Lappeenranta-Lahti University of Technology LUT
LUT School of Business and Management
Master’s Programme in Strategic Finance and Analytics

The Relationship between Environmental Sustainability and Cost of Capital

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ABSTRACT

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The Relationship between Environmental Sustainability and Cost of Capital

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This thesis examines the relationship between environmental sustainability and cost of capital. The dataset comprises data on publicly listed companies from 15 developed European countries. The panel data is unbalanced and covers years 2010–2020. The applied empirical models use fixed effects model with firm and year fixed effects.

The results suggest that environmental sustainability affects cost of capital through cost of equity. No relationship between environmental sustainability and cost of debt is found. The results further show that the relationship between environmental sustainability and cost of equity is likely U-shaped. The U-shape is driven by resource use sustainability and the sustainability of products and technologies. Emission sustainability is found to have no effect or slightly linearly negative effect on cost of equity in the overall set of companies. The results also suggest that environmentally unsustainable companies in environmentally sensitive industries have a larger incentive to improve their practices than corresponding companies in non-sensitive industries. This result is especially driven by emission sustainability. The results also show that environmental sustainability is not a strong predictor of cost of capital.

TIIVISTELMÄ

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Ympäristövastuullisuuden ja Pääoman Kustannusten välinen Yhteys

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Tämä tutkielma tutkii yritysten ympäristövastuullisuuden ja pääoman kustannusten välistä yhteyttä. Tutkimusaineisto sisältää dataa julkisesti listatuista yhtiöistä 15:stä kehittyneen Euroopan maasta. Paneelidata on epätasapainoinen ja kattaa vuodet 2010–2020. Empiirisenä mallina käytetään kiinteiden vaikutusten estimaattoria. Malli huomioi yritysten ja vuosien kiinteät vaikutukset.

Tulokset osoittavat, että ympäristövastuullisuus vaikuttaa pääoman kustannuksiin oman pääoman kustannusten kautta. Ympäristövastuullisuuden ja vieraanpääoman kustannusten välillä ei havaita yhteyttä. Lisäksi tulokset näyttävät, että ympäristövastuullisuuden ja oman pääoman kustannusten välinen yhteys on todennäköisesti U-muotoinen. U-muoto esiintyy etenkin resurssien käytön tehokkuudessa sekä tuotteiden ja teknologioiden ympäristövastuullisuudessa. Kaikkien tutkittujen yritysten tasolla päästöihin liittyvän vastuullisuuden ja oman pääoman kustannusten väliltä löytyy lievästi negatiivinen ja lineaarinen yhteys tai ei yhteyttä lainkaan. Tulokset myös viittaavat, että ympäristöllisesti kriittisillä aloilla toimivilla heikon ympäristövastuullisuuden yrityksillä on suuremmat kannustimet kehittää ympäristövastuullisuuttaan kuin vastaavilla yrityksillä ei-ympäristökriittisillä aloilla. Tätä tulosta ajaa erityisesti päästöihin liittyvä vastuullisuus. Tulokset lisäksi näyttävät, että ympäristövastuullisuus ei toimi hyvin pääoman kustannusten muutosten ennustamisessa

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Sincerely,
Sami Tarvainen

4 October 2021, Espoo

ABBREVIATIONS

2SLS = Two-Stage Least Squares

APT = Arbitrage Pricing Theory

BTM = Book-to-Market ratio

CAPM = Capital Asset Pricing Model

COD = Cost of Debt

COE = Cost of Equity

CSR = Corporate Social Responsibility

EPS = Earnings per Share

ES = Environmental Sustainability

ESG = Environmental, Social, and Governance

EU ETS = European Union Emissions Trading System

FE = Fixed Effects

FROE = Forecasted Return on Equity

FY = Financial Year

MAE = Mean Absolute Error

OLS = Ordinary Least Squares

RE = Random Effects

RIV = Residual Income Valuation (model)

ROE = Return on Equity

SI = (Environmentally) Sensitive Industry

SML = Security Market Line

WACC = Weighted Average Cost of Capital

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1. INTRODUCTION

This thesis studies the relationship between environmental sustainability (ES) and cost of capital. Cost of capital reflects a risk that investors and lenders bear for giving their capital for a company's use. Capital Asset Pricing Model (CAPM) developed in the 1960s suggests that the sensitivity of a stock's returns to market returns captures the risks of equity capital (Sharpe, 1964; Lintner, 1965). Since then, more risk measures have been associated to cost of equity (COE) capital, such as sensitivity to inflation or interest rates (see e.g. Chen et al., 1986), and recently ESG performance has been also documented to affect cost of equity (see e.g. Gupta, 2018; Eliwa et al., 2019). Theories and theoretical concepts associated to the relationship between ESG performance and cost of capital include stakeholder theory, legitimacy theory, and information asymmetry (Freeman, 1984; Suchman, 1995; El Ghoul et al., 2011). Theoretically, ESG practices can also affect cost of debt (COD) by affecting a company's firm-specific risks and sensitivity to market risks (Damodaran, 2012, p. 77-81).

The theoretical framework does not provide a clear answer whether better ESG practices lead to lower cost of capital. This is because even though better practices can reduce for instance regulatory risks, investments to sustainability incur costs and can resultingly increase other risks. This thesis contributes to the question whether environmental sustainability is an important factor in cost of capital and tests the usefulness of the ESG-associated theories. The relationship between environmental sustainability and cost of capital is studied in more depth that is available from prior research and resultingly aims to reveal more complex relationships. The results have important implications not only for science, but also for regulators, companies, investors, and analysts.

A common issue in finance is that the expected returns and cost of capital are not often directly observable and multiple methods for estimating these exist. This thesis is not immune to these issues, and the selected research methods aim to mitigate these. Especially determination of cost of equity is problematic, as future cash flows are not known beforehand. One of the earliest efforts to determine cost of equity is CAPM, which uses realized returns of a stock to determine its expected return. The model has however deemed inaccurate, as correlations between expected returns suggested by CAPM and realized returns have found to be weak (Fama & French, 1997; Elton, 1999). Because of this, many scholars have started to use *ex ante* measures for COE (see e.g. Gode & Mohanram, 2003;

El Ghoul et al., 2011; Chava, 2014; Ng & Rezaee, 2015; Gupta, 2018). These implied cost of equity measures use forecasted accounting measures—such as dividends, earnings, or book values—and current stock prices, to infer internal rate of return or implied cost of equity. This thesis also uses implied cost of equity to better reflect investor expectations.

1.1 Background and Motivation

Environmental sustainability is critical for the wellbeing of humans and nature. The risks of climate change and loss of biodiversity have become ever more apparent. IPCC (2018) report found that increase in global temperatures increases risks for ecosystems, water supply, food security, livelihood, health, and economic growth. Long-term economic losses due to climate change and biodiversity loss is measured in trillions of euros, so the problems are not trivial even from the economic standpoint (PwC, 2010). Thankfully, countries are increasingly addressing environmental issues. On 12 December 2015, 196 countries pledged to limit global warming preferably to 1.5 degrees Celsius compared to the pre-industrial levels by signing the Paris Agreement (UNFCCC, 2021). Additionally, more than 130 countries have pledged or consider reducing emissions to net-zero by 2050 (United Nations, 2021).

Countries are not simply relying on the willingness of people and companies to reduce their environmental burden but are creating regulations and incentives to reduce emissions and prompt environmental sustainability. This is necessary to reach the climate goals, as improvements in green technologies are not often financially profitable without government intervention. In economics, this type of situation is explained by negative externalities. A profit-maximizing company will continue making environmental havoc if it does not financially benefit for improving its practices. Negative externalities will be on a suboptimal level for the society if marginal cost for the company for avoiding these externalities is higher than the marginal cost for the society (Hyytinen & Maliranta, 2015, p. 27-28).

Examples of efforts to bring the marginal costs of society and companies closer together include European Union’s Emissions Trading System (EU ETS) and carbon border taxation system planned by the European Commission. EU ETS covers 40% of total greenhouse gas emissions in the EU. It incentivizes companies in the EU to reduce their emissions by putting a price on emitted greenhouse gases. Additionally, companies that are low emitters in their sector can sell their emission allowances for profit. Carbon border taxation system would in turn place a carbon price for imported goods. (European Commission, 2021a; European Commission, 2021b)

Instead of affecting operative income and costs, negative externalities can also be disincentivized through financing. Financial markets and private lenders can charge higher interest or demand higher rate of return for equity if they see a company's environmental practices as a financial or reputational risk. Again, regulators do not have to only trust private entities to consider environmental practices in financing but can affect the cost of financing through regulations. Additionally, governments can finance green investments and otherwise promote green financing. Examples of government promotion for green finance include EU taxonomy for sustainable activities, European green bond standard, EU climate benchmarks, and significant investments from the US and the EU to environment sustainability through COVID-19 stimulus packages. On 28 July 2021, the US announced to allocate 73 billion USD to clean energy transmission (the White House, 2021). In turn, EU has decided to allocate 401 billion EUR to natural resources and environment from the NextGenerationEU recovery package (European Commission, 2021c).

Since finance is a promising tool for driving towards more sustainable society, research on the relationship between finance and sustainability is critical. For instance, by doing continuous research on the topic, we can see if measures taken by regulators have been effective. The research can reveal if companies making sustainability efforts can obtain better access to capital markets and cheaper financing. Such findings have important implications not just to regulators but for companies as well, as they try to optimize investments to sustainability and as they communicate their efforts to investors. Also, implications for investors and analysts are apparent, as cost of capital has a direct effect on firm value.

This thesis contributes to the existing scientific research in multiple ways. First, most of prior research on ESG matters in finance and economics have been on the relationship between ESG and financial performance, whereas the relationship between ESG and cost of capital has received less scientific focus (El Ghoul et al., 2011). Relationship between ESG and cost of capital could be however just as important, as this can be of use for instance in climate change prevention as discussed above.

Second, this thesis studies shape of the relationship between environmental sustainability and cost of capital, which has not been of focus in the past literature. All but one of the reviewed studies assume that the relationship is linear (see Sharfman & Fernando, 2008; El Ghoul et al., 2011; Chava, 2014; Ng & Rezaee, 2015; Gupta, 2018; Ge & Liu, 2015; Eliwa et al., 2019). This is not however a sound assumption, as improvements in environmental sustainability might theoretically affect cost of capital differently depending on the initial level of environmental sustainability. For instance, companies that are unsustainable could benefit from improving their environmental practices if they resultingly could attract more investors and decrease their sensitivity to market risks. The firm-specific risks (and cost of debt) could also decrease, if better environmental practices lead to lower probability of litigations. In turn, for environmentally sustainable companies the mentioned benefits could be smaller. Smaller benefits and incurred costs from sustainability investments could then increase the cost of capital for environmentally sustainable companies. In this situation the relationship between environmental sustainability and cost of capital would be U-shaped, not linear. Such an information would be valuable to companies that try to optimize the level of sustainability investments.

Third, this thesis breaks down the importance of different environmental sustainability metrics, which is not common in the past literature. Gupta (2018) studied different components in the context of cost of equity. This thesis complements Gupta's (2018) study by broadening the research focus to cost of debt and by adding the shape of the relationship into the model. These together can be of significant value to companies, analysts, investors, and regulators. For instance, if emission reductions would be the most important factor affecting cost of capital, companies and analysts should focus on following and reporting on the matter. Regulators, in turn, can be interested if all necessary aspects affect cost of capital as intended. Meeting net-zero emissions or other environmental goals might not only necessitate investments from unsustainable companies to emission reductions, but also investments to new environmentally friendly technologies from sustainable companies.

Fourth, prior research has not studied extensively moderating effect of industry in the relationship. This could again be important for companies when they consider whether to initiate new sustainability efforts. For regulators, understanding the moderating effect of industry could be important if they focus efforts on specific industries and want to know if markets react as intended.

Finally, this study complements prior research by testing if environmental sustainability scores can be used in predicting changes in cost of capital. This could be of particular interest to investors, analysts, or money managers if they try to anticipate changes in expected or actual stock returns. Predicting power over cost of capital should also provide predicting power over stock returns, as cost of capital affects discounted value of future cash flows and therefore market value of a company.

1.2 Research Problem and Questions

The main research problem is to understand the relationship between environmental sustainability and cost of capital comprehensively. More comprehensive understanding on the topic would advance the current scientific knowledge and provide new tools for multiple groups. The main problem is summarized by the first research question:

Q1: How environmental sustainability affects cost of capital?

The first research question is broken down to three sub-questions to bring a holistic view on the topic. The shape of the relationship between sustainability and cost of capital is of interest to many groups and it is a topic that has not been studied comprehensively in prior research. It is also a natural place to start exploring the relationship. The first sub-question if formulated as follows:

Q1.1: Is there a linear or non-linear relationship between environmental sustainability and cost of capital?

As environmental sustainability is a complex concept and cannot fully be presented with a single score, it is natural to continue by studying the importance of different sustainability metrics. The second sub-question if formulated as:

Q1.2: Do different aspects of environmental sustainability affect cost of capital in the same way?

The role of industry is explored in the third sub-question. Exploring the relationship for each industry separately would be challenging because of reducing degrees of freedom. For this reason, companies are separated into two groups: companies operating in environmentally sensitive and non-sensitive industries. With this research design the moderating role of industry can be studied. The third sub-question is formulated as follows:

Q1.3: Does environmental sensitivity of an industry play a role in the relationship between environmental sustainability and cost of capital?

Second problem of this research is to find if environmental sustainability can be used to predict changes in cost of capital. This is separated as an own research question, as predictive modeling is quite different from traditional empirical research. The results on the first research question are also used as a basis for formulating the predictive models. Should there be no relationships between environmental sustainability and cost of capital, predictive modeling would be of no use. The second research question is formulated as follows:

Q2: Can environmental sustainability scores be used to predict changes in cost of capital?

As the first research question provides useful information to many groups, the second helps a narrower set of parties, e.g. the ones who are interested in stock performance prediction. Together the research questions answer the research problems comprehensively.

1.3 Structure of the Report

The rest of the report is structured as follows. Chapter 2 lays out the theoretical framework for understanding how environmental sustainability can affect cost of capital. The chapter also goes through relevant empirical findings on the topic. Chapter 3 presents the data and defines the variables and methodologies. Chapter 4 presents the results of empirical and predictive models. Finally, Chapter 5 summarizes the findings, reflects how these compare to the presented theories and previous empirical findings, presents implications of the findings to different groups as well as proposes direction for future research.

2. LITERATURE REVIEW

To give a comprehensive understanding why environmental sustainability can be a significant factor in cost of capital, a review on the relationship between risk and cost of capital, basic financial theories, and capital structure is given at first in Section 2.1. After these, stakeholder theory, legitimacy theory and information asymmetry are reviewed to show how environmental sustainability can affect cost of capital and how these theories relate to traditional financial theories. In Section 2.2 relevant studies focused on the relationship between environmental sustainability and cost of capital are reviewed.

2.1 Theoretical Framework

Cost of capital is an important factor from the point of view of a company, its investors, and creditors. For a company, cost of capital is a cost for its operations: the higher the cost of capital, the better profitability and growth it should deliver to continue its operations. For investors and lenders cost of capital represents expected return for the provided capital and carried risk. This means that rational investors and lenders will demand at least the same return for their capital invested to a company than what is available from other companies with the same level of risk.

2.1.1 Risk and Cost of Capital

In finance risk is defined as a deviation of the actual return from the expected return. For instance, even though a stock investor could expect to make a 5% gain on a stock in a year, the actual return could turn out to be -15% or +20% because of share price movements. Similarly, a bank that makes a loan to a firm might not fully recover its receivables if the company goes bankrupt or faces financial distress. (Damodaran, 2012, p. 60-62, 77-81)

When an investor invests in a stock, she will be exposed to two kinds of risks: firm-specific risks and market or systematic risks. Firm-specific risks, as the term suggests, affects only one company. Examples of these risks would be a firm’s investment in a new technology or market campaign. In turn, risks that affect all companies are defined as market risks, and these comprise for instance changes in interest or inflation rates. Additionally, there are risks that affect only a set of companies, e.g. within an industry. An example of this would be new regulations on the use of coal in energy sector. In equity pricing, all types of risks are not equal, since firm-specific risks and risks that only applies to a small set of companies can be diversified away. Modern portfolio theory by Harry Markovitz (1952) is regarded as the first financial theory that made the distinction between firm-specific and market risk and the market risk models presented in Section 2.1.2 are based on this theoretical framework.

In debt financing, expected returns and deviations of actual returns differ significantly from the equity financing. This is because cash flows to a creditor are often promised to be fixed or just to vary by the amount of base interest rate. This reduces risks to a lender since in most cases the returns are known beforehand. Debt financing is considered less risky than equity financing from the capital providers point of view also because debt's seniority is above equity. This means that company will try to meet its debt obligations even in the times of poor financial performance and debt obligations need to be met before distributing profits to shareholders. However, this also means that creditors cannot gain from a good financial performance. Creditors are also subject to losing all the lent capital in the case of bankruptcy. In short, creditors have limited upside potential but high downside potential from firm-specific events. This means that in contrast to equity financing, firm-specific risks are an important factor in the cost of debt financing. (Damodaran, 2012, p. 77-81)

2.1.2 Market Risk Models

CAPM by Sharpe (1964) and Lintner (1965) is one of the most influential theories concerning capital asset pricing. According to the theory, a stock's expected return—or cost of equity—can be determined as the function of risk-free interest rate (r_f), market risk premium ($E(r_M)$) and beta (β). Market risk premium—or expected return of the market portfolio over the risk-free rate—is determined by the line between risk-free interest rate and the tangent of the Efficient Frontier suggested by Markovitz (1952) as presented in Figure 1. The line is called Security Market Line (SML). In CAPM, all stocks lie in the SML, so there are no possibilities for arbitrage profits.

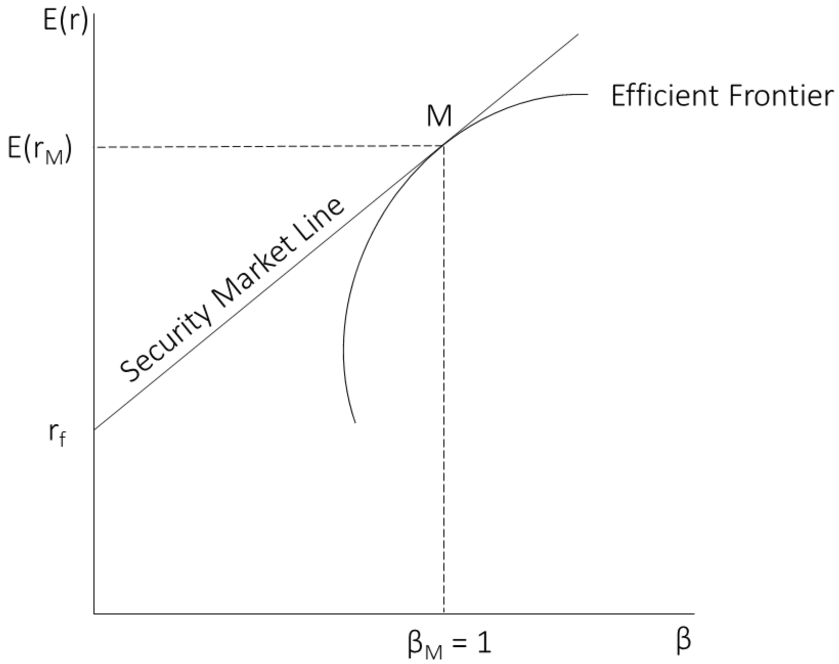

Figure 1. Security Market Line and Market Premium (Markovitz, 1952).

Beta represents a stock's sensitivity to market risk, that is, risk that is undiversifiable. Beta can be measured as a sensitivity of a stock's returns to the market returns (Mullins, 1982). A stock's expected return is given by Equation 1.

$$E(r_i) = r_f + \beta_i(E(r_M) - r_f) \quad (1)$$

where $E(r_i)$ = expected return of security i, r_f = risk-free interest rate, β_i = beta of security i, and $E(r_M)$= expected market return.

CAPM rests on the following assumptions: 1) capital markets are efficient (information is distributed instantly), 2) investors are rational and seek to maximize their return with a given risk level, 3) the markets are frictionless (no transaction costs, taxes or restrictions on short selling or borrowing), 4) all investors can lend and borrow with risk-free interest rate, and 5) investor expectations are homogenous (investors agree on the expected values, correlation coefficients, and standard deviations of investments) (Sharpe, 1964; Mullins, 1982). Sharpe (1964) and Mullins (1982) point out that these assumptions are unrealistic in the real world. The downfalls of these assumptions help to understand why implied cost of equity capital is often used instead of CAPM-based cost of equity in the academic research, and why e.g. environmental sustainability can be a factor in the determination of cost of capital.

Fama and French (2007) developed a framework to understand how asset prices and expected returns are affected by the violation of assumptions 2) and 4) of CAPM presented above. They argue that asset prices and market portfolio can deviate from CAPM if investors are misinformed or if they have tastes for certain stocks. By tastes the scholars mean that investors are not simply maximizing their dollar payoff for a given risk level, but regard stocks more as consumption goods. For instance, socially responsible investing would be an example of a taste. The deviations from CAPM would be dependent on different factors, such as wealth of the misinformed investors / investors with tastes and the extent by which their portfolios diverge from the market portfolio.

Arbitrage pricing theory (APT) developed by Stephen A. Ross (1976) and multi-factor models are also models that apply sensitivity to market risks as a measure of COE. These differ from CAPM in that in addition to considering a stock's returns' sensitivity to market returns, also other market risks can be added to the model. These could include for instance inflation, GDP growth and interest rates. APT and multi-factor models can be written as (Damodaran, 2003):

$$E(r_i) = r_f + \beta_1\big(E(r_1) - r_f\big) + \beta_2\big(E(r_2) - r_f\big) + \cdots + \beta_i(E(r_i) - r_f) \qquad (2)$$

where $E(r_i)$ = expected return of security i, r_f = risk-free interest rate, β_j = beta of the security to market risk j, and $E(r_j)$ = expected return for a portfolio with a beta of one for factor j and beta of zero for all other factors.

A well-known multi-factor model is Fama & French (1993) three-factor model. In a cross-sectional study the scholars found that firm size and book-to-market (BTM) ratio explain differences in stock returns and can therefore be included as additional factors in a multi-factor model.

2.1.3 Capital Structure

A firm's capital structure affects cost of capital in three ways: 1) by affecting cost of equity, 2) by affecting cost of debt, and 3) by affecting the relative weights of equity and debt. Weighted Average Cost of Capital (WACC) gives the required rate of return for all firm's capital. WACC formula is presented in Equation 3. (Brigham & Houston, 2019)

$$WACC = \frac{E}{E+D} r_e + (1 - t_c) \frac{D}{E+D}\, r_d \qquad (3)$$

where E = market value of equity, D = market value of debt, t_c = corporate tax rate, r_e = required return on equity, and r_d = required return on debt.

Since debt is less risky than equity financing and as interest expenses are tax-deductible, increase in relative weight of debt can decrease WACC. However, trade-off theory suggests that increase in debt increases bankruptcy risk and bankruptcy costs, which disincentivizes debt issuance beyond a certain point (Frank & Goyal, 2009). Bankruptcy costs can be direct costs (e.g. legal) when a firm goes bankrupt or indirect costs, which are costs resulting from the avoidance of bankruptcy. Examples of these costs would be loss of value in assets and loss of customers and revenues, as management focuses on the avoidance of bankruptcy instead of running the business. As bankruptcy costs and their probability increase with leverage, so does cost of debt. (Ross et al., 2003)

Leverage also affects cost of equity capital, as the variance of returns to equity investors increase with leverage. This means that a stock's expected return over the risk-free interest rate can be divided into premium of business risk and premium of financial risk (leverage). In the context of CAPM, linkage between leverage and beta can be formulated as follows (Modigliani & Miller, 1958; Hamada, 1969; Brigham & Houston, 2019):

$$\beta_l = \beta_u (1 + (1 - t_c) \frac{D}{E}) \qquad (4)$$

where β_l = levered beta, β_u = unlevered beta, t_c = corporate tax rate, D = market value of debt, and E = market value of equity.

2.1.4 Stakeholder and Legitimacy Theories

Stakeholder theory developed by Freeman (1984) suggests that companies and managers should consider not only the interests of shareholders, but also interests of other stakeholders—such as employees, customers, banks, suppliers, and the public—to run the business successfully. By understanding how a firm's activities affect the different stakeholders and what the stakeholders desire, the firm can bring these different parties together to create economic value. In short, value and profit maximization are the result of successful alignment of different stakeholders' values. (Freeman & McVea, 2001; Freeman et al., 2004)

Stakeholder theory gives a good basis for understanding why ESG performance can be a factor in cost of capital. First, lenders and investors might avoid funding firms with poor ESG rating if they value sustainability, i.e. investors would have tastes in this case. This would violate the CAPM's assumption that investors are simply maximizing dollar return on a given risk level. The recent popularity in ESG investing suggests that investors could have a taste for socially responsible companies. For instance, assets under management of institutional investors and money managers that use ESG strategies have grown for more than 25-fold in the United States in 1995-2020 (US SIF, 2021). Additionally, institutional investors avoid investing into firms with poor ESG ratings (Cox et al., 2004). This could be explained by increased risks in unsustainable companies, but also from a pressure from investors and other stakeholders of the institutional funds.

Second, investors and lenders might perceive that ESG ratings can affect a firm's financial performance or risks. Based on stakeholder theory, this could be the case if customers or competent employees prefer socially responsible companies or if regulators enforce laws delimiting environmental damage. If ESG aspects are viewed as an additional market risk, ESG ratings could be used as an additional factor in a multi-factor model. An example of this would be that companies with high environment sustainability ratings are less sensible to tightening emission reduction targets. Therefore, *ceteris paribus*, their cost of capital should be lower than those of companies with low ESG ratings. However, improvements in sustainability will incur costs, which in turn can expose a company to other market wide risks and resultingly increase both COE and COD. Increased costs would also increase company's firm-specific risks, which would increase COD. Evidence that ESG ratings are related both to firm-specific and market risks was found by Kiesel & Lücke (2019). The scholars found that all ESG aspects are considered in the credit ratings given by credit rating agencies and especially weak ESG performance results to negative abnormal returns in the equity markets.

Legitimacy theory is like stakeholder theory in that it takes a broader view on a company's function than just a shareholder perspective. In legitimacy theory, all organizations are viewed in the context of society at large, and the actions of an organization must be desirable and appropriate—i.e. legitimate—within the societal system for the organization to survive (Suchman, 1995). Strategic view of legitimacy theory considers legitimacy as an organizational resource that can be managed, and disparity between organization's activities and societal norms can result to economic, legal, and societal sanctions (Dowling & Pfeffer, 1975; Suchman, 1995).

Legitimacy theory provides similar reasons as stakeholder theory on why CAPM is not a sufficient model for the estimation of cost of capital, and why ESG factors should also be considered. Based on legitimacy theory, ESG aspects are an important risk factor in a multi-factor model if society values such values. Additionally, if societal values exist, investors would probably not be independent of these values. That is, investors would then have tastes for stocks, and resultingly cost of capital would be lower for legitimate companies than for non-legitimate companies.

2.1.5 Information Asymmetry

Merton's (1987) market equilibrium model relaxes CAPM's assumptions on market efficiency and market friction. Merton assumes in his model that investors are not aware of all securities and therefore investor base will vary by security. Merton shows that larger investor base would then lead to a higher market value and lower cost of capital. In the case of perfect market efficiency and no market frictions, investors would get information on all companies instantly without costs. However, in the real-world information asymmetries persist, as gathering and distribution of information is costly for investors and companies. This, in turn, favors large companies as they can raise large amounts of funds, while costs incurred from the efforts to decrease information asymmetry do not grow linearly with size.

El Ghoul et al. (2011) argue that the existence of information asymmetry does not benefit only large companies, but also companies with better ESG performance. The researchers break down their suggestion into three propositions: 1) responsible firms want to signal about their sustainability, 2) analysts and media prefer to cover responsible firms, and 3) socially conscious investors pay more attention to responsible firms. These together would lead to better awareness of investors on high ESG companies and resultingly lower cost of capital. The first proposition is backed by Dhaliwal et al. (2014) study, which finds that socially responsible firms are significantly more likely to make ESG disclosures. Also, Hong & Kacperczyk (2009) found that stocks with low ESG performance receive lower coverage by analysts, which partially backs the second proposition. However, the claim that media would prefer to cover socially responsible companies seems counterintuitive, as often media tends to focus more on negative news.

Alike stakeholder theory and legitimacy theory, information asymmetry proposes how the financial markets would behave in a more realistic situation than what is allowed by CAPM. If relationship between environmental sustainability and cost of capital is found, these theories can help to understand why this is the case. However, the empirical tests are not designed in a way that they would answer which of these theoretical models are driving the results.

2.1.6 Environmental Sustainability and Cost of Capital

Theoretical review shows that the relationship between environmental sustainability and cost of capital can be complicated. Figure 2 summarizes the theoretical relationship between Environmental Sustainability and WACC. Stakeholder theory, legitimacy theory and information asymmetry suggest that environmental sustainability can affect sensitivity to market risks, firm-specific risks, and investor base. In turn, these will have a direct effect on COE and COD. Additionally, environmental sustainability can affect WACC through debt capacity (Sharfman & Fernando, 2008). For instance, better management of environmental risks could decrease firm-specific risks. This would not only influence COD, but it would also increase a firm’s capacity to raise debt. Finally, increase in leverage would decrease WACC, if benefits from debt’s tax shield exceed increased bankruptcy costs. In this thesis, the focus is on environmental sustainability's direct effects on COE and COD, and the effect on debt capacity is not studied. The green color in Figure 2 indicates the research focus.

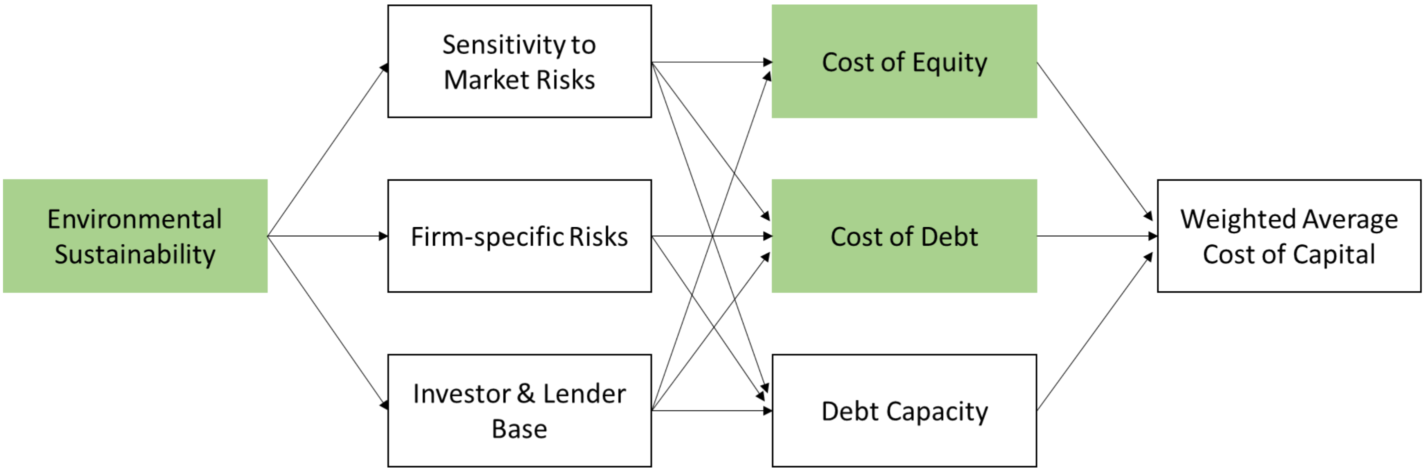

Figure 2. Theoretical Relationship Between Environmental Sustainability and Cost of Capital.

As there are many mechanisms how environmental sustainability might affect COE or COD, it is very well possible that the relationship between these is not simply negative. Even though improving on sustainability might always increase investor and lender base, increase after a certain threshold might also increase firm-specific risks and sensitivity to market risks. There is also a possibility that improvements in environmental sustainability incur so much costs and risks that these outweigh any benefits, regardless of the initial level of sustainability. The theoretical framework leaves open whether the relationship between environmental sustainability is positive, negative or if there is an optimal level, which gives a great basis for this thesis. Also, the theoretical framework does not give clear answers if different sustainability aspects are viewed equally, or if environmental sustainability is viewed differently in different industries. For instance, environmentally sensitive industries might have higher sensitivity to environmental regulations, in which case environmental sustainability's effect on COE and COD would be more signficant.

2.2 Prior Research

Compared to the earliest studies on environmental and economic performance that have been made in the 1970s, studies on environmental performance and cost of capital are relatively new (Sharfman & Fernando, 2008). Sharfman & Fernando (2008) conducted one of the earliest studies focusing on the relationship between environmental sustainability and cost of capital. The scholars argued that abnormal stock returns and higher market values of environmentally sustainable companies were not necessarily only the result of a better use of resources, but reduced cost of capital could also explain these findings. Prior research on cost of capital and environmental sustainability will be presented first in the context of COE and then in the context of COD.

2.2.1 Cost of Equity and Environmental Sustainability

Sharfman & Fernando (2008) used dataset of US firms for years 1999-2001. The used environmental sustainability score was a collective score by the Investor Responsibility Research Center, combining for instance emission, recycling, and waste scores. The researchers found that environmental sustainability is negatively correlated with WACC. Interestingly, this result was driven by the effect on COE, as environmental sustainability affected cost of equity capital negatively, whereas the linkage between COD and environmental sustainability was found to be positive.

After the paper of Sharfman & Fernando (2008), many studies have also found a negative relationship between COE and environmental sustainability. For instance, El Ghoul et al. (2011), Chava (2014), Ng & Rezaee (2015), and Gupta (2018) also reported a negative relationship in their studies. These scholars used implied COE measures, whereas Sharfman & Fernando (2008) relied on CAPM to derive COE. Implied COE is considered a better measure of investor expectations, as it is *ex ante*, whereas CAPM based COE is *ex post* (see Sub-section 3.1.1).

Alike Sharfman & Fernando (2008), El Ghoul et al. (2011) studied the relationship in the US but from a longer time-period, including years 1992-2007. El Ghoul et al. (2011) used KLD Stats database as their source for ESG data. KLD uses strength and weakness dummies to measure corporate social responsibility. By aggregating strengths or weaknesses, scholars can create aggregate measures on environmental and other sustainability aspects.

Environmental sustainability was one of the corporate social responsibility areas studied in the El Ghoul et al. (2011) study. In addition to finding that the relationship between environmental sustainability and cost of capital is negative, the study also found that the relationship has become more significant in the later years. The scholars reasoned that this is a result of investors' increased awareness on ESG issues. Chava (2014) and Ng & Rezaee (2015) also studied the relationship in the US context with a panel dataset and used KLD Stats as the source of ESG data. Both studies confirmed the negative relationship found in the earlier studies. Chava (2014) further explored the importance of environmental strengths and concerns, and found that environmental concerns increase COE, but did not find statistically significant relationship between environmental strengths and COE.

Gupta (2018) contributed to the research by exploring the relationship in an international context. The dataset included data from 43 countries for 2002-2012. Gupta used ASSET4 ESG scores (now known as Refinitiv ESG scores), which allowed to further explore importance of emission, innovation, and resource use sustainability. The study found that environmental sustainability is negatively associated with COE, and the results are driven by emission and resource use scores.

2.2.2 Cost of Debt and Environmental Sustainability

Alike with COE, early studies on COD and environmental sustainability focus on the US. Chava (2014) and Ge & Liu (2015) both used KLD Stats database as their source for ESG data and had panels from almost the same years—1992-2007 for Chava (2014) and 1992-2009 for Ge & Liu (2015). The major difference in the studies was that Chava (2014) used bank loan data, whereas Ge & Liu (2015) used bond spreads as the measure of COD. Chava (2014) found that environmental concerns increase the loan spreads, but environmental strengths do not have a significant effect. This is a similar result that the researcher got when COE was used as a dependent variable. In contrast, Ge & Liu (2014) found that environmental strengths lower bond spreads, but environmental concerns do not have a significant effect. Both studies had contradictory results to the study of Sharfman & Fernando (2008), who found that increase in environmental sustainability increases COD in the US.

Gracia & Siregar (2021) and Eliwa et al. (2019) studied the relationship in international context with Refinitiv ESG data. The study of Gracia & Siregar (2021) comprised data from ASEAN countries for 2004-2019, and therefore the study is more up to date than the studies of Chava (2014) and Ge & Liu (2015). Gracia & Siregar (2021) found no relationship between environmental sustainability performance and COD, which contradicts the results of Chava (2014) and Ge & Liu (2015). Gracia & Siregar (2021) also tested if there is a U-shaped relationship between cost of debt and ESG ratings and found no such relationship. Additionally, they found that there is no negative relationship even in environmentally sensitive industries. This study is interesting from the point of view of this thesis, as it tests for more complex relationships between cost of capital and environmental sustainability than what is available from the earlier studies.

Eliwa et al. (2019) studied ESG practices and cost of debt in 15 EU countries, and therefore this study is closely related to this thesis. The study includes years 2005-2016, so it is quite up to date. The study found that higher ESG and environmental performance results to lower cost of debt. The study also found that a firm's more extensive communication or disclosure on its ESG practices lowers COD. However, it is good to notice that the sample period includes both financial crisis and European debt crisis, and therefore the results might not be fully representative of economically stable times.

2.2.3 Shortcomings of Prior Research

The review of prior research suggests that there is a negative relationship between environmental sustainability and COE. In turn, the results on the relationship between environmental sustainability and COD are more contradictory. The contradictory results could be explained by country and time differences. The similar results of Chava (2014), Ge & Liu (2014) and Eliwa et al. (2019) on COD and environmental sustainability could be due to similar business cultures and levels of stakeholder orientation, as they all focus on developed markets (Dhaliwal et al., 2012; Devinney et al., 2013). Gracia & Siregar (2021) found no relationship, which in turn could be explained by differing cultures and stakeholder orientation, as the study focuses on developing markets. Further, the contradictory results between the US-focused studies of Sharfman & Fernando (2008) and Chava (2014) and Ge

& Liu (2015) could be explained by time differences. This is backed by El Ghoul et al. (2011) finding that ESG awareness has increased in the recent years.

Even though there are already papers from many geographical areas, there is still value on studying the topic further. Firstly, all but the study of Gracia & Siregar (2021) implicitly assume that the relationship between cost of capital and environmental sustainability is linear. However, this could be an unwise assumption, as the effects on firm-specific risks and sensitivity to market risks might be dependent on the initial level of sustainability as discussed in Sub-section 2.1.6. Even though Gracia & Siregar (2021) found no evidence of the U-shaped relationship, the results could differ in the developed markets, or when cost of equity is used as the dependent variable.

Studies that are focused on the US and that use KLD Stats database as the source of ESG data, relate to some extent to testing for the shape of the relationship. This is because KLD ESG measures include both environmental strength and concern dummies and thus allow to study importance of strengths and concerns separately. However, the dummy model is quite rigid and cannot fully reflect changes in a company's environmental sustainability practices. An example of this would be *climchange* measure, which simply takes a value of zero or one, depending on if a company derives substantial revenues directly or indirectly from coal or oil or their derivative products (Chava, 2014). Such a measure is largely industry specific, and hardly can help to answer the question if already environmentally sustainable companies have an incentive to further improve their practices. Also, the reviewed studies are contradictory, as Chava (2014) found that environmental concerns increase cost of capital, but strengths have no effect, whereas the results of Ge & Liu (2014) were the opposite.

Another shortcoming in the past literature is that almost all studies focus on aggregate measures of environmental sustainability. Therefore, there is still value in studies that break-down environmental sustainability to different aspects and reveal which of these affect cost of capital. The only reviewed research paper that studies the different sub-components is Gupta's (2018) study. As the topic is little studied, there is a clear scientific motivation to explore this relationship further. Knowledge on the importance of different components of environmental sustainability would help companies and analysts to focus on the topics that matter.

Also, the prior research has not studied extensively the importance of industry, which could be an important determinant in the relationship between environmental sustainability and cost of capital. It could be hypothesized that lenders and stockholders might focus more on environmentally sensitive industries, as in these, environmental practices of companies can have larger externalities, larger effects on firm-specific risks as well as higher sensitivity to market risks as discussed in Sub-section 2.1.6. Finally, inconsistent results especially with environmental sustainability and COD call for studying this relationship further, so a better consensus can be achieved on whether environmental sustainability is a relevant factor affecting cost of debt.

3. DATA AND METHODOLOGY

In this chapter, the used data, data collection methods and variable definitions are presented first in Section 3.1. These are followed by a review of used empirical and predictive models as well as the model selection methodology in Section 3.2.

3.1 Data and Variable Definitions

The used data comprise financial and environmental sustainability data on publicly listed companies from 15 developed European countries for 2010-2020. The 15 countries are the same as included in MSCI Europe Index, i.e. Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the UK. All data is collected from Refinitiv Datastream. Original source for accounting data is Worldscope, for analyst estimates I/B/E/S and for environmental sustainability measures Refinitv. Only companies which are listed primarily in the main index of one of the countries are included in the sample. To avoid survivorship bias, also delisted and dead companies are included in the sample. Companies that are listed after 2011 are excluded from the sample to make the panel more balanced. The final panel dataset is unbalanced and short and wide. Unbalanced dataset means that there are missing observations, and short and wide datasets include many individual observations from a relatively short period of time (Hill et al, 2018, p. 636).

3.1.1 Cost of Capital as a Dependent Variable

Past literature has used a wide range of measures for cost of equity capital. A common practice in the recent literature has been to use implied COE instead of more traditional asset pricing models, such as CAPM, Fama & French three-factor model or other multi-factor models. Implied COE models are *ex ante* and are based on expected dividends and known stock price, whereas asset pricing models are *ex post* and are based on realized returns (Gode & Mohanram, 2003). Already in the 1990s, Fama and French (1997) stated that asset pricing models are imprecise measures of COE. Implied COE has two major advantages over the asset pricing models. First, these models account for different earnings and cash flow expectations and second, implied COE can better circumvent issues arising from noisy realized returns and failure of asset pricing models to estimate firm-level COE (Pástor et al., 2008; El Ghoul et al., 2011).

COE measure used in the thesis is based on model suggested by Gebhardt et al. (2001). The model is a widely used residual income valuation (RIV) model, in which current stock price is derived from last financial year's (FY) book value and an infinite series of discounted residual income. Gode & Mohanram (2003) found that the model outperforms two others commonly used implied COE models in predicting future stock returns, namely Ohlson-Juettner (2003) and Liu et al. (2002) models. This finding suggests that Gebhardt et al. (2001) model is a good proxy for cost of equity.

Gebhardt et al. (2001) model uses "clean surplus" accounting, that is, changes in book value are assumed to equal earnings minus net dividend in each period. The model further assumes a constant dividend payout ratio and uses analyst estimates for net income for the next three years to calculate forecasted return on equity (FROE). After the three-year period, FROE is set to converge linearly to industry median ROE by the 12th year. The industry median used in this paper is based on 7-year rolling median ROE, while excluding loss companies. To increase the trustworthiness of analyst estimates, it is required that at least four analysts follow a company when calculating FROE. Similarly, for median ROE calculation it is required that at least four companies exist in an industry. When we have estimated FROE and book values for the next 12 years and we know the June-end stock price after last FY end, implied COE (ICOE) can be solved from the following equation using iterative calculation (Gebhardt et al., 2001; Gode & Mohanram, 2003; El Ghoul et al., 2011):

$$P_t = B_t + \sum_{i=1}^{11} \frac{FROE_{t+i} - ICOE_t}{(1+ICOE_t)^i} B_{t+i-1} + \frac{FROE_{t+12} - ICOE_t}{ICOE_t(1+ICOE_t)^{11}} B_{t+11} \tag{5}$$

where P_t = stock price at end of June after FY end, $FROE_{t+i}$ = forecasted return on equity for year $t + i$, $ICOE_t$ = implied cost of equity for year t, B_{t+i}= book value of common equity for year $t + i$ $= B_{t+i-1}(1 - DPR_t)$, and DPR_t = dividend payout ratio, which is equal to last available dividend payout ratio.

Industry classification is based on Fama & French (1997) industry groups. In this study, some of the industry classes have been combined to increase number of observations for each industry group, while keeping in mind that industries should be similar in types of products or services sold. Even when some of the industries were combined, certain industry groups were omitted because of insufficient observations for industry median ROE calculation. These industries include Business Supplies, Healthcare, Fabricated Products, Shipping Containers, Defense, and Miscellaneous. Financial services companies (Banking, Trading & Insurance) were also omitted because they are not comparable with other industries in terms of their capital structure, cost of financing as well as they are subject to special regulations. The combined industry groups and their relation to Fama & French (1997) industry groups are presented in Table 1.

Table 1. Combined Industry Groups vs. Fama & French (1997) Industry Groups.

Combined Industry Groups	Fama & French (1997) Industry Groups
Agriculture	Agriculture
Alcohol and Tobacco	Alcoholic Beverages & Tobacco Products
Chemicals	Chemicals
Construction	Construction & Construction Materials
Consumer Goods	Consumer Goods & Recreational Products
Electronics	Computers, Measuring and Control Equipment, Electrical Equipment & Electronic Equipment
Energy	Petroleum and Natural Gas & Coal
Entertainment	Entertainment
Food Products	Food Products & Candy and Soda
Machinery	Machinery
Metals and Mining	Precious Metals & Nonmetallic Mining
Mobility Manufacturing	Automobiles and Trucks, Aircraft & Shipbuilding, Railroad Eq.
Pharmaceutical Products	Pharmaceutical Products
Printing and Publishing	Printing and Publishing
Real Estate	Real Estate
Restaurants, Hotel, Motel	Restaurants, Hotel, Motel
Rubber and Plastic Products	Rubber and Plastic Products
Services	Business Services & Personal Services
Steel Works	Steel Works
Telecommunications	Telecommunications
Textiles and Apparel	Textiles & Apparel
Transportation	Transportation
Utilities	Utilities
Wholesale and Retail	Wholesale & Retail

To account for changes in risk-free interest rate, risk-free interest is deducted from the implied cost of equity. COE measure corrected for risk-free interest better reflects the perceived risk of a company, as risk-free interest should capture time value of money and inflation expectations. By deducting Germany's 10-year government bond rate from the implied cost of equity, we get the final measure for cost of equity:

$$COE_t = ICOE_t - r_{f,t} \tag{6}$$

where $COE_t =$ cost of equity for year *t*, $ICOE_t$ = implied cost of equity for year *t* based on Gebhardt et al. (2001) model, and $r_{f,t}$ = Germany's 10-year government bond rate at the end of June in year *t*.

Cost of debt used in this study is accounting based, and simply calculated as total interest expense divided by average interest-bearing debt in a financial year. Even though this COD measure is *ex post*, it does not have the same inaccuracy concerns as *ex post* COE proxies have. Accounting based COD has also been used widely in the past literature on ESG investing (see e.g. Ye & Zhang, 2011; Eliwa et al., 2019; Luo et al., 2019; Gracia & Siregar, 2021). As with COE, COD is corrected for risk-free interest rate to reflect interest premium. Formula for COD calculation is given in Equation 7.

$$COD_t = \frac{I_t}{(D_t + D_{t-1})/2} - r_{f,t} \tag{7}$$

where $COD_t =$ cost of debt for year *t*, $I_t =$ total interest expense for year *t*, D_t and $D_{t-1} =$ total interest-bearing debt for FY end *t* and *t-1* respectively, and $r_{f,t}$ = average Germany's 10-year government bond rate in year *t*.

3.1.2 Environmental Sustainability as an Independent Variable

Measuring environmental sustainability is not simple, as there is no one objective measure for sustainability. It could be debated, for example, if it is more important that a company has reached sustainable practices or that a company tries to improve its practices. Additionally, there is the issue regarding how certain sustainability aspects should be measured. For instance, there are multiple types of greenhouse gases, and these can be incurred directly (Scope 1) or indirectly (Scopes 2 and 3) from the company's operations. Also, if absolute measures of greenhouse gas emissions are used, large companies will seem environmentally unsustainable compared to small companies. On the other hand, size-adjusted emission measures can favor large companies, as they have better possibilities to invest in low-emitting technologies and they can produce in scale. Other concerns on measuring environmental sustainability are the lack of common taxonomy and large number of different ESG reports (Drempetic et al., 2019).

ESG measures of rating agencies are commonly used to get an objective view on a firm's ESG performance. Following previous literature (see e.g. Eliwa et al., 2019; Gupta, 2018; Gracia & Siregar, 2021), Refinitiv ESG scores are used as the measure of environmental sustainability. Refinitiv ESG data is collected by trained research analysts from different sources, such as annual reports, company websites, news, and stock exchange filings. The scores range from 0-100 and the scoring is based on a company's relative performance within an industry. (Refinitiv, 2021)

Refinitiv ESG scores provide a single measure for environmental sustainability (ES_Overall). The overall score can be further broken down to three categories: emission (ES_Emission), innovation (ES_Innovation), and resource use (ES_Resource) scores. These categories are also used in this study to obtain deeper insight on the relationship between environmental sustainability and cost of capital.

The scores for the categories are collected from a total of 68 datapoints relevant for a given industry. Emission score measures a company's emission and waste production and the company's efforts to reduce these. Innovation score reflects how well a company can reduce environmental burden for its customers and it is a product and technology-oriented measure. Resource use score measures how effectively a company uses water, energy and raw materials and its efforts to improve on these. Overview of used environmental sustainability measures is presented in Figure 3. (Refinitiv, 2021)

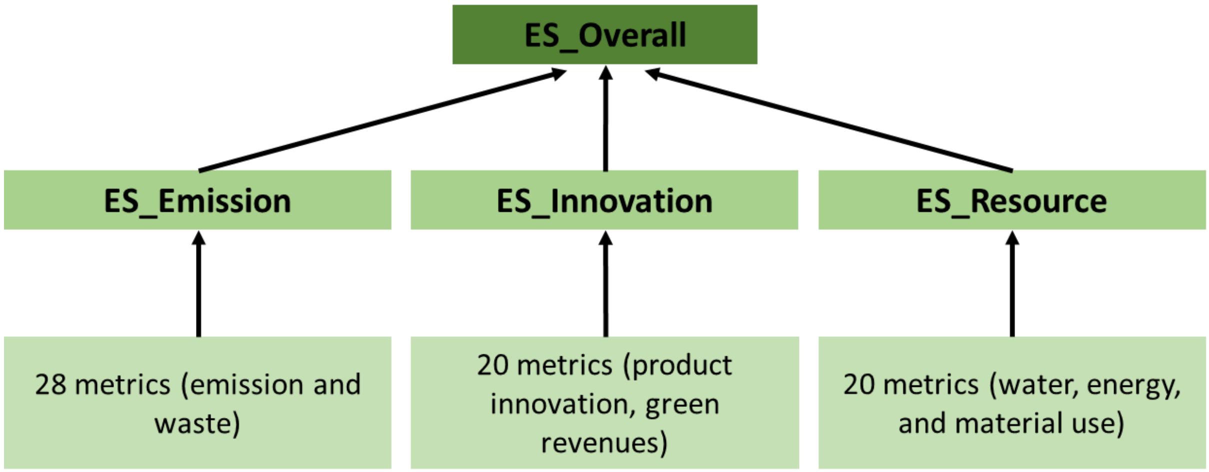

Figure 3. Calculation Principles of Refinitiv Environmental Sustainability Scores (Refinitiv, 2021).

Although Refinitiv ESG scores aim to capture ESG aspects objectively, even this scoring system might suffer from certain biases. Drempetic et al. (2019) found that ASSET4 ESG ratings is prone to firm size bias, i.e., larger firms tend to have higher ESG scores. Another bias concern is that firms with more complex ESG disclosure tend to get higher ESG ratings. This again favors large companies, as they have better resources to disclose complex ESG reports (Gallo & Christensen, 2011; Drempetic et al., 2019). These biases are largely mitigated by the research design, as firm size is included as a control variable in the used models. Further, fixed effects model is the primary model used, which uses only with-in variation in the parameter coefficient estimation. By only using with-in variation, biases due to specific company characteristics can be largely mitigated. This is because the same company is likely to have similar extension of ESG disclosure in consecutive years.

3.1.3 Control Variables

Use of control variables is necessary to ensure that the results are not driven by variables that correlate strongly both with environmental sustainability and cost of capital. Control variables are selected separately for COE and COD, and selection is based on financial theories and prior studies. Control variables for models with cost of equity as the dependent variable comprise beta (BETA), book-to-market ratio (BTM), leverage (LEVERAGE), size (SIZE), analyst forecast dispersion (FOREC_DISP), return on assets (ROA), and operative cash flow to assets (OCFTA). Control variables for models with cost of debt as the dependent variable include LEVERAGE, SIZE, ROA, OCFTA, interest coverage ratio (INT_COV), and capital intensity (CAP_INT).

BETA and BTM are added as controls, as these have been reported to be positively associated with expected returns (see e.g. Gebhardt et al. 2001; Hail & Leuz, 2006; El Ghoul et al., 2011; Ng & Rezaee, 2015). El Ghoul et al. (2011) approach is followed in the calculation of BETA. BETA is determined by monthly excess returns of a stock for the past 60 months against market index MSCI Europe. Germany’s government bond is used as the risk-free interest rate, as it is a large and financially stable country in Europe. Minimum of 24 monthly observations are required to calculate BETA. BTM is determined as common shareholder’s equity at financial year-end divided by the company’s market value at the end of June.

Both BETA and BTM have intuitive reasons why these would be positively correlated with implied COE. BETA is simply *ex post* measure of COE and therefore it is not surprising that it is correlated with implied COE. In turn, BTM approximates how much investors’ view on the firm value differs from the fundamental book value. The higher book-to-market ratio, the lower are the investor expectations for value creation. Theoretically, increase in BTM can either be due to increased risks or decreased expected cash flows, and the former should also correlate with implied COE.

Leverage and firm size are also often used control variables for models with COE as the dependent variable. Theoretically leverage is positively correlated with COE, as leverage affects variation of cash flows to the shareholders, and therefore increase in leverage increases risks and expected returns. COE’s relationship with leverage has reported to be positive and relationship with firm size has been reported to be negative in many empirical studies (see e.g. El Ghoul et al., 2011; Chava, 2014; Gupta, 2018), and thus these are also included as control variables. In this thesis, LEVERAGE is calculated as book value of debt to book value of common shareholder’s equity at the end of financial year. SIZE is a logarithm of total assets to avoid outlier bias. For calculation of SIZE, assets given in foreign currencies are converted to euros with fixed exchange rates.

FOREC_DISP, ROA, and OCFTA are added as additional controls based on prior research. FOREC_DISP is determined as a logarithm of analyst forecast dispersion for next financial year's earnings per share (EPS). A logarithm is taken to reduce outlier bias. ROA and OCFTA are determined as net income or operative cash flows in a financial year divided by average assets in the same financial year.

Gode & Mohanram (2003), Dhaliwal et al. (2006), and El Ghoul et al. (2011) report a positive relationship between analyst forecast dispersion and implied COE. A positive relationship is quite intuitive, as higher dispersion of forecast estimates could be due to higher sensitivity to market risks. In turn, profitability has been reported to influence COE negatively (see Gupta, 2018; Ng & Rezaee, 2015). Profitability is controlled with ROA and OCFTA. In the reviewed studies profitability measures have been only based on income statements. However, such profitability measures can be subject to creative accounting and profitability manipulation, which is why cash flow based OCFTA is added as a control variable.

As with cost of equity models, SIZE, ROA and OCFTA are expected to affect COD negatively and LEVERAGE positively based on Ge & Liu (2015), Eliwa et al. (2019), and Caragnano et al. (2020) studies. OCFTA is again used as an additional control, as it is less subject to creative accounting than income statements-based measures. Cash flow measures have been used by Caragnano et al. (2020) and Gracia & Siregar (2021), and these have been reported to have a statistically significant effect on COD.

Table 2. Variable Definitions.

Variable	Definition	Expected sign
Dependent		
COE	Cost of Equity. Implied COE based on Gebhardt et al. (2001) less risk-free interest rate at end of June.	
COD	Cost of Debt. Total interest expenses for FY / Average debt in FY - Average risk-free interest rate.	
Independent		
ES_Overall	Refinitiv Environmental Sustainability Overall score.	
ES_Emission	Emission component of Refinitiv's Environmental Sustainability Overall score. Measures emission and waste production and efforts to reduce these.	
ES_Innovation	Innovation component of Refinitiv's Environmental Sustainability Overall score. Measures how well a company's products and technologies help to reduce environmental burden of its customers.	
ES_Resource	Resource use component of Refinitiv's Environmental Sustainability Overall score. Measures water, energy, and raw material efficiency and efforts to improve on these.	
SI	Sensitive Industry dummy. Takes a value of one if a company operates in environmentally sensitive industry and zero otherwise.	
Control		
BETA	Beta. Calculation based on monthly excess returns against MSCI Europe Index for the past 60 months. Minimum of 24 observations required.	+
BTM	Book-to-Market. Common shareholder's equity at FY end / Market value at end of June.	+
LEVERAGE	Leverage. Total Debt at FY end / Common shareholder's equity at FY end.	+
SIZE	Company size. Log10(Total assets at FY end).	-
FOREC_DISP	Forecast dispersion of analyst estimates. Log10(Forecast dispersion of analyst forecast estimates for EPS for next financial year as of end of June). A minimum of four forecasts required.	+
ROA	Return on assets. Net income for FY / Average assets in FY.	-
OCFTA	Operative Cash Flow to Assets. Operative cash flow for FY / Average Assets in FY.	-
INT_COV	Interest Coverage. EBIT for FY / Total interest expenses for FY.	-
CAP_INT	Capital Intensity. Fixed assets at FY end / Total assets at FY end.	+

Additionally, INT_COV and CAP_INT are used as control variables in COD models. INT_COV is calculated by dividing a company’s EBIT in a financial year over its interest expenses in the same period. CAP_INT, in turn, is defined as fixed assets at financial year-end divided by total assets at the same date. Negative relationship between interest coverage ratio and cost of debt has been reported by Eliwa et al. (2019), which is an intuitive result, as higher interest coverage implies lower firm-specific risks. In turn, the relationship between CAP_INT and COD is expected to be positive, since lower values in CAP_INT means that a company has higher percentage of its assets as current assets. Better liquidity is often associated with a better capacity to meet debt obligations. Capital intensity's positive effect has also been found empirically by Bauer & Hann (2010). Table 2 summarizes all used variables.

3.2 Methodology

This thesis uses panel data models for empirical analysis. A clear advantage of panel data models is that they can utilize more information in parameter estimation than cross-sectional models can. Another advantage is that panel data models can circumvent certain statistical concerns, such as endogeneity. The predictive models are also trained with panel data models and evaluated with out-of-sample observations using three evaluation metrics. All statistical tests are conducted with Stata.

3.2.1 Empirical Models

Three panel data models are considered for empirical analysis: ordinary least squares (OLS), fixed effects (FE) and random effects (RE) models. RE model can use more information for parameter estimation than FE or OLS and is therefore the preferred model. However, RE model can suffer from endogeneity, in which case FE model is the better alternative. Also OLS is considered, as there might not be important differences between firms, in which case OLS is simpler than FE and RE models and still efficient model for parameter estimation. Simpler models are preferred in statistics if the use of more complex models is not justified.

Statistical notations for the basic empirical model (only first-order terms and no controls for industry sensitivity) are shown with all OLS, FE and RE models, since the best type of model is not known beforehand. Also the criterion for model selection is shown later in this subsection. Other models than the basic models are only shown with FE model estimation for saving space. The basic model with OLS can be expressed as:

$$COE_{i,t}\ (or\ COD_{i,t}) = \\ \beta_1 + \beta_2\ ES_{i,t-1} + \sum_{j=3}^{J} \beta_j Control_{j,i,t-1} + \beta_{J+1} YearFixedEffect_t + e_{i,t} \qquad (8)$$

where $COE_{i,t}$ = cost of equity for firm i in year t, $COD_{i,t}$ = cost of debt for firm i in year t, β_1= unknown term representing mean constant of the population, $ES_{i,t-1}$ = environmental sustainability score (ES_Overall, ES_Emission, ES_Innovation or ES_Resource depending on the model) for firm i in year t-1, J = number of control variables + 2, $Control_{j,t-1}$ = control variable j for firm i in year t-1, except for forecast dispersion which is measured at the same time as COE, $YearFixedEffect_t$ = unobserved effect of time, and $e_{i,t}$ = idiosyncratic error.

OLS does not consider individual characteristics of firms, and alternative panel data models are more efficient if such characteristics exist. Additionally, OLS models may suffer from endogenous explanatory variables. Endogeneity is defined as correlation between explanatory variable and the error term. The problem with endogenous variables is that they result to inconsistent results with regular OLS estimation. One common reason for endogeneity is omitted variables that are correlated both with explained and explanatory variables. (Hill et al., 2018, p. 481-489, 636-639)

Prior research has addressed endogeneity issues in different ways. Typical solutions include the use of control variables and two-stage least squares (2SLS) models. Control variables can capture important omitted variables, and thus solve the endogeneity problem. In turn, 2SLS "converts" the endogenous variable to exogenous by estimating it with instrument variables and exogenous variables of the model. However, finding suitable instrument variables is not easy. This is because instrument variables need to be highly correlated with the endogenous variable and they need to be exogenous, while not having direct effect on the explained variable (Hill et al., 2018, p. 490).

Common practice in prior research is to use industry average sustainability score as the instrument for firm's environmental sustainability (see El Ghoul et al., 2011, Eliwa et al., 2019). However, such a metric is not sensible in the case of Refinitiv ESG scores, as these are benchmark scores within an industry (i.e. all industries should have the same median value). Fortunately, endogeneity concerns arising from the omitted variables bias can be avoided altogether by using fixed effects panel data regression, which is discussed below.

Random effects (RE) model and fixed effects (FE) model are the primary panel data models in this study, as they can account for firm-specific characteristics. Of these two, RE model is considered more efficient as it can use both between (cross-sectional variation) and within (time-variation) information to estimate parameter coefficients. However, the RE model needs to meet stricter conditions than FE model and cannot always be used because of endogeneity issues. The basic model with RE estimation is presented in Equation 9. (Hill et al., 2018, p. 638-661)

$$COE_{i,t}\ (or\ COD_{i,t}) =$$
$$\bar{\beta}_1 + \beta_2\ ES_{i,t-1} + \sum_{j=3}^{J} \beta_j Control_{j,i,t-1} + \beta_{J+1} YearFixedEffect_t + v_{i,t}. \qquad (9)$$
$$v_{i,t} = u_i + e_{i,t}$$

where $\bar{\beta}_1$ = unknown term representing mean constant of the population, u_i = random error term which represents differences between firms and other terms are as in Equation 8.

With RE model, endogeneity concerns arise if error term u_i is correlated with any of the explanatory variables. In this case FE model can be used instead, as the model eliminates firm specific heterogeneity through a transformation. The model does this by capturing u_i in the firm specific constant ($\beta_{1,i}$) and by using within transformation to estimate parameter coefficients. This means that FE model produces consistent results even if omitted variables that are correlated with explanatory variables exist. This holds true if the omitted variables are time-invariant. This is not an unreasonable assumption in this thesis since the used panel data is short. In a short period, these omitted variables will be captured in the firm fixed effects, and thus FE model produces consistent parameter estimates. Using FE model estimation, the basic model is formulated as in Equation 10. (Hill et al., 2018, p.638-650)

$$COE_{i,t}\ (or\ COD_{i,t}) =$$
$$\beta_{1,i} + \beta_2\ ES_{i,t-1} + \sum_{j=3}^{J} \beta_j Control_{j,t-1} + \beta_{J+1} YearFixedEffect_t + e_{i,t} \qquad (10)$$

where $\beta_{1,i}$ = firm fixed effect and other terms are as in Equations 8 and 9.

Unfortunately, omitted variables are not the only source of endogeneity, but reverse causality can also lead to endogeneity and inconsistent results. Following Ferreira & Laux (2007) and Ng & Rezaee (2015), the used models apply lead-lag design, where independent variables are predetermined.

Also model with an additional squared environmental sustainability term is used to study the shape of the relationship between cost of capital and environmental sustainability. The use of a squared term allows to find possible non-linear relationships between the variables. A positive squared term would suggest that there is an optimal level for environmental sustainability, i.e. increase in environmental sustainability would lower the cost of capital for unsustainable firms, whereas the cost of capital would increase for already sustainable firms. With FE model, the model with an additional squared term can be expressed as:

$$\begin{aligned} &COE_{i,t}\ (or\ COD_{i,t}) = \\ &\beta_{1,i} + \beta_2\ ES_{i,t-1} + \beta_3\ ES_{i,t-1}^2 + \textstyle\sum_{j=4}^{J} \beta_j Control_{j,t-1} \\ &+ \beta_{J+1} YearFixedEffect_t + e_{i,t} \end{aligned} \tag{11}$$

where $ES_{i,t-1}^2$ = squared term of environmental sustainability score (ES_Overall, ES_Emission, ES_Innovation or ES_Resource depending on the model) for firm *i* in year *t-1*, *J* = number of control variables + 3 and other terms are as in Equation 10.

Following Lind & Mehlum (2010), derivation is used to solve for minimum or maximum of the model with a squared term for environmental sustainability. Since environmental sustainability scores range from 0 to 100, the minimum or maximum should be within this range. Should the minimum or maximum be outside of the range, no non-linear relationship exists, even if the squared term would be statistically significant. To ensure robustness of the results, an alternative method is also used. The method includes dividing companies into three groups based on their environmental sustainability scores: Low, Medium and High ES Companies. By regressing the basic model by group, we can see if a non-linear relationship exists.

Finally, importance of industry is studied by adding an additional environmental sustainability term with a dummy, which takes a value of one if a firm is in environmentally sensitive industry (SI) and zero otherwise. Following García-Meca & Martínez-Ferrero (2021), Metals and Mining, Energy, Chemicals, Steel Works, and Utilities are defined as environmentally sensitive industries. In addition, Construction, Rubber and Plastic Products, Mobility Manufacturing and Transportation are added into the SI group. The reasoning is that construction industry is a heavy user of steel and concrete, which today are major sources of greenhouse gases (Gates, 2021, p. 98-108). Similarly mobility manufacturing uses emission intensive materials, such as plastics and steel, and therefore it is included in the environmentally sensitive industries. Mobility manufacturers further have significant indirect emissions, as their customers (companies and households) use cars, trains, ships, and airplanes to transport goods and people around the globe. For the same reason transportation is included into the sensitive industry group. Finally, rubber and plastic products do not produce only greenhouse gases and plastic pollution but are also a risk for marine life biodiversity (D'Alessandro et al., 2018; Ribeiro-Brasil et al., 2020).

Non-sensitive industries include Agriculture, Alcohol and Tobacco, Consumer Goods, Electronics, Entertainment, Food Products, Machinery, Pharmaceutical Products, Printing and Publishing, Services, Telecommunications, Textiles and Apparel as well as Wholesale and Retail. Division to environmentally sensitive and non-sensitive industries is to some extent artificial, as there is not a single objective way to make the division. For instance, food producers and agriculture can contribute to climate change significantly and have other adverse effects for environment. Because of this concern an additional robustness test is done, where Food Products and Agriculture are also included in the sensitive industry group. With FE model, the model moderating for industry sensitivity can be formulated as:

$$\begin{aligned} &COE_{i,t}\ \left(or\ COD_{i,t}\right) = \\ &\beta_{1,i} + \beta_2\ ES_{i,t-1} + \beta_3\ ES_{i,t-1} * SI_i + \textstyle\sum_{j=1}^{J} \beta_j Control_{j,t-1} \\ &+ \beta_{J+1} YearFixedEffect_t + e_{i,t} \end{aligned} \tag{12}$$

where SI_i = Sensitive Industry dummy (takes value of one if firm *i* operates on environmentally sensitive industry and zero otherwise), *J* = number of control variables + 3 and other terms are as in Equations 8, 9 and 10.

To test for endogeneity in RE model, a regression based Hausman test, or Mundlak test, is used. The Mundlak test's null hypothesis is that there is no correlation between unobserved heterogeneity and explanatory variables. If the null hypothesis is rejected, FE model should be used instead of RE model. After Mundlak test, F-test or Breusch-Pagan test is used to test for firm fixed effects or random effects. The null hypothesis for these tests is that there are no firm fixed or random effects, in which case Pooled OLS should be used. Selection of suitable panel data model is summarized in Figure 4.

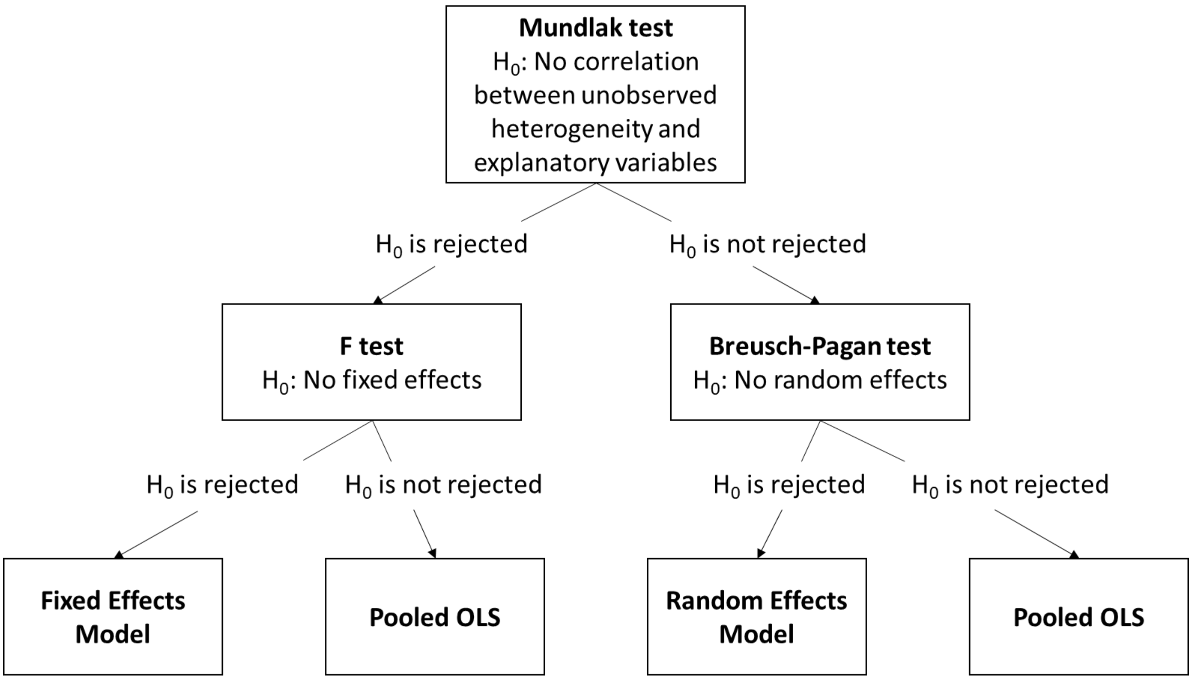

Figure 4. Selection Criteria of the Panel Data Model (Hill et al., 2018, p. 640-646, 651-662).

As is apparent from Equations 8-12, the models capture possible year fixed effects. As firm fixed effects capture time-invariant unobservable heterogeneity between firms, year fixed effects capture unobserved variables that vary over time but not between firms (Hanck et al., 2020). Existence of year fixed effects is tested with F test.

Even though fixed effects model removes unobserved heterogeneity, there may remain heteroskedasticity or autocorrelation within a firm. To account for these possibilities, cluster-robust standard errors (robust t-statistics) are used instead of normal standard errors. Cluster-robust standard errors apply well for wide and short panel datasets, which is the case in this study. Three significance levels are considered in the empirical results: 10%*, 5%**, and 1%***. (Hill et al., 2018, p. 646-651)

3.2.2 Predictive Models

In addition to empirical tests, predictive models are applied to see if environmental sustainability can be used to predict changes in cost of capital. Predictive models are formulated based on the results of empirical models. All models use linear regressions and apply the same model type (Pooled OLS, FE model or RE model) as in empirical models. However, an important distinction with the empirical models is that all variables are differenced. This is done so that changes in cost of capital can be predicted, which helps in model evaluation. Additionally, year effects are not used in predictive models, as year fixed effect cannot be applied to the test set, which can result to systematic overestimation or underestimation of cost of capital changes.

In the predictive modeling, it is important to evaluate performance of the model by applying it to out-of-sample test set. The evaluation is done by using time-series cross validation, which uses chronologically old data for model training, and applies the model to new observations from more recent years (Hyndman & Athanasopoulos, 2018). This evaluation design corresponds to the real life, as models trained today will be applied to data which is not yet available. To lessen the results’ dependence on a certain time, the training and testing are done three times for the last three available years in the dataset. The evaluation design is presented graphically in Figure 5.

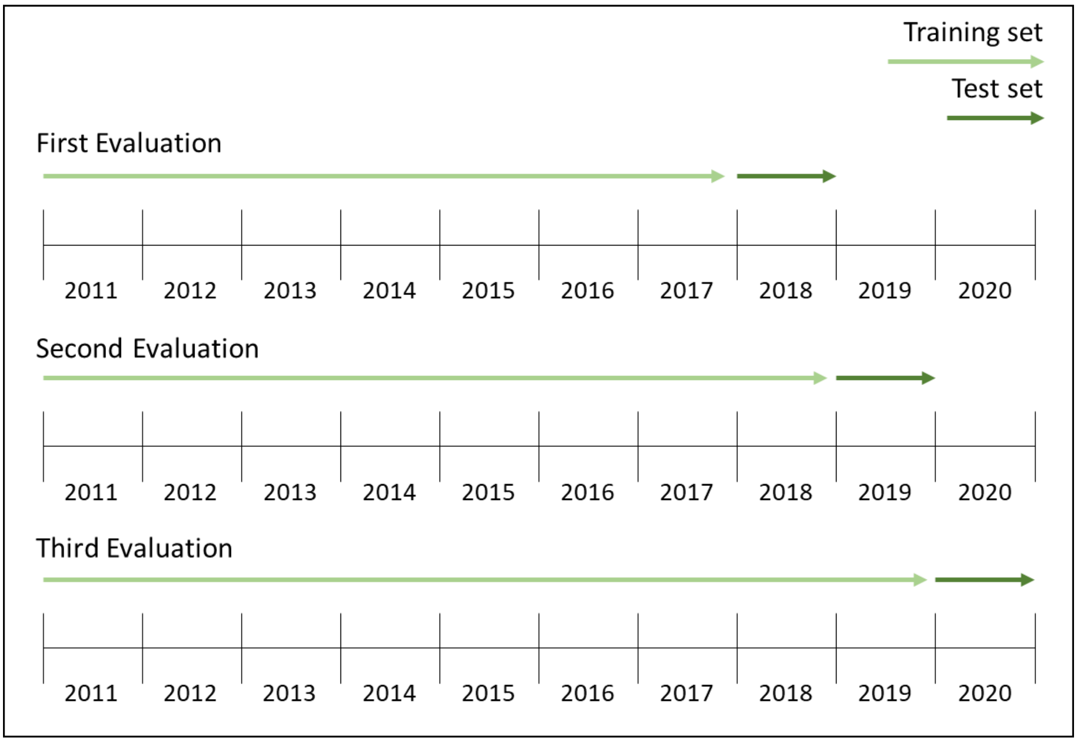

Figure 5. Research Design for Time-series Cross Validation.

To test if environmental sustainability is useful in predictive modeling, a benchmark model is compared to models with ES_Overall score as an additional variable. The models are compared by using three evaluation metrics. The used evaluation metrics cover two important aspects: classification on whether cost of capital increases or decreases and the extent of change in cost of capital. Both are important, as for example analysts and investors might be interested whether a company's cost of capital will increase or decrease in the next year and to what extent.

For evaluation of classification, sensitivity and specificity metrics are used. Equations 13 and 14 show the definitions of sensitivity and specificity in statistical terms (Provost & Fawcett, 2013, p. 202, 360). In the context of this study, sensitivity—or true positive rate—measures how often a model correctly detects an increase in cost of capital. In turn, specificity measures how often the model correctly detects a decrease in cost of capital. Higher values suggest better model performance with both metrics.

$$Sensitivity = \frac{True\ Positives}{True\ Positives + False\ Negatives} \tag{13}$$

$$Specificity = \frac{True\ Negatives}{True\ Negatives + False\ Positives} \tag{14}$$

$$Mean\ Absolute\ Error = mean(\left|e_{i,t}\right|) \tag{15}$$

To test for accuracy of the extent of change, Mean Absolute Error (MAE) is used. MAE simply takes an average of the absolute errors of the predicted values. Put more simply, MAE measures how much the predicted changes in cost of capital differ from the actual changes. Calculation of MAE is presented in Equation 15. (Hyndman & Athanasopoulos, 2018)

4. EMPIRICAL RESULTS

This chapter first presents the descriptive statistics of the data in Section 4.1. Next, the results of empirical models are presented in Section 4.2, and finally, Section 4.3 presents the results of predictive models.

4.1 Descriptive Statistics

The dataset is unbalanced, Firm-Year observations varying from 3,976 for COE to 9,599 for SIZE. Calculation of COE requires median EPS analyst estimates for the first and second year and for long term EPS growth at least from four analysts. These restrictions limit the number of COE observations. Also, environmental scores (ES_Overall, ES_Emission, ES_Innovation, and ES_Resource) are missing for many companies. However, even with the missing observations, the dataset is considered large enough to represent developed Europe's publicly listed companies.

To avoid outlier bias, all financial data (COD, COE, BETA, BTM, FOREC_DISP, LEVERAGE, SIZE, ROA, OCFTA, INT_COV, and CAP_INT) is winsorized (see e.g., Gupta, 2018; Eliwa et al., 2019). Tables 3 and 4 presents summary statistics for the data winsorized at 1st and 99th percentile as well as at 5th and 95th percentile.

Table 3. Summary Statistics, Winsorized at 1st and 99th Percentiles.

	Firm-Year obs.	Mean	Min	Median	Max	Std. deviation
COD	8,990	4.82	-0.60	3.09	74.19	8.79
COE	3,976	9.35	-1.30	8.63	35.56	5.79
ES_Overall	6,912	54.47	0.27	55.89	98.88	24.67
ES_Emission	6,714	61.83	0.15	65.46	99.82	26.41
ES_Innovation	4,591	54.11	0.83	51.39	99.84	25.84
ES_Resource	6,757	61.84	0.32	65.54	99.86	27.02
BETA	9,442	0.74	-0.03	0.70	1.99	0.40
BTM	9,451	66.61	4.71	48.43	414.10	64.52
FOREC_DISP	8,082	0.95	0.09	0.89	2.43	0.46
LEVERAGE	9,597	80.77	-234.20	56.04	630.10	107.20
SIZE	9,599	6.36	4.63	6.34	8.14	0.73
ROA	9,569	6.13	-23.51	5.62	33.51	7.68
OCFTA	9,571	9.21	-11.66	8.24	37.11	7.72
INT_COV	9,345	45.71	-41.93	7.61	1205.00	160.50
CAP_INT	8,911	55.82	4.59	56.89	93.58	20.58

COD, COE, BTM, LEVERAGE, ROA, OCFTA, and CAP_INT shown as percentages. ES scores range from 0 to 100.

Table 4. Summary Statistics, Winsorized at 5^{th} and 95^{th} Percentiles.

	Firm-Year obs.	Mean	Min	Median	Max	Std. deviation
COD	8,990	3.72	0.49	3.09	11.56	2.69
COE	3,976	9.09	0.39	8.63	19.96	4.74
ES_Overall	6,912	54.47	0.27	55.89	98.88	24.67
ES_Emission	6,714	61.83	0.15	65.46	99.82	26.41
ES_Innovation	4,591	54.11	0.83	51.39	99.84	25.84
ES_Resource	6,757	61.84	0.32	65.54	99.86	27.02
BETA	9,442	0.73	0.16	0.70	1.48	0.36
BTM	9,451	61.47	10.80	48.43	177.40	44.86
FOREC_DISP	8,082	0.94	0.31	0.89	1.82	0.41
LEVERAGE	9,597	75.60	0.00	56.04	263.90	71.22
SIZE	9,599	6.36	5.22	6.34	7.65	0.67
ROA	9,569	6.21	-4.65	5.62	18.75	5.54
OCFTA	9,571	9.13	-0.67	8.24	23.65	6.34
INT_COV	9,345	24.06	-3.10	7.61	181.50	43.99
CAP_INT	8,911	56.09	20.39	56.89	88.03	19.47

COD, COE, BTM, LEVERAGE, ROA, OCFTA, and CAP_INT shown as percentages. ES scores range from 0 to 100.

Summary statistics suggest that winsorizing at 5^{th} and 95^{th} percentile cuts many bad outliers compared to 1^{st} and 99^{th} percentile. For instance, winsorization based on 1^{st} and 99^{th} percentile leaves negative cost of debt values and a maximum value of 74.2 percent, whereas with 5^{th} and 95^{th} percentiles COD ranges from 0.5 to 11.6 percent. Outlier concerns are clearly alleviated also with COE and other financial variables when bottom and top 5 percent of the data observations are winsorized. Based on these findings, all financial data is winsorized at 5^{th} and 95^{th} percentiles, and all summary statistics and empirical results hereafter use this winsorization.

The dataset is biased towards the large countries, as the UK, France, and Germany account for around half of the observations (see Table 5). The UK accounts alone for a quarter of the observations. No similar bias exists with regards to industries, as the largest industries account approximately for 10% of the observations (see Table 6). The same tables suggest that there are differences between the different countries and industries in the main variables of interest. In the different countries the mean values range from 2.9% to 4.4% for COD, from 4.9% to 15.2% for COE, and from 38.6 to 67.2 for ES_Overall, whereas in different industries mean COD varies from 3.1% to 5.8%, COE varies from 3.8% to 15.2%, and ES_Overall varies from 38.6 to 66.7. Variations in countries and industries already suggest, that Pooled OLS estimation is not the most efficient estimation method.

Table 5. Mean Values and Number of Observations by Country.

	COD			COE			ES_Overall		
	Firm-Year obs.	%	Mean	Firm-Year obs.	%	Mean	Firm-Year obs.	%	Mean
Austria	228	2.5%	3.54	89	2.2%	10.79	119	1.7%	55.48
Belgium	324	3.6%	3.21	67	1.7%	9.01	206	3.0%	54.34
Denmak	250	2.8%	4.03	99	2.5%	4.85	206	3.0%	51.65
Finland	271	3.0%	2.91	150	3.8%	10.31	225	3.3%	63.91
France	1254	13.9%	2.97	624	15.7%	10.04	901	13.0%	67.23
Germany	1081	12.0%	4.25	582	14.6%	10.05	692	10.0%	55.54
Ireland	71	0.8%	3.21	35	0.9%	10.81	64	0.9%	38.56
Italy	482	5.4%	3.01	151	3.8%	10.28	298	4.3%	56.30
Netherlands	319	3.5%	3.63	111	2.8%	10.51	254	3.7%	59.08
Norway	301	3.3%	4.40	106	2.7%	6.97	196	2.8%	50.43
Portugal	110	1.2%	3.39	24	0.6%	15.15	87	1.3%	58.81
Spain	412	4.6%	4.18	163	4.1%	12.15	306	4.4%	67.22
Sweden	742	8.3%	3.06	376	9.5%	9.69	495	7.2%	56.16
Switzerland	752	8.4%	3.50	318	8.0%	8.03	508	7.3%	49.04
United Kingdom	2393	26.6%	4.33	1081	27.2%	7.45	2355	34.1%	47.62

COD and COE shown as percentages. ES_Overall range from 0 to 100.

Table 6. Mean Values and Number of Observations by Industry.

	COD			COE			ES_Overall		
	Firm-Year obs.	%	Mean	Firm-Year obs.	%	Mean	Firm-Year obs.	%	Mean
Agriculture	69	0.8%	3.36	13	0.3%	9.20	22	0.3%	48.38
Alcohol and Tobacco	126	1.4%	3.16	100	2.5%	5.85	115	1.7%	65.28
Chemicals	288	3.2%	3.46	165	4.1%	7.86	260	3.8%	60.94
Construction	762	8.5%	4.41	291	7.3%	9.72	612	8.9%	59.04
Consumer Goods	262	2.9%	4.18	88	2.2%	7.44	191	2.8%	54.52
Electronics	843	9.4%	3.89	409	10.3%	7.84	555	8.0%	46.43
Energy	305	3.4%	5.19	110	2.8%	7.08	273	3.9%	47.41
Entertainment	125	1.4%	3.90	49	1.2%	6.81	73	1.1%	38.63
Food Products	321	3.6%	3.27	144	3.6%	7.65	234	3.4%	55.69
Machinery	607	6.8%	4.44	279	7.0%	9.16	399	5.8%	53.23
Metals and Mining	169	1.9%	5.80	62	1.6%	3.84	154	2.2%	59.78
Mobility Manufacturing	448	5.0%	3.27	246	6.2%	11.10	324	4.7%	63.75
Pharmaceutical Products	388	4.3%	4.24	176	4.4%	7.29	264	3.8%	58.17
Printing and Publishing	143	1.6%	4.97	42	1.1%	10.77	145	2.1%	44.81
Real Estate	718	8.0%	2.64	258	6.5%	15.16	456	6.6%	56.90
Restaurants, Hotel, Motel	184	2.0%	4.07	88	2.2%	7.99	160	2.3%	57.77
Rubber and Plastic Products	85	0.9%	3.95	27	0.7%	6.83	50	0.7%	47.41
Services	913	10.2%	3.56	438	11.0%	8.35	726	10.5%	42.08
Steel Works	197	2.2%	4.52	78	2.0%	13.13	175	2.5%	65.30
Telecommunications	348	3.9%	3.43	185	4.7%	9.52	345	5.0%	53.61
Textiles and Apparel	120	1.3%	4.03	64	1.6%	8.82	76	1.1%	59.92
Transportation	469	5.2%	3.97	169	4.3%	8.73	375	5.4%	60.22
Utilities	389	4.3%	3.12	147	3.7%	11.45	314	4.5%	66.74
Wholesale and Retail	711	7.9%	3.99	348	8.8%	8.88	614	8.9%	51.98

COD and COE shown as percentages. ES_Overall range from 0 to 100.

To make the dataset more balanced, companies listed after 2011 are excluded from the dataset. The downside of this research design decision is that observations reduce towards the end of observation period, as delisted and dead companies are included in the dataset (see Table 7). The number of observations reduce especially with COE, as many analyst estimates are missing for the most recent years. Fortunately, number of ESG score observations increase throughout the period, which is likely due to increased ESG reporting of companies and broadened coverage of Refinitiv ESG scores. Refinitiv broadened ESG coverage to European small and mid-cap companies in 2019 (Refinitiv, 2021).

Table 7. Mean Values and Number of Observations through Time.

	COD			COE			ES_Overall		
	Firm-Year obs.	%	Mean	Firm-Year obs.	%	Mean	Firm-Year obs.	%	Mean
2011	934	10.4%	2.94	568	14.3%	9.29	598	8.9%	60.81
2012	926	10.3%	4.06	507	12.8%	10.46	613	9.1%	61.39
2013	906	10.1%	3.74	463	11.6%	8.55	622	9.2%	61.41
2014	903	10.0%	3.70	397	10.0%	8.43	624	9.2%	60.94
2015	900	10.0%	3.86	394	9.9%	8.04	629	9.3%	61.01
2016	893	9.9%	4.23	415	10.4%	9.38	645	9.5%	62.59
2017	885	9.8%	3.70	380	9.6%	8.57	643	9.5%	63.97
2018	878	9.8%	3.32	338	8.5%	8.73	674	10.0%	63.67
2019	887	9.9%	3.85	270	6.8%	9.72	851	12.6%	60.31
2020	878	9.8%	3.86	244	6.1%	9.66	858	12.7%	62.41

COD and COE shown as percentages. ES_Overall range from 0 to 100.

Alike with industries and countries, there seem to be non-random variations in COD and COE in different years (see Table 7 and Figure 6). Possible explanations for debt and equity premium variations could be changes in expected inflation as well as European debt crisis and COVID-19 pandemic. Higher inflation rates and uncertainty in cash flows increase the required return on stocks and bonds (Vishwanath, 2007, p. 42). The European debt crisis and the COVID-19 pandemic could have influenced both expected inflation and expected cash flows, since crises affect economic growth and induce uncertainty in the economy. The European debt crisis began in 2009 and caused significant instability in the financial markets at least until the introduction of the European Stability Mechanism in late 2012 (Frieden & Walter, 2017; ECB, 2012). The COVID-19 pandemic caused distress in the financial markets especially in 2020 (McKinsey & Company, 2021).

In Figure 6, COD and COE are presented against 10-year Germany's government bond rate, which is used as the risk-free interest rate. Mean equity premium peaked at 10.5% in 2012, after which the premium was on a declining trend until 2015, when it reached 8.0%. After 2015 COE turned to an increasing trend and was 9.7% at the time of COVID-19 crisis in 2020. Both COE and COD seem to be mirroring to some extent risk-free interest. These findings suggest that COE and COD could be year-dependent, and year fixed effects should be considered in the econometric models.

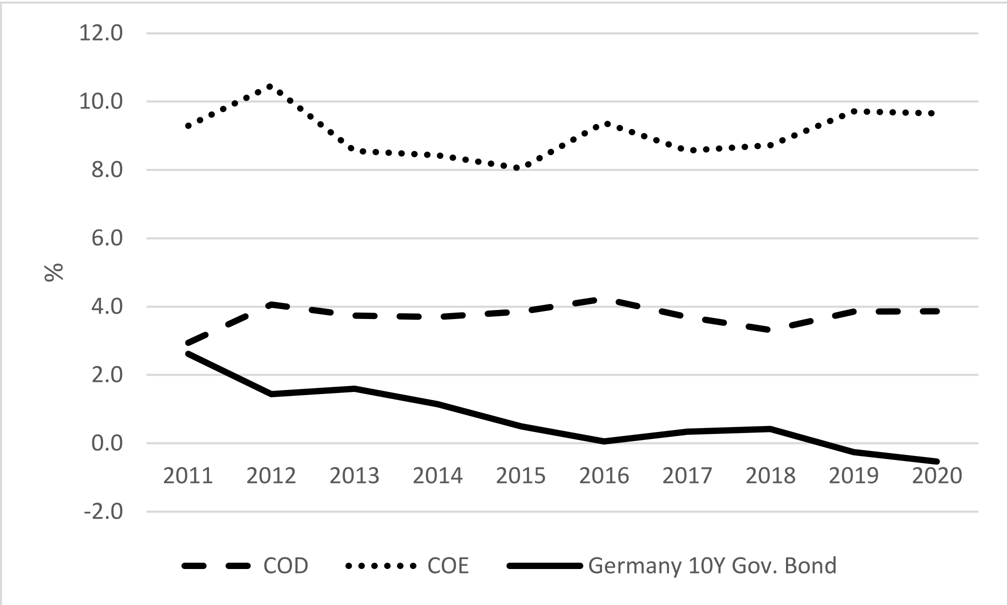

Figure 6. Changes in Mean COD and COE Rates against the Risk-free Interest Rate.

Companies are divided into Low, Medium, and High environment sustainability companies based on ES_Overall score in Table 8. The different groups are later used in empirical and predictive models to study the possible non-linear relationship between environmental sustainability and cost of capital. The firms are divided into the three groups within a sector in each year based on their environmental sustainability score: bottom third to Low ES Companies, middle third to Medium ES Companies, and the top third to High ES Companies. Please note that ES_Overall scores overlap between the groups because the grouping is done for each industry and year separately. Still, there are clear differences in the mean values of the three groups. When components of the ES_Overall score are used in the econometric models, the division is based on the specific environmental sustainability score used, i.e. ES_Overall, ES_Emission, ES_Innovation or ES_Resource. To save space, only summary statistics based on the overall grouping are shown.

Interestingly cost of debt is lowest for the High ES Companies, while cost of equity is the highest for the same group (see Table 8). These observations could well be due to control variables or unobserved firm characteristics. For instance, leverage is clearly higher for High

ES Companies, which can explain the higher COE for the group. In turn, higher leverage for the High ES Companies could be due to their larger size, or possibly better access to finance because of better environmental sustainability performance. Because of these possibly complex causes and effects, multivariate regression analysis is needed to study the relationship between environmental sustainability and cost of capital.

Table 8. Summary Statistics by Environmental Sustainability Group.

	Low ES Companies			Medium ES companies			High ES Companies		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
COD	0.49	4.05	11.56	0.49	3.76	11.56	0.49	3.40	11.56
COE	0.39	8.21	19.96	0.39	8.57	19.96	0.39	9.75	19.96
ES_Overall	0.27	28.16	83.93	19.33	57.01	88.53	34.62	80.02	98.88
ES_Emission	0.15	36.52	98.21	0.26	64.12	99.69	18.00	84.36	99.82
ES_Innovation	0.83	33.26	97.50	2.00	49.96	99.36	8.00	68.15	99.84
ES_Resource	0.32	35.57	99.36	2.63	64.65	99.64	8.33	85.31	99.86
BETA	0.16	0.75	1.48	0.16	0.73	1.48	0.16	0.77	1.48
BTM	10.80	60.17	177.40	10.80	61.10	177.40	10.80	63.51	177.40
FOREC_DISP	0.31	0.91	1.82	0.31	0.95	1.82	0.31	0.94	1.82
LEVERAGE	0.00	66.55	263.90	0.00	80.38	263.90	0.00	89.87	263.90
SIZE	5.22	6.19	7.65	5.22	6.55	7.65	5.22	6.96	7.65
ROA	-4.65	6.61	18.75	-4.65	6.26	18.75	-4.65	5.80	18.75
OCFTA	-0.67	9.72	23.65	-0.67	9.30	23.65	-0.67	8.72	23.65
INT_COV	-3.10	28.86	181.50	-3.10	23.57	181.50	-3.10	16.01	181.50
CAP_INT	20.39	58.41	88.03	20.39	57.87	88.03	20.39	60.43	88.03

COD, COE, BTM, LEVERAGE, ROA, OCFTA, and CAP_INT shown as percentages. ES scores range from 0 to 100. Companies divided into Low, Medium, and High ES Companies based on their ranking in ES_Overall score.

Table 9 presents summary statistics by the Sensitive Industry dummy. On average, companies in environmentally sensitive industries have a higher cost of debt and equity. However, this again could be due to certain firm characteristics, as companies in non-sensitive industries have lower leverage and they are more profitable. Interestingly, all environmental sustainability scores are on average slightly higher in sensitive than non-sensitive industries. This already implies that companies in environmentally sensitive sectors might consider environmental sustainability more important.

Table 9. Summary Statistics for Environmentally Sensitive and Non-sensitive Industries.

	Non-sensitive Industries			Sensitive Industries		
	Min	Mean	Max	Min	Mean	Max
COD	0.494	3.603	11.56	0.494	3.950	11.56
COE	0.388	8.924	19.96	0.388	9.427	19.96
ES_Overall	0.270	51.29	98.44	0.280	59.96	98.88
ES_Emission	0.150	59.21	99.82	0.600	66.26	99.78
ES_Innovation	2.780	52.01	99.84	0.830	57.14	99.67
ES_Resource	0.400	59.81	99.86	0.320	65.32	99.70
BETA	0.162	0.681	1.481	0.162	0.834	1.481
BTM	10.80	55.09	177.4	10.80	74.03	177.4
FOREC_DISP	0.314	0.888	1.824	0.314	1.044	1.824
LEVERAGE	0	67.27	263.9	0	92.13	263.9
SIZE	5.215	6.242	7.654	5.215	6.602	7.654
ROA	-4.650	6.871	18.75	-4.650	4.899	18.75
OCFTA	-0.672	9.632	23.65	-0.672	8.121	23.65
INT_COV	-3.102	28.30	181.5	-3.102	15.85	181.5
CAP_INT	20.39	54.21	88.03	20.39	59.46	88.03

COD, COE, BTM, LEVERAGE, ROA, OCFTA, and CAP_INT shown as percentages. ES scores range from 0 to 100. Environmentally Sensitive Industries comprise Chemicals, Construction, Energy, Metals and Mining, Mobility Manufacturing, Rubber and Plastic Products, Steel Works, Transportation, and Utilities.

Table 10 presents correlations for all used variables. COE is slightly positively correlated with all environmental sustainability scores, while with COD the correlations are slightly negative. Correlations between explained and control variables are largely as predicted by prior research and theories. First, COE and COD are negatively correlated with ROA and OCFTA. Second, SIZE is negatively correlated with COD. Larger firm size often comes with larger cash flows, which would decrease firm-specific risks and lower COD. The three variables have been documented to have a negative effect on COE and COD in prior studies (see e.g. Gode & Mohanram, 2003; Dhaliwal et al., 2006; El Ghoul et al., 2011; Ge & Liu, 2015; Eliwa et al., 2019; Caragnano et al., 2020)

Perhaps most importantly COE is clearly positively correlated with BETA (0.325) and BTM ratio (0.435). The higher the value of BTM ratio, the lower the markets value a firm compared to its equity on balance sheet, which would suggest a higher cost of equity. High positive correlations with both BETA and BTM strengthens reliability on the used implied COE measure by Gebhardt et al. (2001). Also, COE is positively correlated with LEVERAGE and FOREC_DISP. These correlations are as expected from financial theories and relationships found from empirical studies.

Table 10. Correlation Matrix.

	COD	COE	ES_Over.	ES_Emiss.	ES_Innov.	ES_Res.	BETA	BTM	FOREC_DISP	LEVERAGE	SIZE	ROA	OCFTA	INT_COV	CAP_INT
COD	1														
COE	0.086	1.000													
ES_Overall	-0.074	0.080	1.000												
ES_Emission	-0.090	0.079	0.825	1.000											
ES_Innovation	-0.005	0.108	0.701	0.329	1.000										
ES_Resource	-0.074	0.004	0.807	0.689	0.322	1.000									
BETA	0.091	0.325	0.064	0.018	0.171	-0.006	1.000								
BTM	0.056	0.435	0.130	0.134	0.096	0.062	0.315	1.000							
FOREC_DISP	0.066	0.241	0.093	0.073	0.105	0.035	0.359	0.453	1.000						
LEVERAGE	-0.079	0.129	0.198	0.168	0.111	0.156	-0.053	0.014	0.110	1.000					
SIZE	-0.088	0.142	0.560	0.545	0.323	0.473	-0.026	0.278	0.142	0.297	1.000				
ROA	-0.026	-0.244	-0.129	-0.094	-0.143	-0.033	-0.226	-0.465	-0.430	-0.227	-0.286	1.000			
OCFTA	-0.062	-0.201	-0.086	-0.073	-0.120	0.007	-0.249	-0.431	-0.295	-0.164	-0.258	0.630	1.000		
INT_COV	0.007	-0.095	-0.101	-0.045	-0.095	-0.034	-0.111	-0.253	-0.236	-0.367	-0.270	0.521	0.446	1.000	
CAP_INT	-0.204	-0.018	0.084	0.100	-0.046	0.061	-0.252	0.130	-0.082	0.280	0.326	-0.103	0.057	-0.228	1.000

Unexpected correlations exist between COD and LEVERAGE, COD and INT_COV, COD and CAP_INT as well as COE and SIZE. However, these correlations might be due to moderating factors, so the relationships will be reviewed again in Sub-section 4.2.1.

4.2 Empirical Models

Empirical results presented in this section provide answers to the first research question and its sub-questions (see Section 1.2). First, the shape of the relationship between environmental sustainability and cost of capital is studied with ES_Overall score. Next, the shape of the relationship is studied with different components of the overall environmental score. Finally, the impact of industry sensitivity on the relationship is studied and robustness of results is reviewed.

4.2.1 Aggregate Regressions

In Models 1 and 3 in Table 11, ES_Overall score is regressed against COE and COD with all control variables using fixed effects model. The models include firm and year fixed effects to control for unstationary variables and firm-specific characteristics. With the basic regression the signs are negative, but not statistically significantly with cluster robust standard errors.

In Models 2 and 4, a squared term of ES_Overall score is added to study if the relationship between environmental sustainability score and cost of capital is non-linear. Still, there appears no statistically significant relationship between ES_Overall score and COD. In Model 2, however, ES_Overall affects COE negatively with a 1% significance level and coefficient of ES_Overall squared is positive with a 5% significance level. A positive coeffcient for the squared term suggests that there is a U-shaped relationship between environmental sustainability and COE, that is, there is an optimal level after which increasing environmental sustainability score results to higher cost of equity. After derivation and solving for the global minimum, the optimal level for ES_Overall is 62.0, which is within the possible values of ES_Overall score. An optimal value of 62.0 suggests that slightly above average companies in terms of environmental sustainability obtain the lowest cost of equity.

Majority of control variables affect COE and COD as expected. First, all control variables except CAP_INT have an expected effect on COD. Coefficient of CAP_INT is surprisingly negative and highly statistically significant. Second, BETA, BTM, LEVERAGE and SIZE affect COE as expected, and most statistically signficantly. FOREC_DISP has an unexpected negative effect on COE, while ROA and OCFTA have virtually no effect. All in all, most of the control variables have an expected effect, including the most important variables from the theoretical persepctive (BETA, BTM, LEVERAGE, SIZE), which stengthens reliability of the results.

A number of model selection tests were done, based on which fixed effects model with firm and year effects was selected. Firstly Mundlak's tests were conducted to all the models to check if random effects model gives consistent results. All of the Mundlak tests' null hypothesis are rejected, which means that there is correlation between unobserved heterogeneity and explanatory variables, and fixed effects should be used instead of random effects model to avoid endogeneity problems. Secondly, F test for firm and year fixed effects was conducted to check whether Pooled OLS could be used, or if firm and year effects have a significant effect on COE and COD. Both tests are rejected for all the models, which means that COE and COD are dependent on the year and that there is unobserved heterogeneity between the firms.

Table 11. Linear and Non-linear Relationships of ES_Overall and Cost of Capital.

	Model 1	Model 2	Model 3	Model 4
	Dependent: COE	Dependent: COE	Dependent: COD	Dependent: COD
ES_Overall	-0.0112	-0.0623***	-0.0035	0.0114
	(-1.3766)	(-2.5968)	(-0.7245)	(1.0155)
ES_Overall^2		0.0005**		-0.0002
		(2.0801)		(-1.5133)
BETA	0.7621**	0.7082*		
	(2.0089)	(1.8985)		
BTM	0.0366***	0.0365***		
	(7.9068)	(7.9194)		
FOREC_DISP	-0.8711***	-0.7969***		
	(-3.5278)	(-3.2473)		
LEVERAGE	0.0042	0.0045	0.0003	0.0003
	(1.2564)	(1.3724)	(0.3332)	(0.3684)
SIZE	-1.5417*	-1.4217*	-1.6071***	-1.6163***
	(-1.7037)	(-1.6620)	(-3.8916)	(-3.9147)
ROA	0.0136	0.0149	-0.0363***	-0.0357***
	(0.7898)	(0.8645)	(-3.5240)	(-3.4607)
OCFTA	0.0040	0.0036	-0.0145	-0.0141
	(0.1879)	(0.1709)	(-1.2278)	(-1.1935)
INT_COV			-0.0070***	-0.0070***
			(-2.7104)	(-2.7091)
CAP_INT			-0.0231***	-0.0233***
			(-2.7088)	(-2.7241)
CONSTANT	17.3182***	17.4562***	15.3644***	15.1614***
	(2.9144)	(3.0606)	(5.9453)	(5.9397)
U-shape min / max		Min: 62.0		Max: -36.8
Mundlak test	0.000***	0.000***	0.000***	0.00***
F test Firm Effects	0.000***	0.000***	0.000***	0.000***
F test Year Effects	0.000***	0.000***	0.000***	0.000***
Firm-Year obs.	3,108	3,108	6,076	6,076
Number of firms	597	597	912	912
Avg. obs. per firm	5.2	5.2	6.7	6.7
R-squared	0.2294	0.2348	0.0755	0.0763
Adj. R-squared	0.2251	0.2303	0.0731	0.0737

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Table 12, shape of the relationship between ES_Overall score and cost of capital is further explored by running the model for every environmental sustainability group separately. Companies are divided into Low, Medium and High ES Companies based on ES_Overall score since it is used as the explanatory variable. Models 1-3 again suggest that the relationship between ES_Overall score and COE is U-shaped. Increase in environmental sustainability score leads to lower COE for firms that are in the bottom third in their industry statistically significantly with 5% significance level. The coefficient suggests that a 10-point increase in ES_Overall score leads to approximately 0.4 percentage point decrease in COE for Low ES Companies. For Medium ES Companies the coefficient is still negative, but with High ES Companies the coefficient switches sign to positive. However, for Medium and High ES Companies the results are not statistically significant and absolute values of the coefficients are smaller than for the Low ES Companies.

Table 12. ES_Overall and Cost of Capital by ES Group.

	Model 1 Low ES Comp. Dependent: COE	Model 2 Medium ES Comp. Dependent: COE	Model 3 High ES Comp. Dependent: COE	Model 4 Low ES Comp. Dependent: COD	Model 5 Medium ES Comp. Dependent: COD	Model 6 High ES Comp. Dependent: COD
ES_Overall	-0.0383**	-0.0058	0.0264	0.0008	0.0059	-0.0113
	(-2.4628)	(-0.4586)	(1.2860)	(0.0756)	(0.6878)	(-0.7915)
BETA	0.7084	1.5353***	0.1429			
	(1.5144)	(2.9362)	(0.2058)			
BTM	0.0484***	0.0352***	0.0284***			
	(6.4397)	(5.1380)	(3.6407)			
FOREC_DISP	-0.5862	-0.5456	-0.5813			
	(-1.1462)	(-1.5778)	(-1.4545)			
LEVERAGE	0.0117**	0.0045	0.0034	0.0002	0.0016	0.0007
	(2.4139)	(1.0023)	(0.6615)	(0.0888)	(1.1103)	(0.4029)
SIZE	-2.5331	-0.2596	-0.2059	-0.6358	-2.1006***	-2.3683***
	(-1.3948)	(-0.2199)	(-0.1700)	(-0.9003)	(-3.2467)	(-3.0518)
ROA	0.0568*	0.0152	-0.0431**	-0.0544***	-0.0239	-0.0136
	(1.7037)	(0.5617)	(-2.1180)	(-2.6405)	(-1.4016)	(-0.8020)
OCFTA	-0.0024	0.0219	0.0202	0.0138	-0.0257	-0.0187
	(-0.0618)	(0.7276)	(0.5962)	(0.6209)	(-1.5881)	(-0.7968)
INT_COV				0.0020	-0.0098***	-0.0168***
				(0.4382)	(-2.8548)	(-3.3931)
CAP_INT				-0.0279*	0.0078	-0.0311**
				(-1.7061)	(0.6274)	(-2.1791)
CONSTANT	21.7077**	7.4027	7.4454	8.8533**	16.0388***	22.1513***
	(2.0000)	(0.9373)	(0.8929)	(2.0674)	(4.0584)	(4.0718)
Firm Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year obs.	819	1,070	1,219	1,941	2,108	2,027
Number of firms	263	320	267	512	506	347
Avg. obs. per firm	3.1	3.3	4.6	3.8	4.2	5.8
R-squared	0.3790	0.2764	0.2262	0.0516	0.1132	0.1162
Adj. R-squared	0.3664	0.2645	0.2151	0.0440	0.1062	0.1090

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Models 4-6 in Table 12 show that ES_Overall score does not affect COD statistically significantly in any of the groups, and coefficients are even positive for Low and Medium ES Companies. Even though the correlation matrix in Table 10 suggested a negative relationship, fixed effects model with control variables show that ES_Overall score has no effect on COD. Signs of the control variables stay also largely as predicted and statistically significant, which increases reliability of this result.

4.2.2 Components of Environmental Sustainability

Components of ES_Overall score are studied separately to see if there are differences between emission, innovation and resource use scores. Again, there is no statistically significant relationship between environmental sustainability scores and COD, which is why only the models with COE as a dependent variable are reported in this sub-section. The equivalent regressions for COD models can be found from Appendix 1.

In Models 1-4 of Table 13, the regression is run with each first-order environmental sustainability score separately. Results for models with additional squared terms are presented in Models 5-8. Coefficients of all environmental sustainability subcomponents remain negative in the first-order regressions, and the negative effect is statistically significant for ES_Resource score. The robust t-statistic of ES_Emission is also quite high (-1.51), which suggests that there might be a negative linear relationship between emission sustainability and COE.

The models with the squared terms reveal that the relationship is U-shaped for ES_Innovation score with 5% significance level and possibly for ES_Resource score, as its robust t-statistic is 1.56. For ES_Innovation the optimal level is 55.8 and for ES_Resource 80.5. Both optima are within the possible range. The high optimum for resource use sustainability explains why the negative linear relationship is statistically significant in Model 4.

Coefficient of ES_Emission squared is clearly lower than with the other components and the robust t-statistic is only 0.52, suggesting that there is no U-shaped relationship between ES_Emission and COE. Further, the optimum level is 116.9, which is higher than the maxium possible value. This further suggests that there is no U-shaped relationship with ES_Emission and COE.

Table 13. Linear and Non-linear Relationships between ES Components and Cost of Capital.

	Model 1 ES_Overall Dependent: COE	Model 2 ES_Emission Dependent: COE	Model 3 ES_Innovation Dependent: COE	Model 4 ES_Resource Dependent: COE	Model 5 ES_Overall Dependent: COE	Model 6 ES_Emission Dependent: COE	Model 7 ES_Innovation Dependent: COE	Model 8 ES_Resource Dependent: COE
ES	-0.0112	-0.0087	-0.0013	-0.0126**	-0.0623***	-0.0169	-0.0542**	-0.0403**
	(-1.3766)	(-1.5108)	(-0.2440)	(-2.0001)	(-2.5968)	(-1.0862)	(-2.1763)	(-2.4245)
ES^2					0.0005**	0.0001	0.0005**	0.0003
					(2.0801)	(0.5180)	(2.0009)	(1.5614)
BETA	0.7621**	0.6440	0.7449	0.7188*	0.7082*	0.6414	0.6702	0.6982*
	(2.0089)	(1.6467)	(1.3936)	(1.8843)	(1.8985)	(1.6405)	(1.2746)	(1.8461)
BTM	0.0366***	0.0358***	0.0329***	0.0362***	0.0365***	0.0358***	0.0327***	0.0361***
	(7.9068)	(7.7795)	(5.3236)	(7.7583)	(7.9194)	(7.7726)	(5.2898)	(7.7592)
FOREC_DISP	-0.8711***	-0.7932***	-0.7200**	-0.9352***	-0.7969***	-0.7912***	-0.7036**	-0.9157***
	(-3.5278)	(-3.3015)	(-2.5469)	(-3.8822)	(-3.2473)	(-3.2937)	(-2.5013)	(-3.8052)
LEVERAGE	0.0042	0.0031	0.0050	0.0045	0.0045	0.0031	0.0051	0.0045
	(1.2564)	(0.9324)	(1.1268)	(1.3438)	(1.3724)	(0.9449)	(1.1408)	(1.3416)
SIZE	-1.5417*	-1.1563	-0.6079	-1.3286	-1.4217*	-1.1528	-0.4445	-1.3137
	(-1.7037)	(-1.5798)	(-0.5828)	(-1.3762)	(-1.6620)	(-1.5796)	(-0.4395)	(-1.3936)
ROA	0.0136	0.0038	0.0119	0.0085	0.0149	0.0038	0.0123	0.0078
	(0.7898)	(0.2380)	(0.5892)	(0.5025)	(0.8645)	(0.2337)	(0.6141)	(0.4562)
OCFTA	0.0040	-0.0100	-0.0066	0.0090	0.0036	-0.0103	-0.0064	0.0079
	(0.1879)	(-0.4872)	(-0.2781)	(0.4155)	(0.1709)	(-0.5026)	(-0.2699)	(0.3690)
CONSTANT	17.3182***	15.0755***	11.4156	16.1879**	17.4562***	15.2247***	11.4596*	16.6924***
	(2.9144)	(3.1401)	(1.6354)	(2.5543)	(3.0606)	(3.1715)	(1.6752)	(2.6666)
U-shape min / max					Min: 62.0	Min: 116.9	Min: 55.8	Min: 80.5
Firm Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year obs.	3,108	3,047	2,191	3,065	3,108	3,047	2,191	3,065
Number of firms	597	582	439	589	597	582	439	589
Avg. obs per firm	5.2	5.2	5.0	5.2	5.2	5.2	5.0	5.2
R-squared	0.2294	0.2344	0.2138	0.2305	0.2348	0.2345	0.2197	0.2326
Adj. R-squared	0.2251	0.2301	0.2077	0.2262	0.2303	0.2300	0.2132	0.2280

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14. ES Components and Cost of Capital by ES Group.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
	Low ES Companies				Medium ES Companies				High ES Companies			
	ES_Overall	ES_Emission	ES_Innovation	ES_Resource	ES_Overall	ES_Emission	ES_Innovation	ES_Resource	ES_Overall	ES_Emission	ES_Innovation	ES_Resource
	Dependent: COE	Dependent: COE	Dependent: COE	Dependent: COE	Dependent: COE	Dependent: COE	Dependent: COE	Dependent: COE	Dependent: COE	Dependent: COE	Dependent: COE	Dependent: COE
ES	-0.0383**	-0.0139	-0.0193	-0.0215*	-0.0058	0.0066	0.0002	0.0053	0.0264	-0.0137	0.0105	0.0411*
	(-2.4628)	(-1.3858)	(-1.2340)	(-1.8765)	(-0.4586)	(0.6036)	(0.0069)	(0.4282)	(1.2860)	(-0.8905)	(0.3069)	(1.8345)
BETA	0.7084	1.0902*	0.1195	0.7395*	1.5353***	0.9206*	0.8764	0.4101	0.1429	-0.5976	1.0938	0.6101
	(1.5144)	(1.8132)	(0.1147)	(1.6898)	(2.9362)	(1.9002)	(1.1488)	(0.4971)	(0.2058)	(-0.6277)	(0.9202)	(1.0448)
BTM	0.0484***	0.0506***	0.0497***	0.0484***	0.0352***	0.0290***	0.0295***	0.0402***	0.0284***	0.0324***	0.0162	0.0304***
	(6.4397)	(7.0354)	(6.8383)	(6.3378)	(5.1380)	(3.4033)	(3.0579)	(4.2781)	(3.6407)	(4.4171)	(1.3600)	(4.5476)
FOREC_DISP	-0.5862	-0.5429	-0.5197	-0.8105	-0.5456	-0.9649**	-0.7102	-1.0305**	-0.5813	-0.8520**	-0.1825	-0.5879
	(-1.1462)	(-1.1658)	(-1.2496)	(-1.5883)	(-1.5778)	(-2.0581)	(-1.1113)	(-2.3402)	(-1.4545)	(-2.3281)	(-0.3889)	(-1.6436)
LEVERAGE	0.0117**	0.0079	0.0077	0.0144***	0.0045	0.0004	0.0127*	0.0045	0.0034	0.0024	0.0021	-0.0009
	(2.4139)	(1.2687)	(1.4522)	(2.6489)	(1.0023)	(0.1133)	(1.7181)	(0.8806)	(0.6615)	(0.4147)	(0.2794)	(-0.1822)
SIZE	-2.5331	-0.3020	0.9147	-2.6842	-0.2596	-0.4369	-1.7045	-0.7796	-0.2059	-0.2446	-0.1545	-0.2645
	(-1.3948)	(-0.2084)	(0.6203)	(-1.2597)	(-0.2199)	(-0.3829)	(-0.9503)	(-0.5929)	(-0.1700)	(-0.1633)	(-0.0747)	(-0.2269)
ROA	0.0568*	0.0567*	0.0208	0.0532	0.0152	-0.0231	0.0352	0.0350	-0.0431**	-0.0332	-0.0273	-0.0437**
	(1.7037)	(1.8515)	(0.9679)	(1.6417)	(0.5617)	(-0.9372)	(0.8171)	(1.0773)	(-2.1180)	(-1.3360)	(-0.8140)	(-2.1249)
OCFTA	-0.0024	-0.0475*	-0.0028	0.0212	0.0219	0.0324	0.0159	0.0317	0.0202	0.0062	-0.0150	0.0155
	(-0.0618)	(-1.9375)	(-0.0754)	(0.5637)	(0.7276)	(0.8051)	(0.5442)	(0.9323)	(0.5962)	(0.1637)	(-0.2769)	(0.4501)
CONSTANT	21.7077**	7.3224	0.7532	22.3327*	7.4027	9.7898	18.2813	10.6712	7.4454	11.1466	7.7895	5.8814
	(2.0000)	(0.8143)	(0.0778)	(1.7260)	(0.9373)	(1.3171)	(1.5516)	(1.1988)	(0.8929)	(1.0713)	(0.5339)	(0.7455)
Firm Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year obs.	856	859	894	877	1,054	1,036	690	1,022	1,198	1,152	607	1,166
Number of firms	271	279	271	283	328	336	224	335	272	284	160	273
Avg. obs per firr	3.2	3.1	3.3	3.1	3.2	3.1	3.1	3.1	4.4	4.1	3.8	4.3
R-squared	0.3790	0.3486	0.3185	0.3465	0.2764	0.1984	0.2223	0.2490	0.2262	0.2667	0.2203	0.2551
Adj. R-squared	0.3664	0.3354	0.3053	0.3336	0.2645	0.1850	0.2026	0.2363	0.2151	0.2557	0.1978	0.2441

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 14 shows results for models with each environmental sustainability score and group separately. Regressions for Low ES Companies are shown in Models 1-4, for Medium ES Companies in Models 5-8 and for High ES Companies in Models 9-12. The overall scores are included for comparison purposes.

The results are consistent with the results of Table 13 with all sustainability components. First, ES_Innovation score's coefficient is negative for Low ES Companies and positive for High ES Companies, although not statistically significantly. ES_Resource score also gets negative coefficient for Low ES Companies and positive coefficient for High ES Companies, and these effects are statistically significant with 10% confidence level. Although Table 13 did not provide conclusive evidence whether the relationship between ES_Resource and COE is linear or non-linear, Table 14 suggests that the relationship is U-shaped. However, Table 13 shows that the optimum is quite high, and most companies benefit from increasing their ES_Resource score.

ES_Emission score also shows a consistent result, as there does not seem to be an inverse relationship in Table 13 nor in Table 14. This is a hopeful result from the point of view of climate change, if stock markets reward not only largest emitters but also environmentally sustainable companies for their emission reduction efforts. However, both tables suggest that the possible negative relationship is quite weak, as a 10-point increase in ES_Emission decreases cost of equity 0.1 percentage points at best.

Interestingly all environmental sustainability measures with Low ES Companies get a negative coefficient with quite high robust t-statistics. This suggests that improvement in any of the environmental sustainability metrics will lower COE if a company is in the bottom third in its industry. Most critical metric based on the models is resource use score, and a 10-point improvement in this would lead to 0.2 percentage point reduction in cost of equity. In the top third group, ES_Resource score is also the most critical metric. In this group a 10-point improvement in ES_Resource score results to 0.4 percentage point increase in COE.

4.2.3 Environmentally Sensitive Industries

To check whether industry groups are driving these results, an additional term ES*SI (Environmental Sustainability score * Sensitive Industry dummy) is added to the equation. Sensitive Industry dummy takes the value of one if a firm is in one of the environmentally sensitive industries (see Sub-section 3.2.1 for definition) and zero otherwise. Regressions are run only for Low and High ES Companies, as in Sub-sections 4.2.1 and 4.2.2 was found that statistically significant relationships exist only in these groups.

Table 15 shows the results for Low ES Companies. Again, statistically significant relationships are found in models where COE is used as the dependent variable (Models 1-4), but no statistically significant relationships are found between environmental sustainability and COD (Models 5-8).

Coefficient of ES_Overall score (Model 1) remains negative but is statistically insignificant. However, ES_Overall*SI score obtains a very low coefficient value of -0.073, which is statistically significant with a 10% level. Components of environmental sustainability further reveal that this result is driven by emission and resource use scores (Models 2 and 4). Negative coefficient of ES_Emission*SI is statistically significant with a 5% level, and respectively, coefficient of ES_Resource*SI is almost statistically significant with a robust t-statistic of -1.55, or p-value of 0.122. These results suggest that although improvements in emission production and resource use can lower COE for all companies, the impact is significantly larger in environmentally sensitive industries. The results imply that investors perceive higher sensitivity to environment-related market risks for companies in environmentally sensitive industries, which is an intuitive result.

ES_Innovation, however, presents a caveat to the above statement. Model 3 suggests that there are no significant differences between sensitive and non-sensitive industries with ES_Innovation score. In other words, companies both in environmentally sensitive and non-sensitive industries that have not focused on products or technologies that reduce environmental impact of their customers, can lower their COE if they put effort into this.

Table 15. Effect of Industry Sensitivity: Low ES Companies.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	Low ES Companies							
	ES_Overall Dependent: COE	ES_Emission Dependent: COE	ES_Innovation Dependent: COE	ES_Resource Dependent: COE	ES_Overall Dependent: COD	ES_Emission Dependent: COD	ES_Innovation Dependent: COD	ES_Resource Dependent: COD
ES	-0.0190	0.0028	-0.0260***	-0.0113	-0.0030	-0.0116	0.0017	-0.0011
	(-1.2295)	(0.3031)	(-2.6505)	(-1.0720)	(-0.2459)	(-1.2677)	(0.2353)	(-0.1148)
ES*SI	-0.0725*	-0.0534**	0.0268	-0.0368	0.0091	0.0080	0.0021	0.0068
	(-1.7869)	(-2.0994)	(0.4735)	(-1.5494)	(0.5676)	(0.6212)	(0.1263)	(0.5220)
BETA	0.6513	1.1228*	0.1904	0.7184*				
	(1.3715)	(1.9057)	(0.1757)	(1.6529)				
BTM	0.0472***	0.0499***	0.0497***	0.0483***				
	(6.1714)	(7.0309)	(6.8415)	(6.2362)				
FOREC_DISP	-0.5868	-0.4866	-0.5260	-0.8700*				
	(-1.1484)	(-1.0832)	(-1.2618)	(-1.6796)				
LEVERAGE	0.0118**	0.0079	0.0078	0.0145***	0.0002	0.0008	0.0001	0.0008
	(2.2443)	(1.2754)	(1.5182)	(2.6551)	(0.0800)	(0.4912)	(0.0695)	(0.4499)
SIZE	-2.4952	-0.2179	1.0303	-2.8050	-0.6211	-1.0014	-0.0897	-0.4868
	(-1.3520)	(-0.1596)	(0.7000)	(-1.3263)	(-0.8752)	(-1.4772)	(-0.1029)	(-0.6626)
ROA	0.0546*	0.0578**	0.0212	0.0538*	-0.0543***	-0.0418**	-0.0414**	-0.0287
	(1.7811)	(1.9824)	(0.9897)	(1.6542)	(-2.6460)	(-2.0358)	(-2.1153)	(-1.5078)
OCFTA	0.0043	-0.0450*	0.0002	0.0265	0.0134	0.0073	0.0213	0.0057
	(0.1150)	(-1.9157)	(0.0060)	(0.7090)	(0.6041)	(0.3304)	(0.9026)	(0.2666)
INT_COV					0.0019	-0.0056	-0.0032	0.0000
					(0.4169)	(-1.0108)	(-0.6110)	(0.0083)
CAP_INT					-0.0277*	-0.0246	-0.0358*	-0.0112
					(-1.6933)	(-1.4596)	(-1.7388)	(-0.7298)
CONSTANT	21.8533**	6.9192	-0.2224	23.2015*	8.7460**	10.9338***	5.5037	6.6612
	(1.9944)	(0.8163)	(-0.0227)	(1.8078)	(2.0311)	(2.6059)	(0.9583)	(1.4922)
Firm Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year obs.	856	859	894	877	2,025	1,983	1,795	1,991
Number of firms	271	279	271	283	519	529	436	521
Avg. obs per firm	3.2	3.1	3.3	3.1	3.9	3.7	4.1	3.8
R-squared	0.3930	0.3605	0.3198	0.3515	0.0519	0.0837	0.0556	0.0548
Adj. R-squared	0.3799	0.3468	0.3058	0.3379	0.0438	0.0757	0.0466	0.0467

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 16. Effect of Industry Sensitivity: High ES Companies.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	High ES Companies							
	ES_Overall Dependent: COE	ES_Emission Dependent: COE	ES_Innovation Dependent: COE	ES_Resource Dependent: COE	ES_Overall Dependent: COD	ES_Emission Dependent: COD	ES_Innovation Dependent: COD	ES_Resource Dependent: COD
ES	0.0085	-0.0208	0.0020	0.0286	-0.0094	-0.0074	0.0566**	-0.0199
	(0.5205)	(-1.5186)	(0.0677)	(1.4817)	(-0.5003)	(-0.6312)	(2.3607)	(-1.2581)
ES*SI	0.0817	0.0380	0.0305	0.0400	-0.0063	0.0065	-0.0613*	-0.0203
	(1.2141)	(0.6458)	(0.3434)	(0.6890)	(-0.2339)	(0.2526)	(-1.7379)	(-0.7597)
BETA	0.1372	-0.5666	1.0639	0.6052				
	(0.1989)	(-0.6159)	(0.9218)	(1.0339)				
BTM	0.0286***	0.0323***	0.0161	0.0302***				
	(3.6966)	(4.3941)	(1.3526)	(4.4765)				
FOREC_DISP	-0.5938	-0.8500**	-0.1919	-0.5834				
	(-1.4914)	(-2.3183)	(-0.4118)	(-1.6328)				
LEVERAGE	0.0034	0.0024	0.0019	-0.0009	0.0007	0.0006	-0.0002	0.0009
	(0.6517)	(0.4224)	(0.2580)	(-0.1767)	(0.4019)	(0.3566)	(-0.0674)	(0.5283)
SIZE	-0.0554	-0.1704	-0.0905	-0.1144	-2.3712***	-1.6395**	-2.8311**	-2.5082***
	(-0.0464)	(-0.1135)	(-0.0442)	(-0.0993)	(-3.0540)	(-2.3831)	(-2.3079)	(-3.2873)
ROA	-0.0475**	-0.0347	-0.0269	-0.0433**	-0.0132	-0.0131	0.0189	-0.0142
	(-2.2966)	(-1.3990)	(-0.7987)	(-2.1211)	(-0.7882)	(-0.7461)	(0.8270)	(-0.8424)
OCFTA	0.0153	0.0081	-0.0163	0.0149	-0.0187	-0.0084	-0.0013	-0.0292
	(0.4411)	(0.2151)	(-0.3023)	(0.4296)	(-0.7968)	(-0.3887)	(-0.0382)	(-1.1954)
INT_COV					-0.0168***	-0.0153***	-0.0117*	-0.0116***
					(-3.3838)	(-3.2578)	(-1.6865)	(-2.9354)
CAP_INT					-0.0312**	-0.0244*	-0.0381*	-0.0275**
					(-2.1793)	(-1.7554)	(-1.6796)	(-2.0849)
CONSTANT	5.6035	9.9898	6.9526	4.6907	22.2310***	15.9734***	22.3609***	24.4606***
	(0.6659)	(0.9422)	(0.4649)	(0.5864)	(4.0933)	(3.4499)	(2.8070)	(4.7036)
Firm Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year obs.	1,198	1,152	607	1,166	1,997	1,958	994	1,952
Number of firms	272	284	160	273	368	390	221	377
Avg. obs per firm	4.4	4.1	3.8	4.3	5.4	5.0	4.5	5.2
R-squared	0.2303	0.2676	0.2211	0.2562	0.1162	0.1001	0.1139	0.1066
Adj. R-squared	0.2185	0.2559	0.1972	0.2445	0.1086	0.0922	0.0985	0.0988

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 16 is equivalent to Table 15, but the results are for High ES Companies. Even though there were statistically significant differences between sensitive and non-sensitive industries for Low ES Companies, same does not hold true for High ES Companies. In models where COE is used as the dependent variable (Models 1-4), all ES*SI terms are positive but statistically insignificant. Interestingly, based on Model 7 ES_Innovation has increasing effect on COD for High ES Companies in non-sensitive industries, while ES*SI gets a negative coefficient with a 10% significance level. When the same model is run without ES term, ES*SI does not differ from zero statistically significantly. In other words, there is a positive relationship between ES_Innovation and COD in High ES Companies operating in non-sensitive industries, but not in sensitive industries. However, it is possible that the statistical significances of this model are due to chance, as statistically significant relationships were not found in other models where COD is used as the dependent variable.

4.2.4 Robustness of Results

Many measures have been taken to ensure robustness of the results. First, the suitable model type was selected by using various statistical tests. The final model applied was fixed effects model with firm and year fixed effects. By adding firm effects, possible endogeneity concerns arising from correlation of omitted variables and explanatory variables is avoided. In turn, year effects capture possible time varying unobserved factors that are constant over firms. (Hill et al., 2018, p. 638-661; Hanck et al., 2020)

Second, with certain model specifications issues of endogeneity, autocorrelation, and heteroskedasticity were further alleviated. These include use of control variables, firm-level cluster robust standard errors and lagged independent variables. Firm-level cluster robust standard errors makes the results more robust to autocorrelation and heteroskedasticity issues. In turn, lead-lag design alleviates endogeneity issues due to reverse causality. (Ng & Rezaee, 2015; Hill et al., 2018, p. 646-651)

Finally, the use of two alternative model types for studying the U-shaped relationship between environmental score and cost of capital increases reliability of these results. Both model types suggest that there is a U-shaped relationship between COE and environmental sustainability, and this relationship is driven by innovation and resource-use sustainability.

No evidence for the U-shape is found for emission score and COE with either of the model types.

Not untypical to studies on European countries, the UK carries a large portion of the observations. Following Eliwa et al. (2019), selected models are run again without the UK observations to see if the country is driving the results. The focus is on COE models, as no significant relationships were found between environmental sustainability and COD.

Table 17 suggests that the results for the U-shaped relationship between COE and environmental sustainability score remain robust even without the UK firms. Again, the relationship seems to be driven by innovation and resource-use scores, even though neither of the terms are statistically significant. The insignificant coefficients could be due to loss in degrees of freedom.

In Sub-section 4.2.3 it was found that Low ES Companies operating in environmentally sensitive industries obtain more significant COE reduction for increasing environmental sustainability than companies in non-sensitive industries. As noted in Sub-section 3.2.1, division to sensitive and non-sensitive industries is somewhat arbitrary. Therefore, an additional robustness check for model specification is conducted, where Agriculture and Food Products are added to the environmentally sensitive industries (see Table 18). This regression produces the same results as the original model: Low ES Companies in sensitive industries benefit more for their improvements in environmental sustainability than companies in non-sensitive industries. In both models the result is mainly driven by emission score with a 5% significance level and possibly partly by resource use score.

Table 17. Robustness of the U-shape: Exclusion of the UK.

	Model 1 ES_Overall Dependent: COE	Model 2 ES_Emission Dependent: COE	Model 3 ES_Innovation Dependent: COE	Model 4 ES_Resource Dependent: COE
ES	-0.0623**	-0.0156	-0.0492	-0.0455**
	(-2.2381)	(-0.8431)	(-1.5457)	(-2.2049)
ES^2	0.0005*	0.0000	0.0005	0.0003
	(1.7524)	(0.2632)	(1.4644)	(1.3173)
BETA	0.7671	0.7233	0.5107	0.6913
	(1.4774)	(1.3175)	(0.8013)	(1.3018)
BTM	0.0354***	0.0344***	0.0314***	0.0356***
	(5.8875)	(5.7558)	(4.0487)	(5.8648)
FOREC_DISP	0.0065	0.0047	0.0069	0.0067
	(1.3362)	(0.9529)	(1.1486)	(1.3624)
LEVERAGE	-2.5981**	-2.0848*	-1.1629	-2.6330**
	(-1.9817)	(-1.9019)	(-0.9272)	(-1.9791)
SIZE	0.0085	-0.0045	0.0096	0.0019
	(0.3589)	(-0.1868)	(0.3370)	(0.0795)
ROA	0.0143	-0.0087	-0.0125	0.0242
	(0.4942)	(-0.3063)	(-0.3988)	(0.8352)
OCFTA	-0.9138***	-0.9523***	-0.8572**	-1.0358***
	(-2.8426)	(-2.9738)	(-2.3538)	(-3.3004)
CONSTANT	26.1784***	22.5535***	16.8742**	26.5862***
	(3.0065)	(3.1344)	(1.9787)	(2.9963)
U-shape min / max	Min: 60.8	Min: 180.8	Min: 54.3	Min: 82.3
Firm Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
Firm-Year obs.	2,092	2,092	2,092	2,092
Number of firms	401	401	401	401
Avg. obs per firm	5.2	5.2	5.2	5.2
R-squared	0.2092	0.2066	0.1886	0.2075
Adj. R-squared	0.2023	0.1995	0.1794	0.2005

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 18. Robustness Check for the Effect of Industry Sensitivity: Change in SI Definition.

	Model 1	Model 2	Model 3	Model 4
	Low ES Companies			
	ES_Overall	ES_Emission	ES_Innovation	ES_Resource
VARIABLES	Dependent: COE	Dependent: COE	Dependent: COE	Dependent: COE
ES	-0.0179	0.0032	-0.0237**	-0.0122
	(-1.0541)	(0.3440)	(-2.3842)	(-1.1123)
ES*SI	-0.0617*	-0.0521**	0.0175	-0.0269
	(-1.6714)	(-2.1462)	(0.3184)	(-1.2569)
BETA	0.7212	1.1313*	0.1616	0.7746*
	(1.5506)	(1.9119)	(0.1501)	(1.7350)
BTM	0.0478***	0.0500***	0.0497***	0.0486***
	(6.2427)	(7.0296)	(6.8420)	(6.2959)
FOREC_DISP	-0.5491	-0.4770	-0.5263	-0.8495
	(-1.0674)	(-1.0641)	(-1.2546)	(-1.6430)
LEVERAGE	0.0115**	0.0078	0.0078	0.0146***
	(2.1653)	(1.2610)	(1.4967)	(2.6544)
SIZE	-2.5838	-0.2312	0.9873	-2.8436
	(-1.3950)	(-0.1686)	(0.6703)	(-1.3492)
ROA	0.0550*	0.0563*	0.0210	0.0533
	(1.7743)	(1.9414)	(0.9776)	(1.6432)
OCFTA	0.0037	-0.0441*	-0.0008	0.0244
	(0.0974)	(-1.8791)	(-0.0238)	(0.6536)
CONSTANT	22.2214**	7.0414	0.1237	23.3383*
	(2.0176)	(0.8264)	(0.0126)	(1.8233)
Firm Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
Firm-Year obs.	856	859	894	877
Number of firms	271	279	271	283
Avg. obs per firm	3.2	3.1	3.3	3.1
R-squared	0.3904	0.3602	0.319	0.3495
Adj. R-squared	0.3773	0.3465	0.3050	0.3358

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19. Robustness Check for the Effect of Industry Sensitivity: Exclusion of the UK.

	Model 1	Model 2	Model 3	Model 4
	Low ES Companies			
	ES_Overall	ES_Emission	ES_Innovation	ES_Resource
VARIABLES	Dependent: COE	Dependent: COE	Dependent: COE	Dependent: COE
ES	-0.0240	-0.0077	-0.0336***	-0.0179*
	(-1.5990)	(-0.8888)	(-3.9550)	(-1.8179)
ES*SI	-0.0024	-0.0154	0.0548	-0.0086
	(-0.0919)	(-1.0957)	(1.6149)	(-0.3073)
BETA	0.5487	1.1243**	-0.6669	1.2166*
	(1.1478)	(2.1451)	(-0.5345)	(1.9067)
BTM	0.0500***	0.0563***	0.0449***	0.0518***
	(6.1147)	(9.4831)	(4.5264)	(7.0967)
FOREC_DISP	-1.0373**	-0.6482	-1.0517**	-1.0598**
	(-2.0833)	(-1.5870)	(-1.9942)	(-2.1595)
LEVERAGE	0.0154**	0.0032	0.0126*	0.0111*
	(2.1627)	(0.8177)	(1.7411)	(1.6763)
SIZE	-2.9301	1.9182*	0.4884	-4.1596
	(-1.0084)	(1.7400)	(0.3122)	(-1.4205)
ROA	0.0548	0.0257	0.0205	0.0391
	(1.3344)	(0.8791)	(0.5529)	(1.1599)
OCFTA	-0.0043	-0.0558*	-0.0008	0.0458
	(-0.0854)	(-1.8302)	(-0.0187)	(0.9049)
CONSTANT	25.5396	-5.2168	4.7242	33.3205*
	(1.4009)	(-0.7531)	(0.4636)	(1.8026)
Firm Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
Firm-Year obs.	632	602	674	617
Number of firms	198	193	197	200
Avg. obs per firm	3.2	3.1	3.4	3.1
R-squared	0.3998	0.5288	0.2670	0.4016
Adj. R-squared	0.3822	0.5142	0.2469	0.3836

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Robustness to the exclusion of the UK Companies is also tested for the regressions with ES*SI terms. When the UK companies are excluded, robust t-statistics of both ES_Emission and ES_Resource scores reduce significantly, although the coefficients remain negative (see Table 19). This result raises the question if environmental sensitivity of an industry is a significant factor after all. It could be that companies in environmentally sensitive industries can benefit more from their emission reduction efforts in terms of COE reduction, but with a caveat that the importance of industry can be country dependent.

4.3 Predictive Models

To test if environmental sustainability can be used to predict changes in COE, four models are trained first with training dataset and then evaluated with out-of-sample data with the three most recent years. All variables are differenced so that changes in COE can be predicted. Dependent variables are lagged one year as in empirical models, so that the prediction models correspond to a real-life situation. Predictive models are not applied to COD, as environmental sustainability score did not have a statistically significant effect on it in the empirical models.

The benchmark model (Model 1) uses only BETA and BTM as the independent variables, along with firm fixed effects. BTM and BETA are the only control variables selected in the benchmark model since they are approximate measures for COE and have been statistically significant predictors of implied COE in the empirical models. Including too many predictors to the benchmark model could lead to overfitting, and therefore other control variables are not used.

Additional environmental sustainability scores are added to the benchmark model based on the empirical findings. Model 2 adds change in ES_Overall score as an additional predictor. In turn, Model 3 tries to capture the U-shaped relationship by estimating coefficient for change in ES_Overall score for Low ES Companies and High ES Companies separately, and by adding these as additional predictors to Model 1. Finally, Model 4 is the same as Model 3, but the change in ES_Overall score coefficients are estimated only for environmentally sensitive industries to avoid overfitting. Formulae for the four models are presented in the notes of Table 20.

When looking at average sensitivity scores (true positives / (true positives + false negatives)), all models with environmental sustainability as an additional predictor outperform Model 1 (see Table 20). Interestingly, Model 2 obtains the highest average value of 69% and outperforms Model 1 by 6 percentage points. Models 2-4 obtain similar values, and therefore no clear rank order between these models can be made based on sensitivity. Same is true with specificity metric (true negatives / (true negatives + false positives), as all models get values of 58-59%. Even though Models 2-4 outperformed Model 1 with average sensitivity scores, ES_Overall score does not give additional predictive power in terms of specificity. Interesting finding is that all models outperform pure chance, as both sensitivity and specificity values get a value over 50% with all the models.

Table 20. Evaluation of Predictive Models.

	Number of Predictions	Sensitivity	Specificity	Mean Absolute Error
Year-end 2018				
Model 1	242	61%	70%	1.747
Model 2	242	61%	67%	1.794
Model 3	242	60%	68%	1.815
Model 4	242	61%	69%	1.797
Year-end 2019				
Model 1	224	55%	63%	2.163
Model 2	224	64%	65%	2.112
Model 3	224	63%	67%	2.112
Model 4	224	61%	67%	2.102
Year-end 2020				
Model 1	191	72%	43%	1.937
Model 2	191	80%	44%	2.014
Model 3	191	79%	43%	2.007
Model 4	191	81%	39%	2.015
Average				
Model 1	219	63%	59%	1.949
Model 2	219	69%	59%	1.973
Model 3	219	67%	59%	1.978
Model 4	219	68%	58%	1.972

Model 1: $\Delta COE_{i,t} = \beta_{1,i} + \beta_2 \Delta BTM_{i,t-1} + \beta_3 \Delta BETA_{i,t-1}$

Model 2: $\Delta COE_{i,t} = \beta_{1,i} + \beta_2 \Delta BTM_{i,t-1} + \beta_3 \Delta BETA_{i,t-1} + \beta_4 \Delta ES\_Overall_{i,t-1}$

Model 3: $\Delta COE_{i,t} = \beta_{1,i} + \beta_2 \Delta BTM_{i,t-1} + \beta_3 \Delta BETA_{i,t-1} + \beta_4(\Delta ES\_Overall_{i,t-1} * \text{Low ES Company Dummy}) + \beta_5(\Delta ES\_Overall_{i,t-1} * \text{High ES Company Dummy})$

Model 4: $\Delta COE_{i,t} = \beta_{1,i} + \beta_2 \Delta BTM_{i,t-1} + \beta_3 \Delta BETA_{i,t-1} + \beta_4(\Delta ES\_Overall_{i,t-1} * \text{Low ES Company Dummy} * SI_i) + \beta_5(\Delta ES\_Overall_{i,t-1} * \text{High ES Company Dummy} * SI_i)$

Model 1 slightly outperforms Models 2-4, when average of mean absolute errors (MAE) is considered. Based on this metric, adding ES_Overall score as an explanatory variable result to overfitting and therefore it should not be used in predictive models. There are no clear differences between Models 2-4 in MAE, although Model 4 slightly outperforms the other two models.

In summary, ES_Overall score is not an important predictor of COE based on the used models and validation metrics. Even though models with ES_Overall score outperforms the benchmark model based on all evaluation metrics in one year, average of three years out-of-sample predictions reveals that including ES_Overall leads to overfitting especially in terms of MAE. However, including ES_Overall might improve predictive power on the direction of change, as models with ES_Overall score outperform the benchmark model in terms of sensitivity. Finally, there is no clear evidence that distinguishing for Low or High ES Companies or environmentally sensitive industries results to better predictive power. This is somewhat a surprising result, as these are important distinctions in the empirical models.

5. CONCLUSION AND DISCUSSION

The aim of this thesis is to get a deeper understanding of the relationship between environmental sustainability and cost of capital. The relationship is studied separately for cost of equity and cost of debt to get an understanding of the effects on both sides of the cost of capital. Another objective is to provide useful insight for many interest groups by studying the relationship in more detail than what has been done in prior empirical research. This study also contributes to the growing set of financial theories on cost of capital, as it finds new relationships between cost of capital and environmental sustainability. Financial theories have become more complicated over the years, as strict assumptions of early asset pricing models—such as CAPM—have been relaxed and a growing number of risk measures have been associated with cost of capital.

The results are summarized and reflected against the research problems and questions, financial and economic theories as well as previous empirical findings. Finally, limitations of the research are discussed and suggestions for future research are presented based on the limitations and empirical results.

5.1 Summary of Results and Contribution

The results will be summarized by answering first the research question *"Q1: How environmental sustainability affects cost of capital?"* and next the second question *"Q2: Can environmental sustainability scores be used to predict changes in cost of capital?"* The first question is answered by providing answers to the sub-questions: *"Q1.1: Is there a linear or non-linear relationship between environmental sustainability and cost of capital?"*, *"Q1.2: Do different aspects of environmental sustainability affect cost of capital in the same way?"*, and *"Q1.3: Does environmental sensitivity of an industry play a role in the relationship between environmental sustainability and cost of capital?"*

The question Q1.1 was studied by using non-linear equations and by regressing by Low, Medium, and High environmental sustainability companies separately. The empirical results suggest that there is a U-shaped relationship between environmental sustainability and cost of capital. However, this exists only between cost of equity and environmental sustainability, whereas environmental sustainability does not have a statistically significant—linear or non-linear—effect on cost of debt. This result suggests that equity investors perceive a higher sensitivity to market risks for environmentally unsustainable companies and highly sustainable companies, compared to companies with average sustainability ratings. The result that environmental sustainability affects cost of equity is aligned with many previous studies, e.g. Sharfman and Fernando (2008), El Ghoul et al. (2011), Chava (2014), Ng & Rezaee (2015), Gupta (2018). However, all these studies found a negative linear relationship, which contrasts with the findings of this thesis. The finding that environmental sustainability does not affect cost of debt is consistent with the studies of Sharfman and Fernando (2008) and Gracia & Siregar (2021). Gracia & Siregar (2021) also tried to find non-linear relationships but did not find evidence for it. However, some studies (see Chava, 2014; Ge & Liu, 2015; Eliwa et al., 2019) have found a negative relationship between environmental sustainability and cost of debt, and the findings of this thesis are contradictory to the results of these studies.

To answer the question Q1.2, the empirical models were applied to the components of the overall environmental sustainability score—namely emission, innovation, and resource use scores. Again, no relationships between different sustainability metrics and cost of debt were found. The results suggest, however, that the U-shaped relationship between environmental sustainability and cost of equity is driven by innovation and resource use sustainability. In contrast, no evidence for a U-shaped relationship with regards to emission sustainability is found. The relationship between emission score and cost of equity is rather found to be slightly linearly negative, even though not statistically significantly. These results contribute to the existing empirical research as few studies have studied different aspects of environmental sustainability separately. The results are partially in line with the findings of Gupta (2018), who found that emission and resource use scores have a negative effect on cost of equity.

The companies were divided into environmentally sensitive and non-sensitive industries to answer the research question Q1.3. Based on the results, there are differences in the relationship between environmental sustainability and cost of capital in sensitive and non-sensitive industries. However, the results are different for different sustainability scores. First, environmental sustainability has no clear effect on cost of debt, even when distinguishing for environmentally sensitive and non-sensitive industries. Second, the results suggest that environmentally unsustainable companies in environmentally sensitive industries experience more significant cost of equity reduction for improving their emission sustainability compared to companies in non-sensitive industries. Similar result was found with resource use score, even though the result was not quite statistically significant. The conducted robustness tests however reveal that these results can be country dependent. These results are interesting from the perspective of the empirical research, as again few studies make a distinction between sensitive and non-sensitive industries. Of the reviewed studies, only Gracia & Siregar (2021) studied the effect of industry sensitivity and found that there are no significant differences with the sensitive and non-sensitive industries with regards to effects on cost of debt. The results of this thesis are consistent with this finding.

The results do not provide conclusive evidence to the research question Q2. The question is studied by predicting changes in cost of equity and by adding environmental sustainability metrics to a benchmark model. Three models with additional environmental sustainability metrics were compared to the benchmark model, and all of these outperformed the benchmark with one evaluation metric but were as good or worse than the benchmark model based on two other metrics. In short, environmental sustainability is not found to be a strong predictor of cost of equity. This result again contributes to the existing research, as no papers studying the predictive power of environmental sustainability on cost of capital were found.

The results suggest that investors perceive environmental sustainability to affect company's sensitivity to market risks. Alternatively, the results could be driven by investor tastes if they are not just maximizing their payoff. In turn, stakeholder theory and legitimacy theory could explain why investors might have tastes for more sustainable companies or why they would perceive higher sensitivity to market risks for unsustainable companies. Also, changes in information asymmetry between investors and companies could partially explain the findings (see El Ghoul et al., 2011). However, no effect of firm-specific risks is found, which is quite surprising, considering that poor environmental practices could for instance lead to litigations.

The findings of this study can prove useful for many groups—such as companies, investors, analysts, or regulators. For companies, the results show that there is an optimal level of environmental sustainability where cost of equity is the lowest. This study suggests that the optimum is slightly above the average environmental sustainability score of the industry. The U-shape applies for resource use and innovation sustainability, but not for emission sustainability. The results also suggest that environmentally unsustainable companies in environmentally sensitive industries could especially lower their cost of equity if they improve their practices. These findings can also be useful for investors and analysts, who try to evaluate if a company's sustainability efforts are optimal. Finally, regulators can benefit from the findings for instance when they try to find solutions for reaching net-zero emissions. It can be found quite alarming that the relationship between emission sustainability score and cost of equity was found to be quite weak, and no relationship was found between any of the environmental sustainability scores and cost of debt. Also, the U-shaped relationship between cost of equity and innovation score can disincentivize development of new green technologies, which could prove crucial for reaching net-zero emissions.

5.2 Limitations and Suggestions for Future Research

First important limitation is that the thesis focuses on publicly listed companies in the developed Europe and the results are not necessarily generalizable to other economic areas. Publicly listed companies in EU area face regulatory rules for ESG disclosure that do not apply to other companies. Also, previous studies have found that the relationship between ESG practices and cost of capital might differ in countries because of differing business cultures and the level of stakeholder-orientation (Dhaliwal et al., 2012; Devinney et al., 2013). Future research could replicate here applied models to other economic areas.

Another caveat is that environmental sustainability is a multidimensional concept, which is hard to quantify with a single number. This type of quantification is useful from an empirical perspective but can suffer from biases. Also, this thesis studies differences in environmentally sensitive and non-sensitive industries, and division to these categories is debatable. Future research could use alternative measures or definitions for environmental sustainability and environmentally sensitive industries.

Especial caution should be addressed to the selected cost of capital measures. The study only focuses on the direct relationship between environmental sustainability and cost of equity or environmental sustainability and cost of debt separately. However, non-financial performance could theoretically have an alternative way of affecting cost of capital by affecting debt capacity and capital structure (Sharfman & Fernando, 2008).

The selected cost of debt and cost of equity measures can additionally suffer from certain pitfalls. As cost of debt is accounting based, it can vary because of varying exchange rates through translation differences (Gracia & Siregar, 2021). This can produce noise to the data. Additionally, bonds and notes can be of long maturity and therefore changes in environmental sustainability might not be reflected quickly to the cost of debt. Further, the used cost of debt measure is *ex post* and does not necessarily accurately reflect lenders' most recent view on the risk premium. Future research could consider using e.g. bond contracts instead of accounting-based measures for cost of debt to better reflect lenders' expectations.

In contrast to cost of debt, the implied cost of equity measure is market based, and therefore can quickly reflect changes in environmental performance. However, this type of measure can suffer from analyst estimate biases (El Ghoul et al., 2011; Chava, 2014). Also, there are multiple ways of measuring cost of equity, and using an alternative measure could lead to different results. Future research can alleviate these concerns by using multiple measures for cost of equity.

Finally, validation of predictive models is quite limited, as only few predictive models and evaluation metrics are used. Future research could use different types of predictive models with environmental scores as additional predictors and use more evaluation metrics. In this thesis evaluation is done with only a small test set. Future research could consider evaluation techniques that apply multiple divisions to training and test sets—e.g. random division 1,000 times—to obtain more robust results.

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APPENDICES

Appendix 1. Regression of Environmental Sustainability Components Against COD.

	ES_Overall Dependent: COD	ES_Emission Dependent: COD	ES_Innovation Dependent: COD	ES_Resource Dependent: COD	ES_Overall Dependent: COD	ES_Emission Dependent: COD	ES_Innovation Dependent: COD	ES_Resource Dependent: COD
ES	-0.0035	-0.0021	-0.0001	-0.0018	0.0114	-0.0092	-0.0025	0.0027
	(-0.7245)	(-0.5566)	(-0.0231)	(-0.5455)	(1.0155)	(-0.9496)	(-0.2341)	(0.2901)
ES^2					-0.0002	0.0001	0.0000	-0.0000
					(-1.5133)	(0.8247)	(0.2362)	(-0.5462)
INT_COV	-0.0070***	-0.0069***	-0.0080**	-0.0078***	-0.0070***	-0.0069***	-0.0080**	-0.0078***
	(-2.7104)	(-2.6230)	(-2.2196)	(-2.9599)	(-2.7091)	(-2.6166)	(-2.2148)	(-2.9585)
LEVERAGE	0.0003	0.0002	0.0001	0.0002	0.0003	0.0002	0.0001	0.0003
	(0.3332)	(0.2031)	(0.0737)	(0.2712)	(0.3684)	(0.1812)	(0.0771)	(0.2769)
SIZE	-1.6071***	-1.6759***	-1.3081***	-1.6611***	-1.6163***	-1.6806***	-1.3056***	-1.6552***
	(-3.8916)	(-3.9296)	(-2.6333)	(-3.9613)	(-3.9147)	(-3.9409)	(-2.6274)	(-3.9550)
ROA	-0.0363***	-0.0316***	-0.0299**	-0.0334***	-0.0357***	-0.0317***	-0.0299**	-0.0331***
	(-3.5240)	(-3.0959)	(-2.5718)	(-3.2475)	(-3.4607)	(-3.1081)	(-2.5753)	(-3.2012)
OCFTA	-0.0145	-0.0190	0.0007	-0.0145	-0.0141	-0.0192	0.0006	-0.0143
	(-1.2278)	(-1.5719)	(0.0464)	(-1.1802)	(-1.1935)	(-1.6006)	(0.0420)	(-1.1632)
CAP_INT	-0.0231***	-0.0223**	-0.0279**	-0.0224**	-0.0233***	-0.0221**	-0.0279**	-0.0223**
	(-2.7088)	(-2.5536)	(-2.5351)	(-2.5421)	(-2.7241)	(-2.5341)	(-2.5354)	(-2.5389)
Constant	15.3644***	15.7176***	13.3195***	15.5918***	15.1614***	15.8791***	13.3545***	15.4555***
	(5.9453)	(5.8297)	(4.0989)	(5.8914)	(5.9397)	(5.8619)	(4.0703)	(5.8773)
Firm Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year obs.	6,076	5,923	4,028	5,945	6,076	5,923	4,028	5,945
Number of firms	912	890	642	896	912	890	642	896
Avg. obs per firm	6.7	6.7	6.7	6.7	6.7	6.7	6.7	6.7
R-squared	0.0755	0.0764	0.0773	0.077	0.0763	0.0766	0.0773	0.0771
Adj. R-squared	0.0731	0.0739	0.0736	0.0745	0.0737	0.0740	0.0734	0.0744

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1