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ESG rating and ambiguity: an informative and distorted signal-based approach

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Abstract

In an increasingly uncertain, complex socio-economic, and geopolitical environment, the significance of information signals and their perception becomes more crucial, especially in assessing sustainability and environmental impact. The challenges arise from businesses' lack of transparency and reported data, making it difficult for investors and rating agencies to evaluate and manage risks, costs, sustainability, risk-adjusted performance, greenwashing, fiduciary duty clarification, and scoring. This emphasizes the substantial impact of a high level of ambiguity on the market. Considering the three pillars of ESG parameters, we propose a novel model for assessing an ESG Rating based on (i) the level of disclosure, representing the quality of the signal and released information, and (ii) the subjective perception of the signal itself. This perception can be influenced by factors such as personal risk aversion and ESG disagreement arising from controversies in the rating process. Recognizing the identified distortion in the ESG rating as having predictive power, where ambiguity can been seen as a way to represent the market's sentiment, the distortion turns out to play the role of a policy driver capable of identifying sectors where ESG is under/overestimated and testing the robustness of a scoring method

Keywords Ambiguity · Information · ESG rating · Information and Garbling matrix · Distortion matrix

1 Introduction

Considering the devaluation that a given asset or company can incur into due to the transition to decarbonization, as well as the direct impact climate change can have on the environment and society, we must analyse climate risk within the risk management framework. Indeed, there are two channels of climate risk transmission to finance,

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allowing to disentangle the physical and transitional risk (Carney 2015). Physical risk is related to damage of physical assets, natural capital and/or human lives resulting into output losses, because of climate/weather events while transition risk is induced by the transition towards a low-carbon economy, i.e. the evolution in regulations, policies, and technologies, which can potentially cause losses on carbon-intensive assets, affecting investors' portfolios and having a ripple effect on the financial network.

Evaluating and managing climate risk presents unique challenges compared to conventional risks due to its endogenous nature and involvement in multiple scenarios (Battiston et al. 2019). This complexity arises from deep uncertainty regarding the precise location and magnitude of major shocks (Weitzman 2009). The estimated probability distribution of these shocks could vary non-linearly, due to even small changes of the assumed environment's conditions, making it challenging to derive insights from historical data (Ackerman 2017). Moreover, climate policy decisions and the expectations of financial actors regarding future policies introduce further uncertainties, leading to the existence of multiple equilibria (Monasterolo et al. 2019). The interconnectedness of climate risk with other sectors also raises the potential for mispricing its systemic effects (Battiston et al. 2016). In essence, climate risk demands a nuanced approach that considers its inherent uncertainties, the non-linear dependency of estimated probability distributions on external factors, and the intricate interplay with policy decisions and financial expectations. This understanding is crucial for developing effective strategies to assess and manage climate risk in a comprehensive manner.

Besides the environmental aspect of sustainability, which is threatened by climate change, we must consider also two other criteria, i.e. the Social and the Governance dimensions of the problem, therefore leading to the three pillars known as ESG parameters. While the former may be more quantitatively and straightforwardly represented, the latter two concern respectively issues like gender inequality and data privacy, which are hard to measure unequivocally.

It is worth mentioning that among the challenges faced by regulators in setting official standards, there is a clear lack of consensus on sustainable issues (in particular, for the social factor), producing specific regulations for different companies, sectors, and project levels. Moreover, the disclosure requirements and data are often incomplete and customized, producing fuzzy profiles of the companies. However, if regulators may find it premature and challenging to set official standards and disclosure requirements, investors on their side find it confusing not having an agreed-upon sustainability framework. Indeed, among the critiques posed to governments there is a lack of clarity on the ESG terminology (taxonomy) and standards, so there would be no need for companies to "reinvent the wheel" and this would save the costs on customization, as well as avoiding the fear of opportunistic "standard shopping" (Inderst and Stewart 2018). Moreover, a lack of transparency and reported data by businesses, makes it difficult for investors and rating agencies to measure and manage risks, costs, sustainability and risk-adjusted performance, greenwashing, and clarify fiduciary duty and scoring. All these elements support the idea that a great level of ambiguity actually affects the market.

The argument of ambiguity concerning ESG valuation is also supported by the incomparability of companies' ESG data, which can change based on the industry, the location, and company-specific factors, which often renders data incomparable. This element together with the poor understanding of the interaction between ESG ratings agencies and companies, blurred the effectiveness of sustainability measures and how they are assessed.

At this extent we recognize the important role of (i) the level of disclosure, hence the quality of the signal, i.e. the information released; and (ii) the subjective perception of the signal itself, which can be dependent on several factors as the personal risk's aversion and the ESG disagreement due to the presence of controversies in the rating process.

The paper proposes a model, introducing a level of ambiguity in ESG rating though a *distortion matrix* which allows to evaluate alternative scenarios based on hypothesis about both the informative degree of signal and the confidence of the decision maker (DM in the following), already stressed as a fundamental duo in the seminal literature (see Snow (2010)). Therefore the model infers a distortion on the ESG rating which has a forecasting power, if the calibrated ambiguity is assumed to be representative of the market participants' sentiment, and can be recognized as a policy driver able to identify ESG-under/over-estimated sectors based on how the information is perceived. Moreover, the ambiguity dimension of the problem allows to make clear the sensitivity of the ESG rating to the information signal, hence showing its level of robustness.

The paper is organized as follows: Sect. 2 points out the theoretical foundation of the ambiguous and information-based approach, detailing the role of both the information and the beliefs in the distortion process; Sect. 3 empirically implements the distorted ESG scoring given several assumptions concerning the level of information and the perceived reliability of the signal; Sect. 4 describes the results of analysis; Sect. 5 draws some conclusions.

2 An ambiguous and information-based model

Agreeing with Ellsberg (1961), who describes the ambiguity as

> "The nature of one's information concerning the relative likelihood of events (...) a quality depending on the amount, type, reliability and unanimity' of information, and giving rise to one's degree of confidence' in an estimation of relative likelihoods",

we are proposing a new model where the human nature is part of the decision-making process.

In order to descrive the reasoning of the proposed approach, we recall the DM's expected utility is computed with respect to a subjective prior and, in line with the modern decision theory, we distinguish between two categories of subjectively uncertain beliefs, i.e. those unambiguous and those ambiguous. An unambiguous belief can be expressed as a probability distribution while an ambiguous one cannot be represented through a single probability distribution because the DM is uncertain about its true probability. In the following setting and coherently with Klibanoff et al. (2005) we introduce the preferences of the DM in term of smooth ambiguity preferences in order to assure the parametric separation of ambiguous beliefs and ambiguous attitudes. The

Klibanoff et al. (2005) representation of smooth preferences takes the form:

$$V(f) = \int_{\Delta} \phi \left(\int_{S} u(f(s)) d\pi \right) d\mu \equiv \mathbb{E}_{\mu} \phi(\mathbb{E}_{\pi} u \circ f), \tag{1}$$

where $\phi(.)$ is a continuous and strictly increasing function[1] $\phi : \mathcal{U} \to \mathbb{R}$ and $u(.)$ is a von Neumann–Morgenstern utility that represents the preferences of the DM in the state space S. The set Δ denotes the set of all possible distribution over the states while μ is a subjective second-order probability measure over the first-order probabilities $\pi \in \Delta$. In other words, we can say that μ is the given prior information of DM. The Klibanoff et al. (2005) representation assumes a countably additive probability space with appropriate measurability conditions to ensure that the theoretical constructs and applications of distorted probabilities are rigorously defined. Since our goal is to translate the modeling idea into a finite framework, we need at least to deal with a measurable finitely additive probability space.

The Klibanoff et al. (2005) model allows to separate the component that concerns the risk towards acts f (risk-loving or risk-averse), represented by the utility function u, and the component that measures the aversion or preference towards ambiguity (ambiguity aversion or ambiguity loving), explained by a function ϕ, which is unique up to positive affine transformations.

The representation (1) can be described as an "expected utility over expected utilities"; at first, all possible expected utilities of f are calculated for each real probability π, then the expected value of the previously expected utilities is taken with respect to the subjective measure μ, and each utility is transformed through the increasing function ϕ, which captures the DM attitude to ambiguity (the more concave $\phi(.)$ the more adverse to ambiguity). In particular, in this framework we distinguish between ambiguity neutral and ambiguity adverse attitude for affine and increasing concave $\phi(.)$ respectively.

To define the subjective information setup, we aim to represent the dependence structure between π and μ in terms of a *deformation density*. This density gives a distortion to the true joint probability, coherently with the subjective beliefs and the attitude to the ambiguity. To this extent, we need to consider that the DM does not directly observe the true state of the world s (and its distribution δ). In decision-making under uncertainty, the DM often lacks direct access to the actual state of the world, which could affect the outcomes of their decisions. Instead of observing the true state s and its distribution δ, the DM receives a signal s'. This signal serves as an indirect source of information about the state, and its accuracy can vary, introducing ambiguity into the decision process. The concept of second-order probability μ comes into play here, representing the DM's beliefs about the probabilities of different states given the received signal. Since the DM's perception of the signal can vary based on its reliability, μ becomes dependent on the signal rather than the true state itself. This adjustment reflects the idea that the DM's uncertainty isn't just about the state of the world but also about the trustworthiness of the information they receive, making the

[1] The domain $\mathcal{U}$ is considered to be the space of expected utilities, objectively determined under the real probability measure.

decision process more complex and nuanced. The state-dependent nature of μ captures this layered uncertainty, recognizing that the information available to the DM can vary in reliability, and therefore, so can the DM's confidence in their decisions. Therefore, in line with the Blackwell's theory of information [see Blackwell (1953) and Blackwell and Girshick (1979)], we note the copula function[2] between π and μ as $C_{\pi,\mu}(\delta, s) = \mu(\delta|s)\pi(s)$, $\delta \in \Delta$, $s \in S$, where s represents either the state or the signal interchangeably, since they are defined in the same space S. Here, π represents the prior distribution over the states, while μ represents the conditional distribution, or second-order probability, that reflects the decision-maker's updated beliefs after receiving a signal[3]. The copula function $C_{\pi,\mu}$ essentially links these two distributions, capturing the relationship between the prior belief π and the updated belief μ given the state s. We point out that the random signal $s \in S$ is exact expression of the state of the world if and only if the DM is not affected by ambiguity hence completely trusts the signals. We believe that the impact of the ambiguity depends on the confidence of the DM on the signals and on his level of information. Consider for instance the possible ways in which ambiguity may resolve itself which corresponds to different states in statistical decision theory. This way one relates the problem to the notion of experiment and the smooth preference assumption may be seen as a class of functionals on experiments. From this argument, there is an analogy between ambiguity and information where the information power of an experiment determines the level of ambiguity. A completely uninformative experiment leads to a not ambiguous setting while the more informative the experiment, the more ambiguous the context. In line with the theory of informativeness of experiments, we distinguish between *full information* and *partial information beliefs* which turns out to make a variation on the bound of integration over the signal's set.

Therefore we define $\mu : \Delta \to \mathcal{M}^S$, where $\mathcal{M}^S$ stands for a generalized measure space[4] conditioned to the state space S, stating for the informative structure of the process and we denote with $\mu(\delta|s)$ the conditional probability of $\delta \in \Delta$ (induced by the received signal), given the state $s \in S$. Therefore we say that $\hat{\mu}$ is a distortion of μ, if the DM who knows μ can replicate it by randomly drawing $s' \in S$ once he has observed $s \in S$, i.e. there exists $\lambda : \mathcal{M}^S \to \mathcal{M}^{S'}$ acting as connection between two measure spaces such that:

$$\hat{\mu}(\delta|s') = \sum_{s \in S} \mu(\delta|s)\lambda(s|s').$$

Thus $\hat{\mu}$ is a distortion of μ if and only if for any set of actions, the set of probability distributions on the actions that are feasible when considering the μ structure also contains the distributions that are feasible if considering $\hat{\mu}$. Analogously (see Oliveira 2019) we can say that $\hat{\mu}$ is a distortion of μ if there exists a stochastic map λ such that

2 Despite the unconventional notation, this function is indeed a copula, with its marginals being the cumulative distribution functions of the prior and updated beliefs. These marginals can be obtained by integrating the densities π and μ.

3 The proposed two stages-decision functional which takes into account the conditioning of uncertainty on the states is quite connected to the approach of Petturiti and Vantaggi (2020, 2022).

4 In our application, it is indeed a probability space.

$\hat{\mu} = \lambda \circ \mu$, i.e.

$$\begin{tikzcd} \Delta \arrow[r, "\mu"] \arrow[d, "\hat{\mu}"'] & \mathcal{M}^S \arrow[dl, "\lambda"] \\ \mathcal{M}^{S'} & \end{tikzcd}$$

The role of λ is to introduce "noise" into an information structure, making the resulting distorted structure less informative.

Therefore a distortion density can be decomposed into a garbling density and a function λ which acts as a modification of the signals' set and so it is related to the level of DM's information. For this reason we call it *information density*. The distortion is assumed to represent the total impact of the ambiguity on a decisional problem, hence including the subjective level of ambiguity and the overall perception of it, also affected by the attitude to the ambiguity itself. The preferences' representation affected by a distortion leads to a new version of Eq. (1), i.e.

$$\hat{V}(f) = \int_{\Delta \times S} u(f(s))\phi(d\pi)\, d\hat{\mu} = \int_{\Delta \times S} u(f(s)) d\hat{C}_{\pi,\mu}(\delta, s), \tag{2}$$

where $\hat{C}$ denotes the dependence structure affected by a distortion of μ, i.e. $\hat{\mu}$, including the attitude to ambiguity of the DM.[5] As already explained this distortion depends on assumption concerning the level of information and the trustability of signals. Therefore we can identify the following special cases:

- in case of *full information*, i.e. identity information density and fully trusting on the signals we have no bias, i.e.

$$\hat{C}_{\pi,\mu}(\delta, s) = C_{\pi,\mu}(\delta, s), \quad \forall \delta \in \Delta, s \in S.$$

- in case of *full information*, i.e. identity information density and *ambiguity-neutral* DM, who does not trust the signal, the same probabilities are assigned to every state in the world, i.e. $\mu(\delta|s) = \mu(\delta)$, and

$$\hat{C}_{\pi,\mu}(\delta, s) = \mu(\delta) \times \pi(s) \quad \forall \delta \in \Delta, s \in S.$$

On the other hand a partial information assumption identifies a subset of signals to be considered, hence modifies the bounds of integration, i.e. $s \in S' \subset S$.

Inspired by this representation of ambiguous preferences, we propose an ambiguous version of the ESG rating that accounts for varying levels of information and subjective preferences. The ESG score is typically defined as a weighted sum of the individual pillar scores, where these weights represent the relative importance assigned to each Environmental (E), Social (S), and Governance (G) pillar. We assume that these weights are subject to shocks, which means that the relative importance of each pillar can vary due to changes in information availability or shifts in subjective preferences.

[5] Therefore the effect of function ϕ is syntesized by the product of the information and the garbling densities.

This results in an ambiguous ESG rating, as the impact of each pillar on the overall score may differ depending on the current weights and the level of information or bias affecting the evaluation. By incorporating such shocks into the model, we account for how variations in the weights (caused by new information or changing preferences) can influence the ESG score. This approach acknowledges the uncertainty and subjectivity inherent in ESG assessments, providing a more dynamic and comprehensive view of a company's sustainability performance.

To transition from the expected utility under ambiguity to a distortion matrix that represents ambiguity on a probability set and allow us to distort the ESG rates, we need to understand how subjective beliefs alter objective probabilities and how this can be systematically represented. In the context of decision-making under ambiguity, the DM operates with subjective probabilities that are influenced by their perception of uncertainty or risk. This subjective perspective is crucial because it directly impacts the way decisions are evaluated. The core idea of the paper is to translate this subjective distortion into a mathematical framework that captures how ambiguity affects the probability distribution.

We start by examining the expected utility framework, where the decision maker's preferences are assessed using both objective and subjective probabilities. The objective probabilities reflect the true likelihood of events, while subjective probabilities represent how the DM distorts these objective probabilities due to ambiguity. This distortion is captured through a distortion density function. This function modifies the objective probability distribution to align with the DM's subjective beliefs about the likelihood of different outcomes. To represent this distortion more concretely, we use a distortion matrix within a discrete-state model. Therefore, our novel idea is to work with a discrete-state model that allows for implementing a kind of stress analysis on additive shocks to the weights of the pillars in baseline scenarios, considered indicative of specific market sentiments or expected policy changes in the near future. Therefore taking advantage of the finite setting concerning both the states of the world and the signals the DM receives, we use a distortion matrix to represent the ambiguity impact on a probability set. This matrix is given by the product of a garbling matrix to explain the dependency structure between objective and subjective second-order probability (π and $\hat{\mu}$ in Eq. (2)) and an information matrix, representing the subjective informative level. That is, the distortion matrix distorts the true probability, subjective beliefs, and the individual's attitude to ambiguity. We believe our contribution to the literature lies in providing a structured framework for modeling the impact of ambiguity on decision-making. This approach enhances the understanding of how subjective distortions influence outcomes under uncertainty.

Despite the mathematical notation used, we point out that in a finite space of signal, the proposed model is well defined by an information and a garbling matrix, whose product will be a distortion matrix, i.e. $\boldsymbol{D} = \boldsymbol{G} \times \boldsymbol{\Pi}$, resulting into a distortion of the true probabilities. To clarify the transition to the finite framework, note that given the state s, each row of $\boldsymbol{G}$ identifies a probability distribution (specifically, probabilities assigned to different signal classes), and therefore it is the discrete counterpart of the garbling density. Similarly, $\boldsymbol{\Pi}$ is the discrete version of the information density. In fact, the information matrix acts on the garbling matrix by selecting and activating only the accessible information[6]. Therefore the evaluation of the impact of ambiguity on the ESG rating results in a distorted weight of the jth factor, ith pillar recovered as an expectation of the not distorted values modified by the distortion matrix $\boldsymbol{D}$, i.e.

$$\hat{w}_{ij} = \sum_p \sum_l w_{i,j}^{(p,l)} D(p,l),$$

where p, l count rows and columns, respectively. As we can observe the representative values of the weight in every class of states of the world (which are represented by a vector with dimension equal to the number of rows of $\boldsymbol{D}$), i.e. $\boldsymbol{w}_{i,j}$, are averaged by the (p, l)-entry of matrix $\boldsymbol{D}$, $\forall p, l$, which means considering for every state of the world (which select the row of $\boldsymbol{D}$) the subjective weight to attribute to every signal. We observe that once $\boldsymbol{D}$ has been defined, the deformation is linear. Using this linear deformation of weights offers a clear, flexible, and practical approach for modeling changes in ESG ratings. It ensures that the effects of shifting priorities are straightforward to interpret and analyze, aligning well with both theoretical and practical aspects of sustainability performance assessment. Additionally, linear deformation aligns with how organizations and rating agencies typically update their assessment criteria based on new information or policy changes. It provides a transparent method for demonstrating how changes in the importance of each pillar are translated into adjustments in the overall ESG score, thereby enhancing the credibility and comprehensibility of the rating process. Moreover, linear deformation effectively models how subjective preferences and information changes influence the weight of each ESG pillar, allowing for a flexible framework to accommodate different scenarios where the importance of pillars might proportionally increase or decrease. However, non-linear effects can also be incorporated into the definition of the distortion matrix to account for more complex distortions in information processing and weight adjustments. For instance, if ambiguity affects the perception of risk or uncertainty in a non-linear way, the overall impact on outcomes may also be non-linear. Furthermore, psychological and behavioral responses to ambiguity, such as aversion to uncertainty or shifts in preferences, can result in non-linear impacts on decision outcomes. Therefore, including non-linear elements in the distortion matrix provides a more nuanced representation of how ambiguity influences decision-making. Any non-linear effects will certainly be taken into account if we calibrate the garbling matrix to real market data, as will be proposed in the upcoming empirical experiment.

Now, to better illustrate how the distortion matrix affects the scoring procedure for different agents, we present a toy example before discussing the results of our framework.

Example 1 Let us consider a discrete random variable $X \in [0, 100]$ and a state of the world s. The DM does not observe s but a signal s' that provides information about the random variable identifying its range into three classes, i.e. low, medium, and high

[6] This process is realized by assigning unit or zero mass to the information represented by the entries of $\boldsymbol{G}$.

values:

$$s' = \begin{cases} 20 & \text{if } s \le 40 \\ 55 & \text{if } 40 < s \le 70 \\ 85 & \text{if } s > 70 \end{cases}$$

We know that the product of the information matrix and the garbling matrix $\boldsymbol{G} \times \boldsymbol{\Pi}$ determines a bias in the variable X. Assuming that the DM is fully informed about the signals, we set the information matrix or prior as an identity matrix $\boldsymbol{\Pi} = \boldsymbol{I}$, whose rows represent the states of the world and whose columns represent the signals, i.e.

$$\boldsymbol{I} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

Concerning the garbling matrix, we consider an ambiguous DM, i.e.

$$\boldsymbol{G} = \begin{pmatrix} 0.8 & 0.2 & 0 \\ 0.35 & 0.45 & 0.1 \\ 0 & 0 & 1 \end{pmatrix}$$

Given a state of the world s, we proceed by identifying the class of the variable X to which the signal s' belongs and the corresponding row in the Distortion Matrix (which corresponds in this case to the garbling matrix), then we multiply the row associated with the signal by the vector of the classes' averages. If the state of the world, for example, is $s = 17$, that belongs to the first class with signal $s' = 20$, we select the first row of the garbling matrix and recover the distorted value of the low signal, i.e.

$$0.8 \times 20 + 0.2 \times 55 + 0 \times 85 = 27.$$

In the following section, different garbling and information matrices are considered, resulting in different combinations of individual's attitude and information about the sectorial ambiguity recovered by publicly available market data.

3 ESG rating and ambiguity: evidences and scores' robustness

The paper aims to propose an ambiguous version of the ESG rating, accepting the statement that the level of disclosure, hence the quality of the signal released and the subjective perception of the signal itself, must have a pivotal role in the rating process. As a matter of fact both the information and the garbling figures are expected to have an impact in the evaluation process and finally result in a distorsive effect due to a subjective filtration of the available information. The starting point of our analysis is the selection of the Refinitiv-ESG Rating, one of the publicly available rating, as benchmark for the ESG profile of the companies.

Table 1 List of the ESG factors considered by Refinitiv for each pillar

Environmental	Social	Governance
(1) Resource use	(1) Worforce	(1) Management
(2) Emissions	(2) Human rights	(2) Shareholders
(3) Innovation	(3) Community	(3) CSR strategy
	(4) Product responsibility	

The Refinitiv definition of the ESG Score (see Refinitiv) is quite blurred concerning the methodological details; the score depends on a weighted average of ten different categories, as summarized in Table 1. Indeed, among these categories, three are related to the environmental factor (Resource use, Emission, Innovation), four to the social factor (Workforce, Human rights, Community, Product responsibility), and three to the governance factor (Management, Shareholders, Corporate Social Responsability).

Starting from the score of each category, the ESG rating is calculated as a weighted average of these values where the weights depend on the sector to which the company belongs. Finally, an ESG grade is assigned according to the score range, where D- indicates a very low ESG value, and A+ an excellent value and a high degree of transparency. Nevertheless, the explicit determination of the weights is missed and confers an ambiguous shape to the process. We propose to attribute the role of ambiguous parameters to the weights themselves, which are assumed to be the most probable ambiguous impacting factors on the score. However, the choice of the ambiguous factors remains discretional and not restrictive in the application of the proposed Ambiguous and Informative Model to the ESG scoring.

The underlying idea is to identify potential future changes in the weights assigned to the pillars, justified by the ongoing debate and alignment policies with European sustainability objectives. These future scenarios are to be understood as stylized expressions of a distinct sentiment and context, providing a basis for an analysis in line with stress testing approaches. Therefore, the quantification of parameters (which are expression of *ambiguity*) is relevant in trend and not in absolute terms, and it is to be understood as explanatory of the comparative change in weights, assigning more weight to one component than another. We consider three base scenarios in which ambiguity involves a couple of pillars, each with a prevailing role of one or the other, respectively. This choice is to better isolate the influence of each factor in the scoring procedure, trying to avoid complex interplays between the factors which makes it impossible to isolate the contribution of each factor.

For each scenario, the introduction of the ambiguity concerning the ESG pillars is well-founded due to the current debates on how the economic system should evolve and which policies should be adopted, with structural differences between agents' views and perspectives. The choice of the three base scenarios is rooted in the evolving significance and perception of ESG factors in recent years. The rationale for each scenario is based on observed trends, regulatory developments, and shifts in societal and investor priorities, which are detailed below:

First Scenario: Emphasis on the Environmental Factor (E) and Product Responsibility (S4). The first scenario centers on the increasing importance of the E factor and the S4 category within the social pillar. This scenario is justified by several key developments:

- Global Environmental Awareness: Since the Paris Agreement and the adoption of the 2030 Agenda for Sustainable Development, there has been a marked increase in global awareness and commitment to environmental protection. Governments, corporations, and civil society have recognized the urgent need to reduce emissions, pollution, and resource consumption, making the environmental factor a critical consideration.
- Extended Producer Responsibility (EPR): The OECD (see OECD, 2017) has highlighted EPR as a crucial policy approach for environmental protection, particularly in waste management and pollution prevention. This policy framework places financial and physical responsibility on producers for the environmental impact of their products throughout the product lifecycle, especially at the end of life. This underscores the growing importance of product responsibility (S4) within the broader context of social responsibility.
- Consumer and Investor Sentiment: The growing awareness and concern among consumers and investors about environmental issues further validate the focus on the environmental factor. This sentiment is driving companies to prioritize sustainable practices and transparency in their environmental impact, making the E factor increasingly significant in corporate evaluations.

Second Scenario: Ambiguity Between Environmental (E) and Social (S) Pillars, with Predominance of Social (S). The second scenario introduces an element of ambiguity between the E and S pillars, with a slight predominance of the social pillar. This scenario reflects the complex and evolving nature of ESG priorities:

- Impact of the COVID-19 Pandemic: The COVID-19 pandemic has significantly altered perceptions of social factors, highlighting disparities in health, education, and economic opportunities. These issues have drawn greater attention to the social pillar, particularly concerning workforce well-being, community engagement, and equitable access to services.
- Shift in Political and Corporate Focus: While environmental commitments, such as those outlined in the Paris Agreement, remain critical, the pandemic has brought social issues to the forefront. Politicians and corporate leaders are now increasingly concerned with addressing social inequalities and improving resilience against future crises, leading to a reevaluation of the relative importance of the E and S pillars.
- Balanced Approach: The second scenario assumes a balance between environmental and social concerns, with neither pillar experiencing extreme fluctuations. This approach recognizes that both factors are interdependent and crucial to achieving long-term sustainability goals, with the social pillar potentially gaining slight precedence in the post-pandemic context.

Third Scenario: Focus on Governance (G) and Corporate Social Responsibility (CSR). The third scenario emphasizes the governance pillar, particularly focusing on

Corporate Social Responsibility (CSR), as a response to the growing importance of transparency and accountability in addressing climate change:

- Intensifying Climate Change: As climate change continues to accelerate, stakeholders, including investors, regulators, and consumers, are increasingly scrutinizing how companies manage their environmental impact. This scrutiny extends beyond mere compliance, requiring companies to demonstrate proactive engagement with sustainability issues.
- Policy and Market Practices: The evolution of policies and market practices regarding sustainability disclosure is a key driver in this scenario. Effective governance, particularly in terms of CSR, is becoming essential for companies to not only implement sustainable practices but also to communicate these efforts effectively to stakeholders (see Boffo and Catalano 2020).
- Importance of Communication: This scenario recognizes that even companies making substantial efforts to reduce their environmental footprint may not receive due recognition if they fail to communicate their actions effectively. Governance, through robust CSR strategies and transparent reporting, becomes pivotal in ensuring that a company's sustainability efforts are acknowledged and valued by the market.

The implementation of the model is disentangled into three steps. In the first step, we select the weights of E, S, and G pillars as ambiguous parameters and we define the implied stylized scenarios. In the second step we allow for a distortion of the weights due to several garbling-information matrix combinations, and finally, in the third step the distorted ESG rate is calculated.

3.1 Step 1: Definition of the base scenarios

The initial phase of the analysis focuses specifically on the selected ambiguous variables. In our case, we estimate three random samples of joint distributions representing additive shocks on weights, corresponding to the pairs on the E, S, and G pillars, respectively. The fluctuations in these weights are random, and the interdependence between the pillars is assumed to be modeled by Archimedean copulas, a versatile family capable of capturing various forms of tail dependence (see Joe 2014).

In the first baseline scenario, all weights associated with the E pillar, along with the *Product responsibility* category (the fourth category within the S pillar), are considered ambiguous. The choice of distributions and parameters in the initial baseline scenario is based on capturing the realistic dynamics between the E and S pillars, and their impact on sustainability assessments. The shocks within the E pillar are assumed to follow a normal distribution, as this allows for modeling both positive and negative deviations around a central mean, reflecting the inherent uncertainty and variability in environmental impacts. The correlation between E and S pillar shocks acknowledges the interconnected nature of these factors, where changes in environmental policies or practices can have direct social implications, and vice versa. Additionally the E pillar is considered the most impactful due to its influence across all categories of sustainability assessment. This is reflected in the scenario by assigning a higher mean impact of 10% to the E pillar, along with a greater variance compared to the S pillar. This

Table 2 Scenarios' description: first, second, and third base scenario

Scenario	First scenario	Second scenario	Third scenario
Affected factors	E–S	E–S	E–G
Affected categories	E: all/S: only the fourth	E: all/S: all	E: all/G: only the second
$P_1 = E$	$w_{E1} = \sum_{j=1}^{3} \Delta w_{E,j} \sim N(0.10, 12.25 \times 10^{-2})$	$w_{E2} = \sum_{j=1}^{3} \Delta w_{1,j} \sim N(0.04, 12.25 \times 10^{-2})$	$w_{E3} = \sum_{j=1}^{3} \Delta w_{1,j} \sim N(0.15, 9 \times 10^{-5})$
$P_2 = S$	$w_{S1} = \Delta w_{2,4} \sim N(0.02, 0.01)$	$w_{S2} = \sum_{j=1}^{4} \Delta w_{2,j} \sim N(0.15, 0.04)$	-
$P_3 = G$	–	–	$w_{G3} = \Delta w_{3,2} \sim N(0.004, 2 \times 10^{-5})$
Dependence structure	Gumbel	Frank	Gumbel
Dependence parameter	$\theta_1 = 2.5$	$\theta_2 = 8$	$\theta_3 = 4.5$

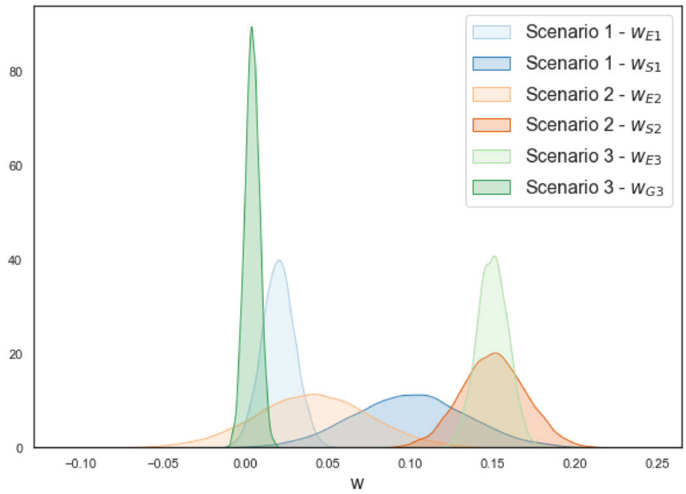


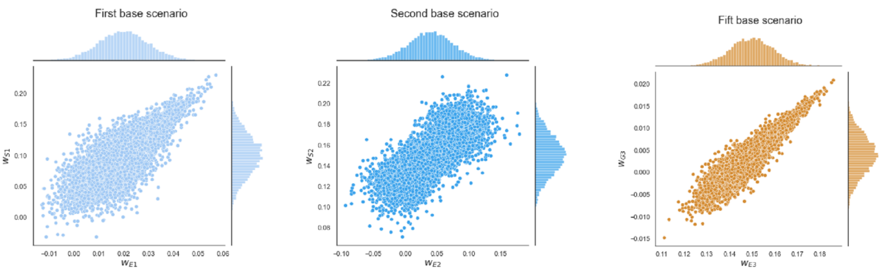
Fig. 1 Density of the random shocks for the three base scenarios

setup indicates that while the E pillar is expected to have a significant average impact, there is also substantial uncertainty or variability associated with environmental outcomes, aligning with the unpredictable nature of environmental risks such as those related to climate change. As depicted in Fig. 1, the possibility of a negative shock on the S pillar is not ruled out, i.e., $P(w_{S1} \leq 0) > 0$, reflecting the realistic potential for adverse social outcomes due to factors like economic downturns or social unrest. Therefore the scenario ensures that the model remains grounded in the complexities of real-world social dynamics. Finally to accurately represent the dependence structure between the E and S pillars, we observed that strong dependence is most evident when both pillars experience substantial increases. This led to the adoption of a Gumbel copula, characterized by a parameter $\theta_1 = 2.5$, which captures moderate dependence with a focus on right tail dependence. This choice reflects the scenario where extreme positive changes in environmental and social responsibility factors are likely to occur together, while less extreme changes show weaker dependence. Overall, the distributional choices and parameters are designed to create a realistic and nuanced scenario that effectively captures the dominant role of the environmental pillar, the interdependence of environmental and social factors, and the potential variability in their impacts on sustainability assessments as illustrated in Table 2.

In the second baseline scenario, the choice of distributions and parameters is designed to reflect the predominant influence of the S pillar over the environmental one. We assume a significant shock to the social factor, with an average impact of 15%, which is higher than the 4% mean shock assumed for the environmental factor, as shown in Table 2. This allocation reflects a scenario where social issues are expected to play a more crucial role in influencing outcomes, possibly due to increased societal awareness and response to social inequities, particularly in the wake of recent global events like the COVID-19 pandemic. As shown in Fig. 1, the environmental factor is modeled with a lower mean shock, indicating that while environmental considerations remain important, their immediate impact is less pronounced compared to social factors. However, the greater dispersion of the E pillar shock indicates a higher level of uncertainty or variability, suggesting that environmental outcomes could still have a wide range of potential impacts, including the possibility of negative shocks. This variability acknowledges the unpredictable nature of environmental risks and their evolving influence on societal and economic systems.

Unlike the first baseline scenario, where right tail dependence was important, the second scenario does not incorporate any type of tail dependence. This decision is based on the assumption that the anticipated mean variations for both the social and environmental factors are moderate and do not exhibit extreme fluctuations that would necessitate modeling tail dependence. Therefore, the dependence structure is modeled using a Frank copula, which is suitable for capturing the general dependence between variables without emphasizing extreme co-movements. The choice of a high-mean parameter $\theta_2 = 8$ for the Frank copula reflects a scenario of almost strong dependence between the E and S pillars. This suggests that, while there is a significant relationship between the two pillars, it does not specifically account for the extreme values, thereby focusing on the overall dependence rather than on the tails of the distribution. This copula choice aligns with the scenario's assumption of constrained variations in the mean values of both factors, providing a realistic representation of their interaction under the given conditions. To sum up, the distributions and parameters in this scenario are chosen to reflect the expected dominance of social factors, the moderated impact of environmental factors, and a realistic dependence structure that aligns with the scenarios assumptions.

In the third scenario, the choice of distributions and parameters is designed to reflect the substantial influence of both E and CSR factors, with a focus on the interaction between these elements in a context of heightened regulatory and social pressures related to climate change. The environmental pillar is attributed a predominant mean shock of 15%, signifying its major role in influencing company scores under this scenario. This high mean shock reflects the expectation that extreme climate events and social demands for environmental responsibility will lead to significant changes in how companies are evaluated. On the other hand, the CSR factor is assigned a smaller mean shock of 0.4%, indicating that while CSR remains important, its immediate impact is more limited compared to the environmental factor. This distinction is crucial as the CSR component affects only one factor within the G pillar, whereas the E pillar impacts three distinct factors, justifying the larger influence of the environmental component. Moreover the CSR shock is characterized by lower volatility compared to the E pillar shock. This is because CSR efforts typically involve long-term strategies and stable policies, resulting in less variability. In contrast, the environmental pillar, which encompasses a broader range of factors, is subject to more unpredictable and wide-ranging influences, hence its greater dispersion. The lower overall dispersion in this scenario is intentional, aiming to model an extreme case where climate change drives widespread policy changes, leading to more uniform and stringent sustainability requirements across industries. In such a scenario, the variations in company scores are expected to be more moderate, as companies across the board will need to adhere to new regulations, resulting in less variability in how they are affected by these changes.



(a) First Base Scenario. **(b)** Second Base Scenario. **(c)** Third Base Scenario.

Fig. 2 Weights Increments: random sample of weights' shocks pairs

The third scenario also features right-tail dependence, captured using a Gumbel copula with a parameter of $\theta_3 = 4.5$. This choice reflects the expectation that, under stringent regulations, the impact of sustainability data and its communication will become increasingly important as companies strive to meet new standards. Right-tail dependence means that when there is a significant increase in the relevance of both environmental and CSR factors, their combined effect on company scores will be more pronounced. However, for smaller changes in these factors, the relationship will be less marked. The Gumbel copula with this specific parameter value effectively models the stronger association between high values of these variables, which is consistent with a scenario where companies face increased scrutiny and regulatory requirements related to sustainability. Therefore this choice of distributions and parameters provides a realistic representation of the interaction between environmental and CSR factors in a future where climate change and social pressures lead to substantial policy shifts, affecting how companies are evaluated and scored based on their sustainability efforts.

Building upon these assumptions regarding the base scenarios, we recover three random samples of 10,000 copulas. Subsequently, by employing the inversion of the marginals, we are able to present in Fig. 2 a graphical representation of the dependence structure that characterizes the baseline scenarios.

3.2 Step 2: Informative set and signal's distortion

In the second step, the ambiguity model described in section 2 is applied to set up the weights. We define the signal set as composed by ten different signals and consequently, we specify both the information and the garbling matrix, whose dimension is 10×10, considering the states of the world in the rows and the signals in the columns. The ambiguity distortion applied to the weights is expected to be given by the product of the information matrix $\boldsymbol{\Pi}$ and the garbling matrix $\boldsymbol{G}$, i.e.

$$\boldsymbol{D} = \boldsymbol{G} \times \boldsymbol{\Pi}.$$

In order to give a wide representation of the range of distortion generated by the model, we consider three possible garbling matrices identifying three different levels of ambiguity and combine them with three different information matrices as well.

The implemented information hypothesis corresponds to the following information matrices:

Π1 Identity matrix. It represents a fully informed DM.
Π2 Sup matrix. In this second case, we have a DM who is not informed about the three highest signals, so he is assumed to not receive the signal when the weights are the highest ones.
Π3 Inf matrix. In this third case, we have a DM who is not informed about the lowest signals, hence about the smallest changes in the weights.

On the other hand, the garbling matrices taken into account are the following:

***G*1** Identity matrix. Here the DM trusts the signal completely, hence there is no ambiguity.
***G*2** Ambiguity Neutral matrix. Here the DM does not trust the signal at all hence its choices are independent of the signal. We therefore consider a constant matrix with entry 0.1.
***G*3** Ambiguous matrix. Here the DM partially trusts the signals. The signals he receives are distorted based on his trust on the reliability of the ESG scores.

To assess the level of ambiguity represented in ***G*3**, we can employ various methods that measure the distance between the available rating and a benchmark assessment considered more reliable. These methods may also rely on challenges recorded by the rating or measure the ESG disagreement. Assuming that the DM is representative of the market, we can "calibrate" the level of ambiguity by comparing the available rating, for us Refinitiv, in relation to sector-specific information obtained from the materiality map. In particular we construct a measure of the ESG scores fuzziness, α, which reflects the agents trust in this measures. To define α we compared the information of the Refinitiv-ESG score and a materiality score, built upon the map provided by SASB, an international organization that defines standards for sustainability reporting.

The materiality map published by the Sustainability Accounting Standards Board (see SASB 2021), is a list of sector specific factors and indicators useful for measuring the ESG scores. SASB uses an overall assessment applied to each industry which determine the significance of each factor and subfactor based on the external environment and business model. It considers the existing body of reporting standards and makes use of the existing metrics where possible. Indeed, thanks to the materiality map investors are becoming able to distinguish what actually creates value and this information can be assimilated exactly to the publicly available materiality map. Informed DM can identify the material dimension of ESG parameters and, by comparing them with the Refinitiv scores, assign a subjective probability reflecting the model reliability, i.e. a higher relevance to those factors with a higher material value.

More specifically, based on this materiality map, which identifies the factors that have material importance in the calculation of the ESG score for each industry sector, a new "material ESG" score was computed. In particular, the "material ESG" score is computed by rescaling the Refinitiv factor weights based on the number of factors considered by Refinitiv and also present in the materiality map for each sector. This ensures that the new score represents only those factors that are commonly accepted to have a material dimension.

Later, the difference between this new score and the Refinitiv score was also determined. Then we compute for each sector the average standardized difference between the ESG score provided by Refinitiv and the material one, i.e.

$$z_k = \frac{\Delta ESG_k - \mu}{\sigma},$$

where ΔESG_k represents the average difference between the two scores in the k-th sector. μ and σ stand for the mean and standard deviation of the distribution of the differences between the Refinitiv and the Material score across all the sample.

Finally we define an implicit level of ambiguity $\alpha_k \in [0, 1], \forall k$, as

$$\alpha_k = P(|Z| > |z_k|) = \Phi(-|z_k|) + (1 - \Phi(|z_k|)),$$

where Z is a standard normal random variable and Φ the cumulative normal distribution function. We observe that if the difference in absolute value between the Refinitiv ESG score and the material score is low, we will have a level of ambiguity α_k close to 0, while for higher difference between the two scores, the ambiguity level is expected to converge to 1. This aims to represent the fact that agents will lower their confidence for sector k as the difference between the material score and the Refinitiv one tends to be larger on average; while when the two scores are similar, the agents ambiguity tends to be smaller. Finally, the agents will have an ambiguous garbling matrix for each sector k, denoted as $\boldsymbol{G3}_k$, to represent their confidence in the signals for each sector. Each element of the matrix for sector k is assumed to be distributed as a beta random variable, i.e.

$$X_{p,l} \sim \mathcal{B}(e^{\alpha_k}, e^{1-\alpha_k}),$$

where $X_{p,l}$ is the (p, l)-entry of the garbling matrix $\boldsymbol{G3}_j$. In this way when we have low ambiguity for sector k, i.e. values of α_k near 1, the distribution of each entry of the garbling matrix will be skewed toward 1, meaning that the investors fully trust almost all the signal they receive. Instead for higher ambiguity, i.e. values of α_k near 0, the distribution of each entry of the garbling matrix will be skewed toward 0, meaning that the investors would perceive weakened the signal received.

Once the garbling and information matrices have been defined, ten equally spaced intervals are defined for each ambiguous variable (the pillar's weight considered in both the base scenarios): to define these intervals from the sample of weights obtained in the first step, the difference between the maximum and minimum weights is calculated and divided by ten. The central value is then calculated for each equally spaced class and it is considered the referent value of the class itself. Starting from the sample of weights specified for every base scenario, the class to which they belong is identified, and consequently, the vector of classes' averages is recovered and multiplied by every row of the distortion matrix, i.e. the couple of information-garbling products considered. The model implementation involves a sample of 10,000 distorted increments to represent the additive shocks of the weights characterizing the baseline scenarios; to each weight and for each sector (and calibrated ambiguity level), we apply every combination of information-garbling matrices.

3.3 Step 3: Distorted ESG rate

In the last step, the new ESG rate is calculated for each company in line with the discrete setting version of the Information-Ambiguous approach in (2), i.e.

$$E\hat{S}G = \sum_{i=1}^{3}\sum_{j=1}^{n_i} \hat{w}_{ij} P_{ij},$$

where P_{ij} represents the score assigned by Refinitiv to the j-th factor of the i-th pillar for the company under consideration. On the other hand, $\hat{w}_{ij}$ is the new distorted weight of the j-th factor of the i-th pillar induced by $\boldsymbol{D}_k$, where k identifies the sector to which the considered company belongs. As previously defined in Step 2, the matrix $\boldsymbol{D}_k$ is computed as the product of $\boldsymbol{G}_k$ and $\boldsymbol{\Pi}$.

The new distorted weights are evaluated assuming that the weight's increment is constant for each sector. Furthermore, to ensure that the sum of the weights equals 1, it is assumed that for the factors not affected by the increments, there is an opposite sign variation in the weights, equally split between them. The distorted ESG rate is calculated for each company, for each scenario and for each information-garbling pair.

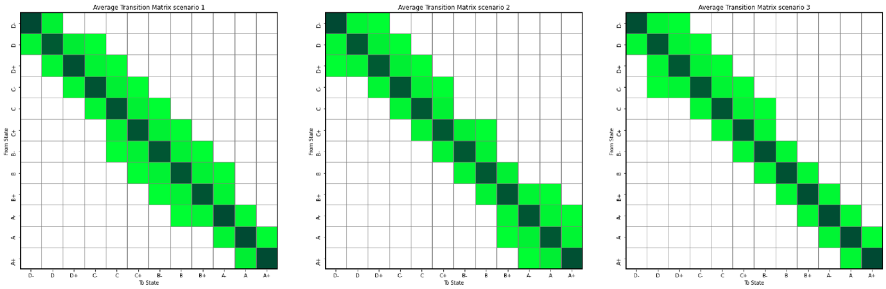
4 Empirical results

Beginning with the 2023 Refinitiv-ESG grades and using the implemented 3-step model, we assess distorted ESG grades for each scenario for a sample of companies. This sample consists of 780 companies, primarily European, representing nearly every industry.

Once the new distorted ESG-grades for each scenario and pair of garbling and information matrices are computed, the transition matrices are computed comparing the original ESG rating with the distorted one for each scenario. Furthermore, for each scenario, the average transition matrix is computed across all possible combinations of the information matrix and garbling matrix considered. The resulting average transition matrix for each scenario is employed to analyze sensitivity to changes in scoring criteria across all different notches. This analysis excludes potential effects of ambiguity, aiming to assess the general robustness of the current structure of ESG scores to policy shocks, highlighting possible differential effects on different notches.

In Fig. 3, the average transition matrices for each scenario are plotted. The y-axis indicates the original notch, while the x-axis denotes the arriving notch. Transition probabilities are depicted using a color spectrum ranging from white to dark green, where darker colors represent higher probabilities to change notch, and vice-versa lighter colors represent lower transition probabilities.[7]

[7] The transition matrices are reported in the appendix, with the probabilities numerically explained up to the 2th decimal place. The details of the construction procedures are included.



(a) First Base Scenario **(b)** Second Base Scenario **(c)** Third Base Scenario

Fig. 3 Mean Transition Matrices across all ambiguity levels

In general, the current scoring procedures are robust to shifts in the relevance of the ESG factors, since across the 3 scenarios on average 84% of the companies remain in the same notch as the starting one. Moving on to a more specific analysis of the first scenario, we observe that lower notches exhibit higher variability compared to the other scenarios. This denotes a greater sensitivity of poorly scored companies to increases in environmental components, resulting in overall increases in their evaluations. In particular, companies that do not engage in initiatives to improve their management practices or participate in any social programs would benefit from an increase in the environmental factor. This could be explained by the fact that most poorly graded companies are obligated to maintain a minimum level of environmental practices by current policies, leading to upgrades in their notches when environmental factors are more influential in the scoring procedures.

For the second scenario, it is noteworthy that, on average, highly-scored companies exhibit a greater variation of the notch, with a higher percentage of downgraded companies compared to the other scenarios. This could be explained by a greater sensitivity of top-ranked companies to shifts from the current structures of the pillars. Consequently, they could be easily penalized by any change in the current hierarchies between the ESG factors. Instead, firms with lower scores tend to exhibit poor performance in each pillar. Consequently, even if the pillar structure changes, they are likely to retain a low score in the new structure.

Finally, the third scenario presents the highest percentages of companies that remain in the same notch. This indicates that the current scoring procedures effectively represent the climate change components and are robust to changes in structures that favor the environmental side and its communication. Indeed, this aligns with the current policies adopted by different rating agencies, which assign high relevance to the environmental factor due to its easier quantitative evaluation compared to the other two factors. The latter factors rely on more qualitative evaluations of the firms.

After the analysis of the transition matrices, we focus our attention on the average variation of the scores across sectors in the different scenarios. This allowed us to evaluate the impacts stemming from alterations in the scoring procedures and how vulnerable the companies in different sectors are to the various factors.

On Tables 3, 4, 5, the average score variation for each sector is reported. Each row corresponds to a sector from our industry samples, classified according to Refinitiv's categorization. Meanwhile, each column represents the pair of garbling and information matrix considered in the implementation of our 3-step model. It is worth mentioning that the calibration of ambiguity has been approached on a sector-by-sector basis. Further details about the calibration are provided in the Appendix.

From Table 3, we observe an average decrease of 0.26. However, for almost every combination of garbling and information matrix, the average difference is slightly positive. Meanwhile, for $\mathbf{\Pi 3 G2}$ and $\mathbf{\Pi 3 G3}$, there is a consistent average decrease. This indicates that, for almost all market agents, an increase in the level of standards regarding environmental and product responsibility does not result in changes in the average evaluation of companies, denoting that most of the companies already are adopting sufficient practices to improve their greenness for most of the agents on the markets.

On the contrary, individuals who are extremely concerned about the pollution caused by companies, anticipating that policymakers will introduce mainly higher environmental standards to which companies must comply (represented by $\mathbf{\Pi 3}$), but are confused by the contrasting signals arising from the current political debate (represented by $\mathbf{G2}$ and $\mathbf{G3}$), will, on average, decrease the evaluation of companies. This suggests that, for environmentally conscious agents, the current environmental standards adopted by companies are not, on average, deemed sufficient.

Moving to the sectors we can observe that most of the environmentally intense industries suffer on average a decrease in their evaluation, while most of those industries that are service-oriented, such as "freight and logistic services", observed an increase in their evaluation. Moreover, we can see that there is not a clear effect of the ambiguity on the sectors' evaluation. Across the different sectors, the one that suffers the worst average decreases are investment-related industries, coal, office equipment, and small electronics companies, with a reduction of at least 7.80 points on average. Instead, the sectors that benefited the most are specialty retailers, media publishing companies, and the packaging industry, with a minimum average increase of 4.79.

Moving to the second scenario, from Table 4, we observe an average increase of 0.85 points when the environmental and social factors increase in relevance. The average effect is positive across all pairs of garbling and information matrices, suggesting that increasing the importance of the social factors would generate positive upgrades of the ESG scores on average for the different sectors. Indeed, we observe that only 17 out of the 51 industries considered experienced a decrease in their average evaluation, with a negative variation across all pairs of information and garbling matrices for almost all of these industries. This shows that most of the industries suffering from this scenario are perceived as inherently vulnerable to both environmental and social factors by all agents in the markets.

Comparing the results obtained in scenario 1 with those of scenario 2, we can see that, in general, the number of industries experiencing an average decrease is smaller. This could suggest that some of the industries considered environmentally detrimental would benefit from an increase in social factors. This aligns with the general belief that industries involved in polluting activities improve their perception by engaging in social projects. Through the positive impact of these projects, their pollution and

Table 3 Relative distortion in ESG score by sector: first baseline scenario

Industry group	$\Pi 1 G1$	$\Pi 1 G2$	$\Pi 1 G3$	$\Pi 2 G1$	$\Pi 2 G2$	$\Pi 2 G3$	$\Pi 3 G1$	$\Pi 3 G2$	$\Pi 3 G3$	Average
Aerospace and Defense	0.16	0.17	0.15	0.16	0.16	0.15	0.78	−9.32	−9.34	−1.88
Automobiles and Auto Parts	−0.24	−0.26	−0.21	−0.24	−0.24	−0.23	−0.75	6.96	6.96	1.31
Banking Services	−0.36	−0.36	−0.33	−0.34	−0.36	−0.34	−1.03	10.49	10.48	1.98
Beverages	−1.58	−1.58	−1.46	−1.52	−1.56	−1.52	−6.21	−1.69	−1.71	−2.09
Biotechnology and Medical Research	0.61	0.53	0.59	0.52	0.60	0.56	0.76	−15.83	−15.65	−3.03
Chemicals	−0.68	−0.69	−0.66	−0.69	−0.68	−0.68	−1.06	−7.62	−7.58	−2.26
Coal	−2.94	−2.93	−2.63	−2.75	−2.90	−2.76	−16.80	−15.78	−16.10	−7.29
Communications and Networking	2.46	2.44	2.17	2.28	2.42	2.29	12.86	5.91	6.27	4.35
Computers, Phones and Household Electronics	−0.87	−0.90	−0.72	−0.81	−0.85	−0.80	−7.22	−26.60	−26.50	−7.25
Construction and Engineering	0.54	0.54	0.54	0.54	0.54	0.54	0.50	−3.93	−3.93	−0.46
Construction Materials	−2.01	−2.01	−1.76	−1.86	−1.97	−1.87	−5.53	12.98	13.18	1.02
Consumer Goods Conglomerates	−1.88	−1.88	−1.61	−1.72	−1.84	−1.73	−14.19	−10.73	−10.75	−5.15
Containers and Packaging	0.92	0.88	0.80	0.81	0.90	0.84	5.25	16.20	16.39	4.78
Diversified Retail	2.35	2.38	2.13	2.25	2.32	2.24	6.39	4.56	4.49	3.24
Electric Utilities and IPPs	0.10	0.10	0.17	0.14	0.11	0.14	−0.86	−2.53	−2.53	−0.57
Electronic Equipment and Parts	−0.70	−0.73	−0.57	−0.65	−0.68	−0.64	−2.66	−9.60	−9.47	−2.86
Food and Drug Retailing	2.19	2.18	2.00	2.07	2.17	2.08	6.50	9.55	9.55	4.25
Food and Tobacco	−0.41	−0.42	−0.43	−0.43	−0.41	−0.43	0.16	0.67	0.68	−0.11
Freight and Logistics Services	0.77	0.74	0.69	0.69	0.76	0.71	2.36	8.25	8.31	2.59
Healthcare Equipment and Supplies	0.38	0.36	0.34	0.33	0.38	0.34	1.13	4.49	4.57	1.37
Healthcare Providers and Services	0.69	0.64	0.58	0.58	0.67	0.61	2.04	12.51	12.53	3.43
Homebuilding and Construction Supplies	−0.60	−0.59	−0.61	−0.59	−0.60	−0.60	−0.35	−4.05	−4.07	−1.34

Table 3 continued

Industry group	$\Pi 1G1$	$\Pi 1G2$	$\Pi 1G3$	$\Pi 2G1$	$\Pi 2G2$	$\Pi 2G3$	$\Pi 3G1$	$\Pi 3G2$	$\Pi 3G3$	Average
Hotels and Entertainment Services	2.68	2.65	2.50	2.55	2.65	2.57	9.96	−3.10	−2.92	2.17
Household Goods	1.06	1.03	0.82	0.89	1.02	0.91	9.21	11.98	12.13	4.34
Insurance	0.40	0.40	0.44	0.42	0.41	0.42	−0.35	11.36	11.37	2.76
Investment Banking and Investment Services	−1.94	−1.97	−1.77	−1.88	−1.92	−1.86	−4.72	−25.43	−25.58	−7.45
Investment Holding Companies	−2.49	−2.52	−2.28	−2.41	−2.46	−2.39	−10.25	−25.70	−25.43	−8.44
Leisure Products	0.37	0.37	0.38	0.38	0.37	0.38	0.26	−34.46	−34.48	−7.38
Machinery, Tools, Heavy Vehicles, Trains and Ships	0.93	0.91	0.89	0.89	0.93	0.90	1.46	−0.82	−0.78	0.59
Media and Publishing	1.70	1.66	1.55	1.58	1.67	1.60	5.53	14.90	15.12	5.03
Metals and Mining	−0.37	−0.39	−0.39	−0.39	−0.38	−0.39	−0.19	−4.03	−4.01	−1.17
Multiline Utilities	0.22	0.23	0.10	0.16	0.20	0.16	1.68	6.89	6.90	1.84
Natural Gas Utilities	−1.21	−1.21	−1.13	−1.16	−1.20	−1.16	−3.80	−8.48	−8.48	−3.09
Office Equipment	−1.88	−1.92	−1.71	−1.82	−1.85	−1.80	−10.92	−41.99	−42.01	−11.77
Oil and Gas	0.44	0.42	0.38	0.39	0.43	0.40	1.52	3.75	3.81	1.28
Oil and Gas Related Equipment and Services	0.37	0.35	0.39	0.36	0.38	0.37	−0.20	5.80	5.86	1.52
Paper and Forest Products	1.44	1.45	1.27	1.35	1.42	1.35	7.73	−0.43	−0.53	1.67
Passenger Transportation Services	0.53	0.49	0.44	0.43	0.52	0.46	2.07	−7.80	−7.68	−1.17
Personal and Household Products and Services	−1.31	−1.31	−1.22	−1.25	−1.29	−1.26	−2.71	12.16	12.12	1.55
Pharmaceuticals	0.17	0.13	0.08	0.08	0.15	0.10	2.70	4.49	4.60	1.39
Professional and Commercial Services	0.83	0.80	0.66	0.70	0.80	0.72	3.47	2.14	2.25	1.37
Real Estate Operations	−2.00	−2.00	−1.76	−1.86	−1.96	−1.87	−7.97	−15.95	−16.01	−5.71

Table 3 continued

Industry group	$\Pi 1 G1$	$\Pi 1 G2$	$\Pi 1 G3$	$\Pi 2 G1$	$\Pi 2 G2$	$\Pi 2 G3$	$\Pi 3 G1$	$\Pi 3 G2$	$\Pi 3 G3$	Average
Renewable Energy	2.00	1.99	1.88	1.91	1.98	1.93	6.34	−5.81	−5.72	0.72
Residential and Commercial REITs	−2.50	−2.49	−2.37	−2.41	−2.48	−2.42	−4.42	3.78	3.76	−1.28
Semiconductors and Semiconductor Equipment	−0.17	−0.19	−0.09	−0.14	−0.16	−0.13	−1.46	6.45	6.51	1.18
Software and IT Services	−0.31	−0.34	−0.34	−0.35	−0.32	−0.34	0.12	−5.37	−5.33	−1.40
Specialty Retailers	1.49	1.47	1.38	1.41	1.47	1.42	2.80	19.69	19.72	5.65
Telecommunications Services	0.61	0.58	0.54	0.54	0.60	0.56	1.60	7.49	7.49	2.22
Textiles and Apparel	0.47	0.46	0.47	0.45	0.47	0.47	0.40	−1.42	−1.37	0.05
Transport Infrastructure	0.20	0.19	0.14	0.15	0.19	0.16	1.79	9.95	9.97	2.53
Water and Related Utilities	4.11	4.12	3.53	3.79	4.03	3.79	15.35	−1.64	−1.86	3.91
Sector average	0.09	0.08	0.08	0.07	0.09	0.08	0.18	−1.50	−1.47	−0.26

Table 4 Relative distortion in ESG score by sector: second baseline scenario

Industry group	$\Pi 1G1$	$\Pi 1G2$	$\Pi 1G3$	$\Pi 2G1$	$\Pi 2G2$	$\Pi 2G3$	$\Pi 3G1$	$\Pi 3G2$	$\Pi 3G3$	Average
Aerospace and Defense	2.31	2.33	2.10	2.19	2.27	2.20	11.79	11.06	11.28	5.28
Automobiles and Auto Parts	0.42	0.41	0.40	0.38	0.39	0.39	1.41	1.27	1.35	0.71
Banking Services	0.62	0.62	0.55	0.58	0.60	0.58	2.63	2.43	2.45	1.23
Beverages	−1.17	−1.19	−1.11	−1.15	−1.18	−1.15	−3.97	−3.75	−3.76	−2.05
Biotechnology and Medical Research	1.37	1.30	1.37	1.24	1.25	1.28	4.68	4.31	4.52	2.37
Chemicals	0.20	0.18	0.15	0.14	0.16	0.15	1.69	1.57	1.58	0.65
Coal	1.81	1.81	1.63	1.68	1.75	1.70	13.32	12.31	12.64	5.40
Communications and Networking	2.55	2.56	2.33	2.40	2.49	2.43	13.38	12.27	12.63	5.89
Computers, Phones and Household Electronics	−1.85	−1.89	−1.61	−1.75	−1.84	−1.76	−13.19	−12.62	−12.56	−5.45
Construction and Engineering	2.15	2.16	2.01	2.06	2.12	2.07	4.49	4.26	4.32	2.85
Construction Materials	−0.93	−0.94	−0.82	−0.88	−0.92	−0.89	−2.57	−2.35	−2.25	−1.39
Consumer Goods Conglomerates	−3.24	−3.26	−2.90	−3.04	−3.17	−3.07	−23.34	−21.61	−21.78	−9.49
Containers and Packaging	−0.50	−0.54	−0.42	−0.52	−0.54	−0.50	−2.62	−2.51	−2.43	−1.17
Diversified Retail	2.23	2.27	2.04	2.17	2.24	2.16	6.07	5.72	5.69	3.40
Electric Utilities and IPPs	1.71	1.72	1.63	1.66	1.68	1.67	3.20	3.05	3.07	2.15
Electronic Equipment and Parts	0.17	0.14	0.22	0.15	0.13	0.16	−0.23	−0.16	−0.12	0.05
Food and Drug Retailing	2.30	2.30	2.15	2.19	2.25	2.21	5.36	5.08	5.18	3.22
Food and Tobacco	1.00	1.00	0.86	0.89	0.95	0.91	5.23	4.95	4.92	2.30
Freight and Logistics Services	0.21	0.18	0.22	0.17	0.17	0.19	0.45	0.40	0.48	0.27
Healthcare Equipment and Supplies	1.35	1.33	1.26	1.24	1.28	1.27	3.96	3.63	3.75	2.12
Healthcare Providers and Services	−0.08	−0.12	−0.05	−0.13	−0.14	−0.11	−0.02	−0.08	−0.00	−0.08
Homebuilding and Construction Supplies	−0.62	−0.61	−0.64	−0.61	−0.61	−0.62	0.42	0.35	0.37	−0.29

Table 4 continued

Industry group	$\Pi 1G1$	$\Pi 1G2$	$\Pi 1G3$	$\Pi 2G1$	$\Pi 2G2$	$\Pi 2G3$	$\Pi 3G1$	$\Pi 3G2$	$\Pi 3G3$	Average
Hotels and Entertainment Services	1.94	1.92	1.89	1.88	1.90	1.89	2.60	2.53	2.62	2.13
Household Goods	−0.51	−0.52	−0.53	−0.55	−0.54	−0.54	−0.71	−0.72	−0.73	−0.60
Insurance	0.37	0.37	0.41	0.39	0.37	0.39	−0.45	−0.40	−0.40	0.12
Investment Banking and Investment Services	−1.59	−1.63	−1.45	−1.57	−1.62	−1.56	−3.99	−3.75	−3.89	−2.34
Investment Holding Companies	−1.73	−1.78	−1.60	−1.73	−1.78	−1.72	−4.41	−4.34	−4.12	−2.58
Leisure Products	0.61	0.61	0.59	0.60	0.61	0.60	0.89	0.80	0.87	0.69
Machinery, Tools, Heavy Vehicles, Trains and Ships	0.96	0.94	0.95	0.92	0.92	0.93	1.43	1.39	1.40	1.09
Media and Publishing	2.25	2.23	2.11	2.11	2.17	2.14	7.43	6.91	7.09	3.83
Metals and Mining	−0.66	−0.67	−0.63	−0.66	−0.67	−0.66	−1.15	−1.13	−1.09	−0.81
Multiline Utilities	0.96	0.98	0.78	0.87	0.93	0.88	3.47	3.23	3.27	1.71
Natural Gas Utilities	−1.18	−1.19	−1.12	−1.15	−1.17	−1.15	−3.73	−3.53	−3.54	−1.97
Office Equipment	−2.47	−2.52	−2.24	−2.40	−2.49	−2.40	−12.49	−11.90	−11.94	−5.65
Oil and Gas	1.04	1.03	0.96	0.96	0.99	0.98	3.39	3.13	3.18	1.74
Oil and Gas Related Equipment and Services	1.51	1.48	1.45	1.42	1.45	1.44	3.16	3.01	3.07	2.00
Paper and Forest Products	2.97	3.00	2.68	2.82	2.93	2.83	12.78	12.14	12.11	6.03
Passenger Transportation Services	−0.42	−0.46	−0.36	−0.45	−0.47	−0.43	−1.15	−1.15	−1.07	−0.66
Personal and Household Products and Services	0.06	0.06	0.01	0.02	0.04	0.03	1.15	1.04	1.07	0.39
Pharmaceuticals	1.47	1.44	1.31	1.31	1.37	1.34	8.03	7.43	7.60	3.48
Professional and Commercial Services	0.51	0.50	0.44	0.43	0.46	0.45	2.64	2.43	2.50	1.15
Real Estate Operations	−0.43	−0.45	−0.39	−0.42	−0.44	−0.42	−1.64	−1.56	−1.57	−0.81
Renewable Energy	0.31	0.31	0.38	0.34	0.32	0.34	−2.31	−2.07	−2.10	−0.50
Residential and Commercial REITs	−2.82	−2.82	−2.69	−2.73	−2.78	−2.74	−5.53	−5.25	−5.31	−3.63

Table 4 continued

Industry group	**Π1*G*1**	**Π1*G*2**	**Π1*G*3**	**Π2*G*1**	**Π2*G*2**	**Π2*G*3**	**Π3*G*1**	**Π3*G*2**	**Π3*G*3**	Average
Semiconductors and Semiconductor Equipment	−0.98	−1.00	−0.81	−0.91	−0.97	−0.92	−3.67	−3.47	−3.44	−1.80
Software and IT Services	0.75	0.73	0.65	0.65	0.69	0.67	3.92	3.68	3.70	1.71
Specialty Retailers	2.01	2.00	1.89	1.91	1.96	1.93	4.24	4.05	4.08	2.68
Telecommunications Services	0.68	0.66	0.65	0.62	0.64	0.64	1.89	1.77	1.81	1.04
Textiles and Apparel	1.76	1.74	1.66	1.66	1.70	1.68	4.16	3.91	3.95	2.47
Transport Infrastructure	2.04	2.04	1.83	1.89	1.98	1.92	9.20	8.58	8.66	4.24
Water and Related Utilities	5.61	5.67	5.00	5.28	5.52	5.32	20.61	19.79	19.61	10.27
Sector average	0.53	0.52	0.49	0.48	0.50	0.49	1.61	1.49	1.54	0.85

environmental controversies become less prominent in the public debate, contributing to a favorable perception of those environmentally intense industries. This element must be considered by policymakers, as policies that promote the adoption of social projects by companies could be exploited by polluting firms to counterbalance their suboptimal environmental performance and be perceived as more sustainable.

Across different sectors, the most affected industries are household electronics, natural gas utilities, and construction materials, with the latter experiencing an average loss of 9.49. On the other hand, industries that would benefit the most include communication and networking, paper and forest products, with water-related utilities being the most favored among all industries, experiencing an average increase of 10.27.

Concerning the third scenario, from Table 5, we observe an average decrease of 2.14 across all pairs of garbling and information matrices. For each pair, the average change is negative, indicating that regardless of the agents' perception, an increase in environmental and disclosure standards would lead to a reduction in the average valuation of companies across most industries.

So, we observe that additional legislative pressure on these factors would penalize almost every industry, even those considered environmentally friendly. This denotes a widespread vulnerability of companies' scores to climate change policies. In particular, the current companies' plans to reduce their environmental footprint are considered insufficient in addressing climate change by most participants concerned about climate issues, regardless of their thoughts on how severe climate change will be and the policies to counter it.

The industries that benefited the most from increasing disclosure would be paper and forest products, water-related utilities, and diversified retail, with an average increase of at least 2.7 points. Instead, the ones that would suffer more in this scenario are investment banking and services, office equipment, and biotechnology products, with a minimum average loss of 8.60 points among these three industries.

5 Conclusion

In a current geopolitical historical period, where wars and conflicts are arising each day, and the awareness of social injustices is spreading worldwide, policymakers have a crucial role in our society. More than ever, policymakers across the globe must try to coordinate their effort and lead global actions towards these issues, assuring convergence to a common good. The undisputed priority is climate change, which is expected to drive future interventions toward concrete actions whose goal and direction are not affected (and perceived) by uncertainty. Several efforts have been made to methodically define pollution containment and facilitate a sustainable economic transition. This includes the introduction of tools such as different ESG metrics to assess the sustainability of different firms and sectors. Indeed, among the critiques posed to governments, there is a lack of clarity on the ESG terminology (taxonomy) and standards, and a lack of transparency and reported data by businesses, which foments an intense debate and relies on the presence of a great level of ambiguity affecting the market.

Therefore starting from the complex ESG factors, their unclear definition, and the doubtless market uncertainty, we proposed a new evaluation model where the role of

Table 5 Relative distortion in ESG score by sector: third baseline scenario

Industry group	$\Pi 1G1$	$\Pi 1G2$	$\Pi 1G3$	$\Pi 2G1$	$\Pi 2G2$	$\Pi 2G3$	$\Pi 3G1$	$\Pi 3G2$	$\Pi 3G3$	Average
Aerospace and Defense	0.69	0.68	0.63	0.63	0.67	0.65	3.64	3.34	3.50	1.61
Automobiles and Auto Parts	−0.94	−0.94	−0.86	−0.86	−0.91	−0.89	−2.71	−2.46	−2.60	−1.46
Banking Services	0.14	0.14	0.12	0.12	0.13	0.13	0.82	0.73	0.77	0.34
Beverages	−1.27	−1.26	−1.21	−1.21	−1.24	−1.23	−4.46	−4.16	−4.29	−2.26
Biotechnology and Medical Research	−5.35	−5.26	−4.82	−4.82	−5.15	−5.02	−20.66	−18.57	−19.69	−9.93
Chemicals	−1.69	−1.68	−1.59	−1.59	−1.65	−1.63	−4.41	−4.14	−4.24	−2.51
Coal	−0.35	−0.37	−0.36	−0.36	−0.34	−0.36	−0.55	−0.54	−0.55	−0.42
Communications and Networking	−0.27	−0.25	−0.23	−0.23	−0.26	−0.24	−1.70	−1.52	−1.62	−0.70
Computers, Phones and Household Electronics	−2.23	−2.19	−1.99	−1.99	−2.14	−2.08	−14.68	−13.79	−14.17	−6.14
Construction and Engineering	0.38	0.39	0.40	0.40	0.38	0.39	0.10	0.13	0.11	0.30
Construction Materials	−1.25	−1.23	−1.13	−1.13	−1.20	−1.17	−3.64	−3.24	−3.38	−1.93
Consumer Goods Conglomerates	−0.63	−0.62	−0.55	−0.55	−0.59	−0.58	−6.15	−5.59	−5.83	−2.34
Containers and Packaging	−2.42	−2.40	−2.22	−2.23	−2.33	−2.30	−12.55	−11.51	−12.01	−5.55
Diversified Retail	2.65	2.64	2.47	2.47	2.56	2.55	6.92	6.37	6.62	3.92
Electric Utilities and IPPs	0.25	0.26	0.29	0.30	0.27	0.28	−0.46	−0.37	−0.41	0.05
Electronic Equipment and Parts	−1.95	−1.92	−1.74	−1.74	−1.87	−1.82	−5.91	−5.47	−5.51	−3.10
Food and Drug Retailing	0.10	0.12	0.15	0.15	0.12	0.14	−1.30	−1.15	−1.20	−0.32
Food and Tobacco	−1.21	−1.20	−1.16	−1.16	−1.19	−1.18	−2.64	−2.52	−2.55	−1.65
Freight and Logistics Services	−1.56	−1.54	−1.41	−1.41	−1.50	−1.47	−5.68	−5.22	−5.47	−2.81
Healthcare Equipment and Supplies	−1.81	−1.79	−1.65	−1.65	−1.74	−1.71	−5.42	−4.90	−5.14	−2.87
Healthcare Providers and Services	−3.13	−3.09	−2.87	−2.87	−3.03	−2.97	−7.88	−7.38	−7.49	−4.52
Homebuilding and Construction Supplies	−0.11	−0.11	−0.15	−0.15	−0.13	−0.13	1.60	1.42	1.51	0.42
Hotels and Entertainment Services	−0.52	−0.48	−0.36	−0.35	−0.46	−0.41	−9.63	−8.66	−9.10	−3.33
Household Goods	−2.57	−2.54	−2.42	−2.41	−2.52	−2.47	−8.41	−7.92	−8.12	−4.38

Table 5 continued

Industry group	$\Pi 1G1$	$\Pi 1G2$	$\Pi 1G3$	$\Pi 2G1$	$\Pi 2G2$	$\Pi 2G3$	$\Pi 3G1$	$\Pi 3G2$	$\Pi 3G3$	Average
Insurance	0.32	0.32	0.35	0.35	0.33	0.34	−0.67	−0.59	−0.62	0.01
Investment Banking and Investment Services	−3.82	−3.77	−3.52	−3.52	−3.71	−3.63	−9.46	−8.61	−9.20	−5.47
Investment Holding Companies	−4.14	−4.10	−3.84	−3.84	−4.02	−3.96	−18.83	−17.35	−17.95	−8.67
Leisure Products	0.18	0.20	0.22	0.22	0.18	0.21	−0.13	−0.05	−0.11	0.10
Machinery, Tools, Heavy Vehicles, Trains and Ships	−1.07	−1.04	−0.91	−0.91	−1.01	−0.97	−4.19	−3.86	−3.97	−1.99
Media and Publishing	−1.46	−1.43	−1.29	−1.29	−1.40	−1.35	−7.47	−6.70	−7.13	−3.28
Metals and Mining	−1.35	−1.34	−1.27	−1.27	−1.32	−1.30	−3.46	−3.25	−3.33	−1.99
Multiline Utilities	0.27	0.26	0.17	0.17	0.23	0.21	1.78	1.58	1.67	0.70
Natural Gas Utilities	−0.71	−0.71	−0.69	−0.70	−0.70	−0.70	−1.47	−1.41	−1.44	−0.95
Office Equipment	−3.80	−3.76	−3.50	−3.51	−3.68	−3.62	−22.81	−21.01	−21.98	−9.74
Oil and Gas	−1.01	−1.00	−0.93	−0.93	−0.98	−0.96	−3.09	−2.82	−2.92	−1.63
Oil and Gas Related Equipment and Services	−1.67	−1.63	−1.46	−1.46	−1.59	−1.54	−7.05	−6.60	−6.78	−3.31
Paper and Forest Products	1.15	1.15	1.06	1.06	1.10	1.10	6.22	5.73	5.92	2.72
Passenger Transportation Services	−2.97	−2.94	−2.73	−2.73	−2.87	−2.82	−9.16	−8.31	−8.76	−4.81
Personal and Household Products and Services	−0.78	−0.78	−0.76	−0.76	−0.77	−0.77	−1.18	−1.13	−1.15	−0.90
Pharmaceuticals	−3.04	−3.01	−2.82	−2.82	−2.96	−2.90	−11.52	−10.60	−11.01	−5.63
Professional and Commercial Services	−2.21	−2.18	−2.06	−2.06	−2.16	−2.12	−5.33	−4.97	−5.14	−3.14
Real Estate Operations	−1.09	−1.07	−0.99	−0.99	−1.05	−1.03	−4.32	−3.99	−4.14	−2.08
Renewable Energy	0.33	0.34	0.38	0.38	0.35	0.36	−2.16	−1.89	−2.01	−0.44
Residential and Commercial REITs	−1.07	−1.07	−1.10	−1.10	−1.08	−1.09	−0.51	−0.59	−0.55	−0.91
Semiconductors and Semiconductor Equipment	−1.21	−1.19	−1.06	−1.06	−1.15	−1.12	−4.23	−3.92	−3.99	−2.10

Table 5 continued

Industry group	**Π1*G*1**	**Π1*G*2**	**Π1*G*3**	**Π2*G*1**	**Π2*G*2**	**Π2*G*3**	**Π3*G*1**	**Π3*G*2**	**Π3*G*3**	Average
Software and IT Services	−2.38	−2.35	−2.21	−2.21	−2.32	−2.27	−7.34	−6.91	−7.05	−3.89
Specialty Retailers	−0.22	−0.20	−0.14	−0.14	−0.19	−0.17	−1.55	−1.40	−1.47	−0.61
Telecommunications Services	−1.51	−1.49	−1.37	−1.37	−1.45	−1.42	−4.35	−4.04	−4.12	−2.35
Textiles and Apparel	−1.18	−1.15	−1.03	−1.03	−1.12	−1.08	−4.60	−4.22	−4.32	−2.19
Transport Infrastructure	−0.75	−0.74	−0.71	−0.71	−0.73	−0.72	−2.03	−1.89	−1.95	−1.14
Water and Related Utilities	2.16	2.13	1.91	1.91	2.05	2.01	8.93	8.49	8.59	4.24
Sector Average	−1.14	−1.12	−1.04	−1.04	−1.10	−1.07	−4.43	−4.07	−4.23	−2.14

information and perception of the signals have a dominant role. Actually, the paper proposes to capture the ambiguity by the comparison of the Refinitiv-ESG rating and a benchmark that gives explicit attention to the industry metrics for materiality. As a matter of fact various bodies are involved in assessing the consistency of ESG information; among them, SASB uses an overall assessment applied to each industry which determines the relative significance of each factor and subfactor based on the external environment and business model.

The proposed model infers a distortion on the ESG rating which is valuable because:

- it has a forecasting power if the calibrated ambiguity is assumed to be representative of the market sentiment;
- it is a useful tool for policy-makers, able to identify ESG-under/overestimated sectors based on a forward-looking perspective;
- it allows to make clear the sensitivity of the official ESG rating to the information signal, hence showing its level of robustness to the singular pillars.

The 2023 Refinitiv-ESG scores reveal that, overall, the E pillar tends to be slightly undervalued for most types of market agents. Significant positive impacts on scoring result from variations in the weight of the S pillar, especially notable for industries with high environmental intensity. Conversely, governance factors, along with environmental considerations, are currently undervalued, consistently yielding negative impacts across almost all sectors and levels of ambiguity.

The transition matrices identified here could help policymakers understand which notches are more sensitive to each factor and how the evaluation of companies would change, identifying possible incentives or penalization that policymakers could implement to lead the transition toward a more sustainable economy. In particular, from our results, we see that if policymakers strengthen their attention toward environmental factors, this would favor the evaluation of poorly performing companies, since they are already obliged by law to adhere to some restrictive environmental standards. Conversely, increasing attention to social factors would penalize highly graded companies, indicating a vulnerability of highly graded companies to shifts in the actual scoring procedure. Finally, expanding the governance factor, particularly the Corporate Social Responsibility (CSR) factor, along with the environmental pillar, would result in fewer changes in notches compared to the other scenarios considered, indicating that they already play a relevant role in the scoring procedure.

Furthermore, the average score deviation that is retrieved for each scenario and pair of garbling and information matrices, can be used by policymakers to quantify the vulnerability of each sector to policy changes and the role of ambiguity of market agents on the evaluation of the companies.

We can observe that increasing the relevance of environmental components together with the product responsibility factor for most of the agents would penalize product-based industries with respect to the services one, and in particular for extremely concerned investors who are doubtful toward the path adopted by legislators the expected policy effects are particularly acute. Instead for the second scenario, we observe that increasing both the E and S pillars would produce generally positive increments of the score for all types of agents, also for some environmentally intense industries. In particular, this element should raise concern for the legislators because a policy with a strong focus on the social and the environmental components could be exploited by environmentally intense industries to compensate for their inadequate environmental standards with social projects.

Finally, in the third scenario, policymakers would understand how implementing stricter environmental and CSR standards, such as imposing new pollution restrictions and adopting new accounting standards for emissions, would lead to a decrease in evaluation for the majority of the sectors considered, regardless of the agents' attitudes. This indicates that on average in almost all sectors companies' efforts to reduce their impact are insufficient, compounded by blurred reporting standards. All these could help policymakers identify which are the most suitable combination of reporting standards and pollution restrictions to align upward the industries' performances.

Appendix A: Scenario-based average transition matrix

Tables 6, 7, and 8 are the average transition matrices computed for each scenario. Each element of these matrices represents the average frequency of industries changing notches from a starting one, reported in the rows of the tables, to the ending one, reported in the columns, once the weight structure changes under the different scenarios.

As the first step to retrieve the average transition matrices, we retrieve the transition matrix for each pair of garbling and information matrices. For each pair of garbling and information matrices, we initially compute the ESG score and then the ESG rating for each company under each simulated shock from our sample of 10,000 observations for each scenario. Once we obtain the new ratings, for each company, we enumerate the number of times its rating changes, considering the starting and ending ratings. Subsequently, we aggregate the number of notch changes for all companies within the same starting notch and then compute the frequency of notch changes.

Once the transition matrices for each pair of garbling and information matrices were retrieved, we computed the average transition matrices for each scenario. This was accomplished by averaging the frequency of transitions from a starting notch to another across all pairs of garbling and information matrices.

In the following tables, each element in the matrices is rounded to the fourth decimal place.

Appendix B Materiality score and sector-based ambiguity factors

We create a proxy measure of the ESG score assigned by market agents to various companies, utilizing the Materiality Map provided by the SASB. Specifically, we adjust the Refinitiv's weights of the ESG factors for each industry to reflect the factors outlined in the Materiality Map, which could be considered by market agents as a widely acknowledged framework.

The Materiality Map delineates, for each of the 77 industries identified by the SASB, the most pertinent sustainable factors from a list of 26 sustainability factors. Unfortunately, the industries highlighted by the SASB and their sustainability factors

Table 6 Average transition matrix: first baseline scenario

Start & End	D−	D	D+	C−	C	C+	B−	B	B+	A−	A	A+
D−	92.27	7.25	0.30	0.18	0	0	0	0	0	0	0	0
D	5.78	83.56	9.75	0.50	0.33	0.06	0.01	0.01	0	0	0	0
D+	0.12	4.71	88.33	6.20	0.47	0.12	0.05	0.01	0	0	0	0
C−	0.05	0.20	4.16	86.97	7.99	0.43	0.18	0.01	0	0	0	0
C	0	0.07	0.16	4.75	86.61	7.87	0.45	0.07	0.02	0	0	0
C+	0	0.01	0.04	0.18	5.72	86.19	7.14	0.56	0.15	0.01	0	0
B−	0	0	0.01	0.08	0.39	6.70	85.21	6.96	0.51	0.12	0.01	0
B	0	0	0	0	0.06	0.53	6.54	85.50	6.83	0.51	0.04	0
B+	0	0	0	0	0.12	0.13	0.42	6.19	87.08	5.96	0.20	0.01
A−	0	0	0	0	0	0	0.08	0.36	4.88	91.00	3.60	0.07
A	0	0	0	0	0	0	0	0.04	0.24	5.78	91.63	2.32
A+	0	0	0	0	0	0	0	0	0.04	0.32	8.72	90.9

Table 7 Average transition matrix: second baseline scenario

Start & End	D−	D	D+	C−	C	C+	B−	B	B+	A−	A	A+
D−	93.99	5.23	0.57	0.13	0.05	0.02	0.01	0	0	0	0	0
D	4.52	86.13	8.58	0.55	0.12	0.06	0.04	0	0	0	0	0
D+	0.43	5.92	84.86	8.08	0.55	0.13	0.04	0	0	0	0	0
C−	0.06	0.27	4.88	87.11	7.19	0.40	0.09	0	0	0	0	0
C	0.02	0.05	0.27	5.87	86.03	7.37	0.33	0.05	0	0	0	0
C+	0.01	0.02	0.06	0.30	5.87	85.51	7.74	0.42	0.07	0	0	0
B−	0	0.01	0.02	0.06	0.26	6.60	85.93	6.62	0.37	0.10	0.03	0
B	0	0	0	0	0.03	0.29	58.70	85.70	7.67	0.28	0.11	0.03
B+	0	0	0	0	0	0.04	0.26	64.20	87.50	5.20	0.47	0.12
A−	0	0	0	0	0	0	0.07	0.25	5.24	87.69	6.19	0.56
A	0	0	0	0	0	0	0.02	0.10	0.50	7.55	86.57	5.25
A+	0	0	0	0	0	0	0	0.03	0.14	0.64	8.99	90.20

Table 8 Average transition matrix: third baseline scenario

Start & End	D−	D	D+	C−	C	C+	B−	B	B+	A−	A	A+
D−	92.59	6.26	0.68	0.25	0.18	0.01	0.02	0	0	0	0	0
D	4.29	88.31	6.44	0.74	0.13	0.07	0.02	0	0	0	0	0
D+	0.37	4.59	87.35	6.92	0.55	0.14	0.09	0	0	0	0	0
C−	0.11	0.48	5.30	87.38	5.98	0.57	0.13	0.03	0	0	0.01	0
C	0.05	0.06	0.30	4.31	89.00	5.67	0.48	0.11	0.01	0	0	0
C+	0	0.02	0.06	0.29	4.15	90.42	4.70	0.31	0.03	0.01	0.01	0
B−	0	0.01	0.03	0.07	0.35	4.16	90.88	4.23	0.21	0.04	0.01	0
B	0	0	0	0.01	0.08	0.29	4.52	90.71	4.08	0.24	0.03	0.02
B+	0	0	0	0	0.01	0.02	0.20	3.57	92.23	3.84	0.12	0.01
A−	0	0	0	0	0	0.01	0.04	0.22	3.77	93.02	2.89	0.05
A	0	0	0	0.01	0	0.01	0.02	0.04	0.20	5.26	92.99	1.47
A+	0	0	0	0	0	0	0	0.08	0.03	0.20	4.24	95.45

Table 9 Refinitiv's factors and SASB's materiality map

ESG pillar	ESG factor	Materiality factor
Enviroment	Emission	GHG emission
		Air quality
		Waste and hazardous material management
		Ecological impacts
	Innovation	Product design and lifecycle management
		Business model resilience
		Physical Impacts of climate change
	Resource Use	Energy Management
		Water and wastewater management
		Supply chain management
		Material Sourcing and Efficiency
Social	Community	Access and affordability
		Customer welfare
		competitive behavior
	Human rights	Human rights and community relations
	Product responsibility	Customer Privacy
		data security
		product quality and safety
		selling practices and product labeling
	Workforce	Labor practices
		Employee health and safety
		employee engagement, diversity and inclusion
Governance	CSR Strategy	Business ethics
		management of the legal and regulatory environment
		critical incident risk management
		systemic risk management
	Management	–
	Shareholders	–

This table indicates, for each ESG factor according to the Refinitiv classification, which Materiality factor it corresponds to

do not have a one-to-one match with Refinitiv's. For this reason, initially, we correlate each factor from the materiality maps with the Refinitiv factors, striving to determine how each ESG factor and Refinitiv data align with the elements identified in the materiality map. In Table 9, different factors are outlined for each ESG pillar, and for each Refinitiv factor, it is outlined which of the materiality factors presents the best correspondence.

Table 10 Sector-based ambiguity factor α, number of companies considered, and materiality factors

TRBC industry group	N. of materiality factors	N. of industries	α
Aerospace and Defense	7	11	0.704
Automobiles and Auto Parts	4	25	0.084
Banking Services	6	42	0.272
Beverages	8	11	0.618
Biotechnology and Medical Research	8	10	0.392
Chemicals	10	33	0.183
Coal	9	1	0.848
Communications and Networking	6	3	0.787
Computers, Phones and Household Electronics	5	7	0.604
Construction and Engineering	5	32	0.119
Construction Materials	9	7	0.171
Consumer Goods Conglomerates	9	5	0.884
Containers and Packaging	8	7	0.504
Diversified Retail	6	2	0.053
Electric Utilities and IPPs	9	21	0.123
Electronic Equipment and Parts	6	6	0.001
Food and Drug Retailing	9	14	0.292
Food and Tobacco	11	26	0.202
Freight and Logistics Services	8	18	0.107
Healthcare Equipment and Supplies	6	19	0.109
Healthcare Providers and Services	13	6	0.000

Table 10 continued

TRBC industry group	N. of materiality factors	N. of industries	α
Homebuilding and Construction Supplies	4	13	0.296
Hotels and Entertainment Services	7	14	0.829
Household Goods	2	8	0.448
Insurance	4	18	0.176
Investment Banking and Investment Services	4	13	0.019
Investment Holding Companies		5	0.622
Leisure Products	2	5	0.027
Machinery, Tools, Heavy Vehicles, Trains and Ships	4	62	0.038
Media and Publishing	5	20	0.297
Metals and Mining	11	33	0.184
Multiline Utilities	13	8	0.015
Natural Gas Utilities	13	1	0.467
Office Equipment	4	3	0.896
Oil and Gas	13	22	0.115
Oil and Gas Related Equipment and Services		19	0.100
Paper and Forest Products	5	9	0.661
Passenger Transportation Services	8	10	0.205
Personal and Household Products and Services	4	5	0.022
Pharmaceuticals	8	25	0.416

Table 10 continued

TRBC industry group	N. of materiality factors	N. of industries	α
Professional and Commercial Services	3	22	0.017
Real Estate Operations	2	16	0.312
Renewable Energy	8	10	0.553
Residential and Commercial REITs	4	21	0.196
Semiconductors and Semiconductor Equipment	9	16	0.059
Software and IT Services	6	38	0.232
Specialty Retailers	5	11	0.078
Telecommunications Services	6	23	0.187
Textiles and Apparel	3	16	0.106
Transport Infrastructure	5	7	0.413
Water and Related Utilities	7	1	0.030

Once the correspondence between Refinitiv's and SASB's factors is outlined, we define the correspondence between the sectors identified by Refinitiv and SASB. The aim is to ensure that for each Refintiv sector, there exists one or more SASB industries that comprehensively cover all or most of the activities performed within each industry. To achieve this alignment, we rely on the industry activity descriptions provided by SASB on their website aligning that to the "Refinitiv Classification System" (TRBC). Then, for each sector identified by Refinitiv, we connected the materiality factors to construct the materiality score. The factors for each sector are determined by the sum of factors for each SASB industry corresponding to the specific sector.

In Table 10, we present each sector included in our sample (first column), along with the number of materiality factors considered for each sector (second column). The third column indicates the number of companies in our sample for each sector. Finally, the last column displays the recovered ambiguity factor α for each sample.

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Declarations

Conflict of interest The authors have no conflict of interest to declare that are relevant to the content of this article.

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