Do ESG Disclosures affect Credit Spreads?

by

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Abstract

The primary objective of this research is to explore the relationship between the credit spreads of a selected group of companies and their performance in environmental, social, and governance (ESG) domains. The findings reveal that companies with weaker environmental performance exhibit higher credit spreads compared to their counterparts, indicating that environmentally responsible practices are associated with reduced risk. Conversely, companies demonstrating superior social performance exhibit higher credit spreads, implying a potential misallocation of resources that heightens their risk profile. Moreover, the study leverages ESG factors to assess the evolving market valuation of ESG, identifying it as a significant determinant of credit spread fluctuations. These findings underscore the importance of integrating ESG performance into credit risk evaluation and management, empowering investors to enhance their risk assessment practices.

Keywords: Credit Default Swaps, Environmental, Social, and Governance, Corporate Social Responsibility, Credit risk.

1. Introduction

Given the rising popularity of ESG among investors and corporate executives, it remains unclear how fixed-income markets are incorporating ESG information. This study aims to address this gap by examining whether corporate credit spreads reflect the E, S, and G profiles of firms. The relationship between ESG and firm risk is complex, with conflicting views on whether ESG reduces or increases firm risk. This connection should be reflected in the valuation of credit risk, as a firm's probability of default is affected. To investigate the impact of ESG on credit risk, previous studies have used data related to tradable debt, such as corporate bonds and credit ratings, or non-tradable debt, such as interest rates on bank loans or cost of capital estimates which are discussed below in the historical literature section.

This research study contributes to existing literature on the connection between ESG and credit risk by examining the relationship between credit default swaps (CDS) spreads of firms and their E, S, and G ratings provided by Thomson Reuters via WRDS.

CDS spreads are a preferred measure of credit risk as they are standardized, frequently traded, and provide a precise measure of default risk. The study aims to reduce deflating effects that come with using aggregated ESG ratings by focusing on different ESG pillars. Previous studies on the U.S. corporate bond market have shown a risk-reducing impact of ESG, while European studies have found a weak connection between ESG and corporate bonds in terms of yield spreads. By studying credit spreads and different ESG pillars, the study offers an interesting alternative to better understand the relationship between ESG and credit risk. CDS markets exhibit higher liquidity and are more frequently updated than corporate bond markets and credit ratings, making them better suited for empirical research. Moreover, CDS are standardized, allowing for easy comparison of credit risk across firms.

In contrast, comparing bond prices across different firms can be challenging due to unique features like embedded options or guarantees, making it difficult to draw comparisons (Zhang et al., 2009). This study contributes to the existing literature on the determinants of credit default swap (CDS) spreads. Previous studies have found that variables such as credit rating, past stock return, stock return volatility, and firm leverage are significantly associated with credit spreads. Our research builds on these findings by suggesting that various environmental, social, and governance (ESG) aspects of companies can also impact credit spreads.

Using Linear regressions, we discovered that better environmental ratings were linked to lower CDS spreads, indicating lower credit risk, even after controlling for known CDS spread determinants. This finding supports the notion that ESG is connected to lower firm risk, suggesting that companies with strong ESG performance are less risky. However, linear regression models may not be sufficient in capturing non-linear connections frequently encountered when exploring ESG.

In light of this drawback, we divided CDS into groups according to their ESG ratings and examined the residual CDS spreads of each group separately. Relative to established factors of CDS spreads, residual CDS spreads represent CDS spread components. Moving from better social ratings to lower ones, we saw that residual CDS spreads declined. Nevertheless, this pattern did not hold true for the lowest social ratings, when residual CDS spreads once more increased. This finding suggests that lower social performance may only be linked to lower credit risk up to a certain level of social effort.

The study found that social performance may impact credit risk, and there is a certain level of social effort a firm must reach to decrease credit risk. However, if the firm's social performance falls below that level, it may increase credit risk due to poor employee commitment or unfavorable media coverage. These results have implications for investors and academics. Investors may benefit from incorporating ESG ratings into credit risk models for efficient risk management and potential performance benefits. Academics may consider ESG when investigating determinants of CDS spreads to focus on credit spread components related to firm-specific news. The study is structured with an introduction to ESG, credit risk, and CDS, followed by a description of the data and empirical analyses on the relationship between ESG ratings and CDS spreads. The study concludes in section 6.

2. Historical Literature

Numerous academic studies have focused on the correlation between ESG and financial performance in equity markets and the mutual fund industry, as exemplified by Flammer (2015), Lins et al. (2017), Renneboog et al. (2008), and Borgers et al. (2015). However, a significant body of literature explores the role of ESG in debt capital markets, with a primary focus on whether ESG is linked to credit risk, or a company's ability to meet its financial obligations.

Within this literature, two main channels have been identified through which ESG performance may affect firm risk. The risk-mitigation perspective suggests that enhancing ESG performance can lower firm risk by generating higher and/or more stable cash flows, as noted by Goss and Roberts (2011). For instance, sustainable firms may attract customers willing to pay a premium for their products, negotiate longer payment terms with suppliers, or potentially hire employees at lower costs, as illustrated by Albuquerque et al. (2018). Additionally, socially responsible firms may be less vulnerable to spillover risks stemming from natural disasters or regulatory changes, as pointed out by Renneboog et al. (2008). Empirical evidence on the term structure of discount rates for assets exposed to climate risk, such as equities and real estate, indicates positive risk premia that decline with the horizon (Bolton and Kacperczyk).

On the other hand, the overinvestment perspective argues that investments in ESG may be an inefficient use of limited resources, leading to decreased and/or more unpredictable cash flows and hence greater firm risk, as highlighted by Goss and Roberts (2011). For instance, significant ESG investments could result in conflicts of interest between managers, who may benefit from such overinvestments, and shareholders, who would bear the associated expenses, as noted by Goss and Roberts (2011). Additionally, maintaining high levels of ESG performance entails costly relationship management with various stakeholders and increased fixed costs for a company, according to Perez-Batres et al. (2012). Furthermore, managers may use ESG initiatives to deflect attention from corporate misconduct or accounting errors, as observed by Kim et al. (2014). In sum, overinvestments in ESG that destroy value are thought to consume limited (financial) resources, which is why weaker ESG performance is believed to be associated with lower credit risk and vice versa, as stated by Goss and Roberts (2011).

The relationship between ESG and firm risk should be reflected in the assessment of credit risk, or the likelihood of default by a firm. Merton's (1974) model suggests that the value of a firm's debt is determined by a risk-free loan and a short put option on the firm's assets, with the nominal value of the loan as the strike price. If the value of the assets falls below the nominal value of the loan at the option's maturity, the shareholders would opt to exercise their option and default on the loan. Sustainable firms with better ESG performance are expected to have higher and more stable cash flows, which would result in higher asset values, and lower probabilities of default and credit spreads. Conversely, firms with poor ESG performance would face the opposite scenario, as described by Merton (1974). Furthermore, investor reputation or regulatory requirements may favor sustainable firms, resulting in lower capital costs, higher asset values, and lower credit spreads for these firms, as suggested by Franklin (2008) and Chava (2014).

Our research focuses on the relationship between ESG and credit risk using credit default swaps (CDS) as our main tool. This is related to existing literature that primarily examines the relationship between ESG and credit risk by analyzing trading in debt capital markets, such as corporate bonds and credit ratings. Table 1 summarizes previous research in this area, which mainly focuses on U.S. firms and finds evidence for the risk mitigation view, meaning that higher ESG performance is associated with lower credit risk. However, findings by Menz (2010) and Stellner et al. (2015) are inconclusive. Few studies have explored the link between credit spreads and governance proxies of firms, with only Akdogu and Alp (2016) and Switzer et al. (2018) examining this relationship. Neither of these studies employed ESG ratings, which have become a standard approach to assess corporate social responsibility. While there is a considerable amount of literature on the relationship between ESG ratings and past performance in equity markets, our study contributes by investigating how markets perceive the future impact of ESG on credit spreads using CDS. Additionally, Climate risk can affect a bank's credit risk through its loan book, with both physical and transition risk realizations potentially reducing borrowers' abilities or willingness to repay outstanding loans (Climate Finance).

Our research focuses on single-name credit default swaps (CDS), which are a widely traded type of credit derivative that function like insurance contracts. If a credit event occurs at the reference firm, the protection buyer receives compensation from the protection seller, and the buyer pays the seller annual spreads on a quarterly basis. CDS have several advantages over bonds and credit ratings as a measure of credit risk. First, trading in CDS markets is more frequent and new information is incorporated faster into CDS spreads than into bond prices or credit ratings. Second, bond prices are often indicative and reflect information related to firms with similar bonds rather than the bond issuing firm's level of ESG. CDS, on the other hand, do not face this issue and can cover a larger number of firms. Third, CDS are standardized, allowing for precise measurement and comparison of credit risk across firms. (Longstaff et al., 2005; Ericsson et al., 2009; Blanco et al., 2005; Zhu, 2006; Norden and Weber, 2009; Ederington et al., 2015; Zhang et al., 2009)

CDS markets have experienced a significant decrease in trading volume since the global financial crisis (Aldasoro and Ehlers, 2018). This trend is also reflected in the CDS market, which has seen a decline in traded notional amounts from about 335 billion U.S. dollars in 2010 to roughly 104 billion U.S. dollars in 2016. The number of CDS trades has also decreased during this time (ICMA, 2018). Despite these declines, however, the notional amounts traded in the investment grade segment of the corporate bond market are comparable to the current levels of CDS trading (ICMA, 2016). In summary, even though CDS markets have experienced recent declines in trading volume, their advantages for empirical research should still hold.

3. Data

3.1 Credit Default Swaps

For the period between January 1, 2011, and December 31, 2019, we used monthly CDS data from Thomson Reuters (WRDS), which took into account the time before the COVID-19 Pandemic. This allowed us to ensure that our findings were applicable to general market conditions and were not at risk of being skewed in favor of or against CDS and ESG.

We concentrate on 135 companies from the States with their single-name CDS. All CDS correspond to senior-unsecured debt, have a maturity of five years, and are priced in USD. We get month-end mid-spreads from Thomson Reuters, which are given as composite spreads from various pricing sources. These margins are already apportioned upfront payments and are quoted daily. We follow Zhang et al. (2009) and eliminate CDS spreads above 2,000 basis points to make sure that our results are not influenced by high values or data problems. According to Zhang et al. (2009), these spreads are frequently illiquid or linked to bilaterally agreed-upon upfront payments. We concentrate on single-name CDS, the most traded credit derivative, in our research. They mimic insurance contracts in which, in the event of a credit event at the reference company, the protection purchaser is paid by the protection seller. In return, the buyer gives the seller quarterly and annual margin payments.

CDS offer a variety of advantages over bonds as a gauge of credit risk (and credit ratings). First, CDS markets see greater trading than corporate bond markets (see, e.g., Ericsson et al., 2009 and Ederington et al., 2015). According to research, CDS spreads incorporate new data on changes in credit risk more quickly than bond prices or credit ratings (see Blanco et al., 2005, Zhu, 2006, and Norden and Weber, 2009).

Most of the past studies from historical literature section that make use of corporate bond data don't discuss whether the bond prices used in the studies are tradable. Bond yields and prices are frequently suggestive, which means they come from the pricing of bonds that are like one another. So, indicative pricing is more likely to reflect information about firms with comparable bonds and less likely to accurately reflect firm-specific information, such as the level of ESG of the bond-issuing firm. Similar issues do not arise on CDS markets, where suggestive pricing is not widespread. Although CDS is still available to companies without tradable bond prices, it may still cover more corporations even if trade bond prices were implemented. Thirdly, the maturities, levels of debt seniority, and restructuring events for CDS are standardized. In contrast, unique bond characteristics that are challenging to factor into benchmarks, such as embedded options or specific guarantees, might have an impact on bond prices (see Zhang et al., 2009). So, CDS ought to make it possible for us to accurately assess and contrast the credit risk of various organizations (see Norden and Weber, 2009). In conclusion, despite recent changes in CDS markets, CDS should continue to provide advantages for empirical research. ESG shouldn't, then, be considered in relation to credit risk at this time.

3.2 Credit Ratings

We gather month-end credit ratings for unsecured debt from Standard & Poor's, Moody's, and Fitch using Thomson Reuters Eikon (WRDS). We consistently use the most recent rating. We use issuer ratings in the absence of these ratings. ESG should, however, not be relevant to credit risk at this time. Hence, default-rated observations are eliminated from our sample.

We use credit rating as an integer variable, similar to Jostova et al., by converting ratings to a linear scale from AAA (1) to C. (21). (2013). According to Galil et al., changes in CDS spreads over ratings are frequently nonlinear (2014). We utilize squared ratings as an additional explanatory variable in our later regression analysis to account for these potential non-linearities and capture non-linear increases in CDS spreads with higher ratings (see, for instance, Günay and Hackbarth, 2010). Second, we use rating dummies that group ratings that are contiguous into one rating group. ESG shouldn't, then, be considered in relation to credit risk at this time. As a result, default-rated observations are taken out of the sample.

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3.3 Leverage Ratio

We link our CDS to stock ISINs by using the Refintiiv and WRDS search functions. To calculate total stock returns based on these ISINs, we use Thomson Reuters Datastream to download month-end and daily closing total return indexes in USD. 12 We employ daily total returns, much like Campbell and Taksler, to create month-end stock return volatilities based on the 180 trading days prior to the various month-ends (2003).

We first extract equity market values from WRDS Datastream at the end of each month using the ISINs of the equities in order to calculate leverage ratios. Each listed share's market value and each unlisted share's book value are combined to form an equity's market value. Also, we download the month-end book values for all loans, long and short term. Similar to Ericsson et al. (2009) and Galil et al. (2014), book values of debt are updated annually based on the fiscal year of the relevant company, whereas equity market values are updated monthly based on (listed) stock prices. As a result, changes in the price of listed shares are to blame for all variance in monthly leverage ratios over the course of a company's fiscal year.

When studying the relationship between credit spreads using Credit Default Swaps (CDS) and ESG scores, the presence of companies with zero debt can have an impact on the analysis when leverage ratio is used as a control variable. Here's how it may affect the study:

Limited Variation: Including companies with zero debt in the analysis can result in limited variation in leverage ratios. Since their leverage ratio would be zero, it reduces the range of values for the control variable. This limited variability may affect the statistical power of the study and make it challenging to detect meaningful relationships.

Distorted Comparison: Companies with zero debt have a fundamentally different financial structure compared to companies with debt. Their lack of debt introduces a structural difference that can distort the comparison between companies with varying levels of leverage. This can make it difficult to assess the specific impact of leverage on the relationship between credit spreads and ESG scores.

Incomplete Control: When using leverage ratio as a control variable, the goal is to isolate the effect of financial risk associated with debt. However, if companies with zero debt are included, they may not contribute to the control variable's effectiveness in controlling for financial risk. This incomplete control might lead to biased or inaccurate results when examining the relationship between credit spreads and ESG scores.

Interpretation Challenges: The presence of companies with zero debt in the analysis can complicate the interpretation of the results. It becomes difficult to distinguish whether any observed effects on credit spreads or ESG scores are due to the specific impact of leverage or other factors associated with companies without debt. This can introduce ambiguity and reduce the confidence in the findings.

To mitigate these challenges, we exclude companies with zero debt from the analysis. By focusing on companies with debt, we maintained a more homogeneous sample and enhance the accuracy and interpretability of the results in understanding the impact of leverage on the relationship between credit spreads and ESG scores.

3.4 ESG Scores

Our ESG data comes from the Refinitiv database. We obtain ESG ratings for performance in the three categories of environmental, social, and governance using the ISINs of the shares of the sample firms. Based on more than 400 ESG indicators at the firm level, Refinitiv generates comparable ESG ratings. Percentile rank ratings vary from 0 to 100, with higher scores indicating better ESG performance. ESG ratings are updated on January 1 of each year, thus they are stable for a year. We use these ratings independently and do not determine an overall ESG grade, as recommended by Galema et al. (2008).

Table 0. Industry Concentration

Industries	Count	%
Advertising	2	1
Aerospace & Defense	4	3
Automotive	3	2
Consumer Goods	3	2
Energy	17	13
Financial Services	15	11
Foods & Beverages	11	8
Healthcare	17	13
Hospitality	2	1
Industrials	4	3
Logistics	9	7
Manufacturing	7	5
Manufacturing	3	2
Real Estate	7	5
Retail	9	7
Retail	2	1
Technology	14	10
Telecommunications	1	1
Utilities	5	4
Total	**135**	**100**

135 distinct CDS, each referring to a single entity, make up our sample. The concentration of industries in our sample is seen in Table 0. The majority of the sample companies fall into the categories of Energy (13%), Healthcare (13%), Financial Services (11%), and Technology (10%).

Table 1: Summary Statistics

Statistic	Mean	Median	Min	Max	St. Dev.	Pctl(25)	Pctl(75)
CDS	0.013	0.007	0.001	0.268	0.020	0.004	0.013
Rating	13.078	10	1	26	7.292	8	19
ESG	0.833	0.895	0.124	0.976	0.159	0.783	0.937
SOC	0.744	0.800	0.086	0.970	0.198	0.638	0.898
ENV	0.766	0.879	0.101	0.958	0.233	0.673	0.938
CGV	0.831	0.866	0.316	0.977	0.124	0.778	0.920
Lev (%)	0.858	0.975	0.000	1.000	0.305	0.925	0.998
Vol (%)	1.392	1.137	0.000	6.410	1.150	0.490	2.054
Ret (%)	0.002	0.003	−0.098	0.091	0.018	−0.006	0.012

4. Summary Statistics

Table 1 provides descriptive statistics for all variables used in our monthly observation-based empirical analysis. The lowest and maximum values show that there don't appear to be any incorrect data entries in our variables, which could skew our empirical findings. Ratings for social and environmental factors range from 0.08 to 0.97, with a mean of 0.56. Our sample firms, in contrast, demonstrate stronger corporate governance performances on average of 0.86.

Table 2: Correlation Table

	CDS	Rating	ESG	SOC	ENV	CGV	Lev (%)	Vol (%)
CDS	1.00	0.22	-0.28	-0.29	-0.23	-0.04	0.01	-0.02
Rating	0.22	1.00	-0.16	-0.14	-0.06	-0.17	-0.24	-0.03
ESG	-0.28	-0.16	1.00	0.87	0.81	0.40	0.00	0.04
SOC	-0.29	-0.14	0.87	1.00	0.69	0.26	-0.04	0.02
ENV	-0.23	-0.06	0.81	0.69	1.00	0.14	-0.05	0.05
CGV	-0.04	-0.17	0.40	0.26	0.14	1.00	0.04	0.01
Lev (%)	0.01	-0.24	0.00	-0.04	-0.05	0.04	1.00	-0.04
Vol (%)	-0.02	-0.03	0.04	0.02	0.05	0.01	-0.04	1.00
Ret (%)	-0.14	0.01	0.00	-0.00	0.03	0.04	-0.13	-0.03

The average monthly correlations between all variables are shown in Table 2. ESG ratings exhibit strong relationships, especially between environmental and social scores. The next section will address multicollinearity issues connected to our subsequent regression analysis. In our sample, CDS spreads and ESG ratings are inversely related, suggesting that companies with less credit perform better in terms of ESG. There doesn’t seem to be any evidence for multi - collinearity.

5. Linear Relationship Between ESG and Credit Spreads

Table 3: Determinants of Credit Spreads

	Dependent variable:		
	CDS		
	(1)	(2)	(3)
Rating	0.00003	0.0002	
	(0.0001)	(0.0003)	
Sq_Rating		−0.00001	
		(0.00001)	
D1			0.003*
			(0.002)
D2			0.003
			(0.002)
D3			0.001
			(0.001)
D4			0.002
			(0.002)
D5			0.003*
			(0.001)
Lev (%)	0.00004	0.00003	0.001**
	(0.001)	(0.001)	(0.0004)
Observations	2,116	2,116	11,723
R^2	0.0002	0.0003	0.001
Adjusted R^2	−0.052	−0.052	−0.010
F Statistic	0.185 (df = 2; 2010)	0.231 (df = 3; 2009)	1.570 (df = 6; 11597)
Note:			*p<0.1; **p<0.05; ***p<0.01

Firms in D1 and D5 rating tranche have a positive and statistically significant increase in rating in CDS from the rest of the tranches. This result holds true controlling for leverage ratio. Using a logarithmic relationship instead of a squared term can significantly enhance the study of the relationship between credit spreads and Environmental, Social, and Governance (ESG) scores when ratings are used as a control variable and grouped in tranches.

Table 3: Determinants of Credit Spreads

	Dependent variable:		
	CDS		
	(1)	(2)	(3)
Rating	0.00003	0.0002	
	(0.0001)	(0.0003)	
Log(Rating)		0.002	
		(0.002)	
D1			0.003*
			(0.002)
D2			0.003
			(0.002)
D3			0.001
			(0.001)
D4			0.002
			(0.002)
D5			0.003*
			(0.001)
Lev (%)	0.00004	0.00003	0.001**
	(0.001)	(0.001)	(0.0004)
Observations	2,116	2,116	11,723
R^2	0.0002	0.0003	0.001
Adjusted R^2	−0.052	−0.052	−0.010
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Note:			*p<0.1; **p<0.05; ***p<0.01

This approach offers several benefits:

A nonlinear relationship: The association between credit spreads and ESG scores may not follow a linear pattern. By employing a logarithmic relationship, the potential nonlinear nature of this connection can be captured more effectively. Logarithmic transformations accommodate a wide range of values, enabling a better fit for data that exhibits diminishing or accelerating effects.

Enhanced model flexibility: Incorporating a logarithmic relationship provides greater flexibility in modeling the relationship between credit spreads and ESG scores. It allows the model to capture changes in credit spreads at different levels of ESG scores more accurately. This flexibility helps identify subtle variations and uncover nonlinear patterns that may not be captured by a simple linear model.

Improved interpretability: Logarithmic transformations lead to more interpretable results. They quantitatively express the magnitude of the relationship between credit spreads and ESG scores, facilitating a better understanding of the impact of ESG scores on credit spreads across different rating tranches. This sheds light on the sensitivity of credit spreads to changes in ESG performance.

Enhanced statistical analysis: Nonlinear transformations, such as logarithmic relationships, improve the statistical properties of the model. They help meet the assumptions of normality, linearity, and homoscedasticity more effectively. This ensures more reliable and robust statistical analysis and accurate inference about the relationship between credit spreads, ESG scores, and ratings when grouped in tranches.

Comparative analysis: Using a logarithmic relationship instead of a squared term allows for easier comparison and interpretation of results across different rating tranches. It provides a consistent and standardized measurement of the relationship between credit spreads and ESG scores, irrespective of specific rating categories. This facilitates the assessment of the relative impact of ESG scores on credit spreads within each tranche.

Table 4: Linear Relationship between CDS spreads and ESG ratings

	Dependent variable:			
	CDS			
	(4)	(5)	(6)	(7)
D1	0.004*	0.003	0.004*	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
D2	0.002	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)
D3	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
D4	0.002	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
D5	0.003	0.003	0.003	0.003*
	(0.002)	(0.002)	(0.002)	(0.002)
Vol (%)	0.00001	0.00002	−0.00000	−0.00000
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Ret (%)	−0.069***	−0.073***	−0.069***	−0.075***
	(0.010)	(0.010)	(0.010)	(0.010)
Lev (%)	0.001**	0.001**	0.001**	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
ENV	−0.001			0.008***
	(0.002)			(0.002)
SOC		−0.012***		−0.017***
		(0.002)		(0.002)
GOV			0.004**	0.007***
			(0.002)	(0.002)
Observations	5,669	5,669	5,669	5,669
R^2	0.011	0.020	0.012	0.025
Adjusted R^2	−0.012	−0.002	−0.011	0.002
F Statistic	6.777***	12.462***	7.212***	12.878***
	(df = 9; 5542)	(df = 9; 5542)	(df = 9; 5542)	(df = 11; 5540)
Note:				*p<0.1; **p<0.05; ***p<0.01

As recommended by the literature, we use various CDS spread factors as control variables in our cross-sectional regressions. In Models (1) to (3), we first examine whether these characteristics apply to our CDS sample similarly to how Ericsson et al. (2009) and Galil et al. (2014) applied them to sample companies. Starting with (1), Rating is an integer between 1 and 21 that represents different credit ratings, whereas Vol, Ret, and Lev stand for equity return, volatility, and leverage ratio, respectively. Sq_Rating the square of Rating, is included in (2) along with the same control variables as (1) to account for any potential non-linear increases in CDS spreads when moving from lower to higher ratings, as Klock et al. similarly did (2005). In (3), instead of the intercept, Rating, and Sq_Rating , five dummy variables that represent five different rating groups are used in their place. We use Barth Huebel Scholz's methodology for their models to run our regressions for (1)- (3).

$$(1): S_{i,t} = \alpha_t + \beta_t^{Rat} Rat_{i,t} + \beta_t^{Vol} Vol_{i,t} + \beta_t^{Ret} Ret_{i,t} + \beta_t^{Lev} Lev_{i,t} + \epsilon_{i,t}$$

$$(2): S_{i,t} = \alpha_t + \beta_t^{Rat} Rat_{i,t} + \beta_t^{ratsq} Ratsq_{i,t} + \beta_t^{Vol} Vol_{i,t+} + \beta_t^{Ret} Ret_{i,t} + \beta_t^{Lev} Lev_{i,t} + \epsilon_{i,t}$$

$$(3): S_{i,t} = \Sigma_{j=1}^{5} \beta_t^{Dj} D_{i,t}^{j} + \beta_t^{Vol} Vol_{i,t+} + \beta_t^{Ret} Ret_{i,t} + \beta_t^{Lev} Lev_{i,t} + \epsilon_{i,t}$$

The outcomes for (1) through (3) are shown in Table 3. The squared rating variable appears to represent nonlinear increases in CDS spreads with higher credit ratings, according to a comparison of Models (1) and (2). The adjusted R2-values support this conclusion. Further increases in adjusted R2-values are attainable in (3)when five different rating groups are represented by rating dummies. To determine whether rating group specifications can more effectively explain CDS spread volatility, various models with four and six dummy variables are tested. No supporting information was discovered. All subsequent regressions in Table 4 (4 – 7) analyzing the relationship between CDS spreads and ESG ratings are built upon (3), which is the starting point.

We use Barth Huebel Scholz's methodology for their models to run our regressions for (4)- (7).

$$(4): S_{i,t} = \Sigma_{j=1}^{5} \beta_t^{Dj} D_{i,t}^{j} + \beta_t^{Vol} Vol_{i,t+} + \beta_t^{Ret} Ret_{i,t} + \beta_t^{Lev} Lev_{i,t} + \beta_t^{ENV} ENV_{i,t} + \epsilon_{i,t}$$

$$(5): S_{i,t} = \Sigma_{j=1}^{5} \beta_t^{Dj} D_{i,t}^{j} + \beta_t^{Vol} Vol_{i,t+} + \beta_t^{Ret} Ret_{i,t} + \beta_t^{Lev} Lev_{i,t} + \beta_t^{SOC} SOC_{i,t} + \epsilon_{i,t}$$

$$(6): S_{i,t} = \Sigma_{j=1}^{5} \beta_t^{Dj} D_{i,t}^{j} + \beta_t^{Vol} Vol_{i,t+} + \beta_t^{Ret} Ret_{i,t} + \beta_t^{Lev} Lev_{i,t} + \beta_t^{GOV} GOV_{i,t} + \epsilon_{i,t}$$

$$(7): S_{i,t} = \Sigma_{j=1}^{5} \beta_t^{Dj} D_{i,t}^{j} + \beta_t^{Vol} Vol_{i,t+} + \beta_t^{Ret} Ret_{i,t} + \beta_t^{Lev} Lev_{i,t} + \beta_t^{ENV} ENV_{i,t} + \beta_t^{SOC} SOC_{i,t} + \beta_t^{GOV} GOV_{i,t} + \epsilon_{i,t}$$

It is noteworthy that we do not take into account potential industry effects in our regressions due to the fact that there are not enough companies in some industries (see Table 0) to create meaningful industry dummies or industry xed effects, as in, for instance, Bauer and Hann's regressions (2010). ESG scores, on the other hand, are adjusted for the industry utilizing a percentile ranking approach and industry benchmarks. Thus, we do not anticipate any substantial industrial consequences. Numerous studies also claim that their findings on the relationship between ESG and credit risk appear to be resistant to changes in the sector (see, e.g., Bauer and Hann, 2010, Chen et al., 2012, and Stellner et al., 2015).

Environmental ratings in (4) do not appear to be linearly related to CDS spreads when they are the emphasis. After adjusting for known CDS spread factors, social ratings in (5) are significantly and adversely connected to CDS spreads. This suggests that lower CDS spreads, or less credit risk, are connected to greater social performance. The risk mitigation theory, which contends that ESG lowers firm risk and, in turn, credit risk, is supported by this data. and the weak linear relationship between the governance ratings in (6) and CDS spreads. Our conclusions are unaffected by the regression results from equation (7), which includes all relative ESG scores simultaneously.

Although non-linear interactions may still exist, our prior conclusions were based on regression analysis, which made the assumption that CDS spreads and environmental ratings have a linear relationship. In the case of environmental ratings and CDS spreads, for instance, our findings might be explained by I greater CDS spreads only for lower ratings, ii) lower CDS spreads only for higher ratings, or iii) by both at the same time. Furthermore, our earlier linear regression models are unlikely to have detected connections between social or governance ratings and CDS spreads if they were non-linear or characterized by asymmetric patterns. The findings of our research reveal a significant and positive relationship between ESG performance, as indicated by ESG disclosures, and credit default swap (CDS) spreads, which in turn suggest higher credit risk for companies in the United States. These results are in line with previous literature that has emphasized the importance of ESG factors in influencing credit risk and the pricing of corporate bonds.

Our study contributes to the existing literature by providing empirical evidence of the impact of ESG disclosures on credit spreads in the US context. Our findings suggest that companies with higher levels of ESG disclosures tend to have higher CDS spreads, indicating increased credit risk. This implies that investors and creditors perceive companies with lower ESG performance as being more exposed to credit risk, potentially leading to higher borrowing costs and reduced access to capital.

The positive relationship between ESG performance and credit risk can be attributed to several factors. First, companies with poor ESG performance may face higher regulatory and legal risks, such as fines, penalties, and lawsuits, which can impact their financial health and creditworthiness. Second, companies with weak ESG performance may face operational and reputational risks, such as environmental accidents, labor disputes, and negative public perception, which can affect their business operations and long-term sustainability. These risks can ultimately lead to higher credit risk and increased credit spreads.

Furthermore, our findings highlight the growing significance of ESG factors in the investment decision-making process of market participants, including investors and creditors.

With increasing awareness and demand for sustainable investing, investors and creditors are increasingly considering ESG factors as material information that can affect a company's financial performance and credit risk. Companies with robust ESG disclosures and performance may be viewed as more responsible and sustainable, which can positively impact their credit risk and borrowing costs. On the other hand, companies with poor ESG disclosures and performance may face higher credit risk and borrowing costs, as investors and creditors perceive them as being more exposed to environmental, social, and governance risks.

Our findings also have important implications for policymakers, regulators, and corporate managers. Policymakers and regulators may consider incorporating ESG disclosures and performance as part of their regulatory framework, to encourage companies to improve their ESG performance and enhance their creditworthiness. Corporate managers should recognize the increasing importance of ESG factors in their strategic decision-making process, and strive to improve their ESG disclosures and performance to mitigate credit risk and attract investors and creditors.

However, it is important to note some limitations of our study. First, our research is based on data from a specific time period and may not capture the long-term dynamics of the relationship between ESG disclosures and credit spreads. Second, our study focuses on the US market and may not be generalized to other markets or regions with different regulatory frameworks and market dynamics. Further research may be needed to explore the relationship between ESG disclosures and credit spreads in different markets and time periods.

Additionally, addressing the optionality in Credit Default Swaps (CDS) and its asymmetric relationship is crucial when studying the impact on regression errors. Here's how this can be approached:

Optionality in CDS: CDS contracts provide the buyer with the right, but not the obligation, to sell the reference asset at a predetermined price if a credit event occurs. This optionality introduces an asymmetric relationship between the CDS spread and the underlying credit risk. When the credit risk increases, the CDS spread rises, but when the credit risk improves, the CDS spread does not necessarily decrease proportionally.

Modeling Asymmetric Relationship: To account for the asymmetric relationship caused by the optionality in CDS, alternative models can be employed. One commonly used approach is the structural credit risk model, such as the Merton model or the reduced-form models like the Jarrow-Turnbull model. These models incorporate default probabilities, recovery rates, and the impact of optionality, allowing for a more accurate representation of the relationship between credit risk and CDS spreads.

Regression Errors: When optionality is not adequately addressed in the regression analysis, it can lead to biased and inconsistent parameter estimates, resulting in regression errors. The asymmetric relationship between CDS spreads and credit risk can introduce systematic errors in the regression, as the impact of credit risk changes may not be symmetric in both directions. Ignoring this asymmetry can lead to misleading conclusions and inaccurate predictions.

Correcting Regression Errors: To mitigate regression errors arising from the optionality in CDS, various techniques can be employed. One approach is to use advanced statistical methods, such as generalized autoregressive conditional heteroskedasticity (GARCH) models or regime-switching models. These models explicitly capture the time-varying volatility and nonlinearity in the relationship, accounting for the asymmetric behavior of CDS spreads.

Robustness Checks: It is essential to conduct robustness checks to ensure the stability and reliability of the regression results. Sensitivity analysis can be performed by employing different modeling techniques, altering control variables, or using alternative estimation methodologies. This helps assess the impact of the optionality and asymmetric relationship on the regression errors and confirms the robustness of the findings.

In summary, addressing the optionality in CDS through appropriate modeling techniques is necessary to capture the asymmetric relationship between credit risk and CDS spreads. Failing to account for this asymmetry can introduce regression errors, leading to biased parameter estimates and inaccurate conclusions. Employing advanced statistical methods and conducting robustness checks can help mitigate these errors and provide more reliable regression analysis results.

For future work, Altman's Z-scores can be a useful tool in studying the relationship between credit spreads and ESG scores. It can be applied by-

Assessing Credit Risk: Altman's Z-scores are a well-established measure of credit risk. They incorporate multiple financial ratios to provide a single numerical value that indicates the probability of a company experiencing financial distress or default. By calculating the Z-scores for different companies within a sample, you can assess their creditworthiness and quantify their credit risk.

Relationship with Credit Spreads: Credit spreads represent the additional yield that investors demand for holding a risky bond compared to a risk-free bond. By examining the relationship between Altman's Z-scores and credit spreads, you can investigate how credit risk, as measured by Z-scores, impacts the pricing of bonds and, consequently, the level of credit spreads. A lower Z-score, indicating higher credit risk, may correspond to wider credit spreads, reflecting the market's perception of higher default risk.

Incorporating ESG Scores: ESG scores measure a company's environmental, social, and governance performance. They provide insight into a company's sustainability practices, risk management, and overall corporate responsibility. When studying the relationship between credit spreads, ESG scores, and Altman's Z-scores, you can use ESG scores as a control variable. By including ESG scores in the analysis, you can assess the additional impact of environmental, social, and governance factors on credit spreads, beyond the influence of credit risk captured by Z-scores.

Multivariate Analysis: A multivariate analysis can be conducted to explore the relationship between credit spreads, ESG scores, and Altman's Z-scores simultaneously. This analysis allows for the examination of how ESG scores influence credit spreads independently of credit risk, as measured by Z-scores. It provides insights into whether companies with higher ESG scores tend to have lower credit spreads, indicating a lower perceived default risk even after accounting for their financial health.

Comparative Analysis: Altman's Z-scores can also be used to compare the credit risk profiles of companies with different ESG scores. By dividing the sample into groups based on ESG performance (e.g., high ESG score group vs. low ESG score group), you can assess if there are significant differences in credit spreads between these groups, after controlling for credit risk measured by Z-scores. This analysis helps determine if companies with better ESG scores enjoy lower credit spreads, indicating a potential market preference for environmentally and socially responsible companies.

By utilizing Altman's Z-scores in conjunction with ESG scores, you can gain insights into the relationship between credit spreads and ESG performance. This approach allows for a comprehensive analysis that incorporates both financial health and sustainability factors, providing a more holistic understanding of how ESG scores impact the pricing of credit and credit spreads.

6. Conclusion

This study looks at how the sustainability performance of our sample US corporations affects their credit spreads. Environmental, social, and governance (ESG) related performance is measured and rated using industry benchmarks.

Our results show that environmental ratings are not solely associated to CDS spreads in the monthly cross-section after controlling for known determinants of CDS spreads, according to Linear Model-based regressions for a sample from January 2011 to December 2019. Specifically in opposition to the widely held belief in our historical literature that lower CDS spreads, or lower credit risk, are associated with greater environmental performance. This result goes against the risk mitigation theory, which claims that improved ESG performance lowers business risk and, in turn, credit risk. Instead it holds the widespread belief when all 3 E, S and G are taken together.

Yet, non-linear relationships between ESG ratings and CDS spreads could escape the detection of linear regressions. To take this into account, we classify CDS into quartiles based on their ESG ratings and examine each quartile in terms of the residual CDS spreads, which correspond to CDS spread components that ought to have no bearing on recognized CDS spread drivers. In conclusion, our findings highlight significant and positive relationship between ESG performance and CDS spreads and, consequently, credit risk in the United States. As a result, the ESG performance of businesses may be considered when determining their CDS spreads. Ultimately, takeaways for investors are that by considering the ESG ratings of the companies that make up their portfolios.

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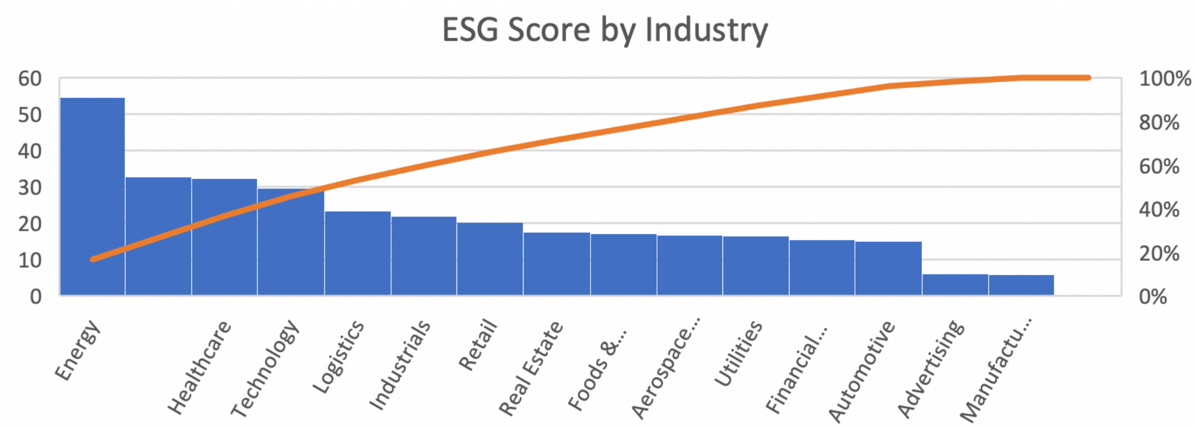
8. Appendix

1.

Key Variables

Variables	Description
CDS	Credit Default Swaps
Rating	Overall Company Rating
ESG	Environment Social Governnace Combined Score
SOC	Scoial Score
ENV	Enviromental Score
CGV/GOV	Governance Score
Lev (%)	Leverage Ratio
Vol (%)	Annualised Volatality
Ret (%)	Returns
Sq_Rating	Squared Ratings
D1	AAA (1) through A (6) Tranche
D2	A- (7) Tranche
D3	BBB+ (8) Tranche
D4	BBB (9) Tranche
D5	BBB- (10) or lower Tranche

2.



3.

```
setwd("C:/Users/srk576/Downloads")
#Copy File Path - This should be the path to the folder you have saved files. Make sure that you change the \ to /

install.packages(c("lmtest","plm","sandwich","stargazer","tidyverse"))
#run this code if you are running R for the first time - this will download all the packages you need

library(tidyverse)
library(lmtest)
library(plm)
library(sandwich)
library(stargazer)
#this will load all the libraries you need

df <- read.csv("C:/Users/srk576/Downloads/Regression Data - V1.csv") #make sure you inclue .csv in the filename
str(df) #check the data type. Run as numeric if the data is stored in chr
df$rating_new <- as.numeric(df$rating_new)
df$esg_ratings <- as.numeric(df$esg_ratings)
df$social <- as.numeric(df$social)
df$env <- as.numeric(df$env)
df$gov <- as.numeric(df$gov)

df_sub <- subset(df, select = -c(equity_val) )
df_sub <- df_sub %>% na.omit()

stargazer(df, summary.stat = c("n", "mean", "median", "min", "max", "sd", "p25", "p75"), type = "text")

model_1 <- lm(data = df_sub, cds ~ esg_ratings + rating_new)
model_2 <- lm(data = df_sub, cds ~ esg_ratings)

stargazer(model_1,model_2, type = "text")

df_corr_data <- subset(df_sub, select = c(esg_ratings,cds,rating_new, env, gov))

cor(df_corr_data)
```

4.

```{r}

install.packages("tidyverse")
install.packages(c("lmtest","lmtest","stargazer","plm","fixest"))
library(tidyverse)
library(lmtest)
library(stargazer)
library(plm)
library(fixest)

df <- read.csv("C:/Users/nyuclassroom/Downloads/Regression Data - V1_2.25.csv")
str(df)
df$rating <- as.numeric(df$rating)
df$sq_rating <- as.numeric(df$sq_rating)
df$esg_ratings <- as.numeric(df$esg_ratings)
df$env <- as.numeric(df$env)
df$gov <- as.numeric(df$gov)
df$social <- as.numeric(df$social)
df$Equity.value <- as.numeric(df$Equity.value)
df$Book.value.of.debt <- as.numeric(df$Book.value.of.debt)
df$Leverage.Ratio <- as.numeric(df$Leverage.Ratio)
df$rating_new <- as.numeric(df$rating_new)

str(df)

df_sub <- subset(df, select = -c(Ticker, Date, qtr, qtr.1, Company, X, ticker_year,Equity.value,Book.value.of.debt, rating))

df_sub <- df_sub %>% na.omit()

stargazer(df, summary.stat = c("n", "mean", "median", "min", "max", "sd", "p25", "p75"), type = "latex")

df_sub

knitr::kable(cor(df_sub))

install.packages(c("Hmisc","xtable"))
library(Hmisc)
library(xtable)

cor(df_sub)
xtable(cor(df_sub))
require(foreign)
require(plm)
require(lmtest)


m_1 <- plm(cds ~ rating_new + Leverage.Ratio, data = df, index = c("Company","Date"))
m_2 <- plm(cds ~ rating_new + sq_rating + Leverage.Ratio, data = df, index = c("Company","Date"))
stargazer(m_1,m_2,covariate.labels = c("Rating", "Sq_Rating","Lev (%)"), type = "latex")



```
```
```

5.

```
df <- read.csv("C:/Users/srk576/Downloads/Regression Data - V1_3.6.csv")
str(df)

df$ratomg <- as.numeric(df$ratomg)
df$sq_rating <- df$ratomg*df$ratomg
df$esg_ratings <- as.numeric(df$esg_ratings)
df$env <- as.numeric(df$env)
df$gov <- as.numeric(df$gov)
df$social <- as.numeric(df$social)
df$Equity.value <- as.numeric(df$Equity.value)
df$Book.value.of.debt <- as.numeric(df$Book.value.of.debt)
df$Leverage.Ratio <- as.numeric(df$Leverage.Ratio)
df$rating_new <- as.numeric(df$rating_new)
df$Annualised.Volatality <- as.numeric(df$Annualised.Volatality)
df$Monthly.Return <- as.numeric(df$Monthly.Return)


str(df)

df_sub <- subset(df, select = -c(Ticker, Date, qtr, Company, X, ticker_year,Equity.value,Book.value.of.debt, r_old, X, X.1, X.2, X.3, rating_new))

df_sub <- df_sub %>% na.omit()

df_sub

stargazer(df_sub, summary.stat = c("n", "mean", "median", "min", "max", "sd", "p25", "p75"), type = "latex")

df_sub_cor <- subset(df_sub, select = -c(Rating.Group.1,Rating.Group.2,sq_rating))

cor(df_sub_cor)

knitr::kable(cor(df_sub_cor), type = "latex")

install.packages(c("Hmisc","xtable"))
library(Hmisc)
library(xtable)

xtable(cor(df_sub_cor))

require(foreign)
require(plm)
require(lmtest)


m_1 <- plm(cds ~ ratomg + Leverage.Ratio, data = df, index = c("Company","Date"))
m_2 <- plm(cds ~ ratomg + sq_rating + Leverage.Ratio, data = df, index = c("Company","Date"))
m_3 <- plm(cds ~ Rating.Group.1 + Leverage.Ratio, data = df, index = c("Company","Date"))

stargazer(m_1,m_2,m_3, type = "latex")

m_4 <- plm(cds ~ Rating.Group.1 + Annualised.Volatality + Monthly.Return + Leverage.Ratio + env, data = df, index = c("Company","Date"))
m_5 <- plm(cds ~ Rating.Group.1 + Annualised.Volatality + Monthly.Return + Leverage.Ratio + social, data  = df, index = c("Company","Date"))
m_6 <- plm(cds ~ Rating.Group.1 + Annualised.Volatality + Monthly.Return + Leverage.Ratio  + gov, data = df, index = c("Company","Date"))
m_7 <- plm(cds ~ Rating.Group.1 + Annualised.Volatality + Monthly.Return + Leverage.Ratio + env + social + gov, data = df, index =
c("Company","Date"))

stargazer(m_4,m_5,m_6,m_7, type = "latex")
```