Green Grades and Financial Shades: the ESG Influence on Default Risk

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Abstract

This paper investigates the relationship between ESG scores and Default Probability (DP) for European firms in the STOXX Europe 600 index. We model this relationship using the Altman Z-Score and Ohlson O-Score as proxies for DP in regression analysis, while controlling for leverage, volatility, and size. The findings of this study show that higher ESG scores are associated with a higher DP for the Altman Z-Score, but with a lower DP when using the Ohlson O-Score. This discordant outcome highlights the sensitivity of results to the choice of DP proxy. The conclusion is that, even though the ESG factors can influence financial stability, their effect on default risk is minimal; hence, ESG is not the primary driver of default risk.

Keywords: ESG Scores, Probability of Default, Altman Z-Score, Ohlson O-Score, Financial Stability, Environmental Performance, Social Responsibility, Corporate Governance, STOXX Europe 600, Sustainable Finance, Risk Management, Fixed Effects Model, Random Effects Model, Default Risk, Credit Risk.

Resumo

Este documento investiga a relação entre as pontuações ESG e a probabilidade de incumprimento (DP) para as empresas europeias do índice STOXX Europe 600. Modelamos esta relação utilizando o Altman Z-Score e o Ohlson O-Score como proxies para a PD numa análise de regressão, controlando simultaneamente a alavancagem, a volatilidade e a dimensão. Os resultados deste estudo mostram que pontuações ESG mais elevadas estão associadas a uma PD mais elevada para o Altman Z-Score, mas a uma PD mais baixa quando se utiliza o Ohlson O-Score. Este resultado discordante realça a sensibilidade dos resultados à escolha do indicador de PD. A conclusão é que, embora os factores ESG possam influenciar a estabilidade financeira, o seu efeito no risco de incumprimento é mínimo; por conseguinte, os ESG não são o principal fator de risco de incumprimento.

Palavras-chave: ESG Scores, Probabilidade de incumprimento, Altman Z-Score, Ohlson O-Score, Estabilidade financeira, Desempenho ambiental, Responsabilidade social, Governação empresarial, STOXX Europe 600, Finanças sustentáveis, Gestão de riscos, Modelo de efeitos fixos, Modelo de efeitos aleatórios, Risco de incumprimento, Risco de crédito.

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List of Abbreviations

ESG	Environmental, Social, and Governance
PD	Probability of Default
SDGs	Sustainable Development Goals
SRI	Socially Responsible Investing
SMEs	Small and Medium-sized Enterprises
CSR	Corporate Social Responsibility
MDA	Multiple Discriminant Analysis
FEM	Fixed Effects Model
REM	Random Effects Model
OLS	Ordinary Least Squares
VIF	Variance Inflation Factor

1. Introduction

Although ESG considerations are becoming increasingly relevant in investment practices and business decision-making processes, research on their impact on default risk is still quite limited, and often not very clear in terms of results. This thesis investigates the relationship between ESG scores and the probability of default (PD) for European firms listed in the STOXX Europe 600 index. More specifically, it tests whether higher ESG scores, arguably indicating better sustainability practices, relate to a lower financial risk reflected in the probability of default.

We consider it important to know the linkage of ESG performance with default risk for several reasons. Firstly, it informs investors of possible benefits from risk reduction that ESG-compliant investments may offer, thereby aligning their financial goals with ethical considerations. Secondly, it can help corporate managers prioritize their sustainability efforts in those areas that are likely to contribute the most to their financial resilience. Thirdly, it can help policymakers design effective regulations, able to enhance sustainable practices without impairing financial stability. Finally, the integration of ESG considerations into the investment process is one step towards a more and better incorporation of the UN SDGs within financial assets, which should ultimately bring a positive impact across economies (Eurosif, 2018).

The contribution of this thesis to the existing literature lies in the comprehensive analysis of ESG scores and default risk across different European sectors and countries. Additionally, this study differentiates itself for its dual-score approach. In fact, we use both the Altman Z-Score and the Ohlson O-Score as proxies for default probability. Furthermore, the use of both fixed and random effects models accounts for possible unobserved heterogeneity, making our results more robust.

To bring some insights in this regard, this study first estimates the probability of default for firms using the Altman Z-Score. It explores its relationship with ESG scores and their subcomponents (E-Score, S-Score, G-Score) after controlling for leverage, volatility, and size, to better isolate the effects of ESG performance. Then, sub-samples by country and industry are used as a further step in the analysis to see whether, across contexts, there may be some differences. Finally, the whole process is repeated, employing the Ohlson O-Score as an alternative proxy for DP.

Results show that the relationship between default probability and ESG scores is not as clear. While a positive relationship between DP and ESG scores was observed under the Altman Z-

Score setting, the robustness test with the Ohlson O-Score showed a lowering DP when the ESG score increased, underlining the sensitivity to the choice of proxy for DP. Noticeably, the overall magnitude of the effect of ESG on DP, remained humble in both settings.

This paper follows earlier studies in the field by Henisz and McGlinch (2019), who discovered a general negative correlation of sustainability with credit risk, and that of Devalle et al. (2017), which focused on conflicting results registered by existing studies about ESG and default probability. Therefore, this research contributes to the ongoing debate on ESG performance and DP, by providing nuanced analysis regarding the use of several default risk proxies, while segmenting in terms of country and industry, and concludes highlighting the clear need to consider plural measurements and contexts in appraising ESG performance with relevant financial implications.

The thesis is organized as follows: after this introduction, Chapter 2 reviews the existing literature on ESG and probability of default. Chapter 3 outlines the hypothesis that, based on the literature, we aim to test. Chapter 4 details the empirical methods used to estimate DP and to perform regression analyses. Chapter 5 presents the data used for the study and the preliminary analysis conducted. Chapter 6 comments on the results and their interpretation, followed by robustness checks. Chapter 7 provides a summary of the results and concludes, discussing the implications of the findings for researchers, practitioners, and policymakers, and suggesting avenues for future research. Finally, the appendices and bibliography are provided in Chapter 8 and Chapter 9, containing supplementary information and detailed data supporting the analyses conducted.

2. Background and Literature

2.1. ESG Score

In its early stages, since at least the early 1980's, ESG was referred to as "Socially Responsible Investing" (SRI). Today, SRI has morphed into ESG and encompasses a much wider agenda (Ribando & Bonne, 2010). The concept of ESG refers to the three key factors that professionals and academics use to determine the sustainability and social impact of a business. Specifically, the ESG Score represents the metric used to assess companies in terms of their degree of Environmental (e.g.: impact on the environment, on biodiversity, consumption of resource, and waste management), Social (e.g. employees' working conditions, relationship with suppliers and stakeholders, impact on the community, and other social impacts), and Governance (e.g.: firm's relationship with its shareholders and the board of directors, degree of transparency of the organization, executive compensation, and board diversity) strength (Ribando & Bonne, 2010). Both tangible and intangibles data are used to come up with an ESG score ranging between 0 and 100, which is then published by private firms whose primary clients are, generally, portfolio managers and other investors (Escrig-Olmedo et al., 2019).

ESG investing has been growing in popularity, and companies are now urged to provide comprehensive non-financial information to meet market demands (Eccles et al., 2011). To further highlight this growing popularity, global investment banks and asset managers have been increasing significantly their supply for the so-called "Green Funds" (Chernyshova, 2021). Idzorek and Kaplan (2022) explain that the reason behind this phenomenon is that investors became more sensitive and eager to align their investments with their non-monetary values. On the other hand, companies are incentivized to perform well in terms of ESG since, according to Chollet and Sandwidi (2018), a higher ESG score can also be linked to a reduction in financial risk, allowing companies to attract more capital (Cheng et al., 2011).

2.2. Probability of Default

The probability of default (hereafter referred to as "DP") is defined as the likelihood that a firm will be unable to meet its debt obligations (Dar & Qadir, 2019).

The DP of a firm can be influenced by several factors, from macroeconomic indicators (Qu, 2006a), to firm-specific factors such as growth, operating cash flow ratio, liquidity, leverage, and tangibility of assets (Hamid & Siddiqui, 2023). Among all the variables, the size of the firm, its degree of leverage, and the volatility of its stock price appear to be consistently reported as three of the main factors that are strongly correlated to the DP of a public company.

Specifically, Anselmi (2018) found that market-based risk measures, including volatility, are negatively related to bank liquidity during financial distress. Zhang et al. (2008) demonstrated that individual firm volatility significantly predicts credit default swap (CDS) spreads. Finally, Löffler and Maurer (2010) support the role of leverage in default prediction, with the inclusion of leverage forecasts significantly increasing the discriminative power of default risk models, and Di Patti et al. (2014) proved how, especially in the case of SMEs, a 10% increase in leverage is associated with a 1% higher DP.

Clearly, DP is crucial for financial analysis. However, it is not a directly observable value, thus it must be estimated. Several methods on how to determine DP have been proposed over the years, each one with its specific characteristics and assumptions. Among many, the "Altman's Z-Score model", developed in 1968, remains a key tool to estimate a firm's DP (Altman, 2018). Despite its age, the Z-Score model remains widely used nowadays, and it has been found to perform reasonably well in most countries, with a prediction accuracy of around 75% (Altman et al., 2016). Formulated in 1980 and named after its creator, James Ohlson, the "Ohlson O-Score" is an alternative financial tool that helps forecast a company's financial distress and bankruptcy threats. Research on the use of the Ohlson O-Score to estimate DP, compared to the Altman Z-Score, has yielded mixed results depending on the specific context. While Mansi et al. (2012) pointed at both Altman's Z-Score and Ohlson O-Score are highly ineffective, Pramudita (2021) proves that the O-Score provides a better accuracy in predicting bankruptcy in the case of SMEs in Indonesia, and, according to Pranav et al. (2021), the Ohlson's model shows the strongest overall results for the prediction of default companies. On the other hand, Sharma et al. (2019) and Gaba et al. (2019) both found the Altman Z-score to be more accurate in predicting default.

2.3. Previous Studies

Despite the many years of research on the correlation between ESG factors and likelihood of default, Devalle et al. (2017) notes that research shows inconclusive results regarding the direction of this correlation up until 2017. Some studies (Chava, 2014; Rizwan et al., 2017) suggest that there is no significant influence of environmental concerns or CSR on a firm's credit ratings. On the other hand, recent studies (Menz, 2010; Albuquerque et al., 2019; Shih et al., 2021) reveal that investing in CSR can be beneficial for firms. According to these studies, firms with higher CSR experience lower cost of equity, and including stocks with higher CSR in a portfolio can reduce overall riskiness. As a matter of fact, it is only since 2017 that, thanks to the "Credit Risk and Rating Initiative" introduced by the United Nations with the aim of "enhance the systematic [...] consideration of ESG issues in the assessment of creditworthiness of borrowers" (UNPRI, 2017), that an academic consensus has started to create around the negative correlation between sustainability and credit risk (Henisz & McGlinch, 2019b; Devalle et al., 2017b).

Given this novelty trait, current literature on ESG score and firm's default probability still yields mixed results. Both the studies from Nadezda and Mckenna (2021), and from Aslan et al. (2021) find that there is indeed a significant correlation between ESG and DP, but their findings show opposite directions. Specifically, Nadezda and Mckenna (2021) report a positive correlation between the two variables, while Aslan et al. (2021) support that a higher ESG Score is associated to a lower DP.

When it comes to the relationship between each individual ESG pillar and the probability of default, the G-Score appears to be the pillar with the strongest influence on PD. In particular, Semet et al. (2021) and Cioli et al. (2023) both found that companies with strong performance on the Governance-pillar are more likely to receive better credit ratings. Razak et al. (2023) further support this, showing that improvements in the G-Pillar of the ESG performance, can reduce credit risk. L. Switzer et al. (2016), and again L. N. Switzer and Wang (2013b), find that specific internal governance variables, such as board composition and CEO power, are crucial in reducing firms' DP. Findings previously highlighted by Lehlou et al. (2014) in their study on default probability for US public firms. As for the other pillars (i.e.: E and S), H. Li et al. (2022) explained how a firm's bond default rate is positively correlated with energy consumption (E-Score), but negatively correlated to social responsibility and corporate governance (G-Score). On the contrary, Palmieri et al. (2024), support the idea that enhancing environmental performance can help banks reduce default risk, while Vivel-Búa et al. (2023) note how the influence of the individual ESG pillars on DP changes depending on the economic cycle and the size of the firm.

Adding a layer of complexity to the matter, the ESG-score assessment of different rating agencies differs from one another, making it a problem for researchers to establish a universal ESG metric (Billio et al., 2021). Due to the methodological variations, as well as variations in sustainability construct, ESG ratings might fluctuate significantly between suppliers (Abhayawansa & Tyagi, 2021).

Finally, existing literature diverges on the method chosen to estimate DP. The traditional method employed to assess default probability refers to the process based on historical accounting data, mainly implemented by commercial banks and financial institutions to conduct a qualitative study in their credit lending practices (Cai & Qian, 2018). The output of this methodology is a creditworthiness index, represented by a numerical score, aiming to indirectly calculate the default probability of the borrower (Resti & Sironi, 2012). This category includes linear discriminant analysis models, regression models, and heuristic inductive models. Among the most known linear discriminant analysis methods, we find the Altman Z-Score, developed by Edward Altman in 1968. Once again, the studies on the relationship between ESG scores and the Altman Z-scores lead to mixed findings. Cohen (2022), Alves and Meneses (2024) both find a negative relationship, with Cohen highlighting the influence of E-Pillar and S-Pillar on financial stability. In contrast, Maquieira et al. (2024) and Choi et al. (2024) report a positive association, with Maquieira focusing specifically on family firms, and Choi focusing on Korean financial firms. Another linear discriminant analysis model used to estimate default probability is the Ohlson O-Score, introduced by James Ohlson in 1980. Also in this case, its relationship with ESG scores yields mixed results. Lisin et al. (2022) found a positive impact of ESG factors on financial stability, with the G-Score having the strongest influence, while Shaikh (2022) found that ESG compliance varied by region and industry, with mixed effects on accounting and market-based firm performance.

3. Theory and Hypotheses

Following the consensus on the matter, the probability of default estimated through the implementation of the Altman Z-sore model is demonstrated to be a reliable proxy for a company credit risk (Altman et al., 2016). Building on that, a negative correlation between a firm's ESG score and its DP is generally observed (Henisz & McGlinch, 2019b; Devalle et al., 2017b). Consequently, the first hypothesis of this study is as follow:

Hypothesis 1: Using the Altman Z-score as a proxy for a firm's probability of default, we expect to find a negative relationship between the latter and the firm's ESG scores.

Additionally, studies by Switzer and Wang (2013), Sassen et al. (2016), and Kim and Li (2021) suggest that to better identify which ESG pillar can significantly impact a firm's default probability, it is important to examine each ESG sub-score individually. Among the three ESG pillars, it appears that corporate governance (G-Score) is the factor with the most significant effect (L. Switzer et al., 2016). Therefore, the second hypothesis of this study is as follow:

Hypothesis 2: Among the three ESG pillars – expressed in terms of E-Score, S-Score, and G-Score – the Governance factor exerts the most notable effect on a firm's default probability, while the E-factor (Environmental) and the S-factor (Social) have a lesser or negligible impact.

Finally, it has been proven by Barth et al. (2022) that the strength of the impact of ESG scores on firm's default probability varies according to the region of investigation. Additionally, Nadezda and Mckenna (2021) note that the relationship is not significant for all firms, with Li (2022) specifying that the effect is smaller for manufacturing firms. Hence, the third hypothesis of this study is:

Hypothesis 3: The strength of the correlation between a firm's ESG score and its probability of default varies significantly across countries and industry sectors.

4. Empirical Methods

4.1. Computing the Probability of Default

The first step in our analysis is to estimate the firm's probability of defaults. As previously mentioned, there are several ways to estimate a firm's DP. Among all, we decided to estimate it through the "Altman's Z-Score model". The reason for this, is that the model, besides being proved reliable, is based on a weighted average of specific accounting ratios, making it less sensible to market dynamics (as it would have been the case for the "Merton's Distance-to-Default Model", or for the CDS spread), nor to specific methodologies used by credit-rating agencies.

According to Altman (1968), companies are categorized into three distinct groups – distressed, uncertain, safe – according to a specific score (i.e.: the "Z-Score") derived from a linear combination of balance sheet ratios. There are several variations of the formula according to the type of company under examination. Given that the companies studied in this paper come from the STOXX Europe 600 index, which includes a mix of manufacturing and non-manufacturing companies, we used two different versions of the Altman Z-Score, according to the sector where each company operates. Specifically, the original version, intended for publicly traded manufacturing companies, is as follow:

$$Z = 1.2 \times X_1 + 1.4 \times X_2 + 3.3 \times X_3 + 0.6 \times X_4 + 1.0 \times X_5 \tag{1}$$

The second version, specifically tailored to non-manufacturing firms, is as follow:

$$Z' = 6.56 \times X_1 + 3.26 \times X_2 + 6.72 \times X_3 + 1.05 \times X_4 + 3.25 \tag{2}$$

Where, in both formula (1) and (2):

X_1 = Working Capital / Total Assets

X_2 = Retained Earnings / Total Assets

X_3 = Earnings Before Interest and Taxes (EBIT) / Total Assets

X_4 = Shareholders' Equity[1] / Book Value of Total Liabilities

X_5 = Sales / Total Assets

[1] Specifically, *Market Value of Equity* is used for the original version, while *Book Value of Equity* is used for the second version of the Altman Z-Score.

The specific weights used in (1) and (2) were determined by Altman through Multiple Discriminant Analysis (MDA), using a dataset of firms that had previously undergone bankruptcy.

4.2. Regression Analysis with Different Models

The two most common panel regression methods employed with longitudinal, or panel data are the fixed-effects model (FEM) and the random-effects model (REM). These models have been previously utilized by Barth et al. (2018), Höck et al. (2020) and Razak et al. (2020) to address grouped structures in data, such as quarterly observations of companies as in the case of this study. Due to their different underlying assumptions, the choice between these two models remains a topic of statistical debate (Nikolakopoulou et al., 2014). According to Clark & Linzer (2014), the random-effects model is generally preferred for its more accurate results. However, this only holds if the covariance between α_i and $x_{i,t}$ (the independent variables) is equal to zero, which is often unrealistic in empirical research (Clark & Linzer, 2014). Following the recommendation of Schmidt et al. (2009), in this study we will use both models, comparing coefficients and p-values, and evaluating their fit based on the R^2. The choice of using both FEM and REM models will work as an additional robustness test for our findings.

Hypothesis 1 wants to investigate the existence of a negative relationship between ESG scores and firm's default probability. Therefore, we began with a preliminary OLS regression, which assumes the form of:

$$DP_{i,t} = \alpha_{i,t} + (ESG\_Score_{i,t})\beta_1 + (Z_{i,t})\beta_2 + \varepsilon_{i,t} \qquad (3)$$ [2]

Where *DP* represent the Default Probability expressed by the Altman Z-Score, *ESG_Score* represents the firm's ESG score, *Z* represents the set of control variables, and *ε* is the error term.

To determine which control variables to use in this study, we relied on the existing literature, looking for variables that have been proved to have a direct impact on DP, with the goal of eliminating possible confounding factors and isolating the effect of our independent variables as much as possible. According to Di Patti et al. (2014), and Löffler and Maurer (2010), our first control variable is firm's leverage (expressed by the debt-to-equity ratio). Following Zhang et al. (2008) and Anselmi (2018), our second control variable is firm's volatility (expressed as the previous three months' volatility of the firm's stock price). Finally, given that Kim and Li

[2] Note that, for every regression of this study:
i represents the *i*'th firm (*i* = 1, …, 296), and *t* represents the time (*t* = Q1 2015, …, Q4 2022).

(2021) found a size effect, where the effect of ESG on financial performance is more pronounced in larger companies, our last control variable is firm's size (expressed as the firm's market capitalization).

Hence, the complete OLS regression, with all the control variables specified, is as follow:

$$DP_{i,t} = \alpha_{i,t} + (ESG\_Score_{i,t})\beta_1 + (Leverage_{i,t})\beta_2 + (Volatility_{i,t})\beta_3 + (Size_{i,t})\beta_4 + \varepsilon_{i,t} \quad (3.1)$$

To better assess the impact and significance of each control variable on the relationship between the dependent variable and the main independent variables of interest, in this study we decided to first run regression (3.1) without any control variables, and subsequently adding the control variables one by one. Finally, we apply both FEM and REM with all control variables included and note the R^2 of both models.

To test Hypothesis 2, we decided to perform a regression similar to the previous one, with the only difference that we substituted the independent variable *ESG_Score* with its individual sub-scores separately:

$$DP_{i,t} = \alpha_{i,t} + (E\_Score_{i,t})\beta_1 + (S\_Score_{i,t})\beta_2 + (G\_Score_{i,t})\beta_3 + (Leverage_{i,t})\beta_4 + (Volatility_{i,t})\beta_5 + (Size_{i,t})\beta_6 + \varepsilon_{i,t} \quad (4)$$ [3]

Again, we apply both FEM and REM, and note their R^2.

Finally, Hypothesis 3 investigates the same effects as in the previous two hypothesis, but on subsets of data. More specifically, we split the original dataset into smaller sub-samples, based on the following firm's characteristics:

- Country of Domicile
- Industry Group

Then, we ran both equation (3.1) and equation (4) for each subset, employing both FEM and REM, for a total of four individual regressions.

4.3. Robustness Test

As a final step of this study, we decided to perform a robustness test to further validate our findings. Specifically, we tested again our three hypotheses, repeating the same process outlined

[3] Note that, to maximize the explanatory power of the independent variables and to avoid multicollinearity issues, each ESG sub-score is never used in the same equation as the comprehensive ESG score.

above. This time, however, we decided to use a different proxy for the dependent variable DP, namely, the Ohlson O-Score. By using a logistic regression model to analyze several financial ratios, the Ohlson O-Score is a financial indicator that can be used to predict bankruptcy. When calculating the likelihood of default as a robustness test, it makes sense to combine the Ohlson O-Score and Altman Z-Score because each score uses distinct variables and approaches that offer complimentary information. Through cross-validation, the limits and biases associated with depending solely on one model are mitigated, resulting in a more thorough and reliable default risk assessment.

4.3.1 Ohlson O-Score

The Ohlson O-Score, developed by James Ohlson, is a financial distress prediction model that has been widely implemented in academia. The model has been tested and validated in various studies, including those by Qi et al. (2000), Morel (2003), He and Kamath (2006), and Dhara and Basu (2021). These studies have used the O-Score to analyze the financial performance of specific companies, test the model's time-series properties, and evaluate its effectiveness in predicting business failure in different industries.

A weighted total of several accounting metrics and financial ratios, including operating efficiency, leverage, profitability, liquidity, and market indicators, is used to compute the score. Based on each component's relative significance in predicting financial difficulty, a weight is assigned:

$$\begin{aligned} \text{O-Score} = &-1.32 - 0.407X_1 + 6.03X_2 - 1.43X_3 + 0.076X_4 \\ &- 1.72X_5 - 2.37X_6 - 1.83X_6 + 0.285X_8 - 0.521X_9 \end{aligned} \tag{5}$$

where the variables from X_1 to X_9 are defined as:

X_1: Log (Total Assets/Gross National Product Price Index Level)

X_2: Total Liabilities / Total Assets

X_3: Working Capital / Total Assets

X_4: Current Liabilities / Current Assets

X_5: 1 if Total Liabilities > Total Assets, 0 otherwise

X_6: Net Income / Total Assets

X_7: Funds from Operations / Total Liabilities

X_8: 1 if net loss for the last two years, 0 otherwise

X_9: Measure of the relative change in net income, normalized by the sum of the absolute values of net income in the current and previous periods.

Finally, the O-Score is converted into a DP, though a logistic transformation:

$$PD = \frac{1}{1+e^{-(O-Score)}} \tag{6}$$

This transformation provides a probability value between 0 and 1, where a higher probability corresponds to a higher likelihood of default for the firm. Hence, contrary to the Z-Score, a higher (transformed) O-Score denotes a higher DP.

5. Data

5.1. Sample Construction

To collect all the data necessary for this study, two databases needed to be consulted, and the resulting datasets had to be merged properly. The main database we used is the LSEG (London Stock Exchange Group) Workspace (formerly Eikon/Refinitiv). Leveraging its DataStream Excel add-in, we were able to retrieve all the financial information relative to equity (stock) data, accounting data, and ESG data. Additionally, the Federal Reserve Economic Data (FRED), database provided by the Federal Reserve Bank of St. Louis, has been consulted for all the data relative to the Gross National Product Price Index Level of each country.

Wanting to investigate the relationship between ESG score and credit risk in the European context, the initial sample chosen for the study is represented by the constituents of the STOXX Europe 600 Index (INDEXSTOXX: SXXP), a free-float capitalization-weighted index, designed by STOXX Ltd, and comprising a total of 600 large, medium, and small capitalization companies, across 17 countries of the European region – i.e.: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Norway, Poland, Portugal, Spain, Sweden, Switzerland and the United Kingdom.

The time horizon for this research is extended in comparison to prior studies, and it covers quarterly data ranging from January 2015 to December 2022, corresponding to the longest period possible for the intended analyses. We choose to not sample prior to 2015, as ESG-related data has experienced a significant increase in quality since 2015 (UN, 2015). Post 2022 data is excluded, given the often lack of ESG-level and firm-level data for the most recent period.

The initial dataset, corresponding to a list of 600 firms identified on the basis of their ISIN code, has been subsequently reduced, excluding (a) any company that dropped out of the index during the studied period, (b) any company for which ESG Score was not available for the entire period, (d) any company for which ESG sub-scores were not available for the entire period, and (e) any company for which was not possible to retrieve reliable accounting data for the entire period. The resulting sample, as described in Table 1, comprised a set of 296 companies.

5.2. Preliminary Analysis and Descriptive Statistics

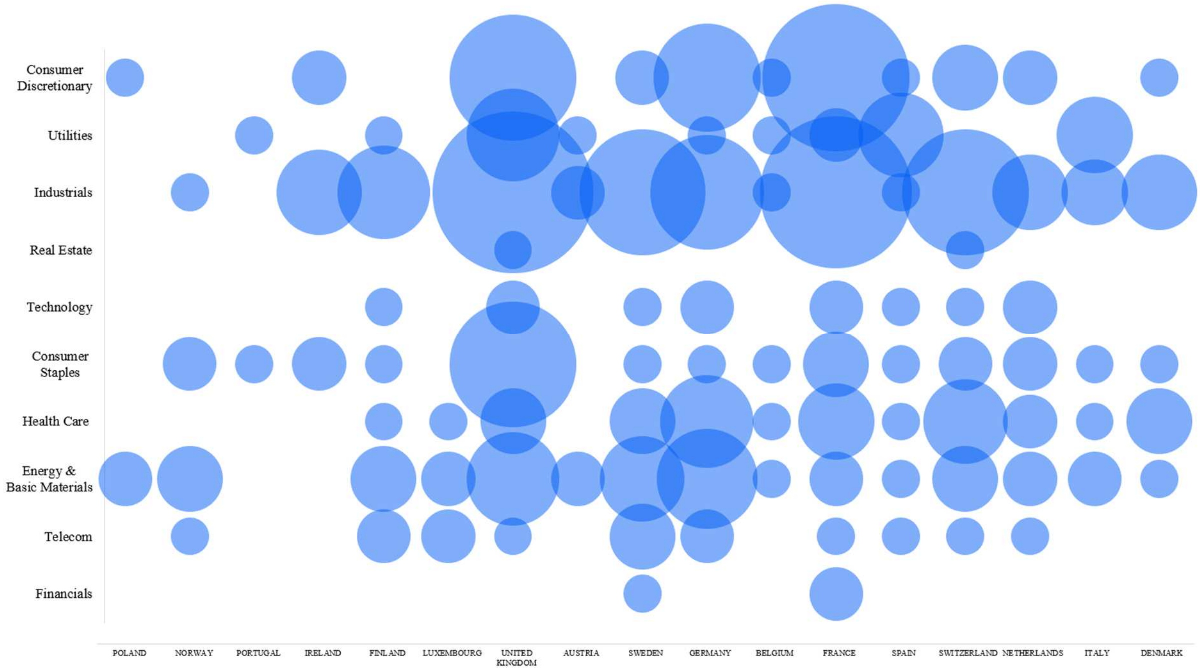
The firms in the sample have been classified in terms of their country of domicile, and in terms of the industry where they operate (according to their ICB code). The Industry Classification Benchmark (ICB) is a comprehensive and transparent classification system designed to reflect market trends and support investment solutions. Introduced in 2005 and updated in 2019 with elements from the Russell Global Sectors (RGS) classification scheme, the ICB taxonomy, initially launched by Dow Jones and FTSE, is now utilized by FTSE International and STOXX to categorize markets into distinct sectors within the macroeconomy. Table 1 summarizes the composition of the sample of 296 companies of our sample.

Table 1 - Country and Industry Distribution

Country	Consumer Discretionary	Consumer Staples	Energy & Basic Materials	Financials	Health Care	Industrials	Real Estate	Technology	Telecom	Utilities	**Country Total**
Austria			2			2				1	**5**
Belgium	1	1	1		1	1				1	**6**
Denmark	1	1	1		3	4					**10**
Finland		1	3		1	6		1	2	1	**15**
France	15	3	2	2	4	16		2	1	2	**47**
Germany	8	1	7		6	9		2	2	1	**36**
Ireland	2	2				5					**9**
Italy		1	2		1	3				4	**11**
Luxembourg			2		1				2		**5**
Netherlands	2	2	2		2	4		2	1		**15**
Norway		2	3			1			1		**7**
Poland	1		2								**3**
Portugal		1								1	**2**
Spain	1	1	1		1	1		1	1	5	**12**
Sweden	2	1	5	1	3	11		1	3		**27**
Switzerland	3	2	3		5	11	1	1	1		**27**
United Kingdom	11	11	6		3	18	1	2	1	6	**59**
Industry Total	**47**	**30**	**42**	**3**	**31**	**92**	**2**	**12**	**15**	**22**	**296**

For an immediate visualization of the sample distribution, we created a bubble chart (Figure 1), where the dimension of each bubble reflects the number of firms populating the relative country-industry combination. From a preliminary analysis of the sample, we can immediately notice the strong concentration of firms from the industrial, consumers, and energy sectors, and from countries such as the United Kingdom, France, and Germany. This information is consistent with the distribution of large corporates in Europe. Besides the real estate and financial sectors, and little economies such as Portugal and Poland, the observations are more evenly distributed on the rest of the sample, in terms of country and industry classification.

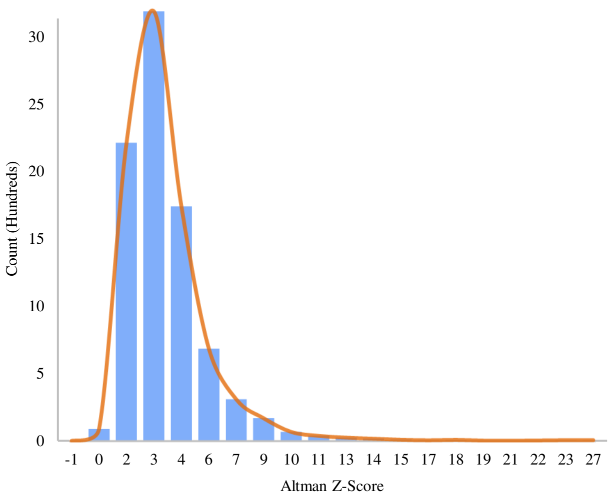
Figure 1 - Bubble Chart of Sample Distribution



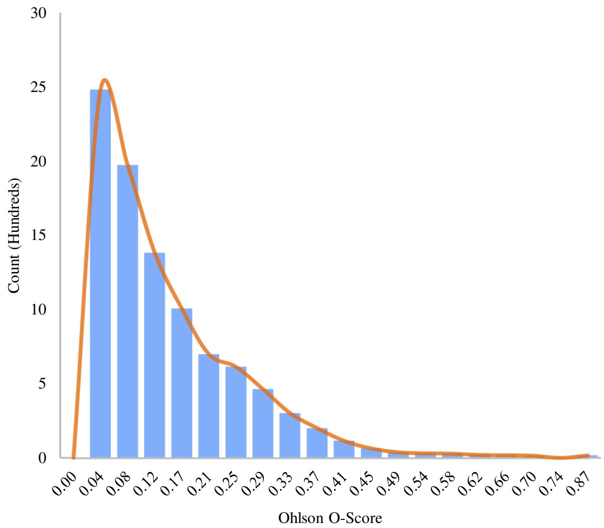
Proceeding with the data exploration process, Table 2 summarizes the descriptive statistics for each of the variables that we used in our regressions. Additionally, we can visually observe the distribution of the Altman Z-Scores and the Ohlson O-Scores in Figure 2a and Figure 2b and the distribution of the main independent variables in Figure 3.

Figure 2 - Distribution of The Depended Variables

(a)



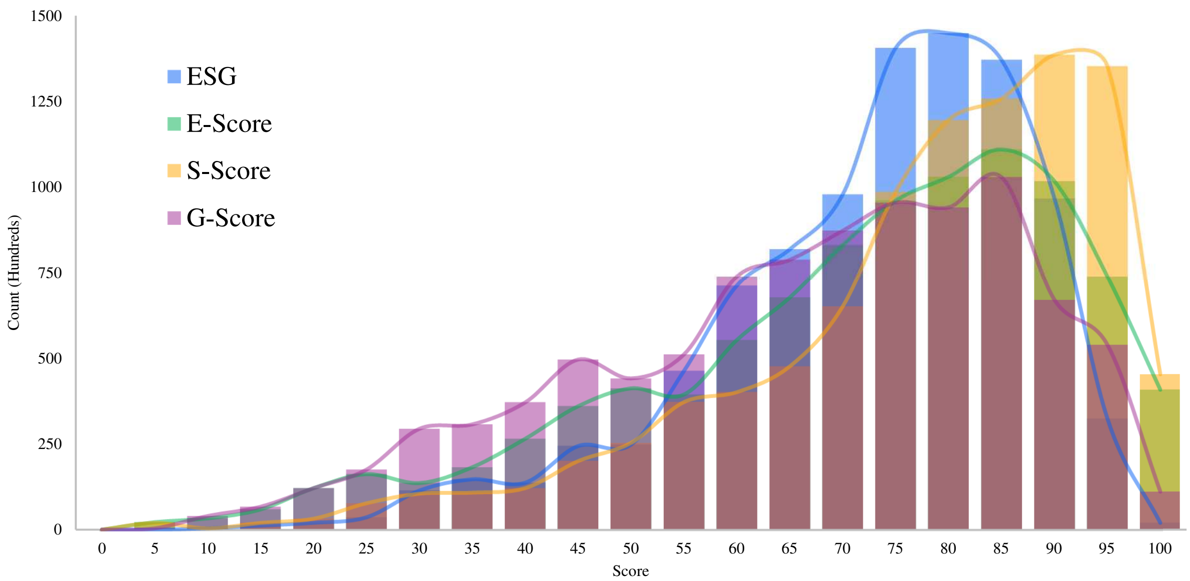
(b)



The DP, expressed as the Altman Z-Score, shows a mean of 3.03 with a standard deviation of 2.20, a minimum value of -0.95, and a maximum of 27.47, suggesting a diverse range of values.

The distribution is positively skewed (skewness = 3.23) and exhibits significant kurtosis (19.66), indicating a leptokurtic distribution with a concentration of data around the mean but with potential outliers on the higher end. When expressing DP using the Ohlson O-score, we notice that the distribution follows a similar trend, displaying a positive skewness (1.78) and considerable kurtosis (4.88), with an average score of 0.12 and deviations gathering around a narrower scale (SD = 0.12). When it comes to the independent variables of our study, we notice how ESG-Score, and its individual sub scores, present similar characteristics with each other. Specifically, all the independent variables display negative skewness, indicating a clustering towards higher scores. The average ESG score value is 69.98. The E-Score and the G-Score are in line with the general average, while the S-Score averages 74.84, above the general average. This higher score may be attributed to increased focus on the social pillar, due to social and regulatory pressure in the European landscape.

Figure 3 - Distribution of the Independent Variables



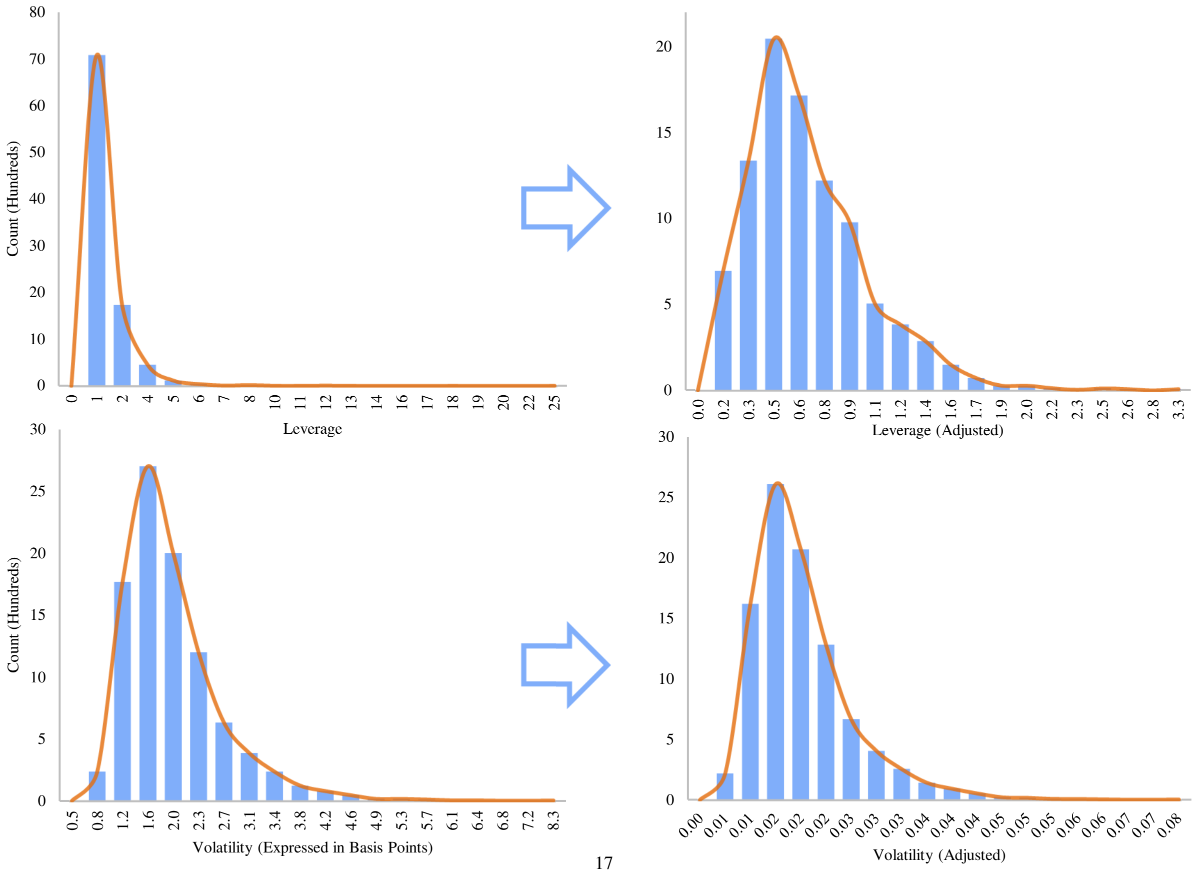
Two of the control variables chosen for our analysis, namely Leverage and Size, portray a highly skewed distribution (7.52 and 4.18, respectively) and pronounced kurtosis (112.05 and 23.34, respectively), highlighting the presence of extreme values which could affect the results of the OLS regressions. Finally, Volatility appears moderately skewed with a kurtosis close to normal, indicating a relatively stable measure across the dataset.

Table 2 - Descriptive Statistics of All the Variables

	Count	Mean	SD	Min	Q (25%)	Median	Q (75%)	Max	Skewness	Kurtosis
Dependent Variables										
Altman Z-Score	9472	3.03	2.20	-0.95	1.69	2.53	3.72	27.47	3.23	19.66
Ohlson O-Score	9472	0.12	0.12	0.00	0.04	0.09	0.18	0.87	1.78	4.88
Independent Variables										
ESG Score	9472	69.98	14.99	9.36	61.34	72.72	81.04	95.57	-0.95	0.78
E Score	9472	68.62	20.09	1.43	57.24	72.71	84.12	98.75	-0.86	0.20
S Score	9472	74.84	17.37	0.25	66.59	78.54	87.78	98.20	-1.19	1.29
G Score	9472	63.87	20.07	4.50	50.71	67.25	79.95	98.56	-0.59	-0.41
Control Variables										
Leverage	9472	0.98	1.15	0.00	0.41	0.69	1.21	25.19	7.52	112.05
Volatility	9472	0.02	0.01	0.00	0.01	0.02	0.02	0.08	1.86	6.27
Size (in € Bilions)	9472	20.80	33.02	0.51	4.91	9.37	20.72	368.98	4.18	23.34

Given the intended use of OLS regressions in our study, attention should be given to the variables' skewness and kurtosis. Since OLS assumes normality on the distribution, the three controlling variables such as Leverage, Volatility, and Size, can cause issues like heteroscedasticity due to their high skewness and kurtosis. Heteroscedasticity implies a non-constant variance which might result in inefficient and biased estimators. To mitigate these issues, and ensure robust and accurate results, we decided to operate a data transformation process to our control variables. Specifically, we added 1 to the variable Leverage and Volatility, and computed the natural logarithm of each observation. In the case of the Leverage, since it cannot take negative values, we computed directly the natural logarithm of the variable. The results of these transformations are highlighted in Figure 4, while Table 3 summarizes the new descriptive statistics for the transformed variables.

Figure 4 - Distribution of Control Variables Before and After Transformation



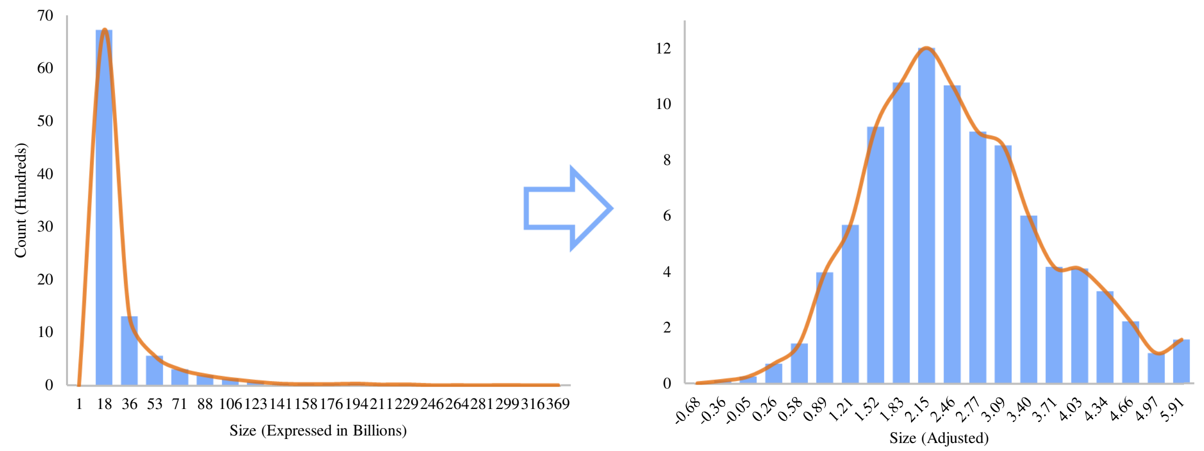


Table 3 - Descriptive Statistics of the Transformed Variables

	Count	Mean	SD	Min	Q (25%)	Median	Q (75%)	Max	Skewness	Kurtosis
Adj. Control Variables										
Leverage	9472	0.60	0.38	0.00	0.34	0.52	0.79	3.27	1.30	3.30
Volatility	9472	0.02	0.01	0.00	0.01	0.02	0.02	0.08	1.81	5.88
Size (in € Billions)	9472	2.37	1.09	-0.68	1.59	2.24	3.03	5.91	0.45	-0.08

Finally, we created correlation matrix (Figure 5), to have a clear picture of how the variables of choice for this study interact with each other. We notice immediately that the two dependent variables of our choice are negatively correlated (-0.44), this result is not surprising since, as previously explained, a higher Altman Z-Score corresponds to a lower likelihood of default while, in the case of the Ohlson O-Score, the value observed corresponds directly to the DP, given the logistic transformation operated. Surprisingly. the relationships between the ESG scores, and each sub score, and both the dependent variables are predominantly weak. For instance, the combined ESG Score displays a correlation with the Altman Z-Score of -0.14, and an almost negligible correlation with the Ohlson O-Score (0.01). This suggests that the direct impact of ESG scores on default probability, as measured by these scores, could potentially be limited, necessitating further studies to uncover additional underlying dynamics. The ESG score and its sub-scores (E-Score, S-Score, and G-Score) show strong positive inter-correlations, especially between ESG and S-Score (0.86), and ESG and E-Score (0.79). This indicates overlapping information among these scores, not surprising given that the ESG score is a combined score of its sub-scores. For this reason, each ESG sub-score is never used in the same equation as the comprehensive ESG score to address any multicollinearity issue. As for the control variables, including Leverage, Volatility, and Size, we notice varying degrees of correlation with the default probability indicators. Once again, given that a higher Z-score indicates a lower DP, while a higher O-score indicates higher DP, it is expected and normal to observe opposite signs in their correlations with these factors. Leverage illustrates this phenomenon with a substantial positive correlation with the O-score (0.74), and a negative correlation with the Z-score (-0.48). This indicates that greater leverage tends to be associated with a higher perceived default risk as per the O-score and a lower financial stability as per the Z-score. On the other hands, Volatility seems to have a relatively minimal relationship with both Z-score and O-score, suggesting that day-to-day market-driven fluctuations may not have a pronounced direct impact on the broader, longer-term assessment of default risk as captured by these scores. Finally, we notice that Size is positively correlated with the ESG scores (0.45), indicating that larger firms typically display stronger ESG practices. However, the influence of Size on DP appears minimal, with only slight variations observed in the correlations with Z-score and O-score. This implies that while bigger firms are potentially engaging more in sustainable practices, this does not directly translate into significantly different default probabilities within the dataset.

Figure 5 - Heatmap Correlation Matrix of all Variables

	Altman	Ohlson	ESG	E-Score	S-Score	G-Score	Leverage	Volatility	Size
Altman	1.00	-0.44	-0.14	-0.14	-0.08	-0.10	-0.48	-0.08	0.05
Ohlson	-0.44	1.00	0.01	0.00	-0.04	0.05	0.74	0.16	-0.15
ESG	-0.14	0.01	1.00	0.79	0.86	0.65	0.06	0.02	0.45
E-Score	-0.14	0.00	0.79	1.00	0.63	0.23	0.04	0.00	0.39
S-Score	-0.08	-0.04	0.86	0.63	1.00	0.32	0.02	-0.02	0.41
G-Score	-0.10	0.05	0.65	0.23	0.32	1.00	0.07	0.06	0.24
Leverage	-0.48	0.74	0.06	0.04	0.02	0.07	1.00	0.07	0.03
Volatility	-0.08	0.16	0.02	0.00	-0.02	0.06	0.07	1.00	-0.18
Size	0.05	-0.15	0.45	0.39	0.41	0.24	0.03	-0.18	1.00

6. Results and Analysis

This chapter encompasses an extensive review of the findings from the regression models designed to determine the relationships between ESG (Environmental, Social, and Governance) scores, and probability of default for European firms. Different models, namely Ordinary Least Squares (OLS) regression and Panel Data Regression (FEM and REM), were adopted to garner a holistic understanding of the dynamics underlying the influencing factors of a company's risk of default.

6.1. Ordinary Least Squares Regression Analysis

To test the Hypothesis 1, which posits a negative relationship between a firm's ESG score and its DP (proxied by the Altman Z-score), we first conducted a series of regressions employing the model from regression (3.1) and displayed the results in Table 4, highlighting the change in the coefficients when adding the control variables one by one. The initial regression was run without any control variables to establish the baseline relationship between the ESG score and the Altman Z-score. Contrarily to what expected, we notice a statistically significant negative relationship between ESG score and the Altman Z-Score (-0.02). This initial finding suggests that higher ESG scores are associated, on average, with lower Altman Z-scores, which corresponds to a higher DP.

Table 4 - Coefficients from Ordinary Least Squares Regressions

# Control Variables →	**0**	**1**	**2**	**3**
ESG	-0.020***	-0.016***	-0.016***	-0.024***
	(0.00)	(0.00)	(0.00)	(0.00)
Leverage		-2.765***	-2.748***	-2.762***
		(0.05)	(0.05)	(0.05)
Volatility			-12.919***	-5.246*
			(2.73)	(2.77)
Size				0.268***
				(0.02)
Constant	4.441***	5.786***	5.994***	5.843***
	(0.11)	(0.10)	(0.11)	(0.11)
# Observations	9472	9472	9472	9472
R^2	0.019	0.242	0.243	0.257

*Note: Standard errors are noted in parentheses. P-values are noted as: *** p < 0.01, ** p < 0.05, * p < 0.1*

When we included the control variable Leverage, the negative relationship between ESG score and DP remained significant, though its magnitude slightly decreased (-0.016). Including

Volatility as a control variable did not affect the coefficient for the ESG score, and the relationship remained significant.

Finally, the model with all control variables included (namely, Leverage, Volatility, and Size) still showed a significant negative relationship between ESG scores and DP (-0.024), reinforcing our initial hypothesis on the existence of a relationship.

6.2. Panel Data Regression Analysis

Following the OLS regression, we addressed potential unobserved heterogeneity by running again regression (3.1), applying both Fixed Effects Model (FEM) and Random Effects Model (REM). The results of these two additional regressions, displayed in Table 5, confirm the robustness of the negative relationship between ESG score and DP. Specifically, the inclusion of firm-specific effects does not alter the significance of the ESG score coefficient, while the results from the REM highlight that the relationship is not an artifact of omitted variable bias either.

Table 5 - Panel Data Regression Results

Model	Constant	ESG	Leverage	Volatility	Size	R^2
Fixed Effects	-	-0.015***	-1.628***	-6.077***	0.843***	0.285
		(0.00)	(0.04)	(1.21)	(0.02)	
Random Effects	3.287***	-0.016***	-1.657***	-5.837***	0.811***	0.279
	(0.13)	(0.00)	(0.04)	(1.21)	(0.02)	

*Note: Standard errors are noted in parentheses. P-values are noted as: *** p < 0.01.*

The magnitude of the effects observed indicates that the ESG score has a relatively small impact on the Altman Z-score. Specifically, a one-point increase in the ESG score is associated with an average 0.01 decrease in the Altman Z-score. This effect, while statistically significant, is extremely small in magnitude. These results challenge recent studies, such as those by Albuquerque et al. (2019) and Henisz & McGlinch (2019b) which highlight the benefits of strong ESG performance. Our initial findings, instead, indicate a more complex relationship where high ESG scores are associated to a higher DP.

As previously highlighted in the variance-covariance matrix (Figure 5), we are not concerned about overlaps in the variations explained by ESG score and the control variables. However, as an additional test, we decided to compute the Variance Inflation Factor (VIF) for each independent variable, which supported the fact that no variables appear redundant in explaining the variations in the dependent variable (Appendix 5.1). Instead, these results may reflect the unique characteristics of our sample, or the time-period studied (encompassing, for example, the Covid-19 pandemic). Alternatively, there could be an industry-specific or regional factor at play that is not fully captured by the control variables, and for which we will conduct further analysis on the next chapter of this thesis.

Finally, it is important to mention that establishing causality would require the use of instrumental variable techniques or natural experiments, which are beyond the scope of this study. Therefore, these results should be interpreted as indicative of a robust association rather than a definitive causal link.

6.3. Investigating the Individual ESG Sub-Scores

In order to test Hypothesis 2, which posits that the G-Score has the most notable effect on a firm's DP, we built on regression (4), employing both FEM and REM.

The results from these regressions, summarized in Table 6, show a consistent negative relationship between each of the ESG sub-scores and the Altman Z-score. This suggests that a higher performance in each of the ESG pillars is associated, on average, to a higher DP, supporting our findings on the overall ESG score. Contrary to the expectation that the G-Score would have the most notable effect, all three ESG sub-scores exhibit similar impacts on DP. It is also important to highlight that the specific coefficients of the analysis, averaging -0.006, indicate an extremely small magnitude of effect. Specifically, a one-point increase in any of the ESG sub-scores is associated, on average, with a decrease of approximately 0.006 units in the Altman Z-score, indicating a slightly higher probability of default.

Table 6 - Regression Results with ESG sub-scores

Model	Constant	E-Score	S-Score	G-Score	Leverage	Volatility	Size	R^2
Fixed Effects	-	-0.005***	-0.008***	-0.004***	-1.626***	-5.971***	0.848***	0.287
		(0.001)	(0.001)	(0.001)	(0.041)	(1.208)	(0.023)	
Random Effects	3.375***	-0.006***	-0.008***	-0.003***	-1.656***	-5.738***	0.816***	0.281
	(0.135)	(0.001)	(0.001)	(0.001)	(0.040)	(1.211)	(0.022)	

*Note: Standard errors are noted in parentheses. P-values are noted as: *** p < 0.01, ** p < 0.05, * p < 0.1*

6.4. Differences between Countries

To test Hypothesis 3, we first divided the dataset into sub-samples based on the country where the firms of our sample are domiciled. Again, we ran equation (3.1) and equation (4) for each subset, employing both FEM and REM, for a total of four individual regressions for each country subset. The results, summarized in Table 7 (FEM) and Table 8 (REM)[4], reveal some heterogeneity within coefficients, aligning with previous literature, noting regional differences in the impact of ESG (Nadezda and Mckenna, 2021; Barth et al., 2022).

Table 7 - Coefficients from Regression (3.2) and (4) by Country (FEM)

Country	ESG	E-Score	S-Score	G-Score
All	-0.015***	-0.006***	-0.008***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
United Kingdom	0.004	0.015***	-0.015***	0.001
	(0.003)	(0.002)	(0.003)	(0.002)
France	-0.012***	-0.010***	-0.007***	0.002
	(0.003)	(0.003)	(0.002)	(0.002)
Germany	-0.017***	-0.015***	0.007***	-0.011***
	(0.003)	(0.003)	(0.003)	(0.002)
Switzerland	-0.015***	-0.011***	0.007*	-0.014***
	(0.004)	(0.004)	(0.004)	(0.003)
Sweden	-0.021***	-0.006***	-0.016***	-0.004***
	(0.003)	(0.002)	(0.003)	(0.001)

*Note: Standard errors are noted in parentheses. P-values are noted as: *** p < 0.01, ** p < 0.05, * p < 0.1*

Table 8 - Coefficients from Regression (3.2) and (4) by Country (REM)

Country	ESG	E-Score	S-Score	G-Score
All	-0.016***	-0.006***	-0.008***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
United Kingdom	0.002	0.014***	-0.016***	0.0004
	(0.003)	(0.002)	(0.003)	(0.002)
France	-0.012***	-0.010***	-0.007***	0.002
	(0.003)	(0.003)	(0.002)	(0.002)
Germany	-0.017***	-0.015***	0.007**	-0.011***
	(0.002)	(0.003)	(0.003)	(0.002)
Switzerland	-0.015***	-0.012***	0.007*	-0.014***
	(0.004)	(0.004)	(0.004)	(0.003)
Sweden	-0.020***	-0.005**	-0.016***	-0.004***
	(0.003)	(0.002)	(0.003)	(0.001)

*Note: Standard errors are noted in parentheses. P-values are noted as: *** p < 0.01, ** p < 0.05, * p < 0.1*

[4] Table 7 and Table 8 only include the most relevant results (i.e.: from the countries for which we had the highest number of observations). For the results of the complete list of country-subsets, please check: Appendix 2 and Appendix 3 (FEM), Appendix 4 and Appendix 5 (REM).

Specifically, in the United Kingdom, the ESG score shows no significant relationship with the Altman Z-score, while the E-Score is positively associated (0.015), and the S-Score is negatively associated (-0.016), significant in both cases. This suggests that, while environmental initiatives could have a positive impact on British companies' health, social initiatives might be seen as increasing short-term financial risk. This aligns with the studies of Albuquerque et al. (2019) highlighting the varied impact of different ESG pillars. In the case of France, ESG score, and its E and S components, show a consistent pattern of significant negative relationships. This could be explained by increased costs associated with high ESG investments (Aslan et al., 2021). Germany follows the same trend, except for the possibility that social initiatives might be beneficial for the financial health of the firms. Switzerland displays a mixed pattern, where the consistently negative coefficients are counterbalanced by the slightly positive coefficient for the S-Score, suggesting different effects of ESG pillars on DP. Finally, in Sweden, ESG score, and each sub-score show significant negative coefficients, supporting the studies of Choi et al. (2024), which suggest that ESG investments may not always enhance financial stability.

6.5. Differences Between Industries

Continuing with the investigation of Hypothesis 3, we divided the dataset into sub-samples according, now, to the industry group where each firm belongs. The results, summarized in Table 9 (FEM) and Table 10 (REM)[5], display again diversity in the relationship between ESG and DP, as expected in Hypothesis 3. We can attribute the differences observed across industries to the different nature of business activities, regulatory requirements, and market dynamics of each specific sector.

[5] Table 9 and Table 10 only include the most relevant results (i.e.: from the industries for which we had the highest number of observations). For the results of the complete list of industry-subsets, please check: Appendix 6 and Appendix 7 (FEM), Appendix 8 and Appendix 9 (REM).

Table 9 - Coefficients from Regression (3.2) and (4) by Industry (FEM)

Industry	ESG	E-Score	S-Score	G-Score
All	-0.015***	-0.005***	-0.008***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Industrials	-0.0003	0.013***	-0.009***	-0.001
	(0.002)	(0.002)	(0.002)	(0.001)
Consumer Discretionary	-0.067***	-0.020***	-0.035***	-0.014***
	(0.005)	(0.004)	(0.005)	(0.003)
Energy & Basic Materials	-0.002	-0.0002	0.004**	-0.005***
	(0.002)	(0.002)	(0.002)	(0.001)
Health Care	-0.030***	-0.014***	-0.016***	-0.002
	(0.003)	(0.004)	(0.003)	(0.003)
Consumer Staples	-0.019***	-0.012***	0.0003	-0.006***
	(0.003)	(0.003)	(0.003)	(0.002)

*Note: Standard errors are noted in parentheses. P-values are noted as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$*

Specifically, in the category "Industrials" the impact of ESG on DP appears to be minimal, with a non-significant ESG-score coefficient. On the other hand, the negative, significant, relationship across all the ESG components and DP in the case of "Consumer Discretionary" and "Consumer Staples", suggests that higher ESG score is associated with a higher DP. The non-significant, or negligible, coefficients in the case of "Energy & Basic Materials" could reflect the complex nature of ESG integration in this specific sector. Similar reasoning could be made for the Health Care, where the high compliance costs and long-term investment horizons of the sector could explain the positive relationships between ESG-scores and DP.

Table 10 - Coefficients from Regression (3.2) and (4) by Industry (REM)

Industry	ESG	E-Score	S-Score	G-Score
All	-0.016***	-0.006***	-0.008***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Industrials	-0.0004	0.012***	-0.009***	-0.001
	(0.002)	(0.002)	(0.002)	(0.001)
Consumer Discretionary	-0.067***	-0.020***	-0.035***	-0.014***
	(0.005)	(0.004)	(0.005)	(0.003)
Energy & Basic Materials	-0.003	-0.001	0.004**	-0.005***
	(0.002)	(0.002)	(0.002)	(0.001)
Health Care	-0.029***	-0.014***	-0.016***	-0.002
	(0.003)	(0.004)	(0.003)	(0.003)
Consumer Staples	-0.019***	-0.013***	0.001	-0.006***
	(0.003)	(0.003)	(0.003)	(0.002)

*Note: Standard errors are noted in parentheses. P-values are noted as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$*

6.6. Results from the Robustness Check

To ensure the robustness of our initial findings, we decided to repeat the whole process seen so far. This time, however, we substituted the Altman Z-Score used as independent variable with the DP derived from the Ohlson O-Score. In the interpretation of the coefficients, now, is important to remember that the dependent variable directly represents DP, thus a positive coefficient indicates that an increase in the independent variable corresponds to an increase in the probability of default.

Table 11 shows the results of the progressive inclusion of control variables in the regression model (3.1). In this case we can see that the coefficient for ESG-score starts positive and insignificant (0.0001) with no control variables but becomes negative and significant (-0.0003) when adding the control variables.

Table 11 - Coefficients from Ordinary Least Squares Regressions

# Control Variables →	**0**	**1**	**2**	**3**
ESG	0.0001	-0.0003***	-0.0003***	0.0003***
	(0.000)	(0.000)	(0.000)	(0.000)
Leverage		0.228***	0.226***	0.227***
		(0.002)	(0.002)	(0.002)
Volatility			1.789***	1.256***
			(0.109)	(0.108)
Size				-0.019***
				(0.001)
Constant	0.120***	0.009**	-0.019***	-0.009**
	(0.006)	(0.004)	(0.004)	(0.004)
# Observations	9472	9472	9472	9472
R^2	0.0001	0.552	0.565	0.588

*Note: Standard errors are noted in parentheses. P-values are noted as: *** p < 0.01, ** p < 0.05, * p < 0.1*

Table 12 presents the results (both FEM and REM) when considering the ESG-Score alone. In both models, the coefficient for ESG-score remains, despite very small, negative and significant, indicating that higher ESG scores are associated with a slightly lower DP (from 2 to 3 basis points).

Table 12 - Panel Data Regression Results

Model	Constant	ESG	Leverage	Volatility	Size	R^2
Fixed Effects	-	-0.0003***	0.248***	0.859***	-0.021***	0.527
		(0.000)	(0.003)	(0.080)	(0.001)	
Random Effects	0.028***	-0.0002***	0.246***	0.872***	-0.020***	0.530
	(0.006)	(0.000)	(0.003)	(0.079)	(0.001)	

*Note: Standard errors are noted in parentheses. P-values are noted as: *** p < 0.01, ** p < 0.05, * p < 0.1*

Table 13 presents the results (both FEM and REM) when distinguishing the individual ESG sub-scores. While the coefficients for S- and G-scores are negligible and non-significant, the coefficient for E-Score is negative and significant (-0.0003), suggesting that better E-score could lead to a reduction in DP.

Table 13 - Regression Results with ESG sub-scores

Model	Constant	E-Score	S-Score	G-Score	Leverage	Volatility	Size	R^2
Fixed Effects	-	-0.0003***	-0.00001	0.00001	0.248***	0.861***	-0.021***	0.528
		(0.000)	(0.000)	(0.000)	(0.003)	(0.080)	(0.001)	
Random Effects	0.029***	-0.0003***	-0.00001	0.00001	0.246***	0.872***	-0.020***	0.53
	(0.006)	(0.000)	(0.000)	(0.000)	(0.003)	(0.079)	(0.001)	

*Note: Standard errors are noted in parentheses. P-values are noted as: *** p < 0.01, ** p < 0.05, * p < 0.1*

Table 14 and Table 15 summarize the results from the country-specific regressions. In both the case of FEM and REM we notice significant negative coefficients for the ESG score in UK. Mixed results with some significant negative coefficients for E-Score and G-Score are discovered in France and Germany. For the other countries, and in general, the results are mostly weak or non-significant.

Table 14 - Coefficients from Regression (3.2) and (4) by Country (FEM)

Country	ESG	E-Score	S-Score	G-Score
All	-0.0003*** (0.000)	-0.0003*** (0.000)	-0.00001 (0.000)	0.00001 (0.000)
United Kingdom	-0.0005** (0.000)	-0.001*** (0.000)	-0.0002 (0.000)	0.0002* (0.000)
France	-0.0002 (0.000)	-0.002*** (0.000)	0.0003* (0.000)	0.0003** (0.000)
Germany	0.0003 (0.000)	0.001*** (0.000)	-0.0001 (0.000)	-0.0001 (0.000)
Switzerland	-0.00003 (0.000)	-0.00003 (0.000)	0.00002 (0.000)	-0.0001 (0.000)
Sweden	-0.0002 (0.000)	-0.0003** (0.000)	0.0005*** (0.000)	-0.0002** (0.000)

*Note: Standard errors are noted in parentheses. P-values are noted as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$*

Table 15 - Coefficients from Regression (3.2) and (4) by Country (REM)

Country	ESG	E-Score	S-Score	G-Score
All	-0.0002*** (0.000)	-0.0003*** (0.000)	-0.00001 (0.000)	0.00001 (0.000)
United Kingdom	-0.0004** (0.000)	-0.0005*** (0.000)	-0.0002 (0.000)	0.0002* (0.000)
France	-0.0002 (0.000)	-0.001*** (0.000)	0.0003* (0.000)	0.0003** (0.000)
Germany	0.0003 (0.000)	0.001*** (0.000)	-0.0003 (0.000)	-0.0001 (0.000)
Switzerland	-0.00003 (0.000)	-0.00002 (0.000)	0.00004 (0.000)	-0.0001 (0.000)
Sweden	-0.0001 (0.000)	-0.0003** (0.000)	0.001*** (0.000)	-0.0002** (0.000)

*Note: Standard errors are noted in parentheses. P-values are noted as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$*

Finally, Table 16 and Table 17 summarize the results from the industry-specific regressions. In both the case of FEM and REM we notice that the ESG-score and the G-Score have significant negative relationships with DP for companies in the industrial sector. Mixed results come from the other sectors, where we notice a few significant positive and negative coefficients, indicating sector-specific dynamics.

Table 16 - Coefficients from Regression (3.2) and (4) by Industry (FEM)

Industry	ESG	E-Score	S-Score	G-Score
All	-0.0003***	-0.0003***	-0.00001	0.00001
	(0.000)	(0.000)	(0.000)	(0.000)
Industrials	-0.0005***	-0.00005	-0.0001	-0.0003***
	(0.000)	(0.000)	(0.000)	(0.000)
Consumer Discretionary	0.0002	-0.001***	0.001***	0.0001
	(0.000)	(0.000)	(0.000)	(0.000)
Energy & Basic Materials	-0.001***	-0.001***	-0.0003	0.0001
	(0.000)	(0.000)	(0.000)	(0.000)
Health Care	-0.0002	-0.0003**	-0.0001	0.0001
	(0.000)	(0.000)	(0.000)	(0.000)
Consumer Staples	-0.0003	-0.0002	0.0001	-0.0001
	(0.000)	(0.000)	(0.000)	(0.000)

*Note: Standard errors are noted in parentheses. P-values are noted as: *** p < 0.01, ** p < 0.05, * p < 0.1*

Table 17 - Coefficients from Regression (3.2) and (4) by Industry (REM)

Industry	ESG	E-Score	S-Score	G-Score
All	-0.0002***	-0.0003***	-0.00001	0.00001
	(0.000)	(0.000)	(0.000)	(0.000)
Industrials	-0.0004***	0.00002	-0.0001	-0.0003***
	(0.000)	(0.000)	(0.000)	(0.000)
Consumer Discretionary	0.0003	-0.001***	0.001***	0.0002
	(0.000)	(0.000)	(0.000)	(0.000)
Energy & Basic Materials	-0.001***	-0.001***	-0.0002	0.0001
	(0.000)	(0.000)	(0.000)	(0.000)
Health Care	-0.0001	-0.0002**	-0.0001	0.0001
	(0.000)	(0.000)	(0.000)	(0.000)
Consumer Staples	-0.0002	-0.0002	0.0001	-0.0001
	(0.000)	(0.000)	(0.000)	(0.000)

*Note: Standard errors are noted in parentheses. P-values are noted as: *** p < 0.01, ** p < 0.05, * p < 0.1*

Overall, when altering the proxy for DP, some differences arise on the results of our analysis. Specifically, the coefficients for the ESG-score and its individual sub-scores appear predominantly negative, suggesting that, in contrasts with our previous findings, higher ESG scores correspond to a lower DP on average.

The differences between the two sets of findings can be reconciled by considering several aspects. Firstly, the Altman Z-Score is more focused on accounting ratios, while the Ohlson O-Score incorporates a broader set of financial indicators, capturing different aspects of DP. Moreover, the broader approach from the Ohlson O-Score might provide a more comprehensive view of a firm's financial health, potentially explaining the higher R-squares observed in the regressions. Secondly, despite the statistical significance, the economic magnitude of the effects discussed appears constantly very low, and this brings us to conclude that, while ESG factors are important, they might not be the primary drivers of DP. Finally, as highlighted by the variability in the impact of ESG scores across different countries and industries observed in both sets of analyses, the relationship between ESG and DP appear complex and influenced by a multitude of factors beyond ESG scores alone.

7. Summary and Conclusion

This thesis has attempted to explore the relationship of ESG scores with Default Probability for European firms, using Altman Z-Score and Ohlson O-Score as proxies for DP. Specifically, the three hypotheses tested were as follows:

1. A significant, and negative, relationship exists between ESG scores and the probability of default.
2. The Governance pillar (G-Score) is the strongest factor in influencing the DP, compared to the Environmental (E-Score) and Social (S-Score) pillars.
3. The relationship between ESG scores and DP significantly differs across countries and economic sectors.

A large dataset encompassing quarterly observations of 296 firms within the STOXX Europe 600 index from Q1 2015 to Q4 2022 was used. The data have been analyzed using various regression models, such as OLS, Fixed Effect Model, and Random Effects Model. Progressively, control variables like leverage, volatility, and size were incorporated into the models to single out the effect ESG has on DP.

The findings of this thesis showed that, in the Altman Z-Score settings, the higher the ESG score, the higher the DP. However, the Ohlson O-Score setting showed coefficients that are mostly negative for the ESG scores, implying that a higher ESG score corresponds to a lower DP. Although the results were somewhat conflicting, the size of the coefficients was generally small. Further, the results did not consistently show that the G-score had the most significant effect on a firm's DP.

Again, we confirmed that the relationship between ESG scores and default probability significantly varied with countries and industries. This variation underlines the importance of context-related issues, namely the regulatory environment and market dynamics, in shaping the impact of ESG on DP.

In conclusion, our contrasting findings suggest the need for further investigation into the most appropriate measures of financial health and default risk. Future research, for example, might consider investigating a broader set of economic indicators, exploring non-linear relationships between ESG scores and DP. The key implication for practitioners, specifically those operating within diverse regulatory and market environments, is to ensure that ESG strategies are embedded in the operation at contextual levels. Firms must invest appropriately in ESG, while keeping a balance with traditional financial metrics to safeguard overall financial health. The policy implication of this variability in ESG impacts across countries and sectors is that standard uniform regulatory approaches will not be practical, so policymakers should consider sector-specific regulations and incentives.

7.1. Limitations and Future Studies

To properly conclude this study, it is essential to recognize certain aspects of it that can be expanded upon. First of all, our research focused on companies from the STOXX Europe 600 index, proving a valuable but non exhaustive view of the broader European corporate landscape. Further, the period of study is too small and may thus require a larger period to facilitate better understanding of long-term trends in ESG performance and default risk. The fact that rating agencies can produce differing results in ESG score measurement justifies a basis for consistency to be developed in subsequent analysis. Future research may consider enlarging this study by increasing the sample size, conducting similar studies based on additional financial and nonfinancial variables, and even using nonlinear methods of modelling. Further work can assess in more detail the effects of specific ESG practices and policies on a firm's probability of default, which could enhance the understanding of the relationship.

8. Appendices

The appendices in this chapter provide supplementary information supporting the analyses conducted in this study. Detailed tables, additional regression results, and other relevant data are included to enhance the understanding of the findings presented in the main text. Additionally, the complete dataset used for this study, along with the R-Studio code employed for all data elaborations, can be made available upon request. This ensures transparency and allows for the replication of the results, providing further robustness to the conclusions drawn from this research. Please contact the author for access to these resources.

Appendix 1 - Variance Inflation Factor

Regression Model	**R^2**	**VIF**
ESG = $\alpha + \beta_1$(Leverage) + β_2(Volatility) + β_3(Size) + ε	0.21	1.27
Leverage = $\alpha + \beta_1$(ESG) + β_2(Volatility) + β_3(Size) + ε	0.01	1.01
Volatility = $\alpha + \beta_1$(Leverage) + β_2(ESG) + β_3(Size) + ε	0.05	1.05
Size = $\alpha + \beta_1$(Leverage) + β_2(Volatility) + β_3(ESG) + ε	0.23	1.31

Note: "VIF" stands for "Variance Inflation Factor", computed as VIF = $1 / (1 - R^2)$.
High VIF values (usually above 10) indicate strong multicollinearity, suggesting that some variables are redundant in explaining the variation in the dependent variable.

Appendix 2 - Results Regression (3.1) - Subsamples by Country (FEM). DP proxy: Altman Z-Score

Country	ESG	Leverage	Volatility	Size	R^2	# Obs.
Denmark	-0.103***	-4.254***	3.467	1.685***	0.629	320
	(0.010)	(0.349)	(8.918)	(0.120)		
Italy	-0.009***	-1.973***	-0.016	0.654***	0.291	352
	(0.003)	(0.219)	(3.748)	(0.096)		
Netherlands	0.014***	-0.825***	-2.34	1.105***	0.58	480
	(0.003)	(0.122)	(3.116)	(0.054)		
Switzerland	-0.015***	-1.982***	4.568	1.240***	0.374	864
	(0.004)	(0.141)	(4.529)	(0.084)		
Spain	-0.023**	-2.590***	-11.411	0.773***	0.186	384
	(0.010)	(0.380)	(8.729)	(0.200)		
France	-0.012***	-1.840***	0.654	0.818***	0.224	1504
	(0.003)	(0.123)	(2.674)	(0.058)		
Germany	-0.017***	-1.224***	-5.140**	0.749***	0.404	1152
	(0.002)	(0.068)	(2.522)	(0.045)		
Sweden	-0.021***	-3.057***	0.482	0.924***	0.594	864
	(0.003)	(0.109)	(2.899)	(0.048)		
United Kingdom	0.004	-1.323***	-15.926***	0.686***	0.267	1888
	(0.003)	(0.081)	(2.829)	(0.055)		
Finland	0.010*	-2.682***	-5.706	0.529***	0.345	480
	(0.005)	(0.239)	(5.001)	(0.078)		
Ireland	-0.059***	1.233***	-34.534***	0.166	0.278	288
	(0.009)	(0.395)	(9.426)	(0.209)		
Austria	-	-	-	-	-	-
Belgium	-	-	-	-	-	-
Luxebourg	-	-	-	-	-	-
Norway	-	-	-	-	-	-
Poland	-	-	-	-	-	-
Portugal	-	-	-	-	-	-

*Note: Standard errors are noted in parentheses. P-values are noted as: *** p < 0.01, ** p < 0.05, * p < 0.1*

Please note: Cells with no values indicate that there were insufficient observations to perform regressions for those specific datasets.

Appendix 3 - Results Regression (4) - Subsamples by Country (FEM). DP proxy: Altman Z-Score

Country	E-Score	S-Score	G-Score	Leverage	Volatility	Size	R^2	# Obs.
Denmark	-0.026***	-0.037***	-0.032***	-4.211***	3.473	1.693***	0.625	320
	(0.010)	(0.010)	(0.004)	(0.361)	(9.185)	(0.127)		
Italy	-0.017***	0.005*	-0.003*	-1.761***	-0.582	0.696***	0.328	352
	(0.004)	(0.003)	(0.002)	(0.220)	(3.675)	(0.095)		
Netherlands	0.012***	-0.001	-0.001	-0.838***	-2.158	1.091***	0.586	480
	(0.003)	(0.003)	(0.002)	(0.121)	(3.106)	(0.056)		
Switzerland	-0.011***	0.007*	-0.014***	-1.947***	7.036	1.336***	0.388	864
	(0.004)	(0.004)	(0.003)	(0.141)	(4.525)	(0.088)		
Spain	-0.023***	-0.025***	0.013**	-2.895***	-4.765	0.726***	0.242	384
	(0.009)	(0.009)	(0.005)	(0.376)	(8.578)	(0.194)		
France	-0.010***	-0.007***	0.002	-1.815***	0.209	0.823***	0.23	1504
	(0.003)	(0.002)	(0.002)	(0.125)	(2.669)	(0.058)		
Germany	-0.015***	0.007***	-0.011***	-1.215***	-2.1	0.825***	0.423	1152
	(0.003)	(0.003)	(0.002)	(0.067)	(2.553)	(0.047)		
Sweden	-0.006***	-0.016***	-0.004***	-3.088***	-0.379	0.947***	0.603	864
	(0.002)	(0.003)	(0.001)	(0.110)	(2.892)	(0.048)		
United Kingdom	0.015***	-0.015***	0.001	-1.359***	-15.875***	0.650***	0.288	1888
	(0.002)	(0.003)	(0.002)	(0.080)	(2.794)	(0.056)		
Finland	-0.002	0.003	0.005	-2.714***	-5.774	0.494***	0.345	480
	(0.006)	(0.005)	(0.004)	(0.245)	(5.022)	(0.091)		
Ireland	-0.005	-0.024***	-0.026***	1.244***	-36.991***	0.055	0.289	288
	(0.009)	(0.008)	(0.005)	(0.395)	(9.445)	(0.213)		
Austria	-	-	-	-	-	-	-	-
Belgium	-	-	-	-	-	-	-	-
Luxebourg	-	-	-	-	-	-	-	-
Norway	-	-	-	-	-	-	-	-
Poland	-	-	-	-	-	-	-	-
Portugal	-	-	-	-	-	-	-	-

*Note: Standard errors are noted in parentheses. P-values are noted as: *** p < 0.01, ** p < 0.05, * p < 0.1*

Please note: Cells with no values indicate that there were insufficient observations to perform regressions for those specific datasets.

Appendix 4 - Results Regression (3.1) - Subsamples by Country (REM). DP proxy: Altman Z-Score

Country	Constant	ESG	Leverage	Volatility	Size	R^2	# Obs.
Denmark	9.618***	-0.103***	-4.236***	3.09	1.669***	0.621	320
	(1.065)	(0.010)	(0.348)	(8.901)	(0.120)		
Italy	2.856***	-0.009***	-1.996***	-0.007	0.630***	0.287	352
	(0.479)	(0.003)	(0.217)	(3.747)	(0.094)		
Netherlands	-0.630*	0.013***	-0.945***	-1.55	1.070***	0.563	480
	(0.339)	(0.003)	(0.122)	(3.197)	(0.054)		
Switzerland	2.874***	-0.015***	-1.984***	4.634	1.194***	0.364	864
	(0.516)	(0.004)	(0.141)	(4.535)	(0.083)		
Spain	4.807***	-0.024**	-2.701***	-10.585	0.751***	0.195	384
	(1.070)	(0.010)	(0.372)	(8.699)	(0.194)		
France	2.594***	-0.012***	-1.855***	0.802	0.819***	0.224	1504
	(0.441)	(0.003)	(0.122)	(2.672)	(0.057)		
Germany	2.843***	-0.017***	-1.251***	-5.141**	0.707***	0.393	1152
	(0.267)	(0.002)	(0.068)	(2.541)	(0.044)		
Sweden	4.001***	-0.020***	-3.044***	0.528	0.909***	0.584	864
	(0.291)	(0.003)	(0.109)	(2.904)	(0.048)		
United Kingdom	2.749***	0.002	-1.369***	-15.775***	0.594***	0.252	1888
	(0.300)	(0.003)	(0.081)	(2.851)	(0.053)		
Finland	3.266***	0.008	-2.684***	-5.88	0.514***	0.337	480
	(0.538)	(0.005)	(0.239)	(5.030)	(0.078)		
Ireland	6.484***	-0.055***	1.169***	-35.923***	0.114	0.267	288
	(0.642)	(0.009)	(0.389)	(9.376)	(0.197)		
Austria	-	-	-	-	-	-	-
Belgium	-	-	-	-	-	-	-
Luxebourg	-	-	-	-	-	-	-
Norway	-	-	-	-	-	-	-
Poland	-	-	-	-	-	-	-
Portugal	-	-	-	-	-	-	-

*Note: Standard errors are noted in parentheses. P-values are noted as: *** p < 0.01, ** p < 0.05, * p < 0.1*

Please note: Cells with no values indicate that there were insufficient observations to perform regressions for those specific datasets.

Appendix 5 - Results Regression (4) - Subsamples by Country (REM). DP proxy: Altman Z-Score

Country	Constant	E-Score	S-Score	G-Score	Leverage	Volatility	Size	R^2	# Obs.
Denmark	8.857*** (1.134)	-0.027*** (0.010)	-0.036*** (0.010)	-0.032*** (0.004)	-4.196*** (0.359)	3.31 (9.161)	1.680*** (0.127)	0.617	320
Italy	3.131*** (0.330)	-0.018*** (0.004)	0.006** (0.003)	-0.004* (0.002)	-1.812*** (0.221)	-0.621 (3.794)	0.611*** (0.093)	0.319	352
Netherlands	-0.316 (0.352)	0.011*** (0.003)	-0.001 (0.003)	-0.00004 (0.002)	-0.968*** (0.122)	-1.364 (3.198)	1.056*** (0.057)	0.566	480
Switzerland	2.705*** (0.501)	-0.012*** (0.004)	0.007* (0.004)	-0.014*** (0.003)	-1.951*** (0.141)	7.098 (4.537)	1.282*** (0.086)	0.377	864
Spain	6.417*** (0.993)	-0.026*** (0.009)	-0.023** (0.009)	0.013*** (0.005)	-3.029*** (0.365)	-3.945 (8.591)	0.718*** (0.186)	0.255	384
France	2.880*** (0.457)	-0.010*** (0.003)	-0.007*** (0.002)	0.002 (0.002)	-1.831*** (0.125)	0.349 (2.666)	0.824*** (0.057)	0.229	1504
Germany	2.596*** (0.279)	-0.015*** (0.003)	0.007** (0.003)	-0.011*** (0.002)	-1.244*** (0.067)	-2.328 (2.575)	0.775*** (0.046)	0.41	1152
Sweden	4.402*** (0.309)	-0.005** (0.002)	-0.016*** (0.003)	-0.004*** (0.001)	-3.076*** (0.110)	-0.327 (2.899)	0.930*** (0.048)	0.593	864
United Kingdom	3.163*** (0.302)	0.014*** (0.002)	-0.016*** (0.003)	0.0004 (0.002)	-1.403*** (0.080)	-15.698*** (2.813)	0.569*** (0.054)	0.274	1888
Finland	3.732*** (0.596)	-0.004 (0.006)	0.004 (0.005)	0.004 (0.004)	-2.728*** (0.246)	-5.995 (5.064)	0.478*** (0.090)	0.337	480
Ireland	6.736*** (0.679)	-0.003 (0.008)	-0.023*** (0.008)	-0.027*** (0.005)	1.201*** (0.388)	-37.967*** (9.323)	0.014 (0.201)	0.285	288
Austria	-	-	-	-	-	-	-	-	-
Belgium	-	-	-	-	-	-	-	-	-
Luxebourg	-	-	-	-	-	-	-	-	-
Norway	-	-	-	-	-	-	-	-	-
Poland	-	-	-	-	-	-	-	-	-
Portugal	-	-	-	-	-	-	-	-	-

*Note: Standard errors are noted in parentheses. P-values are noted as: *** p < 0.01, ** p < 0.05, * p < 0.1*

Please note: Cells with no values indicate that there were insufficient observations to perform regressions for those specific datasets.

Appendix 6 - Results Regression (3.1) - Subsamples by Industry (FEM). DP proxy: Altman Z-Score

Industry	**ESG**	**Leverage**	**Volatility**	**Size**	**R^2**	**# Obs.**
Industrials	-0.0003	-1.461***	-3.668**	0.874***	0.28	2944
	(0.002)	(0.075)	(1.828)	(0.037)		
Utilities	-0.006***	-0.356***	0.693	0.395***	0.346	704
	(0.002)	(0.039)	(1.452)	(0.025)		
Consumer Discretionary	-0.067***	-1.336***	-10.985***	0.817***	0.324	1504
	(0.005)	(0.106)	(4.245)	(0.076)		
Energy & Basic Materials	-0.002	-2.603***	0.579	0.900***	0.556	1344
	(0.002)	(0.106)	(1.785)	(0.037)		
Technology	0.016***	-3.831***	-17.707***	1.271***	0.485	384
	(0.006)	(0.291)	(6.047)	(0.095)		
Consumer Staples	-0.019***	-1.731***	-11.781***	0.670***	0.324	960
	(0.003)	(0.103)	(3.627)	(0.064)		
Health Care	-0.030***	-3.582***	-8.870*	1.173***	0.429	992
	(0.003)	(0.171)	(4.695)	(0.076)		
Telecom	-0.021***	-0.949***	-1.6	0.525***	0.434	480
	(0.003)	(0.086)	(2.747)	(0.056)		
Financials	-	-	-	-	-	-
Real Estate	-	-	-	-	-	-

*Note: Standard errors are noted in parentheses. P-values are noted as: *** p < 0.01, ** p < 0.05, * p < 0.1*

Please note: Cells with no values indicate that there were insufficient observations to perform regressions for those specific datasets.

Appendix 7 - Results Regression (4) - Subsamples by Industry (FEM)

Industry	E-Score	S-Score	G-Score	Leverage	Volatility	Size	R^2	# Obs.
Industrials	0.013***	-0.009***	-0.001	-1.441***	-3.967**	0.842***	0.296	2944
	(0.002)	(0.002)	(0.001)	(0.075)	(1.816)	(0.037)		
Utilities	-0.001	0.002	-0.005***	-0.319***	0.805	0.380***	0.374	704
	(0.001)	(0.001)	(0.001)	(0.039)	(1.424)	(0.025)		
Consumer Discretionary	-0.020***	-0.035***	-0.014***	-1.322***	-11.520***	0.828***	0.329	1504
	(0.004)	(0.005)	(0.003)	(0.107)	(4.233)	(0.076)		
Energy & Basic Materials	-0.0002	0.004**	-0.005***	-2.568***	0.868	0.908***	0.565	1344
	(0.002)	(0.002)	(0.001)	(0.106)	(1.770)	(0.037)		
Technology	-0.014***	0.020***	0.013***	-4.092***	-16.495***	1.351***	0.509	384
	(0.005)	(0.005)	(0.004)	(0.293)	(5.962)	(0.096)		
Consumer Staples	-0.012***	0.0003	-0.006***	-1.699***	-12.388***	0.653***	0.331	960
	(0.003)	(0.003)	(0.002)	(0.104)	(3.631)	(0.064)		
Health Care	-0.014***	-0.016***	-0.002	-3.567***	-9.040*	1.160***	0.439	992
	(0.004)	(0.003)	(0.003)	(0.170)	(4.702)	(0.077)		
Telecom	-0.013***	-0.006**	-0.002	-0.969***	-0.73	0.534***	0.46	480
	(0.002)	(0.003)	(0.002)	(0.087)	(2.709)	(0.055)		
Financials	-	-	-	-	-	-	-	-
Real Estate	-	-	-	-	-	-	-	-

*Note: Standard errors are noted in parentheses. P-values are noted as: *** p < 0.01, ** p < 0.05, * p < 0.1*

Please note: Cells with no values indicate that there were insufficient observations to perform regressions for those specific datasets.

Appendix 8Results Regression (3.1) - Subsamples by Industry (REM)

Industry	Constant	ESG	Leverage	Volatility	Size	R^2	# Obs.
Industrials	2.288***	-0.0004	-1.502***	-3.612**	0.830***	0.268	2944
	(0.195)	(0.002)	(0.075)	(1.841)	(0.036)		
Utilities	1.096***	-0.006***	-0.362***	1.065	0.367***	0.321	704
	(0.146)	(0.002)	(0.039)	(1.467)	(0.025)		
Consumer Discretionary	7.202***	-0.067***	-1.356***	-10.618**	0.827***	0.323	1504
	(0.516)	(0.005)	(0.106)	(4.240)	(0.075)		
Energy & Basic Materials	2.049***	-0.003	-2.624***	0.321	0.868***	0.542	1344
	(0.256)	(0.002)	(0.105)	(1.799)	(0.036)		
Technology	1.829***	0.015**	-3.618***	-17.635***	1.189***	0.46	384
	(0.505)	(0.006)	(0.289)	(6.132)	(0.092)		
Consumer Staples	4.340***	-0.019***	-1.772***	-12.100***	0.566***	0.312	960
	(0.324)	(0.003)	(0.104)	(3.674)	(0.061)		
Health Care	5.177***	-0.029***	-3.607***	-7.65	1.100***	0.415	992
	(0.428)	(0.003)	(0.172)	(4.730)	(0.075)		
Telecom	2.682***	-0.022***	-0.965***	-1.875	0.497***	0.424	480
	(0.383)	(0.003)	(0.086)	(2.754)	(0.055)		
Financials	-	-	-	-	-	-	-
Real Estate	-	-	-	-	-	-	-

*Note: Standard errors are noted in parentheses. P-values are noted as: *** p < 0.01, ** p < 0.05, * p < 0.1*

Please note: Cells with no values indicate that there were insufficient observations to perform regressions for those specific datasets.

Appendix 9 - Results Regression (4) - Subsamples by Industry (REM)

Industry	Constant	E-Score	S-Score	G-Score	Leverage	Volatility	Size	R^2	# Obs.
Industrials	2.238***	0.012***	-0.009***	-0.001	-1.485***	-3.965**	0.800***	0.282	2944
	(0.197)	(0.002)	(0.002)	(0.001)	(0.074)	(1.832)	(0.036)		
Utilities	1.001***	-0.001	0.001	-0.005***	-0.329***	1.229	0.351***	0.345	704
	(0.145)	(0.001)	(0.001)	(0.001)	(0.039)	(1.445)	(0.025)		
Consumer Discretionary	7.391***	-0.020***	-0.035***	-0.014***	-1.346***	-11.159***	0.839***	0.327	1504
	(0.530)	(0.004)	(0.005)	(0.003)	(0.107)	(4.230)	(0.075)		
Energy & Basic Materials	1.911***	-0.001	0.004**	-0.005***	-2.588***	0.602	0.876***	0.551	1344
	(0.262)	(0.002)	(0.002)	(0.001)	(0.105)	(1.784)	(0.037)		
Technology	1.424***	-0.014***	0.019***	0.013***	-3.804***	-16.478***	1.245***	0.477	384
	(0.507)	(0.005)	(0.005)	(0.004)	(0.292)	(6.099)	(0.093)		
Consumer Staples	4.235***	-0.013***	0.001	-0.006***	-1.736***	-12.779***	0.552***	0.319	960
	(0.327)	(0.003)	(0.003)	(0.002)	(0.105)	(3.672)	(0.062)		
Health Care	5.388***	-0.014***	-0.016***	-0.002	-3.596***	-7.736	1.091***	0.425	992
	(0.432)	(0.004)	(0.003)	(0.003)	(0.171)	(4.737)	(0.075)		
Telecom	2.702***	-0.013***	-0.007***	-0.002	-0.992***	-1.134	0.504***	0.449	480
	(0.377)	(0.002)	(0.003)	(0.002)	(0.086)	(2.721)	(0.054)		
Financials	-	-	-	-	-	-	-	-	-
Real Estate	-	-	-	-	-	-	-	-	-

*Note: Standard errors are noted in parentheses. P-values are noted as: *** p < 0.01, ** p < 0.05, * p < 0.1*

Please note: Cells with no values indicate that there were insufficient observations to perform regressions for those specific datasets.

Appendix 10 Results Regression (3.1) - Subsamples by Country (FEM). DP proxy: Ohlson O-Score

Country	ESG	Leverage	Volatility	Size	R^2	# Obs.
Denmark	-0.0001 (0.001)	0.376*** (0.022)	2.475*** (0.567)	-0.015** (0.008)	0.635	320
Italy	-0.001** (0.000)	0.289*** (0.018)	1.000*** (0.309)	0.015* (0.008)	0.474	352
Netherlands	-0.002*** (0.000)	0.305*** (0.015)	0.241 (0.389)	-0.006 (0.007)	0.533	480
Switzerland	-0.00003 (0.000)	0.218*** (0.007)	1.514*** (0.211)	-0.029*** (0.004)	0.673	864
Spain	-0.0002 (0.000)	0.158*** (0.014)	0.551* (0.312)	-0.002 (0.007)	0.31	384
France	-0.0002 (0.000)	0.223*** (0.009)	1.822*** (0.199)	-0.032*** (0.004)	0.385	1504
Germany	0.0003 (0.000)	0.252*** (0.006)	-0.264 (0.226)	-0.021*** (0.004)	0.623	1152
Sweden	-0.0002 (0.000)	0.233*** (0.008)	0.243 (0.200)	-0.008** (0.003)	0.543	864
United Kingdom	-0.0005** (0.000)	0.249*** (0.006)	0.506** (0.197)	-0.027*** (0.004)	0.575	1888
Finland	-0.001*** (0.001)	0.374*** (0.024)	1.886*** (0.493)	-0.027*** (0.008)	0.447	480
Ireland	-0.00001 (0.000)	0.206*** (0.012)	0.246 (0.288)	-0.013** (0.006)	0.552	288
Austria	-	-	-	-	-	-
Belgium	-	-	-	-	-	-
Luxebourg	-	-	-	-	-	-
Norway	-	-	-	-	-	-
Poland	-	-	-	-	-	-
Portugal	-	-	-	-	-	-

*Note: Standard errors are noted in parentheses. P-values are noted as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$*

Please note: Cells with no values indicate that there were insufficient observations to perform regressions for those specific datasets.

Appendix 11 - Results Regression (4) - Subsamples by Country (FEM). DP proxy: Ohlson O-Score

Country	E-Score	S-Score	G-Score	Leverage	Volatility	Size	R^2	# Obs.
Denmark	0.001	0.001**	-0.001**	0.361***	2.774***	-0.019**	0.647	320
	(0.001)	(0.001)	(0.000)	(0.022)	(0.570)	(0.008)		
Italy	-0.001***	0.0005*	0	0.307***	0.888***	0.018**	0.504	352
	(0.000)	(0.000)	(0.000)	(0.018)	(0.302)	(0.008)		
Netherlands	-0.001***	-0.0004	0.001**	0.303***	0.19	-0.009	0.548	480
	(0.000)	(0.000)	(0.000)	(0.015)	(0.384)	(0.007)		
Switzerland	-0.00003	0.00002	-0.0001	0.219***	1.531***	-0.028***	0.673	864
	(0.000)	(0.000)	(0.000)	(0.007)	(0.213)	(0.004)		
Spain	0.0003	-0.001*	0.0002	0.154***	0.633**	-0.003	0.315	384
	(0.000)	(0.000)	(0.000)	(0.014)	(0.316)	(0.007)		
France	-0.002***	0.0003*	0.0003**	0.236***	1.815***	-0.030***	0.405	1504
	(0.000)	(0.000)	(0.000)	(0.009)	(0.196)	(0.004)		
Germany	0.001***	-0.0001	-0.0001	0.252***	-0.217	-0.021***	0.625	1152
	(0.000)	(0.000)	(0.000)	(0.006)	(0.231)	(0.004)		
Sweden	-0.0003**	0.0005***	-0.0002**	0.238***	0.334*	-0.008**	0.55	864
	(0.000)	(0.000)	(0.000)	(0.008)	(0.200)	(0.003)		
United Kingdom	-0.001***	-0.0002	0.0002*	0.250***	0.533***	-0.024***	0.578	1888
	(0.000)	(0.000)	(0.000)	(0.006)	(0.196)	(0.004)		
Finland	0.003***	-0.002***	-0.001***	0.393***	1.957***	-0.019**	0.478	480
	(0.001)	(0.001)	(0.000)	(0.023)	(0.481)	(0.009)		
Ireland	0.0003	-0.0004	0.0001	0.207***	0.196	-0.013**	0.557	288
	(0.000)	(0.000)	(0.000)	(0.012)	(0.289)	(0.007)		
Austria	-	-	-	-	-	-	-	-
Belgium	-	-	-	-	-	-	-	-
Luxebourg	-	-	-	-	-	-	-	-
Norway	-	-	-	-	-	-	-	-
Poland	-	-	-	-	-	-	-	-
Portugal	-	-	-	-	-	-	-	-

*Note: Standard errors are noted in parentheses. P-values are noted as: *** p < 0.01, ** p < 0.05, * p < 0.1*

Please note: Cells with no values indicate that there were insufficient observations to perform regressions for those specific datasets.

Appendix 12 Results Regression (3.1) - Subsamples by Country (REM). DP proxy: Ohlson O-Score

Country	Constant	ESG	Leverage	Volatility	Size	R^2	# Obs.
Denmark	-0.090*	0.0001	0.369***	2.521***	-0.015**	0.63	320
	(0.047)	(0.001)	(0.022)	(0.561)	(0.008)		
Italy	-0.055**	-0.0005*	0.284***	1.026***	0.007	0.475	352
	(0.024)	(0.000)	(0.017)	(0.312)	(0.007)		
Netherlands	0.053	-0.002***	0.295***	0.309	-0.003	0.531	480
	(0.035)	(0.000)	(0.014)	(0.391)	(0.006)		
Switzerland	0.034**	-0.00003	0.217***	1.536***	-0.027***	0.673	864
	(0.015)	(0.000)	(0.006)	(0.210)	(0.004)		
Spain	0.012	-0.0001	0.158***	0.537*	-0.003	0.327	384
	(0.031)	(0.000)	(0.013)	(0.310)	(0.007)		
France	0.055***	-0.0002	0.219***	1.845***	-0.029***	0.39	1504
	(0.018)	(0.000)	(0.009)	(0.198)	(0.004)		
Germany	0.018	0.0003	0.250***	-0.227	-0.023***	0.622	1152
	(0.019)	(0.000)	(0.006)	(0.225)	(0.004)		
Sweden	0.015	-0.0001	0.233***	0.229	-0.009***	0.539	864
	(0.016)	(0.000)	(0.007)	(0.199)	(0.003)		
United Kingdom	0.063***	-0.0004**	0.250***	0.496**	-0.026***	0.579	1888
	(0.017)	(0.000)	(0.005)	(0.195)	(0.003)		
Finland	0.028	-0.001**	0.354***	2.096***	-0.022***	0.438	480
	(0.038)	(0.001)	(0.023)	(0.496)	(0.007)		
Ireland	0.006	-0.0003	0.214***	0.278	-0.006	0.579	288
	(0.015)	(0.000)	(0.011)	(0.283)	(0.005)		
Austria	-	-	-	-	-	-	-
Belgium	-	-	-	-	-	-	-
Luxebourg	-	-	-	-	-	-	-
Norway	-	-	-	-	-	-	-
Poland	-	-	-	-	-	-	-
Portugal	-	-	-	-	-	-	-

*Note: Standard errors are noted in parentheses. P-values are noted as: *** p < 0.01, ** p < 0.05, * p < 0.1*

Please note: Cells with no values indicate that there were insufficient observations to perform regressions for those specific datasets.

Appendix 13 - Results Regression (4) - Subsamples by Country (REM). DP proxy: Ohlson O-Score

Country	Constant	E-Score	S-Score	G-Score	Leverage	Volatility	Size	R^2	# Obs.
Denmark	-0.174*** (0.057)	0.001 (0.001)	0.001** (0.001)	-0.001** (0.000)	0.358*** (0.022)	2.775*** (0.564)	-0.019** (0.008)	0.644	320
Italy	-0.057** (0.025)	-0.001*** (0.000)	0.0004* (0.000)	0.00002 (0.000)	0.301*** (0.018)	0.908*** (0.305)	0.011 (0.007)	0.497	352
Netherlands	0.032 (0.038)	-0.001*** (0.000)	-0.0003 (0.000)	0.001** (0.000)	0.297*** (0.014)	0.232 (0.384)	-0.006 (0.007)	0.547	480
Switzerland	0.034** (0.015)	-0.00002 (0.000)	0.00004 (0.000)	-0.0001 (0.000)	0.218*** (0.006)	1.556*** (0.212)	-0.026*** (0.004)	0.673	864
Spain	0.016 (0.033)	0.0003 (0.000)	-0.0005 (0.000)	0.0002 (0.000)	0.154*** (0.013)	0.620** (0.314)	-0.004 (0.007)	0.331	384
France	0.106*** (0.020)	-0.001*** (0.000)	0.0003* (0.000)	0.0003** (0.000)	0.231*** (0.009)	1.838*** (0.195)	-0.027*** (0.004)	0.407	1504
Germany	0.011 (0.020)	0.001*** (0.000)	-0.0003 (0.000)	-0.0001 (0.000)	0.250*** (0.006)	-0.193 (0.231)	-0.024*** (0.004)	0.626	1152
Sweden	-0.008 (0.018)	-0.0003** (0.000)	0.001*** (0.000)	-0.0002** (0.000)	0.238*** (0.008)	0.325 (0.199)	-0.009*** (0.003)	0.547	864
United Kingdom	0.059*** (0.017)	-0.0005*** (0.000)	-0.0002 (0.000)	0.0002* (0.000)	0.251*** (0.005)	0.519*** (0.195)	-0.024*** (0.004)	0.582	1888
Finland	-0.115** (0.045)	0.003*** (0.001)	-0.001*** (0.000)	-0.001*** (0.000)	0.376*** (0.023)	2.179*** (0.481)	-0.01 (0.008)	0.474	480
Ireland	0.001 (0.016)	-0.00001 (0.000)	-0.0004* (0.000)	0.0001 (0.000)	0.213*** (0.011)	0.258 (0.282)	-0.004 (0.005)	0.579	288
Austria	-	-	-	-	-	-	-	-	-
Belgium	-	-	-	-	-	-	-	-	-
Luxebourg	-	-	-	-	-	-	-	-	-
Norway	-	-	-	-	-	-	-	-	-
Poland	-	-	-	-	-	-	-	-	-
Portugal	-	-	-	-	-	-	-	-	-

*Note: Standard errors are noted in parentheses. P-values are noted as: *** p < 0.01, ** p < 0.05, * p < 0.1*

Please note: Cells with no values indicate that there were insufficient observations to perform regressions for those specific datasets.

Appendix 14Results Regression (3.1) - Subsamples by Industry (FEM). DP proxy: Ohlson O-Score

Industry	ESG	Leverage	Volatility	Size	R^2	# Obs.
Industrials	-0.0005***	0.267***	0.377***	-0.024***	0.454	2944
	(0.000)	(0.006)	(0.142)	(0.003)		
Utilities	0.001	0.270***	0.744*	0.001	0.471	704
	(0.001)	(0.012)	(0.437)	(0.008)		
Consumer Discretionary	0.0002	0.217***	2.068***	-0.036***	0.714	1504
	(0.000)	(0.005)	(0.192)	(0.003)		
Energy & Basic Materials	-0.001***	0.332***	0.563***	-0.0004	0.497	1344
	(0.000)	(0.010)	(0.170)	(0.004)		
Technology	0.0003	0.227***	0.992***	-0.007*	0.553	384
	(0.000)	(0.013)	(0.271)	(0.004)		
Consumer Staples	-0.0003	0.215***	0.496*	-0.030***	0.467	960
	(0.000)	(0.008)	(0.273)	(0.005)		
Health Care	-0.0002	0.231***	0.532***	-0.015***	0.622	992
	(0.000)	(0.006)	(0.169)	(0.003)		
Telecom	0.001	0.220***	0.682	-0.032***	0.38	480
	(0.001)	(0.015)	(0.480)	(0.010)		
Financials	-	-	-	-	-	-
Real Estate	-	-	-	-	-	-

*Note: Standard errors are noted in parentheses. P-values are noted as: *** p < 0.01, ** p < 0.05, * p < 0.1*

Please note: Cells with no values indicate that there were insufficient observations to perform regressions for those specific datasets.

Appendix 15Results Regression (3.1) - Subsamples by Industry (REM). DP proxy: Ohlson O-Score

Industry	Constant	ESG	Leverage	Volatility	Size	R^2	# Obs.
Industrials	0.055***	-0.0004***	0.266***	0.385***	-0.023***	0.457	2944
	(0.012)	(0.000)	(0.006)	(0.141)	(0.003)		
Utilities	-0.056	0.0002	0.264***	1.054**	-0.005	0.469	704
	(0.034)	(0.001)	(0.011)	(0.434)	(0.007)		
Consumer Discretionary	0.030*	0.0003	0.217***	2.063***	-0.035***	0.712	1504
	(0.017)	(0.000)	(0.005)	(0.191)	(0.003)		
Energy & Basic Materials	0.001	-0.001***	0.312***	0.623***	-0.001	0.491	1344
	(0.018)	(0.000)	(0.009)	(0.170)	(0.003)		
Technology	-0.026	0.0003	0.231***	1.004***	-0.009**	0.553	384
	(0.022)	(0.000)	(0.013)	(0.270)	(0.004)		
Consumer Staples	0.081***	-0.0002	0.216***	0.496*	-0.028***	0.468	960
	(0.021)	(0.000)	(0.008)	(0.272)	(0.004)		
Health Care	-0.002	-0.0001	0.228***	0.522***	-0.014***	0.621	992
	(0.010)	(0.000)	(0.006)	(0.168)	(0.003)		
Telecom	0.007	0.001*	0.204***	0.754	-0.037***	0.402	480
	(0.035)	(0.000)	(0.013)	(0.472)	(0.007)		
Financials	-	-	-	-	-	-	-
Real Estate	-	-	-	-	-	-	-

*Note: Standard errors are noted in parentheses. P-values are noted as: *** p < 0.01, ** p < 0.05, * p < 0.1*

Please note: Cells with no values indicate that there were insufficient observations to perform regressions for those specific datasets.

Appendix 16 - Results Regression (4) - Subsamples by Industry (FEM). DP proxy: Ohlson O-Score

Industry	E-Score	S-Score	G-Score	Leverage	Volatility	Size	R^2	# Obs.
Industrials	-0.00005	-0.0001	-0.0003***	0.267***	0.401***	-0.024***	0.455	2944
	(0.000)	(0.000)	(0.000)	(0.006)	(0.142)	(0.003)		
Utilities	-0.0003	-0.0001	0.001***	0.265***	0.718*	0.003	0.477	704
	(0.000)	(0.000)	(0.000)	(0.012)	(0.435)	(0.008)		
Consumer Discretionary	-0.001***	0.001***	0.0001	0.219***	2.094***	-0.035***	0.716	1504
	(0.000)	(0.000)	(0.000)	(0.005)	(0.191)	(0.003)		
Energy & Basic Materials	-0.001***	-0.0003	0.0001	0.327***	0.541***	-0.003	0.506	1344
	(0.000)	(0.000)	(0.000)	(0.010)	(0.169)	(0.004)		
Technology	0.001***	0.0005**	-0.001***	0.225***	1.052***	-0.010**	0.598	384
	(0.000)	(0.000)	(0.000)	(0.013)	(0.259)	(0.004)		
Consumer Staples	-0.0002	0.0001	-0.0001	0.216***	0.479*	-0.030***	0.468	960
	(0.000)	(0.000)	(0.000)	(0.008)	(0.274)	(0.005)		
Health Care	-0.0003**	-0.0001	0.0001	0.231***	0.535***	-0.015***	0.624	992
	(0.000)	(0.000)	(0.000)	(0.006)	(0.170)	(0.003)		
Telecom	0.0003	0.0004	0.0001	0.220***	0.681	-0.032***	0.38	480
	(0.000)	(0.001)	(0.000)	(0.016)	(0.484)	(0.010)		
Financials	-	-	-	-	-	-	-	-
Real Estate	-	-	-	-	-	-	-	-

*Note: Standard errors are noted in parentheses. P-values are noted as: *** p < 0.01, ** p < 0.05, * p < 0.1*

Please note: Cells with no values indicate that there were insufficient observations to perform regressions for those specific datasets.

Appendix 17 - Results Regression (4) - Subsamples by Industry (REM). DP proxy: Ohlson O-Score

Industry	Constant	E-Score	S-Score	G-Score	Leverage	Volatility	Size	R^2	# Obs.
Industrials	0.052***	0.00002	-0.0001	-0.0003***	0.266***	0.415***	-0.023***	0.458	2944
	(0.012)	(0.000)	(0.000)	(0.000)	(0.006)	(0.142)	(0.003)		
Utilities	-0.037	-0.0002	-0.001	0.001***	0.258***	0.999**	-0.002	0.479	704
	(0.035)	(0.000)	(0.000)	(0.000)	(0.011)	(0.431)	(0.007)		
Consumer Discretionary	0.021	-0.001***	0.001***	0.0002	0.219***	2.091***	-0.033***	0.715	1504
	(0.018)	(0.000)	(0.000)	(0.000)	(0.005)	(0.190)	(0.003)		
Energy & Basic Materials	0.02	-0.001***	-0.0002	0.0001	0.308***	0.603***	-0.003	0.497	1344
	(0.019)	(0.000)	(0.000)	(0.000)	(0.009)	(0.169)	(0.003)		
Technology	-0.031*	0.001**	0.0004*	-0.0004**	0.235***	1.081***	-0.016***	0.573	384
	(0.019)	(0.000)	(0.000)	(0.000)	(0.013)	(0.276)	(0.004)		
Consumer Staples	0.080***	-0.0002	0.0001	-0.0001	0.217***	0.483*	-0.028***	0.468	960
	(0.021)	(0.000)	(0.000)	(0.000)	(0.008)	(0.273)	(0.004)		
Health Care	0.0004	-0.0002**	-0.0001	0.0001	0.228***	0.521***	-0.014***	0.623	992
	(0.011)	(0.000)	(0.000)	(0.000)	(0.006)	(0.169)	(0.003)		
Telecom	0.003	0.0002	0.0003	0.0003	0.205***	0.73	-0.037***	0.4	480
	(0.037)	(0.000)	(0.000)	(0.000)	(0.013)	(0.474)	(0.008)		
Financials	-	-	-	-	-	-	-	-	-
Real Estate	-	-	-	-	-	-	-	-	-

*Note: Standard errors are noted in parentheses. P-values are noted as: *** p < 0.01, ** p < 0.05, * p < 0.1*

Please note: Cells with no values indicate that there were insufficient observations to perform regressions for those specific datasets.

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