
Unemployment_Rate	UNEM	ILO	Percentage	Economy & Market
Economic_Resilience	RE	OECD	Index 0–100	Economy & Market
Put/Call_Ratio	PCR	CBOE	Ratio	Economy & Market
Financial_Crisis_2008	FC08	MFI	Binary(0/1)	Economy & Market
Covid_19_Crisis	COVID	WHO,IMF	Binary(0/1)	Economy & Market
Russia_Ukraine_War	WAR	EPU_Index	Binary(0/1)	Economy & Market
Corruption_Index	Co_In	World_Bank	Score0–100	Governance & Institutions
Social_Inovation_Colloborative Governace	SI_CG	OECD	Score0–100	Governance & Institutions
Political_Stability	POL_STA	World_Bank	Score 0–100	Governance & Institutions
Human_Development Index	HDI_Sec	UNDP	Index 0–1	Governance & Institutions
Digitilisation	DI	ITU	Score 0–100	Governance & Institutions
Investor_Confidence Index	IN_CONF	OECD	Score 0–100	Sentiment & Perception
Media_Coverage_Index	ME_COV	Reuters	Index- Value	Sentiment & Perception
Emotional_AI	EMO_AI	WEF	Score 0–100	Sentiment & Perception

rates, unemployment rate, economic resilience, put-call ratio, the 2008 financial crisis, the COVID-19 crisis and the war between Russia and Ukraine (Freeman 1984; Markowitz 1952)).

Governance and institutions: the corruption index, the collaborative governance index for social innovation, the political stability index, the human development index (HDI) and the digitisation index (DiMaggio and Powell 1983; Gompers et al. 2003). The concepts of sentiment and perception: investor confidence index, media coverage index, emotional IA (Kahneman and Tversky 1979; McCombs and Shaw 1972). The thematic grouping, summarised in Table 3, helps to structure the analysis and ensure a coherent interpretation of the clusters identified.¹

3.2 | Topological Characterisation of Contextual Configurations in the Final Temporal Sub-Period (2016 and 2024)

TLEC is applied exclusively to the fifth and final temporal sub-period, comprising the years 2016 and 2024. The analysis therefore concerns the 38 country profiles observed within this final sub-period and is not applied to the other four temporal configurations. All parameter-sensitivity analyses and benchmark comparisons use the same country sample, thematic variables and preprocessing procedure. To complement the ESG-based temporal and spatial typologies, TLEC is used to map local similarities and entropy-based configurations in a separate space of contextual indicators. This procedure is descriptive and unsupervised: it does not estimate causal effects or identify independent determinants of ESG performance.

Previous literature uses various predictive techniques, a discriminant analysis model (Devaud 1984) or multinomial or probit logistic regression models (Daykin and Moffatt 2002). To overcome the limitations of linear discriminant analysis (LDA), which in fact are not always compatible with non-Gaussian or very complex distributions in many cases, we use a more advanced and, in many respects, mathematically more robust approach. More precisely, this model is called Topological Local Entropic Clustering, which could be described as a hybrid, because this method cleverly combines the k/K nearest neighbours and a local entropy estimate. The entropy, in turn, must be estimated using the widely used Kozachenko–Leonenko estimator, which is adapted and even more advantageously applied to high-dimensional spaces and complex topologies. The non-parametric differential entropy estimator uses k-nearest distances as its principal statistic, which makes it particularly useful for high-dimensional thematic datasets. These datasets cannot be adequately characterised by traditional distributions, such as simple Gaussian distributions.

The null hypothesis (H_0) postulates that, in the multi-thematic space composed of the dimensions Environment (ENV), Economy (ECM), Governance (GOV) and Social (SEN), the ESG trajectories of OECD member countries exhibit topological organisations that are locally similar. More precisely, these organisations are characterised by a local conditional entropy that is significantly lower than that which would be observed in a random scatter plot with equivalent variance. Put another way, there is a certain local

structural coherence in the way OECD countries evolve in terms of ESG, a coherence that is not due to mere chance.

3.2.1 | Construction of a Weighted k-NN Graph Designed for the ESG Space

To better capture the complexity, but also the thematic heterogeneity characterising the sustainability dynamics observed within OECD countries, it is proposed to represent each country (designated by i) as a structured vector, evolving in a multi-thematic space. In concrete terms, the approach is as follows:

Consider $X = \{x_1, \dots, x_n\} \subset \mathbb{R}^D$, representing all n countries under study. Each vector $x_i \in \mathbb{R}^D$ is then defined as follows:

$$x_i = [x_i(ENV), x_i(ECM), x_i(GOV), x_i(SEN)] \in \mathbb{R}^D \quad (1)$$

Each component of this vector corresponds to one of the four main central themes of sustainability, namely: $x_i(ENV)$: Environment—including various variables. These include CO₂ emissions, biodiversity indicators, green innovation efforts, and assessment of exposure to climate risks (Hart 1995; Mol and Spaargaren 2000). $x_i(ECM)$: Economy and market—including stock market indices, various measures of volatility, the trade balance, macroeconomic indicators, not forgetting markers signalling an exogenous crisis (Freeman 1984; Markowitz 1952). $x_i(GOV)$: Governance and Institutions—including perceptions of corruption, political stability, the HDI, progress in digitisation and measures of collaborative governance (DiMaggio and Powell 1983; Gompers et al. 2003). $x_i(SEN)$: Sentiment and Perception—reflecting media exposure, investor confidence, emotional signals captured by AI, and behavioural measures of public opinion (Kahneman and Tversky 1979; McCombs and Shaw 1972).

Each bloc $x_i \in \mathbb{R}^{d_t}$ represents the components associated with theme t . The graph $G = (V, E)$ connects each node i to its k nearest neighbours, calculated using a weighted Minkowski distance. In general, to determine p , we need to solve the equation below, knowing that p must be greater than or equal to 1:

$$d_{ij}^p = \left[\sum_{t=1}^4 w_t \left(\frac{1}{d_t \sum_{\ell=1}^{d_t} |z_{it\ell} - z_{jt\ell}|^p} \right) \right]^{\frac{1}{p}}, \quad p \geq 1, \quad \sum_{t=1}^4 w_t = 1 \quad (2)$$

In this expression, p is the Minkowski distance parameter, w_t is the normalised weight assigned to theme t , d_t is the number of variables in that theme and $z_{it\ell}$ is the standardised value of variable ℓ for country i . The thematic weights satisfy $\sum_{t=1}^4 w_t = 1$. Using this distance, each country i is connected to its q nearest neighbours. The baseline graph was constructed using $q = 5$, while alternative values from $q = 3$ to $q = 8$ were examined in the sensitivity analysis.

Before constructing the graph, all contextual variables were standardised within the final temporal sub-period, comprising 2016 and 2024. To prevent themes containing more variables from dominating the distance calculation, the contribution of each thematic block was normalised by its

dimension. The baseline specification used five nearest neighbours ($q = 5$), a Euclidean distance ($p = 2$) and equal thematic weights ($w_i = 0.25$). These values define the reference specification and were not assumed to be uniquely optimal. Their sensitivity was assessed by varying the number of neighbours from $q = 3$ to $q = 8$, the Minkowski parameter over $p \in \{1, 2, 3\}$, and the thematic weighting scheme. The number of clusters was examined over $K = 2, \dots, 10$.

3.2.2 | Estimation of Local Entropy Contributions

To assess the local informational structure of the contextual country configurations, we use the Kozachenko–Leonenko nearest-neighbour differential-entropy estimator (Kozachenko 1987). Consider a continuous random vector $X \in \mathbb{R}^D$ with probability density $f(x)$. Its differential entropy is defined as:

$$H(X) = - \int_{\mathbb{R}^D} f(x) \log f(x) dx \quad (3)$$

Because the underlying density $f(x)$ is unknown, the Kozachenko–Leonenko estimator approximates it using nearest-neighbour distances. Let $\rho_{i,q}$ denote the weighted distance between country i and its q -th nearest neighbour. The country-specific contribution to the entropy estimator is defined as:

$$\hat{h}_{i,q} = \psi(n) - \psi(q) + \log(C_D) + D \log(2\rho_{i,q}). \quad (4)$$

Here, n is the number of countries, q is the number of nearest neighbours, D is the total dimension of the contextual space, $\rho_{i,q}$ is the weighted distance from country i to its q -th nearest neighbour, and $\psi(\cdot)$ is the digamma function.

$$C_D = \frac{\pi^{D/2}}{\Gamma(D/2 + 1)}.$$

is the volume of the D -dimensional unit ball. The corresponding global differential-entropy estimate is $\hat{H}_q = \frac{1}{n} \sum_{i=1}^n \hat{h}_{i,q}$.

In this study, $\hat{h}_{i,q}$ is interpreted as a country-specific local entropy contribution rather than as an independent entropy estimate. A lower value indicates that a country is located in a relatively dense neighbourhood of the contextual thematic space, whereas a higher value indicates a more isolated or locally heterogeneous configuration. This interpretation remains descriptive and does not imply temporal instability or unpredictability.

3.2.3 | Construction of a Dissimilarity Matrix Based on Entropy

The dissimilarity between two countries, say i and j , is calculated by:

$$\delta_{ij}^H = |\hat{h}_{i,q} - \hat{h}_{j,q}|. \quad (5)$$

What we call ‘ $\Delta = \delta_{ij}$ ’, when expressed as (δ_{ij}) , turns out to be a reliable measure of topological proximity. It is independent of

the classical Euclidean distance. The global entropy estimate $\hat{H}_q$ is obtained by averaging the country-specific contributions $\hat{h}_{i,q}$. We highlight latent topological groupings, things that more traditional methods (such as LDA) struggle to capture. This approach gives us the opportunity to assess ESG transitions with greater finesse, identifying sometimes subtle but significant differences in the way sustainability is evolving at country level.

3.2.4 | Clustering by Minimising Entropy Variance (Ward’s Method)

A hierarchical grouping was implemented, and Ward’s method was applied, minimising the total intra-group variance in the local entropy. This approach, which is in line with the principle of minimum description length, is an effective tool for identifying compact and topologically coherent groups in entropy space (Zelnik-Manor and Perona 2004). The complete construction procedure is formalised in Algorithm 1.

$$C = \underset{C}{\operatorname{argmin}} \sum_{c \in C} \sum_{\{i,j \in c\}} \delta_{ij}^2 \quad (6)$$

ALGORITHM 1 | TLEC Construction for the Final Temporal Sub-Period.

Input: Standardised contextual matrix Z for the 38 OECD countries in the final temporal sub-period (2016 and 2024); four thematic blocks; thematic weights w ; Minkowski parameter p ; number of neighbours q ; candidate number of clusters K .
Output: Country-specific entropy contributions, entropy-based dissimilarity matrix, and TLEC cluster partition.

1. Standardise all contextual variables within the final temporal sub-period and normalise each thematic block by its dimension.
2. Compute the weighted thematic Minkowski distance between every pair of countries using Equation (2).
3. For each country i , identify its q nearest neighbours and record the distance $\rho(i, q)$ to its q -th nearest neighbour.
4. Calculate the country-specific local entropy contribution $\hat{h}(i, q)$ using Equation (4).
5. Construct the entropy-based dissimilarity matrix using Equation (6).
6. Apply Ward’s minimum-variance hierarchical clustering to the country-level entropy contributions using Equation (7).
7. Cut the dendrogram at K clusters and record the resulting country assignments.

3.2.5 | The Theoretical Basis of Illustrative Variables in the Context of Thematic Contributions

To make sense of the groupings obtained, it is necessary to examine the discriminating power of each variable within its theme. For a given variable associated with a theme, we perform the following calculation:

$$F(Z(t)) = \frac{(\text{Betwin} - \text{cluster Var}(Z(t)))/(\text{Within} - \text{cluster Var}(Z(t)))}{\text{or } \eta^2 = \text{SSBetwin}/\text{SS total}} \quad (7)$$

The variables with the highest values should be favoured to make illustrative contributions. The thematic organisation of the selection of characteristics facilitates a structured understanding of the dominant forces shaping ESG trajectories. These contributions, according to Lebart et al. (1995), clarify cluster typology, particularly when combined with graphical tools such as thematic projection graphs or entropy-ranked bar charts.

3.2.6 | Parameter-Sensitivity and Cluster-Number Selection

The sensitivity of TLEC was evaluated on the 38 country profiles belonging to the final temporal sub-period, comprising 2016 and 2024. Alternative specifications combined different numbers of nearest neighbours, Minkowski distance parameters, thematic weighting schemes and candidate cluster numbers. For each specification, internal cluster quality was assessed using the silhouette coefficient, the Calinski-Harabasz index and the Davies-Bouldin index. Partition stability was evaluated using bootstrap resampling and leave-one-country-out analyses. Agreement with the baseline partition was measured using the adjusted Rand index and normalised mutual information.

3.2.7 | Comparison With Benchmark Clustering Methods

To determine whether the identified configurations were specific to the TLEC parameterisation, the same standardised country-level data were analysed using Ward hierarchical clustering, k-means, Gaussian mixture models, spectral clustering, DBSCAN, and HDBSCAN. All methods were applied to the same final temporal sub-period and the same contextual variables. For methods requiring a predefined number of clusters, candidate solutions from $K = 2$ to $K = 10$ were evaluated. For density-based methods, the number of detected clusters and the proportion of observations classified as noise were reported. The comparison was based on internal validity, partition stability and concordance with the TLEC classification. The complete parameter-sensitivity and benchmark-comparison procedure is formalised in Algorithm 2.

ALGORITHM 2 | TLEC Parameter-Sensitivity and Benchmark Assessment.

Input: Standardised contextual matrix Z ; q in $\{3, \dots, 8\}$; p in $\{1, 2, 3\}$; alternative thematic weighting schemes; K in $\{2, \dots, 10\}$; benchmark clustering methods.
Output: Parameter-sensitivity results, internal validation indices, partition-stability measures, and benchmark comparisons.

1. For each combination of q , p , thematic weights, and K , rerun Algorithm 1 on the same 38-country sample.
2. For every admissible partition, calculate the silhouette coefficient, Calinski-Harabasz index, Davies-Bouldin index, and minimum cluster size.
3. Assess TLEC stability using bootstrap resampling and leave-one-country-out analysis; quantify agreement using the adjusted Rand index and normalised mutual information.
4. Apply Ward clustering, k-means, Gaussian mixture modelling, spectral clustering, DBSCAN, and HDBSCAN to the same standardised contextual data.
5. For fixed-cluster methods, examine K from 2 to 10. For DBSCAN and HDBSCAN, report the number of detected clusters and the proportion of countries classified as noise.
6. Compare each benchmark partition with the reference TLEC partition using internal validation indices, adjusted Rand index, and normalised mutual information.
7. Retain and interpret the five-cluster TLEC solution only if its quality and stability are supported by the sensitivity and benchmark evidence.

4 | Results

This analysis begins with a temporal analysis of the ESG trajectories of OECD countries over the period 2010–2024, based on E, S, G scores broken down by sector. It continues with a spatial typology of the 38 OECD member countries over defined sub-periods, with the aim of monitoring the dynamic evolution of ESG performance and patterns of convergence. The conclusion of the study (see appendix: Tables 5 and 6) requires the identification of the structural factors at the origin of these trajectories, for which we use an innovative methodology based on topological clustering by local entropy of thematic proximity (TLEC). This method makes it possible to identify latent sustainability regimes as a function of theme and linear and non-linear associations between a set of context variation factors and thus

TABLE 5 | ESG score trajectories for the 38 OECD countries over the five sub-periods.

Period 1 2011, 2012, 2015, 2018, 2019, 2022		Period 2 2020		Period 3 2013		Period 4 2010, 2014, 2017, 2021 and 2023		Period 5 2016–2024	
+ S + G – E	OECD _38		OECD _38		OECD _38		OECD _38	+ S + G – E	OECD _38
+ E +S =G	DNK CAN FRA NZL CHL USA	+E +S +G	FRA CHE FIN EST IRL NLD AUT SWE	+E –S –G	DNK EST FIN IRL ISR	+E ++S +G	AUS AUT BEL CAN CHE DNM FIN FRA GBR ISL LUX NLD NOR	+/= E +S +G	ESP, NZL
= E = S +G	NLD JPN, LTU, CZE HUN.	+E –S ±G	CAN HUN LTU LVA PRT GRC POL	–E –S –G	AUT ESP USA GRC COL NZL SVN MLT SVK	++E +S +G	CZE, DEU, EST, HUN, IRL, LTU, LVA, POL, SVK e SVN.	+ E + S + G	AUS, BEL, CHL, COL, DNK, ISL, ISR, JPN, LVA, POL, SVN, SWE
+E +S –G	GBR CHE	+G –S ±G	DEU NOR NZL JPN CZE KOR	+E +S +G	CHE DEU FRA NLD CZE POL	+E +S ++G	JPN KOR NZL SWE	–/= E –/=S + G	AUT, CZE, EST FIN FRA GBR IRL, Korea, MEX MLT, NOR PRT, SVK Turkey, USA
–E –S +G	BEL DEU MLT PRT NOR FIN COL IRL SVK	–E ++S +G	ISR AUS SVK DNK LUX	–E +S –G	LUX SWE	+E +S +G	CHL COL CRI ISR MEX TUR	–E –S –G	CHE, HUN

(Continues)

TABLE 5 | (Continued)

Period 1 2011, 2012, 2015, 2018, 2019, 2022		Period 2 2020	Period 3 2013		Period 4 2010, 2014, 2017, 2021 and 2023		Period 5 2016–2024		
E–	SWE	–E	USA	–E	AUS	+E	ESP	+E	CAN,
S–	AUS	–S	MEX	–S	CAN	–S	GRC	+S	DEU,
G–	LUX	–G	CHL	+G	MEX	++G	ITA	++G	GRC,
	ISL		ITA		CHL		PRT		ITA,
	ESP		ESP		GRB		USA		LTU,
	GRC		BEL		KOR				LUX,
	TUR		TUR		BEL				NLD
	ITA				LVA				
	SVN				LTU				
	EST				HUN				
	POL				TUR				
	LVA								

Note: Explanation of signs: “+”: score $\geq 0.5 \sigma$ above the OECD average, “=”: $\pm 0.5 \sigma$ around the average, “–”: score $\leq -0.5 \sigma$, “++” $\geq +1\sigma$ (outstanding performance).

facilitates the identification of ESG configurations of countries and over time.

4.1 | Trajectories of the E, S and G Components of the 38 OECD Countries

Figure 3a presents the PCA of the three annual ESG pillar scores, each calculated by averaging the corresponding scores across the six sectors. The first two principal components jointly explain 75.86% of the total variance. The correlation circle shows that the Social and Governance pillars are mainly associated with the first component, whereas the Environmental pillar is primarily represented by the second component. The projection of the years onto the first factorial plane highlights the temporal heterogeneity of the annual ESG configurations.

Figure 3b presents the agglomerative hierarchical clustering obtained by applying Ward's minimum-variance criterion to the PC1–PC2 coordinates (Murtagh and Legendre 2014). Candidate solutions ranging from ($k=2$) to ($k=10$) were compared using the silhouette coefficient, the Calinski–Harabasz index, the Davies–Bouldin index and the Gap Statistic. The silhouette coefficient reached its maximum at ($k=5$), with a value of 0.3687, providing direct statistical support for the retained partition. The five-cluster solution also yielded a Davies–Bouldin index of 0.4619 and a Calinski–Harabasz index of 14.7359. Although some indices continued to improve for higher-order solutions, these solutions excessively fragmented the limited sample of 15 yearly observations. Conversely, the two-cluster solution suggested by the Gap Statistic was considered overly aggregated. Five clusters were therefore retained as the most parsimonious and substantively interpretable representation of the temporal ESG trajectories. The complete cluster-number validation is reported in Appendix A.1, Figure A1.

The robustness of the retained partition was further assessed using neighbouring cluster solutions, three overlapping 13-year windows, leave-one-year-out resampling, k-means clustering

and Ward clustering based on all three standardised ESG dimensions. Ward and k-means produced strongly concordant partitions, with an adjusted Rand index of 0.838 and normalised mutual information of 0.903. The leave-one-year-out analysis yielded a mean adjusted Rand index of 0.842, and nine of the 15 specifications reproduced exactly the full-sample partition for the remaining observations. The overlapping temporal windows produced a mean adjusted Rand index of 0.567 and mean normalised mutual information of 0.783. Overall, the principal temporal configurations remain identifiable across alternative specifications, although some exceptional and boundary years exhibit greater assignment sensitivity. The complete robustness analysis is reported in Appendix A.2, Figure A2.

An additional measurement-sensitivity analysis showed that the 10% trimmed-mean specification reproduced the temporal partition exactly ($ARI=1.000$), while the rank-based specification produced substantial concordance ($ARI=0.601$). The median and leave-one-sector-out specifications generated lower agreement, indicating some sensitivity to the aggregation rule and sectoral coverage. Complete results are reported in Appendix C, Table C1.

The resulting temporal classification is consistent with the findings of Renou-Maissant et al. (2022) on transition dynamics and Dong et al. (2026) and Isogai et al. (2025) on diversified assessments of ESG performance by time group. Tables 4 and 5 and Figure 3b summarise the results of the evolutionary analysis. Figures 3c and 3d display the mean ESG scores and the average ESG components for each of the five groups, respectively. Group 1 combines the years 2011, 2012, 2015, 2018, 2019 and 2022. This group is characterised by moderately positive scores in the social domain (+0.42) and in the governance domain (+0.44). However, there is a gap in the environmental domain (–0.31). This configuration reflects a phase of institutional consolidation after the financial crisis, during which transparency, social responsibility and ethics improved, often to the detriment of climate policies (Bamel et al. 2025). This dynamic was frequently observed in emerging or developing economies under pressure from investors. The second group

TABLE 6 | Summary of the distribution and profiles of the five country clusters across the five sub-periods.

Sub-period	Cluster	n	Active ESG centroid (z)	Leading illustrative variables (cluster mean z)	Countries (ISO-3)	Country names	Data-driven profile label
1	1	2	E = -2.09 S = +1.78 G = -0.15	Stock index—Energy (+1.59) Population—Agriculture (-1.56) GDP growth—Agriculture (-1.54)	CHE, GBR	Switzerland; United Kingdom	Above-average S, below-average E, near-average G profile
1	2	13	E = +0.29 S = +0.90 G = -0.25	HDI—Healthcare (+0.62) Emotional AI—Energy (-0.49) Trade balance—Agriculture (-0.48)	AUS, AUT, GRC, ISL, ISR, ITA, LUX, LVA, MEX, POL, SVK, SVN, SWE	Australia; Austria; Greece; Iceland; Israel; Italy; Luxembourg; Latvia; Mexico; Poland; Slovak Republic; Slovenia; Sweden	Above-average E/S, below-average G profile
1	3	10	E = -0.28 S = -0.61 G = +1.19	Stock index—Technology (-0.75) Trade balance—Technology (-0.67) Political stability—Healthcare (+0.58)	CAN, CHL, DEU, DNK, FRA, IRL, MLT, NOR, NZL, USA	Canada; Chile; Germany; Denmark; France; Ireland; Malta; Norway; New Zealand; United States	Above-average G, below-average E/S profile
1	4	5	E = +1.39 S = -0.91 G = -0.26	Trade balance—Healthcare (-1.51) Population—Automotive (-1.32) Digitalisation—Healthcare (+1.03)	CZE, HUN, JPN, LTU, NLD	Czech Republic; Hungary; Japan; Lithuania; Netherlands	Above-average E, below-average S/G profile
1	5	8	E = -0.46 S = -0.58 G = -0.88	GDP growth—Energy (+0.73) Political stability—Automotive (+0.71) Digitalisation—Technology (-0.62)	BEL, COL, ESP, EST, FIN, KOR, PRT, TUR	Belgium; Colombia; Spain; Estonia; Finland; South Korea; Portugal; Türkiye	Broad-based below-average ESG profile
2	1	6	E = +0.93 S = -0.04 G = +1.37	Trade balance—Finance (-0.80) Unemployment—Healthcare (-0.72) VIX—Agriculture (-0.69)	CHE, EST, FRA, GRC, POL, SWE	Switzerland; Estonia; France; Greece; Poland; Sweden	Above-average E/G, near-average S profile
2	2	9	E = +0.87 S = -0.79 G = -0.20	GDP growth—Healthcare (-0.73) Emotional AI—Automotive (+0.67) Stock index—Technology (+0.65)	CAN, FIN, GBR, HUN, ISL, LTU, LVA, NLD, TUR	Canada; Finland; United Kingdom; Hungary; Iceland; Lithuania; Latvia; Netherlands; Türkiye	Above-average E, below-average S, near-average G profile
2	3	11	E = -1.05 S = -0.61 G = -0.43	Biodiversity – Energy (+0.74) Economic resilience—Agriculture (+0.69) GDP growth—Agriculture (+0.56)	BEL, COL, DEU, DNK, ESP, IRL, JPN, MLT, NOR, NZL, SVN	Belgium; Colombia; Germany; Denmark; Spain; Ireland; Japan; Malta; Norway; New Zealand; Slovenia	Broad-based below-average ESG profile
2	4	3	E = -0.91 S = +1.44 G = +1.28	Inflation – Healthcare (+2.17) Unemployment—Agriculture (+1.93) Corruption index—Technology (+1.54)	AUS, ISR, SVK	Australia; Israel; Slovak Republic	Above-average S/G, below-average E profile

(Continues)

TABLE 6 | (Continued)

Sub-period	Cluster	n	Active ESG centroid (z)	Leading illustrative variables (cluster mean z)	Countries (ISO-3)	Country names	Data-driven profile label
2	5	9	E = +0.10 S = +1.07 G = -0.61	Digitalisation - Energy (-0.69) Inflation—Agriculture (+0.61) Green innovation— Automotive (-0.60)	AUT, CHL, CZE, ITA, KOR, LUX, MEX, PRT, USA	Austria; Chile; Czech Republic; Italy; South Korea; Luxembourg; Mexico; Portugal; United States	Above-average S, below-average G, near-average E profile
3	1	7	E = +0.02 S = -1.15 G = -0.14	CO2 emissions - Global (-0.80) GDP growth—Finance (+0.67) Collaborative governance— Energy (+0.66)	DNK, EST, FIN, IRL, ISR, JPN, PRT	Denmark; Estonia; Finland; Ireland; Israel; Japan; Portugal	Below-average S, near-average E/G profile
3	2	8	E = -0.01 S = -0.32 G = -1.38	Trade balance - Agriculture (-0.93) Population—Finance (-0.92) Collaborative governance— Agriculture (-0.69)	AUT, ESP, GRC, MLT, NZL, SVK, SVN, USA	Austria; Spain; Greece; Malta; New Zealand; Slovak Republic; Slovenia; United States	Below-average S/G, near-average E profile
3	3	9	E = +1.23 S = +0.69 G = +0.47	Collaborative governance - Agriculture (+0.89) GDP growth—Healthcare (+0.81) Stock index—Agriculture (-0.66)	CHE, COL, CZE, DEU, FRA, ISL, ITA, NOR, POL	Switzerland; Colombia; Czech Republic; Germany; France; Iceland; Italy; Norway; Poland	Broad-based above-average ESG profile
3	4	5	E = -0.94 S = +1.33 G = -0.36	HDI - Automotive (+1.08) Political stability—Healthcare (+0.98) Digitalisation—Technology (-0.97)	HUN, LTU, LUX, SWE, TUR	Hungary; Lithuania; Luxembourg; Sweden; Türkiye	Above-average S, below-average E/G profile
3	5	9	E = -0.70 S = -0.26 G = +1.07	Interest rate - Energy (+1.17) Investor confidence—Finance (-1.02) Inflation—Energy (+1.02)	AUS, BEL, CAN, CHL, GBR, KOR, LVA, MEX, NLD	Australia; Belgium; Canada; Chile; United Kingdom; South Korea; Latvia; Mexico; Netherlands	Above-average G, below-average E/S profile
4	1	7	E = -0.56 S = +1.31 G = -1.25	Trade balance - Finance (+1.00) Inflation—Energy (+0.74) Corruption index—Energy (+0.71)	CHL, COL, EST, IRL, KOR, LVA, SWE	Chile; Colombia; Estonia; Ireland; South Korea; Latvia; Sweden	Above-average S, below-average E/G profile
4	2	6	E = -0.59 S = -1.62 G = -0.23	Green innovation - Energy (+1.31) Political stability—Energy (-0.97) Digitalisation—Agriculture (+0.80)	ISL, ITA, LUX, MLT, SVK, USA	Iceland; Italy; Luxembourg; Malta; Slovak Republic; United States	Below-average E/S, near-average G profile
4	3	8	E = +0.75 S = -0.23 G = +1.33	CO2 emissions - Global (-0.93) Put/call ratio—Technology (-0.78) Biodiversity—Agriculture (-0.74)	AUT, DEU, FRA, GBR, LTU, NOR, NZL, POL	Austria; Germany; France; United Kingdom; Lithuania; Norway; New Zealand; Poland	Above-average E/G, near-average S profile

(Continues)

TABLE 6 | (Continued)

Sub-period	Cluster	n	Active ESG centroid (z)	Leading illustrative variables (cluster mean z)	Countries (ISO-3)	Country names	Data-driven profile label
4	4	5	E = +1.14 S = +0.26 G = -0.54	Political stability – Technology (+1.07) Biodiversity – Agriculture (+1.07) Stock index – Energy (-0.94)	CHE, DNK, ESP, GRC, MEX	Switzerland; Denmark; Spain; Greece; Mexico	Above-average E/S, below-average G profile
4	5	12	E = -0.35 S = +0.09 G = +0.18	Put/call ratio – Healthcare (-0.67) Trade balance – Automotive (-0.49) Digitalisation – Finance (+0.49)	AUS, BEL, CAN, CZE, FIN, HUN, ISR, JPN, NLD, PRT, SVN, TUR	Australia; Belgium; Canada; Czech Republic; Finland; Hungary; Israel; Japan; Netherlands; Portugal; Slovenia; Türkiye	Below-average E, near-average S/G profile
5	1	2	E = -1.90 S = -1.24 G = -1.36	GDP growth – Automotive (-1.63) CO2 emissions – Automotive (+1.54) HDI – Healthcare (+1.49)	ESP, NZL	Spain; New Zealand	Broad-based below-average ESG profile
5	2	12	E = +0.58 S = -1.04 G = -0.83	HDI – Automotive (+0.64) Trade balance – Finance (-0.63) COVID-19 crisis – Healthcare (+0.60)	AUS, BEL, CHL, COL, DNK, ISL, ISR, JPN, LVA, POL, SVN, SWE	Australia; Belgium; Chile; Colombia; Denmark; Iceland; Israel; Japan; Latvia; Poland; Slovenia; Sweden	Above-average E, below-average S/G profile
5	3	15	E = -0.65 S = +0.80 G = +0.19	VIX – Automotive (-0.57) Digitalisation – Finance (-0.43) Media coverage – Automotive (+0.40)	AUT, CZE, EST, FIN, FRA, GBR, IRL, KOR, MEX, MLT, NOR, PRT, SVK, TUR, USA	Austria; Czech Republic; Estonia; Finland; France; United Kingdom; Ireland; South Korea; Mexico; Malta; Norway; Portugal; Slovak Republic; Türkiye; United States	Above-average S, below-average E, near-average G profile
5	4	2	E = -0.54 S = -0.51 G = +2.11	GDP growth – Agriculture (+1.76) Media coverage – Energy (+1.63) Digitalisation – Finance (+1.48)	CHE, HUN	Switzerland; Hungary	Above-average G, below-average E/S profile
5	5	7	E = +1.09 S = +0.57 G = +0.80	Biodiversity – Energy (+0.97) HDI – Agriculture (-0.89) Put/call ratio – Healthcare (+0.69)	CAN, DEU, GRC, ITA, LTU, LUX, NLD	Canada; Germany; Greece; Italy; Lithuania; Luxembourg; Netherlands	Broad-based above-average ESG profile

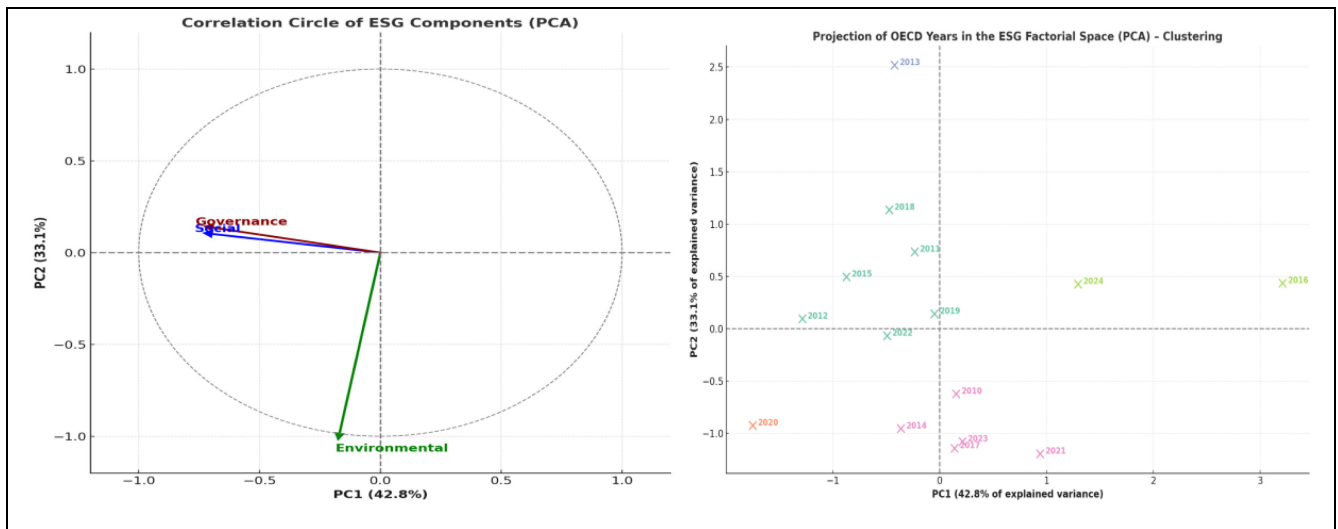


FIGURE 3a | Representation of ESG components and years on the first factorial plane.

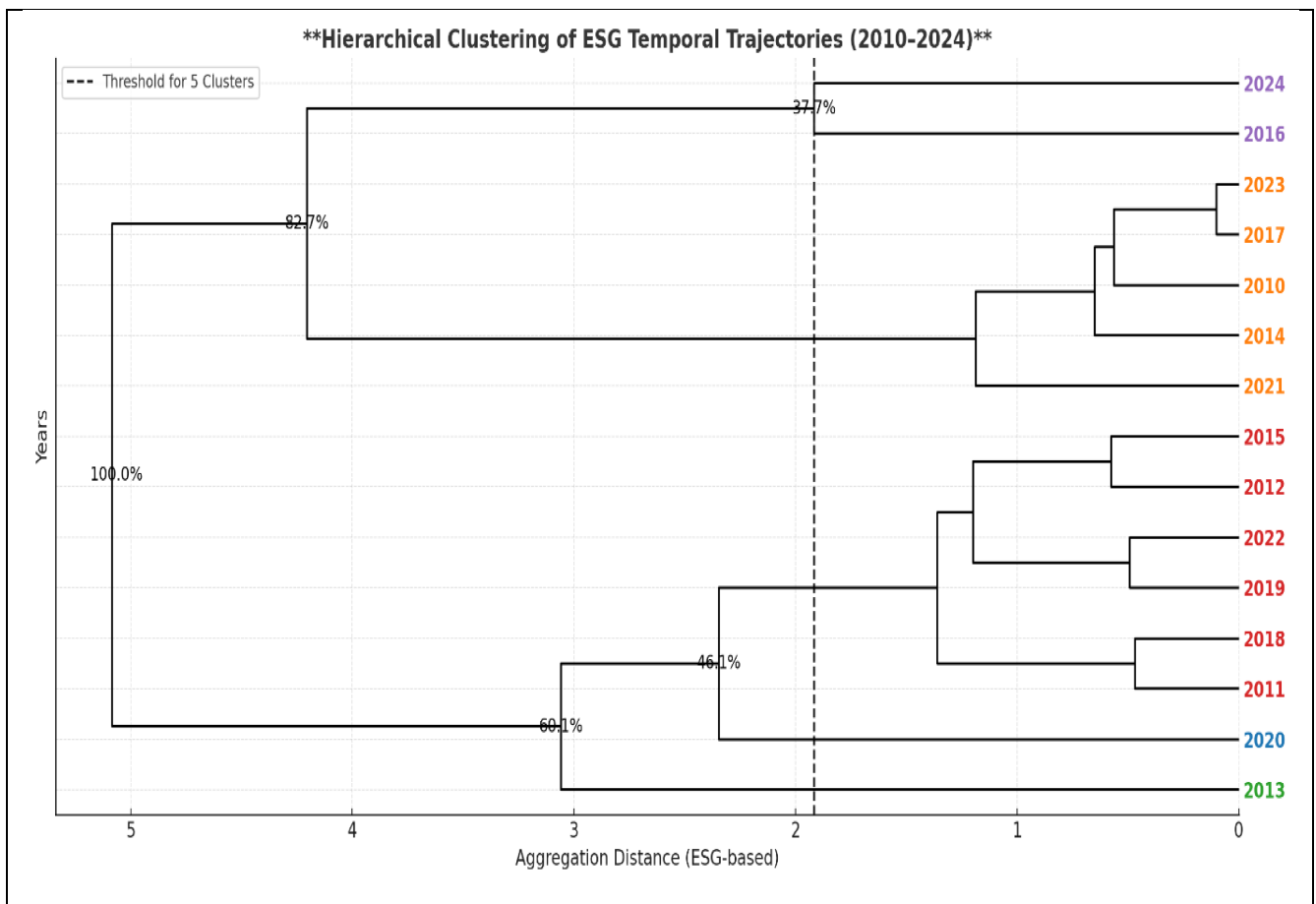


FIGURE 3b | Bottom-up hierarchical clustering of individuals years of ESG components.

(Year 2020) reflects the disruptive impact of the pandemic caused by the SARS-CoV-2 virus. This impact is characterised by a sharp increase.

A silhouette score of 0.369 supports the robustness of the breakdown. Given the temporal structure of the data, this result can be considered satisfactory. This multivariate analysis

also highlights the non-linear nature of ESG trends within OECD countries. There have been breaks, but also trade-offs between the different pillars and varying responses to exogenous shocks. In other words, it validates the need for a disaggregated and time-sensitive assessment (Zhang et al. 2021). More generally, this is in line with recent empirical standards in sustainable finance (Cosma et al. 2024; Bamel et al. 2025).

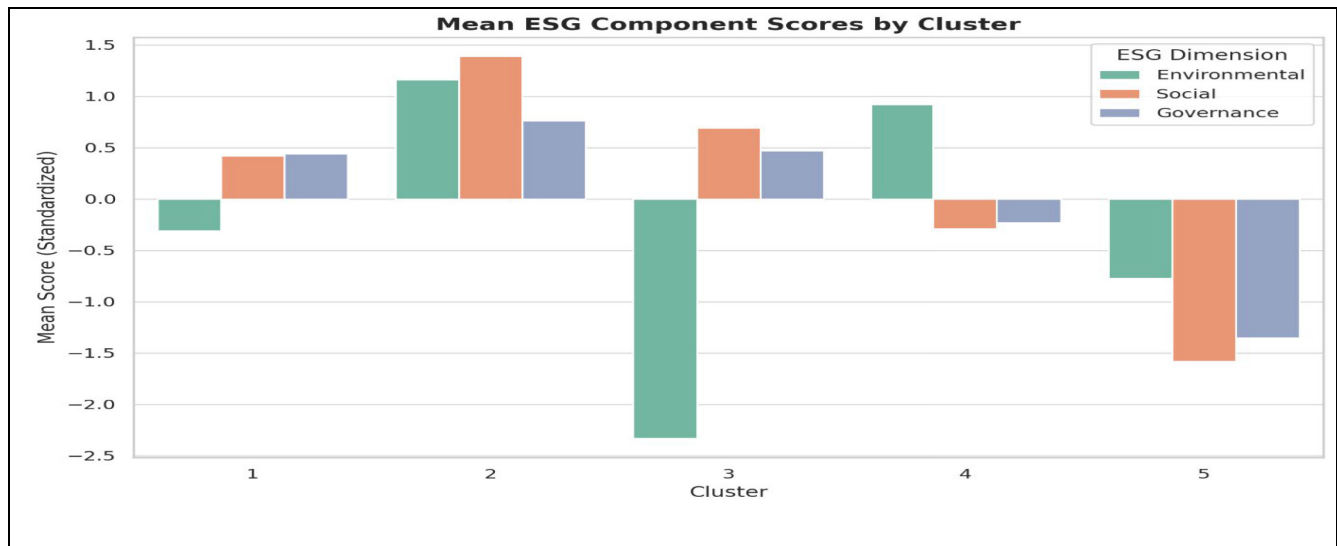


FIGURE 3c | Mean ESG scores by cluster.

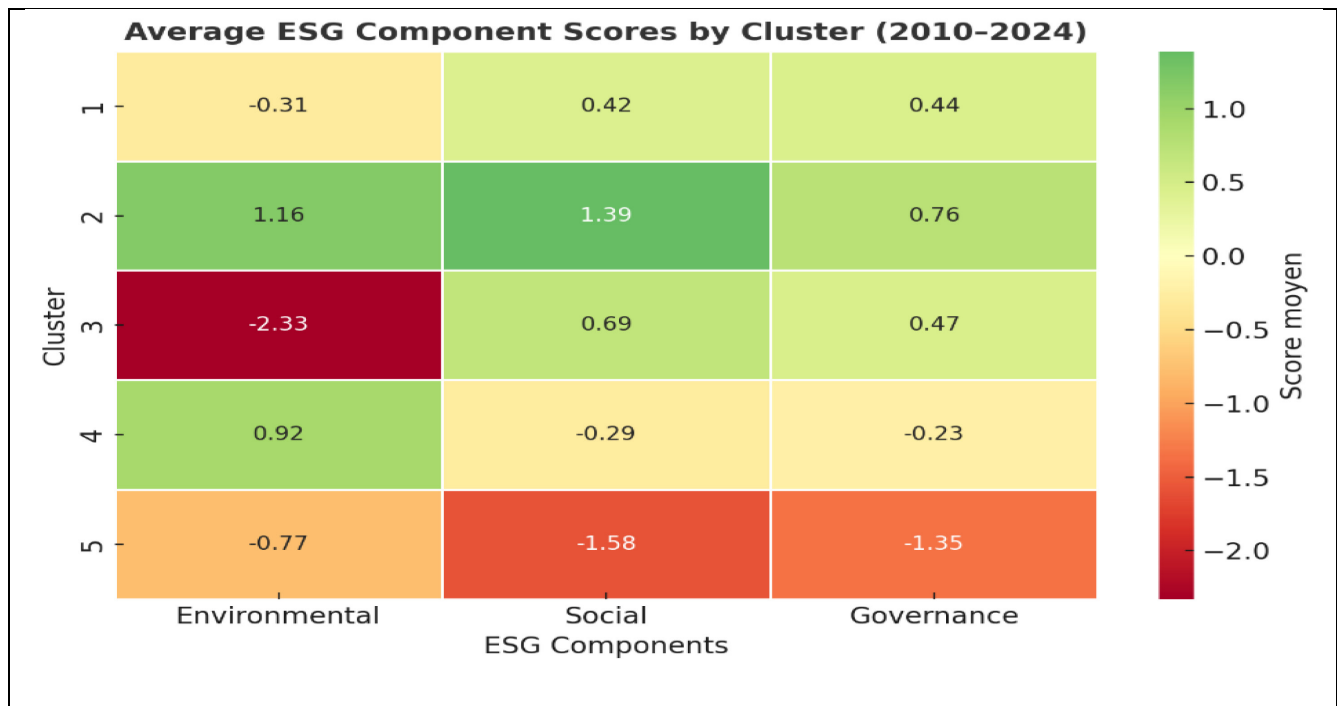


FIGURE 3d | Average ESG Components by cluster.

4.2 | Spatial Analysis of ESG Performance Over Each Sub-Period

Within each of the five temporal sub-periods identified in Section 4.1, the 38 OECD countries were classified using their standardised ESG mean scores as active variables. MFA was used to organise and interpret the additional indicators, which were defined ex ante as illustrative variables and grouped into four theoretically motivated themes: Environment, Economy and Market, Governance and Institutions, and Sentiment and Perception. These illustrative variables did not contribute to the formation of the country clusters but were used to characterise their environmental, economic, institutional and behavioural profiles.

To select a common number of country clusters across the five sub-periods, solutions ranging from ($k=2$) to ($k=10$) were compared using a cross-period one-standard-error rule. Solutions producing singleton clusters were excluded as excessively fragmented. Among the admissible solutions, ($k=6$) produced the highest mean silhouette coefficient (0.2981), with a standard error of 0.0150 and a resulting one-standard-error threshold of 0.2831. The five-cluster solution achieved a mean silhouette coefficient of 0.2882 and was therefore the smallest admissible solution within one standard error of the best-performing specification. By contrast, the four-cluster solution, with a mean silhouette coefficient of 0.2732, fell below this threshold. Accordingly, five clusters were retained as the common

parsimonious resolution, ensuring comparability across the five sub-periods without relying solely on visual inspection.

The robustness of this common partition was further assessed by comparing Ward and k-means solutions. The two methods produced substantially concordant country classifications, with a mean adjusted Rand index of 0.736 and mean normalised mutual information of 0.820. Period-specific silhouette results are presented in Figures 4a and 4b, while the complete cluster-number selection and method-robustness analyses are reported in Appendix B, Figures B1 and B2.

For the country classifications, the 10% trimmed-mean specification showed high concordance with the baseline partitions (mean ARI=0.849), while the rank-based specification also produced substantial agreement (mean ARI=0.702). Lower concordance was obtained for the median and leave-one-sector-out specifications. Consequently, the general evidence of heterogeneous ESG configurations is maintained, but the exact membership of some clusters remains sensitive to the aggregation rule and sectoral coverage. The country classifications are therefore interpreted as exploratory rather than invariant typologies. Complete results are reported in Appendix C, Table C1. Table 6 reports the complete cluster composition, active-variable profiles and descriptive labels for all five sub-periods.

Across the first temporal sub-period, the five country clusters differ primarily in their governance and social positioning

rather than following a uniform environmental gradient. Cluster 1 ($n=2$: Switzerland, United Kingdom) combines an above-average social score with a below-average environmental score and a near-average governance score, most strongly associated with the energy-sector stock index and, negatively, agriculture-sector population and GDP growth. Cluster 2, the largest group ($n=13$: Australia, Austria, Greece, Iceland, Israel, Italy, Luxembourg, Latvia, Mexico, Poland, the Slovak Republic, Slovenia and Sweden), shows above-average environmental and social scores alongside below-average governance, led by healthcare-sector HDI and, negatively, energy-sector Emotional AI and agriculture-sector trade balance. Cluster 3 ($n=10$: Canada, Chile, Germany, Denmark, France, Ireland, Malta, Norway, New Zealand and the United States) is characterised by above-average governance and below-average environmental and social scores, led by the technology-sector stock index and trade balance (both negative) and healthcare-sector political stability (positive). Cluster 4 ($n=5$: Czech Republic, Hungary, Japan, Lithuania and the Netherlands) combines an above-average environmental score with below-average social and governance scores, driven by healthcare-sector trade balance and automotive-sector population (both negative) and healthcare-sector digitalisation (positive). Cluster 5 ($n=8$: Belgium, Colombia, Spain, Estonia, Finland, South Korea, Portugal and Türkiye) shows a broad-based below-average ESG profile across all three pillars, most closely associated with energy-sector GDP growth and automotive-sector political stability and, negatively, technology-sector digitalisation. Consistent with the

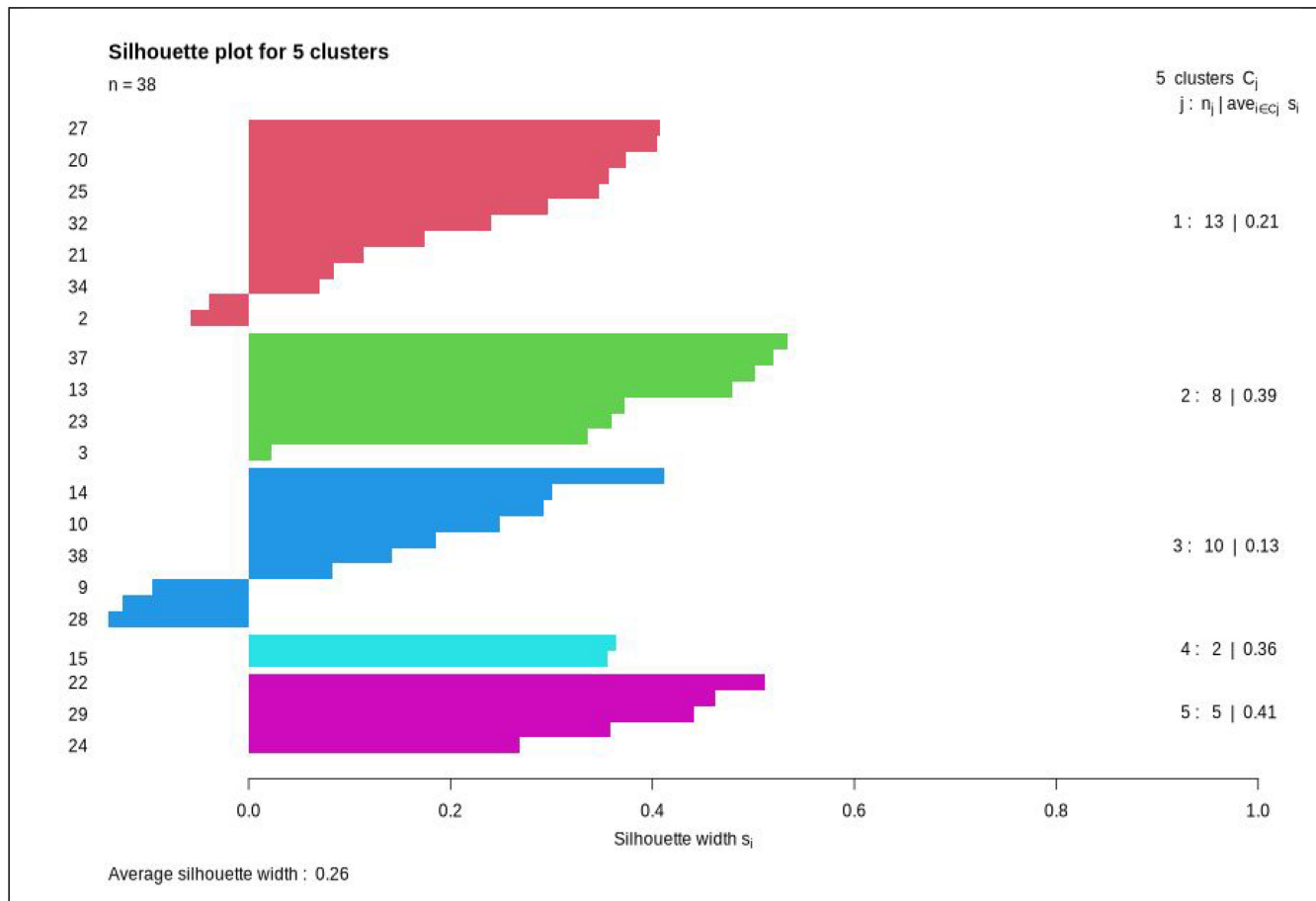


FIGURE 4a | Silhouette plot by cluster for period 1.

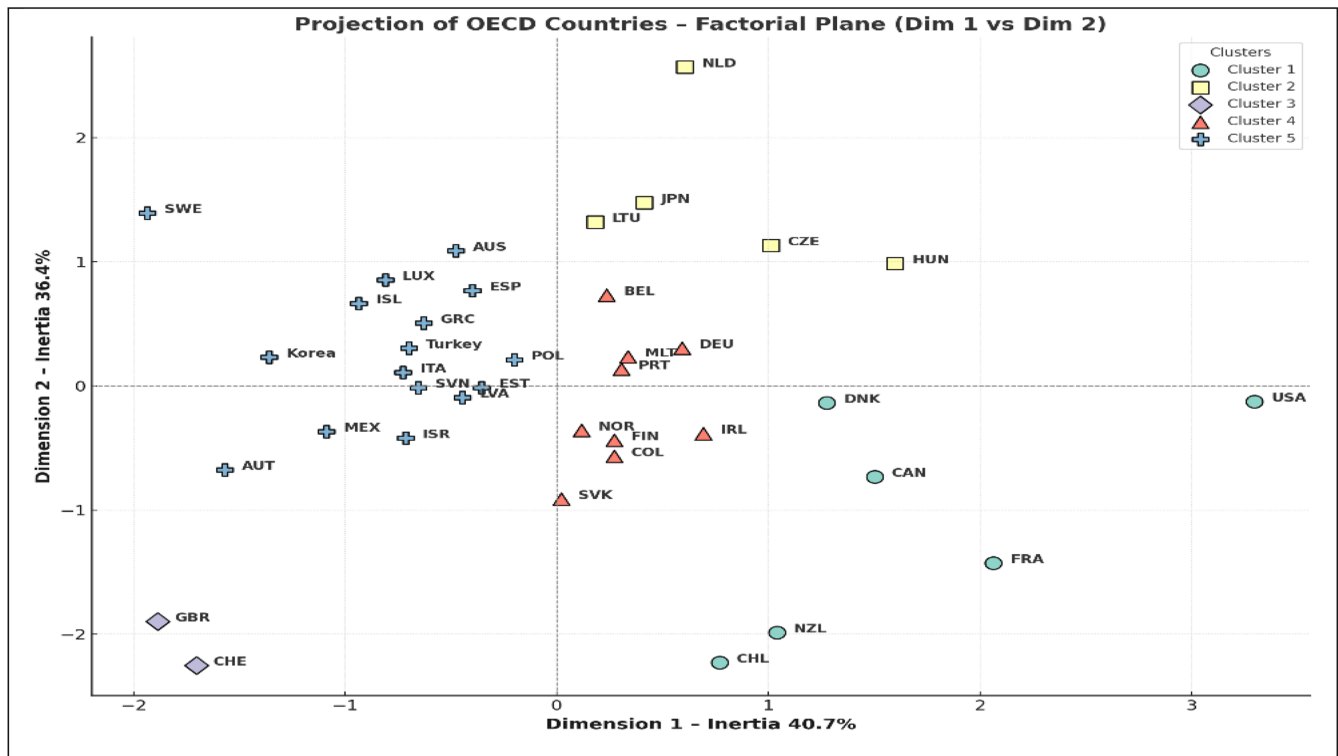


FIGURE 4b | Projection of OECD countries on the factorial plot for sub-period 1.

Environment and the Governance and Institutions thematic blocks introduced in Table 1, this first sub-period indicates that governance and environmental strength are frequently in tension across OECD members, with relatively few countries combining above-average performance on both. This divergence is consistent with the natural-resource-based view of competitive advantage (Hart 1995; Porter and Linde, (1995) and with institutional-quality theory (North 1990), and echoes recent evidence that ESG ratings and governance assessments vary substantially across providers and countries (Berg et al. 2022; Krueger et al. 2020).

A spatio-temporal analysis, particularly of sub-period 2 (where there have been improvements on the social and governance fronts, but a setback on the environmental front), confirms that institutional and social progress has generally been faster than the environmental transition. This finding highlights the need for a more integrated, and above all more ambitious, approach to harmonising ESG policies with global environmental challenges.

Within the second sub-period (2020), the MFA and Ward classification again identify five country clusters, shaped strongly by the economic and governance disruptions associated with the pandemic (Figures 4c and 4d). Cluster 1 ($n=6$: Switzerland, Estonia, France, Greece, Poland and Sweden) combines above-average environmental and governance scores with a near-average social score, led by finance-sector trade balance and healthcare-sector unemployment (both negative) and agriculture-sector volatility index (negative). Cluster 2 ($n=9$: Canada, Finland, United Kingdom, Hungary, Iceland, Lithuania, Latvia, the Netherlands and Türkiye) shows an above-average environmental score with a below-average social score and near-average governance,

associated with healthcare-sector GDP growth (negative) and automotive-sector Emotional AI and technology-sector stock index (both positive). Cluster 3, the largest group ($n=11$: Belgium, Colombia, Germany, Denmark, Spain, Ireland, Japan, Malta, Norway, New Zealand and Slovenia), displays a broad-based below-average ESG profile, most associated with energy-sector biodiversity and agriculture-sector economic resilience and GDP growth. (All positive relative to the cluster mean, despite the overall below-average configuration.) Cluster 4 ($n=3$: Australia, Israel and the Slovak Republic) combines above-average social and governance scores with a below-average environmental score, strongly driven by healthcare-sector inflation and agriculture-sector unemployment and technology-sector corruption index (all positive). Cluster 5 ($n=9$: Austria, Chile, Czech Republic, Italy, South Korea, Luxembourg, Mexico, Portugal and the United States) shows an above-average social score with below-average governance and a near-average environmental score, led by energy-sector digitalisation (negative) and agriculture-sector inflation (positive) and, negatively, automotive-sector green innovation. These configurations are broadly consistent with the Adaptive Market Hypothesis (Lo, forthcoming): the largest cluster in 2020 (Cluster 3) combines the most broadly negative ESG configuration with pronounced economic disruption, while clusters combining governance and social strength (Clusters 1 and 4) appear comparatively more resilient. This pattern of differentiated institutional resilience under shock is consistent with the wider socio-technical transitions literature (Geels 2002) and with evidence that green financial instruments contributed to economic stabilisation in some economies during this period (Flammer 2021).

The inclusion of the third axis (PC3) in a three-dimensional representation refines the reading a little: PC1 reflects

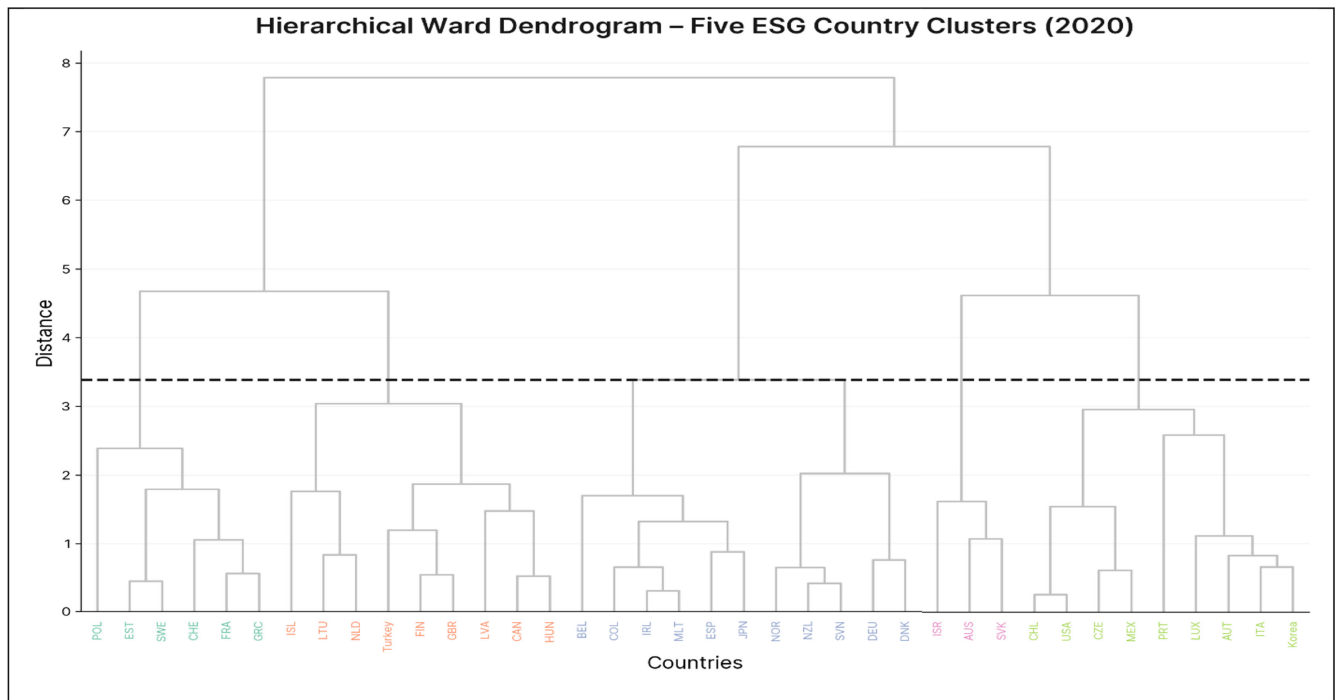


FIGURE 4c | Hierarchical bottom-up clustering. Note: ‘Hierarchical dendrogram, - Five groups of ESG countries (2020)’ shows the aggregation distance between OECD countries on the three E,S,G components. The labels are coloured according to the group and the dotted line marks the cut-off point for the five groups. The Ward dendrogram, which is based on the three components (90% of the inertia), is cut at the dotted line to obtain five compact groups.

environmental and institutional commitment (loadings ≥ 0.6), PC2 social contrasts (loadings > 0.7) and PC3 tensions between governance reform and exposure to shocks. This configuration reinforces a certain criticism of the Efficient Market Hypothesis (Fama 1970) and argues in favour of a more entropic, adaptive and disaggregated reading of ESG performance. All this shows that ESG trajectories are neither linear nor convergent but structurally heterogeneous and guided by trade-offs, vulnerabilities and critical exogenous contexts.

In the third sub-period (2013), the country typology again comprises five clusters (Figures 4e and 4f). Cluster 1 ($n=7$: Denmark, Estonia, Finland, Ireland, Israel, Japan and Portugal) shows a below-average social score alongside near-average environmental and governance scores, led by a negative association with global CO₂ emissions and positive associations with finance-sector GDP growth and energy-sector collaborative governance. This tension between eco-innovation and social/regulatory weakness is consistent with the ‘green growth/lagging governance’ pattern described by Aghion et al. (2021). Cluster 2 ($n=8$: Austria, Spain, Greece, Malta, New Zealand, the Slovak Republic, Slovenia and the United States) combines below-average social and governance scores with a near-average environmental score, most associated with agriculture-sector trade balance and finance-sector population (both negative). This configuration, which includes several economies with historically carbon-intensive energy systems (Austria, Spain, Greece, the United States), is consistent with the carbon lock-in mechanisms described by Unruh (2000). Cluster 3 ($n=9$: Switzerland, Colombia, Czech Republic, Germany, France, Iceland, Italy, Norway and Poland) shows a broad-based above-average ESG profile, led by agriculture-sector collaborative governance and

healthcare-sector GDP growth. This broad-based strength is consistent with the innovation-through-regulation effect described by Porter and Linde (1995). Cluster 4 ($n=5$: Hungary, Lithuania, Luxembourg, Sweden and Türkiye) combines an above-average social score with below-average environmental and governance scores, associated with automotive-sector HDI and healthcare-sector political stability (both positive). The persistence of Luxembourg and Sweden within this below-average-environmental configuration is consistent with evidence that certain planetary boundaries remain under pressure even in socially strong economies (Rockström et al. 2009). Cluster 5 ($n=9$: Australia, Belgium, Canada, Chile, United Kingdom, South Korea, Latvia, Mexico and the Netherlands) shows an above-average governance score with below-average environmental and social scores, most strongly led by energy-sector interest rates and inflation and, negatively, finance-sector investor confidence. This configuration is consistent with the resource-driven ‘green paradox’ described by Sinn (2012), whereby strong governance coexists with continued reliance on natural-resource-intensive sectors. As in the preceding sub-periods, only Cluster 3 combines above-average performance across all three pillars in 2013, underscoring the persistence of governance–environment and social–governance trade-offs identified throughout the temporal analysis.

The 3D projection highlights the overall inertia (PC1 = 34.5%, PC2 = 33.8%, PC3 = 31.7%). CP1 contrasts socio-institutional robustness (left) with regulatory fragility (right); CP2 prioritises environmental performance; CP3 isolates governance outperformance. Cluster 3’s institutional role contrasts with Cluster 2’s poor carbon performance, while the other groups are positioned according to their ESP-GOV trade-offs, which

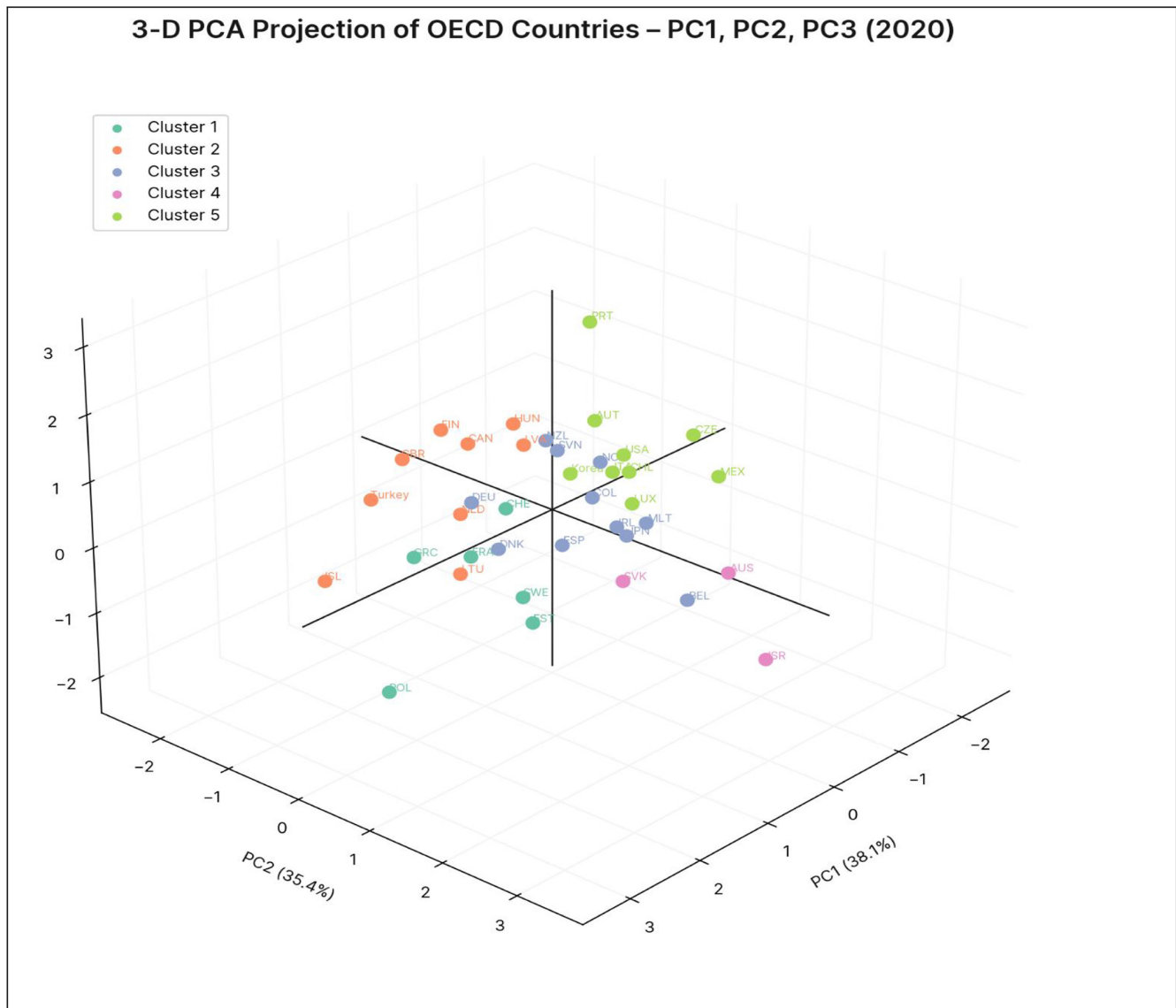


FIGURE 4d | Projection of OECD countries over sub-period 2: 2020. *Note:* Sub-period 2 (2020) reveals five ESG clusters shaped strongly by the economic and governance disruptions associated with the pandemic; see Section 4.2 for cluster composition and profiles.

tends to confirm that carbon density, institutional quality and sector specialisation are determining factors for ESG trajectory.

The joint analysis of the correlation circle, the 2D cluster projection, the hierarchical dendrogram and the projection of illustrative variables (see Figures 4g, 4h and 4i) over sub-period 4 reveals five structurally coherent ESG trajectories among OECD countries. These clusters illustrate the transition from a technology-centred approach to a collaborative sustainability framework (Ostrom 2007), in which technological progress, the quality of institutions and social cohesion collectively influence environmental performance.

The fourth sub-period (2010, 2014, 2017, 2021 and 2023) again yields five clusters (Figures 4g, 4h and 4j). Cluster 1 ($n=7$: Chile, Colombia, Estonia, Ireland, South Korea, Latvia and Sweden) combines an above-average social score with below-average environmental and governance scores, led

by finance-sector trade balance and energy-sector inflation and corruption index (all positive). Cluster 2 ($n=6$: Iceland, Italy, Luxembourg, Malta, the Slovak Republic and the United States) shows below-average environmental and social scores with a near-average governance score, most associated with energy-sector green innovation (positive) and energy-sector political stability (negative) and, positively, agriculture-sector digitalisation. Cluster 3 ($n=8$: Austria, Germany, France, United Kingdom, Lithuania, Norway, New Zealand and Poland) combines above-average environmental and governance scores with a near-average social score, led by a negative association with global CO₂ emissions and technology-sector put/call ratio. This combination of environmental and governance strength is consistent with a natural-resource-based view of competitive advantage (Schmidheiny 1992; Hart 1995). Cluster 4 ($n=5$: Switzerland, Denmark, Spain, Greece and Mexico) shows above-average environmental and social scores with a below-average governance score, driven by technology-sector political stability and agriculture-sector

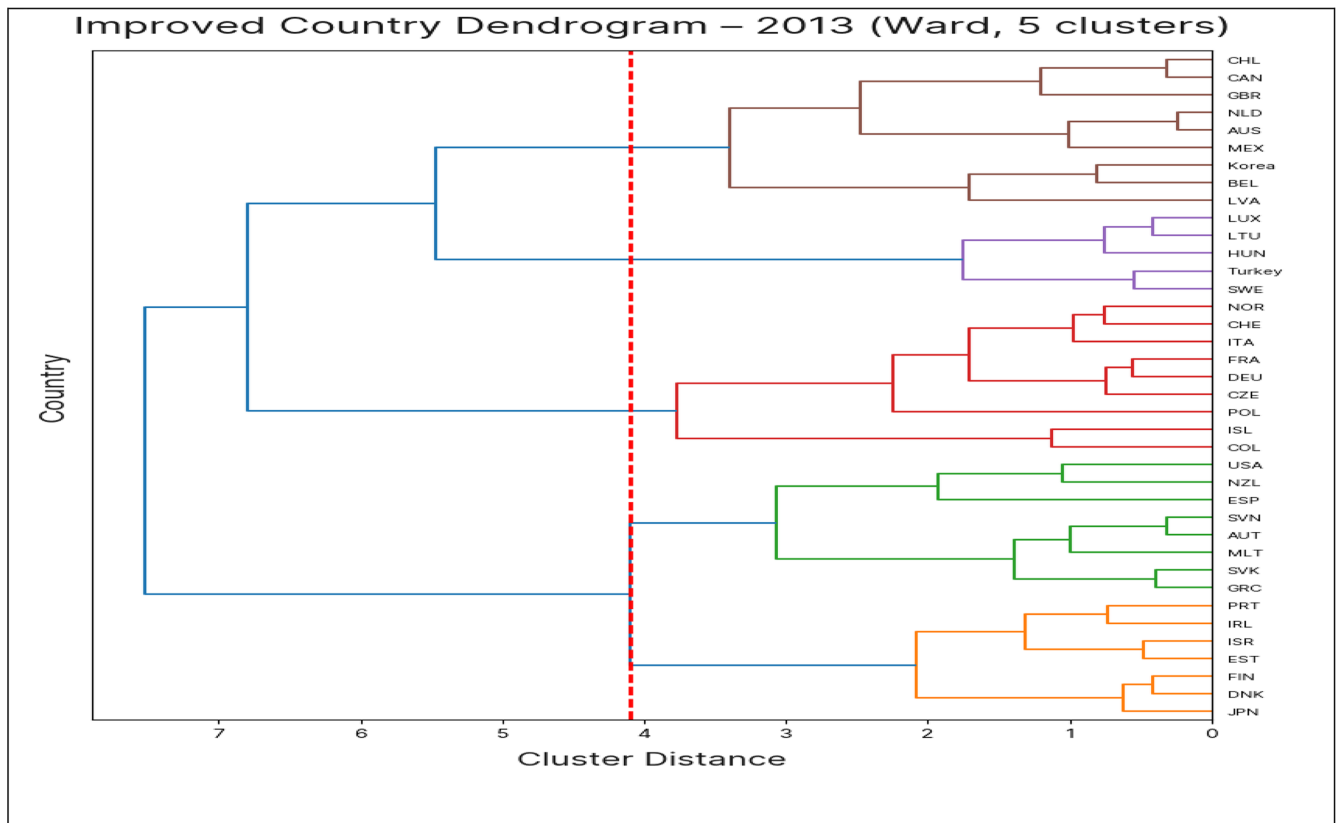


FIGURE 4e | Hierarchical ascendant clustering over sub-period 3.

biodiversity (both positive) and, negatively, energy-sector stock index. Cluster 5, the largest group ($n = 12$: Australia, Belgium, Canada, Czech Republic, Finland, Hungary, Israel, Japan, the Netherlands, Portugal, Slovenia and Türkiye), shows a below-average environmental score with near-average social and governance scores, most associated with healthcare-sector put/call ratio and automotive-sector trade balance (both negative) and, positively, finance-sector digitalisation. Consistent with the Governance and Institutions thematic block, Cluster 3's combination of environmental and governance strength recurs across several sub-periods among a broadly similar set of continental European economies, consistent with the institutional-quality literature (North 1990), while smaller, resource- or trade-exposed economies in Clusters 1, 2 and 4 show more volatile, pillar-specific trade-offs. This persistence of institutional configurations across sub-periods is consistent with path-dependence theory (David 1985).

In the fifth and final sub-period (2016 and 2024), the MFA and Ward classification again identify five clusters (Figure 4i). Cluster 1 ($n = 2$: Spain, New Zealand) shows a broad-based below-average ESG profile, most strongly associated with automotive-sector GDP growth (negative) and automotive-sector CO₂ emissions and healthcare-sector HDI (both positive relative to the cluster mean). Cluster 2 ($n = 12$: Australia, Belgium, Chile, Colombia, Denmark, Iceland, Israel, Japan, Latvia, Poland, Slovenia and Sweden) combines an above-average environmental score with below-average social and governance scores, led by automotive-sector HDI (positive) and finance-sector trade balance and healthcare-sector

COVID-19 crisis exposure. (HDI and COVID-19 crisis exposure both positive; trade balance negative.) Cluster 3, the largest group ($n = 15$: Austria, Czech Republic, Estonia, Finland, France, United Kingdom, Ireland, South Korea, Mexico, Malta, Norway, Portugal, the Slovak Republic, Türkiye and the United States), shows an above-average social score with a below-average environmental score and near-average governance, most associated with automotive-sector volatility index (negative) and finance-sector digitalisation (negative) and, positively, automotive-sector media coverage. Cluster 4 ($n = 2$: Switzerland, Hungary) is distinguished by a markedly above-average governance score alongside below-average environmental and social scores, led by agriculture-sector GDP growth and energy-sector media coverage (both positive). This markedly governance-led profile is consistent with evidence that strong governance and transparent climate-data disclosure are associated with a lower cost of capital (Pagano and Picariello 2022) and with lower climate-related sovereign risk premia (Allen et al. 2020; Pantos 2023). Cluster 5 ($n = 7$: Canada, Germany, Greece, Italy, Lithuania, Luxembourg and the Netherlands) shows a broad-based above-average ESG profile, associated with energy-sector biodiversity and healthcare-sector put/call ratio (both positive) and, negatively, agriculture-sector HDI. This group's broad-based strength is consistent with these countries operating within a comparatively safe environmental and institutional space (Rockström et al. 2009). Taken together with the entropy-based TLEC typology reported in Section 4.3, this final sub-period again shows governance strength (Cluster 4) and broad-based ESG strength (Cluster 5) concentrated in different, largely non-overlapping

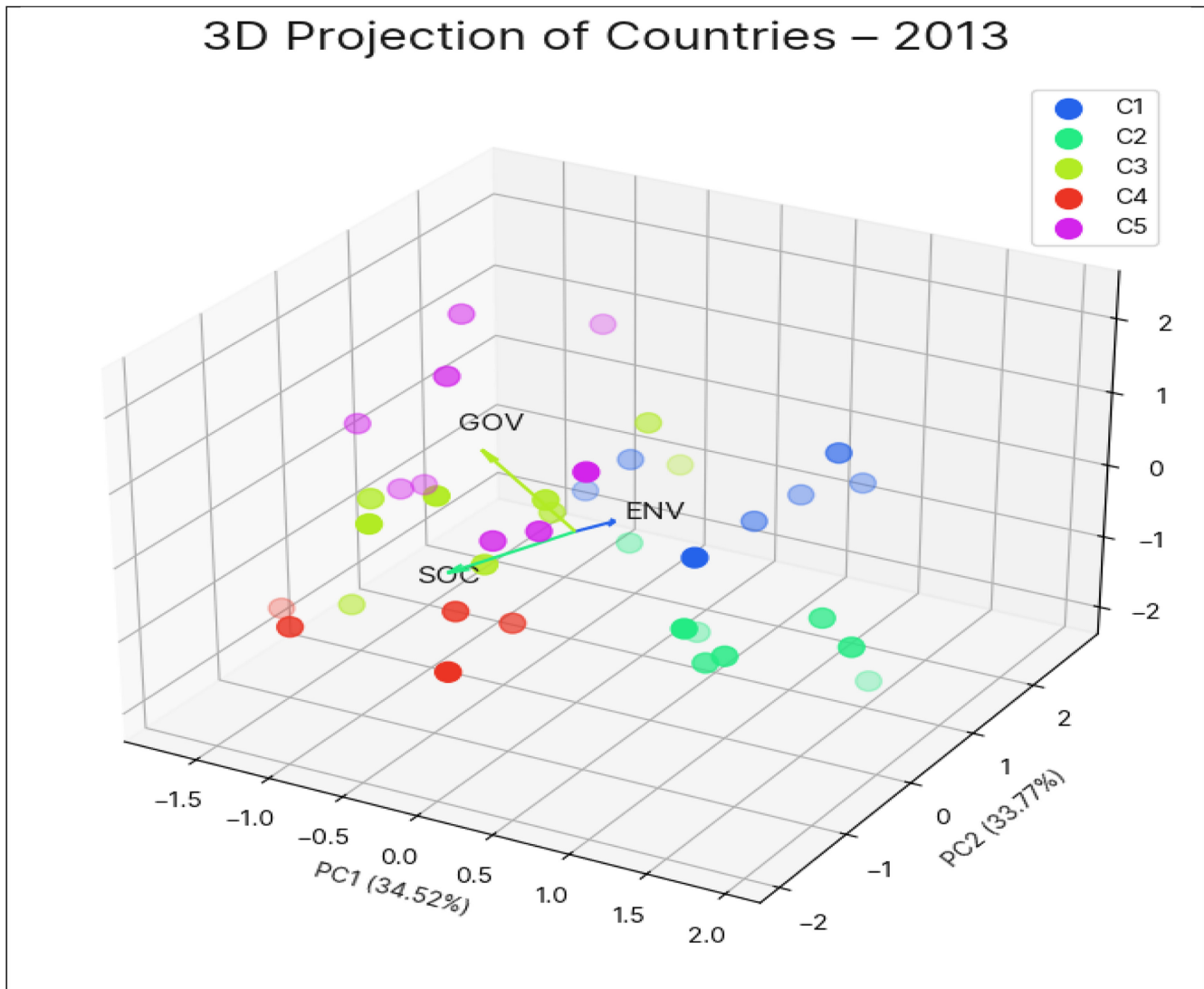


FIGURE 4f | 3D projection of country clusters for period 3: 2013.

sets of countries, reinforcing the paper's central finding that governance, social and environmental performance do not consistently co-move across OECD members.

4.3 | Rationale for an Entropy-Based Approach

Entropy and exposure to high unemployment, high interest rates and various past economic shocks such as financial crises. Their ESG profile seems to correspond to a situation of portfolio risk in a context of uncertainty (Markowitz 1952) as well as to models of systemic fragility. Group 2 'Adaptable on the periphery' includes France, Japan, Norway, Finland, Italy, Greece and South Korea and Ireland. In general, they have entropy profiles that are in the middle of the range and, interestingly, react in a fairly similar way to macroeconomic stress factors (such as the impact of the pandemic or trade imbalances). Their approach to governance illustrates the theory of stakeholder adaptation (Freeman 1984). Group 3 'Resilient Anchors' Canada, Chile, Sweden, the Netherlands, the United States, Denmark and Estonia are countries with high HDI

indicators, a well-developed digital infrastructure and innovation in the field of emotional AI. On the other hand, negative carbon emissions and political instability are a sign of institutional integrity, which corresponds to resource-based governance models. Group 4 'Underperforming Stabilisers'—Germany, Turkey, Spain, Australia and Belgium—are relatively cohesive in terms of governance and innovation but have high emissions and political instability. This is consistent with path-dependent inertia, which indicates that change is slow and uneven. Group 5 constitutes the 'Volatile Convergence in Governance' group—they are Austria, Switzerland, Portugal, Israel, Slovenia, the Czech Republic, Latvia, Luxembourg and Iceland. These countries are at a stage of transition towards ESG. The high entropy in variables such as corruption and uncertainty show that ESG convergence is not linear. Heat maps (Figure 5a; Figure 5b) show a strong positive thematic contribution of environmental and macroeconomic variables (i.e., interest rates and CO₂ emissions) in Groups 1 and 2. Clusters 3 are characterised by a strong thematic in digitalisation and emotional AI, reflecting the cognitive dimension of ESG maturity; and Cluster 5 shows signs of volatility in

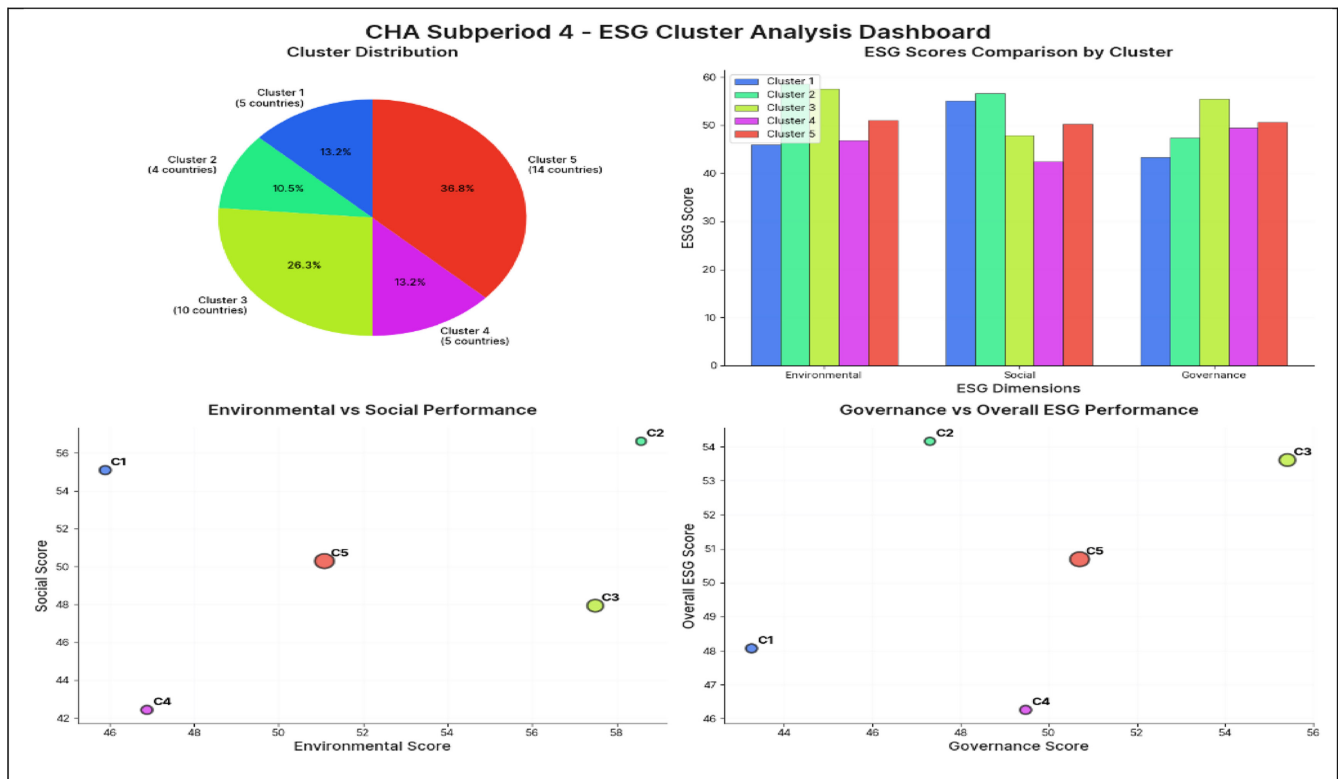


FIGURE 4g | ESG cluster analysis dashboard over sub-period 4.

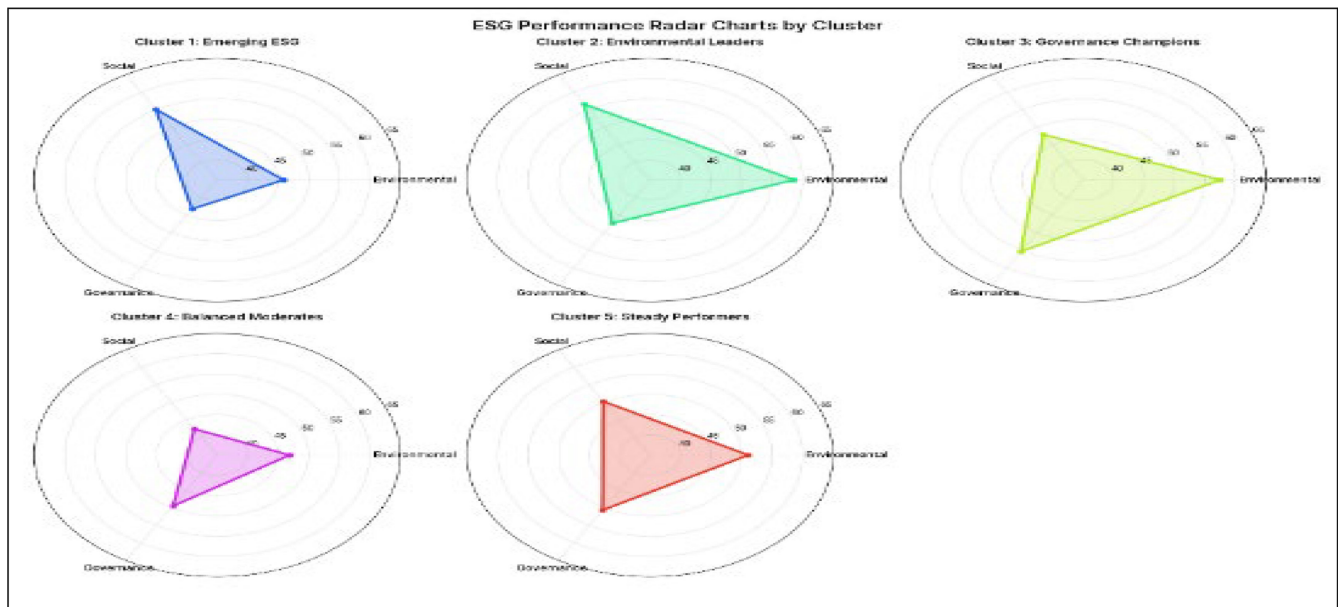


FIGURE 4h | ESG performance radar by cluster over sub-period 4.

governance and perception variables, suggesting institutional fragmentation (Figure 5c). Graph k-NN (Figure 5d) reveals that countries in Clusters 3 and 4 are structurally close, and therefore consistent in terms of entropy, as opposed to outliers such as Mexico or Turkey. These results suggest that entropy proximity of neighbours offers superior structural alignment compared with Euclidean grouping. Spatial map (Figure 5e)

reinforces this conclusion, showing regional ESG trajectories and validating the geo-entropic hypothesis that sustainability follows an evolution parallel to geography, politics and institutional anchorage. This further emphasises that members of the same entropy cluster will face similar investment and management dynamics, so sustainability benchmarking needs to be designed in a context-sensitive way.

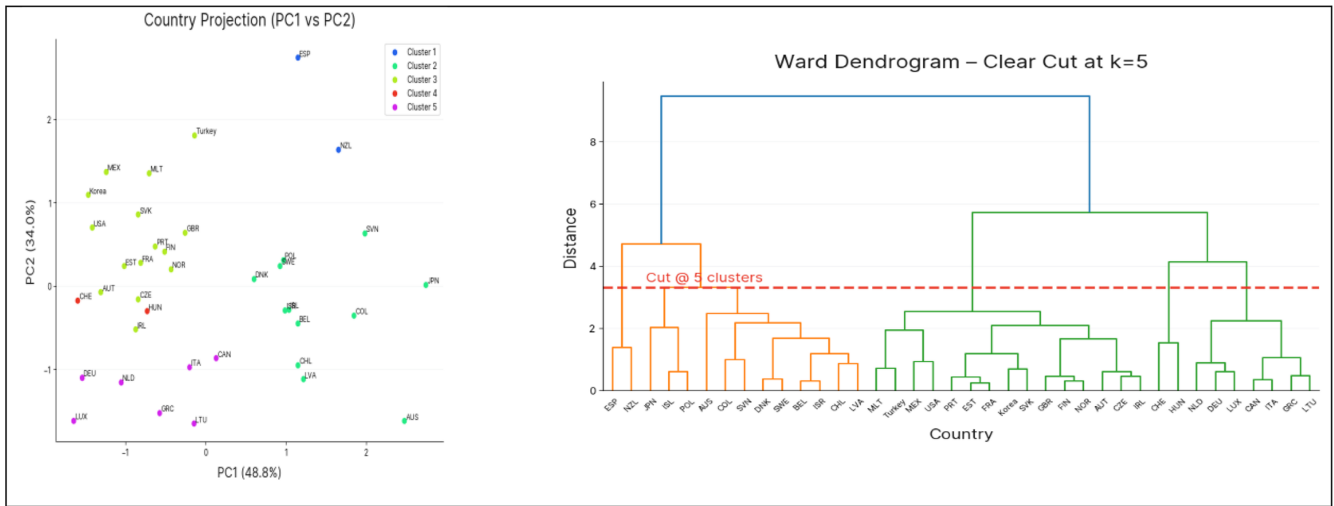


FIGURE 4i | Projection of country clusters and CHA (Ward method) over sub-period 5.

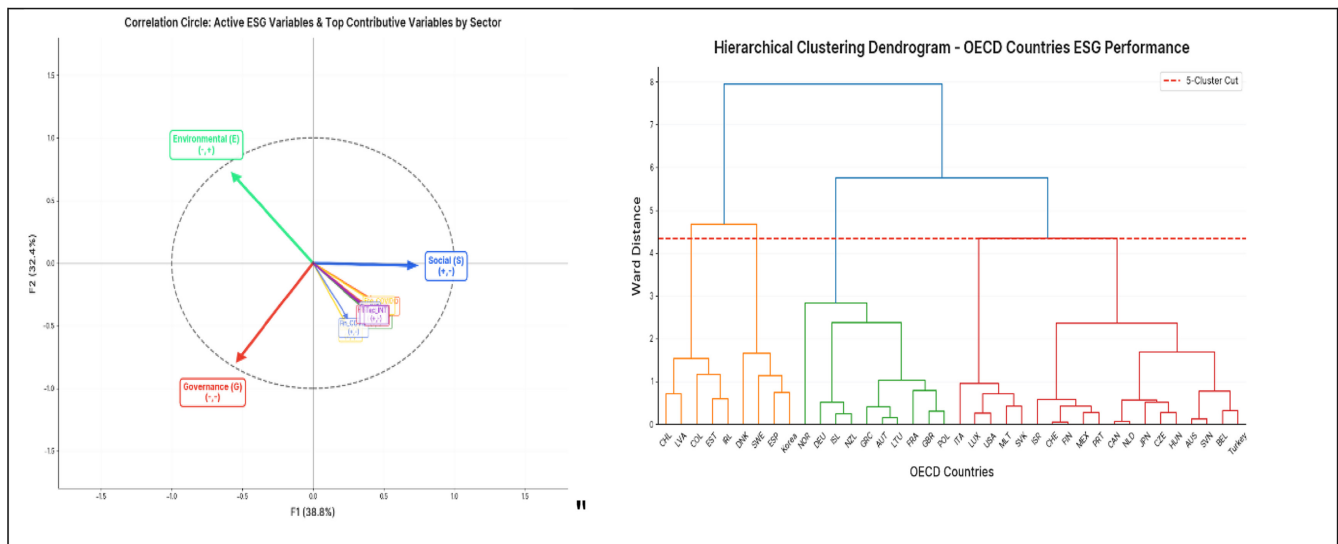


FIGURE 4j | Projection of additional contributing variables on the factorial plane and bottom-up hierarchical clustering over sub-period 4.

4.4 | TLEC Sensitivity and Benchmark Comparison

Additional analyses were conducted to assess whether the five-group TLEC partition was excessively dependent on its parameterisation. Under the reference specification ($q = 5$, $p = 2$, equal thematic weights, and $K = 5$), the partition achieved an entropy-space silhouette coefficient of 0.6633, with a minimum cluster size of three and no singleton clusters. Its mean stability over 100 country-subsampling repetitions was moderate ($ARI = 0.5636$; $NMI = 0.7416$). At the common five-group resolution, this stability was higher than that obtained by Ward, k-means and GMM, and close to that of spectral clustering. Nevertheless, the relatively low ARI concordance with the alternative methods indicates that the exact country membership remains method-sensitive. TLEC is therefore interpreted as a complementary entropy-based representation rather than as a universally superior clustering method. Complete parameter-sensitivity and benchmark results are reported in Appendix D, Figure D1 and Table D1.

5 | Discussion

5.1 | Understanding ESG Divergence and Non-Linear Sustainability Transitions

The findings of this study suggest that ESG transitions across advanced economies are neither linear nor uniformly convergent. Despite increasing global alignment around sustainability principles and ESG governance frameworks, OECD countries continue to exhibit differentiated sustainability trajectories over time (Geels 2002; DiMaggio and Powell 1983). A central insight emerging from the analysis is the persistence of trade-offs across ESG dimensions. Improvements in governance quality and social performance do not necessarily coincide with equivalent environmental progress, suggesting that sustainability transitions involve competing priorities rather than simultaneous optimisation across all ESG dimensions (Porter and Linde 1995; Unruh 2000). This finding challenges simplified assumptions of ESG convergence and reinforces the importance of context-specific sustainability strategies.

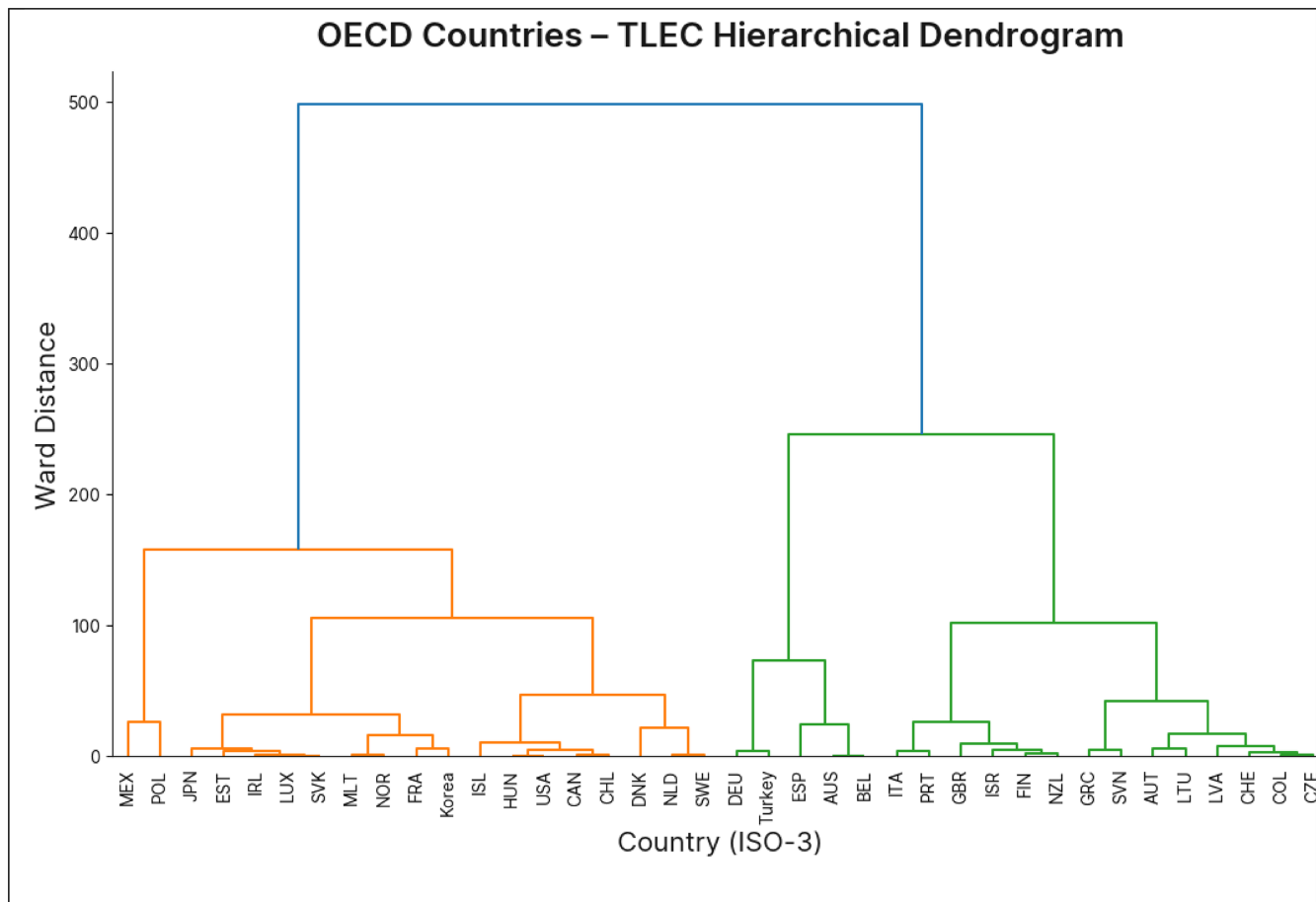


FIGURE 5a | TLEC hierarchical dendrogram. This dendrogram illustrates the hierarchical tree obtained using Ward's method, applied to the 38 OECD member countries. This classification is based on their local entropy profiles, estimated using the Kozachenko–Leonenko method, with $K = 5$. Each leaf of the tree is labelled with the ISO-3 code of the corresponding country. The vertical axis, called 'Ward's distance', quantifies the level of dissimilarity between two branches before a merger is deemed appropriate. By slicing the tree at the height of the longest white vertical portions, we can observe five large coloured groups, which, so to speak, reflect our TLEC groups.

The results also indicate that ESG trajectories evolve through discontinuous and adaptive adjustment processes rather than through stable linear progression. Periods of disruption, particularly during the COVID-19 pandemic, temporarily reconfigured sustainability priorities and exposed tensions between economic resilience, governance stability and environmental performance (Lo, [forthcoming](#); Bebbington and Unerman [2020](#)). These patterns highlight the dynamic nature of sustainability transitions under conditions of uncertainty and systemic stress. Importantly, the study contributes to the sustainability strategy literature by suggesting that ESG performance should not be interpreted solely through static rankings or aggregate indicators. Instead, ESG trajectories represent evolving transition pathways shaped by shifting policy priorities, structural constraints and strategic adaptation processes (Hart [1995](#); Flammer [2021](#)).

More broadly, the findings support the view that sustainability governance requires adaptive and context-sensitive approaches rather than standardised transition models. ESG integration therefore appears less as a universally linear progression and more as a dynamic balancing process involving competing

sustainability objectives and evolving stakeholder expectations (Freeman [1984](#); Meadows [2008](#)).

5.2 | Interpreting ESG Divergence Through Institutional and Economic Contexts

While the previous section highlighted the broader non-linear nature of ESG transitions, the present analysis focuses on the structural conditions that help explain why these trajectories diverge across OECD countries. The findings indicate that ESG evolution is strongly conditioned by differences in institutional quality, economic structure, governance capacity and innovation systems rather than by sustainability commitments alone. Countries characterised by stronger institutional coordination, higher administrative capacity and more diversified economic structures generally demonstrate more stable and coherent ESG trajectories over time (Acemoglu and Robinson [2013](#); Hart [1995](#)). These economies appear better positioned to align environmental objectives with governance effectiveness and long-term policy continuity, thereby supporting more resilient sustainability transitions. By contrast, countries facing structural economic

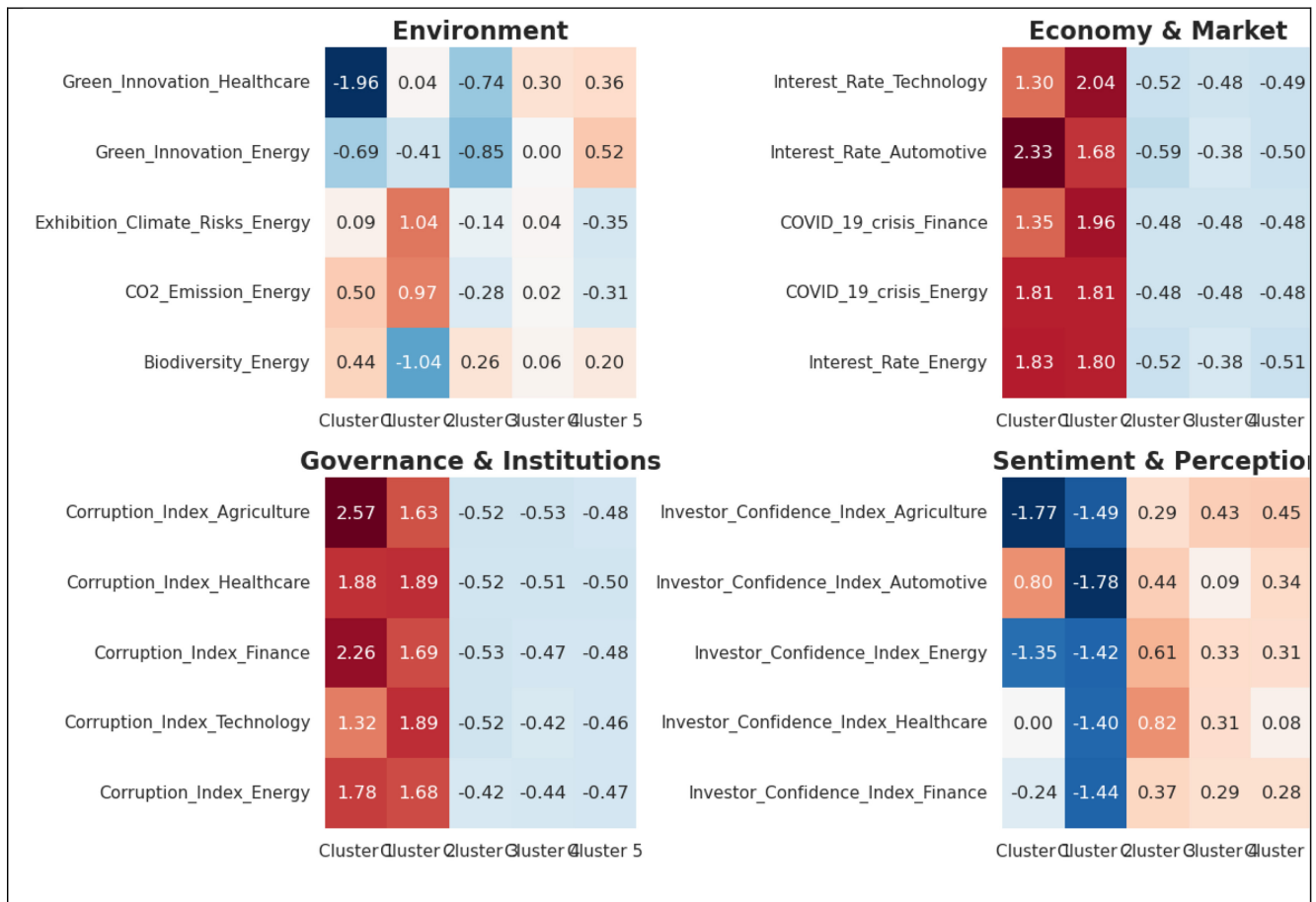


FIGURE 5b | Heat map of the four themes according to TLEC Method. *Note:* The observed transition from indigo blue to lemon yellow coincides with a reduction in the variance of internal entropy, i.e., $\text{Var}(H^k)$. In addition, the existence of a pronounced ‘kink’ after five groupings, as suggested by Mojena (1977), seems to validate the relevance of a segmentation into five distinct groups.

vulnerabilities, resource dependency or fragmented governance systems tend to exhibit less balanced ESG trajectories and greater volatility across sustainability dimensions (Unruh 2000; Chancel 2020).

The findings further suggest that governance quality alone does not automatically translate into stronger environmental performance. In several cases, relatively advanced governance systems coexist with slower environmental transitions due to industrial lock-in effects, carbon dependency or competing macro-economic priorities (David 1985; Sinn 2012). This highlights the importance of considering ESG performance as the outcome of interacting institutional and economic constraints rather than as a uniform policy achievement process. The analysis also reveals the importance of adaptive institutional capacity during periods of systemic disruption. The COVID-19 crisis did not generate a common sustainability response across OECD economies; instead, it amplified existing structural asymmetries. Countries with stronger fiscal flexibility, governance coordination and institutional resilience were generally more capable of maintaining ESG stability during periods of uncertainty, whereas more vulnerable economies experienced sharper sustainability imbalances and policy tensions (Lo, forthcoming; Bebbington and Unerman 2020).

These findings contribute to the broader sustainability transition literature by emphasising that ESG divergence is fundamentally context-dependent and path-dependent (Geels 2002). Sustainability transitions do not unfold through identical or universally convergent pathways. Rather, ESG trajectories emerge through the interaction of institutional arrangements, economic conditions, governance structures and external shocks over time. This perspective reinforces the importance of differentiated and adaptive sustainability governance frameworks capable of responding to varying national conditions and transition pressures.

5.3 | Theoretical Implications: Trade-Offs and Adaptive Sustainability Transitions

Our findings contribute to the growing literature challenging linear and convergence-based interpretations of sustainability transitions. Rather than evolving through uniform or sequential progress, ESG trajectories across OECD countries appear characterised by discontinuities, differentiated adjustment processes and persistent trade-offs between ESG priorities (Geels 2002; Meadows 2008). A particularly important implication concerns the fragmentation of ESG progress across dimensions.

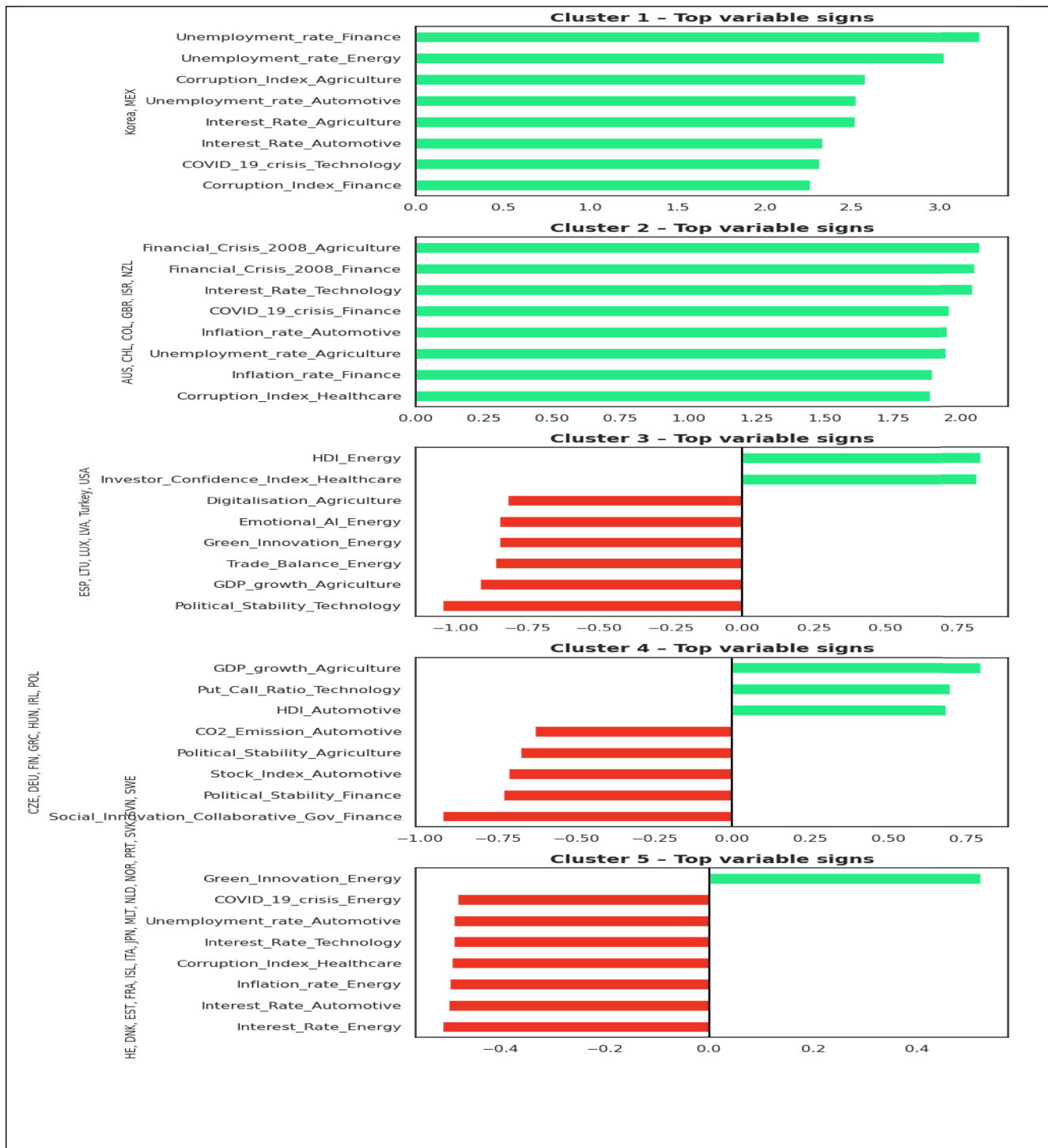


FIGURE 5c | Main thematic signs by group (TLEC, over sub-period 5: 2016–2020). *Note:* This figure shows the most discriminating variables in each group, as identified by the method of entropic local topological clustering (TLEC) and applied to OECD countries under the sub-period 2016 and 2020. Each sub-graph corresponds to one of the five clusters derived from the Ward hierarchical tree and presents the 10 most contributing illustrative variables, based on their standardised values (signs) and variance ratios (Fisher scores or η^2 statistics).

Improvements in governance quality and social performance do not necessarily coincide with stronger environmental outcomes, suggesting that sustainability transitions involve competing institutional and economic priorities rather than simultaneous advancement across all ESG components. This finding aligns with emerging perspectives on ESG fragmentation and

the political economy constraints of sustainability governance (Edmans 2023; Unruh 2000).

The results also reinforce adaptive and evolutionary perspectives on sustainability transitions. Periods of disruption, particularly during the COVID-19 pandemic, temporarily altered

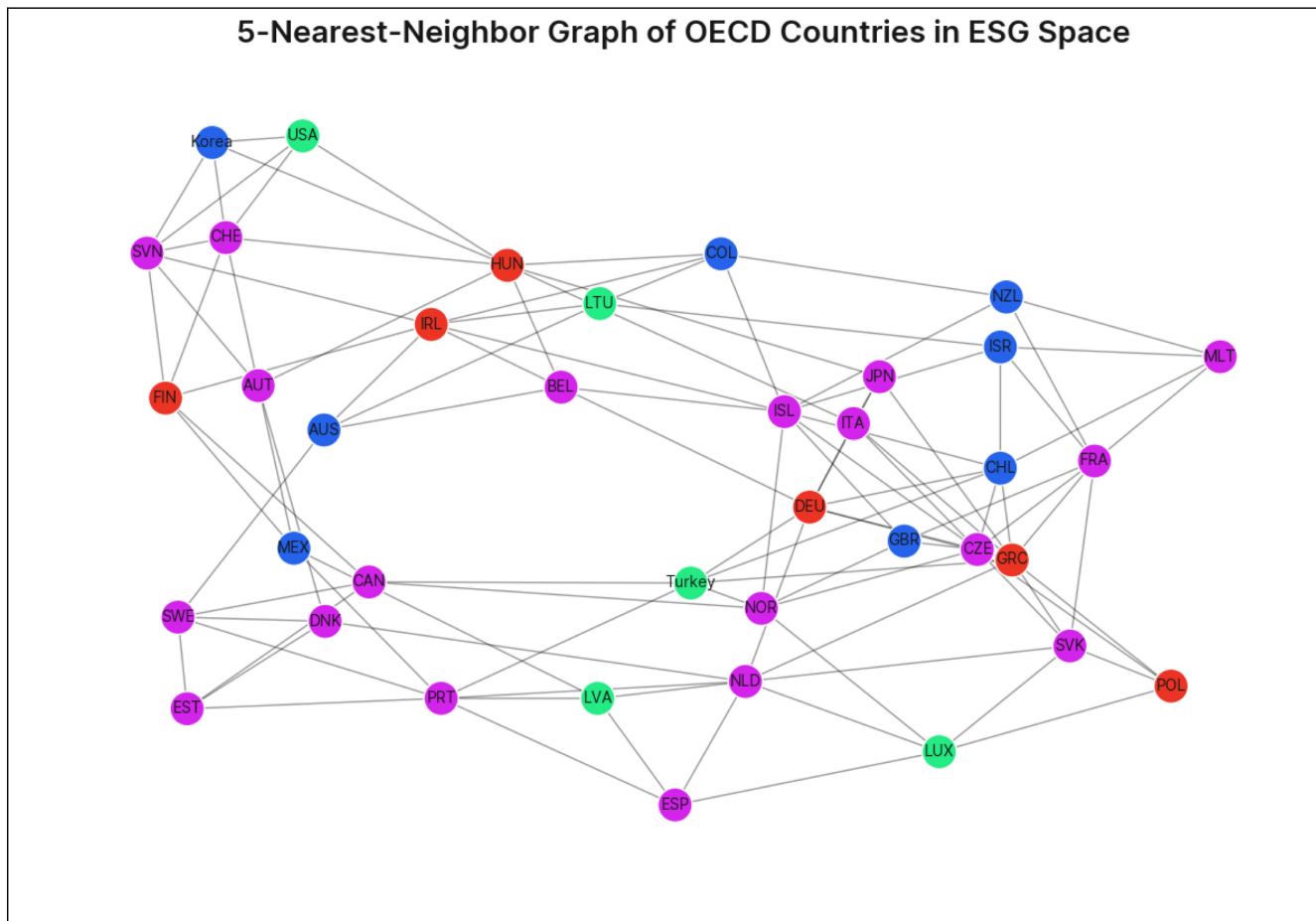


FIGURE 5d | Graph of closest OECD countries in ESG space (TLEC). *Note:* This graph illustrates the structural proximity between OECD countries based on their ESG profiles, as determined by the TLEC method. The connections reflect topological similarity, highlighting strong intra-group links (e.g., between Nordic and Western European countries) and the isolation of atypical countries such as Mexico and Turkey.

sustainability priorities and intensified structural tensions across ESG dimensions. These dynamics support the broader argument of the Adaptive Market Hypothesis that institutional and market responses evolve under changing informational and environmental conditions rather than through stable equilibrium processes (Lo, [forthcoming](#)). From an institutional perspective, the findings suggest that common sustainability pressures do not necessarily produce homogeneous ESG outcomes. Instead, countries appear to develop differentiated modes of institutional adaptation shaped by governance capacity, economic structure and contextual constraints. This interpretation extends Institutional Theory by suggesting that isomorphic pressures may generate clusters of adaptive behaviour rather than complete convergence in sustainability performance (DiMaggio and Powell 1983).

Additionally, the study contributes to sustainability strategy research by emphasising that ESG transitions should be understood as dynamic and context-dependent processes shaped by institutional learning, economic trade-offs and adaptive governance mechanisms. This perspective moves beyond static ESG benchmarking toward a more process-oriented understanding of how sustainability transitions unfold under conditions of uncertainty and structural complexity.

5.4 | Methodological Contribution: The Value of an Entropic Lens

The application of TLEC constitutes a core methodological contribution. While MFA and HCA provided a valuable spatial-temporal typology, TLEC revealed subtler, non-linear structural patterns. For example, linear methods grouped France, South Korea and the United States based on similar aggregate score trajectories. However, their entropy profiles showed significant divergence, reflecting differing levels of institutional resilience and internal socio-economic cohesion. TLEC identified countries with higher informational disorder in their ESG pathways, often those undergoing rapid transition or facing internal contradictions across pillars. This entropy-based approach directly addresses the critique of linear models in sustainability science. By measuring the predictability and local complexity of a country's trajectory rather than its position in a Euclidean space, TLEC offers a complementary descriptive lens on sustainability transitions: nations with greater internal strain (lower local entropy) display more heterogeneous ESG configurations, a pattern that future research could examine as a potential leading indicator of subsequent transitions. It operationalises the complex systems thinking advocated by scholars like Meadows (2008) for the analysis of national sustainability pathways.

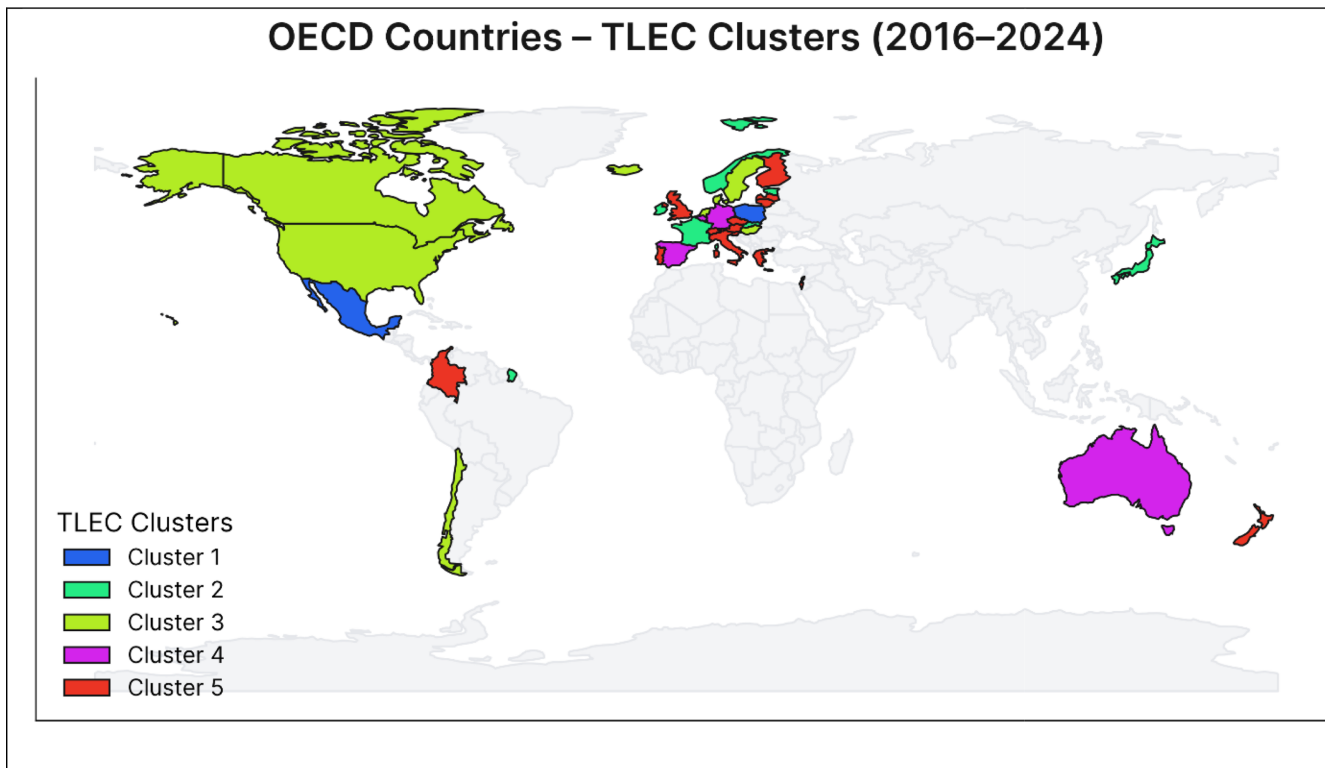


FIGURE 5e | Geographical distribution of TLEC groups over sub-period 5: (2016 and 2024). *Note:* The map presented here delineates the spatial distribution of the five ESG groups identified by TLEC. It reveals clear regional patterns, such as a cohesive group in the North Atlantic and countries with unstable governance scattered across Europe and the Pacific.

6 | Conclusion

This study examined the evolution of ESG trajectories across OECD countries between 2010 and 2024 using a longitudinal and multi-dimensional analytical framework. The findings demonstrate that sustainability transitions across advanced economies are neither linear nor uniformly convergent. Instead, ESG trajectories evolve through differentiated and context-dependent pathways shaped by institutional structures, economic conditions, governance priorities and adaptive responses to external shocks. Our major contribution of the study lies in demonstrating the persistence of trade-offs across ESG dimensions. Improvements in governance quality and social performance do not necessarily coincide with stronger environmental outcomes, suggesting that sustainability transitions involve complex balancing processes rather than simultaneous advancement across all ESG dimensions. The findings also highlight the importance of exogenous disruptions, particularly the COVID-19 pandemic, in temporarily reshaping sustainability priorities and exposing structural vulnerabilities across national ESG systems. In addition, the study contributes to the sustainability strategy literature by moving beyond static ESG benchmarking toward a dynamic understanding of sustainability transitions. The analysis suggests that ESG performance should be interpreted not simply as an outcome indicator, but as a reflection of evolving institutional adaptation processes shaped by uncertainty, economic pressures and governance constraints.

The findings carry important implications for policymakers, firms, investors and sustainability practitioners. *First*, the persistence of differentiated ESG trajectories suggests that sustainability governance frameworks should remain adaptive and context-sensitive rather than relying on standardised transition models. Countries and organisations differ substantially in institutional capacity, economic structure and exposure to sustainability risks, requiring more flexible ESG policy architectures. *Second*, the observed trade-offs across ESG dimensions indicate that sustainability transitions should not be approached as purely linear optimisation processes. Policymakers and corporate leaders must instead manage competing ESG priorities under conditions of uncertainty and resource constraints. This is particularly important during periods of economic disruption, where short-term resilience objectives may conflict with longer-term environmental commitments. *Third*, the findings reinforce the importance of improving ESG data transparency, comparability and standardisation. Persistent inconsistencies across ESG measurement systems continue to complicate cross-country assessment and sustainability benchmarking (Berg et al. 2022). Strengthening disclosure quality and harmonising ESG reporting frameworks therefore remain critical priorities for both regulators and market participants. From a strategic perspective, the study further suggests that firms should approach ESG integration as a dynamic capability rather than as a compliance-oriented exercise. Effective sustainability strategies require continuous institutional adaptation, stakeholder engagement and resilience planning in response to evolving economic and environmental conditions.

Several limitations of this study provide opportunities for future research. *First*, despite the use of sector-disaggregated longitudinal data, the analysis remains dependent on disclosed ESG metrics and standardised databases, which may not fully capture informal economic activity or regional disparities within countries. Although the trimmed-mean and rank-based specifications produced substantial concordance, the median and leave-one-sector-out analyses revealed some sensitivity in exact cluster membership. Moreover, the use of a single ESG-rating provider does not eliminate the measurement, scope and weighting discrepancies documented across ESG-rating agencies. *Second*, the focus on OECD economies limits the generalisability of the findings to emerging and developing contexts characterised by different institutional structures, governance systems and sustainability pressures. Future research should therefore extend this framework to non-OECD countries and comparative regional settings. *Third*, while the study identifies differentiated ESG transition patterns, the analysis remains primarily exploratory rather than causal. Future studies could complement the present framework with causal econometric approaches, threshold models or marked temporal change analyses to further investigate the mechanisms underlying ESG divergence. Fourth, the temporal clustering is based on only 15 annual observations, and the selection criteria did not unanimously support five clusters. Although sensitivity analyses indicated reasonable stability, two clusters contain a single year. The five-cluster solution should therefore be interpreted as an exploratory typology rather than as evidence of deterministic stages. Longer time series and alternative datasets are needed to confirm its stability.

Finally, future research could integrate higher-frequency and alternative data sources, including social media sentiment, satellite imagery and supply-chain intelligence, to support more real-time monitoring of sustainability transitions. Applying the framework at sub-national or city levels may also provide deeper insight into the local dynamics of sustainable development and institutional adaptation.

Acknowledgements

Open Access funding enabled and organized by QNL Hybrid CY26.

Conflicts of Interest

The authors declare no conflicts of interest.

Endnotes

¹ It should be noted that these variables are classified by sector.

References

- Acemoglu, D., and J. A. Robinson. 2013. *Why Nations Fail: The Origins of Power, Prosperity, and Poverty*. Crown Currency.
- Aghion, P., C. Antonin, and S. Bunel. 2021. *The Power of Creative Destruction: Economic Upheaval and the Wealth of Nations*. Harvard University Press.
- Allen, T., S. Dees, C. M. Caicedo Graciano, et al. 2020. "Climate-Related Scenarios for Financial Stability Assessment: An Application to France."

- Al-Shaer, H., M. Zaman, and K. Albitar. 2026. "CEO Gender, Critical Mass of Board Gender Diversity and ESG Performance: UK Evidence." *Journal of Accounting Literature* 48, no. 1: 76–110.
- Bamel, N., K. Khatri, U. Bamel, and S. Kumar. 2025. "ESG Disclosure and Firm Performance in Global South Economy: Does Industry Profile and Board Independence Moderate the Relationship." *International Review of Economics and Finance* 100: 104093.
- Bebbington, J., and J. Unerman. 2020. "Advancing Research Into Accounting and the UN Sustainable Development Goals." *Accounting, Auditing & Accountability Journal* 33, no. 7: 1657–1670.
- Ben Ameer, H., D. Dao, Z. Ftiti, and W. Louhichi. 2024. "Perceived Climate Risk and Stock Prices: An Empirical Analysis of Pricing Effects." *Risk Analysis* 45: 4177–4195.
- Berg, F., J. F. Kölbel, and R. Rigobon. 2022. "Aggregate Confusion: The Divergence of ESG Ratings." *Review of Finance* 26, no. 6: 1315–1344.
- Capelle-Blancard, G., and A. Petit. 2019. "Every Little Helps? ESG News and Stock Market Reaction." *Journal of Business Ethics* 157, no. 2: 543–565.
- Chancel, L. 2020. *Unsustainable Inequalities: Social Justice and the Environment*. Harvard University Press.
- Cosma, S., P. Cucurachi, V. a. Gentile, and G. Rimo. 2024. "Sustainable Finance Disclosure Regulation Insights: Unveiling Socially Responsible Funds Performance During COVID-19 Pandemic and Russia–Ukraine War." *Business Strategy and the Environment* 33, no. 4: 3242–3257.
- David, P. A. 1985. "Clio and the Economics of QWERTY." *American Economic Review* 75, no. 2: 332–337.
- Daykin, A. R., and P. G. Moffatt. 2002. "Analyzing Ordered Responses: A Review of the Ordered Probit Model." *Understanding Statistics* 1, no. 3: 157–166.
- Devaud, J. M. 1984. "Discrimination by Adjusting Indicator Variables." *Revue de Statistique Appliquée* 32, no. 3: 23–41.
- DiMaggio, P. J., and W. W. Powell. 1983. "The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields." *American Sociological Review* 48, no. 2: 147–160.
- Dobre, C., C. M. Baba, C. E. Anton, A. Zamfirache, and D. Aldea. 2025. "Sustainability Reporting and Environmental Responsibility: The Case of Romania." *Administrative Sciences* 15, no. 3: 103.
- Dong, C., X. Fu, and J. Wang. 2026. "ESG Rating Divergence, Investor Heterogeneity and Cost of Equity Capital." *Accounting and Business Research* 56, no. 2: 331–362.
- Dunbar, K., D. Treku, R. Sarnie, and J. Hoover. 2023. "What Does ESG Risk Premia Tell Us About Mutual Fund Sustainability Levels: A Difference-in-Differences Analysis." *Finance Research Letters* 57: 104262.
- Eccles, R. G., I. Ioannou, and G. Serafeim. 2014. "The Impact of Corporate Sustainability on Organizational Processes and Performance." *Management Science* 60, no. 11: 2835–2857.
- Eccles, R. G., L. E. Lee, and J. C. Strohle. 2020. "The Social Origins of ESG: An Analysis of Innovest and KLD." *Organization & Environment* 33, no. 4: 575–596.
- Edmans, A. 2023. "The End of ESG." *Financial Management* 52, no. 1: 3–17.
- Escofier, B., and J. Pagès. 1998. *Analyses factorielles simples et multiples*. Vol. 284, 104–107. Dunod.
- Fama, E. F. 1970. "Efficient Capital Markets: A Review of Theory and Empirical Work." *Journal of Finance* 25, no. 2: 383–417. <https://doi.org/10.2307/2325486>.

- Flammer, C. 2021. "Corporate Green Bonds." *Journal of Financial Economics* 142, no. 2: 499–516.
- Fouejieu, A., A. Popescu, and P. Villieu. 2019. "Trade-Offs Between Macroeconomic and Financial Stability Objectives." *Economic Modelling* 81: 621–639.
- Freeman, R. E. 1984. *Strategic Management: A Stakeholder Approach*. Pitman Publishing Inc.
- Friede, G., T. Busch, and A. Bassen. 2015. "ESG and Financial Performance: Aggregated Evidence From More Than 2000 Empirical Studies." *Journal of Sustainable Finance & Investment* 5, no. 4: 210–233.
- García-Sánchez, I. M., N. Hussain, C. Aibar-Guzmán, and B. Aibar-Guzmán. 2022. "Assurance of Corporate Social Responsibility Reports: Does It Reduce Decoupling Practices?" *Business Ethics, the Environment & Responsibility* 31, no. 1: 118–138.
- Geels, F. W. 2002. "Technological Transitions as Evolutionary Reconfiguration Processes: A Multi-Level Perspective and a Case-Study." *Research Policy* 31, no. 8–9: 1257–1274.
- Gerged, A. M., R. Salem, and E. Beddewela. 2023. "How Does Transparency Into Global Sustainability Initiatives Influence Firm Value? Insights From Anglo-American Countries." *Business Strategy and the Environment* 32, no. 7: 4519–4547.
- Gerged, A. M., R. Salem, and M. Ghazwani. 2025. "Corporate Anti-Corruption Disclosure and Corporate Sustainability Performance in the United Kingdom: Does Sustainability Governance Matter?" *Business Strategy and the Environment* 34, no. 2: 2589–2606.
- Ghazwani, M., R. Salem, X. Song, N. a. Sawan, and K. Al-Hajaya. 2025. "Navigating Corporate Integrity: Anti-Corruption Reporting, Board Cultural Diversity, and ESG-Sustainability Performance in FTSE 350 Companies." *Corporate Social Responsibility and Environmental Management* 32, no. 6: 8442–8463.
- Ghazwani, M., R. Salem, M. a. Usman, and A. T. Somaili. 2026. "Bridging Governance and Integrity: The Consequence of CSR Committee and Audit Committee Characteristics on Anti-Corruption Disclosure in Saudi Arabia." *Corporate Social Responsibility and Environmental Management* 33, no. 2: 2128–2146.
- Gompers, P., J. Ishii, and A. Metrick. 2003. "Corporate Governance and Equity Prices." *Quarterly Journal of Economics* 118, no. 1: 107–156.
- Guo, Z., and X. Zhang. 2025. "Corporate ESG Performance and Low-Carbon Technology Innovation." *Technology Analysis & Strategic Management*: 1–15.
- Hart, S. L. 1995. "A Natural-Resource-Based View of the Firm." *Academy of Management Review* 20, no. 4: 986–1014.
- He, G., and A. Z. Li. 2024. "Does Media Coverage of Firms' Environment, Social, and Governance (ESG) Incidents Affect Analyst Coverage and Forecasts? A Risk Perspective." *International Review of Financial Analysis* 94: 103289.
- Hoang, K., H. T. Doan, T. T. Tran, T. X. Nguyen, and A. Q. Le. 2022. "Anti-Corruption Campaign and Firm Financial Performance: Evidence From Vietnam Firms." *Evaluation Review* 46, no. 2: 103–137.
- Isogai, A., M. Nozaki, and R. Yamamoto. 2025. "ESG Business Diversification and Investment Performance." *Finance Research Letters* 77: 107132.
- Jin, X., H. Qi, and X. Huang. 2024. "Green Financial Regulation and Corporate Strategic ESG Behavior: Evidence From China." *Finance Research Letters* 65: 105581.
- Joshi, B., and H. Joshi. 2024. "Financial Determinants of Environmental, Social and Governance Performance: Empirical Evidence From India." *Investment Management & Financial Innovations* 21, no. 1: 13–24.
- Kahneman, D., and A. Tversky. 1979. Prospect Theory: An Analysis of Decision Under Risk. *Econometrica* 47: 278.
- Khan, M., G. Serafeim, and A. Yoon. 2016. "Corporate Sustainability: First Evidence on Materiality." *Accounting Review* 91, no. 6: 1697–1724.
- Kotsantonis, S., C. Pinney, and G. Serafeim. 2016. "ESG Integration in Investment Management: Myths and Realities." *Journal of Applied Corporate Finance* 28, no. 2: 10–16.
- Kozachenko, L. 1987. "Sample Estimate of the Entropy of a Random Vector." *Problemy Peredachi Informatsii* 23: 9.
- Krueger, P., Z. Sautner, and L. T. Starks. 2020. "The Importance of Climate Risks for Institutional Investors." *Review of Financial Studies* 33, no. 3: 1067–1111.
- Lebart, L., A. Morineau, and M. Piron. 1995. *Statistique exploratoire multidimensionnelle*. Vol. 3. Dunod.
- Liu, Y., H. Zhang, M. Jiang, J. Chen, and M. Wang. 2024. "A Systematic Review of Research on Emotional Artificial Intelligence in English Language Education." *System* 126: 103478.
- Liu, Z., and N. Wang. 2026. "The Effects of Emerging Digital Technologies on Construction Project Resilience: The Mediating Role of Relational Governance." *Building Research and Information* 54, no. 1: 118–134.
- Lo, A. W. Forthcoming. "The Adaptive Markets Hypothesis: Market Efficiency From an Evolutionary Perspective." *Journal of Portfolio Management*.
- Luo, L., and Q. Tang. 2023. "The Real Effects of ESG Reporting and GRI Standards on Carbon Mitigation: International Evidence." *Business Strategy and the Environment* 32, no. 6: 2985–3000.
- Markowitz, H. 1952. "Portfolio Selection/H. Markovitz." *Journal of Finance* 7, no. 1: 77–91.
- McCombs, M. E., and D. L. Shaw. 1972. "The Agenda-Setting Function of Mass Media." *Public Opinion Quarterly* 36, no. 2: 176–187.
- Meadows, D. H. 2008. *Thinking in Systems: A Primer*. Chelsea Green Publishing.
- Mio, C., S. Panfilio, and B. Blundo. 2020. "Sustainable Development Goals and the Strategic Role of Business: A Systematic Literature Review." *Business Strategy and the Environment* 29, no. 8: 3220–3245.
- Mol, A. P., and G. Spaargaren. 2000. "Ecological Modernisation Theory in Debate: A Review." *Environmental Politics* 9, no. 1: 17–49.
- Murtagh, F., and P. Legendre. 2014. "Ward's Hierarchical Agglomerative Clustering Method: Which Algorithms Implement Ward's Criterion?" *Journal of Classification* 31: 274–295.
- Nguyen, H. Q. 2023. "Corruption, Political Connection, and Firm Investments." *International Review of Financial Analysis* 90: 102864.
- North, D. C. 1990. *Institutions, Institutional Change and Economic Performance*. Cambridge university press.
- O'Dwyer, B., C. Humphrey, and N. Rowbottom. 2024. "From Institutional Integration to Institutional Demise: The Disintegration of the International Integrated Reporting Council (IIRC)." *Critical Perspectives on Accounting* 99: 102699.
- OECD. 2022. *OECD Business and Finance Outlook 2022: Sustainable and Resilient Finance*. OECD Publishing.
- Ostrom, E. 2007. "A Diagnostic Approach for Going Beyond Panaceas." *Proceedings of the National Academy of Sciences* 104, no. 39: 15181–15187.
- Pagano, M., and L. Picariello. 2022. Corporate Governance, Favoritism and Careers." *European Corporate Governance Institute-Finance Working Paper*, (821).

- Pantos, S. 2023. "Stress Testing the Climate: SDG Scenarios for Financial Services in Europe." In *SDGs in the European Region*, 1–34. Springer International Publishing.
- Porter, M. E., and C. V. D. Linde. 1995. "Toward a New Conception of the Environment-Competitiveness Relationship." *Journal of Economic Perspectives* 9, no. 4: 97–118.
- Renou-Maissant, P., R. Abdesselam, and J. Bonnet. 2022. "Trajectories for Energy Transition in EU-28 Countries Over the Period 2000–2019: A Multidimensional Approach." *Environmental Modeling & Assessment* 27, no. 3: 525–551.
- Rockström, J., W. Steffen, K. Noone, et al. 2009. "A Safe Operating Space for Humanity." *Nature* 461, no. 7263: 472–475.
- Salem, R., M. Ghazwani, and W. Alshaer. 2025. "ESG Performance–Stock Price Volatility Nexus: The Moderating Effect of Board Cultural Diversity in G20 Markets." *Business Strategy and the Environment* 34: 8172–8193.
- Sandberg, H., A. Alnoor, and V. Tiberius. 2023. "Environmental, Social, and Governance Ratings and Financial Performance: Evidence From the European Food Industry." *Business Strategy and the Environment* 32, no. 4: 2471–2489.
- Schmidheiny, S. 1992. *Changing Course: A Global Business Perspective on Development and the Environment*. Vol. 1. MIT press.
- Schoemaker, D., and W. Schramade. 2018. *Principles of Sustainable Finance*. Oxford University Press.
- Shannon, C. E. 1948. "A Mathematical Theory of Communication." *Bell System Technical Journal* 27, no. 3: 379–423.
- Sinn, H. W. 2012. *The Green Paradox: A Supply-Side Approach to Global Warming*. MIT press.
- Tang, H., L. Xiong, and R. Peng. 2024. "The Mediating Role of Investor Confidence on ESG Performance and Firm Value: Evidence From Chinese Listed Firms." *Finance Research Letters* 61: 104988.
- Tufféry, S. 2005. *Data mining et statistique décisionnelle: l'intelligence dans les bases de données*. Editions Technip.
- Unruh, G. C. 2000. "Understanding Carbon Lock-In." *Energy Policy* 28, no. 12: 817–830.
- Wang, H., S. Jiao, C. Ge, and G. Sun. 2024. "Corporate ESG Rating Divergence and Excess Stock Returns." *Energy Economics* 129: 107276.
- Xiao, S., T. Roh, B. I. Park, O. a. AL-Tabbaa, and K. Seo. 2025. "Unpacking the Role of Digital Dynamic Capabilities in ESG Performance: A Social Exchange Perspective on Organizational Trust and Identification." *Business Strategy and the Environment* 35: 1951–1969.
- Xie, Y. 2024. "The Impact of ESG Performance on Corporate Sustainable Growth From the Perspective of Carbon Sentiment." *Journal of Environmental Management* 367: 121913.
- Zelnik-Manor, L., and P. Perona. 2004. "Self-Tuning Spectral Clustering." *Advances in neural information processing systems*, 17.
- Zeng, L., H. Li, L. Lin, D. J. J. Hu, and H. Liu. 2024. "ESG Standards in China: Bibliometric Analysis, Development Status Research, and Future Research Directions." *Sustainability* 16, no. 16: 7134.
- Zhang, J., M. Johnstone, V. Le, et al. 2021. "Dynamic Time Warp-Based Clustering: Application of Machine Learning Algorithms to Simulation Input Modelling." *Expert Systems with Applications* 186: 115684.
- Zheng, Y., Y. Wu, Y. Zheng, X. Meng, and P. Zheng. 2025. "Greening the Future: How Green Manufacturing Shapes Corporate Environmental and ESG Success." *International Review of Financial Analysis* 100: 103994.

Appendix A: Cluster-Number Selection and Robustness

A.1 | Selection of the Number of Clusters

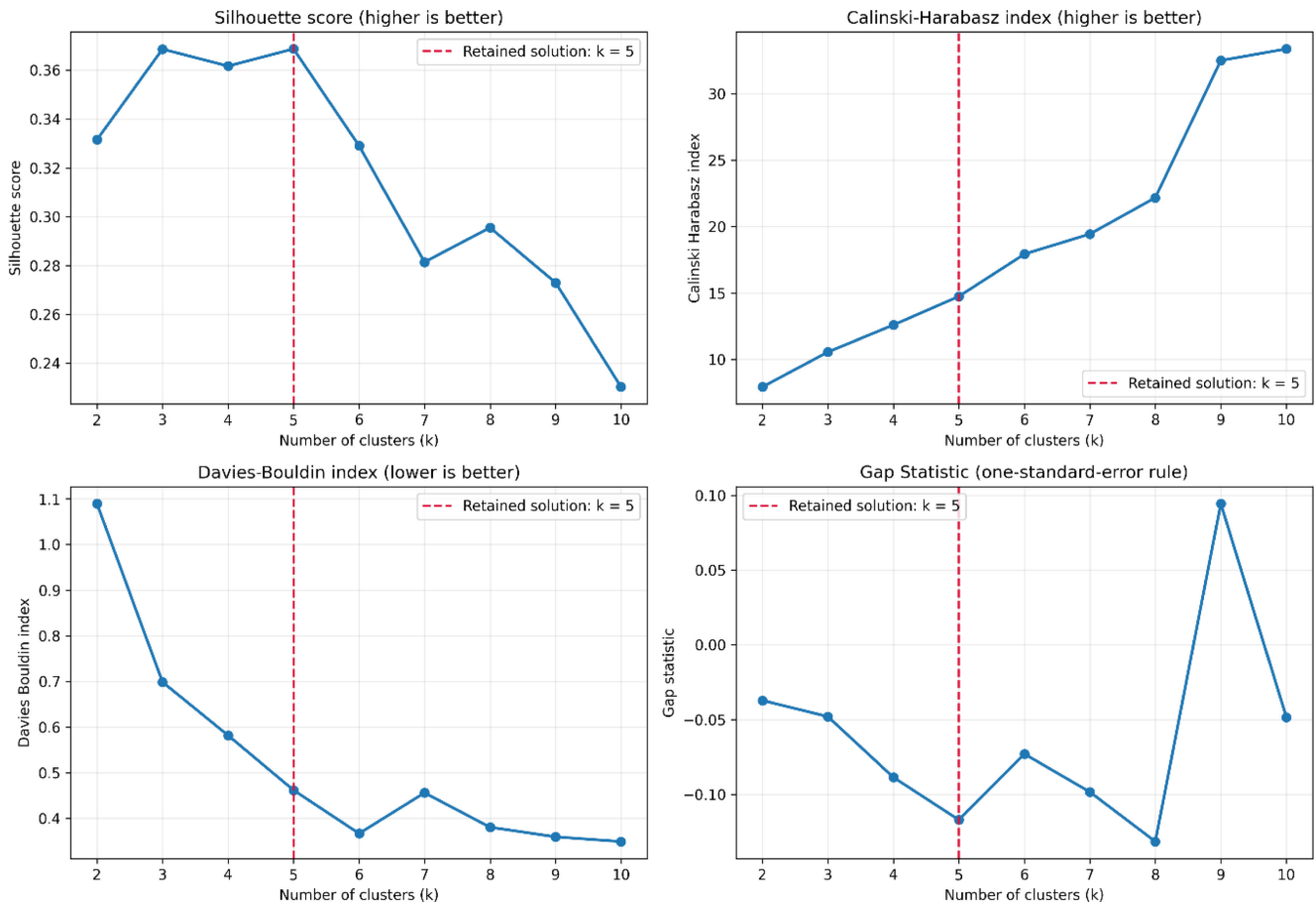


FIGURE A1 | Internal validation indices for Ward clustering solutions ranging from ($k=2$) to ($k=10$). The vertical dashed line indicates the retained five-cluster solution. The silhouette coefficient reaches its maximum at ($k=5$). The remaining criteria are interpreted jointly with sample size, parsimony, dendrogram topology and the substantive interpretation of the temporal ESG profiles.

A.2 | Robustness to Alternative Segmentation Specifications

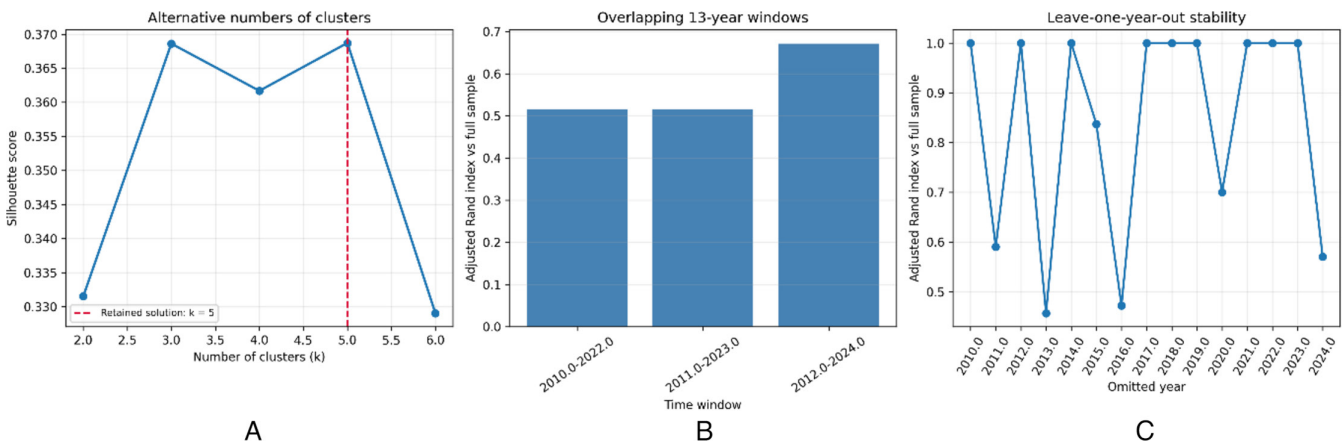


FIGURE A2 | Robustness of the temporal ESG segmentation. Panel A compares silhouette coefficients across alternative numbers of clusters. Panel B reports the adjusted Rand index between the full-sample partition and the partitions obtained from three overlapping 13-year windows. Panel C reports leave-one-year-out stability relative to the full-sample five-cluster solution.

B.1 | Selection of a Common Number of Country Clusters

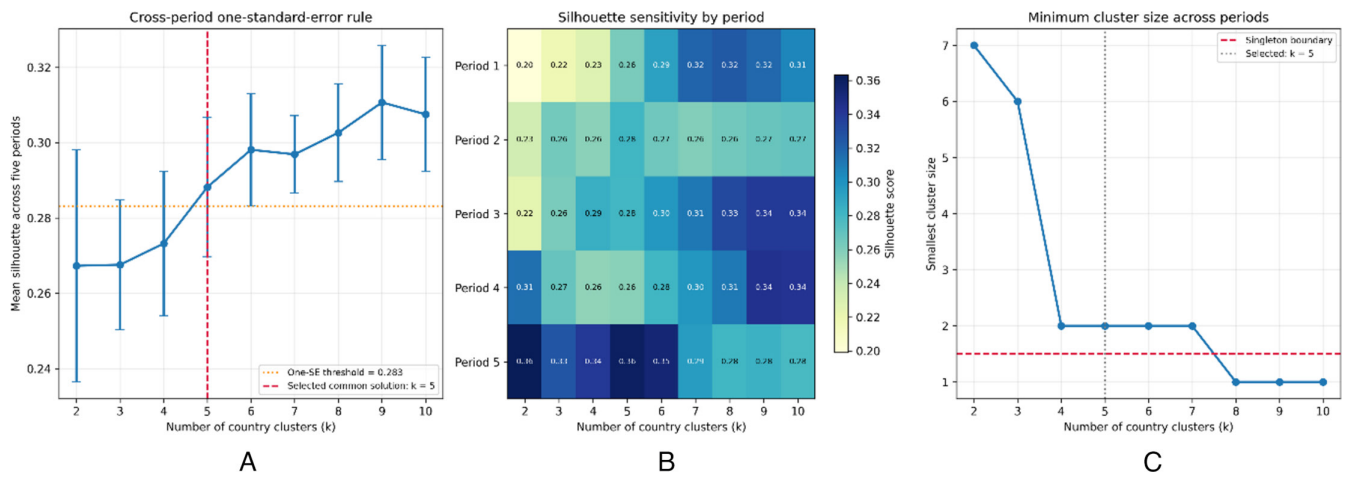


FIGURE B1 | Cross-period selection of the common number of country clusters. Panel A presents the mean silhouette coefficient and its standard error across the five temporal sub-periods. The horizontal dotted line represents the one-standard-error threshold, while the vertical dashed line indicates the retained five-cluster solution. Panel B reports the sensitivity of the silhouette coefficient to alternative numbers of clusters within each sub-period. Panel C presents the minimum cluster size across the five sub-periods and identifies solutions producing singleton clusters.

B.2 | Robustness Across Clustering Methods

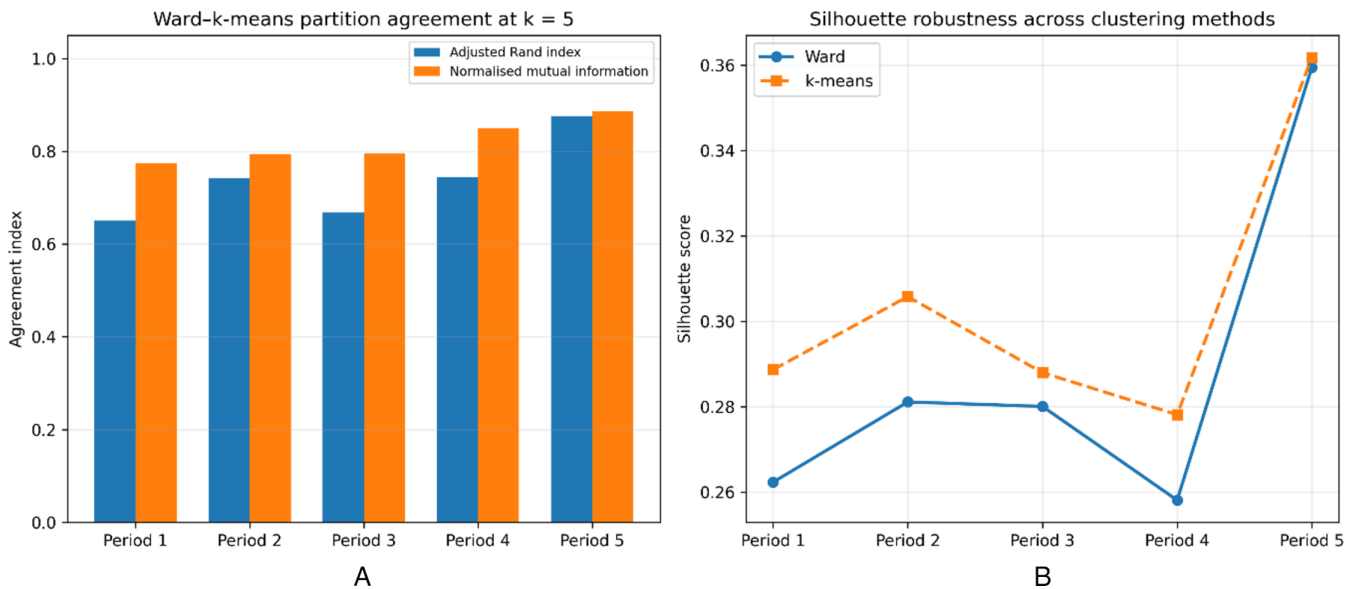


FIGURE B2 | Robustness of the five-cluster country typology across clustering methods. Panel A reports the adjusted Rand index and normalised mutual information between the Ward and k-means partitions for each temporal sub-period. Panel B compares the silhouette coefficients obtained from Ward and k-means clustering. The high agreement indices and similar silhouette patterns indicate that the principal country typology remains broadly stable across the two clustering methods.

Appendix C: Robustness to Alternative ESG-Score Constructions

This appendix examines whether the temporal and country classifications depend on the aggregation and transformation of the Refinitiv-based ESG pillar scores. The baseline arithmetic-mean specification is compared with a 10% trimmed mean, a median aggregation, a rank-transformed specification, and leave-one-sector-out analyses.

TABLE C1 | Concordance between the baseline classifications and alternative ESG-score constructions.

ESG-score construction	Temporal ARI	Temporal NMI	Mean country-level ARI	Mean country-level NMI
Arithmetic mean—baseline	1.000	1.000	1.000	1.000
10% trimmed mean	1.000	1.000	0.849	0.906
Rank-transformed scores	0.601	0.769	0.702	0.799
Median aggregation	0.191	0.498	0.406	0.575
Leave-one-sector-out—mean	0.211	0.554	0.338	0.526

Note: ARI denotes the adjusted Rand index and NMI denotes normalised mutual information. Higher values indicate greater concordance with the baseline classification. Country-level results are averaged across the five temporal sub-periods. Leave-one-sector-out results are averaged across the six sector-exclusion specifications. The 10% trimmed-mean specification reproduced the temporal partition exactly and showed high concordance with the baseline country classifications. Rank-transformed scores also produced substantial agreement. However, the median and leave-one-sector-out specifications generated lower concordance, indicating that the exact composition of some clusters is sensitive to the aggregation rule and sectoral coverage. The classifications should therefore be interpreted as exploratory configurations rather than invariant groupings.

Appendix D: TLEC Parameter Sensitivity and Benchmark Comparison

This appendix reports the sensitivity of TLEC to the number of nearest neighbours, the Minkowski distance parameter and the number of clusters. It also compares the reference TLEC partition with Ward, k-means, GMM, spectral clustering, DBSCAN and HDBSCAN using the same contextual data from the final temporal sub-period.

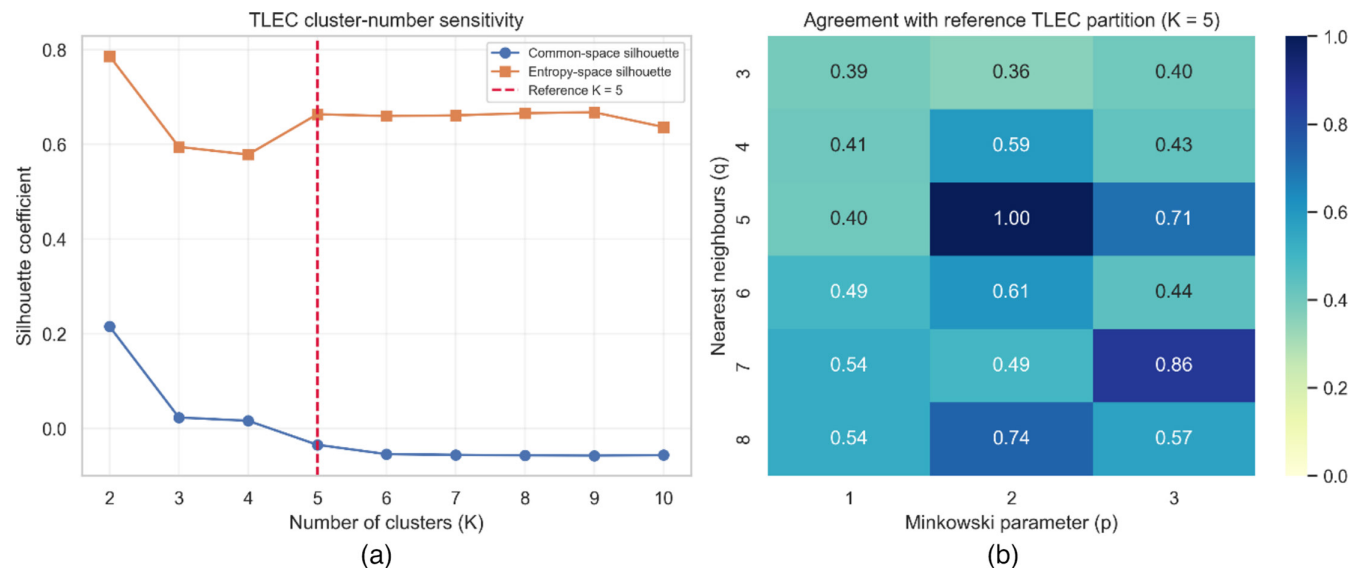


FIGURE D1 | TLEC parameter and cluster-number sensitivity in the final temporal sub-period. Panel (a) compares silhouette coefficients across candidate cluster numbers in the entropy-based and common standardised contextual spaces. Panel (b) reports ARI agreement between alternative values of q and p and the reference specification ($q = 5$, $p = 2$, $K = 5$, and equal thematic weights).

The reference five-group specification displays satisfactory separation in the entropy space, although the results also reveal sensitivity to the number of clusters and neighbourhood parameters. Accordingly, the five-group solution is treated as a detailed descriptive resolution rather than as the only admissible partition.

TABLE D1 | Benchmark comparison of the reference TLEC partition with alternative clustering methods.

Method	K	Silhouette	Calinski–Harabasz	Davies–Bouldin	Minimum size	Singletons	Noise (%)	ARI vs. TLEC	NMI vs. TLEC
TLEC–Ward	5	−0.035	2.608	3.350	3	0	0.0	1.000	1.000
Ward	5	0.037	3.452	2.313	1	1	0.0	0.135	0.388
k-means	5	0.032	3.363	2.692	3	0	0.0	0.138	0.404
GMM	5	0.032	3.185	2.296	2	0	0.0	0.216	0.486
Spectral clustering	5	0.045	3.205	2.607	4	0	0.0	0.207	0.417
DBSCAN	2	0.225	7.003	1.659	6	0	5.3	0.220	0.485
HDBSCAN	2	0.225	7.003	1.659	6	0	5.3	0.220	0.485

Note: Silhouette, Calinski–Harabasz and Davies–Bouldin indices were calculated in the common standardised contextual space to ensure comparability across methods. The TLEC entropy-space silhouette was 0.6633. Ward, k-means, GMM and spectral clustering were evaluated at $K = 5$. DBSCAN and HDBSCAN were not constrained to produce five clusters and identified two clusters with a small proportion of noise observations. ARI and NMI measure agreement with the reference TLEC partition and do not represent absolute performance criteria. Bold values denote the reference TLEC partition; ARI and NMI therefore equal 1.000 by construction.

At the common five-group resolution, TLEC generated no singleton clusters and maintained a minimum group size of three, whereas Ward produced one singleton cluster. The low ARI values obtained by the alternative methods indicate that TLEC identifies a distinct entropy-based organisation of the contextual data. Nevertheless, the density-based methods favoured a broader two-group structure. These results support the complementary descriptive value of TLEC while also indicating that the detailed country membership is method-sensitive.