**Nijmegen School of Management**
**Department of Economics and Business Economics**
**Master's Thesis Economics (MAN-MTHEC)**

# Punish the Bad, Reward the Good? The Effect of Corporate Environmental Performance on Cost of Debt.

K.M.M. (Kelvin) van Aken, BSc

(S1026594)

Nijmegen, 29 June 2025

Program: Master's Program in Economics
Specialisation: Corporate Finance & Control
Supervisor: Dr. S.C. (Sascha) Füllbrunn

Radboud Universiteit

*Statement on generative AI:* ChatGPT was used to assist in coding for R for the analysis of this thesis. Appendix A of this thesis provides a detailed account of the use of generative AI tools during the development of this thesis. By submitting this thesis I declare that I am fully responsible for the accuracy and completeness of its content.

## Abstract

Studies looking at the relation between environmental performance and cost of debt mainly focus on the US and Asia, while work for European listed firms is sparse and yields contradictory results. As such, this thesis aims to add to sustainable finance literature by extending the work on European listed firms with regard to the effect of environmental performance on cost of debt, while also zooming in on the specific driving effects behind environmental performance and different firm characteristics. The panel consists of 499 firms that have been listed on the STOXX Europe 600 between 2020-2023. Using pooled OLS, fixed effects, random effects, system GMM and propensity score matching models, the results turn out to be inconsistent. While some models show a significant effect, the models that account for unobservable firm specific characteristics do not. Omitted variable bias seems most likely to be the driver behind these differing results. The findings refute all seven hypotheses as there seems to be no effect of environmental performance on cost of debt. I argue that the absence of a relation between the two is most likely due to the short time span of the data or interest starting to shift away from sustainability.

# Table of Contents

# 1 Introduction

A recent report by the Intergovernmental Panel on Climate Change (IPCC) points out that the surface temperature worldwide has risen about 1.1 degrees Celsius since the late 1800's (IPCC, 2023). According to the IPCC, this means a severely increased risk for extreme weather conditions like droughts, hurricanes, floods, heatwaves, wildfires and heavy rainfall. Many parts of the world will be uninhabitable as a result of these weather conditions and the rise of the sea level. Following the IPCC reports it becomes clear that climate change is one of the most pressing issues of the current time and has been named the biggest market failure to ever exist by Stern (2006).

Since these threats have become more obvious throughout the last decades, sustainability has become an increasingly important topic for scholars, firms and society as a whole (Li & Zhang, 2023). As a result, investors started to incorporate environmental, social and governance (ESG) scores of firms into their investment decisions (Amel-Zadeh & Serafeim, 2018). Focus started to shift more towards sustainable investing with the purpose of making positive contributions to society (Michelson et al., 2004; Hoepner et al., 2016). Investors have become more inclined to invest in firms with high ESG scores, because they have improved confidence in the performance of those firms and see them as less risky, which in turn improves the financial performance of these firms (Friede et al., 2015). Moreover, financial metrics are no longer the sole determinant of credit decisions for creditors as well, pushing the importance of non-financial factors for firms even further (Birindelli et al., 2015; Hoepner et al., 2016; Eliwa et al., 2021).

As ESG performance of a firm increases, it leads to an increased demand for that firm's debt and equity because investors and creditors value its commitment to sustainability. More demand, ceteris paribus, means that a firm can sell equity for higher prices and pay less interest on debt, which increases the financial performance as total cost of capital decreases (Liu et al., 2022). ESG therefore seems to affect cost of capital through risk (Apergis et al., 2022). Findings in the literature, however, are not unanimous about the effect of ESG on cost of capital (Maaloul et al., 2023). That might be due to mitigating effects caused by the S and the G pillars as investors value the E pillar more than the other two pillars (Ng & Rezaee, 2015; Rapp & Roser, 2024).

Cost of capital consist of the combined cost of debt and equity. Literature however, mainly focusses on the equity side which leaves much unknown about the debt side (Gigante &

Manglaviti, 2022). Since the S and G pillars are seen as less important by investors and little is known about the debt side, this study delves deeper into the effects of corporate environmental performance on cost of debt. The main research question will be: '*To what extent does corporate environmental performance affect cost of debt?*' Sub questions will be focussed on finding out how this effect is driven through the E pillar categories and what roles industry and firm characteristics such as size and leverage play. The E pillar consists of three categories: emissions, innovations and resource use. It is unknown which category is most important to investors and is the driving factor behind the relation between corporate environmental performance and cost of debt. The work in this study contributes to the topic of sustainable finance by separating and comparing the different categories of the E pillar and their effects on cost of debt, which to my knowledge has not been done yet. Especially for European firms, literature on the topic is limited with the only work on the topic being performed by Eliwa et al. (2021) and Gigante & Manglaviti (2022). Their works however, yield contradictory results which shows that the state of knowledge is not complete. As such, this thesis will extend on their works and looks at the effect of environmental performance on cost of debt for European listed firms.

Environmental performance affects cost of debt via risk, as stated by Bauer & Hann, 2010. Risk for regulatory fines, reputational damage and litigation threats is higher for firms that perform badly with regard to sustainability (Cheng et al., 2014; Apergis et al., 2022). These risks are anticipated by creditors who integrate those factors into their creditworthiness assessment. Creditors want to be rewarded for risk that they assume, so any additional risk that a creditor takes on by lending to risky firms has to be rewarded. Firms with superior environmental performance are better organised (Ferrell et al., 2016) and more in line with social values (Dowling & Pfeffer, 1975). However, in a market of asymmetric information, according to the theory of Akerlof (1978), creditors would have a hard time to differentiate between sustainable and unsustainable firms. So in order to be seen as sustainable, firms want to signal to creditors that they are in fact legitimate with regard to their commitment to sustainability. To do so a costly signal has to be sent to creditors to convince them of the firm's legitimacy (Spence, 1978). A costly signal comes in the form of improved environmental performance from which creditors can see that the particular firm is future oriented, better managed and acts in line with social values. As such, creditors will see that firms as less risky which leads the creditors to charge lower interest rates.

To test the hypotheses I use a dataset that spans the years 2020-2023 and consists of 499 European firms that at some point between 2020 and 2023 have been listed on the STOXX Europe 600. Environmental performance is the main independent variable and is measured as the E pillar score of ESG. Cost of debt are measured using accounting-based measures such as interest expense to average debt and interest expense to total debt. To test the hypotheses I use several econometric techniques, consisting of pooled OLS, fixed effects, random effects, system GMM and propensity score matching models. The results from these tests show to be inconsistent with the pooled OLS, random effects and propensity score matching models showing negatively significant results, whereas the fixed effects and system GMM models show that there is no effect.

In the continuously growing amount of research into sustainability related topics, my work ads by extending current work on environmental performance and cost of debt by providing clarity for the European market and the driving factors behind environmental performance using the most recent data. Given the limitations of this thesis, the results show that environmental performance does not affect cost of debt and any significant results that I have found are most likely driven by omitted variable bias. My work shows firms and managers that investments in improving their environmental performance will not result in lower cost of debt. For scholars this thesis is interesting as it challenges the notion that environmental performance and cost of debt are inversely related and I provide different ways to extend the work that I have done. For policymakers it shows that current policy emphasizing sustainable behaviour by firms is not rewarded by lending institutions and as such these policies have to be altered.

Following the introduction, this thesis will continue with chapter 2 which discusses the theory and literature and presents the hypotheses. Chapter 3 explains the methods and data in detail. Chapter 4 presents the results. Chapter 5 interprets, reviews and discusses the implications of the results. Chapter 6 summarizes what has been done in this thesis, what the results mean and how future work should continue based on the results of this thesis.

# 2 Theory & Literature

The theory & literature chapter first establishes a link between environmental performance and cost of debt via economic theory. Then, the literature review section shows how theory relates to practice. The chapter concludes with the hypotheses that flow from the theoretical assumptions.

## 2.1 Theoretical Framework

Cost of debt are the interest expenses that firms pay for capital that they borrow from lenders. Firms want to maximise their debt portion because the increased benefits through a tax shield mean fewer real costs on debt because those tax costs are partly deductible. However, the downside to taking on large amounts of debt is increased bankruptcy risk (Hackbarth et al., 2006). As assumed debt increases, so do the interest costs associated with debt. Since this debt is taken on for, quite often, a long period of time, costs for this debt are also a constant expenditure for a long time. Following this, the firm gets exposed to increased liquidity and credit risk, evolving the firm into a riskier investment in the eyes of investors (Stiglitz, 1972). A steep increase in both the cost of debt and the cost of equity is the result, leading to greatly increased cost of capital. Therefore, the goal for firms is to maximize their debt portion, while keeping the cost of distress in check.

Environmental performance is connected to cost of debt, and as such to cost of distress, via risk, as stated by Bauer & Hann (2010). Risk is the probability that money invested or lent to a firm will not be returned to its owner at some agreed on time in the future. Risk directly affects cost of debt because creditors have to be rewarded for the risk that they take on. This reward is in the form of higher interest. As risk increases, so do cost of debt and when risk decreases, cost of debt do as well.

Firms that perform badly with regard to their sustainability practices, face higher risk for regulatory fines, reputational damage and litigation threats (Apergis et al., 2022). Creditors anticipate these dangers as the chance that these events happen increases with inferior environmental performance. As a result, creditors will demand higher compensation for the additional risk that they take on. Opposite to these firms are the ones displaying superior environmental performance. Showing good environmental performance shows creditors that these firms are better managed, less exposed to climate related risks and more focussed on the long term.

Better environmental performance is seen as a sign of superior corporate governance and future orientation (Ferrell et al., 2016). For creditors, the environmental performance of a firm reflects the extent to which the firm is future oriented. Creditors want to work with future oriented firms because these firms plan for the long term and are not as easily surprised by shocks related to climate, such as droughts, floods and new regulations. Besides, firms aim to keep the nature of their business activities in line with social values or rules (Dowling & Pfeffer, 1975). If the activities of the firm differ from social values in fact or appearance, a firm will be seen as illegit. For firms it is therefore not only important to be future proof by limiting the dangers that climate change poses to them, but also to act in a legitimate way with regard to social values.

As such, recent developments have pushed firms towards not only caring about profits anymore, but also about the general wellbeing of the planet and its inhabitants. Simply put, firms have started to incorporate non-financial factors into their performance review and goals (Hoepner et al., 2016). A growing amount of research argues that firms should not be lead purely for the benefit of its owners, but rather to create value for all stakeholders (Freeman et al., 2010). Following this perspective, environmental performance would not only be something for the purpose of compliance or risk, but rather a necessary responsibility to stakeholders. Firms that have better environmental performance show commitment to stakeholders, which improves its reputation and public trust in the firm (Cheng et al., 2014). By doing so, these firms show creditors that they focus on sustainability and care for the public, which is increasingly valued by creditors. Environmental performance can therefore influence cost of debt via decreased non-financial risk, long term stability and socially responsible practices. Creditors, in turn, recognize that firms with better environmental performance have a lower chance of facing litigation threats, reputational crises and regulatory struggles (Apergis et al., 2022).

On the other hand, if environmental performance of a firm is bad, the public and media will see the firm as illegit and start to ostracise the firm. Creditors are less inclined to do business with such firms as it threatens their public image as well. Investors and lenders often want to create a long term relation with a firm. When a firm shows that it is legitimate, a long term relation is less likely to fail. As a result, share prices increase, firms become more valuable and it gets easier for them to attract cheap debt because lenders are more inclined to lend to firms that seem more legitimate.

For firms the challenge with regard to legitimacy lies in getting their message across to the receiver. In a market of asymmetric information, it is hard for the public and lenders to assess to which extent a firm is legitimate, because the parties do not possess the same information about the firm. Asymmetric information creates the problem that investors do not know whether a firm is trustworthy. As described by Akerlof (1978), if one party has less information than the other party, the uninformed party cannot distinguish legitimate from illegitimate. To avoid this scenario, firms will have to show that they are in fact legitimate. In the case of the corporate debt market, firms can signal that they are of high quality and trustworthy by increasing their environmental performance.

Increasing environmental performance is seen as a costly action. A costly action signals to the creditor that the firm is trustworthy (Spence, 1978). Only firms of high quality, and therefore high credibility, can bear the cost of sending a costly signal to creditors. By doing so, they distinguish themselves from firms of low quality that cannot afford such actions. In practice this is shown by Clarkson et al. (2008) who look at the relation between environmental performance and environmental disclosure. Focussing on voluntary disclosure, they find that firms with better environmental performance are more transparent in their reporting and have improved quality of environmental disclosures compared to firms with lower levels of environmental performance. They argue that this is the case because the firms of lower quality cannot mimic the firms of higher quality as publishing environmental disclosures will show the public that their environmental performance is in fact not good.

Pursuing legitimacy is important to a firm, however it must be done cautiously as it can come with negative consequences, which are outlined by Ashforth & Gibbs (1990). If a firm tries to push their legitimacy when they are in fact not legitimate, it is received by the public as deception. In the case of environmental performance, this threat exists in the form of greenwashing (de Freitas Netto et al., 2020). When firms try to overemphasize their legitimacy with regard to environmental performance, the public can become wary as they fear greenwashing. To avoid being seen as a greenwasher, firms with inferior environmental performance do not disclose voluntarily. As such, high environmental performance can be seen as costly signal to show creditors that a firm is of high quality. Creditors will receive this message and charge lower interest on the loans since they deem that firm trustworthy and credible.

In summary, firms try to keep risk of distress and their distress costs at a minimum, while maximising their debt portion. They signal their legitimacy in order be able to benefit from cheaper debt. Environmental performance is used to signal information about the legitimacy with regard to low levels of distress, commitment to social values and future orientation. These signals are then picked up by creditors that deem these firms legitimate. Increased legitimacy reassures the creditors about the trustworthiness of a firm. These firms are then seen as a safer investment and will be charged lower lending rates, resulting in lower cost of debt for these firms.

## 2.2 Literature Review

The literature review discusses empirical results, starting with the development of research into corporate sustainability, followed by sustainability from the creditor's perspective. The three different branches of research into cost of debt are briefly touched upon, which shows a gap mainly in the research area using accounting-based means of measure. Then firm differences and research into the categories of the E pillar are discussed. The chapter concludes with the development of the hypotheses.

### 2.2.1 Research into Sustainability

The debate about whether corporate environmental performance affects firm performance in practice, has been going on since the 1970's with earliest works on the topic dating back to the late 1950's (Ali et al., 2023). In the work from Levitt (1958) he stated his frustration with the practice of firms concerning themselves with socially responsible activities, stating that welfare is not a firm's business, but its only strive should be to be as profitable as possible. Climate related performance by firms and their performance in financial sense have not always been seen as having a positive relation (Murphy, 2002). Although, this has changed throughout the last decades, many researchers have long seen a relation between the two as a negative development (Sharfman & Fernando, 2008). Expenditures to limit pollution and waste were viewed as a waste of money for a long time by investors as all money spent on these preventative measures could not be invested for profits and was seen as lost funds (Mahapatra, 1984). This view changed however, as investors started to realize that these preventative measures often meant that firms became more efficient with their resources (Barney, 1991; Hart, 1995). Fewer resource use meant that firms became more efficient and therefore more profitable. As such, investments to improve environmental performance started to be seen as positive developments. Some of the earliest empirical work on the relation between environmental performance and firm performance that shows an effect of pollution on firm performance came from Spicer (1978) in which he proposes that firms with better control over their pollution seem to show better financial performance than their peers with less control over their polluting activities. Although, Spicer's work later turned out to be flawed due to statistical inconsistencies as was shown by Chen & Metcalf (1980), it set the stage for further research into the effects of environmental performance on firm performance.

### 2.2.2 Environmental Performance and Cost of Debt

Besides investors, it also triggered banks' interest into environmental performance as to what extent it could affect the credit risk of firms (Ali et al., 2023). Environmental data became more important to banks, as they want reliable and comparable information in order to be able to make considered decisions about a firm's risk and performance with regard to their sustainability. This has been empirically shown to be true as Caragnano et al. (2020) find that corporate information about environmental performance is viewed as very important when assessing credit risk of those firms. In their paper they call for firms to be more open and complete with regard to communication about their environmental performance. In line with those findings, Balvers et al. (2017) empirically show that lenders charge significantly less interest to firms when their environmental performance report is of higher quality and punish firms that publish environmental data of lesser quality. These findings are supported by Du et al. (2017), who find that lenders are more inclined to lend to firms with improved environmental performance and that cost of debt of those firms are significantly lower as a result. In another study performed by Shad et al. (2020) they empirically show that reporting on non-financial information increases value of those firms and is associated with a decrease in interest charged, as in line with legitimacy and signalling theory.

The importance of environmental performance is reflected via the way in which creditors price in its associated risk. In empirical research this risk is measured as cost of debt. Research into environmental performance and cost of debt can be divided into three major categories: accounting-based[1] research which looks at some form of interest expense to debt, market-based[2] research which looks at loan spreads or yield to maturity and rating-based[3] research which looks at credit ratings that a firm receives on their bonds or on the firms as a whole. Although these measures differ slightly in their sensitivity and what they measure, research overall agrees on a negative link between environmental performance and cost of debt.

The only work that I could find that challenges the findings mentioned before is that of Gigante & Manglaviti (2022). In their work they use a sample of European firms over the time span of 2018-2020. Using interest expense to average debt in a sharp regression discontinuity model, they find that ESG performance and its subcomponent the E pillar are unrelated to cost of debt. This is a rather interesting finding as it shows contradiction with regard to findings for the European market. For instance, the work of Eliwa et al. (2022) looks at listed European firms as well, but they do find an effect of the E pillar on cost of debt measured as interest expense to total debt.

### 2.2.3 Firm Differences

Delving deeper into the effects of environmental performance on cost of debt, it appears that these effects are not universal. Cohen et al. (1995) were some of the first to delve into the differences between firms and showing that firms classified as low polluting perform better than firms classified as high polluting. In support of this, Erragragui (2018) argues that the industry to which a firm belongs greatly influences the relation between environmental performance and

[1] See: Nehrt, 1996; Izzo & Magnanelli, 2012; Eliwa et al., 2021; Gigante & Manglaviti, 2022.
[2] See: Cohen et al., 1995; Dowell et al., 2000; Nikolaev & Van Lent, 2005; Graham & Maher, 2006; Chava, 2014; Eichholtz et al., 2019.
[3] See: Graham et al., 2001; Schneider, 2010; Bauer & Hann, 2010; Apergis et al., 2022.

cost of debt. This is further investigated by Zhu et al. (2025), who zoom in on differences between polluting and non-polluting industries in China for the years 2009-2022 and find that indeed the effects are more pronounced for polluting industries as their level of distress is already higher than that of others. These results are substantiated by Li et al. (2023), but they also find that benefits from improvements in environmental performance are stronger for large firms than they are for small ones. Addressing firm differences even further, Alves & Meneses (2024) propose that credit risk is the main reason why environmental performance should have an effect on cost of debt. As such, they state that firms with higher leverage, who face higher levels of credit risk than their counterparts with lower leverage, see stronger effects from environmental performance on cost of debt.

### 2.2.4 Categories

Looking at the categories specifically, only for emissions work has been done with regard to its effect on cost of debt. For instance a study by Pizzutilo et al. (2020) who look at carbon intensity measured as carbon emissions divided by size. They find that firms that are more carbon intense face higher cost of debt. These results have also been found by Kim et al. (2015) and Noh (2018). For innovation and resource use there is no work that looks at their effect on cost of debt. There are however, multiple studies that look at effects of innovation and resource use on some form of firm performance. For instance a study by Griliches (2007), who shows that increased R&D expenditures lead to higher productivity in firms. Looking at the relation between innovations aimed at reducing pollution and productivity, Biggi et al. (2023) find that firms that perform better with regard to reducing pollution score higher levels of productivity. In a study performed by Modi & Mishra (2011) they look at how resource efficiency can affect Tobin's Q, return on assets and stock returns. Findings show that firms focussing more on resource efficiency show improved values for Tobin's Q, return on assets and stock returns. A study focussing on the same relation but for SMEs, shows that even for small and medium firms this effect persists as there seems to be a link between resource efficiency and firm performance (Faisal et al., 2021).

### 2.2.5 Existing Gap

The field of ESG related literature is still changing rapidly as data quality is improving and relations are delved into more elaborately. Literature however, mainly looks at the US[4] or Asia[5]. It seems that for the European market findings are unclear. Eliwa et al. (2021) claim there is an effect for listed firms acting on the European market, whereas Gigante & Manglaviti (2022) find there to be no effect. Add the fact that no work has been done to see which of the categories of the E pillar drives its effect and it becomes clear that there are quite some gaps when looking at environmental performance and cost of debt. The goal of this thesis therefore, will be to extend the work done by Eliwa et al. (2021) and Gigante & Manglaviti (2022) on the European market by focussing specifically on environmental performance and cost of debt, while also delving into the different categories of the E pillar to find which is the driving force behind the effect of environmental performance on cost of debt.

## 2.3 Hypotheses

Based on the theory, and supported by empirical evidence from the literature, there seems to be a relation between environmental performance and cost of debt. Firms want to come across as credible, legitimate and caring about society and do this via costly signals in the form of increased environmental performance. Good environmental performance therefore shows that a firm is trustworthy and future oriented, traits that are appreciated by creditors. As outlined in section 3.2.2, environmental performance is a positive value that increases as performance improves. Cost of debt is a positive value as well, which I expect to decrease for higher values of environmental performance. As such, I expect to find that environmental performance negatively affects cost of debt. For the categories most work has been done with regard to financial performance of the firm and almost no work has looked at their relation with cost of debt. Based on theory and findings in the literature, I expect to find a negative effect of the categories on cost of debt. For the emissions score this will most likely be the strongest as investors find scope 1 & 2 emissions the most important environmental topic (Chalmers et al., 2021). The effects of the

[4] See: Graham & Maher, 2006; Bauer & Hann, 2010; Schneider, 2010; Chava, 2014; Eichholtz et al., 2019; Apergis et al., 2021.

[5] See: Shad et al. 2020; Li et al., 2023; Yan et al., 2024; Zhao et al., 2024; Zhu et al., 2025.

category scores work the same as the score for environmental performance. Namely, the category scores are scored based on performance in that category. For instance, lower $CO_2$ emissions lead a higher emission score and vice versa. A higher score for the categories means that firms perform better in those categories than peers and as such it will lead to lower cost of debt. Therefore, this leads to the following hypotheses:

*$H_1$: Corporate environmental performance has a negative effect on cost of debt.*

*$H_2$: The emissions score has a negative effect on cost of debt.*

*$H_3$: The innovations score has a negative effect on cost of debt.*

*$H_4$: The resource use score has a negative effect on cost of debt.*

Concerning the difference between how firms react, quite some research into it has been done as outlined in the literature review. Via theory it can be argued that firms in polluting industries are already under stricter rules and heavier scrutiny than firms that are in non-polluting industries. In this way it seems logical that for the polluting firms environmental performance is especially important when assessing firm risk. For instance via the legitimacy theory which would argue that firms in polluting industries have a great incentive to show that they are legit and different than the other firms in those industries. Firms in polluting industries have more room to gain in environmental performance than firms in non-polluting industries. In line with the signalling theory this would mean that firms in polluting industries have to take a more costly action to signal that they are in fact focussed on sustainability and the long term. Therefore, this signal can be perceived as more credible and as a results reductions in cost of debt will be stronger. The findings by Cohen et al. (1995), Erragragui (2018) and Zhu et al. (2025) in combination with reasoning from theory, suggest that the effect of environmental performance on cost of debt is indeed stronger for firms in polluting industries than for firms in non-polluting industries. This leads to the following hypothesis:

*$H_5$: The effect of corporate environmental performance on cost of debt is stronger in polluting industries than in non-polluting industries.*

Attracting credit is easier for larger firms than for smaller firms (Li et al., 2024). Creditors find larger firms more trustworthy because they have less risk of bankruptcy and are often more transparent, decreasing asymmetric information and making creditors more inclined to lend to larger firms (Stiglitz & Weiss, 1981). In line with signalling theory is that better transparency should make changes in environmental performance better visible to creditors, decreasing the cost of debt for larger firms more strongly (Li et al., 2024). More trust from lenders in combination with better visibility of changes in environmental performance means that the effect of environmental performance on cost of debt for large firms should be stronger than it is for smaller firms. As such, cost of debt decrease more strongly for larger firms when environmental performance improves. This leads to the following hypothesis:

*$H_6$: The effect of corporate environmental performance on cost of debt is stronger for large firms.*

As outlined by Alves & Meneses (2024), credit risk could the biggest reason why cost of debt are affected by environmental performance. Firms with higher leverage have already higher solvability threats which makes their baseline credit risk higher than firms that have no solvability threats. The trade-off theory argues that this means that strongly levered firms already face higher cost of debt as a result of higher bankruptcy risk (Saba, 2024). Signalling and signs of legitimacy are therefore extra important for these kinds of firms as it will most likely lower their cost of debt more strongly compared to firms with low debt that already face lower cost of debt. In the latter case, decreases in cost of debt as a result of improved environmental performance would only be marginal. This leads to the following hypothesis:

*$H_7$: The effect of corporate environmental performance on cost of debt is stronger for highly levered firms.*

# 3 Methods & Data

## 3.1 Methods

The Methods paragraph provides an extensive overview of the methods that are applied in this thesis. I use Pooled OLS, fixed effects models and a random effects model to see which has the best fit as done by Malik & Kashiramka (2024). Several different forms of those methods are used in order to ensure robustness and to control for possible threats to validity. First as baseline model a pooled OLS will be used to test the main hypothesis. Then fixed and random effects models are applied as well to see which one has the best fit. For the hypotheses about size and leverage having a moderating effect, interaction terms are used to test this effect (Saba, 2024). Further testing will be done via sample splitting in which the samples are split based on size and leverage to see if these results differ per sample (Li et al., 2024). Differences between industries will be tested for by separating polluting vs. non-polluting firms in order to see whether the effects differ. To test for endogeneity in the form of simultaneity, section 3.1.4 details the system GMM model that controls for the possibility that not only environmental performance affects cost of debt but also for the possibility that cost of debt affects environmental performance (Ballester et al., 2025). Then, to test if the sample suffers from selection bias, propensity score matching is applied.

### 3.1.1 Pooled OLS Models

To start the testing, I use a pooled ordinary least squares model. This is a simple model that is often used in cross sectional time series studies. The pooled OLS model provides a good baseline to test the relation between corporate environmental performance and cost of debt and is often used to test assumptions that relate to the topic of this thesis (Chen & Silva Gao, 2012; Eliwa et al., 2021). The baseline model as presented below shows the equation for the pooled model. Based on this model I will test different variations to see how the variables react and which form of the model is the best suiting for the data. I use a model without winsorization to compare to the winsorized model to see whether winsorization effectively rids the data of outliers and improves the model (Eliwa et al., 2021). Then I use models with lagged values for the independent variable followed by models that apply industry (Apergis et al., 2022), country (Loanna & Serafeim, 2012) and year (Rong & Kim, 2024) fixed effects. After that, I run models with interaction terms for environmental performance with debt-to-equity ratio and the logarithm of total assets. Due to the nature of the data, I expect heteroscedasticity to be present but this will be tested via a Breusch-Pagan test in section 3.2.1. To correct for possible intra firm correlation, clustered standard errors at the firm level are used in the models.

The pooled OLS model specifically looks at variation between firms as it does not control for unobservable firm specific characteristics that might affect corporate environmental performance and cost of debt. Unobservable firm specific characteristics are traits that are unique to a single firm and are not in the model. As long as these factors are uncorrelated with the dependent and independent variables, this is not a problem. However, when these unobserved firm specific factors are correlated to the dependent and independent variables, the model may become biased as the pooled model can assign effects that are not caused by the estimator to the estimator, because it is unclear for the model where these effects come from. For instance, if higher corporate environmental performance is associated with lower cost of debt, the pooled model cannot estimate whether this is because firms with higher environmental performance have lower cost of debt due to an effect of A on B or if there is a third factor (e.g. corporate governance) which affects both environmental performance and cost of debt. If the latter is the case, then the pooled OLS is biased and does not give a good representation of the relation.

The baseline pooled OLS model looks the following:

$$Y_{it} = \beta_0 + \beta_1 * ES_{it} + \beta_2 * X_{it} + \varepsilon_{it}$$

In which $Y_{it}$[6] equals either average debt to interest expense or total debt to interest expense for firm i in year t. $ES_{it}$ stands for the environmental performance score for firm i in year t. $X_{it}$ stands for a combination of the control variables for firm i in year t.

### 3.1.2 Fixed & Random Effects Model

The pooled OLS models will provide a good and clear indication of the relation between the dependent and independent variables. But even when industry, country and year fixed effects are taken into account, differences within firms are still not observed and accounted for. In order to be able to control for unobserved firm specific characteristics, a fixed effects model is needed to control for those and to look at the ‘within’ variation instead of the ‘between’ variation. Due to the nature of the data, there will most likely be correlations between unobserved factors and the dependent and independent variables. To control for this, the fixed effects model makes use of demeaning, which subtracts the mean value of every individual observation in order to look at the change and control for unobserved firm factors that stay constant over time. By doing so, the fixed effects model rids itself of omitted variable bias caused by unobserved firm factors and looks

[6] See sections 3.2.2 to 3.2.4 for an in depth explanation of the variables.

specifically at how environmental performance affects cost of debt over time for individual firms. Therefore, the fixed effects model will most likely be the best model to test the hypotheses.

The baseline fixed effects model that is used in this thesis will look the following:

$$Y_{it} = \beta_1 * ES_{it} + \beta_2 * X_{it} + \alpha_i + \varepsilon_{it}$$

In which the intercept is removed because this is a constant and $\alpha_i$ is added as an extra error for time invariant factors within firms. By demeaning, the model is rid from firm specific heterogeneity. A downside to the fixed effects model is that it cannot measure factors that do not change over time and variation between firms cannot be measured. In order to measure factors that do not change over time and variation between firms, a random effects model would have to be used. Random effects models allow for time invariant factors and variation between firms to be measured while controlling for factors that are unobserved in the model. A random effects model however, can only be used when no correlation exists between the error term and estimators in the model. If this would be the case, the estimators are biased which will make the entire model biased. A Hausman test should be used to test whether the error term is correlated with the estimators. If the Hausman test is insignificant it means that the random effects model can be used.[7] If that is the case and that random effects model can be used.

The random effects model looks the following:

$$Y_{it} = \beta_1 * ES_{it} + \beta_2 * X_{it} + \mu_i + \varepsilon_{it}$$

With $\mu_i$ being the firm specific error for the random effects model. The random effects model assumes that $\mu_i$ is uncorrelated with the regressors, which is a necessity for the model to work.

### 3.1.3 Firm Differences

To test the assumption about polluting vs. non-polluting industries, a dummy will be created for firms that fall within a polluting industry as is done by Zhu et al. (2025). Industry categories in this thesis are based on standard industry classification (SIC) codes (Bauer & Hann, 2010). Polluting

[7] The results from the Hausman test are presented in section 4.2.2.

industries are the ones that have a lot of toxic emissions and hazardous waste according to Chava (2014). This broadly corresponds to SIC codes 1000-4999, which are mining, construction, manufacturing and transportation & utilities. Therefore, these firms are determined to be polluting. Firms that do not fall within this range of SIC codes are determined to be non-polluting. Those are wholesale, retail, services, public administration and codes that did not get a classification. The model to test this hypothesis is probably the fixed effects model as this will most likely be the best model for the hypotheses due to expected correlation between the estimators and the error term.

To test whether the effects of environmental performance on cost of debt are more pronounced for large or strongly levered firms, I create a sample split. Large firms, as argued by Saba (2024) are those that fall above the 75$^{th}$ percentile of the logarithm of total assets, small firms on the other hand are those below the 25$^{th}$ percentile of the logarithm of total assets. Saba (2024) further argues that strongly levered firms are those that fall above the 75$^{th}$ percentile of the debt-to-equity ratio and weakly levered firms are those that fall below the 25$^{th}$ percentile of debt-to-equity ratio. In line with the reasoning of Saba (2024) I create samples for firms above the 75$^{th}$ percentile and below the 25$^{th}$ percentile of the logarithm of total assets and for firms above the 75$^{th}$ percentile and below the 25$^{th}$ percentile of debt-to-equity ratio. I will test with these four different samples of firms in order to see whether the effects differ per sample.

### 3.1.4 Endogeneity

Pooled OLS, fixed effects and random effects models can only determine correlation, which make the assumption about causality very easy to make but unjust, because correlation does not mean causation. Reverse causality can easily be resolved by adding a lagged value for the independent variable. Simultaneity, A affecting B but at the same time being affected by B, on the other hand is harder to resolve. Simultaneity is a problem because as long as it persists, causality cannot be determined. Suitable instruments for an instrumental variable analysis are often hard to find. Therefore, a system generalized method of moments (system GMM) as described by Arellano & Bover (1995) and Blundell & Bond (1998) is quite well suited to test assumptions using panel data.

In line with the method of Ballester et al. (2025) a system GMM model will be used which tests for the effect of environmental performance on cost of debt by adding lags as an instrument to resolve the problem of simultaneity while controlling for unobserved, time invariant heterogeneity in firms. The system GMM uses lags of endogenous variables as instruments because values in time t-1 cannot be affected by values in time t which makes these exogenous instruments in the model. For exogenous variables, there is no necessity to create instruments because they are already uncorrelated with the error term so no endogeneity can exist there. For variables in the model that are endogenous, an instrument is created in the form of lagged values of that variable. That is however the weak point of this model. If there are many endogenous variables, then there are many instruments. In the case that there are too many instruments, the model will be weakened. Since all variables in this models are endogenous, instruments need to be created for all variables, which threatens the strength of the model. Since determining the right amount of lags is hard, different models will be tested to see which fits the best. A system GMM with three lags, a system GMM with two lags and a system GMM with collapsed instruments. A system GMM with collapsed instruments uses less instruments by combining these across periods, as a result there are less instruments which leads to more reliable results. For system GMM models to work in general there are a few conditions that need to be met. First, the Sargan test which tests the validity of instruments should be insignificant. Second is that second order autocorrelation should be absent in order for instruments to be valid. Third is that there should not be too many instruments as this weakens the model and causes the Sargan test to be significant.

### 3.1.5 Propensity Score Matching

To delve deeper into the relation between environmental performance and cost of debt, I apply propensity score matching (PSM) to rule out selection bias as driver of the effect. Propensity score matching is a quasi-experimental method where the treatment and control group can be manually determined based on individual characteristics (Benedetto et al., 2018). In this thesis the treatment group is firms with high environmental performance and the control group is firms with a low environmental performance score, in line with the method of Alves & Meneses (2024). Samples for the control and treatment groups are split on the 50$^{th}$ percentile with the treatment group high environmental performance including the firms above the 50$^{th}$ percentile and the control group low environmental performance including the firms below the 50$^{th}$ percentile. The assumption is that firms with similar characteristics, which are the control variables in this case, have an equal chance of having high or low environmental performance. The only differences between two firms is environmental performance. Matching is then done on the nearest neighbour matching in which R matches two firms with similar characteristics but different environmental performance to see if they have different cost of debt. Finally, the differences will be compared to see the average treatment effect on the treated. In this way, given firm characteristics, the differences in cost of debt between firms with high and low environmental performance are isolated so that the effect of environmental performance on cost of debt can be observed. Due to the isolation it offers a different view than the pooled OLS, fixed effects, random effects and system GMM models and serves as a good robustness check.

#### 3.1.6 Testing for the Categories

For categories, the same testing will be done as for environmental performance when used as independent variable. If during testing it turns out that the effect of environmental performance on cost of debt is not as predicted, then testing of the categories will be not as profound as testing for environmental performance. This is because the categories are factors of the environmental performance. So when the environmental performance shows to not have an effect on cost of debt, the separate categories are expected to not show the predicted effect as well. Since the categories are a smaller factor to firm risk then environmental performance is, it is expected that their effects will be weaker anyway. Models for the categories will also look the same as is the case for environmental performance, but then emission score (EMS), innovation score (IS) and resource use score (RUS) will be used instead of environmental performance as independent variable.

### 3.2 Data

#### 3.2.1 Source & Sample

As described in the methods, the statistical analysis uses different types of tests to check the hypotheses. The data that are used in the statistical analysis for this thesis are provided by the LSEG database. Data are retrieved from the database and consist of ESG, financial and firm characteristics data. ESG related data on LSEG are retrieved from self-reported information by firms. Therefore, firms that fall under the EU Taxonomy are most likely to have reliable and comparable data because it provides a clear framework for firms. As a result, the study in this thesis focusses on the STOXX Europe 600. The STOXX Europe 600 includes over 90% of the free floating market capitalization (STOXX Ltd.). Data on the environmental pillar score, and especially on its categories, before 2020 is of inferior quality. When looking at the data before 2020 there are many gaps, as such data before 2020 will not be used. The timeframe considered for the data has 2020 as starting point and will be up until the most recent point in time for which data is available, which is 2023. So, the data will span four years with the time period being 2020-2023.

The initial list consists of 763 firms that at some point have been listed on the STOXX Europe 600 in the period 2020-2023. Financial firms often have different capital structures compared to non-financial firms, which would skew the data very strongly. As a result, firms operating in the financial sector, with SIC codes 6000-6700, have been removed due to their financial abnormalities (Gao et al. 2020). 173 financial firms were in the initial sample, after removing them, the sample consists of 590 firms. After removing firms with incomplete observations for the independent variables, either for the environmental pillar score, the emission score, innovation score and resource use score, 499 firms remain in the final sample. Most firms that were removed from the data had either stopped existing or had not existed for the full span of the dataset.

Table 1 provides an overview of where these firms have their headquarters and in which industry they are active. With regard to industries, mainly manufacturing is strongly represented with 243 firms being active within manufacturing. In the case of the countries the sample is dominated by: Great Britain (107 firms), France (70 firms), Germany (68 firms), Sweden (52 firms) and Switzerland (45 firms). For control variables, missing values were sporadic and were imputed via interpolation or an educated guess. The final dataset consists of 499 firms spanning four years, meaning that 1996 firm-year observations are in the dataset. The firm with ISIN code SE0000825820 had no interest expense, interest coverage ratio and debt for the year 2021. Due to this, no cost of debt could be calculated. This left the panel dataset to be unbalanced with the only gap being data related to debt for firm SE0000825820. To deal with outliers in the sample, winsorization is applied at the $1^{st}$ and $99^{th}$ percentile in accordance with the methodology of Eliwa et al. (2021) and Malik & Kashiramka (2024). Due to heteroscedasticity suspicion, I use a Breusch-Pagan to test for it. For both the winsorized and unwinsorized data the test turned out positive, meaning that there is heteroscedasticity in the data. Heteroskedasticity and intra firm correlation are dealt with via clustered standard errors at the firm level.

TABLE 1: FIRMS PER COUNTRY AND INDUSTRY

| | Agriculture | Construction | Manufacturing | Mining | Retail | Services | Transport & Utilities | Wholesale | Total |
|---|---|---|---|---|---|---|---|---|---|
| Austria | | | 4 | | | | 1 | | 5 |
| Belgium | | 1 | 4 | | 1 | 3 | 3 | | 12 |
| Denmark | | | 12 | | | 3 | 3 | 1 | 19 |
| Estonia | | 2 | 4 | | 1 | 1 | 10 | | 18 |
| Finland | | 1 | 11 | | 1 | 1 | 2 | | 16 |
| France | | 3 | 32 | | 4 | 21 | 7 | 3 | 70 |
| Germany | | 1 | 39 | | 3 | 10 | 13 | 2 | 68 |
| Great Britain | | 6 | 33 | 9 | 16 | 21 | 16 | 6 | 107 |
| Ireland | | | 4 | | | 1 | 1 | | 6 |
| Italy | | | 14 | 1 | 1 | 1 | 8 | | 25 |
| Luxembourg | | | 1 | | | | 2 | | 3 |
| Netherlands | | 1 | 13 | 1 | 1 | 7 | 3 | 1 | 27 |
| Norway | 1 | | 8 | | | 2 | 2 | 2 | 17 |
| Poland | | | 1 | 1 | 2 | | | | 4 |
| Portugal | | | | 1 | 1 | | 1 | | 3 |
| Sweden | 1 | 1 | 32 | | 2 | 10 | 4 | 2 | 52 |
| Switzerland | | 1 | 30 | | 2 | 7 | 4 | 1 | 45 |
| United States | | | 1 | 1 | | | | | 2 |
| Total | 2 | 17 | 243 | 16 | 35 | 88 | 80 | 18 | 499 |

Notes: Total Firms in the Final Sample per Country and Industry

### 3.2.2 Dependent Variables

Measuring cost of debt can be done either via accounting-based, market-based or rating-based measures. For this thesis cost of debt as variable is measured via the accounting-based way. The reason for this is twofold: first, accounting-based measures correlate stronger to ESG performance according to Orlitzky et al. (2003) and Eliwa et al. (2021) and second, data on market-based and rating-based measures were either scarcely or not at all available on LSEG, threatening data quality and inducing selection bias in the cases that it was available. Interest expense does not provide the full picture about the cost of debt for a firm, because it does not account for the size of the debt. To account for this, interest expense is divided by debt so the cost per unit of debt is measured. As a result, cost of debt is measured as a ratio. For robustness purposes cost of debt is measured via two ways. As interest expense to average debt as done by Gigante & Manglaviti (2022) and interest expense to total debt as done by Eliwa et al. (2021). Interest expense to average debt is shown in the statistical analysis as IAD and is calculated as:

$$\mathrm{IAD_{it}} = \frac{\mathrm{Interest\ Expense_{it}}}{\frac{\mathrm{Total\ Debt_{it}} + \mathrm{Total\ Debt_{it\text{-}1}}}{2}}$$

In essence, it means that IAD for firm i in year t is a function of interest expense divided by the average of total debt in year t and the total debt in year t-1. Interest expense to total debt is shown in the statistical analysis as ID and is calculated as:

$$\mathrm{ID_{it}} = \frac{\mathrm{Interest\ Expense_{it}}}{\mathrm{Total\ Debt_{it}}}$$

Since ID is only scaled to this year's debt, the expectation is that differences between years are bigger than is the case for IAD, as IAD is more smoothened by including last year's debt as well. Debt consists of both short and long term debt over which interest is owed. All debt related variables are measured in Euros.

Statistical programs, such as R, assume variables to be continuous unless specified otherwise. The ratio for cost of debt however, is not continuous because it does not go below zero. To avoid this, a logarithmic value for cost of debt could be created. However, since both Gigante & Manglaviti (2022) and Eliwa et al. (2021) have not used logarithmic values but used the unadjusted ratio, the same will be done in this thesis.

### 3.2.3 Independent Variables

Environmental performance is measured as the environmental pillar score. Studies that look at ESG related topics often measure environmental performance as the environmental pillar score (Apergis et al., 2022). Where ESG is a combination of environmental, social and governance factors, the environmental pillar score zooms in on environmental topics only. Since this study only looks at environmental factors, the main independent variable that is used, is therefore the environmental pillar score and is shown in the statistical analysis as ES. The environmental pillar score is part of the overall ESG score and is itself comprised of three categories being: emission score, innovation score and resource use score. The environmental pillar score is scaled from 0 to 100. The environmental pillar score and its categories are measured as relative values compared to industry peers (Apergis et al., 2022). A score of 0 to 25 means that the score of a firm is poor compared to its peers, a score of 25 to 50 means a decent score compared to peers, a score of 50 to 75 means a good and above average score compared to peers and a score of 75 to 100 means that a firms scores very well compared to its peers (London Stock Exchange Group, 2024). Since the way in which scores are build differs per industry, it is important to control for industry differences in the analysis. For instance, a firm that has an emission score of 100 in the mining sector will probably in practice still have more absolute emissions than a firm in finance that has an emission score of 1. The downside to using the environmental pillar score is that it is constructed of data that are reported by firms themselves. If a firm is not transparent or honest about their environmental performance, the environmental pillar score will not reflect their true performance. Considering the fact however, that all data related to environmental performance are based on self-reported data, the environmental pillar score is the best way to measure environmental performance overall.

### 3.2.4 Control Variables

The models have six different control variables to filter out noise and to try and minimise the risk of omitted variable bias in the regressions. These control variables are: current ratio, debt-to-equity ratio, interest coverage ratio, return on assets, price-to-book value and total assets.

The current ratio, shown in the regressions as CURA is measured as the ratio between the current assets and the current liabilities of a firm (Malik & Kashiramka, 2024). It measures how well a firm can pay its debt on the short-term. High levels of liquidity are essential for firms as it signals good financial practices and enables them to pay their short term debt (Wesa & Otinga, 2018). Sound financial management is necessary to prevent financial distress as increased financial distress leads to increased lending risk for banks. As a result, they charge higher interest rates to firms with high current liabilities relative to their current assets. Since it seems as though the current ratio is of influence on cost of debt, the current ratio will be taken into account when testing for the effect of environmental performance on cost of debt. The expectation is that the current ratio will have a negative effect on cost of debt.

The debt-to-equity ratio, shown in the regressions as DE is measured as the ratio between the total debt and the total equity of a firm (Eliwa et al., 2021). According to the trade-off theory by Kraus & Litzenberg (1973) firms opt to finance activities via debt for its tax deductibility. The downside to this is increased risk of default (Hackbarth et al., 2006). When the amount of debt increases, so do the cost with regard to interest. This exposes the firm to increased liquidity and credit risk when cash flows decline, evolving the firm into a riskier investment in the eyes of creditors. High levels of debt are therefore interpreted as an increased bankruptcy risk, which increases overall firm risk (Myers, 2001). The expectation for the regressions is therefore, that the debt-to-equity ratio will have a positive effect on cost of debt.

The interest coverage ratio, shown in the regressions as ICR is measured as the ratio between EBIT and interest expense (Ding et al., 2022). It tells whether a firm earns enough money to fulfil its obligations with regard to its cost of debt. A higher interest coverage ratio shows lenders that a firm will have no trouble in paying its interest costs. This signals creditworthiness and decreases the chance of distress risk. As a result, lenders will have more confidence in the firm, which in turn will lower its cost of debt. The expectation for the regressions is therefore, that the interest coverage ratio will have a positive effect on cost of debt.

Return on assets, shown in the regression as ROA is measured as net income divided by total assets (Eliwa et al., 2021). Return on assets is often used as proxy for profitability and basically measures how much earnings a firm has given its size. High return on assets signals to lenders that the firm is healthy and that it will not have troubles paying its debt due to its high internal cash flows. Rating agencies use return on assets when assigning credit ratings to firms (Aman & Nguyen, 2013). Better credit ratings lead to lower cost of debt because it shows increased creditworthiness. Firms with high return on assets can also better withstand economic downturns which decreases default risk. The expectation for the regression is therefore, that return on assets will have a negative effect on cost of debt.

Price-to-book value, shown in the regression as PB is measured as the market value of equity relative to the book value of equity (Chen & Silva Gao, 2012). Firms with high price-to-book value show strong market expectations which is shown by their equity trading for higher prices than the intrinsic value of the equity justifies. This means that the market sees long-term growth perspectives for the firm. As a result, the firm is seen as less risky and a sound long-term investment opportunity, decreasing the perceived risk for lenders. The expectation for the regression is therefore, that the price-to-book value will have a negative effect on cost of debt.

Firm size, shown in the regression as log_TA is measured as the logarithm of total assets (Eliwa et al., 2021). Larger firms are often more trustworthy, transparent and have more stable cash flows than smaller firms, which decreases the risk of default. Also, large firms often exist for longer periods of time which makes it easier for lenders to assess its credibility. The logarithm of total assets is taken, as in done often in studies, to deal with its non-linearity and skewed nature (Erragragui, 2018). The expectation for the regression is that the logarithm of total assets will have a negative effect on cost of debt.

Since the current ratio and the debt-to-equity ratio have either interest expense or debt in their value, they share a commonality with the dependent variables which could lead to a variety of problems regarding endogeneity or shared measurement errors. To check whether these controls have too much overlap with the dependent variables, a variable inflation factor analysis will be used. As extra check a separate regression without these controls will be ran to check whether it differs from the regression that includes both the current ratio and the debt-to-equity ratio. Based on these two means of checking, I decide whether to remove or keep these two controls.

### 3.2.5 Descriptive Statistics

Table 2 reports the descriptive statistics table which shows the unwinsorized data that is used for the analyses. Observations consist of 499 firms times four which leaves 1996 observations. However, due to one single firm having zero debt and interest expense in the year 2021 it would give a missing value for ID and ICR because those would be impossible to construct, which lead me to decide to remove the observation for that firm for the year 2021. Leaving a total of 1995 observations per variable. Average interest expense to average debt is 0.034, which is exactly the same as average interest expense to total debt. The data on both interest expense to average debt and interest expense to total debt seems a bit skewed towards the lower half as Q75 is for both closer to the mean than Q25 is. This is however no problem as data is allowed to be a bit skewed as long as it does not get too bad. Minima for both are quite low, showing that there are firms that have a ratio as little as 0.2% and 0.1% respectively of interest expense to average debt and interest expense to total debt. Maxima on the other hand are quite high showing that some firms pay 44.1% interest to average debt and 43.4% interest on total debt. For both interest expense to average debt and interest expense to total debt Q25, the mean and Q75 are rather close together despite a high standard deviation. This would suggest that variance is low, hence Q25, the mean and Q75 being close together, but that variance is for a big part determined by outliers as suggested by the high maximum values and standard deviation. This would suggest that both forms of cost of debt are sticky and do not move much over time, which is in line with the reasoning that debt covenants and its associated interest costs are negotiated for longer periods of time and do not change much in the span of 4 years (the length of the dataset). Concerning the independent variables, values of emission score and resource use score are quite comparable, innovation score on the other hand differs somewhat as firms quite often score 0 on innovation which drags down Q25, the mean and Q75, inflates the standard deviation and shows a low median compared to the other categories. The environmental pillar score, as a result, shows to be a combination of the three. Q25 and Q75 are about equally far from the mean for the environmental score, suggesting that it is reasonably normally distributed.

With regard to control variables, all seem quite normally distributed judging from the Q25, mean and Q75 values, except for the interest coverage ratio which has a mean that lies above the Q75 value, which is probably due to some very high outliers. Besides that, debt-to-equity ratio and price-to-book value show to have quite extreme outliers which would suggest that, especially based on the controls, winsorization would indeed be a good option to deal with outliers in the analyses.

TABLE 2: DESCRIPTIVE STATISTICS

| Variables | Mean | Median | SD | Q25 | Q75 | Min | Max | N |
|---|---|---|---|---|---|---|---|---|
| Interest to Average Debt | 0.034 | 0.029 | 0.026 | 0.020 | 0.040 | 0.002 | 0.441 | 1995 |
| Interest to Total Debt | 0.034 | 0.028 | 0.029 | 0.019 | 0.039 | 0.001 | 0.434 | 1995 |
| Environmental Performance | 66.364 | 70.590 | 20.447 | 52.090 | 81.755 | 0.000 | 98.690 | 1995 |
| Emission Score | 74.308 | 80.090 | 21.768 | 61.685 | 91.700 | 0.000 | 99.930 | 1995 |
| Innovation Score | 44.760 | 50.000 | 32.904 | 13.540 | 74.720 | 0.000 | 99.900 | 1995 |
| Resource Use Score | 74.812 | 82.770 | 23.674 | 61.675 | 94.010 | 0.000 | 99.920 | 1995 |
| Current Ratio | 1.624 | 1.290 | 1.292 | 0.980 | 1.800 | 0.140 | 15.570 | 1995 |
| Debt-to-Equity Ratio | 57.907 | 68.690 | 1962.755 | 36.115 | 125.975 | -85985.510 | 9778.570 | 1995 |
| Interest Coverage Ratio | 27.067 | 9.460 | 143.832 | 3.848 | 21.612 | -2988.426 | 4007.710 | 1995 |
| Price-to-Book Ratio | 4.428 | 2.530 | 196.865 | 1.410 | 4.640 | -5623.400 | 1915.420 | 1995 |
| Return on Assets | 6.242 | 5.680 | 13.657 | 2.825 | 9.095 | -67.510 | 358.880 | 1995 |
| Logarithm of Total Assets | 16.027 | 15.997 | 1.413 | 15.092 | 16.918 | 10.767 | 20.190 | 1995 |

# 4 Results

The analysis begins by assessing how variables relate to each other using a correlation matrix. Then the regression analyses follow, starting with the pooled OLS model which features multiple specifications to make sure that results are robust. Means of ensuring robustness are clustered standard errors at the firm level, winsorizing the dataset to control for outliers, including fixed effects to control for industry, year and country specific effects, using a lag of the independent variables to control for reverse causality and applying interaction effects between corporate environmental performance and debt-to-equity ratio and corporate environmental performance and the logarithm of total assets to test whether there are moderating effects of size and leverage. After that, the analysis moves to fixed effects models to test the 'within' entity variation. These models also feature several different additions to ensure robustness, in the form of lags for the independent variable controlling for endogeneity, fixed effects for industry, year and country and a lagged model with industry, year and country fixed effects. For completeness, the random effects model is also included, but to what extent it is useful remains the question due to a failing Hausman test which shows the estimators in the model to be biased. Assessing heterogeneity and robustness further, I create a dummy for industries that are deemed to be polluting to test whether polluting vs. non-polluting industries differ. Sample splits are used to assess the differences for high vs. low leverage firms and large vs. small firms. A fixed effects model, which is the best model to test the hypotheses due to bias in the pooled and random effects models, is used to test the effects for the subsamples. Finally, the environmental score is separated in the different categories to test how the categories drive the effect of environmental performance on cost of debt. For all categories pooled and fixed effects models are used in which the categories are ran together and separately to test their joint and individual effect on cost of debt.

## 4.1 Correlations

Table 3 presents the correlation matrix in which the pairwise correlations for all used variables are shown. Interest expense to average debt and interest expense to total debt seem good substitutes as they have a correlation of 0.893 which means that they resemble each other for 89.3%. Furthermore, interest expense to average debt and interest expense to total debt have correlations with the environmental pillar score of respectively -0.156 and -0.149, meaning that, again, they seem good substitutes. Correlation values of -0.156 and -0.149 suggest that environmental performance and cost of debt are inversely related, which means that cost of debt are lower for higher environmental performance, as is in line with the hypotheses of this thesis. Correlations however are weak which makes it hard to predict what will be the outcome of the regressions. For the emissions score, innovations score and resource use score goes the same. Although they are inversely correlated to both measures of cost of debt, this correlation is not that strong.

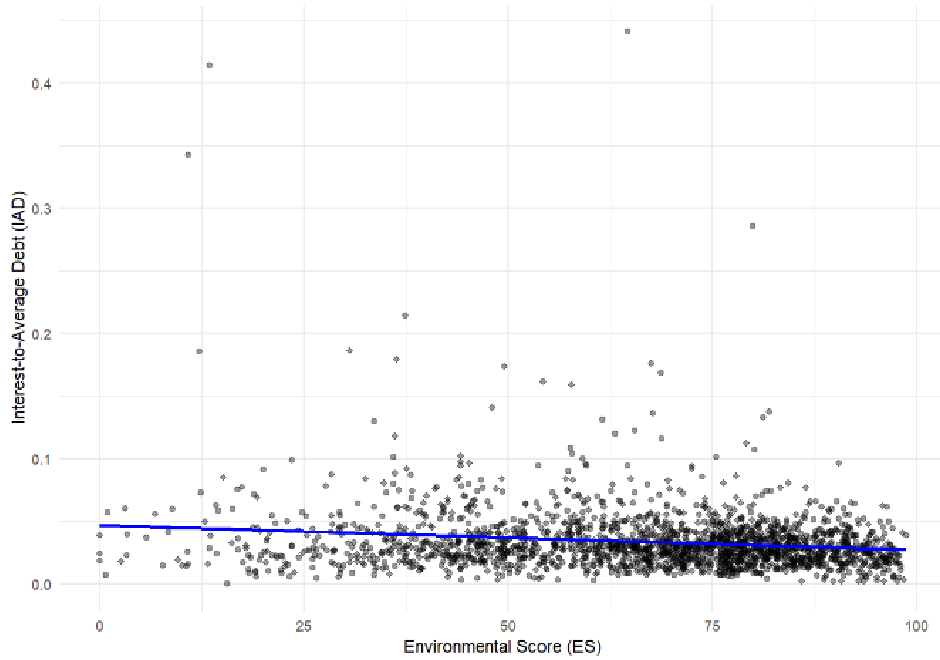
Figures 1 & 2 show the plots for the correlations between environmental performance and both interest expense to average debt and interest expense to total debt. These plots show about the same relations, which suggests again, like the correlation matrix, that there is a weak inverse relation between the environmental pillar score and both measures of cost of debt.

Multicollinearity is no threat to the models as a variance inflation factor (VIF) analysis points out that all of the variables have a VIF between 1.5 and 2, meaning that there is very low multicollinearity in the data. Multicollinearity will therefore not be a problem, so all variables can be included in the models.

TABLE 3: CORRELATION MATRIX

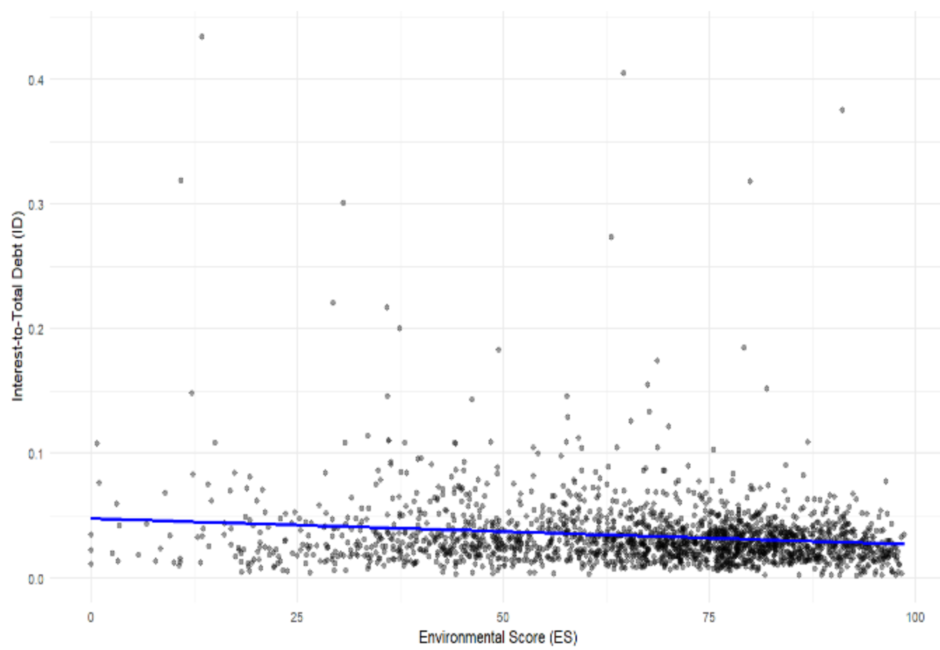
| | IAD | ID | ES | EMS | IS | RUS | CURA | DE | ICR | PB | ROA | log_TA |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Interest to Average Debt | 1.000 | 0.893 | -0.156 | -0.111 | -0.125 | -0.147 | 0.217 | 0.006 | -0.024 | -0.003 | -0.033 | -0.108 |
| Interest to Total Debt | 0.893 | 1.000 | -0.149 | -0.102 | -0.120 | -0.143 | 0.243 | 0.011 | 0.021 | 0.037 | -0.025 | -0.108 |
| Environmental Performance | -0.156 | -0.149 | 1.000 | 0.751 | 0.670 | 0.802 | -0.172 | 0.004 | -0.050 | -0.017 | -0.035 | 0.541 |
| Emission Score | -0.111 | -0.102 | 0.751 | 1.000 | 0.252 | 0.613 | -0.118 | 0.011 | -0.021 | 0.017 | 0.002 | 0.430 |
| Innovation Score | -0.125 | -0.120 | 0.670 | 0.252 | 1.000 | 0.329 | -0.158 | -0.003 | -0.010 | -0.016 | 0.010 | 0.386 |
| Resource Use Score | -0.147 | -0.143 | 0.802 | 0.613 | 0.329 | 1.000 | -0.151 | 0.003 | -0.057 | -0.016 | -0.025 | 0.423 |
| Current Ratio | 0.217 | 0.243 | -0.172 | -0.118 | -0.158 | -0.151 | 1.000 | 0.002 | 0.104 | 0.034 | 0.069 | -0.297 |
| Debt-to-Equity Ratio | 0.006 | 0.011 | 0.004 | 0.011 | -0.003 | 0.003 | 0.002 | 1.000 | -0.004 | 0.565 | -0.024 | 0.037 |
| Interest Coverage Ratio | -0.024 | 0.021 | -0.050 | -0.021 | -0.010 | -0.057 | 0.104 | -0.004 | 1.000 | 0.051 | 0.298 | -0.142 |
| Price-to-Book Ratio | -0.003 | 0.037 | -0.017 | 0.017 | -0.016 | -0.016 | 0.034 | 0.565 | 0.051 | 1.000 | 0.089 | -0.016 |
| Return on Assets | -0.033 | -0.025 | -0.035 | 0.002 | 0.010 | -0.025 | 0.069 | -0.024 | 0.298 | 0.089 | 1.000 | -0.176 |
| Logarithm of Total Assets | -0.108 | -0.108 | 0.541 | 0.430 | 0.386 | 0.423 | -0.297 | 0.037 | -0.142 | -0.016 | -0.176 | 1.000 |

FIGURE 1: LINEAR RELATION BETWEEN ES AND IAD




Notes: The Linear Relation between Environmental Performance (ES) on the X-Axis and Interest to Average Debt (IAD) on the Y-Axis

FIGURE 2: LINEAR RELATION BETWEEN ES AND ID




Notes: The Linear Relation between Environmental Performance (ES) on the X-Axis and Interest to Total Debt (ID) on the Y-Axis

## 4.2 Baseline Regression Results

### 4.2.1 Pooled OLS Models

Tables 4 & 5 present the results for the pooled OLS regressions. The pooled models ran with interest expense to average debt and interest expense to total debt, appear to show results that are quite similar, which indicates good robustness. Looking at the pooled model it shows that for both measures of cost of debt the coefficient of ES is significant and negative, this is in line with the predictions as it shows that firms with higher ES also have higher ID and IAD. If ES increases by 1, it is associated by a decrease of both IAD and ID by 0.0002, which does not seem like it changes a lot but considering that IAD and ID are ratios this shows that the decrease per 1 increase of ES is 0.02% percentage point. The adjusted $R^2$ for the model with IAD is 0.063 and for ID it is 0.071, meaning that the IAD model explains 6.3% in the variance of IAD and for ID the model explains 7.1% of the variance. The model without DE and ICR shows quite similar results to the model that includes them. As such, for following models DE and ICR are included as they do not appear to threaten validity. After that, I apply winsorization to the models, which shows increased adjusted $R^2$ for the IAD model but not for the ID model. Some of the controls became significant but ES kept its significance. Winsorization decreases the coefficient and standard errors of ES while increasing adjusted $R^2$ for IAD, which shows that it is a good way to rid the model of outlier noise as predicted. In the pooled model with fixed effects for country, industry and year it shows that for both IAD and ID the adjusted $R^2$ increases by a lot while ES remains significant. This goes to show that country, industry and year specific factors explain a great deal of variance in IAD and ID. Even when applying a lag of ES the results stay consistent and robust, increasing the adjusted $R^2$ even further. ES in t-1 shows to be a better predictor of differences in cost of debt among firms then ES of the current year, which makes sense as cost of debt will probably need some time to adjust to the new improved environmental performance of a firm. Then, I tested whether there is an interaction effect for size and leverage that moderates the relation between environmental performance and cost of debt. In both cases, for both forms of cost of debt, there is no effect found as the interaction term is insignificant which means that there is no moderating effect of either size or leverage on the relation between environmental performance and cost of debt. The best pooled model for both seems to be the winsorized model with fixed effects and a lag of ES, explaining 26.6% of variance in IAD and 24.6% of variance in ID. Overall, these models show a decent fit, especially when using panel data, where $R^2$ values are often not that high (Kennedy, 2008).

TABLE 4: POOLED OLS REGRESSION RESULTS OF ES ON IAD

| | Pooled | Pooled without DE & ICR | Pooled (Wins.) | Pooled with FE | Pooled with FE + Lag(ES) | Pooled with FE + ES*log_TA | Pooled with FE + ES*DE |
|---|---|---|---|---|---|---|---|
| (Intercept) | 0.0354*** | 0.0344*** | 0.0433*** | | | | |
| | (0.0074) | (0.0074) | (0.0061) | | | | |
| ES | -0.0002*** | -0.0002*** | -0.0001*** | -0.0001** | | -0.0005 | -0.0001* |
| | (0.0000) | (0.0000) | (0.0000) | (0e+00) | | (0.0003) | (1e-04) |
| lag_ES | | | | | -0.0001* | | |
| | | | | | (0e+00) | | |
| CURA | 0.0041*** | 0.0041*** | 0.0036*** | 0.0036*** | 0.0037*** | 0.0036*** | 0.0035*** |
| | (0.0005) | (0.0005) | (0.0004) | (1e-03) | (1e-03) | (0.0010) | (1e-03) |
| DE | 0.0000 | | -0.0000 | -0.0000 | -0.0000 | -0.0000 | -0.0000 |
| | (0.0000) | | (0.0000) | (0e+00) | (0e+00) | (0.0000) | (0e+00) |
| ICR | -0.0000+ | | -0.0000*** | -0.0000* | -0.0000* | -0.0000* | -0.0000* |
| | (0.0000) | | (0.0000) | (0e+00) | (0e+00) | (0.0000) | (0e+00) |
| PB | -0.0000 | -0.0000 | -0.0002+ | -0.0001 | -0.0002 | -0.0001 | -0.0001 |
| | (0.0000) | (0.0000) | (0.0001) | (1e-04) | (2e-04) | (0.0001) | (1e-04) |
| ROA | -0.0001 | -0.0001* | 0.0000 | -0.0000 | -0.0000 | -0.0000 | -0.0000 |
| | (0.0000) | (0.0000) | (0.0001) | (1e-04) | (1e-04) | (0.0001) | (1e-04) |
| log_TA | 0.0002 | 0.0003 | -0.0003 | -0.0006 | -0.0007 | -0.0022 | -0.0006 |
| | (0.0005) | (0.0005) | (0.0004) | (6e-04) | (6e-04) | (0.0016) | (6e-04) |
| ES × log_TA | | | | | | 0.0000 | |
| | | | | | | (0.0000) | |
| ES × DE | | | | | | | 0.0000 |
| | | | | | | | (0e+00) |
| Num.Obs. | 1995 | 1995 | 1995 | 1995 | 1496 | 1995 | 1995 |
| R2 | 0.066 | 0.065 | 0.074 | 0.254 | 0.282 | 0.255 | 0.254 |
| R2 Adj. | 0.063 | 0.062 | 0.071 | 0.241 | 0.266 | 0.241 | 0.241 |
| Std.Errors | HC3 | HC3 | HC3 | by: ISIN | by: ISIN | by: ISIN | by: ISIN |
| FE: industry | | | | X | X | X | X |
| FE: year | | | | X | X | X | X |
| FE: Country | | | | X | X | X | X |

Notes: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Standard Errors in Parentheses. Variables names: Interest Expense to Average Debt (IAD), Environmental Performance (ES), Current Ratio (CURA), Debt-to-Equity Ratio (DE), Interest Coverage Ratio (ICR), Price-to-Book Ratio, Return on Assets (ROA) and the Logarithm of Total Assets (log_TA).

TABLE 5: POOLED OLS REGRESSION RESULTS OF ES ON ID

| | Pooled | Pooled without DE & ICR | Pooled (Wins.) | Pooled with FE | Pooled with FE + Lag(ES) | Pooled with FE + ES*log_TA | Pooled with FE + ES*DE |
|---|---|---|---|---|---|---|---|
| (Intercept) | 0.0309*** | 0.0312*** | 0.0431*** | | | | |
| | (0.0081) | (0.0081) | (0.0065) | | | | |
| ES | -0.0002*** | -0.0002*** | -0.0001*** | -0.0001** | | -0.0006 | -0.0001* |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | | (0.0004) | (0.0001) |
| lag_ES | | | | | -0.0001* | | |
| | | | | | (0.0000) | | |
| CURA | 0.0051*** | 0.0051*** | 0.0039*** | 0.0038*** | 0.0041*** | 0.0038*** | 0.0038*** |
| | (0.0005) | (0.0005) | (0.0005) | (0.0011) | (0.0012) | (0.0011) | (0.0011) |
| DE | -0.0000 | | -0.0000 | -0.0000 | -0.0000 | -0.0000 | -0.0000 |
| | (0.0000) | | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| ICR | 0.0000 | | -0.0000*** | -0.0000 | -0.0000 | -0.0000+ | -0.0000+ |
| | (0.0000) | | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| PB | 0.0000 | -0.0000 | -0.0003** | -0.0002 | -0.0002 | -0.0003 | -0.0002 |
| | (0.0000) | (0.0000) | (0.0001) | (0.0002) | (0.0002) | (0.0002) | (0.0002) |
| ROA | -0.0001* | -0.0001* | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| | (0.0000) | (0.0000) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| log_TA | 0.0004 | 0.0004 | -0.0003 | -0.0007 | -0.0007 | -0.0028 | -0.0007 |
| | (0.0005) | (0.0005) | (0.0004) | (0.0006) | (0.0006) | (0.0017) | (0.0006) |
| ES × log_TA | | | | | | 0.0000 | |
| | | | | | | (0.0000) | |
| ES × DE | | | | | | | 0.0000 |
| | | | | | | | (0.0000) |
| Num.Obs. | 1995 | 1995 | 1995 | 1995 | 1496 | 1995 | 1995 |
| R2 | 0.074 | 0.074 | 0.075 | 0.242 | 0.262 | 0.243 | 0.243 |
| R2 Adj. | 0.071 | 0.071 | 0.071 | 0.229 | 0.246 | 0.230 | 0.230 |
| Std.Errors | HC3 | HC3 | HC3 | by: ISIN | by: ISIN | by: ISIN | by: ISIN |
| FE: industry | | | | X | X | X | X |
| FE: year | | | | X | X | X | X |
| FE: Country | | | | X | X | X | X |

Notes: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Standard Errors in Parentheses. Variables names: Interest Expense to Total Debt (ID), Environmental Performance (ES), Current Ratio (CURA), Debt-to-Equity Ratio (DE), Interest Coverage Ratio (ICR), Price-to-Book Ratio, Return on Assets (ROA) and the Logarithm of Total Assets (log_TA).

### 4.2.2 Fixed & Random Effects Models

Following the pooled OLS models, I ran the fixed effects models and random effects model due to possible bias in the pooled OLS model. Tables 6 & 7 present the results for the fixed effects and random effects models. Again, just like in the case of the pooled models, the results for both measures of cost of debt resemble each other quite well. In the first regression a normal fixed effects model is ran in which the model only controls for the control variables and firm specific characteristics. No effect seems to appear from ES on either IAD and ID, $R^2$ and adjusted $R^2$ are quite decent which shows that the model has good explanatory power. Moving to the model with lagged values of ES, it shows that ES has become significantly positive when lagged. This is rather unexpected as the expectation was that higher ES values would lead to lower cost of debt values, not the other way around. For the third model, fixed effects for country, industry and year are added to control for those specific factors. Although for both IAD and ID no effect of ES seems to appear, the explanatory power increases to 66% for IAD and 63.4% for ID. Again, when adding a lag for ES, the model improves in strength for both measures of cost of debt, especially in the case of the model for interest expense to average debt, but no effect appears of the environmental performance of a firm in t-1 on its cost of debt in time t, which shows that there is no delayed effect of environmental performance on cost of debt within firms. For the fixed effects models, testing interactions with debt-to-equity and size were done as well. Nothing different to the pooled models with interactions shows, as such I did not deem it necessary to show them.

After the fixed effects models, I tested whether a random effects model could be used to test the assumptions. The Hausman test in which the fixed effects model was compared to the random effects model shows to be highly significant for both IAD and ID, which means that the unobserved firm specific characteristics are strongly correlated with the explanatory variables. What that means, is that for instance an unobserved firm specific factor like corporate governance, for which the model does not account, partially drives changes in both cost of debt and environmental performance. Since the model cannot observe this effect, it might attribute these changes in cost of debt to environmental performance, which would make the estimators in the model biased and threatens the validity of its results. For that reason a fixed effects model is the best model to test the hypotheses as it controls for these unobserved firm specific characteristics. I ran the random effects model anyway for completeness and it is shown as the the 5$^{th}$ model in tables 6 & 7. As a random effects model accounts for both within and between variance in firms, it shows the expected negative significant effect of ES on both IAD and ID, but to what extent it is useful remains of question as the estimators in this model are biased. Overall, based on the different fixed effects models, quite a great deal of variance in both IAD and ID is explained by the models, although environmental performance does not seem to have an effect on cost of debt.

TABLE 6: FIXED & RANDOM EFFECTS REGRESSION RESULTS OF ES ON IAD

| | Fixed Effects | Fixed Effects + Lag(ES) | Fixed Effects with FE for CYI | Fixed Effects with FE for CYI + Lag(ES) | Random Effects |
|---|---|---|---|---|---|
| (Intercept) | | | | | 0.0493*** |
| | | | | | (0.0089) |
| ES | 0.0000 | | -0.0000 | | -0.0001** |
| | (0.0001) | | (0.0001) | | (0.0000) |
| lag_ES | | 0.0002** | | -0e+00 | |
| | | (0.0001) | | (0.0001) | |
| CURA | 0.0004 | 0.0000 | 0.0011 | 9e-04 | 0.0025*** |
| | (0.0011) | (0.0015) | (0.0011) | (0.0015) | (0.0005) |
| DE | 0.0000 | 0.0000 | 0.0000 | 0e+00+ | -0.0000 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| ICR | -0.0001** | -0.0001*** | -0.0001* | -0e+00* | -0.0001*** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| PB | -0.0003 | -0.0003 | -0.0001 | 1e-04 | -0.0003* |
| | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0001) |
| ROA | 0.0003*** | 0.0001 | 0.0003*** | 2e-04+ | 0.0002** |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| log_TA | 0.0012 | 0.0099** | -0.0037 | 1e-03 | -0.0008 |
| | (0.0027) | (0.0037) | (0.0029) | (0.0027) | (0.0006) |
| Num.Obs. | 1995 | 1496 | 1995 | 1496 | 1995 |
| R2 | 0.689 | 0.756 | 0.751 | 0.836 | 0.041 |
| R2 Adj. | 0.583 | 0.632 | 0.660 | 0.745 | 0.038 |
| Std.Errors | by: ISIN | by: ISIN | by: ISIN | by: ISIN | HC3 |
| FE: Country | | | X | X | |
| FE: year | | | X | X | |
| FE: ISIN | X | X | X | X | |
| FE: industry | | | X | X | |

Notes: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Standard Errors in Parentheses. Variables names: Interest Expense to Average Debt (IAD), Environmental Performance (ES), Current Ratio (CURA), Debt-to-Equity Ratio (DE), Interest Coverage Ratio (ICR), Price-to-Book Ratio, Return on Assets (ROA) and the Logarithm of Total Assets (log_TA).

TABLE 7: FIXED & RANDOM EFFECTS REGRESSION RESULTS OF ES ON ID

| | Fixed Effects | Fixed Effects + Lag(ES) | Fixed Effects with FE for CYI | Fixed Effects with FE for FE CYI + Lag(ES) | Random Effects |
|---|---|---|---|---|---|
| (Intercept) | | | | | 0.0476*** |
| | | | | | (0.0093) |
| ES | 0.0001 | | 0.0000 | | -0.0001** |
| | (0.0001) | | (0.0001) | | (0.0000) |
| lag_ES | | 0.0003* | | -0.0001 | |
| | | (0.0001) | | (0.0001) | |
| CURA | 0.0019 | 0.0015 | 0.0030* | 0.0025 | 0.0033*** |
| | (0.0013) | (0.0017) | (0.0013) | (0.0017) | (0.0006) |
| DE | -0.0000 | -0.0000 | 0.0000 | 0.0000 | -0.0000 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| ICR | -0.0001* | -0.0001* | -0.0000 | -0.0000 | -0.0001*** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| PB | -0.0003 | -0.0005* | -0.0002 | -0.0001 | -0.0003** |
| | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0001) |
| ROA | 0.0004*** | 0.0003* | 0.0004*** | 0.0004** | 0.0003*** |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| log_TA | -0.0015 | -0.0039 | -0.0104** | -0.0147*** | -0.0008 |
| | (0.0032) | (0.0038) | (0.0038) | (0.0034) | (0.0006) |
| Num.Obs. | 1995 | 1496 | 1995 | 1496 | 1995 |
| R2 | 0.652 | 0.690 | 0.732 | 0.785 | 0.042 |
| R2 Adj. | 0.534 | 0.532 | 0.634 | 0.667 | 0.039 |
| Std.Errors | by: ISIN | by: ISIN | by: ISIN | by: ISIN | HC3 |
| FE: Country | | | X | X | |
| FE: year | | | X | X | |
| FE: ISIN | X | X | X | X | |
| FE: industry | | | X | X | |

Notes: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Standard Errors in Parentheses. Variables names: Interest Expense to Total Debt (ID), Environmental Performance (ES), Current Ratio (CURA), Debt-to-Equity Ratio (DE), Interest Coverage Ratio (ICR), Price-to-Book Ratio, Return on Assets (ROA) and the Logarithm of Total Assets (log_TA).

## 4.3 Firm Differences Analysis

### 4.3.1 Polluting vs. Non-Polluting Industries

To test the hypothesis that the effect of environmental performance on cost of debt is stronger in polluting industries than it would be in non-polluting industries is tested via a fixed effects model as this model has been shown to be the appropriate model for this dataset. The industries that are deemed as polluting are: mining, construction, manufacturing and transportation & utilities. The industries that are deemed as non-polluting are: agriculture, wholesale, retail, services, public administration and others that have no classification. Polluting industries got dummy 1 and non-polluting industries got dummy 0. Table 8 present the results. In order to find a stronger relation for polluting industries than for non-polluting industries, the interaction between ES and the dummy for ‘polluting’ should be significant. In this case, for both measures of cost of debt, environmental performance seems to have no effect and the interaction between the dummy and environmental performance is insignificant as well. The dummy for 'polluting' has been removed from the model because it is either 0 or 1 and cannot be measured in a fixed effects model. In the paper of Saba (2024) he also runs into this problem and removes the dummy from the model to solve it. Therefore, I did the same. Judging from these models there seems no reason to believe that environmental performance has a stronger effect on cost of debt in polluting industries than it does in non-polluting industries and that there seems to be no effect of environmental performance on cost of debt in general. As in the fixed effects models before, the adjusted $R^2$ for these models is quite decent meaning that a good deal of variance in cost of debt is explained by the model. Environmental performance just does not seem to have an effect on cost of debt, even when separating the effect between polluting and non-polluting industries.

TABLE 8: FIXED EFFECTS REGRESSION RESULTS OF ES ON IAD & ID FOR POLLUTING VS. NON-POLLUTING INDUSTRIES

| | Fixed Effects for IAD | Fixed Effects for ID |
|---|---|---|
| ES | -0.0001 | -0.0001 |
| | (0.0001) | (0.0001) |
| CURA | 0.0011 | 0.0030* |
| | (0.0010) | (0.0012) |
| DE | 0.0000 | 0.0000 |
| | (0.0000) | (0.0000) |
| ICR | -0.0001** | -0.0000 |
| | (0.0000) | (0.0000) |
| PB | -0.0001 | -0.0002 |
| | (0.0002) | (0.0002) |
| ROA | 0.0003*** | 0.0004*** |
| | (0.0001) | (0.0001) |
| log_TA | -0.0039 | -0.0107** |
| | (0.0028) | (0.0034) |
| ES × polluting | 0.0002 | 0.0003+ |
| | (0.0002) | (0.0002) |
| Num.Obs. | 1995 | 1995 |
| R2 | 0.752 | 0.733 |
| R2 Adj. | 0.663 | 0.638 |
| Std.Errors | by: ISIN | by: ISIN |
| FE: ISIN | X | X |
| FE: Country | X | X |
| FE: year | X | X |

Notes: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Standard Errors in Parentheses. Variables names: Interest Expense to Average Debt (IAD), Interest Expense to Total Debt (ID), Environmental Performance (ES), Current Ratio (CURA), Debt-to-Equity Ratio (DE), Interest Coverage Ratio (ICR), Price-to-Book Ratio, Return on Assets (ROA) and the Logarithm of Total Assets (log_TA).

### 4.3.2 Size & Leverage

As suggested by theory, size and leverage may play moderating roles in the relation between environmental performance and cost of debt. This has been assessed earlier through interaction terms in the pooled and fixed effects models but nothing was found. So to see whether it has different effects on different subsamples, samples were formed at the 25$^{th}$ percentile and 75$^{th}$ percentile. Firms falling below the 25$^{th}$ percentile are labelled as either low leverage or small firm, for firms above the 75$^{th}$ percentile, these are labelled as either high leverage or large firm. Tables 9 & 10 present the results. ES is not significant for all of the samples, but it shows to be almost significant for large and strongly levered firms. These results reaffirm that, even when splitting samples, environmental performance does not affect cost of debt. Although these models have a good fit as adjusted $R^2$ is rather high, they do not seem to point in the direction that the effect of environmental performance on cost of debt is more pronounced for larger and highly levered firms.

TABLE 9: FIXED EFFECTS REGRESSION RESULTS OF ES ON IAD FOR SIZE AND LEVERAGE

| | Low Leverage | High Leverage | Small Firms | Large Firms |
|---|---|---|---|---|
| ES | 0.0000 | -0.0003+ | 0.0001 | -0.0003+ |
| | (0.0002) | (0.0002) | (0.0002) | (0.0002) |
| CURA | 0.0016 | -0.0003 | 0.0029 | -0.0014 |
| | (0.0020) | (0.0025) | (0.0019) | (0.0013) |
| ICR | -0.0001* | -0.0001 | -0.0000 | -0.0002*** |
| | (0.0000) | (0.0001) | (0.0000) | (0.0001) |
| PB | -0.0004 | 0.0005+ | -0.0001 | -0.0001 |
| | (0.0004) | (0.0003) | (0.0003) | (0.0002) |
| ROA | 0.0005* | 0.0003 | 0.0004+ | 0.0003*** |
| | (0.0002) | (0.0003) | (0.0002) | (0.0001) |
| log_TA | 0.0003 | -0.0093 | | |
| | (0.0043) | (0.0079) | | |
| DE | | | 0.0000 | -0.0000+ |
| | | | (0.0000) | (0.0000) |
| Num.Obs. | 499 | 499 | 499 | 499 |
| R2 | 0.751 | 0.843 | 0.678 | 0.818 |
| R2 Adj. | 0.566 | 0.735 | 0.498 | 0.728 |
| Std.Errors | by: ISIN | by: ISIN | by: ISIN | by: ISIN |
| FE: ISIN | X | X | X | X |
| FE: Country | X | X | X | X |
| FE: year | X | X | X | X |
| FE: industry | X | X | X | X |

Notes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard Errors in Parentheses. Variables names: Interest Expense to Average Debt (IAD), Environmental Performance (ES), Current Ratio (CURA), Debt-to-Equity Ratio (DE), Interest Coverage Ratio (ICR), Price-to-Book Ratio, Return on Assets (ROA) and the Logarithm of Total Assets (log_TA).

TABLE 10: FIXED EFFECTS REGRESSION RESULTS OF ES ON ID FOR SIZE AND LEVERAGE

| | Low Leverage | High Leverage | Small Firms | Large Firms |
|---|---|---|---|---|
| ES | -0.0003 | -0.0002 | 0.0002 | -0.0004+ |
| | (0.0005) | (0.0002) | (0.0003) | (0.0002) |
| CURA | 0.0059* | -0.0022 | 0.0062* | -0.0017 |
| | (0.0029) | (0.0028) | (0.0029) | (0.0016) |
| ICR | -0.0001 | -0.0001 | 0.0000 | -0.0002+ |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| PB | -0.0002 | 0.0004* | 0.0001 | -0.0007+ |
| | (0.0006) | (0.0002) | (0.0004) | (0.0004) |
| ROA | 0.0004 | 0.0003+ | 0.0004 | 0.0005** |
| | (0.0003) | (0.0002) | (0.0003) | (0.0001) |
| log_TA | 0.0054 | -0.0185+ | | |
| | (0.0082) | (0.0096) | | |
| DE | | | -0.0000 | -0.0000 |
| | | | (0.0000) | (0.0000) |
| Num.Obs. | 499 | 499 | 499 | 499 |
| R2 | 0.664 | 0.853 | 0.526 | 0.772 |
| R2 Adj. | 0.412 | 0.752 | 0.262 | 0.660 |
| Std.Errors | by: ISIN | by: ISIN | by: ISIN | by: ISIN |
| FE: ISIN | X | X | X | X |
| FE: Country | X | X | X | X |
| FE: year | X | X | X | X |
| FE: industry | X | X | X | X |

Notes: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Standard Errors in Parentheses. Variables names: Interest Expense to Total Debt (ID), Environmental Performance (ES), Current Ratio (CURA), Debt-to-Equity Ratio (DE), Interest Coverage Ratio (ICR), Price-to-Book Ratio, Return on Assets (ROA) and the Logarithm of Total Assets (log_TA).

## 4.4 Endogeneity Analysis

To control for potential endogeneity in the model and check whether the results from the pooled models are biased, three different system GMM models are ran. Tables 11 & 12 present the results. First a system GMM with 3 lags was tried. The lag for the dependent variable is significant which tells that current values of the dependent value can be partially explained by past values of the dependent variable. Like the fixed effects model, but unlike the pooled model, ES shows to have no effect on cost of debt. The Sargan test, which tests the validity of instruments, is highly significant, meaning that the instruments are not well suited. To solve this, two more models are ran, 'GMM: Two Lags' and 'GMM: Collapsed Instruments' which decrease the amount of instruments and with that improve validity of the instruments. It did not succeed in that as the Sargan test stayed highly significant. Instruments are only created for endogenous variables, which means that if a control variable is exogenous, no lags and therefore no instruments are created for it. All control variables in the model are endogenous since unobserved firm traits will most likely affect the control variables as well. As a result, instruments have to be made for all control variables to control for this. That means that there are a lot of instruments in the model, as shown by the significant Sargan test, which threatens validity of the instruments. In the case of first order autocorrelation AR(1), it is significant for half of the models, which is expected and normal. Second order autocorrelation AR(2) values are presented as NaN (not a number) in R, which is likely due to the time period being too short. Therefore, results have to be interpreted carefully as serial correlation cannot be assessed, which means that the validity of the model cannot fully be assessed. The Wald test is for all models highly significant, showing that the estimators in the model are jointly significant, as was the case for both the pooled and fixed effects models. The system GMM results, in which it controls for endogeneity in the form of simultaneity and omitted variable bias, show overall no effect of environmental performance on cost of debt. Although these findings have to be interpreted cautiously, they are in line with the findings from the fixed effects model and challenge the robustness and validity of the effects found in the pooled models.

TABLE 11: SYSTEM GMM REGRESSION RESULTS OF ES ON IAD

| | GMM: Three Lags | GMM: Two Lags | GMM: Collapsed Instruments |
|---|---|---|---|
| lag(IAD, 1) | 0.3167** | 0.3115** | 0.4210+ |
| | (0.1161) | (0.1186) | (0.2413) |
| ES | 0.0001 | 0.0002 | 0.0005 |
| | (0.0003) | (0.0003) | (0.0004) |
| CURA | 0.0012 | 0.0010 | 0.0049 |
| | (0.0043) | (0.0053) | (0.0125) |
| DE | -0.0001* | -0.0001* | -0.0000 |
| | (0.0000) | (0.0000) | (0.0000) |
| ICR | -0.0001* | -0.0001** | -0.0001 |
| | (0.0001) | (0.0001) | (0.0001) |
| PB | -0.0008 | -0.0010 | -0.0040** |
| | (0.0008) | (0.0007) | (0.0014) |
| ROA | -0.0006 | -0.0007 | -0.0026 |
| | (0.0006) | (0.0006) | (0.0021) |
| log_TA | 0.0020 | 0.0017 | 0.0012 |
| | (0.0013) | (0.0015) | (0.0019) |
| Sargan test | 223.8573 | 223.2657 | 97.3755 |
| | (2.22e-16)*** | (2.22e-16)*** | (2.22e-16)*** |
| AR(1) | -1.3942 | -1.5005 | -1.9989 |
| | (0.1632) | (0.126) | (0.0456)* |
| AR(2) | NaN | NaN | NaN |
| Wald test | 839.9193 | 705.4145 | 418.6186 |
| | (2.22e-16)*** | (2.22e-16)*** | (2.22e-16)*** |

Notes: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Standard Errors in Parentheses. Variables names: Interest Expense to Average Debt (IAD), Environmental Performance (ES), Current Ratio (CURA), Debt-to-Equity Ratio (DE), Interest Coverage Ratio (ICR), Price-to-Book Ratio, Return on Assets (ROA) and the Logarithm of Total Assets (log_TA). For the Sargan test, AR(1), AR(2) and the Wald test p-values are in parentheses.

TABLE 12: SYSTEM GMM REGRESSION RESULTS OF ES ON ID

| | GMM: Three Lags | GMM: Two Lags | GMM: Collapsed Instruments |
|---|---|---|---|
| lag(ID, 1) | 0.4243*** | 0.4367*** | 0.5168** |
| | (0.1184) | (0.1303) | (0.1826) |
| ES | 0.0001 | 0.0000 | 0.0003 |
| | (0.0003) | (0.0004) | (0.0005) |
| CURA | -0.0004 | -0.0003 | -0.0013 |
| | (0.0050) | (0.0056) | (0.0137) |
| DE | -0.0001+ | -0.0001* | -0.0001** |
| | (0.0000) | (0.0000) | (0.0000) |
| ICR | -0.0001* | -0.0001* | -0.0000 |
| | (0.0000) | (0.0001) | (0.0001) |
| PB | -0.0002 | -0.0004 | -0.0030 |
| | (0.0008) | (0.0007) | (0.0025) |
| ROA | -0.0007 | -0.0004 | -0.0035* |
| | (0.0005) | (0.0004) | (0.0016) |
| log_TA | 0.0017 | 0.0021 | 0.0028 |
| | (0.0016) | (0.0018) | (0.0022) |
| Sargan test | 220.4325 | 218.7051 | 102.088 |
| | (2.22e-16)*** | (2.22e-16)*** | (2.22e-16)*** |
| AR(1) | -2.2866 | -2.2592 | -2.1949 |
| | (0.0222)* | (0.0239)* | (0.2817) |
| AR(2) | NaN | NaN | NaN |
| Wald test | 757.8953 | 627.508 | 349.8746 |
| | (2.22e-16)*** | (2.22e-16)*** | (2.22e-16)*** |

Notes: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Standard Errors in Parentheses. Variables names: Interest Expense to Total Debt (ID), Environmental Performance (ES), Current Ratio (CURA), Debt-to-Equity Ratio (DE), Interest Coverage Ratio (ICR), Price-to-Book Ratio, Return on Assets (ROA) and the Logarithm of Total Assets (log_TA). For the Sargan test, AR(1), AR(2) and the Wald test p-values are in parentheses.

## 4.5 Propensity Score Matching Analysis

To control and test for possible selection bias in the sample, I use the quasi-experimental method of propensity score matching (PSM). Two groups are formed based on their environmental score. The control group consists of firms below the 50$^{th}$ percentile and the treatment group consists of firms above the 50$^{th}$ percentile. The PSM test was done via a logistic regression. Based on the results from the logistic regression, measured with a 95% confidence interval, it shows that these groups systematically differ in cost of debt. For interest expense to average debt the t-value is 7.066 and the p-value is 2.263e-12, meaning that it is strongly significant and that comparable firms from the two groups differ systematically. The average interest to average debt for matched high ES firms is 0.02983, whereas the average interest to average debt for matched low ES firms is 0.03593. This shows the average treatment effect of the treated to be 0.0061. The average difference in interest to average debt between matched firms from the two groups is 0.61 percentage points. For interest expense to total debt, average interest to total debt for matched firms is 0.0293 for high ES firms and 0.0361 for low ES firm. For interest to total debt this amounts the average treatment effect of the treated to be 0.0068. The average difference in interest to total debt between matched firms from the two groups is 0.68 percentage points. Results are therefore consistent over the different dependent variables and differences between high ES and low ES groups are significant at the 95% confidence interval. So, after matching firms with similar observable characteristics, firms with high ES show to have significantly lower cost of debt than firms with low ES. Although this seems to point into the direction of causality, it cannot go unstated that this model does not control for unobservable firm characteristics. What can be concluded based on these models is that, when controlling for observable characteristics, firms with higher environmental performance face lower cost of debt (2.98% for IAD and 2.93% for ID) than comparable firms with lower environmental performance (3.59% for IAD and 3.61% for ID).

### 4.6 Regression Models for the Categories

To test the hypotheses about the different categories, I use several models. First combining all different categories of which the results are presented in tables 13 & 14. After that, the categories are ran in separate regressions which are presented in tables 15 & 16. For the pooled model, innovation score and resource use score are significant and negative but as soon as country, year and industry fixed effects are added, these effects disappear. After that, different models with lags for EMS, IS and RUS, are ran but the insignificance persisted. For the model with only firm fixed effects and the model with firm, country, year and industry fixed effects, nothing of significance shows up as well. Then the different categories are split up to see how they behave separately and regressions are ran with them. For the pooled model all categories are significant. When adding fixed effects for country, year and industry these effect disappear for EMS and IS but persist for RUS. After that, lags were added for the categories, which show no effects.

Although these results contradict the prediction, they were expected based on the results from the regressions that are showed before, in which ES was the independent variable. The categories are subparts of environmental performance, a weaker effect was expected. But since ES showed no effect most of the time, testing for the categories was not as profound as testing for ES.

TABLE 13: REGRESSION RESULTS OF THE COMBINED CATEGORIES ON IAD

| | Pooled | Pooled with Fixed Effects | Pooled with FE + lag | Fixed Effects | Fixed Effects with FE for CYI |
|---|---|---|---|---|---|
| (Intercept) | 0.0435*** | | | | |
| | (0.0092) | | | | |
| EMS | -0.0000 | -0.0000 | | -0.0000 | -0.0000 |
| | (0.0000) | (0e+00) | | (0.0001) | (0.0001) |
| IS | -0.0000+ | -0.0000 | | 0.0001 | 0.0000 |
| | (0.0000) | (0e+00) | | (0.0000) | (0.0000) |
| RUS | -0.0001* | -0.0001+ | | -0.0000 | -0.0000 |
| | (0.0000) | (0e+00) | | (0.0001) | (0.0001) |
| lag_EMS | | | -0.0000 | | |
| | | | (0e+00) | | |
| lag_IS | | | -0.0000 | | |
| | | | (0e+00) | | |
| lag_RUS | | | -0.0001 | | |
| | | | (0e+00) | | |
| CURA | 0.0036*** | 0.0036*** | 0.0036*** | 0.0004 | 0.0011 |
| | (0.0010) | (1e-03) | (1e-03) | (0.0011) | (0.0011) |
| DE | -0.0000 | -0.0000 | -0.0000 | 0.0000 | 0.0000 |
| | (0.0000) | (0e+00) | (0e+00) | (0.0000) | (0.0000) |
| ICR | -0.0000** | -0.0000* | -0.0000* | -0.0001** | -0.0001* |
| | (0.0000) | (0e+00) | (0e+00) | (0.0000) | (0.0000) |
| PB | -0.0002 | -0.0001 | -0.0002 | -0.0003 | -0.0001 |
| | (0.0002) | (1e-04) | (2e-04) | (0.0002) | (0.0002) |
| ROA | 0.0000 | -0.0000 | -0.0000 | 0.0003*** | 0.0003*** |
| | (0.0001) | (1e-04) | (1e-04) | (0.0001) | (0.0001) |
| log_TA | -0.0003 | -0.0006 | -0.0007 | 0.0012 | -0.0038 |
| | (0.0006) | (6e-04) | (6e-04) | (0.0027) | (0.0028) |
| Num.Obs. | 1995 | 1995 | 1496 | 1995 | 1995 |
| R2 | 0.077 | 0.254 | 0.283 | 0.689 | 0.751 |
| R2 Adj. | 0.073 | 0.240 | 0.265 | 0.583 | 0.660 |
| Std.Errors | by: ISIN | by: ISIN | by: ISIN | by: ISIN | by: ISIN |
| FE: industry | | X | X | | X |
| FE: year | | X | X | | X |
| FE: Country | | X | X | | X |
| FE: ISIN | | | | X | X |

Notes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard Errors in Parentheses. Variables names: Interest Expense to Average Debt (IAD), Emission Score (EMS), Innovation Score (IS), Resource Use Score (RUS), Current Ratio (CURA), Debt-to-Equity Ratio (DE), Interest Coverage Ratio (ICR), Price-to-Book Ratio, Return on Assets (ROA) and the Logarithm of Total Assets (log_TA).

TABLE 14: REGRESSION RESULTS OF THE COMBINED CATEGORIES ON ID

| | Pooled | Pooled with Fixed Effects | Pooled with FE + lag | Fixed Effects | Fixed Effects with FE for CYI |
|---|---|---|---|---|---|
| (Intercept) | 0.0435*** | | | | |
| | (0.0092) | | | | |
| EMS | -0.0000 | -0.0000 | | 0.0000 | 0.0000 |
| | (0.0000) | (0.0000) | | (0.0001) | (0.0001) |
| IS | -0.0000+ | -0.0000 | | 0.0001 | 0.0000 |
| | (0.0000) | (0.0000) | | (0.0000) | (0.0000) |
| RUS | -0.0001* | -0.0001* | | -0.0000 | -0.0000 |
| | (0.0000) | (0.0000) | | (0.0001) | (0.0001) |
| lag_EMS | | | 0e+00 | | |
| | | | (0.0000) | | |
| lag_IS | | | -0e+00 | | |
| | | | (0.0000) | | |
| lag_RUS | | | -1e-04* | | |
| | | | (0.0000) | | |
| CURA | 0.0036*** | 0.0038*** | 4e-03*** | 0.0019 | 0.0029* |
| | (0.0010) | (0.0011) | (0.0012) | (0.0014) | (0.0013) |
| DE | -0.0000 | -0.0000 | -0e+00 | -0.0000 | 0.0000 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| ICR | -0.0000** | -0.0000+ | -0e+00 | -0.0001* | -0.0000 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| PB | -0.0002 | -0.0002 | -2e-04 | -0.0003+ | -0.0002 |
| | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) |
| ROA | 0.0000 | 0.0000 | 0e+00 | 0.0004*** | 0.0004*** |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| log_TA | -0.0003 | -0.0008 | -8e-04 | -0.0015 | -0.0103** |
| | (0.0006) | (0.0006) | (0.0006) | (0.0032) | (0.0038) |
| Num.Obs. | 1995 | 1995 | 1496 | 1995 | 1995 |
| R2 | 0.077 | 0.243 | 0.264 | 0.652 | 0.732 |
| R2 Adj. | 0.073 | 0.229 | 0.246 | 0.534 | 0.634 |
| Std.Errors | by: ISIN | by: ISIN | by: ISIN | by: ISIN | by: ISIN |
| FE: industry | | X | X | | X |
| FE: year | | X | X | | X |
| FE: Country | | X | X | | X |
| FE: ISIN | | | | X | X |

Notes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard Errors in Parentheses. Variables names: Interest Expense to Total Debt (ID), Emission Score (EMS), Innovation Score (IS), Resource Use Score (RUS), Current Ratio (CURA), Debt-to-Equity Ratio (DE), Interest Coverage Ratio (ICR), Price-to-Book Ratio, Return on Assets (ROA) and the Logarithm of Total Assets (log_TA).

## TABLE 15: POOLED REGRESSION RESULTS OF THE CATEGORIES ON IAD

| | EMS: Pooled | IS: Pooled | RUS: Pooled | EMS: Pooled with FE | IS: Pooled with FE | RUS: Pooled with FE | EMS: Pooled with FE + Lag(EMS) | IS: Pooled with FE + Lag(IS) | RUS: Pooled with FE + Lag(RUS) |
|---|---|---|---|---|---|---|---|---|---|
| (Intercept) | 0.0484*** | 0.0462*** | 0.0474*** | | | | | | |
| | (0.0092) | (0.0093) | (0.0091) | | | | | | |
| EMS | -0.0001* | | | -0.0000 | | | | | |
| | (0.0000) | | | (0e+00) | | | | | |
| IS | | -0.0001* | | | -0.0000 | | | | |
| | | (0.0000) | | | (0e+00) | | | | |
| RUS | | | -0.0001*** | | | -0.0001* | | | |
| | | | (0.0000) | | | (0e+00) | | | |
| lag_EMS | | | | | | | -0.0000 | | |
| | | | | | | | (0e+00) | | |
| lag_IS | | | | | | | | -0.0000 | |
| | | | | | | | | (0e+00) | |
| lag_RUS | | | | | | | | | -0.0001* |
| | | | | | | | | | (0e+00) |
| CURA | 0.0037*** | 0.0036*** | 0.0036*** | 0.0036*** | 0.0036*** | 0.0036*** | 0.0037*** | 0.0037*** | 0.0037*** |
| | (0.0010) | (0.0010) | (0.0010) | (1e-03) | (1e-03) | (1e-03) | (1e-03) | (1e-03) | (1e-03) |
| DE | -0.0000 | -0.0000 | -0.0000 | -0.0000 | -0.0000 | -0.0000 | -0.0000 | -0.0000 | -0.0000 |
| | (0.0000) | (0.0000) | (0.0000) | (0e+00) | (0e+00) | (0e+00) | (0e+00) | (0e+00) | (0e+00) |
| ICR | -0.0000** | -0.0000** | -0.0000** | -0.0000* | -0.0000+ | -0.0000* | -0.0000* | -0.0000* | -0.0000* |
| | (0.0000) | (0.0000) | (0.0000) | (0e+00) | (0e+00) | (0e+00) | (0e+00) | (0e+00) | (0e+00) |
| PB | -0.0002 | -0.0002 | -0.0002 | -0.0001 | -0.0001 | -0.0001 | -0.0001 | -0.0001 | -0.0002 |
| | (0.0002) | (0.0002) | (0.0002) | (1e-04) | (1e-04) | (1e-04) | (2e-04) | (2e-04) | (1e-04) |
| ROA | -0.0000 | -0.0000 | 0.0000 | -0.0001 | -0.0001 | -0.0000 | -0.0000 | -0.0000 | -0.0000 |
| | (0.0001) | (0.0001) | (0.0001) | (1e-04) | (1e-04) | (1e-04) | (1e-04) | (1e-04) | (1e-04) |
| log_TA | -0.0009 | -0.0009 | -0.0006 | -0.0009+ | -0.0010+ | -0.0008 | -0.0010+ | -0.0010+ | -0.0009 |
| | (0.0006) | (0.0006) | (0.0006) | (5e-04) | (5e-04) | (6e-04) | (6e-04) | (5e-04) | (6e-04) |
| Num.Obs. | 1995 | 1995 | 1995 | 1995 | 1995 | 1995 | 1496 | 1496 | 1496 |
| R2 | 0.066 | 0.067 | 0.074 | 0.250 | 0.249 | 0.253 | 0.279 | 0.279 | 0.281 |
| R2 Adj. | 0.063 | 0.064 | 0.071 | 0.237 | 0.236 | 0.240 | 0.262 | 0.263 | 0.265 |
| Std.Errors | by: ISIN | by: ISIN | by: ISIN | by: ISIN | by: ISIN | by: ISIN | by: ISIN | by: ISIN | by: ISIN |
| FE: industry | | | | X | X | X | X | X | X |
| FE: year | | | | X | X | X | X | X | X |
| FE: Country | | | | X | X | X | X | X | X |

Notes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard Errors in Parentheses. Variables names: Interest Expense to Average Debt (IAD), Emission Score (EMS), Innovation Score (IS), Resource Use Score (RUS), Current Ratio (CURA), Debt-to-Equity Ratio (DE), Interest Coverage Ratio (ICR), Price-to-Book Ratio, Return on Assets (ROA) and the Logarithm of Total Assets (log_TA).

## Table 16: Pooled Regression Results of the Categories on ID

| | EMS: Pooled | IS: Pooled | RUS: Pooled | EMS: Pooled with FE | IS: Pooled with FE | RUS: Pooled with FE | EMS: Pooled with FE + Lag(EMS) | IS: Pooled with FE + Lag(IS) | RUS: Pooled with FE + Lag(RUS) |
|---|---|---|---|---|---|---|---|---|---|
| (Intercept) | 0.0486*** | 0.0462*** | 0.0476*** | | | | | | |
| | (0.0064) | (0.0065) | (0.0064) | | | | | | |
| EMS | -0.0001** | | | -0.0000 | | | | | |
| | (0.0000) | | | (0.0000) | | | | | |
| IS | | -0.0001*** | | | -0.0000 | | | | |
| | | (0.0000) | | | (0.0000) | | | | |
| RUS | | | -0.0001*** | | | -0.0001** | | | |
| | | | (0.0000) | | | (0.0000) | | | |
| lag_EMS | | | | | | | -0.0000 | | |
| | | | | | | | (0.0000) | | |
| lag_IS | | | | | | | | -0.0000 | |
| | | | | | | | | (0.0000) | |
| lag_RUS | | | | | | | | | -0.0001** |
| | | | | | | | | | (0.0000) |
| CURA | 0.0039*** | 0.0038*** | 0.0039*** | 0.0039*** | 0.0038*** | 0.0039*** | 0.0042*** | 0.0041*** | 0.0041*** |
| | (0.0005) | (0.0005) | (0.0005) | (0.0011) | (0.0011) | (0.0011) | (0.0012) | (0.0012) | (0.0012) |
| DE | -0.0000 | -0.0000 | -0.0000 | -0.0000 | -0.0000 | -0.0000 | -0.0000 | -0.0000 | -0.0000 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| ICR | -0.0000*** | -0.0000*** | -0.0000*** | -0.0000 | -0.0000 | -0.0000+ | -0.0000 | -0.0000 | -0.0000+ |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| PB | -0.0002* | -0.0003* | -0.0003** | -0.0002 | -0.0002 | -0.0002 | -0.0002 | -0.0002 | -0.0002 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) |
| ROA | 0.0000 | 0.0000 | 0.0000 | -0.0000 | -0.0000 | 0.0000 | 0.0000 | -0.0000 | 0.0000 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| log_TA | -0.0009* | -0.0009* | -0.0006 | -0.0011+ | -0.0012* | -0.0009 | -0.0011+ | -0.0012* | -0.0009 |
| | (0.0004) | (0.0004) | (0.0004) | (0.0006) | (0.0005) | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| Num.Obs. | 1995 | 1995 | 1995 | 1995 | 1995 | 1995 | 1496 | 1496 | 1496 |
| R2 | 0.066 | 0.067 | 0.074 | 0.237 | 0.237 | 0.242 | 0.258 | 0.258 | 0.263 |
| R2 Adj. | 0.063 | 0.064 | 0.071 | 0.224 | 0.224 | 0.229 | 0.241 | 0.242 | 0.246 |
| Std.Errors | by: ISIN | by: ISIN | by: ISIN | by: ISIN | by: ISIN | by: ISIN | by: ISIN | by: ISIN | by: ISIN |
| FE: industry | | | | X | X | X | X | X | X |
| FE: year | | | | X | X | X | X | X | X |
| FE: Country | | | | X | X | X | X | X | X |

Notes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard Errors in Parentheses. Variables names: Interest Expense to Total Debt (ID), Emission Score (EMS), Innovation Score (IS), Resource Use Score (RUS), Current Ratio (CURA), Debt-to-Equity Ratio (DE), Interest Coverage Ratio (ICR), Price-to-Book Ratio, Return on Assets (ROA) and the Logarithm of Total Assets (log_TA).

# 5 Discussion

Using several different econometric techniques such as pooled OLS, fixed effects, random effects, system GMM and propensity score matching models, results are inconsistent. Throughout its different specifications the results of the pooled OLS models stayed consistent for both measures of cost of debt. The same was the case for the propensity score matching. Due to concerns about omitted variable bias, the fixed effects models were used, which found no effect to exist. The random effects model in combination with the Hausman test showed that estimators are correlated with the error term, meaning that results of the random effects model would be biased and could not be used. Further exploring and controlling for endogeneity, the system GMM model showed that there is no effect of environmental performance on cost of debt and that the results of the pooled OLS model are in fact biased.

Results overall point out that differences between firms do exist, however differences within firms are absent. Endogeneity in the form of omitted variable bias most likely drives the effects in the pooled OLS and propensity score matching models as those models only account for observable factors. When unobservable factors are accounted for through fixed effects and system GMM models, any effect disappears. To account for and include those unobservable factors is a tough challenge as many factors could influence the models. For instance, I mentioned corporate governance as one of the factors that could be of influence, but many more could play a role, such as risk management, reputation, capital market access, green finance use, political connections etcetera. All aforementioned factors could very well influence the relation between environmental performance and cost of debt of firms.

As mentioned before, the pooled OLS and random effects models, although biased, show that differences between firms exist. To test for these differences, interaction effects and sample splits were used to investigate and assess these differences. Using a fixed effects model no differences are found between polluting and non-polluting firms and no interactions between environmental performance and either leverage or size turned out to be significant, highlighting that measurable firm specific characteristics do not differ enough to influence the relation. Although sample splits showed that the effects are stronger for large firms, it was not significant and as such not enough to state that the effect is notably stronger for large firms.

Logically flowing from the environmental performance results, the results focussing on the different categories showed no effect as well. Given that the results point towards an absence of a relation between environmental performance and cost of debt, the question remains why this could be the case.

Stock markets are known to be very volatile and react heavily to firm disclosures compared to credit markets, which explains the strong findings by Chava (2014), Kim et al. (2015) and Chen et al. (2023). Credit markets are often more focussed on the long term and classic financial measures to asses firm risk and credibility compared to stock markets, which often react more strongly to non-financial information. When environmental performance improves but classic financial measures remain unchanged, creditors could very well neglect improvements in environmental performance as they do not deem it significant enough.

Besides debt markets reacting more slowly, cost of debt are also very rigid. Debt covenants are often negotiated for long periods of time with interest rates that mostly stay quite constant over that time. Since this is the case, reactions in cost of debt are not that strong over short periods of time. It might be the case that the findings by Gigante & Manglaviti (2022) also suffered from this problem. They only look at the time period 2018-2020, whereas Eliwa et al. (2021) look at the period 2005-2016 and do find an effect. A big difference in years and a possible explanation why these studies differ in outcome.

Then there is the concern about data quality and firm transparency. ESG related data is derived by LSEG via self-reported data by firms. Most of these non-financial reports remain unaudited and those that do get audited only get limited assurance statements which in itself are not very reliable (Gürtürk & Hahn, 2016). As a result, not much trust can be put in these non-financial statements. Based on these reports LSEG compiles the E pillar score, for which all raters use a different framework than others. Here lies the unreliability of ESG reporting. Firstly, the reports by firms themselves are unreliable and secondly, all raters use different frameworks which lead them to different scores. Then the question for creditor becomes to what extent they deem these scores reliable to such an end that they can partly base their credit and trustworthiness assessment on them. My results show that it is not considered by creditors but instead other factors, which remain unidentified in my model due omitted variable bias, are more important to creditors for their assessment. The credibility with regard to ESG reporting, especially in the realm of the E pillar, is further threatened by the possibility of greenwashing. When firms are doing poorly, they want to overemphasize that they are in fact legitimate. To do so they publish false information in which they appear 'greener' than they are in practice (de Freitas Netto et al., 2020). These kinds of practices, or at least the risk for them, decreases trust in statements about environmental performance further.

In line with the signalling theory, firms need to make a costly signal to show creditors that they are environmentally sound. Such a costly signal is often investing in environmental improvements, which decreases liquidity in the short term. The decrease in liquidity could increase distress risk which would offset any effect of a decrease in cost of debt caused by improved environmental performance.

Further, there is the notion of Apergis et al. (2022) that the E pillar score poorly captures actual environmental risks in its score. Although performance is used as a proxy for risk with regard to sustainability, it does however not equal risk, meaning that environmental performance does not actually measure the risk that is created by having a bad environmental score.

Lastly, I want to point out the current worldwide developments with regard to sustainability. After decades of emphasizing and pushing improvements in sustainability, the Paris Agreement was drawn up in which most countries worldwide commit themselves to combat climate change. Throughout the last years however, sustainability and climate agreements have gone through a whirlwind. For example, the Paris Agreement was ratified in 2015, after which the US announced its withdrawal in 2017 and left in 2020, rejoined in 2021 and withdrew again in 2025. It shows that sustainability and its relevance in the eyes of politics, steered by the public, is losing significance. As sustainability is losing significance in the eyes of the public so does it as well for businesses and banks, as shown by Shell loosening its targets with regards to carbon intensity for 2030 and scraping its 2035 targets (Bousso, 2024) or the head of responsible investing of HSBC publicly downplaying climate change (Li & White, 2022). Although climate change is proven to be a big threat to the earth and economy, this threat cannot be accounted for when it is not seen as such.

Based on the argumentation above, it is either that no effect is found because the environmental performance measured as the E pillar does not capture risk sufficiently enough as stated by Apergis et al. (2022), the considered timespan is too short or that the current trend is changing and shifting away from a sustainable and responsible economy. I do not deem the first reason very likely however, because multiple papers testing the E pillar on cost of debt do find a relation to exist (Eliwa et al., 2021; Arora & Sharma, 2022; Apergis et al., 2022; Malik & Kashiramka, 2024; Li et al., 2024). Therefore it is either that the considered timespan is too short, which might have also played a role in the study of Gigante & Manglaviti (2022), or current trends are simply shifting away from viewing sustainability as material. The latter notion is supported by a report from Bain & Company (2024) in which they found that focus from CEOs has shifted away from sustainability and towards artificial intelligence and the current geopolitical situation, because CEOs are currently deeming these topics as more important to their business practices. Either one of these factors, or a combination of the two, could be behind the absence of the investigated relation in this thesis.

# 6 Conclusion

Throughout the last decades climate change and how it can or will affect business practice has become an increasingly important topic for scholars, with research into this topic especially flourishing since the development of ESG frameworks and standards. Since it is quite a new topic, not much is known and many areas remain unexplored. Effects of ESG are shown to be contradictory, with research not agreeing on its effect on business. Some have argued that the environmental aspect in ESG is the most important and that the social and governance aspects are creating noise in this relation. Focussing on the effect of environmental performance of firms on their cost of debt, recent work is quite sparse with contradictions for European firms in recent years. As such, the goal of this thesis has been to investigate the relation between environmental performance and cost of debt, and to see which of the categories of the E pillar is the strongest driver of this effect. The main research question that this thesis seeks to answer is: '*To what extent does corporate environmental performance affect cost of debt?*' To answer this question, a sample has been used that spans the period 2020-2023 and consists of 499 European firms that at some point in time between 2020-2023 have been listed on the STOXX Europe 600.

Although the findings of Gigante & Manglaviti (2022) casted some doubt over the proposed hypotheses, based on theory and other literature it was expected that an effect would be found nonetheless. The hypotheses have been tested using a wide range of econometric techniques, which yielded inconsistent results. After exploring the implication of these results, it seems that the results challenge all of the hypotheses in this thesis. I conclude that for the data and timespan considered in this thesis there is simply no effect of corporate environmental performance on cost of debt. Any effect that has been found using the pooled OLS, random effects and propensity score matching models is most likely driven by omitted variable bias as these effects are absent in the fixed effects and system GMM models that control for unobserved firm specific characteristics. So to answer the main research question: there is no effect of corporate environmental performance on cost of debt. However, this conclusion only holds for the sample of firms and the timespan that is being considered in this thesis.

For managers and firms the findings mean that environmental performance cannot be seen as a means to lowering their cost of debt. As such, improving their environmental performance to decrease their cost of debt is to no avail. For scholars the result are interesting as my thesis is one of few to challenge the notion that environmental performance negatively affects cost of debt. For policymakers it is a clear sign that the current strategies to emphasize the importance of improving corporate environmental performance are not working and that lenders do not respond to such improvements. Policymakers should increase the speed at which sustainability laws are introduced so environmental performance will be seen as material by lenders. These actions would incentivise firms to improve their environmental performance.

Although data on the E pillar from LSEG is used in several highly regarded papers (La Rosa et al., 2018; Eliwa et al., 2021; Apergis et al., 2022), it is but one rater. For this thesis I had no access to data provided by other raters such as MSCI, Sustainalytics and CDP. With the results from this thesis, I can only provide a one sided picture instead of a multi angle viewpoint which would have been possible by using data from other raters. Furthermore, due to inferior data quality before 2020, only data starting from 2020 has been used. As such the considered timespan is rather short which would explain why changes within firms are hardly noticeable.

After consideration, I propose two possible explanations for the absence of an effect of environmental performance on cost of debt. Either due to the short timespan the changes are unnoticeable due to the rigid nature of cost of debt, or due to changes in the perceived importance of sustainability.

Future research has several ways of continuing the work done in this thesis. First of all, market-based or rating-based measures of cost of debt could be used instead of focussing on accounting-based measures. Secondly, data provided by other raters could be used to see whether results stay consistent. Thirdly, to avoid the rigidity problem of cost of debt, cost of newly issued debt could be considered instead of cost of average or total debt. Fourthly, future work could investigate to what extent the effects of sentiment changes and focus shifting away from sustainability and towards other factors such as artificial intelligence and current geopolitical uncertainties can explain why no effect of environmental performance on cost of debt has been found.

To conclude on this thesis, given the limitations, it shows that there is no existing relation between environmental performance and cost of debt and that any effort by a firm to improve its environmental performance is not rewarded by lower cost of debt. Therefore, improvements in corporate environmental performance, for now, cannot be seen as a panacea for lowering cost of debt faced by firms.

## Bibliography


Akerlof, G. A. (1978). The market for “lemons”: Quality uncertainty and the market mechanism. In *Uncertainty in economics* (pp. 235-251). Academic Press.

Ali, K., Nadeem, M., Pandey, R., & Bhabra, G. S. (2023). Do capital markets reward corporate climate change actions? Evidence from the cost of debt. *Business Strategy and the Environment*, *32*(6), 3417-3431.

Alves, C. F., & Meneses, L. L. (2024). ESG scores and debt costs: Exploring indebtedness, agency costs, and financial system impact. *International Review of Financial Analysis*, *94*, 103240.

Aman, H., & Nguyen, P. (2013). Does good governance matter to debtholders? Evidence from the credit ratings of Japanese firms. *Research in International Business and Finance, 29*, 14–34.

Amel-Zadeh, A., & Serafeim, G. (2018). Why and how investors use ESG information: Evidence from a global survey. *Financial analysts journal*, *74*(3), 87-103.

Apergis, N., Poufinas, T., & Antonopoulos, A. (2022). ESG scores and cost of debt. *Energy Economics*, *112*, 106186.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of econometrics*, *68*(1), 29-51.

Arora, A., & Sharma, D. (2022). Do environmental, social and governance (ESG) performance scores reduce the cost of debt? Evidence from Indian firms. *Australasian Accounting, Business and Finance Journal*, *16*(5).

Ashforth, B. E., & Gibbs, B. W. (1990). The double-edge of organizational legitimation. *Organization science*, *1*(2), 177-194.

Bain & Company. (2024). *The visionary CEO’s guide to sustainability 2024*. https://www.bain.com/insights/topics/ceo-sustainability-guide/

Ballester, L., González-Urteaga, A., & Martínez, B. (2025). When is environmental performance most valued? International evidence from the CDS market. *International Review of Economics & Finance*, *99*, 104057.

Balvers, R., Du, D., & Zhao, X. (2017). Temperature shocks and the cost of equity capital: Implications for climate change perceptions. *Journal of Banking and Finance, 77*, 18–34.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of* *management*, *17*(1), 99-120.

Bauer, R., & Hann, D. (2010). Corporate environmental management and credit risk. *Available at SSRN 1660470*.

Benedetto, U., Head, S. J., Angelini, G. D., & Blackstone, E. H. (2018). Statistical primer: propensity score matching and its alternatives. *European Journal of Cardio-Thoracic Surgery*, *53*(6), 1112-1117.

Biggi, G., Mina, A., & Tamagni, F. (2023). There are different shades of green: heterogeneous environmental innovations and their effects on firm performance.

Birindelli, G., Ferretti, P., Intonti, M., & Iannuzzi, A. P. (2015). On the drivers of corporate social responsibility in banks: evidence from an ethical rating model. Journal of Management & Governance, 19, 303-340.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of econometrics*, *87*(1), 115-143.

Bousso, R. (2024, March 14). *Shell weakens 2030 carbon emissions reduction target*. Reuters. https://www.reuters.com/sustainability/climate-energy/shell-loosens-2030-carbon-emissions-target-2024-03-14/

Caragnano, A., Mariani, M., Pizzutilo, F., & Zito, M. (2020). Is it worth reducing GHG emissions? Exploring the effect on the cost of debt financing. *Journal of Environmental Management, 270*, 110860.

Chalmers, J., Cox, E., & Picard, N. (2021). *The economic realities of ESG*. PwC Strategy+Business. https://www.pwc.com/economic-realities-of-ESG

Chava, S. (2014). Environmental externalities and cost of capital. *Management science*, *60*(9), 2223-2247.

Chen, K. H., & Metcalf, R. W. (1980). The relationship between pollution control record and financial indicators revisited. *The accounting review*, *55*(1), 168-177.

Chen, L. H., & Silva Gao, L. (2012). The pricing of climate risk. *Journal of Financial and Economic Practice, Vol12 (2), Spring*, 115-131

Chen, S., Song, Y., & Gao, P. (2023). Environmental, social, and governance (ESG) performance and financial outcomes: Analyzing the impact of ESG on financial performance. *Journal of* *environmental management*, *345*, 118829

Cheng, B., Ioannou, I., & Serafeim, G. (2014). Corporate social responsibility and access to finance. *Strategic management journal*, *35*(1), 1-23.

Clarkson, P. M., Li, Y., Richardson, G. D., & Vasvari, F. P. (2008). Revisiting the relation between environmental performance and environmental disclosure: An empirical analysis. *Accounting, organizations and society*, *33*(4-5), 303-327.

Cohen, M. A., Fenn, S., & Naimon, J. S. (1995). *Environmental and financial performance: are they related?*. Washington, DC: Investor Responsibility Research Center, Environmental Information Service.

de Freitas Netto, S. V., Sobral, M. F. F., Ribeiro, A. R. B., & Soares, G. R. D. L. (2020). Concepts and forms of greenwashing: A systematic review. *Environmental Sciences Europe*, *32*, 1-12.

Ding, X., Appolloni, A., & Shahzad, M. (2022). Environmental administrative penalty, corporate environmental disclosures and the cost of debt. *Journal of Cleaner Production*, *332*, 129919.

Dowell, G., Hart, S., & Yeung, B. (2000). Do corporate global environmental standards create or destroy market value?. *Management science*, *46*(8), 1059-1074.

Dowling, J., & Pfeffer, J. (1975). Organizational legitimacy: Social values and organizational behavior. *Pacific sociological review*, *18*(1), 122-136.

Du, X., Weng, J., Zeng, Q., Chang, Y., & Pei, H. (2017). Do lenders applaud corporate environmental performance? Evidence from Chinese private-owned firms. *Journal of Business Ethics*, *143*, 179-207.

Eichholtz, P., Holtermans, R., Kok, N., & Yönder, E. (2019). Environmental performance and the cost of debt: Evidence from commercial mortgages and REIT bonds. *Journal of Banking & Finance*, *102*, 19-32.

Eliwa, Y., Aboud, A., & Saleh, A. (2021). ESG practices and the cost of debt: Evidence from EU countries. *Critical Perspectives on Accounting, 79*, 102097.

Erragragui, E. (2018). Do creditors price firms' environmental, social and governance risks?. *Research in International Business and Finance*, *45*, 197-207.

Faisal, M., Ahmad, A., Riaz, S., & Rahman, Z. U. (2021). The Impact of Resource Efficiency Actions on Firm Performance, Moderating Role of Eco-Investment and Production Cost. *International*

*Journal of Management Research and Emerging Sciences*, *11*(4).

Ferrell, A., Liang, H., & Renneboog, L. (2016). Socially responsible firms. *Journal of financial economics*, *122*(3), 585-606.

Freeman, R. E., Harrison, J. S., Wicks, A. C., Parmar, B. L., & De Colle, S. (2010). Stakeholder theory: The state of the art.

Friede, G., Busch, T., Bassen, A., (2015). ESG and financial performance: aggregated evidence from more than 2000 empirical studies. *Journal of Sustainable Finance & Investment 5* (4), 210–233

Gao, H., Wang, J., Wang, Y., Wu, C., & Dong, X. (2020). Media coverage and the cost of debt. *Journal of Financial and Quantitative Analysis*, *55*(2), 429-471.

Gigante, G., & Manglaviti, D. (2022). The ESG effect on the cost of debt financing: A sharp RD analysis. *International Review of Financial Analysis*, *84*, 102382.

Graham, A., & Maher, J. J. (2006). Environmental liabilities, bond ratings, and bond yields. *Environmental accounting* 111-142.

Graham, A., Maher, J. J., & Northcut, W. D. (2001). Environmental liability information and bond ratings. *Journal of Accounting, Auditing & Finance*, *16*(2), 93-116.

Griliches, Z. (2007). *R&D and productivity: The econometric evidence.* University of Chicago Press.

Gürtürk, A., & Hahn, R. (2016). An empirical assessment of assurance statements in sustainability reports: smoke screens or enlightening information?. *Journal of cleaner production*, *136*, 30-41.

Hackbarth, D., Miao, J., & Morellec, E. (2006). Capital structure, credit risk, and macroeconomic conditions. Journal of financial economics, 82(3), 519-550.

Hart, S. L. (1995). A natural-resource-based view of the firm. *Academy of management review*, *20*(4), 986-1014.

Hoepner, A., Oikonomou, I., Scholtens, B., & Schröder, M. (2016). The effects of corporate and country sustainability characteristics on the cost of debt: An international investigation. *Journal of Business Finance & Accounting, 43*(1–2), 158–190.

Intergovernmental Panel on Climate Change (IPCC). (2023). *Summary for policymakers. In Climate change 2023: Synthesis report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*.

Izzo, M. F., & Magnanelli, B. S. (2012). Does it pay or does firm pay? The relation between CSR performance and the cost of debt.

Kennedy, P. (2008). *A guide to econometrics*. John Wiley & Sons.

Kim, Y. B., An, H. T., & Kim, J. D. (2015). The effect of carbon risk on the cost of equity capital. *Journal of Cleaner Production*, *93*, 279-287.

Kraus, A., & Litzenberger, R. H. (1973). A state-preference model of optimal financial leverage. *The journal of finance*, *28*(4), 911-922.

La Rosa, F., Liberatore, G., Mazzi, F., & Terzani, S. (2018). The impact of corporate social performance on the cost of debt and access to debt financing for listed European non-financial firms. European Management Journal, 36(4), 519-529.

Levitt, T. (1958). The dangers of social-responsibility. *Harvard business review*, *36*(5), 41-50.

Li, S., & White, L. (2022, May 27). *Exclusive: HSBC feels the heat after senior banker downplays climate risk*. Reuters. https://www.reuters.com/business/sustainable-business/exclusive-hsbc-clients-query-bank-climate-one-review-engagement-sources-2022-05-27/

Li, W., Hu, H., & Hong, Z. (2024). Green finance policy, ESG rating, and cost of debt——Evidence from China. *International Review of Financial Analysis*, *92*, 103051.

Liu, P., Zhu, B., Yang, M., & Chu, X. (2022). ESG and financial performance: A qualitative comparative analysis in China's new energy companies. *Journal of Cleaner Production*, 379, 134721.

Loannou, I., & Serafeim, G. (2012). What drives corporate social performance? The role of nation-level institutions. *Journal of International Business Studies, 43* (9), 834–864.

London Stock Exchange Group. (2024). *Environmental, social and governance scores guide*.

Maaloul, A., Zéghal, D., Ben Amar, W., & Mansour, S. (2023). The effect of environmental, social, and governance (ESG) performance and disclosure on cost of debt: The mediating effect of corporate reputation. *Corporate reputation review*, *26*(1), 1-18.

Mahapatra, S. (1984). Investor reaction to a corporate social accounting. *Journal of Business Finance & Accounting*, *11*(1).

Malik, N., & Kashiramka, S. (2024). Impact of ESG disclosure on firm performance and cost of debt: Empirical evidence from India. *Journal of Cleaner Production*, *448*, 141582.

Michelson, G., Wailes, N., Van Der Laan, S., & Frost, G. (2004). Ethical investment processes and outcomes. *Journal of Business Ethics, 52*, 1-10.

Modi, S. B., & Mishra, S. (2011). What drives financial performance–resource efficiency or resource slack?: Evidence from US based manufacturing firms from 1991 to 2006. *Journal of Operations Management*, *29*(3), 254-273.

Murphy, C. J. (2002). The profitable correlation between environmental and financial performance: a review of the research. *Light Green Advisors*, 1-18.

Myers, S. C. (2001). Capital structure. *Journal of Economic perspectives*, *15*(2), 81-102.

Nehrt, C. (1996). Timing and intensity effects of environmental investments. *Strategic management journal*, *17*(7), 535-547.

Ng, A. C., & Rezaee, Z. (2015). Business sustainability performance and cost of equity capital. *Journal of Corporate Finance, 34*, 128-149.

Nikolaev, V., & Van Lent, L. (2005). The endogeneity bias in the relation between cost-of-debt capital and corporate disclosure policy. *European Accounting Review*, *14*(4), 677-724.

Noh, J. H. (2018). Relationship between climate change risk and cost of capital. *Global Business & Finance Review (GBFR)*, *23*(2), 66-81.

Orlitzky, M., Schmidt, F. L., & Rynes, S. L. (2003). Corporate social and financial performance: A meta-analysis. *Organization studies*, *24*(3), 403-441.

Pizzutilo, F., Mariani, M., Caragnano, A., & Zito, M. (2020). Dealing with carbon risk and the cost of debt: Evidence from the European market. *International Journal of Financial Studies*, *8*(4), 61.

Rapp, M. S., & Roser, M. (2024). The Importance of ESG, Environmental Sustainability, and the EU Taxonomy for Institutional Investors: Survey Evidence. *Social Science Research Network*.

Rong, X., & Kim, M. I. (2024). ESG and the cost of debt: Role of media coverage. *Sustainability*, *16*(12), 4993.

Saba, Z. (2024). Firm-level Climate Risk Exposure and Newly Issued Corporate Debt Maturity.

Schneider, T. E. (2011). Is environmental performance a determinant of bond pricing? Evidence from the US pulp and paper and chemical industries. *Contemporary Accounting Research*, *28*(5), 1537-1561.

Shad, M. K., Lai, W. F., Shamim, A., & McShane, M. (2020). The efficacy of sustainability reporting towards cost of debt and equity reduction. *Environmental Science and Pollution Research, 27*(18), 22511–22522

Sharfman, M. P., & Fernando, C. S. (2008). Environmental risk management and the cost of capital. *Strategic management journal*, *29*(6), 569-592.

Spence, M. (1978). Job market signaling. *Uncertainty in economics* (pp. 281-306). Academic Press.

Spicer, B. H. (1978). Investors, corporate social performance and information disclosure: An empirical study. *Accounting review*, 94-111.

Stern, N. (2006). Stern Review: The economics of climate change.

Stiglitz, J. E. (1972). Some aspects of the pure theory of corporate finance: bankruptcies and take-overs. The Bell Journal of economics and management Science, 458-482.

Stiglitz, J. E., & Weiss, A. (1981). Credit rationing in markets with imperfect information. *The American economic review*, *71*(3), 393-410.

STOXX Ltd. *STOXX Europe 600 Index (SXXP) Factsheet*. Retrieved from https://stoxx.com/index/sxxp/?factsheet=true

Wesa, E. W., & Otinga, H. N. (2018). Determinants of financial distress among listed firms at the Nairobi securities exchange, Kenya. *Strategic Journal of Business and Change Management*, *5*(4), 1056-1073.

Yan, Y., Cheng, X., & Ong, T. (2024). Unravelling the Missing Link: Climate Risk, ESG Performance and Debt Capital Cost in China. *Sustainability*, *16*(16), 7137.

Zhao, Y., Gao, Y., & Hong, D. (2024). Sustainable innovation and economic resilience: deciphering esg ratings' role in lowering debt financing costs. *Journal of the Knowledge Economy*, 1-35.

Zhu, T., Liu, D., & Zhang, L. (2025). Does ESG Performance Help Corporate Deleveraging? Based on an Analysis of Excessive Corporate Debt. *Sustainability, 17*(3), 1274.

## Appendix A: Statement on Generative AI

ChatGPT has been used to assist in the coding for this thesis. It has been used to provide the code for tables 1, 2 and 3 and figures 1 & 2. For table 4 codes have been provided to apply winsorization, categorize firms by industry and to create a lag for ES and to provide a good looking table template. The code for the table template has been copied and used for all following tables and will therefore not be mentioned again. The code for table 4 was copied and altered to fit for table 5. For tables 6 & 7 all codes of table 4 were copied and altered. For table 8 a code was provided to create dummies for firms being polluting or non-polluting. For tables 9 & 10 a code was provided to create different samples based on size and leverage. For table 11 a code was provided to run the system GMM with three lags, two lags and collapsed instruments, this code was copied and altered for table 12. For the propensity score matching codes were provided to apply nearest neighbour matching and to run a logistic regression. For tables 13, 14, 15 and 16 the code of table 4 was copied and altered to fit for these tables.