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RESEARCH ARTICLE

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How to combine ESG scores? A proposal based on credit rating prediction

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Abstract

The diffusion of Environmental, Social and Governance (ESG) metrics is increasingly affecting corporates behaviour and their ability to attract investors. Corporate ESG practices are nowadays considered as a key element in evaluating creditworthiness and the cost of capital, to direct funds to the best-performing companies that limit the harmful impact on the planet and the societies. Due to this increased interest in ESG by companies, investors and policymakers, a high number of ESG scores and metrics have been developed, each with different methodologies and scopes. Because of this variety, it could be therefore challenging for investors to understand and compare ESG measures. In this paper, we address this issue by proposing a method to combine the information provided by different ESG scores into a single aggregate measure of company sustainability and link this combined score to the credit rating of companies. The proposed methodology can help investors to improve their investment decisions by combining more diverse information on company sustainability as a driver of companies' credit rating, thereby reducing information asymmetries.

KEYWORDS
Bayesian models, credit rating, ESG rating, sustainable finance

1 | INTRODUCTION

The impact of business activities on the environment and society has become more and more important over the last decades. Companies are being made accountable for their impact on the planet and on societies through the measurement of their Corporate Social Performance (CSP). The latter is aimed at evaluating the degree to which companies are sustainable, that is, how they perform their business activities in relation to the external stakeholders and taking into account the economic, environmental, social, and time factors (Lozano, 2012, 2018; Muñoz-Torres et al., 2019). Environmental, Social and Governance (ESG) factors are often taken as a proxy for the sustainable behaviour of companies (Pollman, 2022).

- Environment factors relate to the impact on the environment deriving from the production of goods or services and include carbon emissions, preservation of the natural environment, biodiversity protection, and waste and water management (European Commission, n.d.; Financial Times, n.d.; Robeco, n.d.). A company that operates with less harm to the environment might reduce the probability of future scandals, legal actions, losses related to legal claims etc. and benefit from a better reputation and lower risks (Fafaliou et al., 2022).

- Social factors refer to the impact of the company on society, including issues of employee satisfaction, diversity, inequality, gender gap, protection of young and children, investment in human capital and communities, and human rights (European Commission, n.d.; Van Duuren et al., 2016).
- Governance factors instead are accounted for to evaluate the 'good' governance of companies. Shortcomings in governance have been in the past the cause of major scandals and crises, such as the Enron crisis in the US, Volkswagen in Germany, Cirio and Parmalat in Italy, and the banking crisis of 2007–2008 (Shin et al., 2022; Soltani, 2014). Improved governance settings can contribute to a more sustainable and balanced firms' growth, therefore contributing to more sustainable economic development (Adams & Mehran, 2012; Esteban-Sanchez et al., 2017).

Within sustainable financing and the path towards sustainable growth, these three factors have also become the basis for investment decisions and can drive the choice of investors in terms of which companies to finance through equity or debt.

To further underline the importance of ESG behaviour and push companies to improve their CSP or ESG behaviour, policymakers and regulators have developed specific measures. International authorities have started to include sustainability in their agenda (UN, 2015; European Commission, 2018, 2021); European financial regulators request financial intermediaries to include ESG aspects for lending and investment activities (EBA, 2020; ESMA, 2020a, 2020b) and call for the inclusion of ESG aspects into credit ratings issued by credit rating agencies (European Action Plan for Financing Sustainable Growth) (European Commission, 2018). The final objective would be to direct funds only to the best-performing companies that are able to run their business by limiting harmful impacts on the natural environment and society. Apart from the ethical concerns, ESG behaviour has also a link with economic performance. In fact, ESG behaviour can influence companies' revenues and profitability and physical risks deriving from climate change can produce losses that can affect companies' ability to meet their credit obligations, and considering how ESG performance impacts credit ratings is especially important during times of market distress (Kanno, 2023; Devalle et al., 2017; Chodnicka-Jaworska, 2021). Companies are therefore pushed by different actors towards a more virtuous behaviour in terms of Environmental, Social and Governance aspects to obtain more favourable conditions on their financing. Companies are also pushed to disclose more about their ESG behaviour, to reduce asymmetries of information and improve their ability to retrieve cheaper funds (Yu et al., 2021). ESG behaviour and ESG disclosure can reduce the perceived riskiness of companies and hence the cost of capital. According to Horn (2023), ESG ratings reduce idiosyncratic risks and Giese et al. (2019) further find that ESG information also reduces systematic risk. Further, Bax et al. (2023) find that ESG risks are found to contribute to tail risks in portfolio construction.

To improve the ability of investors to understand ESG performance, specialised companies (including rating agencies) have started to provide measures and proxies for ESG behaviour, publishing ESG ratings or ESG scores that should convey the level of sustainability of companies and the degree of accountability of these companies on ESG aspects (Scalet & Kelly, 2010; Avetisyan & Ferrary, 2013).

Each rating provider collects information from different sources (company reports, news, stock exchange information, etc.) and applies proprietary methodologies to combine information and produce a synthetic measure of ESG behaviour. These different methodologies yield different measures, that often produce divergent results (Berg et al., 2022; Dorfleitner et al., 2015; Abhayawansa & Tyagi, 2021; Dimson et al., 2020; Billio et al., 2021), yielding to potential 'sustainability arbitrage' as recently discussed in Pollman (2022). Additionally, ESG scores are sometimes computed on the availability of information relating to ESG issues and this favours larger firms that have a higher availability of information (Drempetic et al., 2020).

Multiple ESG ratings for a given company can differ and create opaqueness in the company's actual ESG performance. A recent survey by KPMG showed the existence of more than 160 ESG ratings and data providers (KPMG, 2020), with multiple agencies (eg. Bloomberg, Thomson Reuters, S&P, etc.) whose ESG ratings may however differ. Dorfleitner et al. (2015) showed little convergence between different ESG ratings. More recently, Abhayawansa and Tyagi (2021) provide evidence of the low correlation between ESG ratings issued by different providers.

Further differences among ratings arise when considering separately the Environmental, Social and Governance dimensions. While Environmental impact can be easier to measure, the weight of qualitative aspects is particularly important for the Social and Governance impacts. Muñoz-Torres et al. (2019) find that the environmental dimension is the most common factor employed by rating agencies when computing ESG scores (e.g., reduction of waste, energy consumption, water management). Less used, the Social and Governance factors are difficult to be measured and compared[1] and might have an unclear impact on the sustainability of a company. Despite some criticisms, evidence shows that rating agencies worked to update their methodologies to compute ESG ratings, although not being able to capture entirely CSP into ratings (Escrig-Olmedo et al., 2019; Muñoz-Torres et al., 2019).

Overall, the presence of ESG scores in the market can push companies to improve their CSP or ESG behaviour (Zeng and Yu, 2019), but it also presents possible drawbacks and these must be tackled to ensure comparability of ESG measures.

Standardisation of ESG metrics is, in fact, of primary importance to enable investors to choose among investment opportunities, to allow companies to take appropriate measures to improve their Environmental, Social and Governance footprint, and to improve the degree of transparency of ESG rating providers, as recently underlined

[1]For instance, in some industries (such as banking), there are specific regulations on the composition and skills of the Board of Directors, which affect the comparability of ratings in the market (see e.g. CRD5 and Hopt (2013) for an overview).

by the International Organisation of Securities Commissions (OICV-IOSCO, 2021).

The importance of ESG metrics is further destined to grow in the future and ESG ratings will influence investors' decisions, therefore affecting firms' ability to finance their investment and also their capability to pursue a more sustainable business model. The need for ESG metric standardisation is therefore strongly felt by the market, motivated by the growing importance of sustainable finance[2] and understanding how ESG ratings provide information to the market and how these ratings can affect creditworthiness is a major managerial and policy challenge.

This article addresses this issue by proposing to combine different ESG scores into an aggregated measure, through an appropriate statistical method. To test the goodness of the combined score, we lever the environment of credit ratings, by testing if the combined metric performs better than the separate scores in predicting credit rating class.

The calculation of the combined ESG metrics relies in this paper on a Bayesian method which assigns likelihood-based weights to each of the ESG ratings to be combined, extending the work of Cerchiello and Giudici (2014) from the binary to the multinomial case and from credit ratings to ESG ratings. We show that the advantage of the method is not only the provision of a unified rating but also the improvement of the predictive accuracy of credit ratings.

This serves two different objectives. The first is to provide a single combined score on firms' ESG behaviour; the second is to test if ESG behaviour combined score has an impact on creditworthiness, as suggested by previous research and prompted by policymakers and regulators (Lagoarde-Segot, 2019; EBA, 2020).

To the best of our knowledge, what is proposed in this paper is the first attempt to obtain a combined indicator that merges information from different ESG scores, taking their predictive accuracy into account. We also provide a statistical proposal to test whether the combined score predicts credit ratings better than each of the individual ESG scores. The outcome of our research has relevant managerial implications: the methodology does not aim at individuating the 'best' ESG score, but it is a tool that could assist investors in exploiting all available information to take the appropriate lending or investment decisions, by combining more and diverse information on sustainability issues and hence, reducing information asymmetries. This could be beneficial for companies that are subject to multiple, possibly divergent, ESG evaluations.

The remainder of this article is organised as follows: Section 2 introduces the proposed modelling approach, Section 3 presents an application of the methodology to a sample of European companies and, finally, Section 4 concludes.

[2]Just as a background, the number of sustainable investment funds available in Europe grew from 200 at the end of 2016 to 3196 at the end of 2020 (Morningstar, 2021), with a corresponding growth in the managed assets.

2 | METHODOLOGY

2.1 | Modelling framework

This paper provides a synthetic indicator for the ESG performance of listed companies by integrating the ESG scores provided by different providers. The indicator is obtained by assigning to each available ESG score a weight that is a function of the likelihood of the observed counts of credit rating classes, under the alternative partitions generated by the ESG scores. The likelihood weights are obtained through. the application of Bayes' theorem.

Additionally, to investigate the validity of our combined score from the investor's perspective, we lever the relationship between ESG scores and credit rating. Indeed, we investigate the possibility of improving credit risk prediction through the efficient use of different ESG data sources. We resort to the methodology proposed by Cerchiello and Giudici (2014), who considered the case of estimating a company's probability of default using a set of explanatory financial variables. In the cited work, it is assumed that the partition g_k generated by the k-th among K covariates is made up of $j=1,\ldots,J_k$ levels and that the probability of default of company i ($\mathrm{Prob}(Y_i=1)$), where Y_i is a binary variable equal to 1 if company i defaults, 0 otherwise) is constant within the same j level of the covariate and equal to θ_j.

Letting Y_i be a Bernoulli (θ_j) variable and the θ_j's Beta random variables with parameters α and β, which implies that, a priori, $E(\theta_j)=\frac{\alpha}{\alpha+\beta}$, the marginal likelihood contribution of level j can be obtained as:

$$p(y|j)=\int_0^1 p(y|\theta_j)p(\theta_j)d\theta_j$$

$$=\int_0^1 \theta_j^{d_j}(1-\theta_j)^{n_j-d_j}\frac{1}{B(\alpha,\beta)}\theta_j^{\alpha-1}(1-\theta_j)^{\beta-1}d\theta_j=$$

$$=\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\frac{\Gamma(\alpha+d_j)\Gamma(\beta+n_j-d_j)}{\Gamma(\alpha+\beta+n_j)},$$

where $p(\theta_j)$ is the prior distribution of θ_j, $B(\alpha,\beta)$ is the Beta function, d_j is the number of defaulted companies and n_j is the total number of companies sharing level j of the k covariate.

Under the assumption that the θ_j's are independent random variables, the marginal likelihood of the partition g_k is:

$$p(y|g_k)=\prod_{j=1}^{J_k}p(y|j),$$

which determines the posterior probability of the partition:

$$p(g_k|Y)\propto p(y|g_k)p(g_k),$$

where $p(g_k)$ can be set a priori, for example according to the uniform distribution: $p(g_k)\propto 1/M$, where M is a constant.

The expected probability of default of company i, conditional on the available set of covariates X, can then be obtained as follows:

$$E(\theta_i|X,Y) = \sum_{k=1}^{K} E(\theta_j|g_k,Y)p(g_k|Y),$$

with $E(\theta_j|g_k,Y) = \frac{\alpha+d_j}{\alpha+\beta+n_j}$, in which the posterior probability $p(g_k|Y)$ acts as k-th covariate weight in determining the expected probability of the default event.

2.2 | Multinomial response variable

In this section we introduce the extension of the modelling approach by Cerchiello and Giudici (2014) to the case of a multinomial target variable. Indeed, in our application to credit rating and ESG score data, each company belongs to one among $s = 1,\ldots,S$ credit rating classes. Thus, the Y response can be modelled as a multinomial variable with parameters θ_{js}, and the θ_{js}'s are, a priori, Dirichlet($\tilde{\alpha}$) random variables, with $\tilde{\alpha} = \tilde{\alpha}_1 + \ldots + \tilde{\alpha}_S$. Note that, when $S = 2$, the Dirichlet reduces to the Beta distribution.

The marginal likelihood contribution of level j of the k covariate can then be obtained as:

$$p(y|j) = \int_0^1 p(y|\theta_j)p(\theta_j)d\theta_j$$

$$= \int_0^1 \prod_{s=1}^{S} \theta_{js}^{n_{js}} \frac{\Gamma\left(\sum_{s=1}^{S}\tilde{\alpha}_s\right)}{\prod_{s=1}^{S}\Gamma(\tilde{\alpha}_s)} \prod_{s=1}^{S} \theta_{js}^{\tilde{\alpha}_s-1} d\theta_j =$$

$$= \frac{\Gamma\left(\sum_{s=1}^{S}\tilde{\alpha}_s\right)}{\Gamma\left(n_j + \sum_{s=1}^{S}\tilde{\alpha}_s\right)} \prod_{s=1}^{S} \frac{\Gamma(n_{js}+\tilde{\alpha}_s)}{\Gamma(\tilde{\alpha}_s)},$$

where n_{js} is the number of companies sharing level j of the k covariate and belonging to the s credit rating class.

As in the binary specification, $p(y|g_k) = \prod_{j=i}^{J_k} p(y|j)$ is the total marginal likelihood of the g_k partition and can be used as the covariate weight of the same partition in determining the expected probability of company i belonging to the s credit rating class.

We thus have:

$$E(\theta_{is}|X,Y) = \sum_{k=1}^{K} E(\theta_{js}|g_k,Y)p(g_k|Y),$$

and given that, a priori, $E(\theta_{js}) = \frac{\tilde{\alpha}_s}{\sum_{s=1}^{S}\tilde{\alpha}_s}$, it follows that

$$E(\theta_{js}|g_k,Y) = \frac{\tilde{\alpha}_s + n_{js}}{\sum_{s=1}^{S}\tilde{\alpha}_s + n_j}.$$

3 | EMPIRICAL STUDY

3.1 | Data

In the present section, we apply our proposed methodology to a sample of 791 European companies for which we retrieve:

TABLE 1 Distribution by country in the company sample

Country	Frequency	Percentage
United Kingdom	189	23.89%
Germany	100	12.64%
France	80	10.11%
Sweden	71	8.98%
Switzerland	51	6.45%
Italy	46	5.82%
Spain	41	5.18%
Netherlands	30	3.79%
Belgium	29	3.67%
Norway	26	3.29%
Denmark	23	2.91%
Ireland	21	2.65%
Finland	20	2.53%
Greece	16	2.02%
Austria	15	1.90%
Luxembourg	13	1.64%
Portugal	9	1.14%
Other	11	1.41%

TABLE 2 Distribution by industry in the company sample

Industry	Frequency	Percentage
Consumer	189	23.92%
Industrials	166	20.99%
Financials	93	11.76%
Basic Materials	79	9.99%
Technology	70	8.85%
Healthcare	67	8.47%
Real Estate	58	7.33%
Energy	44	5.56%
Utilities	24	3.03%
Academic & Educational Services	1	0.13%

- The Refinitiv ESG Score: a continuous variable ranging from 0 (lowest sustainability) to 100 (highest sustainability). Given that the score is not necessarily updated continuously, we take the most recent score available in the period 2018–2020;
- The Standard and Poor's (S&P) Global ESG Score Rank for the same year: a discrete variable defined as the total sustainability percentile rank, ranging from 0 (lowest sustainability) to 100 (highest sustainability)[3];
- The Moody's Structural Implied Credit Rating at the end of the year when the ESG score was assigned: an ordinal variable whose categories in the sample range from AAA (highest creditworthiness) to CC (lowest creditworthiness).

[3]S&P also provides ESG Scores, but data availability was limited for our sample and hence we relied on ranking. For further details on ESG Scores by S&P see https://www.spglobal.com/ESG/solutions/data-intelligence-ESG-scores

TABLE 3 Descriptive statistics for the ESG scores in the company sample

Score	Mean	Median	Standard deviation
Refinitiv	56.31	58.29	20.13
S&P	48.93	47	29.68

TABLE 4 Measures of correlation between the two considered ESG scores

Correlation metric	Value
Pearson correlation	0.170
Spearman correlation	0.184
Kendall's Tau	0.127

Data are retrieved from various sources, including Bloomberg and Eikon Refinitiv.

Tables 1 and 2 show the observed distribution of companies in the analysed sample by country and industry[4] respectively, while Table 3 reports descriptive statistics for the two ESG scores considered. It can be noticed from Table 4 that the correlation between the Refinitiv and the S&P ESG scores is quite low in the analysed sample. This increases the interest in reaching a sustainability metric that combines the two measures based on their capability to order the observed companies by their creditworthiness.

We then use the credit rating information to create the multinomial response variable according to the model described in Section 2.2. Specifically, we aggregate the 19 Moody's rating classes represented in the sample into 8 rating macro-classes, namely AAA, AA, A, BBB, BB, B, CCC, CC.[5] Limiting the classes to 8, each of them contains a sufficient number of observations and the arbitrariness in the choice of the credit rating partition is reduced.

Table 5 shows the distribution by credit rating aggregated as described above of all the companies in the analysed sample.

3.2 | Results

3.2.1 | In-sample analysis

The first step in our empirical analysis consists of the calculation of the posterior probability-based weights according to the methodology described in Section 2.2. The weights associated to ESG Score 1 and ESG Score 2 are estimated on a random training sample of 457 companies (60% of the available observations) and are shown in Tables from 6 to 9 for different choices of $\tilde{\alpha}$ (the prior probability of a company belonging to each rating class) and for alternative partitions of the ESG scores (number of quantiles from 2 to 6). Specifically, in the first three cases (Tables 6–8) all credit rating classes

TABLE 5 Distribution by credit rating in the company sample

Credit rating	Frequency	Percentage
AAA	8	1.01%
AA	36	4.55%
A	174	22.00%
BBB	295	37.29%
BB	202	25.54%
B	70	8.85%
CCC	4	0.51%
CC	2	0.25%

TABLE 6 Weights derived from the posterior probabilities associated to the ESG scores when the prior $\tilde{\alpha}$ parameter assigned to each rating class is equal to 1

Number of score classes	ESG score 1	ESG score 2
2	0.4981	0.5019
3	0.4936	0.5064
4	0.5026	0.4974
5	0.5034	0.4966
6	0.4977	0.5023

TABLE 7 Weights derived from the posterior probabilities associated to the ESG scores when the prior $\tilde{\alpha}$ parameter assigned to each rating class is equal to 5

Number of score classes	ESG score 1	ESG score 2
2	0.4996	0.5004
3	0.4946	0.5054
4	0.5006	0.4994
5	0.5007	0.4993
6	0.4953	0.5047

TABLE 8 Weights derived from the posterior probabilities associated to the ESG scores when the prior $\tilde{\alpha}$ parameter assigned to each rating class is equal to 10

Number of score classes	ESG score 1	ESG score 2
2	0.4998	0.5002
3	0.4947	0.5053
4	0.5003	0.4997
5	0.5003	0.4997
6	0.4950	0.5050

[4]For the industry information we use the TBRC Economic Sector classification provided by Refinitiv.

[5]The original Moody's credit rating classes in the sample are AAA, AA+, AA−, AA, A+, A−, A, BBB+, BBB−, BBB, BB+, BB−, BB, B+, B−, B, CCC+, CCC−, CC. By aggregating the (+) and (−) modalities we end up with 8 macro-classes.

TABLE 9 Weights derived from the posterior probabilities associated to the ESG scores when the prior $\tilde{\alpha}$ parameter assigned to each rating class is equal to the empirical frequency of the class

Number of score classes	ESG score 1	ESG score 2
2	0.6380	0.3620
3	0.8189	0.1811
4	0.5481	0.4519
5	0.5280	0.4720
6	0.6372	0.3628

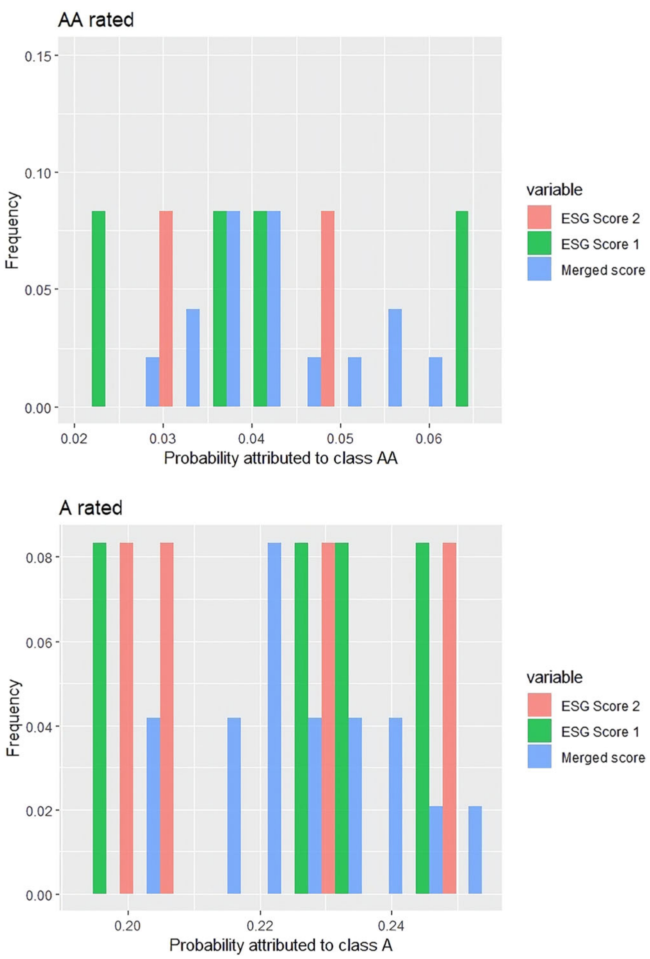

FIGURE 1 Distribution of the probability of belonging to the observed rating class estimated for the AA rated companies (panel 1.) and the A rated companies (panel 2.).

have the same prior probability, equal to 1/8, while in the last one (Table 9) the a priori probability associated to each credit rating class is equal to its empirical frequency in the validation set, composed of 316 companies (40% of the total sample).[6]

[6]As already declared this article does not aim at understanding if and which is the best ESG metric to estimate the credit rating class. For this reason, the ESG scores are coded into ESG Score 1 and ESG Score 2.

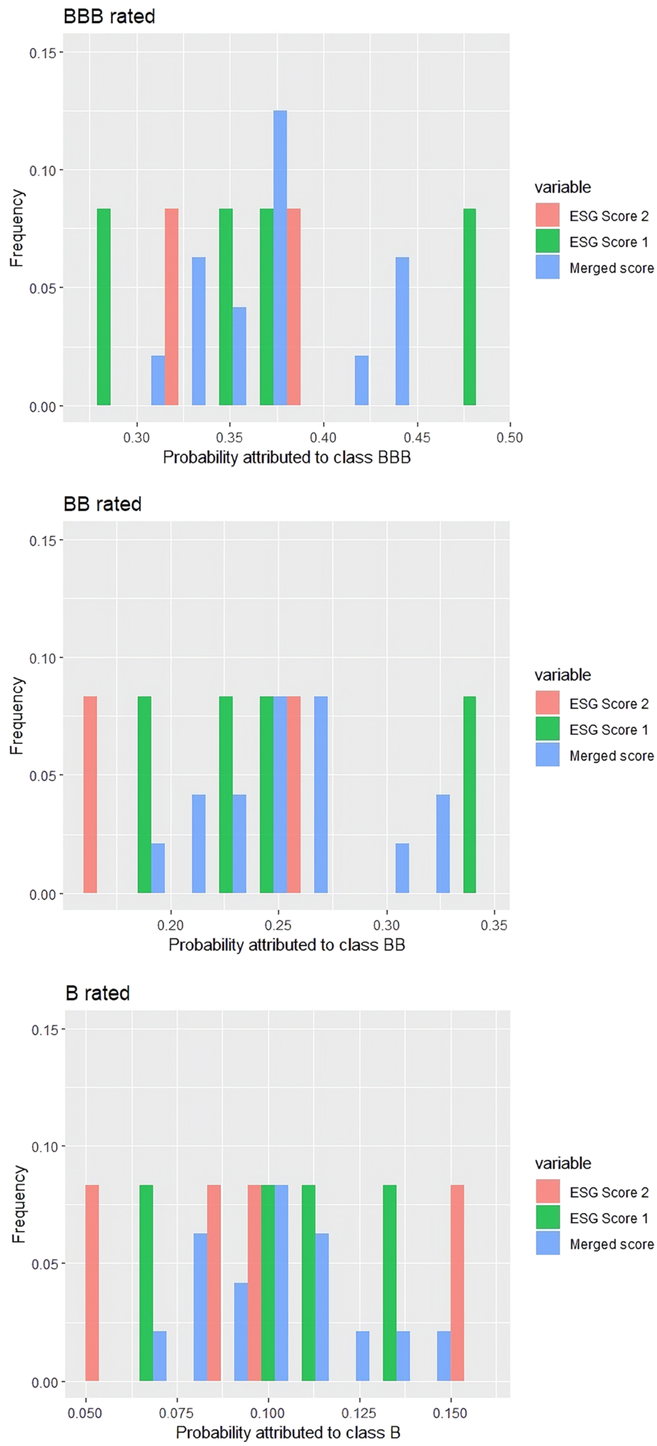

FIGURE 2 Distribution of the probability of belonging to the observed rating class estimated for the BBB rated companies (panel 1.), the BB rated companies (panel 2.) and the B rated companies (panel 3.).

The tables show that, in the equal prior probability cases (Tables 6–8), the estimated weights are close to 50% and stable under a variation of the number of considered scoring classes. When the a priori expectation reflects instead the observed distribution of companies among credit rating classes (Table 9), the contribution of the ESG

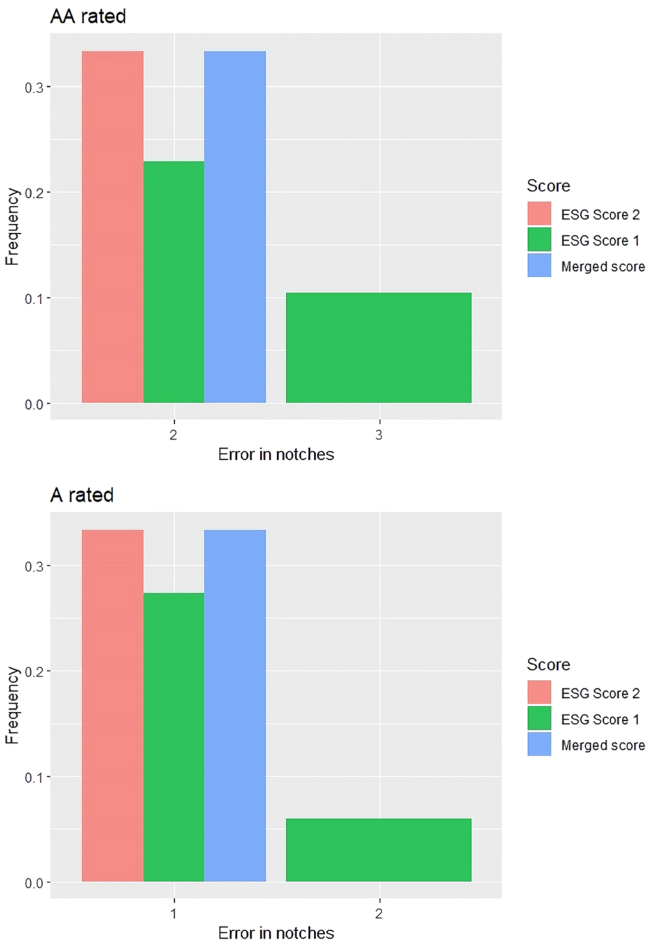

FIGURE 3 Distribution of the credit rating class prediction error for the AA rated companies (panel 1.) and the A rated companies (panel 2.).

Score 1 becomes relatively higher for all choices of the score partition.

3.2.2 | Out-of-sample analysis

We now provide a predictive analysis where the probability that a company belongs to a certain rating class conditional on the ESG score is estimated based on the methodology described in Section 2.2.

Specifically, we use the weights associated to the ESG scores estimated on the training sample (see Section 3.2.1) to predict the credit rating in the validation sample. According to the proposed merged scoring methodology, these weights are then used to determine the probability associated to the different credit rating classes for a given company, based on the quartile of ESG scores it belongs to. The predicted rating class for the company is that with the highest posterior probability, calculated as a weighted average of the probability attributed by the single scores according to Section 2.2.

Figures 1 and 2 compare the posterior probabilities estimated through the single and the merged scores. The results are only shown for the credit rating classes from AA to B, which include a number of observations higher than 5 in the validation sample.

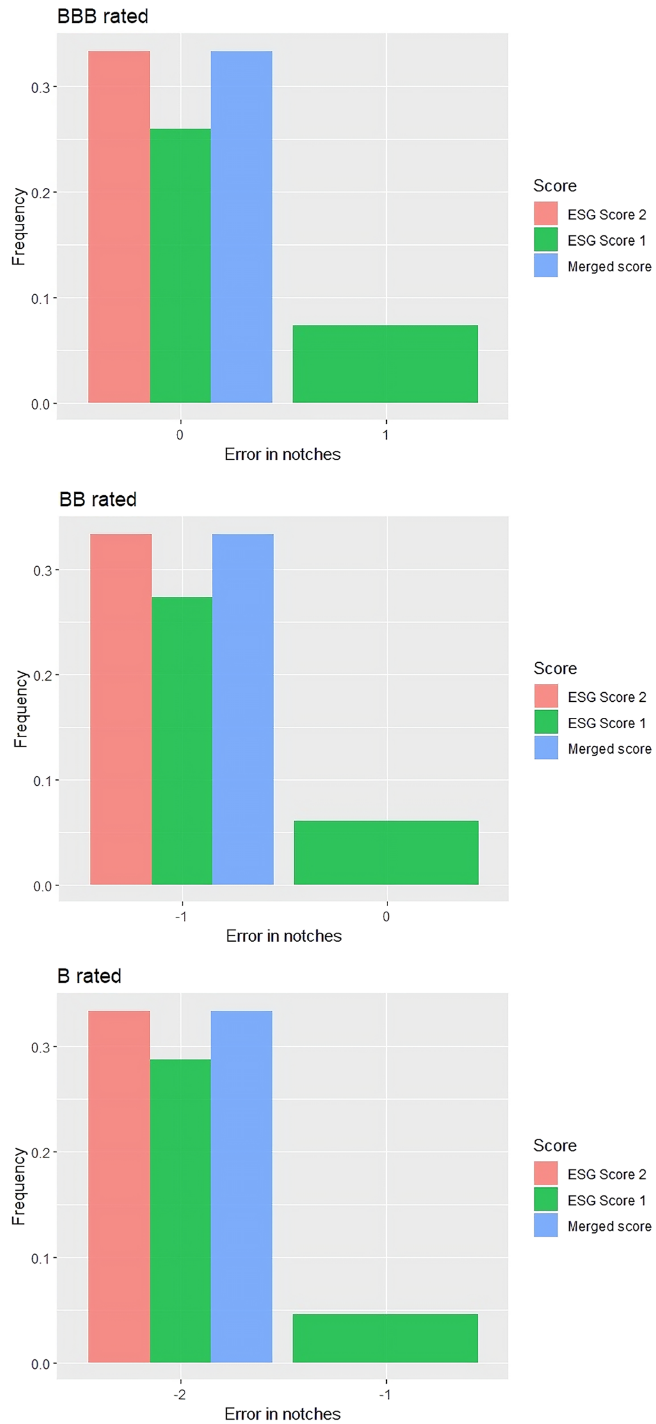

FIGURE 4 Distribution of the credit rating class prediction error for the BBB rated companies (panel 1.), the BB rated companies (panel 2.) and the B rated companies (panel 3.).

Figures 1 and 2 show that the merged score acts as a smoother of the estimated probabilities, thinning the tails in their distribution and reaching a more granular evaluation of a company's credit reliability, shrunk from the tails towards the mean.

To assess and compare the goodness of the predictions made through the single and the merged scores, we employ as an error measure the number of classes (notches) between the predicted and the observed rating class:

$$e_i = \widehat{s}_i - s_i,$$

where the rating classes expressed in numbers go from 1 (AAA) to 8 (CC).

According to this metric, the credit risk is overestimated when the predicted rating class is worse than the observed one (positive values of e_i) and, conversely, the credit risk is underestimated when the predicted rating class is better than the observed one (negative values of e_i).

Figures 3 and 4 show the distribution of the prediction error in notches for the single and the merged scores and for different observed credit rating classes.

From Figures 3 and 4, it is immediate to note that, in the analysed case, though the ESG score with the highest attributed weight is the ESG Score 1, the predictions obtained through the combined score are in line with the ones made through the ESG Score 2. The attribution to a given rating class depends indeed not only on the weights attributed to the two scores but also on the probabilities estimated through the single ESG metrics. Concerning the goodness of predictions in terms of the error in notches, the merged score reduces overestimation of credit risk (lower positive error) for the best rated companies (AA, A and BBB classes, see Figures 3 and 4 panel 1.) with respect to the ESG Score 1, while, for the BB and B rated companies (Figure 4 panel 2. and panel 3.), the cases of credit risk underestimation (negative errors) are more frequent and severe (higher absolute value of error) with the combined ESG score than with the ESG Score 1. This means that the merged sustainability rating seems to better recognise the most credit reliable companies, for which the credit rating class prediction is more accurate than that obtained through a single ESG metric such as the ESG Score 1.

4 | CONCLUSIONS

ESG behaviour of companies is being subject to increased scrutiny by the market and policymakers. The effort of companies to become more sustainable are generally measured, especially for listed companies, by ESG ratings and ESG scores. These are computed by specialised rating agencies that combine multiple sources of information and provide a synthetic score on the ESG performance of companies. The increased attention to sustainability issues yielded the proliferation of rating agencies and ESG scores, with multiple ESG scores on the market that are often divergent and provide different types of information. This paper attempts at providing a single ESG score that combines the information from different providers. Additionally, it brings evidence of the capability of the combined ESG score to predict the credit rating class. Our empirical study on a dataset of European companies has shown that the combined ESG score can, besides improving ESG standardisation, also improve credit risk assessments, and better recognising companies with higher creditworthiness.

The methodology presented can be especially useful for investors that can exploit the information provided by different ESG scores in a comprehensive setting, reducing information asymmetries on ESG company performance and on the effects of ESG factors on credit ratings, to the benefit of the best-performing companies in terms of sustainable behaviour.

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