Corporate Social Responsibility and Credit Risk: Empirical Evidence from the United States

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Abstract (EN)

In the past few years, Corporate Social Responsibility (CSR) has become the central pillar of business strategy for companies as it has attracted the interest of stakeholders. This empirical study examines the relationship between CSR performance and credit risk using corporate credit ratings and Ohlson (1980)'s bankruptcy prediction model as a measure. The focus is to analyze whether companies with superior ESG scores enhance their risk profile and mitigate risk. Using a sample of 429 US companies from 2006 to 2016, companies with good CSR performance can decrease their cost of debt by being awarded better credit ratings. Credit rating agencies factor in the ESG component in credit ratings, especially when the company is a high-quality borrower. In addition, the environmental and corporate governance pillars are the most significant factors. However, I do not find strong evidence to support the hypothesis that superior CSR performance decreases the probability of default, except for large companies and firms operating in the services industry.

Keywords: Corporate social responsibility, corporate credit ratings, probability of default, credit risk

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Resumo (PT)

Nos últimos anos, a Responsabilidade Social Corporativa (RSC) tornou-se o pilar central da estratégia de negócios das empresas, pois atraiu o interesse dos stakeholders. Este estudo empírico examina a relação entre o desempenho da RSC e o risco de crédito usando classificações de crédito e o modelo de previsão de incumprimento de Ohlson (1980) como medida. O objetivo é analisar se as empresas com pontuações Ambiente, Social e Governança corporativa (ASG) superiores aprimoram o seu perfil de risco e mitigam o risco. Usando uma amostra de 429 empresas norte-americanas de 2006 a 2016, as empresas com bom desempenho de RSC podem reduzir o custo da dívida obtendo melhores classificações de crédito. As agências de classificação de crédito consideram o componente ASG nas classificações de crédito, especialmente quando a empresa é um devedor de alta qualidade. Além disso, os pilares ambiental e de governança corporativa são os fatores mais relevantes. No entanto, não encontro fundamentos fortes para a hipótese de que um desempenho superior de RSC diminui a probabilidade de incumprimento, exceto para grandes empresas e para firmas que operam no setor de serviços.

Palavras-chave: Responsabilidade social corporativa, classificação do risco de crédito, probabilidade de incumprimento, risco de crédito

Título: Responsabilidade Social Corporativa e Risco de Crédito: Evidência Empírica dos Estados Unidos

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1. Introduction

Since the creation of the ESG (environmental, social, and governance) framework, businesses' approach towards it has changed. Recently, there has been an increased focus on the importance of companies in the economy, community, and environment. The increase in attention has been rising significantly since the scandals revolving around the Global Financial Crisis of 2008. This crisis exposed many companies' unethical behavior and risk-management-deficiencies surrounding corporate social responsibility (CSR). Conventional business models prioritized yielding profits for shareholders while disregarding other stakeholders. However, sustainable companies are reinventing the corporate ecosystem by creating new business models prioritizing all stakeholders. Investors are paying closer attention to CSR performance forcing companies to reevaluate their operations. Thus, sustainable development has become a strategic decision by top management, given its potential effect on financial performance.

The definition of CSR has been changing over the years. The current permutation of CSR considers the "License to Operate" approach, which encompasses the broad stakeholder view on the company's conduct and reputation. Hence, CSR can be considered as how companies identify and evaluate environmental, social, and governance (ESG) consequences and risks and what they do to mitigate these. The question then becomes whether the cost of mitigation is beneficial for companies and if it results in sustained profitability and cost reduction. Previous empirical research used accounting measures to examine the relationship between CSR and corporate financial performance. For instance, Kim (2021) finds a positive impact of CSR on profitability measured by return on assets. However, findings are ambiguous and inconsistent in studies analyzing the relationship between CSR and corporate financial risk using non-accounting measures like credit ratings and cost of debt (such as Goss, 2011and Lian, 2023).

This research explores the relationship between CSR performance and company credit risk from different angles. First, I build upon the empirical study of Stellner (2015), which finds that superior CSR performance can affect corporate credit ratings using a European sample. In addition, few studies use alternative default risk models like Ohlson (1980)'s bankruptcy prediction model. In contrast to Altman's Z-score, which uses only accounting-based data, the Ohlson O-score incorporates macroeconomic data that could help determine emerging risks and opportunities not yet contemplated in a company's financial statements. Furthermore, studying the US corporate market, which has transformed and grown since the Global Financial Crisis, provides an opportunity for assessment. This study investigates a range of research questions, including the cost/benefit analysis of whether CSR performance is connected to corporate credit ratings and the probability of default in the US. Does corporate sustainability impact corporate credit risk? Do companies that engage in CSR activities mitigate risk and enjoy a lower cost of debt? Conversely, do companies that fail to consider ESG factors harm their creditworthiness?

There are two hypotheses regarding the relationship between CSR performance and corporate financial performance. The risk mitigation view argues that engagement in CSR activities can reduce risks. Godfrey (2005)'s study supports this view and claims that CSR activities targeting society at large can serve as an insurance policy against adverse events. Companies can build moral capital and benefit from consumer loyalty by engaging with stakeholders and reducing risks. Furthermore, companies can cultivate a relationship with the local community and government, reducing agency costs. Credit rating agencies, investors, and debtholders are focusing more on CSR, given the increased importance in today's economic environment. Opposingly, the overinvestment view, coupled with the agency theory, regards CSR efforts as a waste of company resources. Managers may overinvest in costly CSR projects to boost their reputation while shareholders bear the costs. Friedman (1962)'s shareholder theory argues that a company's purpose is profit maximization, and CSR activities do not contribute to this purpose. This issue creates agency conflict between managers and shareholders that leads to potential penalties and fines. Therefore, this agency conflict harms company cash flows and firm value. The overinvestment hypothesis implies that these companies represent a greater level of risk and are assigned lower credit ratings.

Based on a sample of 429 companies in the US from 2006 to 2016, I find significant evidence that companies with superior CSR performance are assigned better corporate credit ratings. Interestingly, when the company belongs to the speculative-grade ratings group, companies with good ESG scores are penalized with lower credit ratings. These findings follow the risk-mitigating view and the overinvestment view. Results are consistent after lagging the independent variables and separating the ESG scores into their pillars. Furthermore, results remain robust after creating subsamples based on industry and company size. However, when using the probability of default as a credit risk measure, I find a negative relationship between companies belonging to the services industry and large firms. Nevertheless, I find no statistical evidence that companies with good CSR performance represent a lower or high level of risk for the other regressions. Regardless of the period under analysis, superior ESG scores can enhance corporate credit ratings. I structure the research paper as follows. The following section discusses previous literature that explores the relationship between CSR and credit risk, exogenous shocks and credit risk, CSR and probability to default, and the Ohlson O-score. Section 3 explains the data sample, the variables incorporated, and the methodological approach. The following section presents the empirical findings and additional robustness checks. Finally, the last section presents a summary and conclusion.

2. Literature review

2.1. CSR and credit risk

In a recent study, Lian et al. (2023) examines the relationship between company ESG performance and bond credit spreads in China. The study's sample size includes 988 bonds issued by 443 companies between January 2009 and December 2020, with the Sino-Securities Index ESG rating system used to evaluate ESG ratings. The authors employ regression analysis to control for other factors and find a significant correlation between a company's ESG performance and bond credit spreads. Specifically, an increase of one standard deviation in ESG performance is associated with a 12.42% standard deviation decrease in the average bond credit spread. Findings corroborate the risk-mitigation viewpoint, demonstrating that CSR efforts can reduce bond credit spreads and corporate financial risks. Furthermore, the study finds a positive relationship between ESG performance and corporate information transparency, which could help subdue debt agency issues.

A similar study by Attig et al. (2013) evaluates the relationship between CSR and credit ratings within the United States. The study is based on a large dataset containing 1,585 firms from 1991 to 2010. The authors utilized MSCI ESG STATS (an alternative ESG integration tool) to gather CSR data on companies and included some firm control variables in the analysis. The research reveals that rating agencies assign companies with superior CSR performance higher credit ratings. Further analysis of the CSR components reveals that investments in primary stakeholder management have the most significant impact on a company's creditworthiness. Through additional testing to control for endogeneity, results are robust. Therefore, superior CSR performance can result in a lower cost of debt, so companies can raise capital at a lower expense and obtain higher credit ratings.

Opposingly, Menz (2010)'s empirical research of a sample of European corporations finds a weak but statistically significant positive relationship between credit spreads and CSR. The study examines 498 bonds issued between July 2004 and August 2007, using CSR data from the SAM Corporate Sustainability Assessment (CSA) index. Even though the observed effect is marginal, the findings of this study indicate that firms that employ CSR investments do not enjoy lower risk premiums compared to their low-CSR counterparts. Such an inference suggests that bond investors may value credit ratings more than CSR ratings, highlighting the prospect that CSR activities have yet to be factored into the pricing of corporate bonds. There may be a lag in recognizing the risk-mitigating effects of CSR investments within Europe.

Including a broader geographical area and a wider timeframe, Izzo and Magnanelli (2012) examine the relationship between CSR and the cost of debt financing from 2005 to 2009. The SAM Corporate Sustainability Assessment (CSA) index is used to obtain CSR data from 332 companies in Asia, Europe, and the United States. The authors regress the cost of debt and CSR data, in addition to additional control factors, using interest expenses divided by debt as the cost of debt. The findings demonstrate a significant positive relationship between CSR performance and the cost of debt, thus, demonstrating that banks do not view CSR activities as profitable but rather as expensive and a waste of scarce resources. Hence, no “ethical financial premium” exists. These findings are consistent with the overinvestment view, which argues that superior CSR performance is not rewarded with improved financial performance.

Goss and Roberts (2011) exploit the role of banks within the private debt market, given their distinction from other stakeholders. Based on a sample of 3996 US bank loans from 1991 to 2006, the authors investigate the impact of CSR on the cost of bank loans. Using Kinder Lydenburg Domini (KLD) rating system for CSR data, the authors categorize CSR components into strengths and concerns to test their hypotheses separately. The results suggest that banks perceive CSR concerns as risks and respond with less favorable lending conditions. However, borrowers with low CSR strengths and poor credit quality are required to pay higher spreads and face shorter maturities. Also, the study finds that lenders show no preference for CSR investments made by high-quality borrowers. Following the overinvestment perspective, CSR efforts made by companies with weak credit quality are more likely to be seen as “greenwashing” and can damage shareholder value.

2.2. Exogenous shocks and credit risk

Testing the risk management hypothesis, Godfrey (2005) conducts an event study to examine the relationship between CSR and shareholder value in the face of adverse events. To test the risk management hypothesis, the author performs an event study based on data from 1991 to 2003 which covers 160 firms. By regressing stock returns and controlling for CSR and firm factors, the author examines the change in shareholder value. Results reveal that investment in CSR activities targeting society at large can serve as an insurance policy, protecting companies from adverse events. Furthermore, building moral capital can assist firms in dealing better with pre-event shocks and minimizing post-event losses caused by adverse events. As a result, companies with superior CSR performance are exposed to less risk.

2.3. CSR and probability to default

Cooper and Uzun (2019) exploit the relationship between CSR and bankruptcy by analyzing firms that went bankrupt from 2007 to 2014 in the United States. The data sample included 78 companies that filed for Chapter 11 bankruptcy together with a matched set of companies that did not, utilizing MSCI's STATS and LoPucki's database. Consistent with the risk-mitigating view and stakeholder theory, the findings show a significant negative relationship between CSR and the probability of bankruptcy. Companies that value CSR are less likely to file for bankruptcy, and the relationship between CSR and the likelihood of bankruptcy is stronger for companies with better Z-scores. Testing for corporate governance variables, the authors find that companies with a dual CEO/Chairman policy tend to have higher probabilities of bankruptcy. These findings stress the importance of the governance pillar score in the ESG metrics. Overall, the research emphasizes the potential benefits of prioritizing CSR practices in mitigating the risk of filing for bankruptcy.

In a comparable study, Hogan et al. (2014) examine the relationship between corporate philanthropy and CSR using different measures for CSR, including ESG scores and Corporate Governance Quotient Index Scores. The dataset includes 540 firm observations over nine years, from 2003 to 2011. Firm scores are obtained from Bloomberg and Institutional Shareholder Services, and Altman's Z-score is used to measure corporate risk and probability of default. The authors run a regression with community spending as a percentage of EBITDA as the dependent variable. The regression analysis shows that the dependent variable is significantly and positively related to changes in the firm's Altman's Z-score. Thus, companies with a lower probability of bankruptcy tend to participate more in community giving than riskier firms. Additionally, community spending as a percent of EBITDA is directly related to Board size and women ratio on the Board.

2.4. Ohlson O-score

Bankruptcy prediction models have been widely used in empirical studies as indicators of financial distress. Ohlson (1980) uses a sample from the 1970s comprising 105 bankrupt companies and 2,058 non-bankrupt industrial companies. To develop the model, nine explanatory variables are used to predict the likelihood of bankruptcy. Since its development, numerous researchers have employed the Ohlson model to predict company failure and measure distress risk. Begley et al. (1997) employ Ohlson's and Altman's models using a sample of 1,365 industrial companies, and the Ohlson model displays the most robust overall performance, with a classification accuracy of 98%. Grice and Dugan (2003) conclude that the predictive accuracy improves by re-estimating the model's coefficients. In a study using a sample of 90 Iranian listed firms from 2007 to 2010, Karamzadeh (2013) uses the original coefficients and finds a predictive accuracy of 53.3% for the year before defaulting.

3. Methodology and data

3.1. Methodology

The empirical study aims to analyze the relationship between CSR performance and credit risk by incorporating two models. In this thesis, I use two measures of credit risk: company credit ratings and the probability of default, which are captured using Ohlson's bankruptcy prediction model. Then, the measure of CSR performance is the ESG scores. More precisely, the research aims to determine how Refinitiv's ESG scores affect S&P long-term issuer corporate credit ratings and the likelihood of default while controlling for other variables. Furthermore, I include a *Crisis* dummy to analyze the role of exogenous shocks, precisely the Global Financial Crisis, on credit risk while controlling for potential bias. Following Stellner (2015), the first empirical model uses an ordered logistic regression with credit ratings as the dependent variable, given its categorical scaling, to test the relationship between CSR performance and credit ratings. In the second setup, Ohlson's probability model is used as a proxy for financial distress and the probability of default, as in Grice and Dugan (2003). For this approach, the probability of default using the Ohlson O-score is implemented as a dependent variable in an ordinary least squares (OLS) regression, following Schultz et al. (2015), who study the effects of corporate governance factors on default risk. Both models incorporate six firm-specific and four external control variables that are foreseen to impact both credit risk measures based on theoretical and empirical evidence.

Moreover, the *Crisis* dummy is included in the analysis to represent the tumultuous period during the Global Financial Crisis. The benchmark model includes the entire sample and consists of ESG scores and explanatory variables, including the *Crisis* dummy. Then, I divide the data sample into two groups: high- and low-performing. This division is based on the mean company ESG score (44.515). Standard errors are adjusted using the Huber-White estimator to account for heteroskedasticity, as not controlling for this could lead to biased and incorrect estimates and interpretations about the statistical significance of the results.

To examine the impact of ESG scores on credit ratings and probability of default, I use the following two regression equations:

$$Rating_{i,t} = \beta_1 ESG_{i,t} + \beta_2 X_{i,t} + \beta_3 Z_{\ t} + \beta_3 Crisis_{\ t} + \varepsilon_{it} \quad (1)$$

where the quarterly rating, $Rating_{i,t}$, for a company (i) issued at time (t), is determined by the $ESG_{i,t}$ score, a vector of six firm-specific control variables (represented by $X_{i,t}$), four external control variables (represented by $Z_{\ t}$), and the dummy $Crisis_{\ t}$. The standard error term is ε_{it}.[1]

$$\mathrm{P}(default)_{i,t} = \alpha + \beta_1 ESG_{i,t} + \beta_2 X_{i,t} + \beta_3 Z_{\ t} + \beta_3 Crisis_{\ t} + \varepsilon_{it} \quad (2)$$

where the quarterly probability of default, $\mathrm{P}(default)_{i,t}$, for a company ($i$) issued at time ($t$), is determined by the $ESG_{i,t}$ score, a group of six firm-specific control variables (represented by $X_{i,t}$), four external control variables (represented by $Z_{\ t}$), and the dummy $Crisis_{\ t}$. The standard error term is ε_{it}.

3.2. Sample overview and data description

After incorporating ESG scores, company credit ratings, and control variables, the final dataset comprises 8,381 observations for 429 US-based companies. To reduce potential bias or outliers, I exclude financial firms (SIC codes 6000-6999) and governmental firms (SIC codes 9000 and above). The sample covers the period from 2006 to 2016, with quarterly periodicity. Figure 1 displays the distribution of company industries based on their respective SIC codes, with all industries represented in the study.

[1] The proportional odds assumption holds so the ordered logistic regressions do not include a constant term.

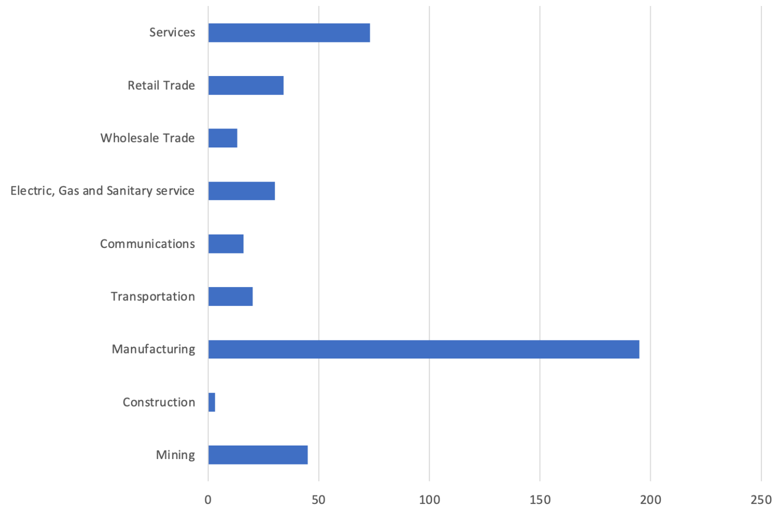

Fig. 1. Industry distribution

First, company credit ratings are gathered from S&P provided by Compustat. Credit ratings are coded on a scale from "20" (representing AAA) to "1" (representing CC) to conduct the ordered logistic regressions. Notably, credit ratings of "C," "D," and "SD" are excluded from the analysis. The second measure of credit risk utilized in the study is the Ohlson model for the probability of default, which incorporates nine variables. Firm-specific variables are collected from Compustat, while external/global variables are collected from Datastream and Chicago Boards Options Exchange (CBOE). The Ohlson O-score model is expressed as:

$$O_s = -1.32 - 0.407\alpha_1 + 6.03\alpha_2 - 1.43\alpha_3 + 0.0757\alpha_4 - 1.72\alpha_5 - 2.37\alpha_6 - 1.83\alpha_7 + 0.285\alpha_8 - 0.521\alpha_9 \quad (3)$$

where O_s is the company's O-score. α_1 is the log of total assets over the US gross national product price index level. α_2 is total liabilities over total assets. α_3 is working capital over total assets. α_4 is current liabilities over current assets. α_5 is equal to "1" if total liabilities are greater than total assets and "0" otherwise. α_6 is net income over total assets. α_7 is funds from operations (FFO) over total liabilities. In this case, cash flow from operations was used as a proxy, given that FFO is a measure mostly used to test the performance of real estate investment trusts (REITs) (Kim (2012)). α_8 is equal to "1" if net income was negative for the last two periods and "0" otherwise. Finally, α_9 is the change in net income from the last period to the current period divided by the sum of the current net income and the last period's net income in absolute values. The probability of default is determined using a logistic function with the overall index:

$$p(default) = \frac{e^{O-score}}{1+e^{O-score}} \quad (4)$$

The number and quality of firms that provide ESG data have increased significantly over recent years, given the increased focus on ESG-related topics. This research is based on Refinitiv ESG scores, which have replaced and developed upon the prior ASSET4 ESG ratings using a new strategic ESG framework. Refinitiv ESG scores are found in Datastream and cover over 12,000 companies across 22 global and regional indices. This framework encompasses over 630 company-level ESG measures across ten primary themes, all of which are based on publicly reported data. The ten themes are grouped into three main pillars to form the overall ESG score. The score is scaled from 0 to 100, where a low score indicates weak ESG performance and poor transparency in reporting ESG data. First, the environmental pillar considers resource use, emissions, and innovation factors. The second pillar, the social pillar, integrates human rights, workforce welfare, community impact, and product responsibility. Lastly, the governance pillar includes factors like shareholder engagement, management practices, and CSR strategy.

The initial group of control variables comprises the subsequent company-specific factors: operating income/revenues (*OPMAR*), log of total assets (*SIZE*), total debt/total assets (*LEV*), capital expenditures /total revenues (*CAPX*), return on equity (*ROE*), and current assets/total assets (*LIQ*). First, companies with higher profitability in operating margin should reduce default risk, resulting in a rise in credit ratings. During financial crises, larger firms in terms of total assets are assumed to be better suited to manage fluctuations in profitability and cash flow as this measure reflects the resources a firm has available (Bhojraj and Sengupta, 2003). Firms with higher debt levels in proportion to their total assets are expected to have a higher probability of default. Thus, they tend to receive lower ratings as the credit risk is higher (Ashbaugh et al., 2006). A higher capital expenditure ratio is assumed to be positively associated with higher credit ratings and a lower likelihood of default. This is because financially stable firms have the capacity and are more inclined to allocate funds toward capital-intensive projects (Stellner et al., 2015). Nevertheless, higher levels of capital expenditures can be seen as a waste of resources and damage cash flows, reducing the funds allocated to CSR activities (Jiraporn et al., 2014). Return on equity is an essential metric from a credit risk perspective, as a higher ratio indicates that a firm is generating income to cover its debt obligations (Ashbaugh et al., 2006). A higher liquidity ratio is expected to be associated with higher credit ratings and lower default risk, given that these companies can readily convert current assets to cash (Lian et al., 2023). All the firm-specific control variables are winsorized at the 1st and 99th percentiles to control for extreme values. The company-specific variables are obtained from Compustat.

Both the rating and the probability of default setup incorporate control variables that act as proxies for the state of the economy and have been demonstrated to impact credit risk. First, stock market indices, such as the Nasdaq Index, can reflect changes in investor sentiment and market expectations (Smales, 2017). Thus, the empirical analysis includes a control variable, namely, the continuously compounded returns of the Nasdaq index (*NASDAQ*) obtained from Datastream. The empirical analysis includes the volatility index (*VIX*) obtained from CBOE, given that a higher level of volatility is associated with higher distress risk and lower ratings. This volatility index reflects the level of uncertainty in the market (Lian, 2023). The risk-free term structure and the slope are incorporated in this study as measures of the economic environment based on previous research by Landschoot (2008) that finds that changes in these variables impact US dollar yield spreads. For the risk-free component (*RF*), the 2-year US treasury note is used, and to calculate the US slope, the 10-2 Treasury Spread is used, which is the 2-year treasury note subtracted from the 10-year treasury bond (*SLOPE*) as in Collin-Dufresne (2002). The abovementioned variables for the US term structure are obtained from Datastream.

In addition to the abovementioned explanatory variables, a dummy variable for the Global Financial Crisis is included to provide further insight into the impact of the Great Recession on credit risk. The shocks of the Global Financial Crisis were more pronounced in the US as the collapse of the US-housing market triggered it. The Great Recession is acknowledged for its high unemployment rates and low GDP, as it had a widespread impact on the global economy and financial markets. The analysis encompasses a timeframe that includes 2008 to analyze the impact of this economic shock. At this point, investor sentiment was at its worst, and markets crashed, leading to worldwide repercussions. During this tumultuous period, perceived credit risk increased, and financial aid was critical to help businesses recover. To capture the effects of this crisis, a dummy variable "*Crisis*" is included, which is equal to "1" if the period falls within Quarter 1, 2008 to Quarter 1, 2009, and "0" otherwise. By including the dummy variable for the Global Financial Crisis, the research can provide a more accurate analysis of the effects of the explanatory variables on credit ratings and the probability of bankruptcy. This method helps to avoid biased estimates by controlling for other factors that may have influenced credit risk, enabling a more reliable assessment of the impact of the controlling variables.

Table 1 displays an overview of the variables used in the research. The next sections summarize the company credit ratings, the descriptive statistics, and correlation matrix.

Table 1
Overview of variables

Variable	Description	Units	Source
Ratings			
Corporate rating	S&P long-term issuer corporate credit rating, ratings have been coded from "20" (AAA) to "1" (CC)	None	Compustat
Probability of default			
Ohlson O-score	Total assets, Total liabilities, Working capital, Current liabilities, Current assets, Net income	None	Compustat
	Cash flow from operating activities as a proxy for Funds from operations	None	Compustat
	Gross national product price index = real GNP / nominal GNP multiplied by 100	None	Datastream
ESG factors			
ESG Score	From 0 to 100	None	Datastream
Environmental Score	From 0 to 100	None	Datastream
Social Score	From 0 to 100	None	Datastream
Governance Score	From 0 to 100	None	Datastream
Company factors			
Operating margin	Operating income before depreciation / Total revenues	None	Compustat
Size	Log of Total assets	None	Compustat
Leverage	(Short term debt + Long term debt) / Total assets	None	Compustat
Capex ratio	Capital expenditures / Total revenues	None	Compustat
Return on equity	Net income / Stockholders equity	None	Compustat
Liquidity	Current assets / Total assets	None	Compustat
Global/external factors			
VIX	CBOE S&P500 Volatility Index	Basis points	CBOE Index
US risk-free	2- year US treasury note	Percent	Datastream
US slope	10-year US Treasury bond minus 2-year US treasury note (10-2 Treasury spread)	Percent	Datastream
Nasdaq	Continuously compounded returns of the Nasdaq Index	Basis points	Datastream
Crisis	Dummy variable taking value of "1" for the Great Recession (Quarter 1, 2008 to Quarter 1, 2009)	None	-

3.2.1. Rating distribution

Tables 2 and 3 show the S&P Long-Term Issuer Credit Rating assigned to 429 non-financial and non-governmental companies, categorized by their SIC code, from 2006 to 2016. The ratings presented include both the high and low ends of each rating category, with “AAA+” and “AAA-” being included in the “AAA” rating and similarly for other ratings.

Throughout the analyzed period, it is noticeable that the ratio of investment grade to speculative grade vastly changes. Most of the ratings are speculative, and the proportion of these ratings has been rising over time. Additionally, the sample size increases significantly from 2008 to 2009, during the Global Financial Crisis. There is a noticeable downward trend in AAA, AA, and A ratings over time but an upward trend in B ratings, particularly from 2008 to 2010. This trend reflects the effects of the financial crisis as many companies were more exposed to credit risk, thus, experiencing downgrades. Among the observed ratings, the B category is the most volatile, followed by the A rating. The number of AAA and CC ratings is relatively stable over time.

Table 2
Credit rating distribution in numbers

Year	AAA	AA	A	BBB	BB	B	CCC	CC	Investment grade	Speculative grade	Total
2006	4	17	37	66	21	8	3	0	124	32	156
2007	4	12	54	65	23	14	4	0	135	41	176
2008	3	14	62	103	39	32	4	0	182	75	257
2009	10	19	159	302	172	90	10	0	490	272	762
2010	10	21	158	322	203	91	13	1	511	308	819
2011	9	19	167	337	202	102	17	2	532	323	855
2012	11	21	157	341	204	108	16	1	530	329	859
2013	10	19	169	356	205	117	15	0	554	337	891
2014	9	22	177	341	239	122	11	2	549	374	923
2015	8	23	178	403	412	194	20	2	612	628	1240
2016	10	24	186	399	485	321	17	1	619	824	1443
Total	88	211	1504	3035	2205	1199	130	9	4838	3543	8381

Table 3
Credit rating distribution in percentages

Year	AAA	AA	A	BBB	BB	B	CCC	CC	Investment grade	Speculative grade	Total
2006	2.6%	10.9%	23.7%	42.3%	13.5%	5.1%	1.9%	0.0%	79.5%	20.5%	4.6%
2007	2.3%	6.8%	30.7%	36.9%	13.1%	8.0%	2.3%	0.0%	76.7%	23.3%	5.2%
2008	1.2%	5.4%	24.1%	40.1%	15.2%	12.5%	1.6%	0.0%	70.8%	29.2%	7.5%
2009	1.3%	2.5%	20.9%	39.6%	22.6%	11.8%	1.3%	0.0%	64.3%	35.7%	22.3%
2010	1.2%	2.6%	19.3%	39.3%	24.8%	11.1%	1.6%	0.1%	62.4%	37.6%	24.0%
2011	1.1%	2.2%	19.5%	39.4%	23.6%	11.9%	2.0%	0.2%	62.2%	37.8%	25.0%
2012	1.3%	2.4%	18.3%	39.7%	23.7%	12.6%	1.9%	0.1%	61.7%	38.3%	25.2%
2013	1.1%	2.1%	19.0%	40.0%	23.0%	13.1%	1.7%	0.0%	62.2%	37.8%	26.1%
2014	1.0%	2.4%	19.2%	36.9%	25.9%	13.2%	1.2%	0.2%	59.5%	40.5%	27.0%
2015	0.6%	1.9%	14.4%	32.5%	33.2%	15.6%	1.6%	0.2%	49.4%	50.6%	36.3%
2016	0.7%	1.7%	12.9%	27.7%	33.6%	22.2%	1.2%	0.1%	42.9%	57.1%	42.3%
Total	1.0%	2.5%	17.9%	36.2%	26.3%	14.3%	1.6%	0.1%	57.7%	42.3%	100.0%

3.2.2. Descriptive statistics and correlation analysis

Table 4 provides the descriptive statistics for company characteristics and other variables used in the empirical analysis. The mean of the credit ratings is 10.950, indicating that the average rating falls between the BB+ and BBB- range. The probability of default has a mean of 0.484, meaning that, on average, the companies in the study have a probability of 48.4% defaulting on their obligations. ESG scores have a mean and median of 44.515 and 42.630, respectively, showing that the data sample is roughly symmetrical, nevertheless slightly skewed to the right, and there may be a few companies with higher-than-average ESG scores. The minimum is 0.770, indicating that some companies have extremely weak ESG scores. To be more precise, firms with high ESG scores are mostly large firms (greater than 8.915 in *SIZE*), and most low-ESG score firms are small (lower than 8.915 in *SIZE*). Overall, most standard deviations for the company factors and external factors are close to the mean, implying a relatively low degree of variability in the dataset.

Table 4

Summary statistics on issuer characteristics

Variables	Mean	Std. dev	Minimum	25%	Median	75%	Maximum
Rating	10.950	3.233	1.000	8.000	11.000	13.000	20.000
P(default)	0.484	0.268	0.000	0.272	0.474	0.699	1.000
Ohlson O-score	-0.053	50.347	-4430.146	-0.986	-0.106	0.843	236.360
Altman's Z-score	2.316	2.111	-1.118	1.052	1.868	2.942	12.673
ESG	44.515	20.447	0.770	28.050	42.630	60.650	92.540
OPMAR	0.198	0.189	-1.153	0.120	0.183	0.276	0.707
SIZE	8.915	1.213	3.222	8.067	8.819	9.739	11.983
LEV	0.300	0.183	0.000	0.180	0.278	0.391	1.156
CAPEX	0.278	0.590	0.003	0.042	0.093	0.232	4.921
ROE	0.036	0.162	-0.763	0.011	0.033	0.056	1.315
LIQ	0.343	0.186	0.041	0.184	0.341	0.470	0.857
VIX	19.364	7.604	11.037	14.233	17.033	20.486	58.588
RF	0.788	0.824	0.200	0.320	0.690	0.850	4.970
SLOPE	1.740	0.659	-0.090	1.350	1.710	2.280	2.810
NASDAQ	0.029	0.093	-0.447	-0.021	0.043	0.077	0.324

Table 5 presents the correlation matrix for the firm characteristics and other variables in the empirical study. Most control variables have an absolute value below 0.4, which implies a weak linear relationship. Additionally, the correlation coefficient between ESG and most explanatory variables is generally low, suggesting that the regression model is unlikely to be affected by multicollinearity problems.

Table 5
Correlation matrix

	Rating	P(default)	ESG	OPMAR	SIZE	LEV	CAPX	ROE	LIQ	VIX	RF	SLOPE	NASDAQ
Rating	1	-0.31***	0.40***	0.08***	0.49***	-0.24***	-0.09***	0.24***	0.04***	0.05***	-0.02***	0.08***	0.02**
P(default)	-0.33***	1	-0.12***	-0.26***	-0.20***	0.60***	-0.08***	-0.11***	-0.07***	-0.08***	0.05***	-0.12***	-0.03***
ESG	0.41***	-0.13***	1	-0.0038	0.52***	-0.07***	-0.0155	0.16***	-0.0148	-0.0145	-0.06***	0.03***	0.0074
OPMAR	0.08****	-0.25***	-0.0024	1	0.18***	0.10***	0.39***	0.17***	-0.39***	-0.02**	-0.02**	0.0156	0.0103
SIZE	0.50***	-0.23***	0.51***	0.15***	1	0.02*	0.14***	0.05***	-0.28***	-0.02*	-0.05***	0.04***	0.0173
LEV	-0.27***	0.61***	-0.11***	-0.0086	-0.03***	1	0.12***	-0.09***	-0.36***	-0.12***	0.05***	-0.15***	-0.03***
CAPEX	-0.17***	0.04***	-0.14***	0.0028	0.04***	0.12***	1	-0.19***	-0.49***	-0.04***	-0.0093	-0.05***	0.03***
ROE	0.09***	0.04***	0.08***	0.10***	0.02*	-0.03**	-0.05***	1	0.22***	0.0128	0.0013	0.03***	-0.0024
LIQ	0.06***	-0.07***	-0.0157	-0.22***	-0.27***	-0.31***	-0.35***	0.06***	1	0.03***	-0.06***	0.07***	0.0108
VIX	0.05***	-0.08***	-0.02**	-0.02**	-0.0097	-0.11***	-0.0017	-0.0171	0.03**	1	0.12***	0.33***	-0.21***
RF	0.07***	-0.06***	-0.07***	0.03***	0.03***	-0.05***	0.0131	0.02**	-0.04***	-0.04***	1	-0.21***	-0.08***
SLOPE	0.04***	-0.09***	0.04***	0.03***	0.02*	-0.12***	-0.02**	0.0071	0.07***	0.27***	-0.50***	1	0.24***
NASDAQ	0.01***	-0.0125	0.0100	0.03***	0.0121	-0.02*	-0.0080	0.0127	0.0095	-0.40***	-0.05***	0.24***	1

Note: (1) The lower half of the correlation matrix is the Pearson correlation coefficient and the upper half is the Spearman correlation coefficient.
(2) ***、**and* suggest the correlation coefficients are significant at 1%, 5% and 10% significance levels, respectively.

4. Empirical results

4.1. Credit risk and ESG: Ratings

The first analysis uses an ordered logistic regression with credit ratings as the dependent variable, as mentioned in the methodology. The research explores whether higher Refinitiv ESG scores are related to better credit risk evaluations by credit rating agencies. Standard errors are adjusted using the Huber-White estimator to account for heteroskedasticity. Table 6 exhibits the ordered logistic regressions for corporate credit ratings. This table displays the five models with the control variables, the dummy variable, and the split sample. The respective robust standard errors are shown in parentheses. *, **, *** indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6

Ordered logistic regressions results for corporate credit ratings

	Full sample			High ESG Score	
				Yes	No
	(1)	(2)	(3)	(4)	(5)
Dependent variable	Corporate ratings	Corporate ratings	Corporate ratings	Corporate ratings	Corporate ratings
Corporate sustainability					
ESG score	0.0389***	0.0159***	0.0171***	0.0249***	0.0169***
	(0.0010)	(0.0012)	(0.0012)	(0.0027)	(0.0029)
Control variables					
OPMAR		0.4301***	0.4109***	0.7015***	0.1896*
		(0.1030)	(0.1029)	(0.2267)	(0.1145)
SIZE		0.8351***	0.8256***	0.8770***	0.7895***
		(0.0225)	(0.0227)	(0.0350)	(0.0303)
LEV		-2.3303***	-2.1847***	-2.1221***	-2.3803***
		(0.1265)	(0.1281)	(0.2544)	(0.1490)
CAPEX		-0.4151***	-0.4150***	-0.7157***	-0.4483***
		(0.0313)	(0.0317)	(0.1041)	(0.0359)
ROE		0.7961***	0.7662***	1.0657***	0.3637**
		(0.1803)	(0.1784)	(0.3675)	(0.1670)
LIQ		1.0008***	1.0502***	1.4647***	0.5676***
		(0.1236)	(0.1248)	(0.1964)	(0.1706)
VIX			0.0108***	0.0097*	0.0117**
			(0.0036)	(0.0054)	(0.0049)
RF			0.2246***	0.2600***	0.2490***
			(0.0292)	(0.0450)	(0.0404)
SLOPE			0.1017***	0.0759	0.1435***
			(0.0394)	(0.0576)	(0.0548)
NASDAQ			0.3075	0.2057	0.4589
			(0.2588)	(0.3966)	(0.3514)
Dummy variable					
Crisis	0.5712***	0.4143***	0.1090	-0.0366	0.1913
	(0.0863)	(0.0846)	(0.1178)	(0.1792)	(0.1644)
Pseudo R^2	0.0369	0.0909	0.0927	0.0777	0.0696
N	8,381	8,381	8,381	3,962	4,419

The respective robust standard errors are shown in parentheses with the corresponding significance levels indicated by ***p < 0.01, **p < 0.05, and * p < 0.1.

The first model (1) includes the regression of credit ratings with ESG scores and the *Crisis* dummy. The results show a statistically significant and positive coefficient for ESG scores at the 1% level, signaling a positive relationship between CSR performance and corporate credit ratings. In the second model (2), company credit ratings are regressed with ESG scores, six firm-specific control variables, and the *Crisis* dummy. As in the first model, Model 2 shows a positive statistically significant coefficient for ESG scores and most firm-specific variables. The third model, the benchmark model, incorporates external control variables, with most coefficients being significant at the 1% level. A positive coefficient for ESG indicates that higher CSR performance is related to better (higher) credit ratings. More precisely, for each standard deviation increase in ESG score, the average corporate credit rating increases by 10.81% [2]. These findings suggest that credit rating agencies consider CSR performance when assessing a firm's credit risk. The findings align with the risk mitigation hypothesis that argues that more socially responsible companies are allocated better credit ratings.

For Models 4 and 5, the benchmark specification is used. The sample is divided into two groups: companies with a high ESG score (above the mean, 44.515) and companies with a low ESG score (below the mean, 44.515). Based on the previous models, the results are as expected, as the ESG score coefficient is highly statistically significant with a positive sign in both models. Furthermore, the coefficient is greater for companies with high ESG scores than those with low ESG scores, suggesting that companies that value CSR efforts are rewarded with more favorable credit ratings. These results support the analysis of Jiraporn et al. (2014) and Attig et al. (2013), which find that companies with higher CSR performance receive better credit ratings. However, Stellner (2015)'s findings show that higher ESG performance is not related to higher credit ratings. One potential explanation is that their study comprises only European companies. In contrast, the studies mentioned above are based on US companies, as Menz (2010) finds that there may be a lag in recognizing the risk-mitigating effects of CSR investments within Europe. All the models in Table 6 show significant coefficients for firm-specific explanatory variables. Interestingly, the sign for *CAPEX* is negative, suggesting that firms with heavy investments are prone to have lower credit ratings. Furthermore, most of the external explanatory variables are significant.

[2] The change in the dependent variable (Rating) is measured by multiplying the independent variable coefficient (ESG) and the independent variable (ESG) standard deviation and dividing by the dependent variable (Rating) standard deviation: 0.0171 x 20.447 / 3.233 = 10.81%. Based on Lian (2023).

To further confirm the results obtained in Table 6, the sample is divided into Panel A and Panel B, as shown in Table 7. The first group contains investment-grade ratings, comprising corporate credit ratings ranging from AAA to BBB-. These companies represent a higher level of creditworthiness and lower risk of defaulting on their obligations to credit rating agencies. The second group comprises speculative-grade ratings ranging from BB+ to CC. In contrast, these represent a lower level of creditworthiness and a higher risk of defaulting on their obligations.

Table 7
Ordered logistic regressions results for investment grade ratings and speculative grade ratings

	Panel A: Investment grade ratings			**Panel B: Speculative grade ratings**		
	Benchmark	High ESG Score		Benchmark	High ESG Score	
		Yes	No		Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Corporate ratings	Corporate ratings	Corporate ratings	Corporate ratings	Corporate ratings	Corporate ratings
Corporate sustainability						
ESG score	0.0091***	0.0071**	0.0071*	-0.0087***	-0.0167***	0.0066
	(0.0016)	(0.0033)	(0.0038)	(0.0022)	(0.0064)	(0.0040)
Control variables						
OPMAR	1.0589***	0.8540***	1.0104***	0.0206	0.3136	0.0531
	(0.2092)	(0.2753)	(0.2891)	(0.1352)	(0.3518)	(0.1397)
SIZE	0.8493***	0.9573***	0.7363***	0.2616***	-0.0608	0.4534***
	(0.0293)	(0.0359)	(0.0547)	(0.0378)	(0.0581)	(0.0414)
LEV	-0.9408***	-0.2657	-1.7600***	-0.8792***	-1.266***	-0.6459***
	(0.2280)	(0.2900)	(0.3543)	(0.1419)	(0.2947)	(0.1624)
CAPEX	-0.3374***	-0.5744***	-0.2510***	-0.3119***	-0.3689**	-0.3133***
	(0.0777)	(0.1183)	(0.0964)	(0.0342)	(0.1576)	(0.0366)
ROE	1.3329***	1.503***	0.1539	-0.0043	0.1550	-0.0275
	(0.2941)	(0.3148)	(0.5170)	(0.1772)	(0.3217)	(0.1891)
LIQ	1.6108***	2.777***	-0.1524	1.2501***	0.3397	1.7757***
	(0.1902)	(0.2502)	(0.3101)	(0.1810)	(0.3559)	(0.2038)
VIX	0.0118***	0.0128**	0.0115*	-0.0012	-0.0006	0.0035
	(0.0045)	(0.0061)	(0.0067)	(0.0061)	(0.0116)	(0.0070)
RF	0.1722***	0.2087***	0.1773***	0.0018	0.1332	-0.0490
	(0.0356)	(0.0545)	(0.0520)	(0.0613)	(0.1391)	(0.0740)
SLOPE	0.0261	0.0745	-0.0098	0.0551	-0.0265	0.0812
	(0.0553)	(0.0700)	(0.0889)	(0.0619)	(0.1076)	(0.0754)
NASDAQ	0.2960	0.2990	0.3897	0.2040	-0.6431	0.7083
	(0.3364)	(0.4597)	(0.4982)	(0.4299)	(0.8368)	(0.4856)
Dummy variable						
Crisis	0.0588	-0.0786	0.1848	-0.0696	-0.8003**	0.2224
	(0.1388)	(0.2001)	(0.1997)	(0.2119)	(0.3941)	(0.2501)
Pseudo R^2	0.0850	0.0801	0.0590	0.0197	0.0128	0.0365
N	4,838	2,902	1,936	3,543	1,060	2,483

The respective robust standard errors are shown in parentheses with the corresponding significance levels indicated by ***p < 0.01, **p < 0.05, and * p < 0.1.

Generally, companies with better financial health and more stable cash flows are expected to be assigned investment-grade ratings. When running the benchmark regression (1) with investment-grade ratings, the coefficient for the ESG score is positive and highly significant, suggesting a strong relationship between superior ESG performance and higher credit ratings. Corroborating the study by Godfrey (2005), which finds that companies that value CSR are exposed to less risk and CSR efforts can serve as an “insurance policy.” Analyzing models 2 and 3, we can see that the coefficient for the ESG score remains positive and is the same.

However, the degree of significance is lower for firms with lower ESG scores. Considering the sample size and other factors in both regressions, firms with better ESG scores are more strongly related to higher credit ratings than low ESG firms. These results confirm the risk-mitigating view where high-quality borrowers with similar financial ratios who invest more in CSR activities are assigned better credit ratings than their counterparts. Thus, investment-grade firms that are financially stable can reduce credit risk by further investing in CSR activities.

In the benchmark regression (4) in Panel B, the coefficient for the ESG score is negative and highly significant. Low-credit quality companies that invest in CSR efforts are penalized with lower ratings. These results are consistent with Goss and Roberts (2011), who argue that CSR investments made by speculative-grade companies are more likely to be seen as greenwashing and can damage shareholder value. Thus, these results affirm the overinvestment view. Similarly, Model 5 displays a significant negative coefficient for the ESG score, even greater than in Model 4. Investments in CSR activities are perceived to be a waste of valuable resources that fail to generate value for shareholders. Following the agency theory, CSR activities represent an agency cost. Thus, credit rating agencies assign lower grades to these companies. In Model 6, the ESG score coefficient is positive, but there is no statistically significant relation between ESG scores and credit ratings. Credit rating agencies may not consider CSR efforts when assessing a company's creditworthiness. Nevertheless, most firm-specific variables are highly significant, suggesting that these financial ratios have a greater impact.

The following section investigates the impact of CSR performance on the probability of default.

4.2. Credit risk and ESG: Probability of default

The second analysis uses OLS regression to examine the relationship between Refinitiv ESG scores and the probability of default using the Ohlson O-score. Furthermore, I run a Hausman test and find that the fixed-effects model adequately models the individual-level effects in Appendix 1. Thus, fixed effects are incorporated in the OLS regression to account for unobserved heterogeneity and improve the accuracy of the estimated coefficients. Additionally, robust standard errors are adjusted to control for heteroscedasticity and outliers. Not doing so would lead to incorrect estimations of the standard errors and statistical significance of the control variables. Table 8 displays the OLS regression for the probability of default. As in the regressions with credit ratings as a measure for credit risk, I run five models with the control variables, dummy variable, and the split sample.

Table 8

OLS regression results for the probability of default

	Full sample			High ESG Score	
				Yes	No
	(1)	(2)	(3)	(4)	(5)
Dependent variable	P(default)	P(default)	P(default)	P(default)	P(default)
Corporate sustainability					
ESG score	0.0009*	-0.0002	-0.0004	-0.0001	-0.0005
	(0.0005)	(0.0004)	(0.0004)	(0.0006)	(0.0008)
Control variables					
OPMAR		-0.2209***	-0.2200***	-0.2644***	-0.1731***
		(0.0308)	(0.0307)	(0.0366)	(0.0341)
SIZE		-0.0279*	-0.0346**	-0.0428**	-0.0287
		(0.0147)	(0.0156)	(0.0185)	(0.0228)
LEV		0.7779***	0.7674***	0.7248***	0.8028***
		(0.0674)	(0.0692)	(0.0847)	(0.0958)
CAPEX		-0.0267***	-0.0265***	-0.0623**	-0.0143
		(0.0097)	(0.0096)	(0.0253)	(0.0108)
ROE		-0.0635***	-0.0628***	-0.0082	-0.1026***
		(0.0249)	(0.0247)	(0.0253)	(0.0375)
LIQ		-0.1268**	-0.1309**	-0.0571	-0.2204**
		(0.0592)	(0.0604)	(0.0599)	(0.0951)
VIX			-0.0002	0.0000	-0.0006
			(0.0005)	(0.0006)	(0.0007)
RF			-0.0087*	-0.0183**	-0.0045
			(0.0051)	(0.0059)	(0.0081)
SLOPE			-0.0099**	-0.0243***	0.0029
			(0.0049)	(0.0064)	(0.0077)
NASDAQ			0.0119	0.0040	0.0131
			(0.0211)	(0.0294)	(0.0297)
Constant	0.4430***	0.6093***	0.7098***	0.8003***	0.6445***
	(0.2306)	(0.1253)	(0.1463)	(0.1940)	(0.2136)
Dummy variable					
Crisis	-0.0024	-0.0028	0.0053	0.0207	-0.0017
	(0.0156)	(0.0128)	(0.0124)	(0.0174)	(0.0197)
Fixed effects	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.0164	0.4420	0.4442	0.4505	0.4430
N	7,763	7,763	7,763	3,740	4,023

The respective robust standard errors are shown in parentheses with the corresponding significance levels indicated by ***p < 0.01, **p < 0.05, and * p < 0.1.

As in the setup with credit ratings, Model 1 shows the regression of the ESG score with the probability of default, including the *Crisis* dummy. The coefficient for the ESG score is positive and significant at the 10% level. This outcome is in line with the overinvestment hypothesis. Companies with superior CSR performance are value-destroying and, therefore, are more likely to default on their debt and obligations. The second model incorporates company-specific variables, and the third model includes external control variables. Most control variables have the expected signs and are significant.

In contrast with the setup using credit ratings as the measure for credit risk, the *CAPEX* variable is negative, indicating that financially stable companies have low-risk profiles given that they have the capacity to allocate funds towards capital-intensive projects. Overall, profitable and highly liquid companies have better risk profiles. In the third model, most control variables are significant, apart from *VIX* and *NASDAQ*. However, I do not find a relevant relationship between CSR performance and the probability of default, given that in models 2 and 3, the coefficient is not significant. While the coefficient for the ESG score is negative, other variables appear to improve a company's risk profile. For models 4 and 5, the sample is split between high ESG scores and low ESG scores to investigate whether the probability of default is greater in high-ESG companies or low-ESG companies. The sign for the ESG score is negative in both regressions, following the risk-mitigating hypothesis that investments in CSR and superior CSR performance can provide stability and lower levels of distress risk. However, I find no statistically significant relationship between the two measures. As seen in models 2 and 3, "hard" financial ratios are more important when assessing the chances of a borrower defaulting on their debt and obligations.

The following section describes a series of robustness checks, specifically to ensure the validity of the results and address possible effects of endogeneity or reverse causality.

4.3. Further analysis and robustness checks

4.3.1. Endogeneity

It is necessary to consider the causality of the relationship to evaluate the impact of CSR performance in the setups that use credit ratings and the probability of default to measure credit risk. Previous credit ratings and default risk may also affect succeeding CSR performance. Thus, to address potential endogeneity issues, the analysis follows the methodology proposed by Lian (2023) and lags explanatory variables. This approach helps to reduce any problems that may arise due to endogeneity. The explanatory variables are lagged by one, two, and three periods. The following two regression models are set to control for endogeneity and reverse causality:

$$Rating_{i,t} = \beta_1 ESG_{i,t-n} + \beta_2 X_{i,t-n} + \beta_3 Z_{\,t-n} + \beta_3 Crisis_{\,t} + \varepsilon_{it} \quad (5)$$

where the quarterly rating, $Rating_{i,t}$, for a company (i) issued at time (t), is determined by the previous quarter n's, $ESG_{i,t-n}$ score, a group of six firm-specific control variables (represented by $X_{i,t-n}$), four external control variables (represented by Z_{t-n}), and the dummy $Crisis_{t}$. The standard error term is ε_{it}.

$$\mathrm{P}(default)_{i,t} = \alpha + \beta_1 ESG_{i,t-n} + \beta_2 X_{i,t-n} + \beta_3 Z_{t-n} + \beta_3 Crisis_{t} + \varepsilon_{it} \qquad (6)$$

where the quarterly rating, $Rating_{i;t}$, for a company (i) issued at time (t), is determined by the previous quarter n's, $ESG_{i,t-n}$ score, a group of six firm-specific control variables (represented by $X_{i,t-n}$), four external control variables (represented by Z_{t-n}), and the dummy $Crisis_{t}$. The standard error term is ε_{it}.

Table 9 displays the regressions for Panel A and B using equations 5 and 6 respectively. The first panel regresses corporate ratings using ordered logistics regression, and the second panel uses an OLS regression to examine the probability of default using the Ohlson O-score, as mentioned in the methodology. Firm-specific and external variables, including the *Crisis* dummy, are incorporated in all six models where *n* represents the number of periods lagged in quarters.

Panel A examines the relationship between S&P corporate ratings and Refinitiv ESG scores by lagging firm-specific and external variables, including the *Crisis* dummy. The benchmark regression in Table 6 shows that CSR performance is positively related to corporate credit ratings. However, this could be the consequence of firms with higher credit ratings having a greater capacity to invest in CSR activities, creating a reverse causality problem. Models 1, 2, and 3 report the regression results when lagging the independent variables by one, two, and three periods respectively. As in Table 6, the ESG score coefficient is positive and highly significant. The results remain robust and match the analysis of Attig (2013) and confirm the risk-mitigating hypothesis that companies that employ CSR activities enhance their credit risk profile. Furthermore, most of the firm-specific and external variables remain robust. Similarly, Panel B analyzes the relationship between the probability of default and Refintiv ESG scores. As in Panel A, I use the benchmark regression and lag the independent variables by one, two, and three periods, displayed in models 4, 5, and 6. In line with the prior results shown in Table 8, I find no significant relationship between CSR performance and the probability of default, in contrast to the study of Coopper and Uzun (2019), which finds a statistically strong relationship.

In the next section, I examine the relationship between CSR performance and credit risk by distinguishing among the three pillars in the ESG score.

Table 9

Robustness tests for endogeneity with lagged explanatory variables

	Panel A: Corporate ratings			Panel B: Probability of default		
	(1)	(2)	(3)	(4)	(5)	(6)
	n = 1	n = 2	n = 3	n = 1	n = 2	n = 3
Dependent variable		Corporate ratings			Probability of default	
Corporate sustainability						
ESG score	0.0166***	0.0163***	0.0162***	-0.0003	-0.0001	0.0004
	(0.0013)	(0.0013)	(0.0013)	(0.0004)	(0.0004)	(0.0005)
Control variables						
OPMAR	0.2599**	0.3486***	0.3744***	-0.2269***	-0.1806***	-0.1531***
	(0.1032)	(0.1069)	(0.1146)	(0.0283)	(0.0321)	(0.0271)
SIZE	0.8313***	0.8433***	0.8444***	-0.0258	-0.0018	0.0135
	(0.0234)	(0.0240)	(0.0248)	(0.0158)	(0.0173)	(0.0180)
LEV	-2.2211***	-2.2278***	-2.2364***	0.6529***	0.5580***	0.4983***
	(0.1360)	(0.1402)	(0.1453)	(0.0609)	(0.0582)	(0.0578)
CAPEX	-0.4008***	-0.3947***	-0.4060***	-0.0005	0.0061	-0.0051
	(0.0344)	(0.0327)	(0.0344)	(0.0102)	(0.0121)	(0.0122)
ROE	0.9161***	0.9821***	0.9451***	-0.0821***	-0.0457**	-0.0376*
	(0.1919)	(0.2042)	(0.2228)	(0.0228)	(0.0190)	(0.0203)
LIQ	1.0006***	1.0505***	1.0737***	-0.1225**	-0.0487	-0.0261
	(0.1315)	(0.1358)	(0.1388)	(0.0621)	(0.0645)	(0.0662)
VIX	0.0120***	0.0114***	0.0105***	-0.0001	-0.0008**	-0.0011***
	(0.0033)	(0.0032)	(0.0032)	(0.0004)	(0.0004)	(0.0004)
RF	0.2121***	0.2161***	0.2214***	-0.0130**	-0.0114**	-0.0063
	(0.0302)	(0.0314)	(0.0327)	(0.0051)	(0.0052)	(0.0052)
SLOPE	0.0748*	0.0719*	0.0582	-0.0160***	-0.0133**	-0.0050
	(0.0405)	(0.0430)	(0.0467)	(0.0050)	(0.0055)	(0.0056)
NASDAQ	0.2382	-0.0386	0.1136	0.0199	-0.0504**	-0.0490**
	(0.2649)	(0.2614)	(0.2599)	(0.0228)	(0.0208)	(0.0223)
Constant				0.6627***	0.4395***	0.2771
				(0.1540)	(0.1628)	(0.1690)
Dummy variable						
Crisis	0.2158*	0.1129	0.0496	0.0133	0.0165	0.0186
	(0.1149)	(0.1152)	(0.1251)	(0.0127)	(0.0138)	(0.0154)
Fixed effects	No	No	No	Yes	Yes	Yes
Pseudo R^2	0.0909	0.0907	0.0896	-	-	-
Adjusted R^2	-	-	-	0.4195	0.3667	0.2932
N	7,782	7,408	7,024	7,763	7,323	6,951

The respective robust standard errors are shown in parentheses with the corresponding significance levels indicated by ***p < 0.01, **p < 0.05, and * p < 0.1.

4.3.2. Separating the three pillar scores in ESG: environmental, social, and governance

As the sample overview and data description section mentioned, Refinitiv's ESG score is the overall firm score based on self-reported data in the environmental, social, and corporate governance pillars. Previous studies by Cooper and Uzun (2019) and Darrat (2016) investigate the relationship between CSR performance and bankruptcy risk by focusing on corporate governance. Similarly, Dorfleitner (2020) analyzes CSR performance and credit ratings using only the environmental and social pillar scores. Thus, to confirm the robustness of the results obtained in Tables 6 and 8, I regress each ESG score separately. Furthermore, to control for endogeneity and reverse causality problems, the independent variables are lagged by one period, as in Dorfleitner (2020).

Table 10 shows the ordered logistic regression results for company credit ratings using equation 5, where *n* is set to 1. Firm-specific control variables and external variables that proxy for the state are included in the regression, along with the *Crisis* dummy.

Table 10
Ordered logistic regression results for corporate credit ratings

	Full sample			High ESG Score	
				Yes	No
	(1)	(2)	(3)	(4)	(5)
Dependent variable	Corporate ratings	Corporate ratings	Corporate ratings	Corporate ratings	Corporate ratings
Corporate sustainability					
Environmental score	0.0276***	0.0188***	0.0192***	0.0196***	0.0230***
	(0.0012)	(0.0012)	(0.0012)	(0.0017)	(0.0019)
Social score	0.0044***	-0.0029**	-0.0022	0.0007	-0.0007
	(0.0015)	(0.0015)	(0.0015)	(0.0022)	(0.0026)
Governance score	0.0016	-0.0028***	-0.0028***	-0.0046***	0.0018
	(0.0010)	(0.0010)	(0.0010)	(0.0017)	(0.0015)
Control variables					
OPMAR		0.3392***	0.3473***	0.5523**	0.2246*
		(0.1051)	(0.1053)	(0.2292)	(0.1198)
SIZE		0.7958***	0.7884***	0.8691***	0.7277***
		(0.0228)	(0.0230)	(0.0344)	(0.0320)
LEV		-2.300***	-2.1596***	-2.0870***	-2.2231***
		(0.133)	(0.1340)	(0.2523)	(0.1608)
CAPEX		-0.393***	-0.3854***	-0.7087***	-0.4123***
		(0.034)	(0.0342)	(0.1192)	(0.0384)
ROE		0.941***	0.9130***	1.0189***	0.5892***
		(0.197)	(0.1949)	(0.3713)	(0.2003)
LIQ		1.122***	1.1992***	1.5836***	0.7679***
		(0.129)	(0.1307)	(0.1987)	(0.1844)
VIX			0.0119***	0.0088*	0.0159***
			(0.0033)	(0.0048)	(0.0046)
RF			0.2255***	0.2700***	0.2362***
			(0.0314)	(0.0484)	(0.0438)
SLOPE			0.0589	0.0305	0.1015*
			(0.0403)	(0.0579)	(0.0571)
NASDAQ			0.2284	0.0466	0.4958
			(0.2648)	(0.3935)	(0.3681)
Dummy variable					
Crisis	0.7422***	0.531***	0.1690	0.1000	0.1967
	(0.1072)	(0.098)	(0.1172)	(0.1846)	(0.1622)
Pseudo R^2	0.0449	0.0945	0.0965	0.0834	0.0724
N	7,782	7,782	7,782	3,753	4,029

The respective robust standard errors are shown in parentheses with the corresponding significance levels indicated by ***$p < 0.01$, **$p < 0.05$, and * $p < 0.1$.

Models 1, 2, and 3 use the complete sample. The environmental pillar score coefficient is highly significant and positive, implying that companies that employ more effort in the environmental area are awarded better credit ratings by agencies in line with Dorfleitner (2020)'s findings using a sample from 2003 to 2013. However, I do not find a significant relationship between the social pillar score and credit ratings. A possible explanation is that credit rating agencies do not factor in social initiatives compared to environmental and governance activities. In Model 3, the coefficient for the governance pillar score is negative and highly significant. This result is in accordance with the overinvestment hypothesis that, based on agency theory, suggests that CSR investments create an agency conflict between managers and shareholders. Barnea and Rubin (2010) argue that managers receive most of the credit for CSR initiatives at the expense of shareholders. In models 4 and 5, the sample is split between companies with high ESG scores and low ESG scores. The coefficient for the environmental pillar score remains positive and highly significant, confirming the previous results. In contrast, the governance score is only significant in Model 4. Thus, all else equal, companies with superior CSR performance are penalized with higher credit ratings when engaging in activities related to the environment. Instead, those companies that engage in activities related to corporate governance are penalized with lower credit ratings. These efforts can be interpreted as greenwashing and damage a company's creditworthiness. The regression results in Table 10 exhibit robust coefficients for most of the firm-specific and external control variables. These results align with the previous literature findings in section 3.2.

Table 11 exhibits the OLS regression results for the probability of default using equation 6, where *n* equals 1. As in the previous OLS regression, fixed effects are incorporated to improve the accuracy of the results and control for unobserved heterogeneity. Company-specific control variables and external variables that proxy for the economy are included, along with the *Crisis* dummy.

Analyzing the relationship between the probability of default using the Ohlson O-score and CSR performance, I find no significant results. Keeping all else equal and splitting the ESG score into its three pillars, the findings are the same as in Table 8. Results highlight that "hard" financial ratios are more important when measuring distress risk. These findings contrast with the analysis of Cooper and Uzun (2019), who find that companies that prioritize CSR practices mitigate the risk of filing for bankruptcy using Altman's Z-score as a proxy for default risk. However, Darrat et al. (2016) use other measures for corporate governance and conclude that governance changes made at a later stage may not be sufficient to save a company from filing for bankruptcy.

Table 11
OLS regression results for the probability of default

	Full sample			High ESG Score	
				Yes	No
	(1)	(2)	(3)	(4)	(5)
Dependent variable	P(default)	P(default)	P(default)	P(default)	P(default)
Corporate sustainability					
Environmental score	0.0005	0.0002	0.0000	0.0003	-0.0001
	(0.0004)	(0.0003)	(0.0003)	(0.0004)	(0.0006)
Social score	0.0004	0.0000	-0.0002	-0.0001	-0.0002
	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0006)
Governance score	0.0001	-0.0001	-0.0001	-0.0004	0.0005
	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Control variables					
OPMAR		-0.2279***	-0.2268***	-0.2540***	-0.1795***
		(0.0285)	(0.0283)	(0.0417)	(0.0319)
SIZE		-0.0166	-0.0259	-0.0365*	-0.0169
		(0.0150)	(0.0160)	(0.0197)	(0.0238)
LEV		0.6692***	0.6530***	0.6393***	0.6602***
		(0.0592)	(0.0608)	(0.0663)	(0.0875)
CAPEX		0.0003	-0.0004	0.0008	0.0043
		(0.0105)	(0.0103)	(0.0169)	(0.0115)
ROE		-0.0834***	-0.0820***	-0.0382	-0.1161***
		(0.0230)	(0.0228)	(0.0267)	(0.0320)
LIQ		-0.1174**	-0.1222**	-0.0949	-0.1716*
		(0.0604)	(0.0621)	(0.0637)	(0.0964)
VIX			-0.0001	0.0003	-0.0002
			(0.0004)	(0.0005)	(0.0006)
RF			-0.0129**	-0.0197***	-0.0100
			(0.0053)	(0.0063)	(0.0084)
SLOPE			-0.0160***	-0.0234***	-0.0081
			(0.0050)	(0.0066)	(0.0080)
NASDAQ			0.0201	0.0143	0.0287
			(0.0228)	(0.0337)	(0.0338)
Constant	0.4423***	0.5223***	0.6630***	0.7734***	0.5596***
	(0.0230)	(0.1344)	(0.1543)	(0.2069)	(0.2264)
Dummy variable					
Crisis	-0.0012	0.0050	0.0133	0.0273	0.0065
	(0.0155)	(0.0134)	(0.0127)	(0.0183)	(0.0192)
Fixed effects	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.0201	0.4075	0.4195	0.4249	0.4186
N	7,763	7,763	7,763	3,740	4,023

The respective robust standard errors are shown in parentheses with the corresponding significance levels indicated by ***p < 0.01, **p < 0.05, and * p < 0.1.

4.3.3. Subsamples based on industry and firm size

As an additional robustness check, I perform subsample regressions to analyze the CSR performance and credit risk relationship. First, the subsample is divided between manufacturing and services companies based on SIC codes. Then, I split the subsample between smaller-than-average-sized firms (log of total assets below 8.915) and larger-than-average-sized firms (log of total assets above 8.915). Table 12 shows the regression results for corporate credit ratings using ordered logistics. The ESG score coefficients in models 1 and 2 are statistically significant and positive, confirming previous results. Socially responsible companies in the manufacturing and services industry enjoy better credit ratings. In models 3 and 4, the ESG score coefficient remains positive and significant. Smaller and larger firms, measured by total assets, can enhance their risk profile by engaging in CSR activities. These results are in line with the risk-mitigating view.

Table 12

Ordered logistic subsample regression results for corporate credit ratings

	Industry		Firm size	
	Manufacturing	Services	Small	Large
	(1)	(2)	(3)	(4)
Dependent variable	Corporate ratings	Corporate ratings	Corporate ratings	Corporate ratings
Corporate sustainability				
ESG score	0.0238***	0.0192***	0.0163***	0.0210***
	(0.0019)	(0.0036)	(0.0019)	(0.0016)
Control variables				
OPMAR	1.8944***	-0.7373**	0.1324	0.8720***
	(0.3062)	(0.3812)	(0.1462)	(0.1669)
SIZE	0.8830***	0.7010***	0.7279***	1.0280***
	(0.0338)	(0.0565)	(0.0476)	(0.0440)
LEV	-3.2710***	-3.3547***	-1.8984***	-2.5037***
	(0.2296)	(0.3519)	(0.1515)	(0.2245)
CAPEX	-2.3032***	-0.4235*	-0.5709***	-0.1857***
	(0.3822)	(0.2225)	(0.0396)	(0.0541)
ROE	0.7362**	0.4118	0.5669***	0.5151
	(0.3222)	(0.6111)	(0.1867)	(0.3561)
LIQ	-0.3371	1.3539***	-0.1165	2.5386***
	(0.2266)	(0.3273)	(0.1643)	(0.2016)
VIX	0.0084	0.0015	0.0104**	0.0096*
	(0.0053)	(0.0097)	(0.0049)	(0.0053)
RF	0.3254***	0.2345**	0.2114***	0.2248***
	(0.0421)	(0.0960)	(0.0461)	(0.0399)
SLOPE	0.1877***	0.0827	0.1979***	0.0615
	(0.0597)	(0.0998)	(0.0532)	(0.0591)
NASDAQ	0.5650	-0.0958	0.4885	0.2098
	(0.3866)	(0.6556)	(0.3492)	(0.3920)
Dummy variable				
Crisis	0.3623**	0.5573	0.2681	-0.0027
	(0.1695)	(0.3681)	(0.1672)	(0.1715)
Pseudo R^2	0.1227	0.0844	0.0504	0.0845
N	3,949	1,263	4,492	3,889

The respective robust standard errors are shown in parentheses with the corresponding significance levels indicated by ***$p < 0.01$, **$p < 0.05$, and * $p < 0.1$.

Table 13 presents the OLS regression results for the probability of default as a credit risk measure. For companies in the manufacturing industry, I find no statistical evidence for a relationship between CSR performance and the probability of default. However, Model 2 displays a statistically significant and negative coefficient for the ESG score. The likelihood of default for companies within the services industry is lower for socially responsible companies. In Model 4, the coefficient for the ESG score is negative and significant. Larger-than-average-sized firms can mitigate and reduce credit risk by engaging in CSR activities. A possible explanation could be that larger firms have greater access to capital.

Table 13

OLS regression subsample results for the probability of default

	Industry		Firm size	
	Manufacturing	Services	Small	Large
	(1)	(2)	(3)	(4)
Dependent variable	P(default)	P(default)	P(default)	P(default)
Corporate sustainability				
ESG score	-0.0004	-0.0012**	0.0004	-0.0009**
	(0.0005)	(0.0006)	(0.0007)	(0.0004)
Control variables				
OPMAR	-0.5416***	-0.5294***	-0.2066***	-0.2321***
	(0.0986)	(0.1138)	(0.0454)	(0.0289)
SIZE	-0.0356	-0.0340	-0.0042	-0.0747***
	(0.0264)	(0.0284)	(0.0292)	(0.0173)
LEV	0.8805***	0.8276***	0.6655***	1.0622****
	(0.0996)	(0.1683)	(0.0972)	(0.0833)
CAPEX	-0.1657**	-0.0583*	-0.0224*	-0.0291**
	(0.0739)	(0.0340)	(0.0119)	(0.0120)
ROE	-0.0220	-0.0970	-0.0772***	-0.0157
	(0.0362)	(0.1024)	(0.0305)	(0.0328)
LIQ	-0.1949***	0.2191	-0.1804**	0.0273
	(0.0677)	(0.1451)	(0.0896)	(0.0755)
VIX	0.0010*	0.0005	-0.0001	-0.0002
	(0.0006)	(0.0008)	(0.0007)	(0.0006)
RF	0.0009	-0.0108	0.0039	-0.0194***
	(0.0070)	(0.0086)	(0.0080)	(0.0057)
SLOPE	0.0011	-0.0033	0.0007	-0.0231***
	(0.0058)	(0.0139)	(0.0074)	(0.0061)
NASDAQ	-0.0289	0.0560	0.0009	0.0323
	(0.0287)	(0.0456)	(0.0301)	(0.0298)
Constant	0.7225***	0.6523***	0.4612**	1.0227***
	(0.2295)	(0.2729)	(0.2480)	(0.1884)
Dummy variable				
Crisis	-0.0098	0.0186	0.0143	-0.0054
	(0.0160)	(0.0131)	(0.0187)	(0.0155)
Fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.5234	0.5813	0.4486	0.4001
N	3,674	1,149	4,116	3,647

The respective robust standard errors are shown in parentheses with the corresponding significance levels indicated by ***$p < 0.01$, **$p < 0.05$, and * $p < 0.1$.

The following section changes the measure of credit risk by using Altman's Z-score to analyze the relationship between CSR performance and credit risk.

4.3.4. Using Altman's Z-score as a measure of credit risk

Thus far, the analyses that use S&P corporate credit ratings as a measure of credit risk indicate that credit rating agencies factor in CSR performance when assessing companies. The findings follow the risk-mitigation view and overinvestment view. Low-risk firms with superior ESG scores are assigned higher ratings, while high-risk firms with better ESG scores are penalized with lower ratings. However, the analysis that uses the probability of default using the Ohlson O-score suggests that financial ratios are more significant in evaluating a firm's creditworthiness. Thus, as an additional measure for corporate credit risk, I use Altman (1968)'s Z-score, as used in numerous previous works of literature.

$$Zscore = \frac{1.2WorkingCapital + 1.4RetainedEarnings + 3.3EBIT + Revenues}{Total\ Assets} + \frac{0.6MVEquity}{Total\ Liabilities} \tag{7}$$

To test the relationship between the two measures, I run an OLS regression. As in the prior regressions with the probability of default, I execute the Hausman test and incorporate fixed effects into the regressions, as shown in Appendix 2. Furthermore, firm-specific and external control variables are included, along with the *Crisis* dummy. Results are displayed in Table 14.

In the benchmark model (3), I find a positive but not statistically significant relationship between CSR performance and Altman's Z score. For models 4 and 5, the sample is divided between high- and low-ESG scores. Interestingly, the ESG score coefficient in Model 5 is positive and significant at the 5% level. Following the risk-mitigating hypothesis, companies with poor CSR performance that engage in CSR activities can improve their financial health and reduce their exposure to credit risk. Companies with better financial health are less likely to default, decreasing their cost of debt. Consistent with Lian (2023)'s study, good ESG performance can significantly improve Z-scores using a Chinese sample and a different index for ESG scores. In a similar research, Hogan (2014) uses Altman's Z-score and discovers that companies that tend to give more to the community are less likely to file for bankruptcy.

In the following section, I present an extension of the study encompassing the role of CSR during the Global Financial crisis within the credit and debt market.

Table 14
OLS regression results for Altman's Z-score

	Full sample			High ESG Score	
				Yes	No
	(1)	(2)	(3)	(4)	(5)
Dependent variable	Z-score	Z-score	Z-score	Z-score	Z-score
Corporate sustainability					
ESG score	-0.0123**	0.0047	0.0046	0.0082	0.0127**
	(0.0060)	(0.0039)	(0.0036)	(0.0051)	(0.0053)
Control variables					
OPMAR		0.9404***	0.9036***	1.1954***	0.6006***
		(0.1850)	(0.1805)	(0.3187)	(0.1492)
SIZE		-0.6494***	-0.7368***	-0.4945***	-0.7667***
		(0.1387)	(0.1426)	(0.1294)	(0.1903)
LEV		-4.8978***	-5.1145***	-4.5263***	-5.3540***
		(0.6300)	(0.6443)	(0.8661)	(0.8900)
CAPEX		0.1370***	0.1530***	0.1730*	0.0479
		(0.0552)	(0.0553)	(0.0968)	(0.0593)
ROE		0.0397	0.0309	-0.1931	0.2215***
		(0.1986)	(0.1975)	(0.3868)	(0.0874)
LIQ		2.4627***	2.4470***	1.3064*	3.1269***
		(0.6700)	(0.6325)	(0.7066)	(0.9220)
VIX			-0.0254***	-0.0212***	-0.0269***
			(0.0032)	(0.0038)	(0.0042)
RF			0.0291	0.0815*	-0.0099
			(0.0434)	(0.0460)	(0.0538)
SLOPE			-0.0555	0.0250	-0.0667
			(0.0349)	(0.0395)	(0.0481)
NASDAQ			-0.2760***	-0.1739*	-0.2814**
			(0.0917)	(0.1045)	(0.1168)
Constant	2.8743***	8.3124***	9.7192***	7.3197***	9.5552***
	(0.2660)	(1.2925)	(1.3976)	(1.2570)	(1.6901)
Dummy variable					
Crisis	-0.1688*	-0.2908***	0.1573**	0.2616***	0.1001
	(0.0937)	(0.0734)	(0.0716)	(0.1038)	(0.0923)
Adjusted R^2	0.0003	0.3155	0.3069	0.2574	0.3895
N	8,381	8,381	8,381	3,962	4,419

The respective robust standard errors are shown in parentheses with the corresponding significance levels indicated by ***p < 0.01, **p < 0.05, and * p < 0.1.

4.3.5. Global Financial Crisis

The Global Financial Crisis was a significant exogenous shock that impacted all industries and markets. Some companies were able to manage the crisis and emerge stronger financially by pivoting to new strategic blueprints. In contrast, other companies did not survive the economic turmoil and defaulted on their obligations. Volatility and uncertainty prevailed during this period, and consequently, the cost of debt increased along with credit risk. Therefore, as an extension of the empirical research, I examine the relationship between CSR performance and credit risk during this period.

Table 15
Ordered logistic regression results for corporate credit ratings

	Panel A: Global Financial Crisis			Panel B: Non-Global Financial Crisis		
	Benchmark	High ESG Score		Benchmark	High ESG Score	
		Yes	No		Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Corporate ratings	Corporate ratings	Corporate ratings	Corporate ratings	Corporate ratings	Corporate ratings
Corporate sustainability						
ESG score	0.0119***	0.0308**	0.0065	0.0174***	0.0246***	0.0172***
	(0.0050)	(0.0138)	(0.0134)	(0.0013)	(0.0028)	(0.0030)
Control variables						
OPMAR	-0.0982	2.2638	-0.5034	0.4259***	0.6544***	0.2213*
	(0.5600)	(1.4908)	(0.4983)	(0.1074)	(0.2309)	(0.1207)
SIZE	0.9552***	0.9956***	1.0031***	0.8183***	0.8815***	0.7735***
	(0.0894)	(0.1568)	(0.1231)	(0.0234)	(0.0364)	(0.0312)
LEV	-2.6713***	-2.5731**	-2.2537***	-2.1915***	-2.0741***	-2.4122***
	(0.6907)	(1.1069)	(0.9191)	(0.1311)	(0.2615)	(0.1521)
CAPEX	-0.6364***	-0.4252	-0.8464***	-0.4010***	-0.7489***	-0.4206***
	(0.1347)	(0.7469)	(0.1513)	(0.0321)	(0.1071)	(0.0360)
ROE	2.4311*	4.0002**	0.9159	0.7062***	0.9346***	0.3389**
	(1.2997)	(2.0596)	(0.9051)	(0.1805)	(0.3659)	(0.1734)
LIQ	1.8960***	4.0788***	1.2518	0.9996***	1.3948***	0.5172***
	(0.6333)	(1.1215)	(0.8715)	(0.1273)	(0.1999)	(0.1743)
VIX	0.0227	0.0012	0.0261	0.0105**	0.0069	0.0128**
	(0.0891)	(0.1415)	(0.1190)	(0.0042)	(0.0061)	(0.0058)
RF	0.9989	-0.1781	1.2292	0.2219***	0.2598***	0.2479***
	(3.0304)	(4.7900)	(4.0638)	(0.0295)	(0.0456)	(0.0409)
SLOPE	0.8281	-0.6504	1.1766	0.0989**	0.0751	0.1414***
	(4.4034)	(6.8163)	(5.9430)	(0.0398)	(0.0580)	(0.0554)
NASDAQ	-1.2434	-1.0120	-0.7201	0.4551	0.5370	0.4671
	(0.9441)	(1.6600)	(1.2666)	(0.2871)	(0.4301)	(0.3967)
Pseudo R^2	0.1149	0.1232	0.0977	0.0916	0.0765	0.0674
N	447	184	263	7,934	3,778	4,156

The respective robust standard errors are shown in parentheses with the corresponding significance levels indicated by ***p < 0.01, **p < 0.05, and * p < 0.1.

Table 15 displays the ordered logistic regression results for credit ratings, where Panel A analyses the Global Financial Crisis period, and Panel B excludes this period. In models 1 and 2, the ESG score coefficient is positive and statistically significant, in line with the risk-mitigating view and Godfrey (2005)'s study. Socially responsible companies were able to mitigate risk during the Great Recession and therefore were assigned better credit ratings. However, I find no statistically significant evidence when the company has lower-than-average ESG scores. Instead, financial ratios like size, leverage, and capital expenditures are more important for credit rating agencies. Results in Panel B are consistent with previous findings. Companies with superior CSR performance can enhance their risk profile and receive better credit ratings.

In Table 16, I investigate the relationship between CSR performance and credit risk during the Global Financial Crisis using the probability of default as a credit risk measure. I find no statistically significant evidence that superior CSR performance reduces the likelihood of a company defaulting regardless of the period under analysis. Evidently, financial ratios are more critical for companies to mitigate the exposure to credit risk.

Table 16
OLS regression results for the probability of default

	Panel A: Global Financial Crisis			**Panel B: Non-Global Financial Crisis**		
	Benchmark	High ESG Score		Benchmark	High ESG Score	
		Yes	No		Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	P(default)	P(default)	P(default)	P(default)	P(default)	P(default)
Corporate sustainability						
ESG score	0.0008	0.0016	-0.0016	-0.0004	0.0002	-0.0006
	(0.0016)	(0.0045)	(0.0032)	(0.0004)	(0.0006)	(0.0009)
Control variables						
OPMAR	-0.0305	0.3697**	-0.0191	-0.2206***	-0.2614***	-0.1731***
	(0.0949)	(0.1532)	(0.1119)	(0.0307)	(0.0370)	(0.0363)
SIZE	-0.1498	0.4450	-0.2541	-0.0367**	-0.0450**	-0.0268
	(0.1949)	(0.5522)	(0.1979)	(0.0159)	(0.0190)	(0.0236)
LEV	1.3468***	1.6739**	1.3599***	0.7639***	0.7042***	0.8025***
	(0.3810)	(0.7251)	(0.4646)	(0.0706)	(0.0840)	(0.0968)
CAPEX	-0.0508	-0.1166*	-0.0421	-0.0261***	-0.0586**	-0.0168
	(0.0387)	(0.0637)	(0.0390)	(0.0102)	(0.0255)	(0.0111)
ROE	-0.2889***	-0.2977***	-0.3245***	-0.0540**	-0.0029	-0.0970***
	(0.0795)	(0.0913)	(0.0728)	(0.0239)	(0.0243)	(0.0378)
LIQ	0.0326	-2.0506*	0.7442	-0.1260**	-0.0405	-0.2245**
	(0.4823)	(1.1788)	(0.5350)	(0.0610)	(0.0628)	(0.0976)
VIX	0.0010	0.0060	0.0033	-0.0001	-0.0006	0.0000
	(0.0038)	(0.0051)	(0.0045)	(0.0005)	(0.0006)	(0.0008)
RF	0.0268	0.1928	0.1712	-0.0089*	-0.0164***	-0.0044
	(0.1528)	(0.1672)	(0.2021)	(0.0050)	(0.0057)	(0.0081)
SLOPE	0.0591	0.3149	0.2345	-0.0102**	-0.0238***	0.0018
	(0.2193)	(0.2543)	(0.2927)	(0.0049)	(0.0064)	(0.0078)
NASDAQ	0.0781	0.0236	-0.0045	0.0024	0.0076	-0.0061
	(0.0708)	(0.0710)	(0.1166)	(0.0224)	(0.0309)	(0.0311)
Constant	1.2561	-4.8663	1.2894	0.7253***	0.8129***	0.6266***
	(2.0808)	(5.8183)	(2.0102)	(0.1493)	(0.2000)	(0.2174)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.3291	0.0095	0.1034	0.4453	0.4427	0.4445
N	297	122	175	7,466	3,618	3,848

The respective robust standard errors are shown in parentheses with the corresponding significance levels indicated by ***$p < 0.01$, **$p < 0.05$, and * $p < 0.1$.

5. Summary and conclusion

This empirical research examines whether a company's creditworthiness is affected by its CSR practices. There are several measures available to assess a company's risk profile. In this study, I use corporate credit ratings and the probability of default using the Ohlson O-score. Previous studies focused on the relationship between financial performance and CSR. However, only some studies explore this relationship within the debt and credit market. Prior results have been inconsistent, where the direction of this relationship was ambiguous. Some findings find a positive relationship, following the risk-mitigating hypothesis, which argues that firms can improve their creditworthiness by investing in CSR efforts. These firms can unlock opportunities within the communities and foster better relationships with stakeholders, thus, building moral capital that can act as an "insurance policy" against adverse events. Companies can justify higher prices for this premium attributed to sustainable projects. The opposing hypothesis suggests that companies that engage in CSR practices harm their risk profiles. These companies are then penalized with lower credit ratings and increase their likelihood of default. Given that CSR projects are considered to drain a company's cash flow and decrease profitability, these projects can reflect an inefficient use of resources and poor management decisions. Furthermore, agency conflict can arise and lead to additional costs for penalties and fines. In addition, low-quality companies that engage in CSR activities can be regarded as greenwashing activities to boost reputation and harm company value further. As long as the marginal benefits of investing in CSR activities exceed the marginal costs, shareholders and debtholders will view such projects as beneficial.

The hypothesis aligns with the risk-mitigating view and is supported based on a sample of 429 companies in the US from 2006 to 2016. There is statistically strong support that the benefits of CSR exceed the costs and improve corporate credit ratings. Findings show that companies with higher-than-average ESG scores receive even better credit ratings than those of below-average companies. Results remain consistent after controlling for endogeneity by lagging the independent variables one, two, and three periods. However, statistically significant evidence shows that only companies with investment-grade ratings benefit from sustainable investments. Interestingly, speculative-grade companies harm their risk profile when engaging in CSR activities. Furthermore, I discover that environmental and corporate governance pillars are the most important when managing credit risk. Results remain consistent regardless of whether the companies are small or large, pertain to the manufacturing or services industry, or the period under analysis. In contrast, I find no statistically significant evidence that more socially responsible firms have a lower probability of default. However, this is an exemption of companies in the services industry and large firms where I find a negative and statistically significant relationship.

Given that the credit market is linked to many different external factors, credit risk is also affected by other circumstantial factors outside the scope of this research. The regression analyses included the Global Financial Crisis overlooking other specific exogenous shocks that could have affected the findings. Furthermore, missing data relating to the timeframe analyzed limits the empirical research. In addition, the number of observations is not equally distributed by year, as there are more observations following 2008. Another limitation is the exclusion of the constant term in the ordered logistic regressions, given that the model assumes that the coefficients are constant across the credit rating levels based on the proportional odds assumption. Nevertheless, this empirical research presents different ways for possible extensions of future research. Given that S&P long-term issuer corporate credit ratings are only available until February 2017, conducting this study for a longer time horizon would be advantageous, such as including other exogenous shocks such as the COVID-19 pandemic and the Russo-Ukraine War. As different credit rating agencies assess companies slightly differently, the study could be replicated using an alternative credit rating agency. It would also be insightful to use another metric for CSR. Additionally, industries could be classified to investigate the relationship between CSR performance and credit risk within specific industries.

Appendix

Appendix 1

Hausman test for OLS regression for the probability of default using the Ohlson O-score

	Coefficients		
	(b) Fixed	(B)	(b-B) Difference
ESG score	0.0004	-0.0003	-0.0001
	(0.0001)		
OPMAR	0.2200	-0.2222	0.0022
	(0.0031)		
SIZE	0.0346	-0.0396	0.0050
	(0.0050)		
LEV	0.7674	0.7807	-0.0133
	(0.0091)		
CAPEX	0.0265	-0.0257	-0.0008
	(0.0018)		
ROE	0.0628	-0.0613	-0.0014
	(0.0014)		
LIQ	0.1309	-0.0968	-0.0341
	(0.0186)		
VIX	0.0002	-0.0002	0.0000
	(0.0001)		
RF	0.0087	-0.0092	0.0004
	(0.0009)		
SLOPE	-0.0099	-0.0104	0.0005
	(0.0007)		
NASDAQ	0.0119	0.0120	-0.0001
	(0.0015)		
Crisis	0.0053	0.0046	0.0007
	(0.0005)		
Chi^2	20.09		

b: consistent under H0 and Ha
B: inconsistent under Ha, efficient under H0

Test of H0: difference in coefficients not systematic

Appendix 2

Hausman test for OLS regression for Altman's Z-score

	Coefficients		
	(b) Fixed	(B)	(b-B) Difference
ESG score	0.0046	0.0045	0.0001
	(0.0004)		
OPMAR	0.9036	0.9373	-0.0337
	(0.0103)		
SIZE	-0.7368	-0.5366	-0.2003
	(0.0208)		
LEV	-5.1145	-5.0805	-0.0340
	(0.0328)		
CAPEX	0.1530	0.1454	0.0076
	(0.0061)		
ROE	0.0309	0.0420	-0.0112
	(0.0048)		
LIQ	2.4470	2.7359	-0.2889
	(0.0712)		
VIX	-0.0254	-0.0231	-0.0023
	(0.0002)		
RF	0.0291	0.0624	-0.0333
	(0.0037)		
SLOPE	-0.0555	-0.0322	-0.0233
	(0.0028)		
NASDAQ	-0.2760	-0.2333	-0.0427
	(0.0063)		
Crisis	0.1573	0.1549	0.0024
	(0.0021)		
Chi^2	146.96		

b: consistent under H0 and Ha

B: inconsistent under Ha, efficient under H0

Test of H0: difference in coefficients not systematic

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