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Be good to be wise: Environmental, Social, and Governance awareness as a potential credit risk mitigation factor

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Abstract

Integrating Environmental, Social, and Governance (ESG) factors into credit risk assessment is the new frontier for credit risk management as regulators and investors increasingly require banks to channel loans to "sustainable" borrowers and ultimately foster sustainable growth. Our findings show that higher ESG awareness is strongly associated with better creditworthiness (proxied by the Altman *Z*-score). We apply a two-step methodology to 3331 companies from various industries and geographies in the 2000–2016 period which reveals that high ESG awareness scores are strongly and very significantly associated with a reduction in firm credit risk. We check the robustness by using the Probability of Default as a dependent variable and an instrumental variable constructed with a factor analysis. Our results support the appropriateness of the introduction of ESG awareness parameters in the creditworthiness assessment of borrowers.

KEYWORDS

banks, credit, ESG risk, risk management, sustainability

1 | INTRODUCTION

Policymakers, regulators, and investors worldwide are increasingly requiring banks to consider Environmental, Social, and Governance (ESG) in their financing decisions. ESG is a new strategic perspective, a new approach to business that is certainly virtuous, probably profitable in the near future, but it is also a new risk configuration (Engle et al., 2021). The financial industry is largely predisposed to the exposure to ESG risk which is an increasingly important element in strategic planning, decision making, and risk management. This paper investigates the potential benefits of the introduction of ESG in the credit risk management (CRM) process.

Integrating ESG factors into credit risk assessment is the most novel challenge for the financial industry (Brogi, 2020) but at the same time it is an opportunity to channel loans to "sustainable" borrowers and to create sustainable lending. "Sustainable lending" may be defined, in analogy with sustainable finance, *as lending that contributes to the achievement of strong, sustainable, balanced and inclusive growth, through supporting directly and indirectly the framework of the Sustainable Development Goals*. In our view, sustainable lending implies in turn a sustainable CRM process.

Indeed, in the quest for introducing sustainability in the CRM process, policy makers and regulators worldwide are working on integrating the legislative framework with ESG.

From a regulatory perspective, this debate has given rise to a series of Consultation Proposals, Regulations, Final Reports and Guidelines to which all countries are required to align. For example, the creditworthiness assessment is the cornerstone of the European Banking Authority's (EBA) approach to loan origination, bringing together prudential, governance, and consumer protection requirements (EBA, 2020). The objective is to ensure that banks have robust and prudent lending standards which encompass ESG factors both at origination and monitoring.

From the practitioners' standpoint, the UN-convened Net-Zero Banking Alliance, which is driven by the banking industry, brings together 94 banks from around the world (39 countries), representing over 40% of global banking assets, who are committed to aligning their lending and investment portfolios with net-zero emissions by 2050. This ambitious pledge, which combines near-term action with accountability, sees signatory banks set an intermediate aim for 2030 or sooner, based on robust, science-based principles. The Alliance will strengthen, accelerate, and promote the implementation of decarbonization policies by offering a globally consistent framework and operating rules, as well as peer-learning from pioneering institutions. It acknowledges the critical role of banks in assisting the global real-economy transition to net-zero emissions.

In this perspective, our paper contributes to the debate involving policy makers, banks, and borrowers by providing new empirical evidence supporting the effectiveness of the integration of ESG factors in the creditworthiness analysis of borrowers. We test ESG awareness in the firm's business model as a potential credit risk mitigation factor.

We provide a two-step methodology to investigate the relation between the ESG awareness of firms and their creditworthiness (proxied by the Altman *Z*-score). First, we implement an ESG scoring model using MSCI ESG KLD stats on a sample of 3331 companies from 79 countries in the world and operating in 19 industrial sectors (considering the NAICS classification with two digits). We calculate a score for each of the three dimensions of ESG (e.g., Environment, Social, and Governance) and for the overall assessment of ESG awareness. We use all of the obtained scores as independent variables of different regression models, using *Z*-score as dependent variable. Then, we further explore the consistency of our analysis by exploring the relationship within the different industries and different Continents where the firms are bases. We find that *ESG*-scores are negatively and very significantly correlated with *Z*-score, suggesting that an increase in the ESG awareness of firms is likely to foster their creditworthiness. To check the robustness of our results, we also employ several strategies: (i) we use the Probability of Default (PD) following Vassalou and Xing (2004) approach instead of our measure of *Z*-score; (ii) we construct an instrumental variable of the *ESG*-score. The latter is calculated with a factor analysis based on PCA over a set of (aggregated) data retrieved from the Worldbank database. These tests confirm that environmental, social, and governance awareness (even proxied by our instrumental variable) is strongly associated with a reduction in firm firm's credit risk.

To the best of our knowledge this is the first attempt to integrate ESG factors in the creditworthiness assessment and in CRM process. The contribution of our paper is manifold and likely to raise the interest of policy makers, regulators, practitioners, and researchers. Our results are like to greatly contribute in terms of policy by developing a new perspective of the whole CRM process. Also, our findings are addressed to the attention of practitioners, as this new paradigm may involve corporate governance (Brogi & Lagasio, 2021) and bank credit risk culture, also in line with EBA LOM. This is likely to be considered as a disruptive change oriented toward the attention to ESG factors also in the assessment of credit risk and, therefore, in the definition of credit risk variables, losses, impairment aiming to reach sustainable lending activity with the final aim to reduce capital requirements (for credit risk) and to improve capital adequacy. Policy makers and regulators are invited to reflect on the role of ESG attention in the regulatory framework, in the prudential treatment of sustainable lending and in the supervisory review and evaluation process (SREP) assessment overall.

Our findings help credit risk managers to reflect on two main issues: (i) the role of ESG awareness in credit risk assessment, also in crises period where the fundamental of the firms are not as good to shift the focus of nonfinancial indicators; (ii) the opportunity to adopt new credit risk policy to achieve competitive advantage and, potentially, to implement a *Sustainable CRM* process compliant with EBA LOM. Risk Management should also consider the social and environmental considerations in the decision-making process and to assess, measure, and monitor ESG factors and the impact on bank's risk profile, key risk metrics in the Risk Appetite Framework and monitoring process. Lending to sustainable firms is less risky, more advantageous from a competitive point of view and presumably produces less risk weighted assets when computing banks' capital requirements.

From the academic research perspective, we contribute to the literature on ESG and credit risk assessment in several ways. First, we add knowledge to the research on the association between ESG and borrower's credit risk, which is still a topic without univocal consensus. Second, we also link our findings related to ESG risk with potential implication for the financial sector, that is nowadays an under investigated topic that is populating policy-makers and regulators' agenda worldwide.

The remainder of the paper is organized as follows. Section 2 presents the literature review on ESG Credit Rating Agency (CRA) and about the relation between ESG' business model attention and firm's performance, Section 3 describes the database and methodological framework employed in the investigation. Section 4 presents and discusses the empirical results and finally, Section 6 contains the overall conclusions.

2 | LITERATURE REVIEW

Given the increasing importance that investors, financial intermediaries, and financial regulators are putting on ESG, traditional rating agencies are performing ESG rating assessments and making initial assessments of ESG credit implications. Similarly, from a literature point of view, increasing attention is paid in understanding how CRAs are incorporating "Environmental, Social, and Governance" (ESG) into their credit risk analyses and there is growing literature related to ESG attention and firm risk/performance of both stock return and accounting performance. We focus in those fields of literature because we would expect that (i) CRAs are used to constantly improve their rating model assessment, and it is interesting to investigate whether and how ESG is being incorporated in their methodologies; (ii) and (iii) firm risk/performance (from both market and accounting perspectives) is in turn related with the scoring of the firm.

McAdam (2012) underlines that there is no evidence of ESG embedded in CRA rating criteria partially explains by the absence, in the regulatory framework for CRA valid in 2012, of sustainability issues. It also argues that focus on ESG would enable CRAs to provide a more fundamental development in the credit risks assessment. Some years later, Hoerter (2016) suggests that ESG risks are increasingly considered in the CRA standard credit risk analysis and could be material for rating activities. Thereby, the integration of ESG into rating decisions most often appears in the context of a negative rating action like a downgrade probably due to the fact that in Hoerter's opinion environmental and social issues are indirectly assessed by other factors like firm solvency or liquidity.

Kiesel and Lücke (2019), analyzes the proportion to which CRAs consider ESG in their rating decisions, in particular they apply the latent Dirichlet allocation (LDA) method, originally described by Blei et al. (2003), to determine ESG in credit rating. The results show that CRAs consider ESG factors in their rating decisions. However, the degree of integrating ESG is limited.

In this regard, Do and Kim (2020) investigate the effects of the level and changes in (ESG) rating on the stock market returns of Korea Composite Stock Price Index (KOSPI) listed firms (over the period 2011–2018) and find that changes in ESG ratings have statistically significant short-term effects on their abnormal returns. Tarmuji et al. (2016), using panel data analyze the relation between *ESG*-score of a sample of firms in Malaysia and Singapore (ASSET4® Thomson Reuters) and economic performance and show that responsible management of ESG issues creates a business spirit and environment that builds both a company's integrity within society and the trust of its stakeholder. Therefore, companies that disclosure ESG practices in universal media were reported as having reputation gains, thereby increasing investor confidence; efficient use of resources and remain competitive (Lagasio & Cucari, 2019). Khan et al. (2016) find that firms with better material ESG ratings have superior future stock returns. Dyck et al. (2019) analyze the impact of institutional investors on environmental and social performance based on ESG rating data from more than 45 countries. They report that the higher the social norm index, the higher the level of investment by institutional investors in ESG firms, leading to their higher financial performance in the stock market.

It is intuitively appealing that some ESG items are important for one industry but largely irrelevant for another; all this creates a further difficulty in evaluating the attention to ESG factors in different industrial sectors with different weight. We believe that the same considerations can be made obviously for the internal rating/scoring system. The banks interest to modify their creditworthiness assessment with ESG business model attention will face the same problems in the knowledge that the weight of each ESG pillar should be related to its relevance within the company's value-creation process (Eccles et al., 2014). Obviously, we are aware that this is the added value of a sustainable credit rating system

The literature on ESG have instead a lot of contributions that try to understand the impact of ESG attention on firm performance or better, what kind of relationship exists between ESG performance and value creation, also for the case of financial institutions. We can divide all them in two groups: (a) the studies that analyze separately the impact of the three pillars of ESG on firm performance; (b) the studies that analyze impact of the three pillars of ESG, together considered, on firm performance.

In financial companies specifically, the environmental dimension is associated with a higher level of profitability when compared with other companies (Brogi & Lagasio, 2019; Lagasio, 2020). Shen et al. (2016) produce a global analysis on banking sector (data set of 65 socially responsible banks corresponding to 18 countries during the period 2000–2009). The results reveal that socially responsible banks have significantly higher financial performance than nonsocially responsible banks. Miralles-Quirós et al. (2019), show that there is no homogeneity in the value relevance of environmental, social, and governance practices adopted by the selected banks over the entire sample period. More precisely, they observe that there exists a positive and significant relationship of banks' environmental and corporate governance performance with shareholder value creation. Esteban-Sanchez et al. (2017) analyzed the effect of different CSR dimensions on the financial performance of 154 banks in 22 countries, before and during the years of financial crisis obtaining mixed results, depending on the dimension analyzed.

In the second strand, Gillan et al. (2010) found that stronger ESG performance increases firm operating performance, efficiency and value Yoon et al. (2018) reflect on ESG attention and firm value creation. Sassen et al. (2016), on the basis on a European large panel data set investigate the impact of *Corporate Social Performance* (materialized by environmental, social, and governance factors attention) on market-based firm risk and show a significantly negative effect. Specifically, environmental performance generally decreases idiosyncratic risk, whereas total risk and systematic risk are only affected in environmentally sensitive industries. In contrast, the authors cannot detect a significant effect of corporate governance performance on firm risk; their findings suggest that a higher ESG attention and a higher performance regarding the social dimension in particular have the potential to increase firm value through lower firm risk. Friede et al. (2015) conduct a meta-analysis to identify the dominant subfactor in the relation of ESG on corporate financial performance. Their outcome is used as a starting point in the discussion of the effect of each E, S, and G factor on corporate financial performance.

Atan et al. (2018) using a panel study on Malaysian companies examine the impact of ESG factors on the performance of public-limited companies in terms of profitability, firm value, and cost of capital and find no significant relationship between individual and combined factors of ESG and firm profitability (i.e., ROE) as well as firm value (i.e., Tobin's *Q*). Moreover, individually, none of the factors of ESG is significant with the cost of capital (Weighted Average Cost of Capital, WACC), but the combined score of ESG positively and significantly influences the WACC.

A number of studies have found both positive and negative relationships between them. Still there is lack of clarity and ambiguity with regard to the nature of the ESG and firm performance, though most of the studies found that the above relation is positive. Useful in this perspective could be the research work of Fulton et al. (2012) that examine more than 100 academic studies on sustainable investing and found that ESG factors are correlated with superior risk-adjusted returns at a securities level or better 100% of the academic studies agreed that highly rated ESG companies have a lower cost of capital (loans, bonds, and equities). Although there is a continuing and increasing debate on that arguments, in summary, it seems that there is a positive association between ESG ratings and firms' accounting performance or stock return. We aim at contributing to the literature on this argument that moves in the direction of deepening how the attention to ESG factors can change the assessment of creditworthiness (via internal rating/scoring system and no external rating) and what the evolutionary perspectives are within the CRM in banking.

However, some recent work in the literature (Ahmed et al., 2018) try to understand how incorporate ESG risk factors into loan decision-making processes and highlights that pioneering banks in incorporating ESG factors into loan decisions are offset by better financial performance here are not contribution that try to understand the possible impacts of ESG factors on internal credit rating on which bank based the lending activity.

Based on general finding of previous literature, we propose the following hypothesis:

H1 *ESG awareness is negatively correlated with firm's credit risk*

3 | METHODOLOGY

3.1 | Strategy

We use a two-step methodology: first, we create an ESG index by equally weighting the scores registered in each of the Environmental (E), Social (S), and Governance (G) dimensions of ESG by each company in the sample (Brogi & Lagasio, 2019). Second we run a different regression models to test whether companies' ESG strengths scores has an impact on risk—identified by *Z*-score. We run the model over the three different components of *ESG*-score—(*E*), (*S*), (*G*)—to identify which is the most influential driver of *Z*-score.

Before choosing the most adequate version of *Z*-score to compute, we survey all the method proposed in previous literature (Table 1). Because our sample is composed of large listed firms operating in different sectors, our proxy of firm risk is based on the original version of the Altman's *Z*-score (1968). Indeed, even though Altman and Hotchkiss (1993) and Altman et al. (2013) provide a modified *Z*-score, we chose to avoid it because the authors suggest that it is more appropriate for unlisted firms. Similarly, we do not compute the *Z*-score as lately suggested by Altman et al. (1995) because it is recommended when the sample includes firms operating in business sectors other than manufactory and/or operating in emerging markets, which restrictions both cannot be referred to our sample.

Considering the above-mentioned characteristics for each of the *Z*-scores identified, we observe that specification which is more appropriate to our use is the following (Altman, 1968; Altman et al., 1977):

$$Z = 1.2 \times 1 + 1.4 \times 2 + 3.3 \times 3 + 0.6 \times 4 + 1.0 \times 5,$$

where X_1 measures liquid assets in relation to the size of the company; X_2 measures profitability that reflects the company's age and earning power; X_3 indicates operating efficiency apart from tax and leveraging factors; X_4 adds market dimension to the analysis; X_5 is a standard measure for total asset turnover (which varies greatly from industry to industry).

TABLE 1 Comparing different Z-scores

Authors	Variables included	Details	Subject
Altman (1968) and Altman et al. (1977)	Original version $Z = 1.2 \times 1 + 1.4 \times 2 + 3.3 \times 3 + 0.6 \times 4 + 0.99 \times 5$ where X_1 = working capital/total assets X_2 = retained earnings/total assets X_3 = EBIT/total assets X_4 = MVE/book value of total debt X_5 = sales/total assets	$Z < 1.81$ distress zone $1.81 < Z < 2.99$ gray zone $Z > 2.99$ safe zone	Listed manufactory companies in US
Altman and Hotchkiss (1993) and Altman et al. (2013)	Z'-score $Z' = 0.717 \times 1 + 0.847 \times 2 + 3.107 \times 3 + 0.420 \times 4 + 0.998 \times 5$ where X_1 = working capital/total assets X_2 = retained earnings/total assets X_3 = EBIT/total assets X_4 = MVE/book value of total debt X_5 = sales/total assets	$Z' < 1.23$ Distress zone $1.23 < Z' < 2.90$ gray zone $Z' > 2.90$ safe zone	US private firms (not listed) + Italian private firms
Altman et al. (1995)	$Z'' = 6.56 \times 1 + 3.26 \times 2 + 6.72 \times 3 + 1.05 \times 4$ where X_1 = working capital/total assets X_2 = retained earnings/total assets X_3 = EBIT/total assets X_4 = MVE/book value of total debt	$Z' < 4.48$ distress zone $4.48 < Z' < 6.15$ gray zone $Z' > 6.15$ safe zone	Firms operating in business sectors other than manufactory + firms operating in emerging markets

Note: This table compares the different Z-scores as proposed by the literature.

Table 2 shows the distribution of firm-year observations included in the sample by *Z*-score, which results to be skewed. Companies (for each year) are unequally distributed between each class of risk (identified by the rating assigned by S&P), as also reflected by the high level of standard deviation of *Z*-score reported in Table 4 (2.13149). "Investment grade" observations (from AAA to BBB−) as whole represent approximately the 5% of the sample. "High-yield" (from BB+ to D) companies are 95% with a higher frequency in the worse rating classes. We control for this skewness in our analysis by applying the natural logarithm to *Z*-score.

3.2 | Data

We collect data from MSCI ESG KLD STATS, which is an annual data set of positive and negative environmental, social, and governance (ESG) performance indicators applied to a universe of publicly traded companies. For computing our *ESG*-score we only select positive

TABLE 2 Distribution of firm-year observations included in the sample by *Z*-score (and assigned S&P's rating)

Rating	*Z*-score	*n*	Freq.
AAA	≥8.15	188	1.07
AA+	<8.15	52	0.29
AA	<7.60	36	0.20
AA−	<7.30	36	0.20
A+	<7.00	26	0.15
A	<6.85	36	0.20
A−	<6.65	51	0.29
BBB+	<6.40	39	0.22
BBB	<6.25	154	0.87
BBB−	<5.85	96	0.54
BB+	<5.65	215	1.22
BB	<5.25	238	1.35
BB−	<4.95	198	1.12
B+	<4.75	297	1.68
B	<4.50	496	2.81
B-	<4.15	700	3.97
CCC+	<3.75	1562	8.86
CCC	<3.20	2938	16.67
CCC−	<2.50	3956	22.44
D	<1.75	6314	35.82
Total		17,628	100.00

Note: The following table shows the distribution of firm-year observations included in the sample by *Z*-score.

performance (strengths). Table 3 details the variables included in the analysis divided by the three ESG dimensions, including 16 indicators for Environment, 29 indicators for Social, and 17 for Governance. Our initial sample included 3331 large listed companies from 79 countries in the world and operating in 19 industrial sectors (considering the NAICS classification—two digits), the exclusion of missing values from the estimation of the models led us to a final sample of 2061 firms. The investigation covers the period 2000–2016. Table 4 also specifies the composition of the sample in terms of the different industries and Continents. Most of the companies (36% of the total sample) operate in the Manufacturing sector, Oil and Gas companies represent the 10% of the total sample, followed by Professional Services and Real Estate companies (7%). In terms of geographical distribution, American companies represent almost the 50% of the total sample, followed by European companies (20%), Asian (16%), Oceanic (11%), and African (3%).

3.3 | ESG scoring model

The variables included in our scoring model are based on a binary evaluation, thus each variable can be considered as already normalized. Hence, when the company meets the assessment criteria established for an indicator, then its value is equal to "1". Conversely, if a company does not meet the assessment, then the variable assumes value "0". Berg et al. (2020) underline that ESG ratings diverge not only on the extent of the definition of ESG but they also differ on: (a) the scope of the selection of the different sets of categories or aspects that are included in "environment," "social," and "governance," (b) the quantification of those categories or aspects within "environment," "social," and "governance," (c) the relative weight of the importance of the different categories or aspects. We overcome these issues with the proposed methodology. Indeed, computing the *ESG*-score with this method has a double purpose. First, we do not arbitrarily give more value to one of the dimensions (Environmental, Social, and Governance) as they are equally weighted within the overall score, and this allows us to better observe which dimension is the most meaningful when computing firm risk; second, since the calculation methods offered by rating agencies are private and apply different weights, ratings produced by the companies are always misaligned with each other, and we avoid an arbitrary choice of one rating over another.

Following Brogi and Lagasio (2019), we first compute separately the *E*-score, *S*-score, and *G*-score by simply averaging the values in the related area of investigation. The scoring obtained for the three dimensions are then included into the computation of the overall *ESG*-score for each company by applying a simple average.

For each firm-year observation, we calculate the following:

$$E\text{-score} = \frac{1}{n}\sum_{i=1}^{n} E_i, \tag{1}$$

where E_i are the selected Environment indicators and n is the number of the selected Environment indicators.

$$S\text{-score} = \frac{1}{n}\sum_{i=1}^{n} S_i, \tag{2}$$

TABLE 3 Variables included in the scores (*source*: MSCI)

***E*-score variables**	***S*-score variables**	***G*-score variables**
Pollution prevention	Generous giving	Ownership strength
Recycling	Support for housing	Reporting quality
Clean energy	Support for education	Political accountability
Management system	Non-US charitable giving	Public policy
Natural capital—Water stress	Volunteer programs	Corruption & political instability
Natural c.—Biodiversity & land use	Community engagement	Financial system instability
Natural c.—Raw material sourcing	Other strength	Other strength
Climate change—Financing env. impact	Union relations	CEO
Opportunities in green building	Cash profit sharing	Representation
Opportunities in renewable energy	Employee involvement	Board of directors—Gender
Pollution & waste—Electronic waste	Retirement benefits strength	Work/life benefits
Climate c.—Energy efficiency	Health and safety strength	Women & minority contracting
Climate c.—Product carbon footprint	Supply chain policies	Employment of the disabled
Climate change—Vulnerability	Compensation & benefits	Gay & lesbian policies
Environment other strength	Employee relations	Empl. of underrepresented
	Professional development	Other strength
	Human capital development	
	Labor management	
	Controversial sourcing	
	Human capital—Other strength	
	Indigenous people relations strength	
	Labor rights strength	
	Human rights policies & initiatives	
	Product safety and quality	
	R&D/innovation	
	Social opportunities—Access to healthcare	
	Social O.—Access to finance	

TABLE 3 (Continued)

E-score variables	*S*-score variables	*G*-score variables
	Social O.—Access to communications	
	Social O.—Nutrition and health	
	Product S.—Chemical safety	
	Product S.—Financial product safety	
	Product S.—Privacy and data	
	Product S.—Responsible investment	
	Product S.—Health and demographic	
	Other strength	

Note: This table shows the different variables included in the calculation of the scores and subscores. All the variables are dichotomous and take the value equal to 1 if the policy is implemented, or 0 whether it is not implemented. For a better definition of the different variables, we suggest looking at the official guide published in the MSCI website.

where S_i are the selected Social indicators and n is the number of the selected Social indicators.

$$G\text{-score} = \frac{1}{n}\sum_{i=1}^{n} G_i, \tag{3}$$

where G_i are the selected Governance indicators and n is the number of the selected Governance indicators.

Lastly, we include (1), (2), and (3) for calculating the overall *ESG*-score:

$$ESG\text{-score}_t = \text{Avg}(E\text{-score}_t + S\text{-score}_t + G\text{-score}_t). \tag{4}$$

In Table 4 we report the descriptive statistics of the variables computed as above-described. Companies shows on average a very low level of *ESG* (both overall and sub-) scores, with a greater focus on Governance aspects (which shows the highest mean value, equal to 0.10). This may reflect the fact that the attention on governance related aspects (from both authorities and companies) is an on-going debate since a decade and is consequently more mature. Authorities started to set principles and rules on governance-related aspects, that companies are implementing from a longer period. On the other side, Environmental and Social related awareness is being raised since a few years, leading to an unripe consciousness and policies implementation by companies. The Pearson's correlations (Table 5) between *Z*-score and all the other independent variables are always negative and lower than 0.1 (in module).

3.4 | Analysis

We run different regression models to test our hypothesis and assess the reliability of our results. In detail, first we run a pooled ordinary least squares (OLS) regression model

TABLE 4 Description and descriptive statistics of the variables included in the analysis

Variable	Source	Description	Count	Mean	SD	Min	Max
Z-score	Osiris BvD	Proxy of credit risk	17,270	2.39	2.13	−35.26	41.88
E-score	MSCI KLD Stats	Environmental score	31,056	0.08	0.18	0	1
S-score	MSCI KLD Stats	Social score	31,058	0.07	0.14	0	1
G-score	MSCI KLD Stats	Governance score	29,325	0.10	0.20	0	1
ESG-score	MSCI KLD Stats	*ESG*-score	31,069	0.09	0.14	0	1

Industry	*N*	%	*E*-score	*S*-score	*G*-score	*ESG*-score	*Z*-score
Manufacturing	1183	35.51	0.097	0.075	0.102	0.092	2.550
Oil and Gas	332	9.97	0.082	0.085	0.097	0.089	2.038
Professional Services	225	6.75	0.060	0.061	0.103	0.075	1.907
Real Estate	222	6.66	0.075	0.066	0.074	0.074	1.584
Finance	213	6.39	0.067	0.076	0.093	0.079	2.735
Information	212	6.36	0.067	0.084	0.108	0.087	1.930
Wholesale	149	4.47	0.053	0.057	0.090	0.067	3.824
Retail	138	4.14	0.051	0.070	0.120	0.080	3.304
Utilities	126	3.78	0.127	0.104	0.147	0.127	0.976
Transportation	113	3.39	0.092	0.087	0.090	0.091	1.737
Construction	98	2.94	0.090	0.076	0.099	0.089	2.177
Waste Management	82	2.46	0.064	0.070	0.105	0.080	2.338
Food	78	2.34	0.072	0.059	0.122	0.084	2.112
Health Care	47	1.41	0.033	0.046	0.091	0.057	2.170
Other	32	0.96	0.046	0.058	0.063	0.055	1.531
Arts	31	0.93	0.048	0.053	0.079	0.060	1.700
Agriculture	25	0.75	0.061	0.057	0.096	0.071	2.490
Educational	16	0.48	0.030	0.055	0.098	0.061	2.696
Public Administration	9	0.27	0.136	0.092	0.178	0.139	2.935
Total	3331						

Continent	*N*	%	*E*-score	*S*-score	*G*-score	*ESG*-score	*Z*-score
America	1635	49.08	0.073	0.068	0.093	0.079	2.522
Europe	679	20.38	0.096	0.088	0.121	0.103	1.914
Asia	534	16.03	0.093	0.081	0.116	0.097	2.414
Oceania	375	11.26	0.088	0.078	0.100	0.090	1.887
Africa	108	3.24	0.089	0.081	0.091	0.088	2.461
Total	3331						

Note: This table reports sources of data and summary statistics of the variables included in the analysis. We first show the Environmental score; Social score; Governance score; *ESG*-score as calculated in the proposed analysis, retrieving data from MSCI KLD Stats. We also report the results of our calculation of *Z*-score, used a proxy of credit risk. The number of observations of the latter are fewer due to missing financial observations in some of the companies included in the sample. Below, we report the industrial and geographical breakdown of the sample.

TABLE 5 Pearson's correlation matrix

	Z-score	*E*-score	*S*-score	*G*-score	*ESG*-score
Z-score	1.00				
E-score	−0.08	1.00			
S-score	−0.07	0.81	1.00		
G-score	−0.06	0.78	0.53	1.00	
ESG-score	−0.09	0.82	0.42	0.46	1.00

Note: This table reports the cross-correlations between our dependent variables and the *Z*-score.

(Equation 5), with constant coefficients for both intercepts and slopes. Then, we use a fixed-effects (Equation 6) and a random-effects model (Equation 7) over the above specifications. The fixed-effect model is used to capture the differences across cross-sectional observations with the values computed for intercepts and slopes and thus controls for the effects of time-invariant variables with time-invariant effects; the random-effects assumes (and is used to capture) the individual effects to be randomly distributed across the cross-sectional observations. The above-mentioned models include each four different specifications, where: (i) *Z*-score is regressed over the three different subscores (*E*-score, *S*-score, and *G*-score) without fixed effects; (ii) *Z*-score is regressed on the overall *ESG*-score without fixed effects; (iii) and (iv) are use the same variables but with the introduction of fixed effects for Year, Industry, and Country. We do not include at this stage control variables because most of the financial items that can be considered as comparable over all the industrial sectors of the companies in our sample are already included in the calculation of the *Z*-score as above presented. Moreover, we do not include macroeconomic variables at this stage, because we use some of them for constructing our instrumental variable, as exposed in the chapter 4.2. To sum up, we compute the following equations:

$$Z\text{-score}_{i,t} = \alpha + \beta_i X_{i,t} + \varepsilon_{i,t}, \tag{5}$$

$$Z\text{-score}_{i,t} = \alpha_i + \beta_i X_{i,t} + FE + \varepsilon_{i,t}, \tag{6}$$

$$Z\text{-score}_{i,t} = \alpha + \beta_i X_{i,t} + RE_{i,t} + \varepsilon_{i,t}, \tag{7}$$

where α is the intercept; X is the dependent variable calculated for each bank (i) and year (t); β is the coefficient; ε is the error term; FE and RE are respectively used to consider fixed and random effects. To ensure that our analysis is not biased by heteroscedasticity, we include the robust option; thus, our estimation is not affected by this issue.

4 | RESULTS

We obtain that high scores of ESG are highly associated with a reduction in borrower risk, whit a 1% level of significance in each of the models' specifications (Tables 6 and 7). This is a promising confirm of the robust relationship between *ESG* and *Z*-score of firms, thus we can positively respond to our research question, and accept our hypothesis: *ESG*-scores and firm risk are (negatively) correlated.

Successfully, the results obtained for the relationship between ESG and risk when running the fixed and random effects models resembles that of the pooled OLS regression model. This high level of consistency within the estimations confirms the robustness and trustworthiness of our findings. Nonetheless, as showed in the next section, we run two different robustness tests to check which of the implemented models is more reliable.

As concerns the three dimensions of ESG, the pooled OLS estimators (Model 1 and Model 3) results show once again a negative relationship with risk, meaning that improving ESG awareness may help firms in reducing their risk. Results are consistent between the two models (without and with fixed effects) with a 1% level of significance in all of the relationships investigated. When looking at fixed and random effects panel regressions (Table 7), we lose some degrees of significance in the relationships observed (*p*-values of the coefficients which identify the association between *Z*-score and both *E*-score and *G*-score exceed the significance level of 10%). Thus, we carefully do not derive any conclusion from these observed values, even though the signs of the relationships are always positive and ideally confirm the findings

TABLE 6 Pooled OLS regression model specification

Variables	OLS—Model 1	OLS—Model 2	OLS—Model 3	OLS—Model 4
E-score	−0.669***		−0.543***	
	(0.110)		(0.108)	
S-score	−0.435***		−0.296**	
	(0.145)		(0.144)	
G-score	−0.224**		−0.159*	
	(0.0940)		(0.0897)	
ESG-score		−1.319***		−0.992***
		(0.112)		(0.114)
Constant	2.503***	2.513***	1.490***	1.526***
	(0.0196)	(0.0192)	(0.202)	(0.199)
Observations	16,357	17,257	16,316	17,216
R^2	0.008	0.008	0.109	0.109
Controls	No	No	No	No
Year FE	No	No	Yes	Yes
Industry FE	No	No	Yes	Yes
Country FE	No	No	Yes	Yes

Note: This table reports the results of the OLS regression models with the *Z*-score above calculated used as a dependent variable. Model 1 is the specification including the three subdimensions *E*-score, *S*-score, *G*-score and does not control for fixed effects within the panel. Model 2 synthetize the three dimensions with the overall *ESG*-score that we calculated. Model 3 and 4 extend Model 1 and 2 respectively, by also including fixed effects in terms of Year, Industry, and Country. All the specifications give significant and consistent results to help us in interpreting the relationship with the dependent variable: the better the scores (*E*, *S*, *G*, *ESG*) the lower the credit risk (proxied by the *Z*-score). Standard errors in parentheses.

Abbreviations: ESG, Environmental, Social and Governance; OLS, ordinary least squares.

***$p < .01$; **$p < .05$; *$p < .1$.

TABLE 7 Fixed and random effects panel regressions

Variables	Fixed effects—Model 1	Fixed effects—Model 2	Random effects—Model 3	Random effects—Model 4
E-score	−0.0669		−0.0715	
	(0.0644)		(0.0639)	
S-score	−0.209**		−0.211***	
	(0.0819)		(0.0813)	
G-score	−0.0417		−0.0592	
	(0.0548)		(0.0544)	
ESG-score		−0.285***		−0.311***
		(0.0766)		(0.0757)
Constant	2.415***	2.418***	2.244***	2.245***
	(0.0106)	(0.0103)	(0.0607)	(0.0603)
Observations	16,357	17,257	16,357	17,257
R^2	0.001	0.001		
N	2040	2061	2040	2061
Controls	No	No	No	No
Year FE	Yes	Yes	No	No
Industry FE	Yes	Yes	No	No
Country FE	Yes	Yes	No	No

Note: This table reports the results of the fixed and random effects regression models with the *Z*-score above calculated used as a dependent variable. Model 1 is the FE specification including the three subdimensions *E*-score, *S*-score, *G*-score controlling for fixed effects within the panel. Model 2 is also a FE analysis including the overall *ESG*-score. Model 3 and 4 replicate Model 1 and 2, respectively, by including random effects in place of fixed effects. All the specifications give significant and consistent results proving that the better the scores (*E*, *S*, *G*, *ESG*) the lower the credit risk (proxied by the *Z*-score). In particular, this is definitely clear when looking at the *ESG*-score and the Social score. Standard errors in parentheses.

Abbreviation: ESG, Environmental, Social, and Governance.

***$p < .01$; **$p < .05$.

already commented for the previous estimations.[1] Nonetheless, we obtain strong and robust evidences that the Social dimension is strongly (and negatively) correlated with *Z*-score, hence, this result once again confirms that the attention placed in social aspects by companies, may increase their creditworthiness.

We further investigate whether there exists any difference when looking at different geographical areas. Hence, we run the above analysis over three different subsamples, related to the Continent where the companies are based. Bearing in mind that data set is unbalanced in terms of countries composition, in Table 9 we report the results for the American (1125 firms included), European (487), and Asian panels (323, which together with the formers represent more than the 85% of the total sample of companies). Results show differences and similarities when looking at the different geographical areas. Specifically, the *ESG*-score is strongly significant and negatively related to firm risk for American and European, but we lose the statistical significance in the Asian subsample. Moreover, the *S*-score seems to be strongly

TABLE 8 OLS, fixed, and random effects panel regressions using PD

Variables	OLS—Model 1	OLS—Model 2	Fixed effects—Model 3	Fixed effects—Model 4	Random effects—Model 5	Random effects—Model 6
E-score	0.0224		−0.0124		0.0224	
	(0.0225)		(0.0392)		(0.0225)	
S-score	−0.167***		−0.318***		−0.167***	
	(0.0209)		(0.0336)		(0.0209)	
G-score	−0.0182		−0.131***		−0.0182	
	(0.0154)		(0.0274)		(0.0154)	
ESG-score		−0.159***		−0.479***		−0.159***
		(0.0210)		(0.0402)		(0.0210)
Constant	0.272***	0.271***	0.293***	0.292***	0.272***	0.271***
	(0.00282)	(0.00280)	(0.00386)	(0.00386)	(0.00282)	(0.00280)
Observations	1911	1926	1911	1926	1911	1926
R^2	0.046	0.029	0.162	0.134		
Controls	No	No	No	No	No	No
Year FE	No	No	Yes	Yes	No	No
Industry FE	No	No	Yes	Yes	No	No
Country FE	No	No	Yes	Yes	No	No
N			1004	1009	1004	1009

Note: This table reports the results of the OLS, fixed, and random effects regression models with the PD used as a dependent variable. Model 1 and 2 are the OLS specification respectively including the three subdimensions *E*-score, *S*-score, *G*-score, or the *ESG*-score. Model 3 and 4 are the FE estimations controlling for fixed effects within the panel. Model 5 and 6 replicate Model 3 and 4, respectively, by including random effects in place of fixed effects. All the specifications give significant and consistent results proving that the better the scores (*E*, *S*, *G*, *ESG*) the lower the credit risk (proxied by the PD). In particular, this is definitely clear when looking at the *ESG*-score and the Social score, confirming the results obtained in the *Z*-score models. Standard errors in parentheses.

Abbreviations: OLS, ordinary least squares; PD, probability of default.

***$p < .01$; **$p < .05$; *$p < .1$.

relevant especially for American companies rather than for the others. We further propose a breakdown by industry in Table 10. We select the first eight industries in terms of companies in our sample (i.e., Manufacturing represents more than the 35% of the companies). Some interesting differences emerge. First, we find that the *ESG*-score is strongly (and negatively) associated with *Z*-score of Manufacturing, Oil and Gas, Construction and Transportation companies. Conversely, *ESG*-score seems not relevant for Services, Real Estate, Utilities, and Wholesale companies. Moreover, there are also some differences in terms of subscores: the *E*-score is really relevant for Manufacturing and Oil and Gas companies; the Social dimension is strongly significant for Oil and Gas and Construction companies; within the latter we also find as important the Governance dimension. Breakdown by year after the introduction of Paris agreement is not possible due to the restricted number of observations.

TABLE 9 OLS, fixed, and random effects panel regressions breakdown by Country

Variables	US OLS—Model 1	US OLS—Model 2	US FE—Model 3	US FE—Model 4	EU OLS—Model 1	EU OLS—Model 2	EU FE—Model 3	EU FE—Model 4	Asia OLS—Model 1	Asia OLS—Model 2	Asia FE—Model 3	Asia FE—Model 4
E-score	−0.710***		−0.0942		−0.0162		−0.304*		−0.745		−0.983**	
	(0.130)		(0.0668)		(0.217)		(0.167)		(0.535)		(0.496)	
S-score	−0.412**		−0.315***		−0.0589		0.0253		0.345		−0.0670	
	(0.175)		(0.0864)		(0.284)		(0.212)		(0.648)		(0.545)	
G-score	−0.157		−0.0377		−0.474***		−0.186		0.382		0.254	
	(0.110)		(0.0586)		(0.173)		(0.136)		(0.383)		(0.365)	
ESG-score		−1.265***		−0.391***		−0.680***		0.0372		−0.0409		−0.551
		(0.135)		(0.0814)		(0.233)		(0.194)		(0.562)		(0.538)
Constant	2.776***	2.819***	2.556***	2.557***	2.020***	1.984***	1.889***	1.910***	−0.105	−0.0282	2.481***	2.463***
	(0.359)	(0.356)	(0.0109)	(0.0107)	(0.482)	(0.470)	(0.0309)	(0.0299)	(1.363)	(1.329)	(0.0701)	(0.0646)
Observations	11,694	12,260	11,694	12,260	2912	3120	2925	3133	1225	1310	1235	1320
R^2	0.117	0.116	0.003	0.002	0.074	0.073	0.002	0.000	0.153	0.159	0.005	0.001
N			1123	1125			477	487			315	323
Controls	No	No	No	No	No	No	No	No	No	No	No	No
Industry FE	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No
Country FE	No	No	No	No	No	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows the breakdown by Country of the previous OLS models presented in Table 6, using the *Z*-score as a dependent variable and controlling for fixed effects given by different industries and years observed. Standard errors in parentheses.

Abbreviation: OLS, ordinary least squares.

***$p < .01$; **$p < .05$; *$p < .1$.

TABLE 10 OLS regressions breakdown by Industry

Variables	Manufacturing		Oil and Gas		Services		Construction	
E-score	−0.903***		−1.381***		0.920		0.132	
	(0.151)		(0.495)		(0.793)		(0.419)	
S-score	−0.0767		−1.410***		0.0298		−1.416**	
	(0.214)		(0.473)		(0.901)		(0.614)	
G-score	−0.246*		0.886**		0.141		−0.673**	
	(0.134)		(0.364)		(0.578)		(0.329)	
ESG-score		−1.366***		−1.732***		1.168		−1.324**
		(0.161)		(0.533)		(0.740)		(0.523)
Constant	1.325***	1.386***	2.090***	2.153***	1.443*	1.700**	1.310	1.219
	(0.291)	(0.289)	(0.461)	(0.492)	(0.868)	(0.846)	(0.836)	(0.844)
Variables	**Real Estate**		**Transportation**		**Utilities**		**Wholesale**	
E-score	−1.163		−0.568		−0.0358		−0.0550	
	(0.781)		(0.529)		(0.278)		(0.608)	
S-score	−0.471		−0.449		0.156		−0.273	
	(0.948)		(0.729)		(0.344)		(0.695)	
G-score	0.251		−0.223		−0.337		0.272	
	(0.634)		(0.499)		(0.236)		(0.370)	
ESG-score		−1.123		−1.396**		−0.256		0.102
		(0.807)		(0.620)		(0.284)		(0.682)
Constant	2.701***	2.632***	2.009**	2.023**	0.740	0.750	2.427**	2.414**
	(0.618)	(0.556)	(0.951)	(0.935)	(0.861)	(0.849)	(1.189)	(1.184)
Observations	8256	8699	747	769	799	839	503	518
R^2	0.051	0.049	0.155	0.117	0.043	0.041	0.264	0.261
Controls	No	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows the breakdown by Industry of the previous OLS presented in Tables 6 and 7, using the *Z*-score as a dependent variable, including fixed effects for years and countries. Standard errors in parentheses.

Abbreviation: OLS, ordinary least squares.

***$p < .01$; **$p < .05$; *$p < .1$.

4.1 | Robustness checks

We check the robustness of our results by proposing an alternative measure for calculating firm risk. Specifically, following Vassalou and Xing (2004),[2] we use the following:

$$P_{\text{def}} = N(-DD) = N\left(-\frac{\left(\ln\left(\frac{V_{\text{A},t}}{X_t}\right) + \left(\mu - \frac{1}{2}\sigma_{\text{A}}^2\right)T\right)}{\sigma_{\text{A}}\sqrt{T}}\right),$$

where V_{A} is the firm's assets value; X the book value of the debt at time t, that has the maturity equal to T; μ is the mean of the change in $\ln(V_{\text{A}})$; r is the risk-free rate; σ_{A} the standard deviation of V_{A}; N is the cumulative density function of the standard normal distribution.

To calculate σ_{A} we use an iterative procedure, retrieving daily data from the past 12 months to estimate of the volatility of equity σ_{E}, which is then used as an initial value of σ_{A}. Using the Black–Scholes formula, and for each trading day of the past 12 months, we compute V_{A} using V_{E} as the market value of equity of that day. We apply this calculation over only US data, since they were the the only available with an historical daily frequency. We then compute the standard deviation of V_{A}, which is used as the value of σ_{A}, for the next iteration. This procedure is repeated until the values of σ_{A} from two consecutive iterations converge. The tolerance level that we consider for convergence is 10E−4.

In formulas, the above is equal to (Black & Scholes, 1973):

$$V_{\text{E}} = V_{\text{A}}N(d_1) - Xe^{rT}N(d_2),$$

where

$$d_1 = \frac{\left(\ln\left(\frac{V_{\text{A}}}{X}\right) + \left(r - \frac{1}{2}\sigma_{\text{A}}^2\right)T\right)}{\sigma_{\text{A}}\sqrt{T}}, \, d_2 = d_1 - \sigma_{\text{A}}\sqrt{T}.$$

Once we obtain the PD values, we re-run our proposed models over the sample of US companies.

Table 8 shows the results, that definitely confirm our previous findings: we obtain negative and significant relationship between ESG awareness and firm risk, computed by using the PD. Thus, we proof the reliability of the Z-score proposed models.

4.2 | Instrumental variable

We further investigate the reliability of our models by computing an instrumental variable. We use the following variables to include in our instrument: Gross domestic product (GDP) Growth rate; Gini index; Rule of Law; School. All these data are retrieved from the WorldBank database. Gini index measures the extent to which the distribution of income (or, in some cases, consumption expenditure) among individuals or households within an economy deviates from a perfectly equal distribution. Rule of Law captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. School is the gross enrollment ratio is the ratio of total enrollment, regardless of age, to the population of the age group that officially corresponds to the level of education. We run a factor analysis over this variable, using a principal component analysis (PCA), that is a statistical technique used for data reduction. The leading eigenvectors from the eigen decomposition of the correlation or covariance matrix of the variables describe a series of uncorrelated linear combinations of the variables that contain most of the variance.

This computation leads us to identify one factor that represents our instrumental variable. Once we use this factor for testing the viability and reliability of being used as instrument, we acknowledge it as very strongly associated with our *ESG*-score (Table 11). Thus, we run the instrumental variable regression with the models we proposed. Table 12 reports the results obtained with the IV regressions. Specifically, we obtain negatively and significant associations between our instrument (Factor) and the dependent variable, suggesting that our findings are strongly supported by the methodologies implemented.

5 | DISCUSSION

Financial industry is lagging behind in considering attention to ESG factors when assessing borrower risk. What are the reasons for this? Some are certainly related to the difficulty of summarize the three pillars of the ESG in a homogeneous and standardized way in internal

TABLE 11 Instrumental variable construction

Variables	IV—Model OLS	IV—Model OLS
GDP	0.00432***	
	(0.000463)	
Gini	0.00185***	
	(0.000231)	
Rule of Law	0.01210***	
	(0.00185)	
School	0.25600***	
	(0.0624)	
Factor		0.00500***
		(0.000896)
Constant	0.16500***	0.08380***
	(0.00892)	(0.000896)

Note: The table shows the construction of our Instrumental Variable which synthetizes the overall *ESG*-score with the following: GDP Growth rate; Gini index; Rule of Law; School. All these data are retrieved from the WorldBank database. Gini index measures the extent to which the distribution of income (or, in some cases, consumption expenditure) among individuals or households within an economy deviates from a perfectly equal distribution. Rule of Law captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. School is the gross enrollment ratio is the ratio of total enrollment, regardless of age, to the population of the age group that officially corresponds to the level of education. We obtained our instrument by running a factor analysis on the already mentioned variables. The results below report the strong significance of the IV in representing the ESG, thus supporting the reliability of our IV regression further reported. Standard errors in parentheses.

Abbreviations: GDP, gross domestic product; OLS, ordinary least squares.

***$p < .01$; **$p < .05$; *$p < .1$.

TABLE 12 Instrumental variable regressions

Variables	IV—Model OLS	IV—Model OLS	IV—Panel FE	IV—Panel RE
Factor	−0.0387*	0.0141	−0.0313**	−0.0329**
	(0.0201)	(0.0350)	(0.0145)	(0.0141)
Constant	2.405***	1.609***	2.404***	2.178***
	(0.0171)	(0.361)	(0.00771)	(0.0659)
Observations	15,328	15,308	15,328	15,328
R^2	0.000	0.113		
Controls	No	No	No	No
Year FE	No	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes
N			1771	1771

Note: Standard errors in parentheses.

Abbreviation: OLS, ordinary least squares.

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

scoring system. These issues are partly related to those faced by financial intermediaries, in past years in incorporating the qualitative aspects (financial planning, positioning in the relevant product sector, customer portfolio, supplier portfolio, managerial skills) in credit scoring, but the introduction in the credit risk assessment of ESG factors is probably held back by other considerations. Perhaps the state of the art of CRM processes in bank is also the result of a lack of attention that the prudential Supervisor has given to ESG in the prudential supervision framework, in prudential treatment or sustainable lending activities.

As known, the European Union (EU) has a long-term commitment toward sustainability, innovation sustainable, greener economy, sustainable finance. EU Commission is studying, from long ago, how to integrate sustainability consideration into financial policy frameworks to use finance for sustainable growth. In March 2018, the European Commission published its Action Plan on Sustainable Growth, setting an EU strategy on sustainable finance and a roadmap for future work across the financial system. On December 20, 2019, the Technical Expert Group on Sustainable Finance (TEG) published a *handbook on climate benchmarks and benchmarks' ESG disclosures*, including a detailed mapping of classifications of economic activities. On December 6, 2019, EBA published its A*ction plan on sustainable finance* outlining its proposed timeline for delivering mandates relating to ESG factors. In 2020, the NGFS (Network for Greening the Financial System) also issued guidelines on climate scenarios for the Supervisors' climate stress tests, recognizing that "climate-related risks are a source of financial risk." It therefore falls within the mandates of central banks and supervisory authorities to ensure that the financial system is resilient to these risks. Indeed, the ECB in its Guide (2020) emphasizes that "climate change and environmental degradation give rise to structural changes that affect economic activity and, consequently, the financial system; there is also evidence of an interconnection between climate-related change and environmental risks, resulting in combined effects capable of potentially generating even greater impacts."

With regard to ESG strategy and risk management, the EBA Loan Origination and Monitoring requires to include the ESG factors in their CRM policies, including credit risk policies and procedures. The guidelines also set out the expectation that institutions that provide green lending should develop specific green lending policies and procedures covering granting and monitoring of such credit facilities. Despite the many regulatory interventions in the perimeter of sustainable finance, we believe that our results allow us to formulate further reflections in this regard.

Despite the many regulatory interventions in the perimeter of sustainable finance, we believe that our results allow us to formulate further reflections in the field of credit risk measurement that should be "sustainable oriented." From a banker perspective, given the negative (and strong) relationship between ESG and risk, banks should consider choosing ESG-aware firms to finance (trough equity or debt). Furthermore, if firm risk is reduced, we presume that risk weights associated are lower. In our opinion ESG business model's attention is a credit risk mitigation element enables to guarantee an "insurance-like" effect on credit risk of lending activity. In this perspective it would be useful to give capital requirement incentives to realize adjustment in credit scoring related to business model' s ESG attention. If it is true that ESG attention produce an "insurance-like" effect on credit risk the reduction in the capital requirement could be appreciable by recognizing this attention among the unfunded collateral of the framework dedicated to the credit risk mitigation. It could be imagined as a tangible benefit for a bank that decides to re-engineer the CRM process and the creditworthiness assessment system in relation to the ESG sustainability of the borrower's business model. In general, the recognition of a favorable prudential treatment in the calculation of the capital requirement for the credit risk of the ESG lending activity is also important. However, the positive reputation effect that the intermediary would achieve in the market from this strategic direction would remain important and valid, in particular if the intermediary had the possibility to explain in pillar three the ESG sustainability of the CRM process. Equally important could be a regulatory recognition in the SREP score in the assessment dedicated to Risk Management (also CRM) and Governance which in fact would translate into a reduction in the Pillar 2 requirement and therefore in the overall capital requirement. ESG attention in the near future is not only a topic for the nonfinancial reporting but it must represent a driver of development of the strategic planning of the banks also in the field of risk, capital and liquidity and in the SREP assessment, in our opinion, the right regulatory incentive should be found for this attention.

6 | CONCLUSION

We propose a model to support inclusion of ESG factors when assessing the risk of firms by banks (PD). Our findings show that higher ESG awareness is strongly and very significantly associated with better creditworthiness (proxied by the Altman *Z*-score).

We show that ESG variables are so critical in determining a borrower's creditworthiness and have the potential to affect many aspects and measures in both qualitative and quantitative credit analysis. The 2021 European Banking Authority report on managing and supervising ESG risks for credit institutions and investment firms confirms that "environmental, social or governance matters that may have a positive or negative impact on the financial performance or solvency of an entity, sovereign or individual." It recognizes that these elements might manifest themselves in the financial risk disciplines of credit risk via various transmission mechanisms. Indeed, when ESG concerns are included into the credit assessment, any downgrades may have an effect on lenders' capital needs, hence raising financial risks. Failure to handle ESG concerns may result in a negative reputation, misbehavior risks, pricing mistakes, and company development difficulties, among other consequences. Similarly, lower investor and market confidence might result in liquidity concerns, increased finance costs, difficulty obtaining bank facilities, and eventually, assistance.

We support the intuition that ESG factors can affect expected loss through the basic credit parameters of PD, exposure at default, and even loss given default. To more thoroughly address major market and idiosyncratic risk in debt capital markets, underwriters, CRAs, and investors should strategically and systematically examine the financial materiality of ESG issues. Transparency on which ESG variables are examined, how they are incorporated, and the extent to which they are considered relevant in credit assessment.

We are aware of the limits of our research. For each of them, we discuss the issue and propose a solution. First, from a methodological standpoint, we may have a problem of omitted variables, because we include only few covariates within our regression models. However, (i) the *Z*-score is itself computed by including different variables, thus, including other covariates may expose to a multicollinearity issue; (ii) the fraction of variance due to the error u_i is always around a value of $\rho = 0.90$; (iii) we address this problem by computing random effects panel regressions. Second, we may have a functional form misspecification (e.g., $E[y_j x]$ may not be linear in x). Although we are aware that this issue can be handled by nonparametric methods, we do not run this second investigation because we are not specifically interested at this stage in perfectly modeling the dynamic of $E[y_j x]$, as we only want to check for the sign of the relationship between *ESG* (and its dimensions) and *Z*-score. A third issue may be related to a sample selection bias because we only select large listed firms operating in different sectors. We focus on large listed firms to rely on a high number of observations, as to the best our knowledge there is no accessible data warehouse containing ESG data for private firms. To address the issue of having a multi sector sample we apply fixed effects to our regression models. At the same time our research provides insights regarding ESG differences between one sector to another. The last concern is related to endogeneity, that we solve by using an instrumental variable calculated with a factor analysis to avoid simultaneous causality issues.

We suggest future investigation on the relationship between ESG and credit risk assessment to contribute to the policy debate. Specifically, it would be interesting to develop further analysis expanding the sample. Researchers may also compare and contrast different ESG scoring methods by using data provider other than MSCI, as already proposed in this study. A deeper investigation devoted to find difference and similarities between countries and industrial sectors may also be relevant. Additionally, because we showed the high relationship between ESG and credit risk, future researchers may also try and include *ESG*-scores within the assessment of creditors, possibly by relying on bank-specific data. Finally, since we focused on the PD, it would be interesting to also analyze the effect on the Exposition at Default (EAD) and on the Loss Given Default (LGD). Therefore, our research provides new evidence to support the effectiveness of the integration of ESG factors in the creditworthiness analysis of borrowers and the inclusion of ESG awareness as a potential credit risk mitigation factor.

ENDNOTES

[1] Table A1 reports the Hausman's test run over the independent variables. It suggests that fixed effects models are reliable and more appropriate for the investigation than random effects. Complementary, the Breusch and Pagan Lagrangian multiplier test (A2) suggests panel regressions are more appropriate for the investigation than OLS estimators, thus we can rely on that results with a higher level of trustworthiness.

[2] This method assumes, like the same approach of B&S, that the trend of the firm asset value has a trend like random walk (Brownian motion) that is not actually found in empirical tests. Equally untrue is the hypothesis

that the firm has only one form of debt which is represented by the bank loan. The same B&S framework is conceptualized in a risk neutral context that is not perfectly compliant with the risk-oriented assessments of the credit risk measurement framework.

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APPENDIX A

See Tables A1 and A2

TABLE A1 Hausman's test

Coefficient	(*b*) Fixed	(*B*) Random	($b - B$) Difference	sqrt(diag($V_b - V_B$)) SE
E-score	−0.0724319	−0.0767992	0.0043673	0.0079796
S-score	−0.2056139	−0.2076463	0.0020324	0.0100751
G-score	−0.0419854	−0.0592025	0.0172171	0.0070547

Notes: b = consistent under H_o and H_a; obtained from xtreg. B = inconsistent under H_a, efficient under H_o; obtained from xtreg. Test: H_o: difference in coefficients not systematic. $\chi^2(3) = (b - B)'[(V_b - V_B)^{-1}](b - B) = 7.04$ Prob > $\chi^2 = 0.0707$.

TABLE A2 Breusch and Pagan Lagrangian multiplier test for random effects

Coefficient	*Var*	SD = sqrt(*Var*)
Z-score	4.517.403	2.125.418
e	0.9903043	0.9951403
u	7.213.749	2.685.842

Z-score$[ID, t] = Xb + u[\mathrm{ID}] + e[ID, t]$.

Test: H_o: $Var(u) = 0$. $\chi^2(01) = 25617.29$ Prob > $\chi^2 = 0.0000$.