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The Impact of Carbon Emissions on the Cost of Debt: A European Perspective

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Abstract

This thesis investigates the impact of carbon emissions on the cost of debt of European firms, by analyzing robust OLS regression models. The findings reveal that there is a statistically significant positive association between carbon emissions and cost of debt, with profitability moderating this relationship. The findings suggest that higher emissions could lead to higher borrowing costs, highlighting the economic incentives for adopting sustainable practices. This study contributes to the academic literature by providing empirical evidence on how environmental risks can translate into financial costs.

Keywords: Cost of debt, Emissions, Carbon Risk, Credit Risk, CSRD, ESG

Chapter 1: Introduction

Since the Paris Agreement was enacted in 2016, there has been a major force of global sustainability efforts to combat climate change, marking it as a pivotal moment. This international accord aims to limit global warming to well below 2°C above pre-industrial levels, primarily by reducing carbon emissions (UNFCCC, 2016). Central to achieving this goal is the need for governments to cooperate in implementing measures that significantly cut greenhouse gas emissions by necessitating a shift towards more sustainable and environmentally friendly practices around the world.

Subsequently, many governments and institutions have pledged to implement the necessary measures to tackle this global problem, one example is the European Union (EU). In line with the objectives of the Paris Agreement, the EU has introduced several regulatory frameworks designed to reduce carbon emissions and promote sustainability. One of the most significant of these is the Emissions Trading Scheme (ETS), which was launched as the world's first major carbon market that aims to financially incentivize companies to reduce emissions, by setting a cap on the total amount of greenhouse gases that can be emitted by factories and plants (European Parliament, 2023). The ETS coupled with the EU carbon taxes, provides a formidable force of regulatory framework designed to directly penalize polluting behaviors and encourage investments in greener technology (Metcalf, 2021).

In addition to these measures, the EU has introduced the Corporate Social Responsibility Directive (CSRD), as part of the EU Green Deal, which mandates extensive Environmental, Social, and Governance (ESG) disclosures from large companies and those listed on EU-regulated markets. This directive builds on the earlier Non-Financial Reporting Directive (NFRD) by requiring more detailed and rigorous reporting standards (PwC, 2023). This directive will force firms to increase their transparency regarding sustainable activities, further incentivizing firms to engage in socially responsible activities and reduce emissions to enhance their reputation with both stakeholders and investors.

1.1 Research question

It is believed that there may be potential financial benefits in having more sustainable practices and empirical evidence underscores the benefits of such greener initiatives. For instance, Zumente and Bistrova (2021) highlight that firms with strong ESG practices tend to have better long-term shareholder value. In addition, from the borrowing side, Mendiratta et al. (2021) show that high ESG-rated issuers exhibit statistically significant lower levels of systematic and idiosyncratic risks, underscoring the positive effect of ESG on credit risk.

Building on this literature, it is evident that there might be a link between carbon emissions and financial performance, specifically from the borrowing side. This is mainly due to the presence of carbon risk, which causes a firm to have long-term risks in the form of regulatory, market, transition, and reputational risks (Görgen et al., 2020). This carbon risk can hurt the creditworthiness of a firm and increase its long-term credit risk as a result. With a higher credit risk, a higher premium is expected by lenders to compensate for the extra risk, thus borrowing costs increase as well. To investigate whether carbon emissions are associated with higher borrowing costs, the following research question is formulated: *How do carbon emissions impact the cost of debt for companies within Europe?*

In addition, the effect of profitability on this association will be investigated to see whether profitable companies can mitigate the negative effects of carbon emissions.

1.2 Social and scientific relevance

This investigation into the financial impact of carbon emissions holds substantial social relevance, especially for policymakers and corporate managers across Europe. As the EU intensifies its efforts to fight climate change through initiatives like CSRD, understanding the financial implications of a major contributor to climate change (carbon emissions) is crucial. This research provides evidence of the association between emissions and borrowing costs as well as the effect profitability has on this association. Thus, it can provide guidance on whether regulations such as CSRD, which aims at increasing transparency, can actually promote sustainable practices or are more stringent measures needed for firms who can mitigate this possible adverse effect. For corporations, this study can offer insights for managers into the economic viability of adopting low-emitting technologies. Hence, it can help in the cost-benefit analysis of determining whether to invest in such technologies, by including the possibility of lower financing costs.

From a scientific standpoint, this study addresses a research gap in the current body of literature by focusing on the impact of carbon emissions on the cost of debt, which is a less explored topic compared to the vast literature on the impact of emissions on equity and shareholder value. While extensive studies have been conducted on the effect of ESG factors on investor confidence and stock prices, less attention has been paid to how these factors might affect borrowing terms and costs (Friede et al. 2015). By exploring this dimension, this study contributes to a more comprehensible understanding of the effect ESG practices and policies have on financial performance, particularly in the context of borrowing.

1.3 Thesis outline

In this research, there will be five chapters. The following chapter is the theoretical framework, which includes a literature review of the scientific literature regarding this topic. This will lay the foundation of the thesis and will ultimately end in the development of the hypothesis. In Chapter 3, the data and methodology of this research will be discussed. In Chapter 4, the methodology will be executed, and the results will be presented and interpreted accordingly. Then, based on the findings, Chapter 4 will conclude with whether the null hypothesis will be rejected. Lastly, Chapter 5, will conclude with a discussion of the findings, the limitations of the study, and how the findings answer the research question.

Chapter 2: Theoretical framework

In this chapter, the theoretical foundation needed for the rest of the research will be presented. Firstly, 2.1 will define the necessary concepts and explain the background information needed to correctly interpret the analysis of this research. Chapter 2.2 will then go on to present the literature regarding the relationship between carbon emissions and credit risk, which will lay the foundation for 2.3, which will discuss the relationship between carbon emissions and the cost of debt. Lastly, 2.4 will encompass the hypothesis development and will explain the literature that led up to the two hypotheses that will be tested in the analysis.

2.1 Background

ESG and regulatory frameworks

The regulatory landscape in Europe concerning ESG practices has seen major changes throughout the years, prominently led by the introduction of the new Corporate Social Responsibility Directive (CSRD). This directive stems from the European Green Deal and aims to transform Europe into the world's first economic power to achieve net zero greenhouse emissions by 2050 (EU monitor, 2023). This directive aims to contribute to the EU Green Deal by mandating extensive ESG disclosures from all large companies and those listed on EU-regulated markets (PwC, 2023). Compared to the previous sustainability directive, the Non-Financial Reporting Directive (NFRD), the CSRD not only requires listed companies to report on sustainability metrics but any firm that fulfills two of the three criteria below:

- net turnover of EUR40 million or more and/or
- a balance sheet of EUR20 million or more and/or
- minimum of 250 employees

This is a significant increase in the scope of sustainability reporting as it expands the number of companies from 11,000 to almost 50,000, which is about 75% of European companies' total turnover (KPMG, 2023). The CSRD ultimately increases the depth and breadth of the reporting requirements and aims to increase the transparency and comparability of sustainability data across all entities. This is seen as a crucial step towards integrating sustainable practices into strategic planning for firms by informing both shareholders and stakeholders about their sustainability practices and performance (European Commission, 2023).

Following the CSRD, new reforms to the Emissions Trading Scheme (ETS), further exemplify Europe's commitment to regulating corporate environmental impact. Launched in 2005, the ETS was the world's first major carbon market that regulates the number of emissions by following a "cap and trade" system that sets a cap on the total amount of greenhouse gases that can be emitted by factories and plants. Firms must hold permits for each ton of CO2 they emit, incentivizing companies to emit less, as under the ETS, the more you pollute the more you pay. Due to the recent reforms, the cap on carbon permits is gradually decreasing to meet the more optimistic EU climate targets (under the EU Green Deal), as a result, firms now face higher costs of emissions, propelling them towards more sustainable operational practices (European Parliament, 2023).

Both the CSRD and ETS are crucial elements in the broader EU Green Deal policies that aim to create an economy that is sustainable, carbon neutral, and circular. The combination of comprehensive sustainability reporting with strict environmental regulations forms a robust foundation for addressing the objectives of both transparency and environmental accountability. This alignment is also supported by empirical evidence, such as the findings of Khan et al. (2015), which suggest that firms that actively manage and report on material sustainability issues tend to perform better financially. In addition, Krueger et al. (2021) present positive effects of ESG disclosure mandates on firm-level stock liquidity, stating also that the effects are strongest if the disclosure requirements are implemented by government institutions. This is in line with the EU's approach, as it shows the benefits and financial rewards of stringent ESG and carbon emission standards (Khan et al., 2015).

In essence, the EU regulatory frameworks, such as the CSRD and ETS, not only aim to mitigate environmental risks but also attempt to enhance the financial alignment of firms with global sustainability initiatives. The EU taxonomy further clarifies these frameworks by classifying economic activities based on their environmental sustainability, to prevent greenwashing activities and support investors in identifying greener investments (European Commission, 2023). This approach is supported by empirical evidence that shows that mandatory ESG disclosures are associated with an enhanced information environment, leading to beneficial capital market effects, in the form of better decision-making by both lenders and equity providers (Krueger et al., 2021).

Carbon emissions and carbon risk

In November 2016, the biggest collective global effort to address climate change came into force: The Paris Agreement, which aims to limit global warming to well below 2°C above pre-industrial levels (UNFCCC, 2016). Central to this objective is the reduction of carbon emissions, which refers to the release of carbon dioxide (CO2) into the atmosphere, mainly through the combustion of fossil fuels and industrialization. As a result, carbon emissions contribute significantly to global warming due to their greenhouse effect, by trapping heat in the earth's atmosphere (Huisingh et al., 2015). An example of this is the cement industry, which is known to be a major source of carbon emissions, due to the energy-intensive process of cement production, hence contributing significantly to global CO2 levels (Barcelo et al., 2014).

Görgen et al. (2020) define carbon risk as “a price to emit carbon, with expectations of future increases coupled with institutional divestment, which leads to lower equity prices and higher expected returns for carbon-intensive firms to compensate for their additional risk” (p. 2). These risks can take many forms, including regulatory, market, transition, and reputational risks. Regulatory and transition risks emerge from the rapidly evolving and tightening regulations that impose carbon pricing, caps, or penalties on emissions, as seen in the ETS and carbon taxes, hence forcing companies to transition to more sustainable practices (Bolton & Kacperczyk, 2021). Market risk reflects the changes in market demand that are driven by shifts in consumer preferences towards low-carbon, sustainable products that are becoming increasingly available (Görgen et al., 2020). As a result of this shift in market demand, reputational risks, associated with stakeholder’s negative perception of companies that fail to manage their carbon footprint effectively, arise and lead to adverse long-term effects on brand image (Jung et al., 2016).

It is evident that the financial implications of carbon risks are profound and can potentially influence a company’s financial health, through the adverse effect emissions have on credit risk and consequently the cost of debt (Apergis & Poufinas., 2022). Thus, it can be concluded from this that firms with higher carbon emissions face higher financing costs as they are perceived to have higher credit risk due to potential regulatory penalties, operational disruptions, and transition risks. This is supported by research that demonstrates the impact of carbon emissions on a company’s financial health (Bolton & Kacperczyk, 2021).

Cost of debt and financing

In corporate finance, the cost of debt and overall cost of capital are pivotal concepts that greatly influence a firm’s investment strategy. Going back in time, Modigliani and Miller (1958) first introduced a foundational theory that states that the cost of capital is unaffected by the firm’s capital structure, assuming an environment free of taxes, bankruptcy costs, and asymmetric information. However, Van Binsbergen et al. (2010) go on to show how this is not the case in reality, by elaborating on the practical aspects of cost of debt, highlighting how real-world factors such as tax shields, default risk, and agency costs affect the cost of debt and hence the cost of capital. Their paper provides empirical evidence on the roles market conditions and firm-specific risk profiles play in determining the cost of debt of firms.

Furthermore, the overall costs of financing and cost of debt are crucial metrics that assist in assessing a firm’s financial health and are significantly influenced by a firm’s creditworthiness and market perceptions. According to Trade-off Theory, firms try and balance the costs and benefits debt to reach an optimal capital structure by considering both the tax advantages of debt and the risks of financial distress (Campbell, 1994). In addition, higher leverage can lead to greater financial risks and leads to an increase in the cost of debt due to the potential for default. Consequently, firms that have a track record in conservative, responsible financial management and demonstrate strong creditworthiness tend to face lower interest rates on their debt and hence lower financing costs (Van Binsbergen et al., 2010). However, the rising importance of sustainability coupled with carbon risks, introduces new complexities to these financial metrics, as firms with higher emissions may face higher financing costs to compensate lenders for additional risks (Görgen et al., 2020).

Credit risk

Another crucial aspect that affects a firm's cost of debt is credit risk. Credit risk refers to the likelihood that a borrower will fail to meet its obligations under the terms and conditions on which lenders provide funds. Credit Default Swaps (CDS) serve as a measure for this risk, as it offers investors a hedge against the credit risk of different issuers. Moreover, the pricing of CDS is heavily influenced by the perceived credit risk of an entity, thus it helps in providing a market reflection of credit risk (Ericsson et al., 2009). This in turn directly affects the cost of debt as, as higher credit risk leads to higher interest demanded by lenders to compensate for the increased likelihood of default (Van Binsbergen et al., 2010).

2.2 Relationship between carbon emissions and credit risk

As has been witnessed so far, the relationship between carbon emissions and credit risk is linked through regulatory and transition risks, as economies and markets shift towards low-carbon practices. Carbon regulations, such as the ETS and carbon taxes, aim at reducing emissions by creating a cost for emitting carbon, hence directly influencing a company's operating costs and financial liabilities (Metcalf, 2021). This, in turn, affects their credit risk profiles. For instance, the ETS imposes costs on firms that exceed their emissions quotas, which can lead to strains on financial resources and evidently alter credit risk perceptions among lenders and investors (Zhang & Zhao, 2022). Carbon taxes further increase the costs of emitting CO2, forcing firms to innovate or adopt cleaner technologies but at the same time impacting their short-term financial stability (Bolton & Kacperczyk, 2021).

Additionally, the implementation of the CSRD is reshaping how companies report and manage their environmental impact. This regulation aims to enhance transparency and encourage firms to integrate sustainable practices into their core operations. PwC (2023) notes that the CSRD will lead to increased scrutiny of companies' environmental records, due to the increased sustainability metrics disclosure, which could heavily influence credit ratings, and consequently, credit risk. This enhanced transparency might expose long-term hidden risks but may also offer the opportunity for companies to demonstrate their sustainability commitment as well as their risk management capabilities to creditors and investors (European Commission, 2023).

Coupled with the CSRD is the EU taxonomy for sustainable activities, which aims to direct financial flows towards sustainable investments and help mitigate greenwashing activities. The EU taxonomy provides a clear framework for investors and creditors by classifying economic activities that significantly contribute to climate mitigation (European Commission, 2023). This classification not only guides investment decisions but also influences the creditworthiness of a firm, thus affecting its credit risk profile. Mendiratta et al. (2021) provides empirical evidence to support this theory, as they show that firms with high ESG scores experienced lower levels of systematic and idiosyncratic risks. In addition, the research concluded that ESG-related risks were not fully captured in credit ratings, highlighting the importance of ESG ratings and the extra information they provide for investors and creditors. This study underscores the impact CSRD as well as the EU taxonomy might have on a firm's perceived credit risk.

Furthermore, Dumrose and Höck (2023) provide empirical research that also supports this claim. As data collected highlights how firms with high carbon risk exposure face wider credit spreads, reflecting an increased perceived risk by lenders. This is more evident in regions with stringent environmental regulations. Hence compliance with the CSRD requirements as well as alignment with EU taxonomy can eliminate such risks by demonstrating proactive management of perceived carbon risks. Jang et al. (2020) also support this notion by showing that ESG information provides creditors with additional downside protection by reducing credit risk associated with small firms, which often face informational disadvantages due to limited data. Hence ESG disclosures can increase transparency and consequently decrease the credit risk of firms committed to sustainable practices.

2.3 Relationship between carbon emissions and cost of debt

In the previous section, it was evident that carbon emissions negatively impact a firm's creditworthiness and hence increase its credit risk. Building on that, we could see that a firm's cost of debt would also be adversely affected as a result. This section will focus on the direct impacts of carbon emissions on the cost of debt, including compliance costs, potential penalties, and operational adjustments needed to meet emission targets. These factors can have significant financial implications, specifically in the form of a higher cost of debt. As Jung et al. (2016) illustrate, a heightened carbon risk awareness greatly influences how credit markets assess the risk associated with a firm's debt, with those having poor carbon risk management facing higher costs of debt. In addition, Caragnano et al. (2020) highlight the economic feasibility of reducing greenhouse gas (GHG) emissions, as they show that a decrease in GHG emissions leads to a reduction in the cost of borrowing. They also found that this positive relationship is relevant for both high and low-emitting industries.

Furthermore, various empirical studies highlight the positive effect ESG has on a firm's costs of debt. For example, Polbennikov et al. (2016) show that corporate bonds with high ESG ratings tend to have lower bond spreads, indicating a lower risk premium on the outstanding debt and consequently lower overall borrowing costs for the firm. In addition, they underscore the fact that this outperformance of highly rated ESG bonds is not accompanied by increasing relative valuation, suggesting that this outperformance is not due to buying pressure. This relationship is reinforced by a more up-to-date study where Apergis & Poufinas (2021) find that firms within the S&P 500 with superior ESG scores have significantly lower bond yield spreads, stating that this is primarily due to a decreased risk of bankruptcy or default. They also highlight that this relationship is constant with all 3 ESG pillars.

Contrary to these studies, Amiraslani et al. (2022) conducted an empirical study and found no relationship between environmental and social pillars (social capital) with bond spreads from the period 2006 to 2019. However, they found that during the 2008-2009 financial crisis, which represented a shock to trust and default risk, high social capital firms were able to raise more debt at lower spreads and longer maturities, indicating that trust with both investors and stakeholders is crucial, especially in times of crisis. This also applied to shareholder returns as Lins et al. (2017) found that, during the 2008-2009 financial crisis, high social capital firms experienced higher profitability, growth, and sales per employee relative to low social capital firms.

2.4 Hypothesis development

Building on the theoretical framework and empirical evidence discussed in the previous sections, two hypotheses are developed to address the research question.

The first hypothesis is derived from the various literature discussed which consistently shows a positive relationship between carbon emissions and the cost of debt. Studies such as Jung et al (2016) and Caragnano et al. (2020) have highlighted how carbon emissions can adversely affect a firm’s financial health, through increased financial liabilities and higher perceived credit risk by lenders, leading to higher borrowing costs as a result. By extending this relationship to European firms, this hypothesis anticipates that similar patterns will hold and will reflect the stringent EU regulatory framework such as the ETS and carbon taxes that increase accountability for firms within Europe. Hence, the following first hypothesis is developed: *Hypothesis 1: Carbon emissions are positively associated with the cost of debt for European firms.*

The second hypothesis explores the role profitability has on the relationship between carbon emissions and the cost of debt. This hypothesis is mainly based on the literature of Pierluigi Santosuosso (2014), who finds that there is a significant negative correlation between the cost of debt and firm profitability. The research shows that highly profitable firms are better able to mitigate the indirect costs of financial distress. Building on this, this hypothesis posits that more profitable companies might be able to buffer the negative financial effects of carbon emissions better than less profitable ones. As highly profitable firms have more resources at their disposal to effectively invest in carbon management practices and quickly transition to more sustainable practices and may mitigate the risk perceptions associated with high emissions. Therefore, the adverse effects of emissions on the cost of debt could be less pronounced in more profitable firms, due to their stronger financial health and greater resilience to regulatory costs. As a result, the following second hypothesis is developed:

Hypothesis 2: The relationship between carbon emissions and cost of debt is weaker with highly profitable companies.

Chapter 3: Data and methods

This chapter will focus on the methods and data used to perform this analysis. Firstly, the regression models are represented in section 3.1, including an explanation of the regression models and the rationale behind them. Following that, a description of the independent and dependent variables will be provided in section 3.2 as well as a description and an analysis of the control variables in section 3.3. Finally, the data sources used to retrieve the data will be mentioned briefly.

3.1 Regression models

Before performing the regression models, a comprehensive analysis of the data was conducted to ensure that the chosen statistical method for modelling is appropriate. First, the normality of the distribution of all the variables was assessed using the Shapiro-Wilk test. The results indicated that none of the variables were normally distributed, as all the tests produced a p-value below 0.05 (check Table A1). To address this issue each variable was transformed using a logarithm transformation of one plus the variable value (log $(x + 1)$), to ensure there are no undefined values (Hammouri et al., 2020). This was done to all variables expect the credit rating variable (as it is a categorical variable) and ROA (as it contains negative values).

For the first hypothesis, the relationship between emissions and the cost of debt will be investigated using an OLS (Ordinary Least Squares) regression. Thus, the analysis will be performed using Model (1):

(1) $$CODt_{it} = \beta_0 + \beta_1 \log(EMI_{it}) + \beta_2 \log(ENV_{it}) + \beta_3 \log(MV_{it}) + \beta_4 ROA_{it} + \beta_5 \log(LEV_{it}) + \beta_6 \log(RF_{it}) + \beta_7 CR_{it} + \varepsilon_{it}$$

In this formula, $CODt_{it}$ represents the Cost of Debt and EMI_{it} represents the Emissions Score. ENV_{it} represents the Environment Pillar Score under ESG, MV_{it} is the Market Value of a firm, ROA_{it} is the Return on Assets, LEV_{it} represents the Leverage Ratio, RF_{it} represents the Risk-Free Rate, and CR_{it} is the Credit Rating. Lastly ε_{it} represents the error term. For all the variables in this formula, i represents firm i and t represents year t. A description and the sources of all the variables can be found in Table 1 below.

Table 1 Definition of variables

Variable	Abbreviation	Definition	Source
Cost of Debt	COD	The average interest rate a firm pays on its outstanding debt	Refinitiv DataStream
Emissions Score	EMI	A score that measures a company's commitment and effectiveness towards reducing environmental emissions in its production and operational processes	Refinitiv DataStream
Market Value	MV	The outstanding company shares multiplied by share price	Refinitiv DataStream
Environment Pillar Score	ENV	A score that evaluates a company's overall environmental impact	Refinitiv DataStream
Return on Assets	ROA	Net income divided by total assets	Refinitiv DataStream
Leverage	LEV	Ratio of total debt to total capital and short-term debt	Refinitiv DataStream
Risk-free Rate	RF	The Euro Area 10 Years Government Benchmark Bond Yield	ECB Data Portal
Credit Rating	CR	A rating that reflects the relative credit risk of fixed-income obligations with an original maturity of one year or more	Moody's

Note. This table provides information on the variables used in Model (1) and Model (2). Column 1 provides the name of the variable, column 2 the abbreviation, column 3 the definition of the variable, and lastly column 4 provides the source of the variables retrieved.

For the second hypothesis, the effect of profitability on the relationship between emissions and the cost of debt will be analyzed. This will be done by performing another OLS regression which will include an interaction term $(ROA_{it} * EMI_{it})$, hence the second model is written as follows:

(2) $$CODt_{it} = \beta_0 + \beta_1 \log(EMI_{it}) + \beta_2 \log(ENV_{it}) + \beta_3 \log(MV_{it}) + \beta_4 ROA_{it} + \beta_5 \log(LEV_{it}) + \beta_6 \log(RF_{it}) + \beta_7 CR_{it} + \beta_8 (ROA_{it} * \log(EMI_{it})) + \varepsilon_{it}$$

The interaction term is included to explore the impact of profitability, measured by ROA, on the relationship between cost of debt and emissions. A negative coefficient for this interaction term would indicate that the effect is weaker as ROA increases. Conversely, a positive coefficient would mean that the relationship strengthens with a higher ROA. A coefficient of zero will lead to the conclusion that ROA has no effect on the relationship between cost of debt and emissions.

Moreover, a multicollinearity test was performed using the Variance Inflation Factor (VIF) as a measure of how much the variance estimated regression coefficient is increased due to collinearity. For the first regression model, there was an average VIF of 1.91 (check Table A2), indicating no significant multicollinearity issues as VIF values below 10 are generally acceptable (Kutner et al., 2005). For the second regression model a multicollinearity test was not needed as including an interaction term in a model leads to inflated VIF values, therefore the interpretation of the test is not useful (Francoeur, 2013). In addition, a heteroskedasticity test was conducted using the Breusch–Pagan test, and the results indicated that there is significant heteroskedasticity, as evidenced by chi-square statistic of 29.07 and a p-value of less than 0.0001. This suggests that the variance of the residuals is not constant across the levels of the independent variables. To address this issue and ensure reliable standard errors, a robust regression model will be employed.

3.2 Independent and dependent variables

Firstly, this dataset compromises a sample of 135 major European companies, all based and operating within Europe with market capitalizations above €100 million and an average of €27 billion. Based on The Refinitiv Business Classification (TRBC), the financials and industrial sector dominate the sample, each accounting for 17.91% of the total number of companies. These sectors include major companies from countries like France, Germany, and the Netherlands. Other significant sectors include consumer cyclical and non-cyclical (20.9%), technology (12.68%), materials (8.96%), utilities (8.96%), healthcare (6.72%), and energy (5.22%). This diverse sector representation aims at providing a comprehensive overview the European market, encompassing essential and non-essential goods and services, technological ventures, and core industrial operations.

The independent variable in this study is the Emissions Score (EMI_{it}) and it is retrieved from the Refinitiv DataStream (previously known as Thomson Reuters) ESG data. A higher emissions score indicates a lower carbon emissions output as the emissions score "measures a company’s commitment and effectiveness towards reducing environmental emissions in its production and operational processes" (LSEG, 2023, p. 29). The score primarily employs the TR.AnalyticCO2 data point provided by Refinitiv, which quantifies the total CO2 emissions of a firm relative to its sales (LSEG, 2023). This metric reflects the efficiency and environmental impact of a company’s operations using carbon emissions data; hence it is an excellent proxy to use for carbon emissions.

The dependent variable, Cost of Debt ($CODt_{it}$), is also retrieved from the Refinitiv DataStream database. It is known as the “Estimated Average Interest Rate” or “WC08356” and is calculated using the formula: $\text{WC08356} = (\text{Interest Expense on Debt}) / (\text{Short Term Debt \& Current Portion of Long} - \text{Term Debt} + \text{Long Term Debt}) * 100$ (Refinitiv Datastream, 2024). This calculation provides a measure of the average interest rate a company incurs on its total loans, hence effectively capturing the cost of debt.

3.3 Control variables

During this study, several control variables are added to the model to mitigate potential omitted variable bias (OVB) that might affect the results of the regression models. These control variables are employed to account for firm-specific characteristics that might influence the cost of debt.

Market Value (MV_{it}), retrieved from Refinitiv DataStream, serves as a proxy for firm size. This is a crucial control variable as larger firms have access to better capital markets, due to the benefits of economies of scale, thus having lower costs of debt. This variable is very commonly used in various financial studies to account for firm size effects (Caragnano et al., 2020). Return on Assets (ROA_{it}) is also sourced from Refinitiv DataStream (WC08711) and it is used to proxy for profitability. ROA is calculated as net income divided by total assets to underscore how efficient a firm is in generating earnings using its assets (Refinitiv DataStream, 2024). Profitable firms are less likely to default as they are better able to generate enough resources to meet their debt obligations, and thus may have a lower cost of debt regardless of environmental impact (Brealy et al., 2022). Leverage (LEV_{it}), which is the ratio of total debt to total capital and short-term debt, is another important variable that is retrieved from Refinitiv DataStream. A higher leverage indicates a greater financial risk due to potential financial distress that might lead to a higher risk premium, and thus a higher cost of debt (Modigliani & Miller, 1958).

The last variable obtained from the Refinitiv DataStream database is the Environmental Pillar Score (ENV_{it}), and is used to control for the overall environmental impact of a firm. This score, ranging from 1-100, compromises three sub-scores: resource use, emissions, and innovation. The resource use score measures the efficiency of the use of resources and waste reduction, the emissions score measures a company's commitment to reducing its environmental footprint through gas emissions, and the innovation score measures a company's efforts in developing new technologies for environmental solutions (LSEG, 2023). The aim of adding the Environmental Pillar Score as a control is to mitigate OVB and isolate the specific effect of carbon emissions on the cost of debt.

The Risk-free Rate (RF_{it}) is proxied by the Euro Area 10 Years Government Benchmark Bond Yield and it is retrieved from the ECB Data Portal. This variable reflects the yield of a risk-free European government bond over a decade; thus, it is appropriate in providing a consistent baseline to evaluate the cost of debt of European companies. Finally, the Credit Rating (CR_{it}) is obtained from Moody's via the Erasmus Data Center and it serves as a control for credit risk. The chosen metric is Moody's Long-Term Debt Rating, which reflects the relative credit risk of fixed-income obligations with an original maturity of one year or more, indicating the likelihood of default (Moody's, 2024). This categorical variable is then further quantified into a numerical scale ranging from 2 to 14, 14 being the highest credit rating score of Aa1 and 2 being the lowest credit rating score of B2. The descriptive statistics of the regression variables used in the analysis can be seen in Table 2 below.

Table 2 Descriptive statistics for log-transformed regression variables

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
log (Cost of Debt)	1.331	0.460	0.122	3.215
log (Emissions Score)	4.361	0.417	0	4.614
log (Environment Pillar Score)	4.291	0.365	0	4.604
log (Market value)	9.709	1.058	4.830	12.667
Return on Assets	4.318	4.913	-22.16	39.9
log (Leverage)	3.702	0.604	0.642	5.060
log (Risk-free Rate)	0.817	0.409	0.182	1.398
Credit Rating	9.006	2.138	2	14

Note. This table provides descriptive statistics on the variables used in the regression, there are 1465 observations for each variable.

Chapter 4: Results

In this chapter, the results and findings will be discussed. Firstly, in sub-chapter 4.1 the first hypothesis will be restated to provide context, then the findings of the first Model (1) will be analyzed and discussed including an interpretation of the coefficients as well as the significance of the independent variable as well as notable control variables. In 4.2, the same steps will be followed as the previous sub-chapter, including an analysis and interpretation of the findings of Model (2) as well as an analysis of the interaction term. Lastly, sub-chapter 4.3 will include an overview of the findings of both regression models and whether the null hypothesis is rejected or not. Throughout this chapter a significance level of 5% is assumed.

4.1 Model (1) regression results

The first regression model is aimed at testing the first hypothesis, which suggests that carbon emissions have an adverse effect on the cost of debt of European firms. This hypothesis is based on past literature that was thoroughly discussed in 2.3. The results for the sample of European firms can be seen in Table 2 The model includes log-transformed cost of debt as the dependent variable and log-transformed emissions score as the main independent variable, along with several control variables clearly shown in Table 2.

The overall model is statistically significant, indicating that the included variables collectively explain a significant portion of the variance in the cost of debt. The R-squared value is 0.2822, suggesting that approximately 28.22% of the variability in the cost of debt can be explained by the model.

The coefficient for the log-transformed emissions score is -0.1897 ($p < 0.001$), which indicates a statistically significant negative relationship between emissions and the cost of debt. This result suggests that a 1% increase in the emissions score (meaning lower emissions) is associated with an 0.19% decrease in the cost of debt. This finding supports Hypothesis 1, as well as past literature such as Caragnano et al. (2020), aligning with the theoretical prediction that lower emissions and better environmental practices can lead to favorable financing conditions due to lower perceived risks by lenders.

The log-transformed environment pillar score surprisingly has a positive coefficient of 0.2438 ($p < 0.001$), which might indicate that higher environment pillar scores are associated with higher costs of debt. This goes against past academic literature on this subject, which indicates that a higher environment pillar score leads to lower costs of debt (Apergis et al., 2022). This could be explained by the cost of implementing stringent environmental practices and transitioning to more environmentally friendly core operations. This might be a short-term cost which would then translate to long-term benefits. The coefficient of ROA is -0.0112 ($p < 0.001$), indicating that more profitable firms tend to have lower costs of financing. This negative relationship underscores the importance of profitability in having access to cheaper costs of financing, as profitable firms often have lower perceived risks by lenders (Santosuosso, 2014).

Another unexpected result was the negative coefficient of the log-transformed leverage, which indicates that the higher the leverage the lower the costs of debt. This goes against conventional economic theory that suggests that the financial distress costs of over levering are higher than the opportunity costs of tax shields of under levering (Van Binsbergen et al., 2010). A possible reason for this negative relationship is the size of firms in this sample, as the sample consists of major European companies with an average market capitalization of €27 billion (check Table A3). This may suggest that the firms in this sample benefit more from tax shields than the costs of financial distress, due to their huge size and thus easier access to capital markets.

Moreover, other control variables, such as, market value, risk-free rate, and credit rating exhibited expected relationships with the cost of debt. Market value has a negative coefficient, indicating that as firm size increases, cost of debt decreases. The risk-free rate exhibited a positive coefficient that shows that a higher base interest rate leads to a higher cost of debt. Lastly, the credit rating also shows a negative relationship confirming that better credit ratings lead to lower costs of debt.

In summary, the statistically significant negative coefficient of the log-transformed emissions score proves that there is a significant negative correlation between carbon emissions and cost of debt. This directly supports Hypothesis 1 and aligns with theoretical expectations that a decrease in carbon emissions lowers financing costs, as discussed in 2.3.

Table 3 Linear regression results for the relationship between Cost of Debt and Emissions Score

Variable	Model (1)	Model (2)
log (Emissions Score)	-0.190***	-0.140***
	(0.052)	(0.048)
log (Environment Pillar Score)	0 .244***	0.287***
	(0 .053)	(0.051)
log (Market Value)	-0.047***	-0.043***
	(0.013)	(0.013)
Return on Assets	-0 .011***	0.110***
	(0.002)	(0.024)
log (Leverage)	-0.316***	-0.043***
	(0.025)	(0.013)
log (Risk-free Rate)	0.299***	-0.330***
	(0.025)	(0.025)
Credit Rating	-0.046***	0.298***
	(0.006)	(0.025)
log (Emissions Score) *Return on Assets	-	-0.048***
		(0.006)
Constant	2.954***	2.585***
	(0.174)	(0.181)
Observations	1,465	1,465
R-squared	0.282	0.292
F-statistic	64.57	60.58

Note. This table shows the linear regression results of Model (1) and Model (2) with log (Emissions Score) as the independent variable and log (Cost of Debt) as the dependent variable. In Model (2) the results of the interaction term log (Emissions Score) *Return on Assets are shown. Log (Environment Pillar Score), log (Market Value), Return on Assets, log (leverage), log (Risk-free Rate), and Credit Rating are added as control variables. The constant, R-squared, and F-statistic are also given. All coefficients are rounded up to three decimal points. Robust standard errors are in parentheses. * p < 0.1, ** p < 0.05, and *** p < 0.01.

4.2 Model (2) regression results

In this sub-chapter, the second hypothesis will be tested by running the regression of Model (2). Model (2) investigates the interaction effect of profitability (ROA) on the relationship between the log-transformed emissions score and the log-transformed cost of debt. This directly tests the second hypothesis, which predicts that the relationship between emissions and cost of debt weakens with profitability (ROA). Model (2) investigates this hypothesis by introducing an interaction term log (Emissions Score) *ROA.

Model (2) has a slightly higher explanatory power than Model (1). The overall model is statistically significant with an R-squared value of 0.291, indicating that approximately 29.15% of the variance in the cost of debt is explained by the independent variables and the interaction term.

Similar results were obtained from the main independent variable compared to Model (1), with the log-transformed emissions score having a negative coefficient. For the ROA, the coefficient was positive, which indicates that profitability, independent of emissions, increases the cost of debt. This may seem counterintuitive, but a likely reason for this is the fact that having an emissions score of 0 in this sample is virtually impossible, as only two firms had a 0 emissions score in only two out of the 10 sample years. So, the interpretation of the ROA coefficient in this case is unnecessary.

The interaction term (log (Emissions Score) *ROA) has a negative coefficient of -0.0279 (p=0.000), indicating that the negative effect of carbon emissions on the cost of debt is weaker as profitability increases. In other words, profitable firms are less affected by the adverse effect of carbon emissions on the cost of debt, supporting the second hypothesis. This finding aligns with the literature suggesting that profitability can help mitigate some of the financial risks associated with higher emissions (Santosuosso, 2014).

Among other control variables, many experiences the same results as Model (1). For example, the log-transformed environmental pillar score showed a positive coefficient, indicating a higher environmental score might have an adverse effect on financing costs within these models. In addition, the log-transformed leverage variable still had a significant negative coefficient, potentially highlighting the positive effects of tax shields on the cost of debt (Van Binsbergen et al., 2010). Other control variables, such as log (Market Value), and log (Risk-free Rate), have the expected significant signs and coefficients, confirming their established relationships with the cost of debt. The credit rating variable exhibited a positive coefficient, indicating that an increase in credit rating score results in an increase in the cost of debt, which seems counterintuitive. After running a separate regression between the cost of debt and credit rating (shown in Table A4), it is evident that the credit rating shows a negative coefficient, which is what is expected. Hence, it can be concluded that the positive coefficient in Model (2) was a result of the interaction term log (Emissions Score) *ROA.

Overall, Model (2) provides robust evidence of the effect of both carbon emissions and profitability have on cost of debt, with profitability mitigating the adverse of effect emissions have on financing costs. This supports the second hypothesis and aligns with prior research claiming that the financial implications of carbon emissions are contingent on a firm's profitability.

4.3 Overview of regression results

This sub-chapter consolidates the findings of both regression models discussed in the analysis above, focusing on the implications for the null hypothesis presented in the study.

The first regression model established a significant relationship between emissions and cost of debt, with the log-transformed emissions score variable showing a negative coefficient. This indicates that higher emissions are associated with a higher cost of debt, allowing us to reject the null hypothesis that emissions have no effect on the cost of debt.

In the second regression model, which included an interaction term between the emissions score and ROA, the results were more nuanced as the complexity of the relationships became more pronounced. As the significant interaction term suggests the impact of emissions on the cost of debt is moderated by a firm's profitability. In other words, as ROA increases, the negative impact of emissions on the cost of debt diminishes. Thus, based on the findings obtained, the null hypothesis that profitability does not influence the relationship between emissions and the cost of debt is rejected.

Chapter 5: Conclusion

This thesis aims to contribute to the ongoing literature regarding sustainability practices and their importance in financial reporting and consequently financial decision-making. This research has explored the nuanced relationship between carbon emissions and the cost of debt within European firms by attempting to answer the central research question:

How do carbon emissions impact the cost of debt of European firms?

The analysis offers compelling evidence that carbon emissions can adversely affect the cost of debt, implying that higher emissions are associated with a higher cost of debt.

After running two OLS regressions, we find that both regressions are statistically significant and support the hypothesis that higher emissions are associated with lower costs of debt. For the second regression model, it provides insights into the effect of profitability on the relationship between emissions and cost of debt, showing that as profitability increases the relationship significantly weakens. This can provide useful insights for policymakers, as the results of this model show that highly profitable firms have less incentive to transition and invest into more sustainable business practices. Hence, in this specific case, a policy like CSRD, which aims at increasing transparency of non-financial reporting, may not be effective in promoting more sustainable practices.

From a corporate strategy perspective, the results of this research indicate that it is financially viable to transition to more sustainable practices by opting for operations that lead to lower carbon emissions. As the analysis shows, decreasing carbon emissions may not only help promote a healthier environment but can also yield tangible financial benefits, by lowering the cost of debt. This suggests that firms implementing better environmental practices may be viewed more favorably by lenders. This could stem from the fact that lenders often perceive firms with sustainable and environmentally friendly practices as lower risk, because these firms are likely prepared for future regulations and are less exposed to environmental liabilities.

Furthermore, the adoption of greener practices, in the form of emitting lower emissions, could enhance a company's reputation, leading to improved relationships with stakeholders (customers, regulators, employees, etc.). This boost in reputation can translate into financial advantages, such as increased investor confidence and customer loyalty. This is relevant for the borrowing side as financial institutions and rating agencies increasingly consider ESG factors when assessing risk, and firms that excel in these areas are often able to secure lower interest rates on borrowed funds (Moody's, 2024).

Despite the results of the statistical models being significant, there are some significant limitations to this study that need to be taken into consideration. Firstly, the main methodological approaches employed in this research are regression models, which inherently have many limitations. It is crucial to recognize that OLS regression models do not establish causation, but only identifies statistical associations between variables. This research demonstrates an association between lower carbon emissions and reduced costs of debt; however, it does not prove that reducing emissions directly causes lower borrowing costs. In addition, the models have a weak explanatory power, with an R-squared value hovering around 30%, suggesting that while a significant portion of the variance in the cost of debt is explained by the model, a substantial amount of variability is unexplained by the variables included. This means that there are other unobserved factors that influence the cost of debt, which could potentially lead to different interpretations of the findings.

Another significant limitation to this research is the data used to perform the regression models. First, the reliability and consistency of the ESG scores are subject to the quality of reporting and the metrics used by data providers. As many of the data points that are used to determine ESG scores rely on self-reported data, inconsistencies and potential biases in the scores can occur. Additionally, the generalizability of the results is constrained by the sample used in the analysis, which predominantly includes large European firms with a market capitalization above €500 million. This means that the findings of this research are representative only for large firms operating within Europe, as they may not accurately reflect the behaviors or financial conditions of smaller firms or firms operating outside Europe.

In conclusion, this thesis has provided valuable insights into the dynamic relationship between carbon emissions and the cost of debt. It builds on existing literature regarding carbon risk, credit risk, and borrowing costs, and adds value by investigating these aspects from the lens of a European firm. As the European Union intensifies its focus on sustainable business operations through the Corporate Sustainability Reporting Directive (CSRD), this study’s findings are particularly timely. While the findings highlight a clear association between carbon emissions and costs of debt, the study acknowledges the limitations inherent in its methodology and data. These findings pave the way for future research to explore the potential benefits of integrating sustainable metrics into financial reporting, as well as the benefits of greener practices that come with increased transparency.

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Appendix

Table A1 Shapiro-Wilk test for assessing normality

Variable	W	Prob > z
Cost of Debt	0.80392	0.00000
Emissions Score	0.81675	0.00000
Environment Pillar Score	0.89913	0.00000
Market Value	0.71606	0.00000
Return on Assets	0.90233	0.00000
Leverage	0.98605	0.00000
Risk-free Rate	0.93373	0.00000

Note. This table provides the results of the Shapiro-Wilk test for assessing whether the variables are distributed normally or not.

Table A2 Variance Inflation Factor (VIF) test for assessing multicollinearity for Model (1) variables

Variable	VIF
log (Environment Pillar Score)	3.46
log (Emissions Score)	3.36
log (Market Value)	1.45
log (Leverage)	1.38
Return on Assets	1.36
Credit Rating	1.32
log (Risk-free Rate)	1.03

Note. This table shows the VIF test of multicollinearity to detect whether there is any multicollinearity between variables used in Model (1). The mean VIF is 1.91.

Table A3 Descriptive statistics for regression variables

Variable	Mean	Std. Dev.	Min.	Max.
Cost of Debt	3.22	2.24	0.13	23.90
Emissions Score	81.55	19.01	0	99.87
Environment Pillar Score	75.427	17.79	0	98.91
Market value	27244.18	30590.96	124.17	317038.00
Return on Assets	4.32	4.91	-22.16	39.9

Leverage	45.37	20.47	0.90	156.65
Risk-free Rate	1.46	0.97	0.20	3.05
Credit Rating	9.01	2.14	2	14

Note. This table provides descriptive statistics on the variables, before being transformed into logarithms, used in the regression, there are 1465 observations for each variable.

Table A4 Regression results between Cost of debt and Credit rating

Variable	**Cost of Debt as dependent variable**
Credit Rating	-0.214***
	(0.028)

Note. This regression model is done as a robustness check to ensure that the credit rating variable results are consistent across other models, this regression provides evidence that the positive coefficient shown in Model (2) is a result of the interaction term.