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Mapping ESG compliance and sustainability pathways in multinational companies: a PC-Mahalanobis analysis

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ABSTRACT

This paper investigates how multinational companies are navigating the evolving landscape of ESG (Environmental, Social, and Governance) compliance, in the context of new regulatory frameworks, technological disruption, and geopolitical concerns. Combining the theoretical approach with the empirical analysis, the paper explores the influence of Artificial Intelligence, how disclosure dynamics affect ESG reporting, and which transition costs derive from sustainability strategies. At the same time emphasizing how both current geopolitical turbulences and – to some extent – the rapid development of AI may represent a “decelerating” factor for ESG adoption.

Building on a *Principal Component–Mahalanobis* framework, the empirical section maps ESG behaviour across a sample of multinational companies from 2015 to 2023, focusing not just on the quality of ESG conducts but also gauging their deviation from a statistical benchmark. The PCM-A identifies three latent dimensions of ESG activity - environmental footprint, compliance trade-offs, and the balance between financial performance and sustainability alignment - capturing over 85 % of variance. By integrating Mahalanobis distance, our “spatial approach” reveals a varied set of trajectories: some firms exhibit consistent, benchmark-aligned behaviours, while others diverge significantly, and a few of them follow a stable but idiosyncratic path. These results reveal structural and strategic shortcomings underpinning the ESG framework and provide robust arguments for a reconsideration of aggregated ESG scores in favour of more transparent, disaggregated evaluation mechanisms, mostly focused on the Environmental component.

1. Introduction, literature, context

1.1. Introduction

The transition to the sustainability and the ESG (Environmental, Social, and Governance) principles has gained significant relevance over the past two decades. This paper examines how multinational companies tackle such transition while facing fast-evolving geopolitical challenges, technological advancements, and regulatory pressures. While financial markets progressively integrate ESG criteria, concerns persist regarding corporate disclosure, greenwashing, and the true effectiveness of sustainability initiatives.

After a paragraph taking stock of the literature about latest developments in the field, we comment on a few crucial issues currently gaining the attention of observers, or whose relevance can hardly be evaluated, like the consequences of new geopolitical scenarios, and the role of AI as a driver or inhibitor for decarbonisation. More specifically, the key challenges in ESG implementation are discussed.

The second part of the work consists in the empirical section, where the authors try to unveil how a selection of multinational companies did behave over an eight-year period between 2015 and 2023. More precisely, a “spatial” comparative analysis, in the space of the first three Principal Components is performed, having executed the mapping of the companies according to the main ESG indicators, and reduced the size of dataset to the smaller linear combination of the original variables. This allows to draw the path of each company, and to map their position, approaching or moving away from the benchmark.

Diverse ESG trajectories emerge: some companies exhibit a stable and ESG-aligned behaviour over time, maintaining a close position to the benchmark. Others deviate consistently, showing a persistent high environmental impact and diverging ESG strategies. A few more display smooth and very linear trajectories, suggesting coherent internal ESG

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strategies without major shifts or any ESG-related policy reversals.

Significant outliers are identified as well: a small group of firms stands out as ESG outliers, with the greatest Mahalanobis distances from the benchmark, indicating substantial divergence in ESG behaviour. On the other hand, another group remains closer to the benchmark, serving as reference points for average ESG conduct in their sectors.

1.2. Literature review

The literature around the issues discussed in this paper is evolving rapidly, and some issues are entering the scholarly debate forcefully, like for instance the role of Artificial Intelligence in driving or inhibiting the ESG process. The relationship between AI and ESG, the evolving geopolitical order, as well as transition and transparency (or disclosure), are all hot topic now, which is worth to deepen. In general, many authors investigate the benefits for companies that embrace ESG.

There is a growing and flourishing literature that we synthesize below providing useful information, and sometimes innovative approaches, on ESG. Even so, seldom in literature there are resources that single out Artificial Intelligence, Geopolitics, or Disclosure as factors influencing ESG performance, leaving unexplored an integrated and dynamic evaluation of how these factors redefine the ESG conduct of firms over time. This paper aims to fill this void, introducing – through the spatial approach adopted – a unified framework for such a multifaceted context.

Starting from AI, Kar et al. (2022) offer, by means of a PRISMA based method, an exhaustive and systematic literature review on Artificial Intelligence and Sustainability (how AI impacts it), identifying key application areas, from energy efficiency to supply chain transparency. There is growing attention towards the role of AI in all social and economic facets of modern life. AI has a considerable potential to influence the ESG domain: AI applications and AI-supported analytical tools can enhance the way companies allocate resources; monitor and forecast the environmental aspects of their production and distributions processes; devise and simulate business strategies and scenarios. The authors foresee also the potential for AI to address disclosure aspects as well as the asymmetry of information that may affect the ESG space.

The ongoing debate is enriched and stimulated by relevant research across the many domains of ESG and technology advancements, including AI. Innovative analytical mechanisms support and facilitate the decision-making process which instructs ESG investment, though automation may alter the ESG ratings and scoring mechanisms. Zhang and Yang (2024) identify clear benefits from AI in accelerating initiatives under the E and S building blocks of ESG; AI has yet to demonstrate its positive dynamics for initiatives under the Governance domain. AI-empowered tools and mechanisms have a considerable role in promoting virtuous environmental practices: energy-intense sectors yield considerable benefits, as described by Wang et al. (2024). AI also brings about innovation at process level: Sætra (2022) puts forward an AI-based protocol to enhance accuracy in ESG reporting. Borenstein and Howard (2021), emphasize the ethical risks of deploying AI without adequate oversight, since it poses "complex ethical concerns" highlighting the potential for bias in ESG scoring. Zechiel et al. (2024) investigate the role of AI in defining ESG approached of technology multinational corporations (Amazon, Google, IBM, Meta, Microsoft, SAP). Yet, technology may provide for challenges.

Fast-evolving international and geopolitical scenarios are another feature affecting ESG. Governance may gain traction over Environment and Social in times of political uncertainty. Kovacs et al. (2024) show that pending any international conflict, such as the war in Ukraine, investors tend to prioritize well governed companies, and to privilege governance factors over environmental or social ones, by concluding that relevance of ESG factors depend on context. Similarly, Tian et al. (2024) examine how the digital economy enhances ESG performance in Chinese listed firms, but the effect is moderated by regional economic conditions and institutional quality. Pompella and Costantino (2023) question the reliability and transparency of ESG reporting.

In addition to the bias-related concerns raised by Jiao et al. (2024), Sætra (2022) highlight the lack of operational linkages between environmental improvements and governance structures. Tian et al. (2024) raise the concern about data reliability despite any AI-induced improvements at process levels. Pompella and Costantino (2023) developed a Disclosure-Adjusted Index (*DAdj index*) to account for potential issues on reliability of ESG reporting and address asymmetry of information.

On transparency, Tamimi and Sebastianelli (2017) as well as Pompella and Costantino (2023) notice how the indicators pertaining to governance (G) tend to have higher levels of disclosure than the indicators for environment (E). Yu and Van Luu (2021) observe that ESG disclosure is more influenced by firm-specific traits than country-specific regulations, like corruption or domestic political issues. McBrayer (2018) observes quite an intuitive relationship between management tenure and disclosure: companies with longer tenure of executives provide for stability in ESG disclosures. ESG disclosure level and ESG disclosure variability are reduced as management tenure increases. De Silva Lokuwaduge and De Silva (2022) conclude that the lack of standardised and universally accepted systems for reporting (as is the case for financial reporting) render ESG disclosure and reporting less reliable and comparable. Lee et al. (2023) focus on a very sensitive profile, that is the comparability between the measures adopted by rating agencies. Lee et al. observe how rating agencies have the discretion to choose among many comparable E, S, and G measures "that are not the same in scope and measurement, leading to variations in component weights that can cause material differences in reported weighted average ESG scores". As noted by Dwivedi et al. (2019), the integration of AI into policy and corporate governance demands a multidisciplinary approach, to promote responsible innovation.

Altogether, the reviewed literature suggests that AI and digital technologies, while disrupting traditional approach in many different domains, also offer an enormous potential to enhance ESG processes. However, their benefits, and effectiveness of adopted policies depend on appropriate governance, ethical principles, and the institutional frameworks within which they operate.

1.3. How geopolitical scenarios and technology advancements influence the green transition

Scientific evidence coupled with societal concerns accelerated the green transition: climate change is becoming tangible and visible to most. The societal consensus and scientific evidence on the need to preserve our planet are interpreted by diverse political narratives, depending on the country or regional bloc, the level of socio-economic development and exposure to climate change risks. Such evolutions are best captured by the yearly gathering of the Conference of the Parties (COP), the main decision-making body of the United Nations Framework Convention on Climate Change (UNFCCC)[1].

The awareness among policy makers that actions are required is now consolidated; users and consumers gradually are embracing the green transition by adjusting consumption behaviours ;[2] industry and businesses are also transforming their processes for greener products and services. Yet, the geographical, social and economic unbalances among countries trigger questions at policy and practice levels on how to accelerate the green transition by bridging the gaps between strategies,

[1] The latest COP29 meeting in Baku of the 2024 United Nations Conference of the Parties of the UNFCCC shed light on the hurdles to reach global consensus on policy remedies to climate change.

[2] Irrespective of specific political approaches towards climate change, a large part of consumers in OECD countries gradually develop environmentally conscious attitudes and behaviour, pushing for ESG adoption among companies.

policies and enforcement: parameters and targets should be less ambitious? The set of incentives (not just financial ones) could be revisited? Should regulations be stronger in imposing green transition targets with global coordination?

The current global conjuncture intervenes negatively in this dynamic, imposing a slowdown - if not a full stop - on the path toward a greener world. And this happens just when, as mentioned above, a greater level of societal consensus and scientific awareness has finally been achieved. Both geopolitical scenarios and technological change - particularly AI (see the next § *I.4*) - pose problems in this respect. The former through pollution generated not only by increased weapons production, but also by bombings and destruction; the latter through the staggering rise in global energy demand linked to digital infrastructures.

This is part of the rationale behind the empirical analysis that follows: it represents an initial attempt to monitor how the industrial world (represented by our sample of multinational companies) is reacting to these slowdown factors - each firm/sector with its own peculiarities maybe - and whether any distinction should be made between them. At the same time developing innovative tools to begin addressing this issue.

1.4. Artificial intelligence and decarbonisation

AI advancements and AI-supported tools provide for promising applications to accelerate the green transition and facilitate the implementation of ESG practices. AI models can help in predicting energy requirements and environmental dynamics of production and processes, introduce operational efficiencies and so on. Yet, at the current juncture of AI development – in its constant evolution – some traits of AI advancements may raise concerns on the “net effect” of AI on ESG as a whole:

i) AI is an energy-intense technology that requires considerable use of resources, not only the energy to run processing units but also land and other resources required to build and maintain large data centres. Such intensity and energy requirements may raise concerns about the “green coefficient” of AI.[3]
ii) The efficiency gains in the production capacity may lead to a conundrum of increased production that may not adequately keep the pace with environmental requirements. The swift increase in production may unleash environmental concerns due to the lower pace of environmental protection in manufacturing processes.
iii) The AI-empowered accelerations may also lead to increased anthropization, i.e. the human impact on the planet and its environment.
iv) The digital divide among countries and companies may be exacerbated by the availability and use of AI systems, also affecting the ability of laggards to accompany enhanced growth with improved environmental and societal practices.

The above concerns deserve careful consideration and monitoring to discern the real impact of AI as a driver or inhibitor in the quest towards green transformation and even decarbonization to which selected countries and companies have committed.

1.5. ESG dimensions and lack of disclosure

These renewed dynamics of ESG triggered by technology advancements and geopolitical transformations require new means and mechanisms to provide for certainty, transparency and predictability. The evolutions in ESG dynamics, and the related risks and costs, mandate the identification of new means to identify, manage and oversee risks for companies, financial intermediaries and regulatory agencies. The three dimensions of Environment (E), Social (S) and Governance (G) may deserve to be considered in isolation: splitting the three building blocks of ESG may lower – if not eliminate – the temptation of companies to tinker with indicators and reporting to alter cost and impact of ESG strategies.

The indicators and domain of Governance can be considered as relatively straightforward and not too costly to implement. Simple measures can be taken by companies to boost their ratings in the G dimension with considerably positive impact on their overall ESG rating and reputation. A careful balance between professional qualifications and other “soft factors” (such as gender/sexual orientation, racial background, disability, etc.) to select board members and / or executives may instantly increase the rating of a company under the Governance domain.

Indicators under the Social domain can also be easily met with a positive impact on the overall ESG ranking, although with a slightly higher operational and financial commitment from the company. Boosting the Social score may require a unit or department to devise and implement social initiatives and related costs, but still at a relative speed, ease and marginal financial commitment. Launching social engagement campaigns with local communities, enacting work-life balance internal policies, promoting diversity or merely contributing to philanthropic causes may gain considerable ESG ratings’ benefits to any company.

Conversely, boosting the score under the Environmental domain requires considerable efforts and investments. Improving environmental indicators require the introduction and implementation of environment friendly practices throughout the entire value chain of the company, from supply to production, and finally distribution. Such endeavours require time, effort and financial commitments to yield benefits and positively impact the overall ESG ratings.

The above considerations clarify the commitment, cost and impact for a company to act on all three dimensions of ESG, which remains a convoluted and unbalanced model to gauge the environmental, social and governance viability of a company.

1.6. Unpacking ESG transition dynamics and costs

While the social and political support for the green revolution has been trending for the past two decades, the transition to a greener economy is still at its infancy. Technological advancements, societal models and economic systems have yet to reach the maturity to produce critical mass and the economies of scale typical of validated models. Divides and differences at country, social and sector/company levels persist in the quest to implement the green transition that has yet to reach the maturity of validated socio-economic cycles.

In this process of continued evolution, the green transition may trigger new forms of “ESG-related transition costs” and “ESG-relevant risks”. The ESG-related costs are associated with the costs and investments required by companies – and governments – to embrace the green transition, embed ESG principles and values. The “ESG-relevant risks” are represented by the social, operational and financial risks that companies – and other socio-economic actors – may face when implementing ESG initiatives. Social risks pertain to the possible implications in labour-related domains and any relevant social pressure, such as underemployment, unemployment and the industrial transformation of considerable parts of an economy (the shift away from traditional heavy manufacturing, extractive industries, etc.). Environmental risks relate to the climate change dynamics of mitigation and adaptation, triggering renewed dynamics of project financing and operational implications.

The fact that ESG is gaining traction and appeal with retail investors makes it even more relevant to clear the ground from uncertainty and asymmetry of information. The concept of “responsible finance” and ESG-finance is now a household name for retail investors and not only confined to the world of institutional investors and regulatory

[3] See here for example: https://www.iea.org/reports/electricity-2024/executive-summary.

authorities. The proliferation of ESG-related financial products imposes a more cleared approach to taxonomies, ratings and rankings. Retail investors are increasingly being exposed to financial products labelled as responsible and / or sustainable, and ESG is increasingly becoming a factor in financial decision-making processes for the most common investor.

Consolidating the three dimensions of E, S, and G under the same model may be misleading, providing inaccurate generic information to retail investors that lack the acumen, patience or simply the competence to distinguish between the different dimensions of ESG and investigate the real nature of the underlying components of an investment or financial product labelled as ESG.

1.7. From disclosure to transparency incentives

Hence, reliability and transparency in ESG become crucial for investors and the general public to gauge the effective performance of companies against environmental, social and governance criteria. Sætra (2022) developed an AI-structured protocol to enhance ESG reporting standards, in an effort to facilitate companies to disclose reliable and verifiable data. Pompella and Costantino (2023) devised an innovative "disclosure adjusted" model based on publicly available data on *GHG Scope-1*. Such *DAdj index* aims at reducing asymmetries of information to the benefit of conscious investors. Tian et al. (2024) highlight how digital transformation enhances ESG disclosures, enabling firms to leverage big data for more accurate sustainability reporting.

A traditional model of ESG metrics bundling three dimensions that are so heterogeneous and prone to be interpreted, implemented and measured in different ways, is no longer well-positioned to provide for the comparability and transparency that it was meant to establish at inception. Moreover, the increasing wealth of information, data and statistics and the availability of meaningful time series may justify the evolution of the ESG model. In addition, the improvements in the techniques for data processing and interpretation lend to an evolution of the ESG model prone to encompass also the evolutions of concepts such as "social" and "governance" that are changing over time. Those evolutions may even expose a vulnerability of the ESG model to political nuances that have no room in models to assess the viability of a company from environmental, social and governance perspectives. The emergence of trends such as the "woke" and "anti-woke" narratives in the USA may undermine the viability and meaning of the ESG model as a whole. Topics such as environmental protection, green, diversity and inclusion are increasingly becoming politically polarising features from which the ESG model shall be immune.

Exactly because ESG in finance is not a political feature or narrative, there is a renewed opportunity to reinforce the ESG metrics with the ultimate goal of providing for a transparent mechanism able to provide robust grounding for informed financial decision making. The three building blocks of ESG are functionally distinct and deserve their own "dignity": combining those three unrelated features of how companies engage in business and society may no longer be relevant to safeguard the transparency and overcome the asymmetry of information that may undermine financial intermediation, affecting all market participants:

a. Investors – both institutional and retail – may base their financial and investment decisions on ratings and rankings based on unrelated indicators and domains.
b. Virtuous companies with a proven environmental record may score lower due to "traditional" governance practices or lack of social initiatives.
c. Polluting companies may have a leeway to compensate for their poor environmental record by enacting social initiatives and governance practices that would allow them to improve their ESG ratings.

2. Empirical analysis, a PC-Mahalanobis spatial approach

2.1. Methodology

This methodological introduction explains how Principal Component Analysis (PCA) combined with Mahalanobis distance was adopted here, in order to evaluate the evolution and similarity of ESG (Environmental, Social, and Governance) behaviour among firms. The objective is not to judge ESG quality, but to understand how far each firm deviates from a benchmark ESG profile over time. The benchmark is defined as the statistical mean ESG profile across all companies and years in the sample. It is worth noting that, as such, it constitutes a statistical reference point suggesting typical behaviour within our specific dataset, not a final judgement on what constitutes good or virtuous ESG performance.

More precisely, we used PCA + Mahalanobis distance to understand how similar or different companies are in their ESG behaviour, not whether they are "good" or "bad", but how far they walk away from the benchmark ESG profile from 2015 to 2023.

We applied then PCA to ESG variables GHG, Energy, Water, Waste, Revenue, BESG Score,[4] and extracted PC1-PC2-PC3, which together captured 85.4 % of the ESG variance.

The following interpretation seemed reasonable, that is looking at: i- PC1 as ESG footprint intensity (GHG, Energy, Water); ii- PC2 as symptomatic of a Waste vs ESG compliance trade-off; iii- PC3 showing ESG alignment vs financial scale (inverse relationship).

Mahalanobis Distance in PCA Space was then calculated to correct scale distortion deriving from non-spherical data distribution and better detect outliers.

We selected companies from different sectors and segments of the economy. Specifically, only those companies from those diverse sectors for which ESG data and rankings from the Bloomberg® ESG score (BESG) were available for the time series between 2015 and 2023 (latest considered data).[5]

The sampling and selection of companies was purposive, and followed a pragmatic approach that allowed to benchmark meaningfully across sectors, as follows:

- Traditional manufacturing sectors such as automotive and consumer goods that are exposed to environmental and technological dynamics.
- Advanced technology sectors of well-established companies that are leading the technological transformation in both hardware and software segments.
- Banking and finance companies that cover the whole spectrum of financial intermediation, encompassing retail and corporate banking services.

This strategic selection allows for a cross-sectional comparison of ESG trajectories across different industries, despite the limited sample size. The reason why the sample is heterogeneous across sectors is therefore to: i- expose cross-sector ESG pathways, but also to ii- avoid single-industry artefacts in the PCA.

Moreover, the authors took into consideration the global exposure of

[4] The PCA includes therefore six variables: P (GHG Scope 1), E, W, A, R, and BESG. BESG is a proprietary Bloomberg score. It provides the Bloomberg score evaluating the company's aggregated Environmental performance. The score is based on Bloomberg's view of financial materiality. The Pillar Score is a weighted generalized mean (power mean) of Issues Scores.

[5] While BESG provides a consistent and proprietary metric, we acknowledge that the specific methodology behind it, and its focus on financial materiality may influence the results, particularly for PC2 and PC3 where BESG loadings are significant. Future research could benefit from comparing results across multiple ESG rating providers

companies to factor in the sampling global competitive dynamics across regional markets, as all the companies are multinational corporations. Table 1 shows the list of the companies in the sample (by sector), and the variables considered:

2.2. Principal components approach

PCA (Principal Components Analysis; Hotelling, 1933) is a technique used to reduce the dimension of multivariate datasets, at same time preserving the most important patterns of variation. It creates new orthogonal axes (principal components) which are linear combinations of the original variables (in our case they will be Revenues, GHG Scope 1, Energy, Water, Waste, BESG).[6] These components are ranked by the amount of variance they capture from the original dataset.

The direction and magnitude of each variable's contribution to the principal components is called a "'loading'". A high positive loading indicates that the original variable strongly contributes to that principal component in a positive direction, while a high negative loading implies a strong inverse contribution (see Table 2 and the corresponding Fig. 1). By examining the loadings, each principal component can be interpreted as a latent dimension or pattern summarizing the original variables. In PCA, we distinguish between two fundamentally different variables:

i- *Loadings* (Eigenvectors or Weights), one value per variable per component:
-These tell us how much each original variable contributes to a principal component.
-They define the direction of each PC in the original variable space. Example: In PC1, if GHG = 0.56 and Energy = 0.57, it means PC1 is mostly measuring environmental intensity.
-These are the same for all observations — they do not depend on the company.
For our case: 6 variables × 3 components → 18 loadings.

Table 1
– Companies in the sample and considered variables key.

Code	Company	Sector
F US Equity	FORD	Automotive
MBG GR Equity	MERCEDES	Automotive
7203 JT Equity	TOYOTA	Automotive
VOW GR Equity	VOLKSWAGEN	Automotive
BMW GR Equity	BMW	Automotive
JPM US Equity	JPMORGAN	Financial (Banking)
GS US Equity	G SACHS	Financial (Investments)
DBK GR Equity	DEUTSCHE BANK	Financial (Banking)
CL US Equity	COLGATE-PALM	Consumer (Household)
NESN SW Equity	NESTLE	Consumer (Food)
KMB US Equity	KIMBERLY-CLARK	Consumer (Personal care)
MSFT US Equity	MICROSOFT	Tech (Software)
INTC US Equity	INTEL	Tech (Semiconductors)
SAP GR Equity	SAP	Tech (Software & platforms)
GOOGL US Equity	ALPHABET	Tech (Internet)
ANA SM Equity	ACCIONA	Construction
Symbols key	**Meaning**	
R	Revenues (Firm financial performance)	
P	Pollution (= GHG Scope 1 Emissions)	
E	Total Energy Consumption	
W	Total Waste Produced	
A	Total Water Consumption	
BESG	Bloomberg ESG score	

[6] As specified in the above table.

Table 2
– Loadings.

Variable	PC1	PC2	PC3
BESG	0.09	−0.60	0.51
Energy	0.57	0.02	−0.04
P (GHG)	0.56	−0.01	−0.02
Revenue	0.35	−0.24	−0.69
Waste	0.07	0.75	0.12
Water	0.47	0.06	0.48

ii- *Scores* (Coordinates or Projections), one value per observation per component:
-These tell us where each company sits along each principal component.
-They are obtained by projecting each company's original data onto the PC axes defined by the loadings. Example: If Volkswagen has a PC1 = +3.5, it means it lies far in the direction of high GHG, Energy, etc.

For our case: 16 companies × 3 components x 9 years → 432 scores.[7]

2.3. Interpretation of PCs

Looking at the PCs, average values shown in the Table 3, we may observe the following.

PC1: Reflects ESG footprint *intensity*,[8] with strong positive contributions from GHG, Energy, and Water.

PC2: Captures a *trade-off* between Waste and ESG scores (BESG), with Waste loading positively and BESG negatively.

PC3: Represents a tension between *Revenues* (negative loading) and *ESG alignment* (BESG and Water, positively loaded).

The following picture (Fig. 2) presents all companies in the PC space, as per the average 2015–2023 (Table 3). Contour ellipsoid is fixed at 2σ (contains ~89 % of the companies, assuming a roughly Gaussian distribution of their ESG PCA scores). Balloons' size is proportional to revenues. It shows the situation in a given "benchmark year", then, without any whitening.[9]

Concerning PCA Orientation and Plot Consistency, note that in PCA the orientation (sign) of the principal components is mathematically arbitrary: PC1 (positive) and –PC1 (negative) both represent the same direction of variance. This means that different software implementations may return components with flipped signs, depending on internal numerical factors or data preprocessing steps. Since PC1 in our analysis captures a composite environmental footprint intensity (driven by

[7] The math behind PCA is the following. The principal components are directions in space (vectors). These directions are the eigenvectors of the covariance matrix of the data. So, the loadings we assign to each variable on a component are the coordinates of those eigenvectors. That is why the term "loadings" and "eigenvectors" often refer to the same thing — but used differently: i- in statistics: we call them loadings (to emphasize variable contributions); ii- in linear algebra: we call them eigenvectors (from the covariance matrix).

[8] *Footprint intensity* refers to the overall magnitude of a company's environmental impact per unit of activity, typically measured through a combination of resource consumption and pollutant emissions. It captures how resource-demanding and emission-heavy an organization is in its operations, regardless of its size, and is commonly derived from key indicators such as:
GHG emissions (Scope 1) – direct atmospheric pollutants.
Total energy consumption – overall energy footprint.
Water use – resource extraction and pressure on ecosystems.
Waste production – material inefficiencies and pollution.
In multivariate analysis (e.g., PCA), footprint intensity can be understood as a latent dimension summarizing how environmentally heavy a firm is, with higher values indicating a greater ecological burden across several channels.

[9] Meaning that no Mahalanobis adjustment has been made (see below).

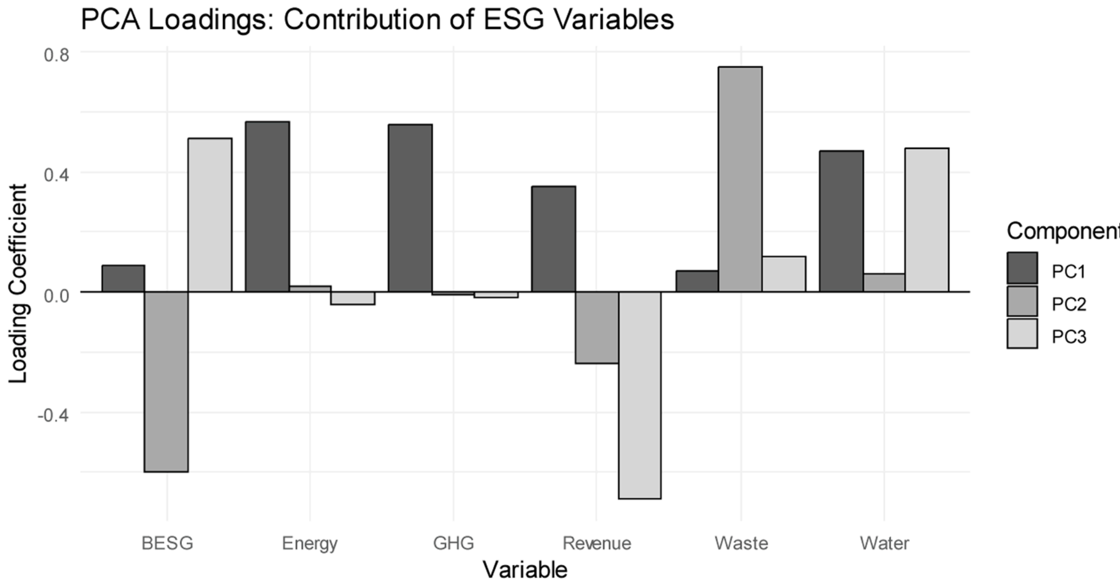

Fig. 1. Loadings (histogram).

Table 3
– PCs average values 2015–2022 (non-whitened).

Company	PC1	PC2	PC3
7203 JT Equity	1,77	−0,51	−1,39
ANA SM Equity	−1,31	3,12	1,10
BMW GR Equity	−0,69	−0,34	−0,29
CL US Equity	−1,51	−0,54	0,71
DBK GR Equity	−1,78	0,23	−0,26
F US Equity	0,39	0,05	−0,53
GOOGL US Equity	−0,24	−0,56	−0,79
GS US Equity	−1,84	0,55	−0,57
INTC US Equity	0,51	−0,87	1,27
JPM US Equity	−1,25	0,10	−0,93
KMB US Equity	1,16	0,23	1,50
MBG GR Equity	−0,14	−0,13	−0,81
MSFT US Equity	−0,32	−1,26	−0,22
NESN SW Equity	3,43	0,10	1,59
SAP GR Equity	−1,56	−1,15	0,87
VOW GR Equity	3,37	0,96	−1,23

variables like GHG emissions, energy and water consumption, and revenue), we made an intentional choice to display PC1 increasing upward in all 3D plots. This directional choice does not affect the underlying PCA results — which are symmetric with respect to sign — but it ensures an intuitive visual interpretation, where “higher” means “more intense” and “lower” means “less impactful”.

In Fig. 3, on the other hand, a most intuitive plot describes the “Sustainability path” for a shortlisted group of companies, 2015 to 2023. They are the companies showing most peculiar and distinct patterns. This methodology allows tracking how far companies move from the ESG benchmark over time. It is especially useful for identifying persistent outliers, convergence or divergence in ESG behaviour, and sector-level consistency. Importantly, it evaluates ESG behavioural similarity, and not ESG quality or impact.

Contour sphere at 2σ as well. Balloons’ size is revenues proportional again, and 2023 “ghost” means the last value on the paths has been estimated.

It shows how over the years our four companies (out of the 16 considered), selected because of their peculiar path, did behave in the PCs space. More precisely, the PCA-Mahalanobis approach was adopted (Pompella-Dicanio, 2017), to emphasize the differences in terms of ESG performance.

Mahalanobis distance (M-distance) is a statistical measure of how far a point is from the centre of a multivariate distribution, considering the scale and correlation of the variables. Unlike Euclidean distance, which treats all axes equally, Mahalanobis adjusts for axes with higher or lower variance, and for correlations between variables. Mathematically, M-distance is defined as: $D^2 = (x - \mu)^T \Sigma^{-1} (x - \mu)$, where x is a point (e.g. a company’s ESG position), μ is the mean vector (the benchmark ESG profile), and Σ is the covariance matrix. In the whitened PCA space, M-distance can be interpreted using thresholds based on the Chi-squared distribution with degrees of freedom equal to the number of principal components (here 3).

These distances correspond to spheres of radius 1 and 2 centered at the origin (mean ESG profile).

- Distance < 1: Company is very typical — close to the benchmark ESG profile
- Distance ≈ 2: Moderate deviation — still within the mainstream ESG behavior
- Distance > 2: Significant deviation — considered an ESG outlier

In PCA space, M-distance provides a more accurate representation of how unusual a company’s ESG profile is, if compared to the average. To visualize this properly, a whitening transformation was applied then, so that M-distance becomes equivalent to Euclidean distance, and this reshapes the data space into the sphere.

From the first graph (the ellipsoid) to the second one (the sphere), we shift from a static to a chronological perspective. The ellipsoid captures the distance from the benchmark based on each firm’s average ESG behaviour in fact (i.e., average PC1–PC3 coordinates across years). The sphere, by contrast, illustrates full trajectories, and individual positions are adjusted to M-distance: each path shows how a firm evolves in ESG space over time. As mentioned at the beginning, the aim is not to evaluate how effective that performance is, but to understand how far each firm deviates from a benchmark ESG profile over time.

2.4. More on Mahalanobis distance

Still from a spatial perspective, the following Fig. 4 presents a *Directional Bullseye Plot*, and, again, it is based on M-distances computed in the PCs space (Table 4) we derived from ESG-related variables. Each company is positioned here to two dimensions: *angular* and *radial*. Angular direction shows the orientation of the company ESG behaviour in the PCA space, while its radial distance from the centre (representing

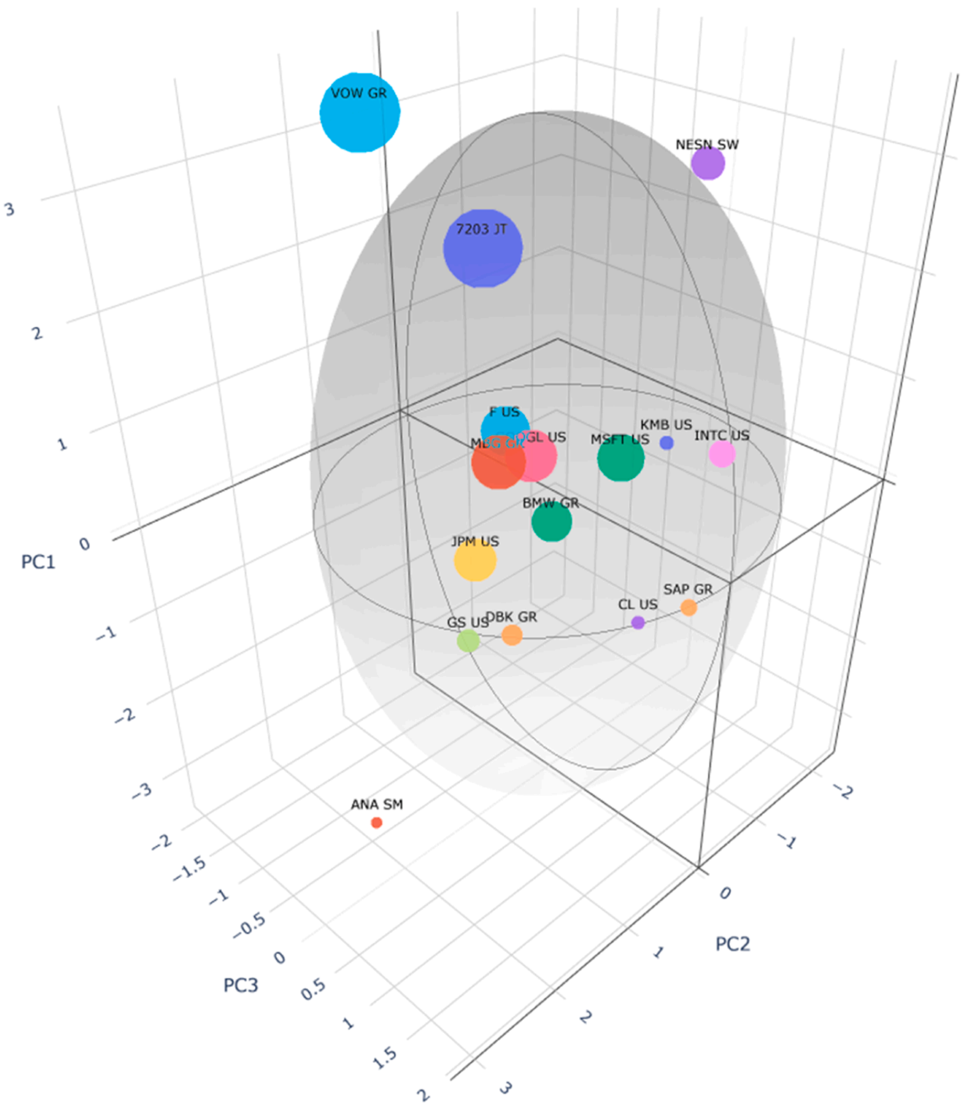

Fig. 2. Average 2015–2023 firms' position in PC1–PC3 (non-whitened). 2σ ellipsoid; bubbles' dimension is proportional to revenues.

the benchmark) corresponds to its M-distance from the multivariate average ESG profile.

The plot captures therefore both the *degree* and the *type* of divergence in ESG behaviour across firms. In other words: companies located near the center (low σ-levels) exhibit ESG characteristics closely aligned with the benchmark, while those positioned beyond the outer rings (e.g. >2σ) are structurally divergent outliers, as matter of fact. Notably, the aim of the visualization is not to assign a judgment of ESG quality, but to measure - through the angular dimension - the *behavioural similarities*, within a multivariate framework which takes into account the correlations.

This approach enables the identification of firms with consistent deviations, potential ESG misalignment, or unique sustainability pathways, offering may be useful insights for analysts, regulators, and "responsible investors".

While the actual angle is not interpretable in absolute terms, companies close in angle are somehow similar in their type of ESG behaviour, even if their magnitudes differ. This is a “"direction of divergence"”: two companies at similar angles but different radii may both diverge along the same ESG dimension (e.g. overuse of water), but to different extents. Concerning the angular position of each company, the angle (0°_360°) is determined by the first two Principal Components (PC1 and PC2). Each company has a coordinate (PC1, PC2) from the PCA transformation, basically a compressed representation of its ESG behaviour.

Then we compute the angle θ like this: θ =arctan 2(PC2, PC1). This gives an angle in radians, which is then converted to degrees (arctan2 ensures the angle covers the full circle from 0° to 360°, with: 0° pointing *right* (positive PC1), 90° pointing *up* (positive PC2), 180° pointing *left*, 270° pointing *down*.

Companies peripherical to the centre—such as ANA, NESN, and VOW—show the most peculiar ESG profiles relative to the benchmark. In contrast, firms like F, BMW, and MBG lie closer to the centre, indicating that their ESG behaviours align better with the average.

Only a small group of firms lie beyond the 2σ ellipse, anyway, indicating a statistically significant deviation from the ESG benchmark, and emphasizing how the majority has a consistent behaviour instead. Clustering traces in the right half (focus on the markers), on the other hand, suggests that a substantial number of companies (mostly MSFT, INTC, and GS, SAP together with DBK, JPM) exhibit broadly similar ESG structures, possibly reflecting sectoral (like in case of financial intermediaries) or regional homogeneity. The observation of the clustering of technology and financial sector companies seems to suggest industry-specific trends such as technology resilience and regulatory pressures. Technology companies are at the forefront of digital transformation, empowering them to adopt state-of-the-art technologies.

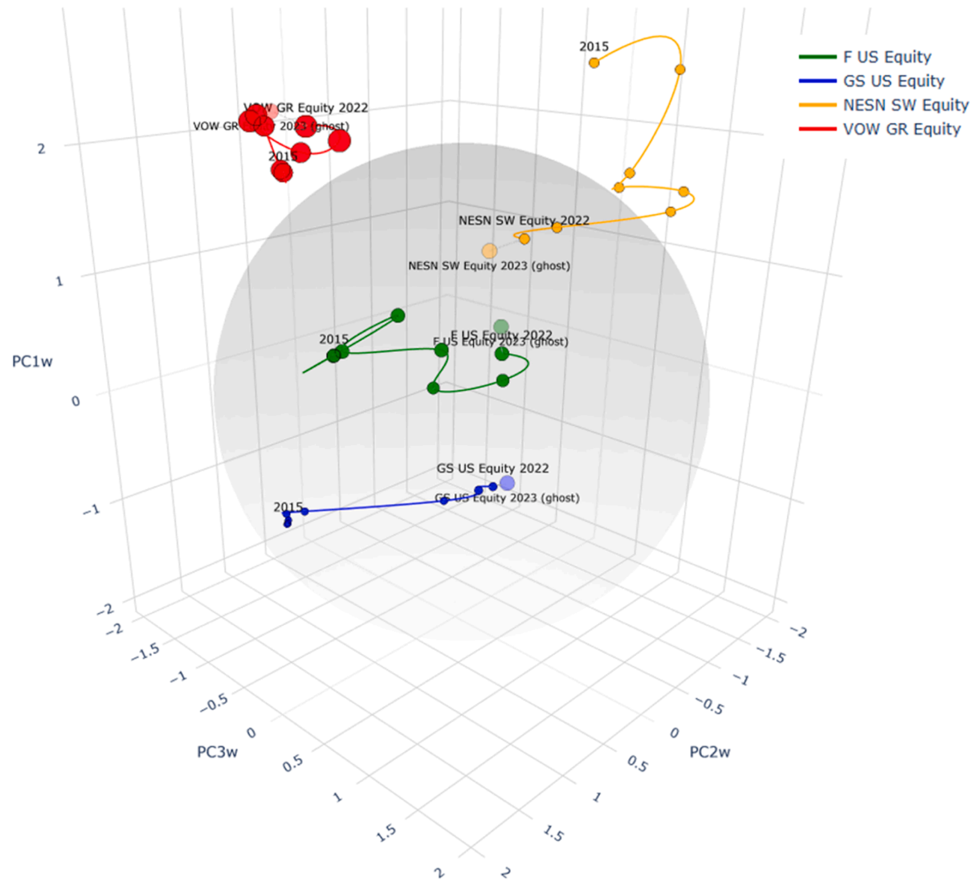

Fig. 3. Shortlisted companies' trajectories (*Volkswagen, Nestlé, Goldman Sachs, Ford*), 2015–2023, in the PC space (whitened), illustrating different ESG pathways. The sphere represents a Mahalanobis distance of 2σ from the benchmark. Paths show temporal evolution, with markers = annual positions.

Financial sector companies are typically swift in adjusting to evolving regulatory environments and have inherent compliance mentality.

The upper-left region, finally, contains more isolated firms (e.g. NESN), pointing to unique ESG practices or reporting characteristics.

2.5. Spatial approach main findings

Interestingly, we may draw some preliminary conclusions from the framework we have been illustrating till now, synthesized in Table 5 below.[10]

Our spatial analysis shows distinct clusters, and some outlier profiles that require a contextual interpretation. VOW GR Equity (Volkswagen) seems to be the most peculiar and interesting case, as it represents a high-impact, low-responsiveness profile. In other words, a good example of a company that is clearly far from the ESG benchmark, and remains like that over time, both in Euclidean and Mahalanobis terms. Such a high-footprint outlier profile over time for VOW GR Equity may be a function of corporate vision – or lack thereof – to address the ESG restructuring at strategic level across business functions. Other peer companies from the same sector appear to have adjusted to the ESG transition over time, adopting industrial and corporate approaches to embed ESG components in their operations.

Grouping of financial firms (GS, JPM, DBK) with low environmental impact (PC1) but moderate divergence is somehow expected. Their ESG profiles are naturally dominated by governance (G) and social (S) factors in fact, with a minimal direct environmental impact, and this is consistent with the literature proving that governance – as mentioned above – gains traction in uncertain times (Kovacs et al., 2024).

The steadiness of trajectories of firms like DBK and CL (see Fig. 5) suggests a high degree of strategic coherence and stable ESG policies, potentially reflecting strong and long-lasting governance structures (McBrayer, 2018). Conversely, the improvement trajectory in case of Nestlé (NESN) could be a consequence of consumer pressures in the consumer goods sector, claiming for better environmental disclosure and performance.

It is worth specifying that, to ensure visual and interpretive consistency across all plots in this analysis, we explicitly aligned PC1 so that it increases with environmental intensity (meaning companies with higher energy use, GHG emissions, water consumption, and revenue appear higher on the PC1 axis). We also fixed the 3D camera perspective so that PC1 corresponds visually to the vertical dimension, removing any ambiguity caused by default rendering angles. All PCA-based plots in this project are therefore normalized not only in statistical space, but also in visual semantics.

Along with GS US equity shown in the whitened framework above (the sphere in the Fig. 3) a few more companies (DBK GR, CL US) show at the bottom of PC1 a very clear and almost linear trend, which is a "steadiness" symptom.[11] That is, the company is moving over our 8-year interval considered by keeping its ESG strategies mostly unchanged over time. They are neither moving closer to the centre (that would mean they converge to the benchmark, that is the average – not necessarily

[10] For full PCA coordinates, Mahalanobis distances, and trajectory trends for all 16 companies, see Appendix A. Again, as above specified, the terms "bad" or "worst" are not directly referred to the ESG performance *per se*. The terms worst performer and bad refer to the magnitude and direction of deviation from the benchmark, not necessarily an absolute ethical or performance judgement.

[11] Look at the zoom graph (Fig. 5) below.

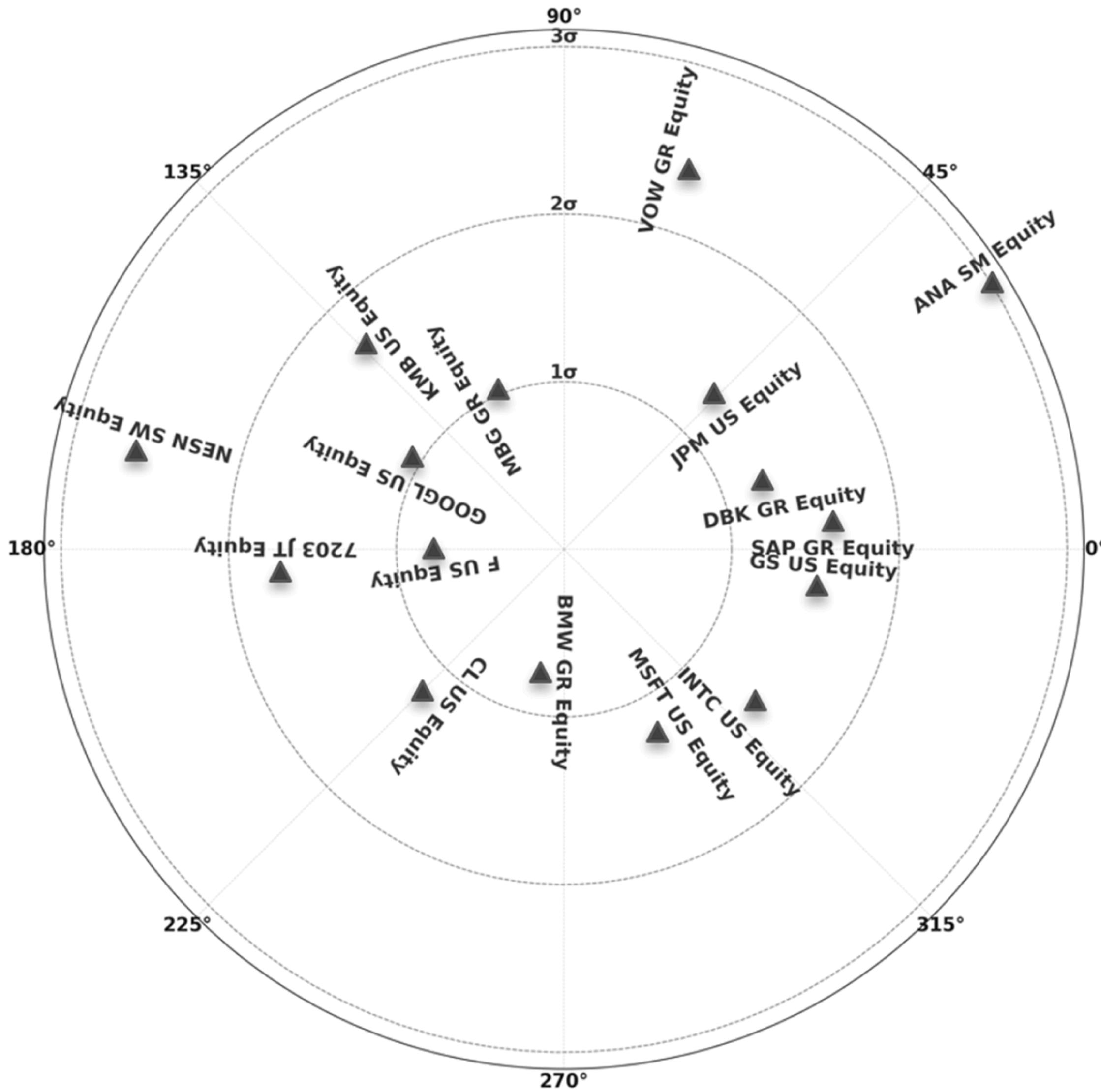

Fig. 4. Directional Bullseye plot: angle = arctan2(PC2, PC1); radius = distance.

Table 4
– M-distances from the benchmark.

Company	Mahalanobis
ANA SM Equity	3,04
NESN SW Equity	2,61
VOW GR Equity	2,46
7203 JT Equity	1,72
KMB US Equity	1,69
SAP GR Equity	1,60
GS US Equity	1,55
INTC US Equity	1,51
DBK GR Equity	1,34
JPM US Equity	1,31
MSFT US Equity	1,26
CL US Equity	1,24
GOOGL US Equity	1,09
MBG GR Equity	1,04
BMW GR Equity	0,79
F US Equity	0,78

Table 5
– ESG dynamics for a subset of companies.

Company	ESG Position	Stability (2015–2022)	Mahal.	Reference role
Volkswagen	Worst performer PC1, above-average environmental impact	High footprint, stable	~2.08	Bad PC1 and stable
Ford	Closest to average	ESG-conforming	~0.78	Neutral benchmark aligned
Nestlé	Bad, Distant from center, above-average environmental impact	Improving over years	~2.61	Bad as well, differing in PC2–3
Goldman Sachs	low environmental impact below the average	Most stable on PC1, consistently low impact all over the period	~1.55	Best performer PC1

virtuous- behaviour), nor moving away. They are instead somehow tangent to the sphere, thus also keeping the distance, over time. On the other hand, a linear, smooth path implies that – probably – there have not been any abrupt strategic ESG shifts, policy reversals, or inconsistent

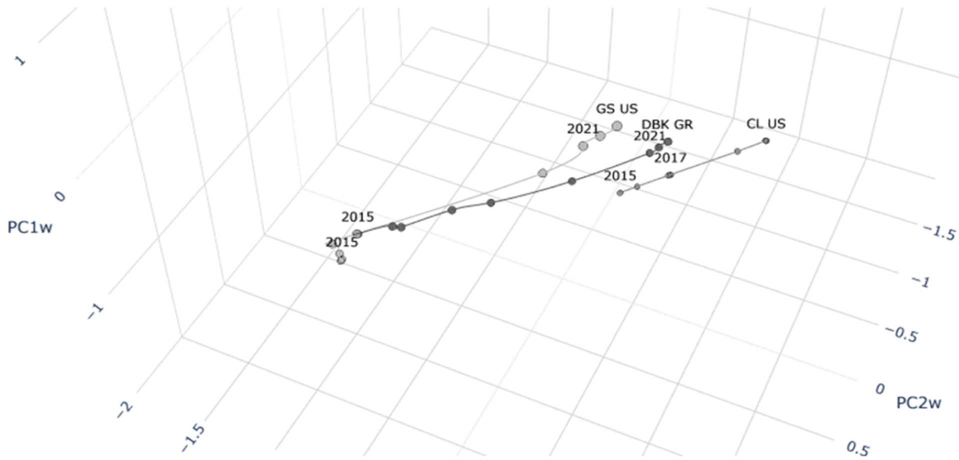

Fig. 5. PC1 Steadiness companies with a linear pattern: stable footprint with evolving PC2/PC3 trade-offs.

reporting.

The linear trajectory shown, anyway, is not a symptom of steadiness *tout court*. While the position of the company remains about unchanged over time *in terms of PC1*, a clear trend towards a constant decrease of PC2 at the same time that PC3 increases suggests that pairing *Revenues* and *ESG compliance* was more and more hard to achieve for these companies over time.[12] Linearity only means a likely more coherent and internally aligned company's ESG evolution.

3. Conclusions

This paper tried to explore, by mean of a comparative analysis, how a set of multinational companies (from different sectors) have been evolving during the recent years in terms of their ESG strategies, not by ranking their sustainability performance, but by examining their relative positioning within a multidimensional benchmark space. This has been done by combining Principal Component Analysis with Mahalanobis distance and introducing a sort of "spatial method" capable of highlighting patterns of convergence, divergence, and internal consistency in ESG strategies across diverse firms and sectors, during a period of eight years.

Our findings suggest that ESG behaviour is far from uniform. While some companies remain stable, showing a position aligned with the benchmark, others display a persistent distance from the centre, due either to structural challenges, maybe sector-specific constraints, or strategic inertia. A small group exhibits steady but very peculiar trajectories, revealing coherent ESG behaviour over time, though not necessarily aligned with the benchmark. Importantly, these patterns often remain hidden when relying on traditional ESG scores only, which tend to merge environmental, social, and governance factors into a single index.

The spatial approach adopted here also reveals the limitations of any aggregate ESG assessment, in fact, and emphasizes the need for a disaggregated, path-sensitive analysis. In this framework, the distance from the benchmark should not be interpreted as a sign of failure or virtue per se, but as a meaningful indicator of behavioural divergence that merits further scrutiny. Such nuance is essential currently, when sustainability moves at the core of corporate strategy and investors' attention.

The study confirms that ESG transitions are deeply influenced by broader dynamics, including technological shifts, regulatory asymmetries, and increasing (we may easily suppose) geopolitical tensions. Artificial Intelligence, while promising, emerges as a double-edged sword capable of supporting sustainability strategies but also introducing new risks of opacity, bias, asymmetries and environmental cost, which are at the moment systematically underestimated but that may distort the market. These findings strengthen the case for more transparent, modular ESG frameworks, capable of handling complexity without reducing sustainability to a single score.

In sum, our results invite a rethinking of how ESG behaviour is tracked, interpreted, and possibly incentivized. A firm's sustainability journey is not a static position on a rating chart, but a trajectory shaped by internal choices and external conditions. Future research may build on this spatial framework to explore sector-specific dynamics, policy effectiveness, or the long-term financial implications of divergent ESG paths. This would help making explicit the specificity of individual components E, S and G, while inferring the relationship between E and G, to the extent that Governance choices become manifest by steadiness or volatility of the adopted strategies. Future research can: i- test regulation-specific shocks in such a spatial framework; ii- experiment sector-level PCM; iii- extend the analysis to Scope 2 and 3, as well as to alternative ESG providers to enhance robustness.

Submission declarations

- The work described has not been published previously.
- The article is not under consideration for publication elsewhere.
- The article's publication is approved by all authors and tacitly or explicitly by the responsible authorities where the work was carried out.
- If accepted, the article will not be published elsewhere in the same form, in English or in any other language, including electronically, without the written consent of the copyright-holder.
- The authors declare no potential conflict of interest with respect to the research, authorship, and/or publication of this article.
- The authors received no financial support for the research, authorship, and/or publication of this article.
- The data used to support the findings of this study are available from the corresponding author upon reasonable request.
- No generative AI tool was used to produce this scientific work.

CRediT authorship contribution statement

Maurizio Pompella: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Lorenzo Costantino:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization.

[12] Let's remind that PC2 captures a tradeoff between Waste and ESG scores, and PC3 represents a tension between Revenues (negative loading) and ESG alignment (BESG score).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.finr.2025.100075.

Appendix A

Full ESG Trajectory Summary (PCA–Mahalanobis Diagnostics, 2015–2022)

Company	PC1	PC2	PC3	Mahalanobis	Δ Mahalanobis Trend	Interpretation
7203 JT Equity	1.77	−0.51	−1.39	1.72	↓ Decreasing	Strong divergence in ESG-financial balance (PC3 extreme)
ANA SM Equity	−1.31	3.12	1.1	3.04	~ Stable	Strong outlier from ESG benchmark
BMW GR Equity	−0.69	−0.34	−0.29	0.79	~ Stable	Close to benchmark ESG profile
CL US Equity	−1.51	−0.54	0.71	1.24	~ Stable	Moderate divergence with sector-specific traits
DBK GR Equity	−1.78	0.23	−0.26	1.34	~ Stable	Moderate divergence with sector-specific traits
F US Equity	0.39	0.05	−0.53	0.78	~ Stable	Close to benchmark ESG profile
GOOGL US Equity	−0.24	−0.56	−0.79	1.09	↓ Decreasing	Moderate divergence with sector-specific traits
GS US Equity	−1.84	0.55	−0.57	1.55	~ Stable	Moderate divergence with sector-specific traits
INTC US Equity	0.51	−0.87	1.27	1.51	↑ Increasing	Strong divergence in ESG-financial balance (PC3 extreme)
JPM US Equity	−1.25	0.1	−0.93	1.31	~ Stable	Moderate divergence with sector-specific traits
KMB US Equity	1.16	0.23	1.5	1.69	↑ Increasing	Strong divergence in ESG-financial balance (PC3 extreme)
MBG GR Equity	−0.14	−0.13	−0.81	1.04	↑ Increasing	Moderate divergence with sector-specific traits
MSFT US Equity	−0.32	−1.26	−0.22	1.26	↑ Increasing	Moderate divergence with sector-specific traits
NESN SW Equity	3.43	0.1	1.59	2.61	↓ Decreasing	Strong outlier from ESG benchmark
SAP GR Equity	−1.56	−1.15	0.87	1.6	↑ Increasing	Moderate divergence with sector-specific traits
VOW GR Equity	3.37	0.96	−1.23	2.46	~ Stable	High environmental footprint (PC1 extreme)

Data availability

Data will be made available on request.

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