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Environmental performance and credit ratings: A transatlantic study

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ABSTRACT

This paper investigates the impact of the firms' environmental performance on their credit rating. To this end, we conduct a transatlantic study covering companies in the United States (US) and in the European Union (EU). Our study reveals that firms' environmental improvements positively contribute to their credit ratings. However, this effect varies between the US and the EU. If US and European firms enhance their environmental performance by the same scale, the former's creditworthiness benefits more than the latter's. Additionally, we show that improvements in environmental performance affect credit ratings linearly in the US but nonlinearly in the EU. These findings shed light on the implications of the firms' environmental performance and provide critical insights into the impact of corporate sustainability indicators on credit ratings.

1. Introduction

In this study, we investigate whether high environmental performances contribute to improvements in the US and European firms' credit ratings and how the influence of corporate environmental indicators differs between firms in the two regions. This question is of particular significance given the increasing attention to companies' environmental performance over time (Bauer & Hann, 2010; Christensen et al., 2021; Dyck et al., 2019; Klassen & McLaughlin, 1996; Trinh et al., 2023), and uncovers the environmental determinants of credit ratings in two of world's largest economies. The implications are substantial: even minor improvements in credit ratings can result in reduced debt costs, fewer debt issues, and increased capital investment (Baghai et al., 2014; Tang, 2009).

This paper provides an important update on this research question, since the leading credit rating agencies (CRAs) have incorporated climate-related and environmental risk measures into their assessments of debt issuers' creditworthiness (Fitch, 2019; Moody's, 2023; Standard & Poor's, 2023). This is due to the growing importance of the firms' environmental and social activities, which impact both their financial and non-financial attributes, such as management strength and long-term sustainability (Attig et al., 2013). Given the differing perceptions and regulatory requirements of ESG/CSR between the US and the EU, we further posit that the influence of environmental performance on credit ratings differs across these two regions.[2]

Our study focuses on a sample of US and EU firms, which is motivated by previous research investigating country-level differences in ESG ratings in an international setting (see, for example, Cai et al., 2016; Liang & Renneboog, 2017). There are several reasons why we have focused our research on these two jurisdictions. First, the US and the EU are two of the largest and most industrialized economies. Therefore, our research on the impact of environmental factors on credit ratings in these two regions may have broad implications for other industrialized countries that are also major emitters of carbon dioxide. Second, although the EU and the US are signatories to international agreements on climate change, such as the Kyoto Protocol and the Paris Agreement, discrepancies in their regulatory requirements may have global implications on how regional differences can affect corporate environmental performance and creditworthiness. Third, environmental regulations in Europe, such as the European Green Deal, are typically issued by the European Commission and apply to all EU countries. Since the EU consists of 28 member states (27 after Brexit), the stringency of implementation of the same EU environmental regulations may differ across EU countries. Therefore, including the EU in our sample allows

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[1] The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Federal Financial Supervisory Authority (BaFin) or its staff.

[2] We follow Gillan et al. (2021) to treat the terms ESG and CSR as if they are interchangeable and use the terminology ESG/CSR.

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us to examine country-level differences in the adoption of environmental regulations. Fourth, firm-level ESG and ratings data are mostly available for firms in the US and the EU, and less so for countries in other regions.

To empirically examine the effects of firms' environmental indicators on their credit ratings, we use the environmental pillar of the ESG ratings provided by Thomson Reuters ASSET4 ESG database as a measure of the company's environmental performance. Our rating sample includes long-term foreign currency issuer ratings issued by S&P, Moody's, and Fitch. We employ two methodologies to transform credit rating into scores: (1) we combine credit ratings, watches and outlooks together into numerical values ranging from 0 to 58 for the OLS model, and (2) we only consider credit rating signals and transform rating notches into ordinal numbers from 1 to 20 for the ordinal logit model.

Our findings suggest that rating agencies tend to grant firms with higher environmental scores better credit ratings. Moreover, we find that the impact of environmental performances on firms' ratings differs between the US and the EU. This can be partially explained by the differences in the level of environmental performance in the two regions, in line with Cai et al. (2016) and Liang and Renneboog (2017). The EU's more strict ESG/CSR regulations result in better environmental performance of their firms (Christensen et al., 2021), whereas environmental or social performance disclosure is optional in the US. Thus, credit rating agencies are likely to evaluate the implications of an increase in environmental performance differently across these two regions. For instance, US firms that improve their environmental scores can be perceived as more proactive due to their country's less stringent environmental policy (Chava, 2014), and such voluntary improvements may be rewarded. In contrast, the EU has the norm of a high-level environmental consciousness, and thus an additional improvement in EU firms' environmental performance may have smaller benefits on their credit ratings, especially considering strict penalties for non-compliance (Paris Agreement, 2015).

Our first contribution is to investigate how improvements in firms' environmental performance affect their credit ratings. Previous studies have examined the factors that influence credit rating in several areas. A few of these focus on CSR and corporate social performance (CSP) in the US (Attig et al., 2013; Ge & Liu, 2015; Oikonomou et al., 2014) and in the EU (Menz, 2010; Stellner et al., 2015). Some studies document the correlation between firms' credit ratings and environmental performance in the US (Bauer & Hann, 2010; Safiullah et al., 2021; Seltzer et al., 2022). We extend this line of research by investigating the relation between firm-level environmental scores and credit ratings with a more comprehensive credit rating measure and a more recent dataset in both the US and the EU.

Our second contribution is to provide insights on the regional differences between the US and the EU regarding the impact of firms' environmental performance on credit ratings. Cai et al. (2016), Christensen et al. (2021), and Liang and Renneboog (2017) find that the ESG/CSR level is generally higher in the EU than in the US. In a related study, Dorfleitner et al. (2020) investigate the out-of-sample prediction performance for corporate credit ratings by considering information on CSP, based on the coefficients estimated in the in-sample period. They also find regional differences during their study period: an improvement in the prediction quality can be found only in North America, but not in Europe. Inspired by this line of research, our findings enrich the existing literature by showing that regional environmental norms also affect the influence of firms' environmental performance on their credit ratings.

The remainder of this paper is organized as follows. Section 2 presents the hypothesis development. Section 3 elaborates on the construction of numerical credit ratings and the baseline model. Section 4 outlines the data and provides summary statistics. Sections 5 and 6 present the main results and endogeneity tests, respectively. Section 7 offers additional robustness tests, and Section 8 concludes.

2. Hypothesis development

International treaties and guidelines on climate change have significantly increased the importance of climate and environmental factors in the practice of risk assessment and management. The United Nations Framework Convention on Climate Change (UNFCCC) was a pioneering treaty that set the goal of "stabilising greenhouse gas concentrations in the atmosphere". In 1997, the Kyoto Protocol set out a roadmap for implementing the UNFCCC's measures. The Paris Agreement on climate change, which was signed in 2015 and replaced the Kyoto Protocol, marked a historic commitment to transition to a more sustainable global economy. Following the Paris Agreement, a number of countries have published their national climate action plans, including proposals for new regulations for both financial and non-financial firms. In this context, the Big Three CRAs have incorporated climate and environmental factors into their credit risk assessments of debt issuers (Fitch, 2019; Moody's, 2023; Standard & Poor's, 2023).

A firm's credit ratings can be indirectly affected by its ESG factors, through the effects of corporate financial performance (CFP) and cost of debt. A number of previous studies find a positive correlation between firms' ESG dimensions and CFP (Clarkson et al., 2011; Gompers et al., 2003; Kang et al., 2016; Klassen & McLaughlin, 1996; Konar & Cohen, 2001; Oikonomou et al., 2018; Russo & Fouts, 1997). There is also empirical evidence of the positive impact of carbon disclosure on CFP, while carbon disclosure is a key determinant of a company's environmental score. Liesen et al. (2017) show that disclosure of firms' carbon emissions has a positive impact on their financial performance. Moreover, the costs associated with carbon disclosure do not impose a burden on firms' financial resources. Siddique et al. (2021) also confirm in a global context that a company's carbon disclosure positively affects its financial performance.

Although the leading CRAs have not disclosed their rating methodology in detail, they confirm that good CFP and low cost of debt have a positive impact on their credit rating assessment (see e.g. Fitch, 2023; Standard & Poor's, 2019). In this sense, a company's ESG achievements can help to reduce its credit risk via the improvement of CFP. Moreover, empirical evidence shows that companies with good ESG performance have a lower cost of debt (Apergis et al., 2022; Chava, 2014; Eliwa et al., 2021; Goss & Roberts, 2011; Javadi & Masum, 2021). Since a firm's cost of debt is negatively correlated with its credit risk (Kisgen, 2006), an improvement of the firm's ESG performance can have a positive impact on its external credit ratings.

Firms' environmental performance is also a crucial criterion for their interactions with stakeholders. In view of stakeholder theory (Freeman, 1984), firms that demonstrate high social responsibility are more likely to establish good relationships with various stakeholders, including employees, consumers, suppliers, investors and regulators (Fombrun & Shanley, 1990; Waddock & Graves, 1997). Successful relationship management can help increase a firm's intangible value and market reputation, such as higher customer loyalty, better ability to attract and retain high quality employees (Greening & Turban, 2000; Turban & Greening, 1997), and more external financial resources (Chava, 2014; Dyck et al., 2019; Fernando et al., 2017; Tang & Zhang, 2020). These enhancements can further improve the company's credit risk profile.

In line with these theoretical and empirical arguments, we posit that the rating agencies treat improvements in the firms' environmental performance as a positive determinant of credit ratings. Hence, we propose the following hypothesis:

H1. In both the US and the EU, an enhancement in a firm's environmental performance contributes to an improvement in its credit rating.

Although we expect that the positive impact of a firm's environmental improvement on its creditworthiness exists in both regions, the magnitude of this effect may differ between the US and European firms. Cai et al. (2016) use a sample of firms from 36 countries to investigate country-level differences in ESG ratings. Their results confirm that country factors are more influential for ESG ratings than firm characteristics and other economic factors. Moreover, most of the EU countries in their study present greater ESG ratings than the US. Liang and Renneboog (2017) use an extended sample of companies from 114 countries and come to a comparable conclusion: The legal origin of the country is the strongest explanatory factor for firms' ESG ratings. As a result, the US, as a common law country, has a lower average ESG performance than European countries, which are mostly civil law jurisdictions.

Differences in regulatory requirements and political ambitions between the EU and the US may further exacerbate the differential impact of corporate environmental performance on credit ratings. The EU Non-Financial Reporting Directive (NFRD), adopted in 2014, requires companies in scope to publish a non-financial report on their ESG performance. The NFRD contributes to the assessment of the non-financial performance of large companies as measured in ESG dimensions. In contrast, US firms publish CSR-related information either on a voluntary basis or when disclosure is material to investors under existing securities law, as in Christensen et al. (2021). In 2018, the EU published its Action Plan on Sustainable Finance, which aims to guide more investment in projects and companies that take ESG considerations into account. A year later, the European Commission presented the European Green Deal, with the political ambition to become the world's first climate neutral continent by 2050. As a crucial component of the Green Deal, European Climate Law set a legally binding target to reduce greenhouse gas emissions by 55% by 2030 compared to 1990. Unlike the EU, the US has not passed any major climate change legislation in the past decade. In addition, political uncertainty in the US, with the withdrawal from the Paris Agreement under the Trump administration being the most prominent example, may negatively affect the average level of US firms' environmental performance.

The ambitious political goals and strict regulations accelerate the adoption of a more sustainable business model in the EU, which can lead to good environmental performance becoming the new normal for European companies. As a result, further improvements in European firms' environmental indicators may not lead to substantial increases in credit ratings. By contrast, since the average level of ESG ratings is low in the US, firms demonstrating superior environmental performance are likely to be rewarded by rating agencies as recognition of their proactive environmental efforts. These considerations lead to our second hypothesis:

H2. The improvement in a firm's credit rating brought forward by enhancements in its environmental performance is more pronounced in the US than in the EU.

3. Data

In this section, we illustrate the data sample and summary statistics. Our sample consists of firm-level environmental performance (measured by environmental scores from the Thomson Reuters ASSET4 ESG database) and long-term foreign-currency credit ratings issued by the three leading credit rating agencies (CRAs), namely Standard & Poor's, Moody's, and Fitch. Detailed definitions of the variables are provided in Table A.1 of the Appendix.

3.1. Sample construction

The credit rating sample is extracted from Bloomberg and contains three types of rating signals for all non-financial firms in the US and the EU: long-term foreign currency issuer ratings, credit watches and outlooks. The rating signals are issued by one of the three leading CRAs in the period from January 2003 to December 2022. According to Alsakka and Ap Gwilym (2013) and Alsakka et al. (2014), issuer ratings are transformed into numerical values according to a 20-point scale. Based on the numerical rating scale, upgrades (downgrades) are identified if the numerical current rating is higher (lower) than the previous one. Next, we consider credit watches and outlooks as additional rating signals. Positive (negative) watch signals, which by definition consist of placements on a rating agency's positive (negative) watch list, are either solo or combined signals. The former are identified as 'stand-alone' watch list placements, while the latter are watch signals accompanied by the same agency's rating changes. Positive (negative) outlook signals are additions to positive (negative) outlook lists for the countries with stable outlooks or no outlook announcement in advance. Similarly, outlook signals can also be solo or combined with rating changes.

In order to differentiate between solo and combined rating signals in a precise way, it is necessary to introduce a more powerful rating scale which fully takes the differences between solo and combined rating signals into consideration. For this purpose, the initial transformation based on a 20-point scale is extended to a 58-point system in line with Alsakka and Ap Gwilym (2013) and Ferreira and Gama (2007). The new rating scale is named as comprehensive credit rating (CCR) scale by prior literature. The CCR incorporates ratings, watch and outlook signals simultaneously in a new scale as follows: AAA/Aaa = 58, AA+/Aa1 = 55, AA/Aa2 = 52, ..., CCC-/Caa3 = 4, CC/Ca, SD-D/C = 1. In addition, "+2" ("−2") is adjusted for positive (negative) watch signal, while "+1" ("−1") is adjusted for positive (negative) outlook signal and "0" for stable outlook and no watch/outlook assignments.

We source our data of firms' environmental performance from the Thomson Reuters ASSET4 ESG database. This database gathers information from various sources such as annual reports, corporate sustainability reports, nongovernmental organizations, and news media, focusing on large, publicly traded companies across more than 45 countries on an annual basis. According to Thomson Reuters, the selection of data items aims at optimizing factors like company coverage, timeliness, data availability, quality, and perceived relevance for investors. To assess firms' environmental commitment, ASSET4 issues scores to three key areas: Emission Reduction, Product Innovation, and Resource Reduction. These environmental scores range from 0 to 100, where higher scores indicate better environmental performance.

The original frequency of both firm-level fundamentals and environmental scores is yearly. As company credit ratings can be updated multiple times per year, in order to align the frequency of firm-level variables with that of rating signals, we establish a panel data with monthly frequency integrating both data sources through the following steps: Step (1) we convert the data with yearly frequency (firm-level fundamentals and environmental scores) into one with a monthly frequency by using the yearly observation for each month of the year; Step (2) transform the credit rating data into a monthly frequency by always using the latest available rating, ensuring that each data point reflects the latest available rating; Step (3) we then combine the monthly panels created in Steps (1) and (2) using the company identifier and the year-month index as matching keys, to create a monthly dataset that synchronizes firm-level fundamentals, environmental scores, and credit ratings. As a result, our initial sample contains 523,522 firm-month level observations of 1734 firms. We eliminate 138,044 firm-month observations that are missing the environmental scores and 37,548 firm-month observations that are missing financial statement data from Compustat. Our final sample consists of 347,930 observations of 1486 firms.[3]

Table 1 presents the sample distribution by credit rating agency, industry, and year. S&P is the most widely used credit rating agency in both subsamples. From the point of view of industry representation, Consumer Discretionary and Industrials are most present in both US and EU samples. Overall, the number of observations has risen gradually over the sample period, with a slight decrease in the final year, likely due to incomplete data availability for that particular year.

[3] The final EU sample incorporates data from 20 EU countries, including the United Kingdom, France, Germany, Italy, Netherlands, Spain, Sweden,

Table 1
Sample description by agency, industry, and year.

Panel A: Composition by agency			Panel B: Composition by industry			Panel C: Composition by year		
Agency	Observations		Industry	Observations		Year	Observations	
	EU	US		EU	US		EU	US
Fitch	25,638	54,109	Real estate	102	6140	2003	1954	2947
Moody's	30,973	77,273	Telecommunications	10,775	7459	2004	2327	3418
S&P	48,060	111,877	Technology	2259	21,352	2005	3060	4779
			Energy	4895	19,717	2006	3987	5573
			Health care	6327	19,817	2007	4226	6036
			Basic materials	9672	16,712	2008	4429	6763
			Consumer staples	9804	19,935	2009	4609	8516
			Utilities	14,288	21,612	2010	4758	9288
			Industrials	24,897	54,504	2011	5010	9830
			Consumer discretionary	22,483	57,946	2012	5163	10,396
						2013	5204	10,649
						2014	5516	11,350
						2015	5860	12,190
						2016	6034	15,947
						2017	6204	18,373
						2018	6670	20,033
						2019	7125	20,834
						2020	7425	22,023
						2021	7946	23,943
						2022	7164	20,371
Total	104,671	243,259		104,671	243,259		104,671	243,259
Firms	472	1014		472	1014		472	1014

Notes: This table presents the number of observations by agency, industry, and year in Panels A, B, and C, respectively. This sample covers the long-term issuer credit ratings from S&P, Moody's, and Fitch, 10 ICB industries, and the period ranging from January 2003 to December 2022.

3.2. Summary statistics

Table 2 (Panel A) presents the descriptive statistics for all variables employed in our empirical analyses. The mean $RATING\_20$ score sits just under 11 (equivalent to a BBB– rating), with a standard deviation of around 3 and an interquartile range of 4.[4] Notably, the statistics for $RATING\_58$ are roughly triple that of $RATING\_20$. The average environmental score is around 45, with a standard deviation of about 29, which suggests a wide range of environmental performance across firms. On average, debt leverage is around 34% of the total assets of the firms, while the mean ROA is 4.23%. The mean $SIZE$ is around 9, indicating that our sample firms are generally large. The mean of $BIG4$ is 0.9489, which demonstrates that the majority of firms in our sample are audited by one of the Big 4 audit firms.

Panel B of Table 2 provides a comparative summary of the statistics between firms in the US and the EU. Credit ratings appear to be slightly higher for EU firms than for their US counterparts. EU firms also show higher environmental scores, capital intensity, profit margin, and larger firm size. By contrast, they present lower losses, lower leverage, and a smaller standard deviation of operational cash flow and ROA compared to US firms. These findings suggest that, on average, EU firms demonstrate stronger financial and environmental performance compared to US firms.

In Fig. 1, we illustrate the average environmental scores by firms in different industries and years for the US and EU samples. Considerable variation can be observed in the environmental scores across different industries and years. Fig. 1(a) displays the average environmental scores for various industries. It is to be noted that environmental scores are consistently higher for firms in the EU sample, and this trend persists even in industries known to have high emissions, such as Energy and Utilities. In the EU sample, these industries demonstrate relatively high environmental scores over 60. Fig. 1(b) shows the fluctuations in the environmental score throughout the sample period, spanning from 2003 to 2022. The disparities in environmental scores between US and EU firms persist on a year-to-year basis, as evidenced by the industry-level differences. EU firms consistently outperform their US counterparts in terms of environmental scores over the entire period. In summary, the differences in environmental scores displayed in Fig. 1 suggest that EU firms tend to be more environmentally conscious compared to US firms, which is observable across industries and over time. These findings emphasize the substantial role that geographical location and industry characteristics may play in the environmental performance of firms.

The Pearson correlation matrix of the firm-level variables in the US and EU samples are reported in Table 3. The correlation coefficients between credit ratings and environmental scores are positive. The US sample correlation is around 0.37 while the EU sample presents a correlation of about 0.25. The results suggest that firms with higher environmental scores are likely to receive higher credit ratings and this positive relation might differ across the US and EU.

The Pearson correlation coefficients demonstrate that there are no extreme correlations between our control variables. To further test for multicollinearity issues, we investigate the variance inflation factors (VIFs). The average of the VIFs in our model is (1.46) 1.45 for the US (EU) sample, and none of the variables have VIFs greater than the critical value of 2.5 (Johnston et al., 2018).[5]

4. Methodology

In our empirical tests, we employ OLS (ordinal logit) model for the numerical 58-point (ordinal 20-point) scale of credit ratings, controlling for several firm characteristics. The benefit of using the ordinal logit model is that it does not assume that each rating notch represents the same increase in a firm's rating; higher numbers are considered better ratings, but the exact magnitude of the rating is irrelevant. As our numerical rating scaled from 0 to 58 is linear as opposed to the regular numerical rating scaled from 1–20, which does not require such as assumption, there are benefits of employing the OLS estimation because it is more straightforward and it allows the analysis of economic significance based and it is consistent with the use of additional

Finland, Luxembourg, Ireland, Portugal, Austria, Denmark, Belgium, Greece, Czech Republic, Hungary, Cyprus, Romania, and Slovenia.

[4] Although $RATING\_20$ is a categorical variable, we keep it in Table 2 for statistical purposes.

[5] Variables used in the multicollinearity test are $RATING\_58$, ENV, and all firm-level control variables.

Table 2
Summary statistics.

Panel A: Full sample statistics (N = 347,930)							
Variables	Mean	S.D.	Min	Q1	Median	Q3	Max
RATING_58	30.1242	9.7803	0.0000	23.0000	31.0000	37.0000	58.0000
RATING_20	10.9990	3.1713	1.0000	9.0000	11.0000	13.0000	20.0000
ENV	45.8616	29.3326	0.0000	20.0000	48.8653	71.6250	99.1667
SIZE	9.2748	1.3743	4.3633	8.3168	9.1587	10.2401	14.1525
ROA	0.0423	0.0670	−0.2479	0.0173	0.0412	0.0740	0.2346
LOSS	0.0738	0.2615	0.0000	0.0000	0.0000	0.0000	1.0000
LEV	0.3404	0.1772	0.0021	0.2178	0.3215	0.4383	1.0013
INT_COV	13.8769	22.2931	−3.7178	4.7070	7.9797	13.9413	168.0000
CAP_INTEN	0.6003	0.4140	0.0045	0.2490	0.5383	0.8975	1.9075
BIG4	0.9489	0.2201	0.0000	1.0000	1.0000	1.0000	1.0000
CFO_STD	0.0296	0.0237	0.0033	0.0135	0.0225	0.0377	0.1357
ROA_STD	0.0373	0.0473	0.0019	0.0117	0.0223	0.0427	0.3302
MARGIN	0.2055	0.1455	−0.1643	0.1104	0.1762	0.2777	0.7180

Panel B: Descriptive statistics of firm variables in the two regions						
Variables	US (N = 243,259)			EU (N = 104,671)		
	Mean	Median	S.D.	Mean	Median	S.D.
RATING_58	29.3796	31.0000	10.0124	31.8546	34.0000	8.9831
RATING_20	10.7536	11.0000	3.2426	11.5694	12.0000	2.9203
ENV	39.1938	38.8154	28.6842	61.3580	66.9823	24.5840
SIZE	9.1420	9.0339	1.3380	9.5836	9.5435	1.4076
ROA	0.0449	0.0446	0.0704	0.0364	0.0358	0.0579
LOSS	0.0771	0.0000	0.2667	0.0663	0.0000	0.2487
LEV	0.3516	0.3309	0.1835	0.3144	0.3009	0.1586
INT_COV	14.1841	7.8934	23.2267	13.1628	8.1413	19.9372
CAP_INTEN	0.5877	0.5090	0.4154	0.6294	0.5989	0.4093
BIG4	0.9688	1.0000	0.1739	0.9028	1.0000	0.2962
CFO_STD	0.0313	0.0241	0.0245	0.0258	0.0193	0.0213
ROA_STD	0.0399	0.0236	0.0504	0.0313	0.0197	0.0383
MARGIN	0.2030	0.1790	0.1402	0.2112	0.1710	0.1568

Notes: Panel A presents full sample descriptive statistics. Panel B presents the sample descriptive statistics for the two regions, the US and the EU.

Table 3
Correlation matrix.

Variables		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
RATING_58	(1)	1	**0.9628**	**0.2486**	**0.4691**	**0.2983**	**−0.2960**	**−0.1925**	**0.1311**	**0.0157**	**−0.0453**	**−0.2862**	**−0.3277**	**0.1753**
RATING_20	(2)	**0.9514**	1	**0.2702**	**0.5151**	**0.3016**	**−0.3058**	**−0.1929**	**0.1325**	**0.0326**	**−0.0331**	**−0.2972**	**−0.3354**	**0.1781**
ENV	(3)	**0.3722**	**0.4045**	1	**0.4728**	**0.0128**	**−0.0519**	**−0.0610**	**0.0261**	**0.0486**	**−0.0128**	**−0.2118**	**−0.2074**	**−0.0250**
SIZE	(4)	**0.5013**	**0.5434**	**0.5291**	1	**−0.0207**	**−0.0920**	**−0.1488**	**−0.0068**	**0.0350**	**−0.0196**	**−0.3041**	**−0.2546**	**0.0206**
ROA	(5)	**0.3771**	**0.3808**	**0.1354**	**0.0817**	1	**−0.4433**	**−0.1525**	**0.3703**	**−0.0647**	**0.0401**	**0.0154**	**−0.1554**	**0.2629**
LOSS	(6)	**−0.2957**	**−0.3141**	**−0.1003**	**−0.1346**	**−0.4875**	1	**0.1201**	**−0.1247**	**0.0282**	0.0044	**0.1353**	**0.2354**	**−0.1581**
LEV	(7)	**−0.3205**	**−0.3330**	**−0.0856**	**−0.1250**	**−0.1920**	**0.1651**	1	**−0.3783**	**0.1713**	**0.0304**	**0.0170**	**0.0761**	**0.4529**
INT_COV	(8)	**0.2117**	**0.2015**	**0.0600**	**0.0276**	**0.3607**	**−0.1373**	**−0.4379**	1	**−0.0500**	**−0.0309**	**0.0896**	**−0.0158**	**0.0433**
CAP_INTEN	(9)	**−0.0511**	**−0.0426**	**0.0690**	**0.0237**	**−0.1630**	**0.0718**	**0.1086**	**−0.1027**	1	**0.0716**	**−0.0618**	**−0.0572**	**0.2609**
BIG4	(10)	**0.2074**	**0.2056**	**0.1525**	**0.2175**	**0.1079**	**−0.0978**	**−0.0962**	**0.0437**	**−0.0569**	1	**0.0128**	**0.0304**	−0.0018
CFO_STD	(11)	**−0.2232**	**−0.2475**	**−0.1538**	**−0.2609**	**−0.0413**	**0.1590**	**0.0260**	**0.0568**	−0.0007	**−0.0545**	1	**0.4731**	**−0.0664**
ROA_STD	(12)	**−0.2999**	**−0.3290**	**−0.0963**	**−0.2034**	**−0.2619**	**0.2728**	**0.0959**	**−0.0413**	**0.1398**	**−0.1008**	**0.4676**	1	**−0.1096**
MARGIN	(13)	**0.1883**	**0.1944**	**0.0642**	**0.2286**	**0.3104**	**−0.1852**	**0.1205**	**0.0813**	**0.1918**	**−0.0281**	**−0.1476**	**−0.0864**	1

Notes: This table presents the Pearson correlation matrix of the firm-level variables. The numbers below (above) the diagonal are the Pearson correlation coefficients for US (EU) sample. Correlations significant at the 10% level are highlighted in bold.

tests (Baghai et al., 2014). To account for possible correlations in the error terms, we adjust standard errors via firm-level clustering. The fundamental empirical specification in the baseline regression is given by the following equation:

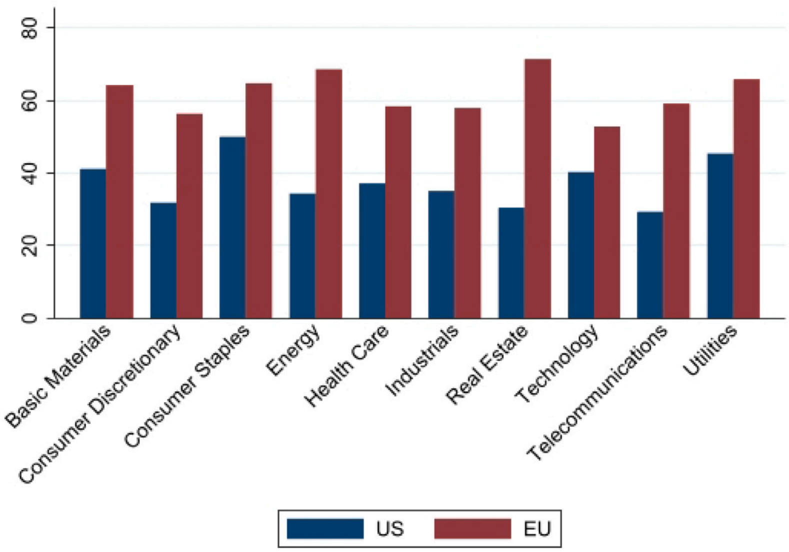
$$RATING_{i,t} = \alpha + \beta ENV_{i,t-12} + \gamma X_{i,t-12} + \Lambda + \epsilon_{i,t}, \tag{1}$$

where $RATING_{i,t}$ constitutes the numerical conversion of the credit rating of firm i' at year-month t, with a higher value signifying superior creditworthiness, denoted as $RATING\_58$ or $RATING\_20$. $ENV_{i,t-12}$, the key variable of interest, designates the environmental score from Thomson Reuters ASSET4 ESG database attributed to firm i at year-month $t-12$. If credit rating agencies consider a firm's environmental performance as one of the credit risk factors, we would expect β to be positive. The control variables in vector $X_{i,t-12}$ are also lagged by a year (twelve months) and are common throughout the different specifications. Λ are year-month, country, and industry fixed effects.

To isolate the effects of key variable of interest (environmental score), we control for a set of variables commonly used in literature of firm credit ratings (Attig et al., 2013; Bhandari & Golden, 2021; Cornaggia et al., 2017). These include: $SIZE$, the natural logarithm of total assets, expressed in millions of USD; ROA, the income before extraordinary items scaled by total assets; $LOSS$, an indicator variable set to 1 if income before extraordinary items is negative in the current and previous year, and 0 otherwise; LEV, total debt (long-term plus the portion of long-term debt in current liabilities) scaled by total assets; INT_COV, earnings before interest and taxes scaled by interest expense; CAP_INTEN, gross property, plant, and equipment scaled by total assets; $BIG4$, an indicator variable set to 1 if the auditor is a Big4 auditor, and 0 otherwise[6]; CFO_STD, the standard deviation

[6] The Big4 auditor are the four largest global accounting networks in the world: Deloitte, Ernst & Young (EY), KPMG, and PwC.

(a) Average environmental scores by industry



(b) Average environmental scores by year

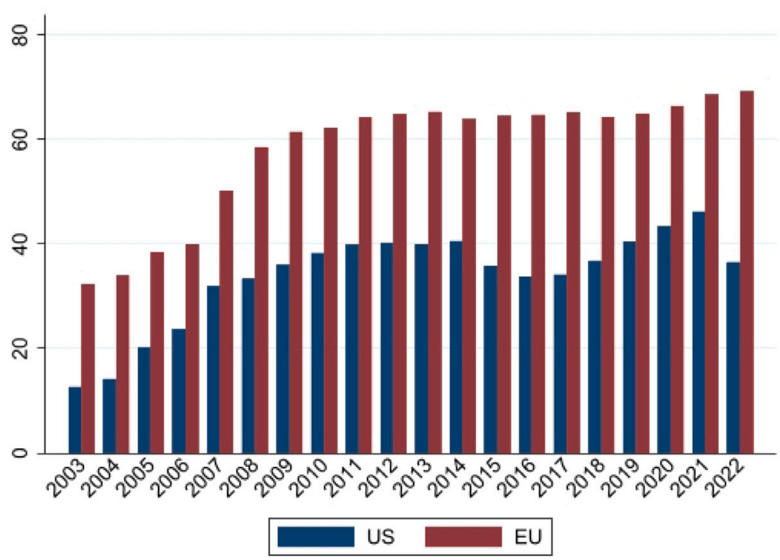


Fig. 1. This figure shows equal-weighted average environmental scores for US and EU firms. Figure (a) demonstrate the average environmental score of firms in each of the ICB industries, while figure (b) shows the average environmental scores of firms ranging from 2003 to 2022.

of operating cash flows scaled by total assets for the previous 60 months; ROA_STD, the standard deviation of ROA for the previous 60 months; $MARGIN$, income before extraordinary items divided by sales. To mitigate the impact of outliers, we winsorize all continuous firm-level controls at the one and ninety-nine percentiles, except for $SIZE$, $LOSS$, and $BIG4$. Finally, we employ year-month, agency, industry, and country indicators to control for variations in ratings across different aspects.[7]

5. Empirical results

Table 4 reports the baseline regression results demonstrating the relation between environmental scores and credit ratings. In Column (1), the coefficient of ENV for the US firms is 0.0570, associated with a t-statistic of 6.50, signifying that the variable ENV is statistically significant at a 1% level. As for the EU sample (Column 2), the coefficient of ENV maintains its significance at 1% level, with a coefficient value of 0.0498. Columns (3) and (4) present results of the ordinal logit model, showing that the coefficients of ENV for both US and EU samples are notably positive and significant at 1% level, with a value of 0.0158 and 0.0117, respectively. These results suggest that the environmental score is a crucial determinant of credit ratings, for both US and EU firms. The economic impact of our empirical results is also significant. Under the OLS regression specification, one standard deviation increase in ENV is associated with a 1.6349 (0.0570×28.6842) increase in the 58 scaled credit ratings in the US, and a 1.2224 (0.0498×24.5840) increase for EU firms.

Results of the baseline regression by OLS and ordinal logit model confirmed our Hypothesis 1. Moreover, it should be noted that the

[7] The industry and country classification in this study is based on the Industry Classification Benchmark (ICB) and ISO country code, respectively.

Table 4
Baseline results.

Panel A: Main results

Variables	(1)	(2)	(3)	(4)
	US	EU	US	EU
	OLS		Ordinal logit	
	Dependent variable = RATING_58		Dependent variable = RATING_20	
ENV	0.0570***	0.0498***	0.0158***	0.0117***
	(0.0088)	(0.0142)	(0.0021)	(0.0038)
SIZE	2.1373***	2.1609***	0.7089***	0.7722***
	(0.2409)	(0.2850)	(0.0662)	(0.0958)
ROA	31.0905***	24.2721***	8.6754***	8.5351***
	(2.7146)	(4.2376)	(0.7648)	(1.3279)
LOSS	−1.5701***	−2.8409***	−0.4406***	−0.7144***
	(0.4887)	(0.5210)	(0.1168)	(0.1668)
LEV	−8.2153***	−8.9565***	−2.3536***	−2.7639***
	(1.3907)	(2.0326)	(0.3434)	(0.6339)
INT_COV	0.0178	0.0190	0.0060*	0.0101**
	(0.0124)	(0.0117)	(0.0033)	(0.0039)
CAP_INTEN	−0.7527	0.0523	0.0240	0.0651
	(0.6258)	(0.8323)	(0.1690)	(0.2539)
BIG4	2.2613***	−0.6900	0.4230***	−0.1714
	(0.8419)	(0.6830)	(0.1627)	(0.2170)
CFO_STD	−11.7620	−40.4239***	−3.1004	−9.6492***
	(7.2890)	(10.7059)	(1.9111)	(3.3716)
ROA_STD	−16.3137***	−26.4226***	−5.5213***	−7.2303***
	(3.3958)	(6.7155)	(0.9794)	(2.2292)
MARGIN	2.8696*	11.6559***	0.7609*	3.2536***
	(1.7003)	(2.3208)	(0.4448)	(0.7268)
Time F.E.	YES	YES	YES	YES
Agency F.E.	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES
Country F.E.	NO	YES	NO	YES
Firm clustered	YES	YES	YES	YES
Observations	243,259	104,671	243,259	104,671
Adj. R^2/Pseudo R^2	0.484	0.512	0.157	0.169

Panel B: Marginal effects of the ordinal logit model

Rating	US			EU		
	Probability at 75th pct.E-Score High E-Score [E-Score = 63.855]	Probability at 25th pct. E-Score Low E-Score [E-Score = 11.416]	High - Low	Probability at 75th pct.E-Score High E-Score [E-Score = 80.640]	Probability at 25th pct. E-Score Low E-Score [E-Score = 45.834]	High - Low
AAA (=20)	0.3411%	0.1508%	0.1902%	No Obs.	No Obs.	
AA+ (=19)	0.2271%	0.1022%	0.1248%	0.0462%	0.0309%	0.0153%
AA (=18)	0.7559%	0.3492%	0.4066%	0.6588%	0.4523%	0.2065%
AA− (=17)	1.5697%	0.7607%	0.8090%	2.0761%	1.5004%	0.5758%
A+ (=16)	3.5453%	1.8537%	1.6915%	5.0371%	3.8238%	1.2133%
A (=15)	8.5612%	5.0919%	3.4693%	5.9753%	4.7572%	1.2181%
A− (=14)	7.4822%	5.0674%	2.4148%	12.1848%	10.3313%	1.8536%
BBB+ (=13)	13.0778%	10.0972%	2.9806%	17.9299%	16.5893%	1.3406%
BBB (=12)	16.7046%	15.1272%	1.5774%	19.2936%	19.5677%	−0.2741%
BBB- (=11)	11.9538%	12.4810%	−0.5273%	12.6802%	13.8488%	−1.1686%
BB+ (=10)	8.4827%	9.8087%	−1.3261%	6.5641%	7.5257%	−0.9616%
BB (=9)	8.3198%	10.4968%	−2.1769%	5.6672%	6.7200%	−1.0528%
BB- (=8)	7.2974%	10.0442%	−2.7468%	3.7675%	4.5869%	−0.8194%
B+ (=7)	4.7368%	7.0399%	−2.3031%	2.3647%	2.9279%	−0.5632%
B (=6)	3.6591%	5.8233%	−2.1642%	2.3069%	2.8915%	−0.5847%
B- (=5)	1.7291%	2.9220%	−1.1929%	1.7529%	2.2238%	−0.4710%
CCC+ (=4)	0.6181%	1.0806%	−0.4626%	0.8624%	1.1142%	−0.2518%
CCC (=3)	0.3418%	0.6069%	−0.2652%	0.2439%	0.3213%	−0.0774%
CCC- (=2)	0.0976%	0.1746%	−0.0770%	0.1154%	0.1535%	−0.0381%
C/CC/D (=1)	0.4991%	0.9215%	−0.4223%	0.4730%	0.6337%	−0.1608%

Notes: This sample contains firm-month observations from January 2003 to December 2022, using Eq. (1) regression models. Numerically transformed long-term issuer ratings by S&P, Moody's, and Fitch are used, with $RATING\_58$ scaled from 0 to 58 and $RATING\_20$ scaled from 1 to 20 (Section 3.1). The environmental score (ENV) is provided by Thomson Reuters ASSET4. All regressions include year-month, agency, and industry fixed effects; country fixed effects apply only to the EU sample. Reported significance is based on robust standard errors clustered at firm level. Significance at 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. Panel A outlines the baseline model coefficients with OLS results in columns (1) and (2), and ordinal logit in (3) and (4). Panel B details the marginal effects from the ordinal logit regression reported in Panel B, displaying probabilities for various ratings at low (25th percentile) and high (75th percentile) environmental scores for companies in the US and EU samples.

difference in coefficients between the US and the EU indicates that this effect is more prominent for US firms. This finding aligns with our second hypothesis, which suggests that the credit rating benefits associated with improved environmental performance are indeed more pronounced in the US than in the EU.

The results on the control variables in the model are generally consistent with prior research (Ashbaugh-Skaife et al., 2006; Attig et al., 2013; Bhandari & Golden, 2021; Bonsall IV et al., 2017; Cornaggia et al., 2017; Hossain et al., 2023). Specifically, accounting variables that capture financial risk, such as $SIZE$, ROA, INT_COV, and

$MARGIN$ (LEV, CFO_STD, $LOSS$ and ROA_STD), are significantly positively (negatively) associated with credit ratings, and their signs are consistent across all model specifications. CAP_INTEN is positively significant under the ordinal logit regressions which is in line with the literature, but for OLS regressions the coefficient is significantly negative for US companies and insignificant for EU firms. Finally, the corporate governance proxy, $BIG4$, reduces managerial opportunistic behavior, which increases credit ratings for the US sample but decreases it for the EU sample. Panel B reports the probability of different ratings when the environmental score is at the 25th and 75th percentiles. Consistent with expectations, in both samples, the probability of higher ratings is higher when environmental score is high. However, when we compare the marginal effects on ratings between high scores and low scores, their difference is greater for the US than the EU sample for all rating grades, except for BBB- ratings. The greatest difference in the US sample is the probability of being rated A, with a value of 3.4693%, whilst in the EU sample the greatest difference is for the A- rating, 1.8536%. These results again prove Hypothesis 1.

Another way to investigate the difference between US and EU is by using a dummy variable ($HIGH\_ENV$) which is equal to one if the firm's environmental score is above the median of the environmental score, and zero otherwise. We conduct OLS and ordinal logit regressions using $HIGH\_ENV$ as an alternative measure for the environmental score to test whether the difference between the two markets is significant for firms with higher/lower environmental scores. The results are reported in Table 5. For the OLS regression specification, we find that the coefficient estimate on $HIGH\_ENV$ is positive and statistically significant at 1% level, with a value of around 2.15 for the US and 1.22 for the EU sample. This means that the relation between credit ratings and environmental scores is stronger for the US sample than the EU sample, which is consistent with expectations. Also the coefficient estimate on $HIGH\_ENV$ for the US sample is significantly higher than the coefficient estimate from for EU sample (p-value < 0.05).[8] In terms of the ordinal logit model specification, the coefficient for the US sample (0.5647) is twice as large as the one of the EU sample (0.2897), and the difference is statistically significant.[9] This provides further evidence for our Hypothesis 2 that firms with high environmental scores are more likely to have a higher credit rating, and the effect is more pronounced for US firms as compared to firms in the EU.

A question that arises naturally is why the relation between credit ratings and environmental scores is stronger in the US than in the EU. First, we visually examine the link between credit ratings and environmental scores. We sort the credit ratings into four groups and compare them across the environmental score bins. Fig. 2(a) depicts the average credit ratings by environmental score bins, for both markets. The figure clearly demonstrates that firms with lower environmental scores tend to have lower average credit ratings in both samples. However, when the environmental scores are below 50, EU firms, on average, have higher credit ratings than their US counterparts. In contrast, in the 50–100 range, US firms demonstrating superior environmental performance achieve better ratings than EU firms with similar environmental scores.

Fig. 2(b) displays the histogram of environmental scores among firms in each group. In the US, more than 40% of observations are concentrated at levels with environmental scores below 25, and the number of observations decreases as the environmental score level increases. In contrast, the EU sample has only about 33% of observations with environmental scores below 50, while the remaining observations are evenly distributed across the two highest levels. This distribution in the EU sample is the other way around, with most of the observations having higher environmental scores. Interestingly, in the 0–25 environmental score bin, approximately 40% of observations have an environmental score of 0 in the US, compared to 22% in the EU.

[8] $(2.1494 - 1.2218)/\sqrt{(0.3558^2 + 0.4330^2)} = 1.6552$ (p-value for the one tailed t-test = 0.049).

[9] $(0.5647 - 0.2897)/\sqrt{(0.0881^2 + 0.1331^2)} = 1.7229$ (p-value for the one tailed t-test = 0.042).

To further explore the observed patterns, we extend our baseline model to capture potential non-linear relation between environmental scores and credit ratings by adding a quadratic term for environmental scores, obtaining the following regression:

$$RATING_{i,t} = \alpha + \beta_1 ENV_{i,t-12} + \beta_2 ENV^2_{i,t-12} + \gamma X_{i,t-12} + \Lambda + \epsilon_{i,t}, \qquad (2)$$

where the dependent variables is the credit rating scaled from 0 to 58. ENV is the environmental score. We again include the same control variables and also control for fixed effects of agencies, industries, year-months, and countries (EU only). The results are reported in Table 6. In this setup we find that the relation between environmental performance and credit ratings is weakly significant in the US. However, for the EU sample, the coefficient of ENV is 0.1095 and statistically significant with a p-value below 0.01, which is twice as large as the coefficient of ENV from the baseline results (0.0498). The coefficient of ENV^2 is significantly negative at 10% level (−0.0006). This shows that there is a diminishing effect of the environmental score on credit ratings in the EU. In other words, the relation is strong and positive for low environmental scores, but it weakens for high values of the environmental score.

Fig. 3 presents the relation between the environmental score and the numerical transformation of credit ratings, ranging from 0 to 58, for both US and EU samples. In the US, the relation appears almost linear. In contrast, the EU depicts a decrease in marginal effects as ENV increases. Also, the relation between the two variables disappears for firms with an environmental score larger than about 80. The marginal impact on ratings spans from 0.1095 (evaluated at the minimum environmental score) to 0 (evaluated at 91.25) and it even becomes negative.

Diverse regulatory environments and market perceptions in the EU and US may explain the detected discrepancies in the link between environmental scores and credit ratings. In the US, firms cluster at lower environmental scores, hence those achieving high environmental performance are often viewed as pioneering protectors of the environment, resulting in a more noticeable positive impact on their credit ratings. Conversely, in the EU, where environmental regulations are stricter and a larger proportion of firms attain high environmental scores, being environmentally conscious might be seen as a baseline expectation, rather than a distinguishing factor. This sheds light on the left-skewed distribution of environmental scores and diminishing marginal effect observed in the EU as environmental scores increase: firms are still rewarded for improved environmental performance, but the magnitude of the reward diminishes.

6. Endogeneity tests

In this section we present the results of tests to address the potential endogeneity issues. Additionally, we employ instrumental variable estimation method to address the endogeneity concern.

6.1. Test for omitted variable bias

One concern with our analysis is that relevant variables might have been omitted from our model. To assess whether omitted variable bias is present, we carry out a test proposed by Oster (2019), for our OLS regression results displayed in Table 4, Panel A, Columns (1) and (2). This test addresses the stability of regression coefficients and R-squared with and without controls to establish an identifiable set for the coefficient of interest. If zero is not included in this set, then the null hypothesis that an omitted variable is driving the result can be dismissed. One boundary of this identifiable set is $\tilde{\beta}$, the coefficient of interest in the model with controls. The other bound, denoted as β^*, is computed as follows:

$$\beta^* \approx \tilde{\beta} - \delta[\dot{\beta} - \tilde{\beta}]\frac{R_{max} - \tilde{R}}{\tilde{R} - \dot{R}}, \qquad (3)$$

Table 5
Effect of above median-level environmental scores on credit ratings.

Variables	(1)	(2)	(3)	(4)
	US	EU	US	EU
	OLS		Ordinal logit	
	Dependent variable = RATING_58		Dependent variable = RATING_20	
HIGH_ENV	2.1494***	1.2218***	0.5647***	0.2897**
	(0.3558)	(0.4330)	(0.0881)	(0.1331)
SIZE	2.4114***	2.3964***	0.7833***	0.8256***
	(0.2360)	(0.2643)	(0.0645)	(0.0889)
ROA	32.5187***	25.4248***	9.0690***	8.8153***
	(2.7179)	(4.2758)	(0.7682)	(1.3366)
LOSS	−1.5251***	−2.7656***	−0.4243***	−0.6902***
	(0.4887)	(0.5329)	(0.1179)	(0.1680)
LEV	−8.4331***	−8.8714***	−2.3918***	−2.7321***
	(1.3916)	(2.0549)	(0.3409)	(0.6311)
INT_COV	0.0181	0.0196*	0.0061*	0.0102***
	(0.0126)	(0.0115)	(0.0033)	(0.0039)
CAP_INTEN	−0.4982	0.1927	0.0991	0.1004
	(0.6328)	(0.8245)	(0.1702)	(0.2511)
BIG4	2.5243***	−0.6608	0.5071***	−0.1508
	(0.8569)	(0.6743)	(0.1602)	(0.2139)
CFO_STD	−11.9825	−41.8765***	−3.1690*	−9.9325***
	(7.2976)	(10.8517)	(1.8918)	(3.3507)
ROA_STD	−15.6522***	−26.6548***	−5.2592***	−7.2299***
	(3.3785)	(6.8675)	(0.9611)	(2.2680)
MARGIN	2.3261	11.2268***	0.5716	3.1392***
	(1.7055)	(2.3403)	(0.4428)	(0.7366)
Time F.E.	YES	YES	YES	YES
Agency F.E.	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES
Country F.E.	NO	YES	NO	YES
Firm clustered	YES	YES	YES	YES
Observations	243,259	104,671	243,259	104,671
Adj. R^2/Pseudo R^2	0.477	0.506	0.153	0.168

Notes: This table reports the results from regressions of credit ratings on high environmental score group. Columns (1) and (2) present results from the OLS specification, and columns (3) and (4) present those from the ordinal logit specification. We use the numerical transformation of domestic long-term issuer ratings by S&P, Moody's, and Fitch, increasing in credit quality. $RATING\_58$ is the credit rating scaled from 0 to 58, while $RATING\_20$ is scaled from 1 to 20, details in Section 3.1. $HIGH\_ENV$ equals one if the environmental score is above its median level, zero otherwise. All regressions include year-month, agency, and industry fixed effects, while country fixed effects are only employed in the EU sample. Reported significance is based on robust standard errors clustered at firm level. Significance at 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

(a) Average ratings by levels of environmental score

(b) Histogram of environmental scores

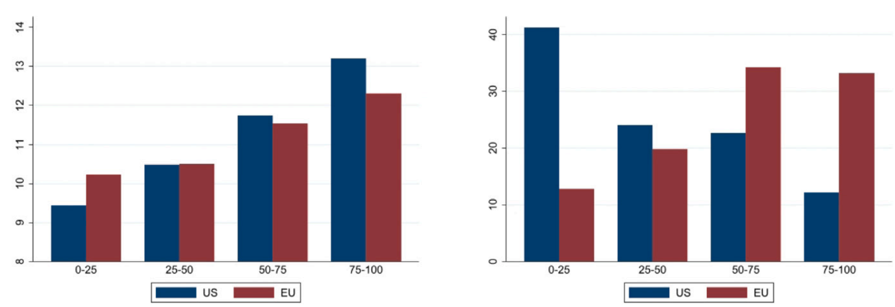


Fig. 2. This figure shows (a) equal-weighted average ratings for different categories of environmental scores and (b) the histogram of environmental scores, for US and EU samples.

where $\dot{\beta}$ stands for the coefficient of interest from the regression without control variables. $\tilde{R}$ is the R^2 when all controls are included while $\dot{R}$ is the R^2 without controls. Oster (2019) suggests that a suitable upper bound for δ is 1, although no standard approach exists. R_{max} symbolizes the R-squared of a hypothetical model including both observable and unobservable covariates, and is suggested to be $R_{max} = 1$ (the most stringent case), $R_{max} = min(2\tilde{R};1)$, or $R_{max} = min(1.5\tilde{R};1)$. Using the coefficient of environmental score from US and EU samples in Table 4, Panel A Columns (1) and (2) as the upper bounds, as well as the coefficient of environmental score and R^2 without any control variables as the lower bounds, we construct Oster's identifiable set, with $\dot{\beta}$ for US (EU) samples being 0.1230 (0.0912) and $\tilde{R}$ for US (EU) samples being 0.1302 (0.0645). Assuming $\delta = 1$ and $R_{max} = 1$, the identifiable set for the EU sample regression is $[0.0049, 0.0498]$, excluding zero in the most stringent case. Assuming $\delta = 1$ and $R_{max} = min(1.5\tilde{R};1)$, the identifiable set for the US sample regression is $[0.0118, 0.0570]$. Oster comments that employing $\delta = 1$ and $R_{max} = 1$ results in only about one-third of empirical research studies in leading economic journals being robust, thus suggesting less restrictive alternatives such as $R_{max} = min(1.5\tilde{R};1)$ as acceptable.

Table 6
Test for non-linear relation.

Variables	(1)	(2)
	US	EU
	Dependent variable = RATING_58	
ENV	0.0336†	0.1095***
	(0.0213)	(0.0388)
ENV^2	0.0003	−0.0006*
	(0.0003)	(0.0003)
SIZE	2.1297***	2.1939***
	(0.2406)	(0.2802)
ROA	31.0117***	24.3053***
	(2.7138)	(4.2397)
LOSS	−1.5826***	−2.8526***
	(0.4870)	(0.5189)
LEV	−8.3066***	−8.8792***
	(1.3966)	(2.0336)
INT_COV	0.0176	0.0187
	(0.0123)	(0.0116)
CAP_INTEN	−0.7414	0.0535
	(0.6250)	(0.8268)
BIG4	2.3424***	−0.6315
	(0.8370)	(0.6658)
CFO_STD	−12.2237*	−39.6285***
	(7.2357)	(10.6845)
ROA_STD	−16.2214***	−26.7302***
	(3.3983)	(6.6894)
MARGIN	2.8571*	11.5162***
	(1.6985)	(2.2872)
Time F.E.	YES	YES
Agency F.E.	YES	YES
Industry F.E.	YES	YES
Country F.E.	NO	YES
Firm clustered	YES	YES
Observations	243,259	104,671
Adjusted R^2	0.484	0.513

Notes: this table reports the results from OLS regression of credit ratings on the environmental score and the square of environmental score. We use the numerical transformation of foreign long-term issuer ratings by S&P, Moody's, and Fitch, increasing in credit quality. $RATING\_58$ is the credit rating scaled from 0 to 58, while ENV is the environmental score provided by Thomson Reuters ASSET4. All regressions include year-month, agency, and industry fixed effects, while country fixed effects are only employed in the EU sample. Reported significance is based on robust standard errors clustered at firm level. Significance at 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. † indicates that, performing an one-sided significance test, the parameter estimate is significantly larger than zero at 10% significance level.

6.2. Instrumental variable estimation

In our second endogeneity test, we verify the stability of our evidence to potential endogeneity bias stemming from reverse causality. One might argue that firms with better credit ratings can support more environmental-related investments. We control for this potential bias by employing the two-stage least squares (2SLS) regression to examine whether our results are driven by endogeneity between environmental scores and credit ratings. Following the spirit of Attig et al. (2013) and El Ghoul et al. (2011), we use an instrumental variable labeled as IV_INDUS in our analysis, which represents the average monthly environmental score of the firms in a given industry. This is directly related to firm-level environmental scores within the industry but it holds no direct connections to the individual credit ratings.

The 2SLS regression results are presented in Table 7, showing the first and second stage regression results for both the US and EU samples. The first stage of the 2SLS regression indicates a significant positive relation between the instrumental variable and firm-level environmental score, suggesting that the instrumental variable is valid for the study. In the second stage, the instrumented environmental score is used in the regression analysis with credit ratings. The results show a positive and significant relation between the instrumented environmental score and credit ratings, with the coefficient being significant at 1% level in the EU. For the US sample, it is significant at 10% level. We also

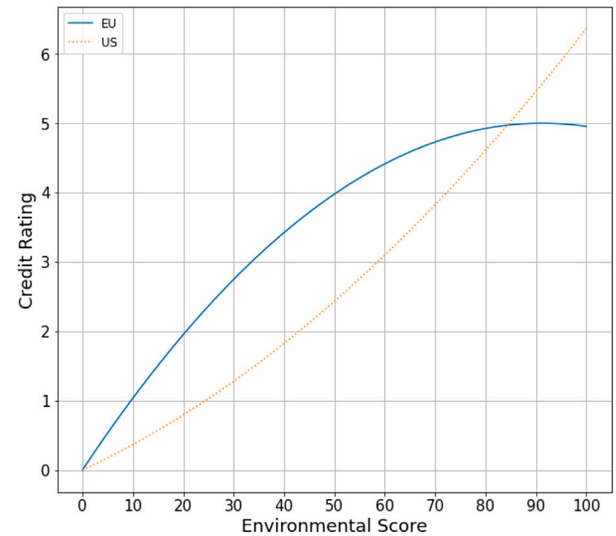


Fig. 3. Environmental performance versus credit ratings. The horizontal axis represents the environmental score. The vertical axis represents the predicted value of the numerical transform of credit rating scaled from 0 to 58. The solid blue (dotted orange) line shows the relation in the EU (US). The figure is based on the parameter estimates of Eq. (2) reported in Table 6. For simplicity, the control variables are held at zero.

conduct several tests to further validate the use of the instrumental variable. The results of the underidentification test (Kleibergen-Paaprk LM-statistic) and the weak identification test (Cragg-Donald Wald F-statistic) show that the instrumental variable is strong and relevant. The Anderson-Rubin Wald test further confirms that the instrumented variable is robust to the weak instrument bias. All these tests support the choice of the instrumental variable and the validity of the results of the study. Thus, the analysis supports the hypothesis that better environmental performance, as measured by environmental scores, is positively associated with credit ratings.

6.3. Propensity score matching & entropy balancing

The existing literature documents that firms with better financial performance have higher ESG/CSR performance (Borghesi et al., 2014; Hong et al., 2012). One may argue that firms with greater financial performance have the ability to expend more resources on ESG/CSR activities. This means that the ESG scores of financially well-performing companies could differ from those which are under-performing. To address the potential differences between firms with high and low environmental performance, we employ the propensity score matching model (PSM) developed by Rosenbaum and Rubin (1983) to address the concern that the treated sample is not similar to the control (see Fang et al., 2014). Unlike conventional selection models such as the one proposed by Heckman (1979) that estimate the effects of treatments based on certain functions, PSM does not make any assumptions about functional relation. Instead, it provides a more direct way to estimate the effect of treatments (see Kai & Prabhala, 2007).

To implement this approach in our study, we first divide our sample into two subsamples based on the median environmental score. Firms scoring above (below) the median are defined as the treatment (control) group. Similar to Table 5, $HIGH\_ENV$ is used. This variable equals one when the firm is part of the treatment group and zero otherwise. A logit model is used to estimate the propensity score using control variables from the baseline regression, agency indicators, and year-month indicators: $SIZE$, ROA, $LOSS$, LEV, INT_COV, CAP_INTEN, $BIG4$, CFO_STD, ROA_STD, $MARGIN$, $Agency\ dummies$, and $Time\ dummies$. Ultimately, we perform a one-to-one matching, allowing a maximum caliper distance of 1% without replacement (Lawrence et al., 2011; Shipman et al., 2017).

Table 7
Instrumental variable (2SLS) results.

Variables	(1)	(2)	(3)	(4)
	US		EU	
	First-stage	Second-stage	First-stage	Second-stage
	Second-stage Dependent variable = RATING_58			
ENV		0.0603*		0.1327***
		(0.0355)		(0.0450)
IV_INDUS	0.6173***		0.6606***	
	(0.0751)		(0.0738)	
SIZE	11.9570***	2.0971***	8.9396***	1.4074***
	(0.4381)	(0.4708)	(0.6114)	(0.5043)
ROA	59.1454***	30.8919***	33.5890***	21.1324***
	(8.0570)	(3.5440)	(10.6274)	(4.4218)
LOSS	2.1582	−1.5767***	1.4704	−2.9701***
	(1.3735)	(0.4900)	(1.4231)	(0.5298)
LEV	−8.3104**	−8.1872***	3.5638	−9.2850***
	(3.7701)	(1.4126)	(5.0859)	(2.0413)
INT_COV	0.0102	0.0178	0.0268	0.0168
	(0.0236)	(0.0123)	(0.0288)	(0.0127)
CAP_INTEN	10.1156***	−0.7868	4.6577**	−0.3382
	(2.0250)	(0.7195)	(2.0792)	(0.8795)
BIG4	6.4841***	2.2390***	2.2123	−0.8933
	(2.2284)	(0.8674)	(2.1225)	(0.7478)
CFO_STD	−16.7461	−11.7075	−16.2546	−39.0591***
	(21.5907)	(7.3427)	(29.3178)	(10.6166)
ROA_STD	27.4377***	−16.4053***	−9.9813	−25.3562***
	(10.2650)	(3.5738)	(12.8412)	(6.4896)
MARGIN	−22.7740***	2.9481	−10.6332*	12.6400***
	(4.8315)	(1.9056)	(5.7656)	(2.3972)
Constant	−118.9133***	5.9092*	−65.8254***	13.7237***
	(6.2754)	(3.2309)	(9.3967)	(3.4955)
Time F.E.	YES	YES	YES	YES
Agency F.E.	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES
Country F.E.	NO	NO	YES	YES
Firm clustered	YES	YES	YES	YES
Observations	243,259	243,259	104,671	104,671
Underidentification test				
Kleibergen-Paaprk LM statistic		56.33***		46.64***
Weak identification test				
Cragg-Donald Wald F statistic		3342.230***		2683.453***
Weak-instrument-robust inference				
Anderson-Rubin Wald test		3.11*		8.33***

Notes: This table reports the results of two-stage least square regressions for US and EU samples in Columns (1)–(2) and (3)–(4), respectively. We use the numerical transformation of foreign long-term issuer ratings by S&P, Moody's, and Fitch, increasing in credit quality. $RATING\_58$ is the credit rating scaled from 0 to 58, details in Section 3.1. ENV is the environmental score provided by Thomson Reuters ASSET4. IV_INDUS is the monthly average of the environmental score of firms in a given industry. All regressions include year-month, agency, and industry fixed effects, while country fixed effects are only employed in the EU sample. Reported significance is based on robust standard errors clustered at firm level. Significance at 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Table 8 (Panel A) presents the OLS and ordinal logit regression results using samples treated with PSM. When comparing observations in PSM with our primary results in Panel A of Table 4, nearly half of the observations are eliminated after the matching, and this removal rate is similar for both the US and EU samples. Nonetheless, our findings consistently show a positive and significant coefficient for both OLS and ordinal logit regressions in the US and EU samples. These results are consistent with our main regression results in Table 4 (Panel A) that firms with higher environmental score exhibit higher credit ratings.

Although PSM offers an effective approach to address endogeneity concerns, one criticism of PSM is that variations in design choices, including maximum caliper width, matching with/without common support, with/without replacement, and whether one-to-one matching is used or not can influence the conclusions (see DeFond et al., 2016). Another criticism is that unmatched units from PSM are discarded, reducing the number of observations for subsequent tests (Chapman et al., 2019; Wilde, 2017).

For these reasons, we also implement entropy balancing, an alternative technique to tackle endogeneity concerns. This method, which does not require a model specification or criteria, is a weighting technique designed to improve balance between the treatment and control groups without losing observations (Hainmueller, 2012; Hainmueller & Xu, 2013). Specifically, this method adjusts the weights of the control group observations such that the first, second, and third moment (i.e., mean, standard deviation, and skewness) of all covariates in the control group to match those of the treatment group. As shown in Panel B of Table 8, we continue to observe a significant and positive relation between credit ratings and environmental scores. Compared to the results in Panel A, the regression results from a complete sample indicate that the magnitudes of all coefficients of our variable of interest (ENV) are larger than those from the PSM-matched sample.

7. Transmission channel analysis

Our prior results in Tables 4 and 5 show that the improvement of environmental performance has positive impact on credit ratings and this impact is more pronounced in the US than the EU. To further investigate what causes such a regional difference between the US and the EU, we conduct a transmission channel analysis to investigate why the effect is more pronounced in the US. According to Frohm et al. (2023), the OECD Environmental Policy Stringency Index (EPS) is a

Table 8
Test for propensity score matching and entropy balancing.

Variables	(1)	(2)	(3)	(4)
	US	EU	US	EU
	PSM		Entropy balancing	
	Dependent variable = RATING_58			
ENV	0.0523***	0.0397***	0.1400***	0.1243***
	(0.0084)	(0.0146)	(0.0096)	(0.0147)
SIZE	2.1876***	2.0636***	−0.0565	0.3544***
	(0.2351)	(0.3038)	(0.1425)	(0.0822)
ROA	31.1018***	25.2797***	10.5263***	18.3535***
	(3.1000)	(5.1699)	(2.7406)	(4.2356)
LOSS	−1.7555***	−2.9791***	−2.4628***	−2.3367***
	(0.5554)	(0.5853)	(0.8476)	(0.6163)
LEV	−10.1247***	−11.7249***	−4.5664***	−8.2097***
	(1.3794)	(2.3521)	(1.2494)	(1.8527)
INT_COV	0.0204*	0.0153	−0.0031	0.0140
	(0.0109)	(0.0144)	(0.0073)	(0.0127)
CAP_INTEN	−0.9717	0.2836	−0.5430	−0.6709
	(0.6932)	(0.8504)	(0.4748)	(0.6291)
BIG4	3.9811***	−0.6117	2.0509	−1.0008*
	(1.2078)	(0.6931)	(1.7265)	(0.5672)
CFO_STD	−17.6050**	−20.5286*	2.8375	−20.8999**
	(7.5569)	(12.3927)	(7.6702)	(9.1136)
ROA_STD	−16.6919***	−35.3795***	−20.1634***	−36.8475***
	(4.0673)	(8.5785)	(4.3772)	(7.8634)
MARGIN	4.4787***	12.0939***	3.2416***	11.4335***
	(1.6583)	(2.2142)	(1.1045)	(2.1802)
Time F.E.	YES	YES	YES	YES
Agency F.E.	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES
Country F.E.	NO	YES	NO	YES
Firm clustered	YES	YES	YES	YES
Observations	131,942	64,122	243,259	104,671
Adj. R^2	0.411	0.450	0.362	0.406

Notes: This table reports the OLS regression results of the sample constructed using propensity score matching (PSM) and entropy balancing. We use the numerical transformation of foreign long-term issuer ratings by S&P, Moody's, and Fitch, increasing in credit quality. $RATING\_58$ is the credit rating scaled from 0 to 58, details in Section 3.1. ENV is the environmental score provided by Thomson Reuters ASSET4. All regressions include year-month, agency, and industry fixed effects, while country fixed effects are only employed in the EU sample. Reported significance is based on robust standard errors clustered at firm level. Significance at 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

country-specific and internationally-comparable measure of the stringency of environmental policy, which ranges from 0 (not stringent) to 6 (highest degree of stringency) and covers 40 countries for the period 1990−2020. We consider EPS as the proxy for the stringency of country-level environmental regulation and examine how EPS influences the marginal effect of environmental performance on credit ratings.

The results are presented in Table 9. Column (1) demonstrates that, without controlling for EPS, the environmental performance has a positive impact on the credit ratings of firms in all countries in our sample. Column (2) shows that EPS has a significantly negative effect on the credit ratings while the marginal effect of environmental performance almost doubles. In Column (3), we report the evidence at 10% significance level that the marginal effect of environmental score on credit ratings reduces when EPS increases, as indicated by the negative coefficient on the interaction term. This matches our previous finding that the marginal effect of improving environmental score on credit rating is more pronounced in the US (with a low level of EPS) than in the EU (with a high level of EPS). Overall, the stringency of environmental policy can be regarded as a transmission channel for the effect of environmental score on credit ratings.

8. Robustness tests

We carry out several additional studies to prove the robustness of our results, including re-running regressions by distinguishing between investment-grade and speculative-grade ratings, re-running regressions for individual rating agencies, replacing foreign-currency issuer ratings with domestic-currency ratings, employing alternative measures for the environmental performance, industry-size matched sampling, as well as investigating the non-linear relation of social and governance performance on credit ratings.

8.1. Investment grade versus speculative grade

Following Ashbaugh-Skaife et al. (2006), Bhandari and Golden (2021), and Cornaggia et al. (2017), we employ an alternative measure for credit ratings. We construct a dummy variable (INVESTMENT_GRADE), which is assigned 1 if the long-term issuer credit rating falls in the top tier (BBB- or above), and 0 otherwise. We apply the logit model for our regression analysis. We aim to evaluate whether firms with above median-level environmental scores have a higher likelihood of receiving an investment-grade rating compared to those with lower environmental scores. We also incorporate the binary variable $HIGH\_ENV$ in this analysis. The logit regression results are reported in Table 10. The coefficients on ENV are positive and statistically significant, with a value of 0.0212 (0.0144) for the US (EU) sample. However, the coefficient of $HIGH\_ENV$ is 0.7839 and significant at 1% level for the US, while in the EU it is only 0.3220 and significant at 10% level only. This suggests that EU firms with higher or lower environmental scores do not show as significant differences as US firms, aligning with our Hypothesis 2.

8.2. Regression analysis by CRA

As credit ratings might vary across rating agencies due to differing rating methodologies, we study the effect of environmental scores on credit ratings by running CRA-specific regressions. The results are reported in Table 11. We find solid evidence that environmental

Table 9
Transmission channel analysis.

Variables	(1)	(2)	(3)
	Dependent variable = RATING_20		
ENV	0.0073***	0.0129***	0.0224***
	(0.0017)	(0.0018)	(0.0054)
EPS		−0.7814***	−0.6460***
		(0.0733)	(0.1078)
ENV∗EPS			−0.0036*
			(0.0019)
SIZE	0.7723***	0.7082***	0.7151***
	(0.0587)	(0.0587)	(0.0590)
ROA	9.7138***	9.3268***	9.3241***
	(0.7714)	(0.7652)	(0.7654)
LOSS	−0.4871***	−0.5532***	−0.5484***
	(0.1081)	(0.1079)	(0.1073)
LEV	−2.7731***	−2.3606***	−2.3639***
	(0.3107)	(0.3199)	(0.3193)
INT_COV	0.0064**	0.0074**	0.0075***
	(0.0029)	(0.0029)	(0.0029)
CAP_INTEN	0.0847	−0.0042	−0.0072
	(0.1502)	(0.1503)	(0.1498)
BIG4	0.1520	0.0332	0.0579
	(0.1663)	(0.1624)	(0.1604)
CFO_STD	−2.6984	−4.7040**	−4.6374**
	(1.8953)	(1.8842)	(1.8812)
ROA_STD	−5.7230***	−6.0302***	−6.0496***
	(0.9033)	(0.9083)	(0.9138)
MARGIN	1.4422***	1.5451***	1.5285***
	(0.4204)	(0.4297)	(0.4281)
Time F.E.	NO	NO	NO
Agency F.E.	YES	YES	YES
Industry F.E.	YES	YES	YES
Country F.E.	YES	YES	YES
Firm clustered	YES	YES	YES
Observations	288,470	288,470	288,470
Pseudo R^2	0.141	0.149	0.149

Notes: this table reports the results from ordinal logit regression of credit ratings on the environmental score, the environmental policy stringency index, and their cross product, from January 2003 to December 2020. We use the numerical transformation of foreign long-term issuer ratings by S&P, Moody's, and Fitch, increasing in credit quality. $RATING\_20$ is the credit rating scaled from 0 to 20. ENV is the environmental score provided by Thomson Reuters ASSET4. EPS is the environmental policy stringency index from the organization for economic co-operation and development (OECD). All regressions include year-month, agency, industry, and country fixed effects. Reported significance is based on robust standard errors clustered at firm level. Significance at 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Table 10
Results for investment grade dummy.

Variables	(1)	(2)	(3)	(4)
	US		EU	
	Dependent variable = INVESTMENT_GRADE			
ENV	0.0212***		0.0144***	
	(0.0033)		(0.0053)	
HIGH_ENV		0.7839***		0.3220*
		(0.1290)		(0.1823)
Controls	YES	YES	YES	YES
Time F.E.	YES	YES	YES	YES
Agency F.E.	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES
Country F.E.	NO	NO	YES	YES
Firm clustered	YES	YES	YES	YES
Observations	243,259	243,259	104,340	104,340
Adj. R^2/Pseudo R^2	0.385	0.376	0.356	0.351

Notes: This table reports the coefficients of logit regression for the US and EU samples. The dependent variable is $INVESTMENT\_GRADE$, an indicator variable which equals one if the long-term issuer credit rating is in the top group (also known as investment-grade BBB- or higher), and zero otherwise (the bottom group, also known as the speculative-grade BB+ or lower). We use the long-term foreign currency issuer ratings by S&P, Moody's, and Fitch. ENV is the environmental score provided by Thomson Reuters ASSET4. $HIGH\_ENV$ equals one if the environmental score is above the median level of the environmental score, zero otherwise. All regressions include year-month, agency, and industry fixed effects, while country fixed effects are only employed in the EU sample. Reported significance is based on robust standard errors clustered at firm level. Significance at 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

scores positively impact credit ratings across all subsets, validating our Hypothesis 1 that higher environmental performance leads to a higher credit rating. However, the strength of this relation varies across different rating agencies and regions. For instance, Moody's displays the highest environmental coefficient in the US with a value of 0.072, compared to 0.046 in the EU, while Fitch exhibits a higher coefficient in the EU than in the US. The results in Table 11 are consistent across both OLS regressions (Panel A) and ordinal logit regressions (Panel B).

8.3. Domestic-currency ratings

We analyze whether the positive relation between environmental scores and ratings changes if we use domestic-currency issuer credit ratings as the dependent variable instead of foreign-currency ratings. The rationale is that foreign currency ratings could incorporate exchange rate and inflation risks, which are absent in domestic currency ratings, and could potentially weaken the correlation between environmental scores and foreign currency ratings. Table 12 presents the regression results using domestic currency credit ratings as the dependent variable. Compared to the baseline regression results in Table 4, the coefficients of all regressions with domestic currency ratings are higher than those with foreign currency ratings. As expected, excluding potential risks from exchange rates and inflation yields a higher coefficient, with the difference being more pronounced when employing OLS regressions with 58 scaled ratings in columns 1 and 2.

8.4. Alternative measures for environmental performance

To corroborate the validity of our primary results, we perform a robustness check by employing alternative measures for the environmental scores. The necessity of such robustness check is to ensure that our findings are not solely dependent on the particular measure of environmental score used. For our analysis, we turn to two key alternatives: Green House Gas (GHG) emissions and Bloomberg's environmental scores.

GHG emissions, as identified in the Thomson Reuters ASSET4 ESG database, constitute a major determinant of the overall environmental score. We consider the logarithm of total CO_2 and CO_2 equivalent emissions in tonnes, which includes both direct and indirect emissions from owned or controlled sources, as our first alternative measure for environmental performance. We re-run the baseline regression using this variable (denoted $EMISSION$) and the results are presented in Table 13. Given the implied inverse relation between emissions and environmental friendliness, it is expected that the coefficients for $EMISSION$ are negative and statistically significant. In line with this expectation, the results from the EU sample are consistently more negative than those from the US. This suggests that credit rating agencies are incorporating information on carbon emissions when evaluating credit ratings, and this is more pronounced in the EU than in the US.

Next, we use the environmental scores issued by Bloomberg as our second alternative measure for environmental performance. Since Bloomberg's environmental scores range from 0 to 10, unlike the 0–100 scale used in Thomson Reuters ASSET4, the coefficients obtained based on the scores issued by Bloomberg are typically larger than those from our baseline regressions.

8.5. Industry and size matched sampling

Since the distribution of environmental scores might vary across industries, we employ an industry- and size-matched sample with the high environmental scores group and the low environmental scores

Table 11
Results for rating subsamples according to credit rating agencies.

Panel A: OLS regressions						
Variables	(1)	(2)	(3)	(4)	(5)	(6)
	US			EU		
	SP	Moody's	Fitch	SP	Moody's	Fitch
	Dependent variable = RATING_58					
ENV	0.0566***	0.0720***	0.0304**	0.0555***	0.0460**	0.0412**
	(0.0092)	(0.0117)	(0.0152)	(0.0171)	(0.0201)	(0.0192)
Controls	YES	YES	YES	YES	YES	YES
Time F.E.	YES	YES	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES	YES	YES
Country F.E.	NO	NO	NO	YES	YES	YES
Firm clustered	YES	YES	YES	YES	YES	YES
Observations	111 877	77 273	54 109	48 060	30 972	25 638
Adj. R^2/Pseudo R^2	0.495	0.443	0.497	0.531	0.514	0.543

Panel B: Ordinal logit regressions						
Variables	(1)	(2)	(3)	(4)	(5)	(6)
	US			EU		
	SP	Moody's	Fitch	SP	Moody's	Fitch
	Dependent variable = RATING_20					
ENV	0.0162***	0.0181***	0.0113***	0.0125***	0.0113***	0.0129***
	(0.0021)	(0.0025)	(0.0032)	(0.0041)	(0.0055)	(0.0064)
Controls	YES	YES	YES	YES	YES	YES
Time F.E.	YES	YES	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES	YES	YES
Country F.E.	NO	NO	NO	YES	YES	YES
Firm clustered	YES	YES	YES	YES	YES	YES
Observations	111,877	77,273	54,109	48,060	30,973	25,638
Adj. R^2/Pseudo R^2	0.174	0.141	0.160	0.188	0.155	0.188

Notes: This table reports the results from regressions of credit ratings on environmental score for subsamples of different credit rating agencies. We use the numerical transformation of foreign long-term issuer ratings by S&P, Moody's, and Fitch, increasing in credit quality. $RATING\_58$ is credit rating scaled from 0 to 58, while $RATING\_20$ is scaled from 1 to 20, details in Section 3.1. ENV is the environmental score provided by Thomson Reuters ASSET4 ESG database. Panel A reports coefficients estimated using OLS regressions with credit ratings that are scaled from 0 to 58, while Panel B reports the ordinal logit regression results with credit ratings scaled from 1 to 20. All regressions include year-month, agency, and industry fixed effects, while country fixed effects are only employed in the EU sample. Reported significance is based on robust standard errors clustered at firm level. Significance at 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Table 12
Results for credit ratings with domestic currency.

Variables	(1)	(2)	(3)	(4)
	US	EU	US	EU
	OLS		Ordinal logit	
	Dependent variable = Domestic RATING_58		Dependent variable = Domestic RATING_20	
ENV	0.0593***	0.0505***	0.0159***	0.0118***
	(0.0084)	(0.0143)	(0.0021)	(0.0039)
Controls	YES	YES	YES	YES
Time F.E.	YES	YES	YES	YES
Agency F.E.	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES
Country F.E.	NO	YES	NO	YES
Firm clustered	YES	YES	YES	YES
Observations	244,134	104,214	244,134	104,214
Adj. R^2/Pseudo R^2	0.486	0.511	0.157	0.169

Notes: This table reports the results from regressions of credit ratings on environmental score. We use the numerical transformation of domestic long-term issuer ratings by S&P, Moody's, and Fitch, increasing in credit quality. $RATING\_58$ is rating scaled from 0 to 58, while $RATING\_20$ is scaled from 1 to 20, details in Section 3.1. ENV is the environmental score provided by Thomson Reuters ASSET4 ESG database. All regressions include year-month, agency, and industry fixed effects, while country fixed effects are only employed in the EU sample. Reported significance is based on robust standard errors clustered at firm level. Significance at 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

group to fully capture differences across industries. By using the $HIGH\_ENV$ dummy variable introduced at the beginning of Section 5, we obtain the same effect as dividing our sample into two subsamples based on the median level of ENV. Re-running the baseline regression with industry and size matched sampling, the results are presented in Table 14. The implications from this analysis suggest that our results are not sensitive to industry variations.

8.6. Effects from social and governance performance

To further investigate whether the non-linear relation in Table 6 only exists between firms' environmental performance and credit ratings, we replace the environmental score (ENV) with the social ($SOCIAL$) and governance (GOV) scores provided by the Thomson Reuter ASSET4 ESG ratings. Re-running the nonlinear regressions from the beginning of Section 5, the regression results are presented in Table 15. Our findings, which align with our expectations, show no statistical evidence of a non-linear relation between the other ESG components ($SOCIAL$ and GOV) and credit ratings. These results confirm the uniqueness of the relation between environmental performance and credit ratings, thereby emphasizing that it is not a common attribute of ESG performance.

9. Conclusion

Credit rating agencies play an essential role in the financial markets by issuing assessments of the companies' creditworthiness. In recent years, CRAs started to include environmental aspects into their rating assessments due to the increasing importance of firms' environmental performance. Inspired by the increasing global awareness of environmental sustainability, our study introduces a transatlantic perspective by investigating the impact of the firms' environmental performance on their credit ratings in the US and the EU. Considering differentiated regulatory requirements of ESG/CSR between the two economies, we

Table 13
Results using alternative environmental performance measures.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	US		EU		US		EU	
	OLS				Ordinal logit			
	Dependent variable = RATING_58				Dependent variable = RATING_20			
EMISSION	−0.6259**		−0.6708***		−0.1436**		−0.1946**	
	(0.2487)		(0.2378)		(0.0596)		(0.0803)	
ENV_BlOOMBERG		0.4319***		0.2849*		0.1318***		0.1119**
		(0.1400)		(0.1566)		(0.0352)		(0.0545)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Time F.E.	YES	YES	YES	YES	YES	YES	YES	YES
Agency F.E.	YES	YES	YES	YES	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES	YES	YES	YES	YES
Country F.E.	NO	NO	YES	YES	NO	NO	YES	YES
Firm clustered	YES	YES	YES	YES	YES	YES	YES	YES
Observations	141,743	190,070	91,732	72,569	141,743	190,070	91,733	72,569
Adj. R^2/Pseudo R^2	0.424	0.464	0.524	0.507	0.140	0.150	0.179	0.182

Notes: This table reports the results from regressions of credit ratings on various environmental measures. We use the numerical transformation of foreign long-term issuer ratings by S&P, Moody's, and Fitch, increasing in credit quality. $RATING\_58$ is the credit rating scaled from 0 to 58, while $RATING\_20$ is scaled from 1 to 20, details in Section 3.1. $EMISSION$ is the logarithm of the total CO_2 emission (the CO_2 emission scope 1 plus scope 2) provided by Thomson Reuter ASSET 4, while $ENV\_BLOOMBERG$ represents the environmental score provided by Bloomberg ranging from 0 to 10. All regressions include year-month, agency, and industry fixed effects, while country fixed effects are only employed in the EU sample. Reported significance is based on robust standard errors clustered at firm level. Significance at 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Table 14
Results based on industry and size matched sampling.

Variables	(1)	(2)	(3)	(4)
	US		EU	
	Dependent variable = RATING_58			
ENV	0.0524***		0.0445***	
	(0.0086)		(0.0139)	
HIGH_ENV		1.9374***		1.0759***
		(0.3405)		(0.4014)
Controls	YES	YES	YES	YES
Time F.E.	YES	YES	YES	YES
Agency F.E.	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES
Country F.E.	NO	NO	YES	YES
Firm clustered	YES	YES	YES	YES
Observations	93,884	93,884	38,966	38,966
Adj. R^2/Pseudo R^2	0.439	0.433	0.48	0.476

Notes: This table reports the OLS and ordinal logit regression results of the sample constructed using industry-size Matching. We use the numerical transformation of foreign long-term issuer ratings by S&P, Moody's, and Fitch, increasing in credit quality. $RATING\_58$ is the credit rating scaled from 0 to 58, while $RATING\_20$ is scaled from 1 to 20, details in Section 3.1. ENV is the environmental score provided by Thomson Reuters ASSET4. $HIGH\_ENV$ is an indicator variable which equals one if the environmental score is above the median, otherwise 0. All regressions include year-month, agency, and industry fixed effects, while country fixed effects are only employed in the EU sample. Reported significance is based on robust standard errors clustered at firm level. Significance at 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Table 15
Results based on social and governance scores.

Variables	(1)	(2)	(3)	(4)
	US		EU	
	Dependent variable = RATING_58			
SOCIAL	0.0377		0.0251	
	(0.0344)		(0.0501)	
GOV		0.0563**		−0.0421
		(0.0281)		(0.0348)
$SOCIAL^2$	0.0003		0.0001	
	(0.0004)		(0.0004)	
$GOV2^2$		−0.0002		0.0004
		(0.0003)		(0.0003)
Controls	YES	YES	YES	YES
Time F.E.	YES	YES	YES	YES
Agency F.E.	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES
Country F.E.	NO	NO	YES	YES
Firm clustered	YES	YES	YES	YES
Observations	243,259	243,259	104,671	104,671
Adj. R^2	0.485	0.472	0.507	0.503

Notes: This table reports the OLS regression results on the effects on credit ratings of the social and governance score and their quadratic terms. We use the numerical transformation of foreign long-term issuer ratings by S&P, Moody's, and Fitch, increasing in credit quality. $RATING\_58$ is the credit rating scaled from 0 to 58, while $SOCIAL$ and GOV are the social and governance scores provided by Thomson Reuters ASSET4 and $SOCIAL^2$ and GOV^2 are the squared social and governance scores. All regressions include year-month, agency, and industry fixed effects, while country fixed effects are only employed in the EU sample. Reported significance is based on robust standard errors clustered at firm level. Significance at 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

further examine whether the influence of environmental performance on credit ratings differs across these two regions.

The baseline analysis explores the effect of environmental performance on credit ratings. Our analysis uses numerical ratings that account for the rating outlook and watch. Our findings suggest that an improvement in the firms' environmental scores contributes to higher credit ratings. However, we note a weaker relation in the EU compared to the US. We undertake additional investigation to corroborate our initial analysis. Our results indicate the main cause for this weaker effect: the effect of environmental performance on credit ratings is non-linear in the EU, resulting in a diminishing marginal effect of environmental score improvement on credit ratings. This is because firms in the EU are more environmentally friendly, hence good environmental performance is viewed as the norm, rather than a stand-out performance. Thus, improvements in environmental scores are rewarded (in terms of credit rating improvements) less in the case of EU firms with good environmental performance.

Our empirical results have significant implications for corporate financial management. Besides the profitability-related factors that can improve the firms' credit ratings, we reveal an additional way in which firms can enhance their creditworthiness by improving their environmental performance. Therefore, firms can reduce financing costs via improvements in their environmental performance. Our results also suggest that this channel to reduce financing costs is more effective in the US than in the EU. Based on these results, global firms can optimize their investments and costs associated with the environmental enhancements within their institutions.

Table A.1
Variable definitions.

Variable definitions			Data source
RATING_58	=	The long-term issuer credit ratings translated into numerically increasing credit quality as follows: CC/Ca, SD-D/C = 1, CCC-/Caa3 = 4, …, AA/Aa2 = 52, AA+/Aa1 = 55, AAA/Aaa = 58. In addition, "+2" ("−2") is adjusted for positive (negative) watch signal, while "+1" ("−1") is adjusted for positive (negative) outlook signal and "0" for stable outlook and no watch/outlook assignments.	Bloomberg S&P, Moody's, and Fitch ratings database
RATING_20	=	The long-term issuer credit ratings translated into numerically increasing credit quality as follows: CC/Ca, SD-D/C = 1, CCC-/Caa3 = 2, …, AA/Aa2 = 18, AA+/Aa1 = 19, AAA/Aaa = 20.	Bloomberg S&P, Moody's, and Fitch ratings database
ENV	=	The firm-level environmental score scaled from 0 to 100;	Thomson Reuters ASSET4
SIZE	=	The natural logarithm of the firm's total assets (AT);	Compustat Database
ROA	=	return on assets, calculated as income before extraordinary items (IB), divided by total assets (AT);	Compustat Database
LOSS	=	1 if net income before extraordinary items is negative, 0 otherwise;	Compustat Database
LEV	=	total debt (DLC + DLTT) divided by total assets (AT);	Compustat Database
INT_COV	=	operating income before depreciation (OIBDP) divided by interest expense (XINT);	Compustat Database
CAP_INTEN	=	property, plant and equipment (PPEGT) scaled by total assets (AT);	Compustat Database
BIG4	=	1 if the auditor is a Big4 auditor, and 0 otherwise;	Compustat Database
CFO_STD	=	The standard deviation of cash flows from operation (CFO) scaled by total assets for the previous five years;	Compustat Database
ROA_STD	=	The standard deviation of ROA for the previous five years;	Compustat Database
MARGIN	=	The operating income before depreciation (OIBDP) divided by gross sales (SALE);	Compustat Database
HIGH_ENV	=	1 if the environmental score is above the median level of the environmental score, 0 otherwise;	Thomson Reuters ASSET4
ENV^2	=	square of environmental score;	Thomson Reuters ASSET4
IV_INDUS	=	The monthly average of the environmental score of firms in a given industry;	Thomson Reuters ASSET4
EMISSION	=	The natural logarithm of the total CO2 emission (CO2 emission scope 1 + CO2 emission scope scope 2);	Thomson Reuters ASSET4
ENV_ BLOOMBERG	=	The environmental score provided by Bloomberg ranging from 0 to 10;	Bloomberg
SOCIAL	=	The firm-level social score scaled from 0 to 100;	Thomson Reuters ASSET4
$SOCIAL^2$	=	The square of social score;	Thomson Reuters ASSET4
GOV	=	The firm-level governance score scaled from 0 to 100;	Thomson Reuters ASSET4
GOV^2	=	The square of governance score.	Thomson Reuters ASSET4

This study opens up avenues for further exploration. Some of the potential extensions of our research include: study of the relation between environmental scores and credit ratings across different industries; analysis of the dynamic of this relation across time, as well as assessment of the influence of social and governance indicators on credit ratings. Furthermore, similar studies can be undertaken in an even more international context, considering countries that have not been considered for this study, to obtain an even broader set of results of global significance. We see these questions as opportunities to enrich the literature and broaden our understanding, and we leave these to be explored in future research.

Declaration of competing interest

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

Data availability

The data that support the findings of this study is openly available from Bloomberg, Thomson Reuters, and Compustat.

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Appendix

See Table A.1.

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