Rotterdam School of Management
Erasmus University

Erasmus Platform for Sustainable Value Creation

Thesis working paper

Examining the impact of carbon intensity on cost of debt: the moderating effects of forward-looking indicators

Max Vullinghs

RSM - a force for positive change

RSM Erasmus

Working paper

Examining the impact of carbon intensity on cost of debt: the moderating effects of forward-looking indicators

July 2021

Max Vullinghs
Student

Abstract

With temperatures increasing and sea levels rising, enterprises and investors play an important role in reducing emissions and accurately pricing the risks associated with emitting. This study examines the effect of carbon performance on cost of debt by analysing panel data of 2,737 enterprises operating in Europe and the United States for the period from 2013 to 2019. Results show a significantly positive effect of enterprises' historic carbon intensity on cost of debt across the full sample suggesting lenders incorporate climate risks into lending decisions through the cost of debt. Second, a demonstrated carbon reduction policy presents to be a statistically mitigating factor on this relationship. Therefore, lenders incorporate forward-looking indicators of carbon performance not visible yet in historic emission intensities into their risk assessment. Furthermore, the effects appear to be invisible before the Paris Agreement and in The United States and are stronger in Europe post the Paris Agreement compared to the results on the full sample. Moreover, the effect is only visible for enterprises where emissions are a material issue (high emitting industries). Lastly, in a sample of 57 Green Bonds with matching conventional bonds from the same issuers, this study finds that the 'green' label on a bond can fully mitigate the positive effect of carbon intensity on bond spread. The results suggest that investors perceive the issuance of a Green Bond as a signal of commitment towards a greener future independent of historic carbon intensities.

Master Thesis
MSc Finance & Investments

Examining the impact of Carbon Intensity on Cost of Debt: The moderating effects of forward-looking indicators

by

Max Vullinghs
424494

Supervisor
Prof. Dirk Schoenmaker

Co-reader
Yonghan Li

Rotterdam School of Management (Erasmus University)

Rotterdam, The Netherlands

June 10, 2021

Acknowledgements

I would like to express my gratitude to my friends and family for their unconditional support throughout the writing of this thesis. Their share in the completion of this thesis, and subsequently the MSc Finance & Investments, is greatly acknowledged. Moreover, I would like to thank my supervisor Prof. D. Schoenmaker for the guidance and feedback he provided during the entire process. Next, I would like to thank MSc. Y. Li for the constructive feedback and effort as co-reader. To conclude, I would like to thank the team of the Erasmus Data Service Centre (EDSC) for their quick and accurate support in collecting the data during the COVID-19 crisis.

Contents

1 Introduction

1.1 Relevance

Climate change driven by excessive carbon emissions has become one of societies' most urgent problems. In the transition towards a low-carbon sustainable economy, enterprises play a pivotal role. Currently, the 100 most polluting enterprises are responsible for over 70% of the global emissions where the top 20 is accountable for more than a third (Griffin & Heede, 2017; Taylor & Watts, 2019). Enterprises seem to excessively focus on profit and shareholder value, which according to Friedman (1970) should be the only societal responsibility of an enterprise. Therefore, regulators have to act upon this attitude and increase the urgency. On 12 December 2015, 196 parties adopted the Paris Agreement which formed a framework for a collective approach to undertake the biggest threats the climate is facing (United Nations, 2020). Nonetheless, the intentions did not yet lead to the desired results. The Emissions Gap Report of 2020 provides information that despite a reduction in emissions caused by the COVID-19 pandemic, the world is still on a path to a rise in temperature of over 3 degrees Celsius. Therefore, it seems that enterprises need extra incentives to overcome the prevalence of short-termism and actively contribute to a greener world.

Lately, investors have shown increased interest in enterprises' Environmental (E), Social (S) and Governance (G) performance which are the three pillars Corporate Social Responsibility (CSR) is built upon (Amel-Zadeh & Serafeim, 2018). With the rising urgency of climate change mitigation, environmental performance received extra attention in particular. Academics conducted research on the effects environmental performance could bring for investors and enterprises. Environmental performance can positively impact stock market performance (Cohen et al., 1997; Derwall et al., 2005; Klassen & McLaughlin, 1996), enterprise value (King & Lenox, 2002; Konar & Cohen, 2001; Matsumura et al., 2014) and operating performance (Hart & Ahuja, 1996; Russo & Fouts, 1997). Intuitively, as a result of better financial performance and less exposure to environmental risks (Hoffmann & Busch, 2008), cost of capital should benefit as well from becoming greener.

The effect of environmental performance on cost of equity has been studied elaborately with overall an intuitively negative relationship (El Ghoul et al., 2011; Ng & Rezaee, 2015; Sharfman & Fernando, 2008). The relationship between environmental performance and cost of debt is remarkably, with debt markets being larger in size in comparison to equity markets, insufficiently understood with varying and even contrasting findings (Menz, 2010; Polbennikov et al., 2016; Schneider, 2011; Sharfman & Fernando, 2008). Differences in sample formation and metrics for environmental performance may contribute to these inconsistencies (Semenova & Hassel, 2015). Using carbon emissions to measure environmental performance offers an objective and easily quantifiable measurement directly linked to climate risks (Labatt & White, 2011). Studies have focused on the effect of carbon emissions on enterprise value (Matsumura et al., 2014), operating performance (Hart & Ahuja, 1996), cost of equity (Kim et al., 2015; Li et al., 2014) and cost of debt (Caragnano et al., 2020; Kumar & Firoz, 2018; Li et al., 2014; Maaloul, 2018). The results on cost of debt are not consistently resulting in a positive relationship and are based on small geographic regions which could significantly influence the outcomes (Gupta, 2018). Therefore, it is still unclear how lenders perceive enterprise emission performance.

Extending the literature on the relationship between carbon emissions and cost of debt, Jung et al. (2018) find that carbon risk awareness by enterprises can effectively mitigate the positive relationship. This indicates that lenders value enterprises' willingness to change, or at least their awareness of the exposure to environmental risks. One way of signalling possible awareness to the public is issuing a Green Bond (Flammer, 2021; Tang & Zhang, 2020). A Green Bond has the same basic features as a conventional bond, but with a 'Green' purpose. Academics have tested the relationship between environmental performance and bond spreads, where overall they find a positive relation (Ge & Liu, 2015; Schneider, 2011). Furthermore, studies focused on the general performance of Green Bonds and find that they trade at a significant negative premium compared to conventional bonds (Gianfrate & Peri, 2019; Zerbib, 2019). However, it was not considered whether the current environmental performance of an enterprise effects this premium. In contrary to a sign of awareness, issuing a Green Bond can also be considered as a form of greenwashing to exploit the possible green premium attached to Green Bonds.

This study aims to contribute to the current literature examining the relationship of environmental performance, measured as carbon intensity (carbon emissions/sales), and cost of debt. More interestingly, this study extends the literature on possible mitigating factors affecting this relationship by adding the carbon policy variable. Adding this variable to the model will test whether incorporating a carbon policy can benefit enterprises' cost of debt as it demonstrates awareness and commitment of carbon risk mitigation not visible in historic emissions. Furthermore, the study aims to fill in the research gap of the relationship between environmental performance and Green Bond spreads. The effect of the 'Green' label on a bond could function as a sign of carbon risk awareness and therefore mitigate the relationship similar to a carbon policy . Hence, the research question of this study is structured as follows:

"Can forward-looking indicators moderate the effect of historic Carbon Intensity on Cost of Debt?

1.2 Data & Methodology

This study examines the effect of carbon intensity on cost of debt and the mitigating role of carbon policy for the U.S. and Europe in the period from 2013 to 2019. Caragnano et al. (2020) and Jung et al. (2018) apply similar tests on which this study bases their methodology. The carbon data, scope 1 and 2 emissions (ENERDP123) and carbon policy (ENERDP0051), is obtained from the Thomson Reuters ASSET4 database. Moreover, cost of debt data and the included control variables (Size, Leverage, Profitability, Marktet to Book, ICR and Z-Score) are collected from the CompuStat and Datastream databases. This study employs OLS regressions which include time, industry and country fixed effects. To test the robustness of the results, a different proxy for carbon policy is introduced (Jung et al., 2018). Furthermore, similarly to Bolton and Kacperczyk (2020), the effect of absolute carbon emissions instead of carbon intensity is examined. To gain deeper knowledge about the results, multiple tests are performed on specific sub-samples. Since the Paris Agreement was adopted in December 2015, more emphasis towards emission performance should be expected in the years following (Delis et al., 2019). Therefore, to test the impact of the Paris Agreement the sample is divided into two groups, before and after the agreement. In addition, Europe and the U.S. are analysed separately since cultural and governance differences can impact the effect (Gupta, 2018). Moreover, in line with Jung et al. (2018), this study tests whether the effect is more significant for enterprises in high emitting industries as carbon emissions are material for these enterprises (Khan et al., 2016). Lastly, as the 100 most polluting enterprises are responsible for over 70% of the global emissions (Taylor & Watts, 2019), the desired effect should be greater for these enterprises to promote emissions improvements. Additional analysis on these top 100 emitting enterprises is conducted. Furthermore, for additional analysis, a bond sample from the same period is examined to test whether this effect holds when testing bond spreads, and more interestingly, to test whether the 'Green' label on a bond can equally mitigate this effect. To create a valid sample, the 57 collected Green Bonds from the Bloomberg database are matched to conventional bonds based on propensity scores similar to Gianfrate and Peri (2019). The propensity matching is performed with the nearest neighbour technique with 5 matches per Green Bond. To test for robustness of the results, the matching is also performed with 3 and 8 matches.

1.3 Results

The results show a significantly positive effect of carbon intensity on cost of debt across the full sample. The Granger causality test strengthens the causal interpretation from carbon intensity to cost of debt. In line with Caragnano et al. (2020) and Jung et al. (2018), the results suggest that lenders incorporate climate risks into lending decisions through the cost of debt. Second, carbon policy presents to be a statistically mitigating factor on the effect of carbon intensity on cost of debt. Therefore, lenders incorporate forward-looking indicators of carbon performance not visible yet in historic emission intensities into their risk assessment (Jung et al., 2018). Furthermore, the effects appear to be invisible before the Paris Agreement and in The United States and are stronger in Europe post the Paris Agreement compared to the results on the full sample (Delis et al., 2019). Moreover, the effects are only visible for enterprises where emissions are a material issue (high emitting industries). Undesirably, carbon intensity has no impact on cost of debt in a sample of the top 100 emitting enterprises. Lastly, this study finds that the 'green' label on a bond can mitigate the positive effect between carbon intensity and bond spreads. The results suggest that investors perceive the issuance of a Green Bond as a signal of commitment towards a greener future independent of historic carbon intensities.

This study contributes to the existing literature in multiple ways. First, the results enhance the inconclusive results on the understanding of environmental performance and cost of debt for both Europe as the United States. More specifically, by measuring carbon intensity, a key metric is measured which is both internally as externally to the enterprise used by decision makers. Carbon intensities provide clear insights into an enterprises' operational sustainability given the finite carbon fuels supply. Compared to the use of CSR performance scores (Ge & Liu, 2015; Magnanelli & Izzo, 2017), emission data is more directly used by regulatory bodies and for enterprise policy decisions. Empirical research containing carbon data is still sparse, therefore this study addresses this shortfall. Furthermore, the impact of forward-looking emission performance indicators on financing costs in a sample of U.S. and European enterprises is something that has not been studied before. At last, this is the first study to address the relation between historic carbon intensities and Green Bond spreads. Green Bonds are a relatively new instrument on which the exact implications for climate change mitigation is still unknown. This study finds new results which suggests that historic carbon intensities do not influence the spreads for Green Bonds. Therefore, lenders perceive the issuance as an adaption to climate risks or they are simply overestimating the effect of the Green Bond (Maltais & Nykvist, 2020). Addressing these new insights in research is not only relevant for scholars but also for practical implications. Enterprises should implement emission reduction policies as the impact on reduced financing cost demonstrates the tangible value of these policies for both public and private debt markets. Furthermore, issuing a Green Bond can be extra beneficial for enterprises which have relatively high historic carbon intensities. Financial institutions, lenders and policy makers should be aware of the possible exploitation of this effect.

2 Literature review

This literature review is structured in the following way; first the emergence and the theoretical framework of Corporate Social Responsibility are introduced (section 2.1). Then, the metrics for CSR performance used in studies are described including the shortcomings of ESG-ratings and the benefits of using carbon emissions data (section 2.2). This is followed by linking the carbon emission metric to the urgency of climate change (section 2.3). Afterwards, the focus moves specifically to environmental performance and the effect on corporate financial performance (section 2.4). Thereafter, Green Bonds are introduced and the empirical findings are discussed (section 2.5). Lastly, all relevant theory on environmental performance and cost of debt are concluded to construct the hypotheses of the study (section 2.6).

2.1 Corporate Social Responsibility

The European Commission (2011) defines Corporate Social Responsibility (CSR) as 'the responsibility of enterprises for their impact on society'. Next to complying with regulations related to harmful behaviour prevention, enterprises can act socially responsible by incorporating environmental, social and ethical interests into their business activities and strategy. This is in contrast with the shareholder model where the main goal and purpose of an enterprise should be to maximise shareholder value and profits (Friedman, 1970). Opposed to this shareholder-centred perspective, contradicting beliefs emerged where alongside the interests of shareholders, attention should be apportioned to a larger group of interested parties. Stakeholder theory argues that an enterprise should drive for maximising stakeholder value, not solely shareholder value (Freeman, 1984). CSR builds further on the foundations set by stakeholder theory where next to profits, the emphasis is on people and planet (Elkington, 1998). Employing a strategy built around CSR can improve enterprise value via elevated employee productivity, advanced operating performance, better access to capital and enhancing enterprise reputation (Malik, 2015). However, the CSR investments should be in line with the stakeholders' preferences as managers may pursue to over-invest in CSR for personal reputation benefits (Barnea & Rubin, 2010). Furthermore, to create a source of competitive advantage and innovations enterprises should only engage in the CSR activities which align their core business and strategy (Porter & Kramer, 2006). Hence, enterprises should try to create shared-value instead of merely attempting to comply with standard CSR approaches. van Marrewijk (2003) suggests that enterprises should work on a tailor made CSR approach on which their activities and purpose should be built or altered around and not the other way around. Stakeholders', including investors', interest in enterprises' CSR performance is rising (Matsumura et al., 2014). However, testing whether an enterprise acts more responsible than another remains difficult as each enterprise is unique in purpose and nature and so is their CSR activity. Therefore, while it is crucial for enterprises to account for CSR activity, it may not be optimal to test every enterprise with one specific model. Nevertheless, with the increased emphasis of investors on CSR disclosures, there is a demand for quantification and possibly standardisation of CSR (Moneva & Cuellar, 2009). A leading method for measuring CSR are ESG-ratings.

2.2 CSR Metrics

The measurement of CSR differs considerably across studies and over time. A widely used metric are ESG-ratings. However, the ESG-ratings used per study can still differ significantly as there are variations in ratings per ESG data provider. Furthermore, more specific metrics are used to test enterprise performance within a certain ESG pillar. An example is carbon emissions for environmental performance.

2.2.1 ESG-ratings

ESG-ratings are constructed around the performance in three pillars, the environmental, social and governance pillar. Each pillar is scored based on certain criteria which will lead to a combined score, the ESG-rating. The choice of criteria included is done by ESG-rating agencies. Nowadays, there are more than 100 rating agencies which are among others Thomson Reuters, Sustainalytics, MSCI and RobecoSAM. They provide the ratings and reports at enterprise level, on which subscribed investors can act upon. According to Amel-Zadeh and Serafeim (2018) investment performance is the most frequent motivation for investment organisations to incorporate ESG-ratings, followed by client demand, product strategy, and as last frequent motivation ethical considerations. Sustainable investing is growing rapidly and investment funds that invest based on ESG-ratings experience significant inflows (Hartzmark & Sussman, 2019). Therefore, enterprises are expected to manage their CSR issues affecting their ESG-rating (Krueger et al., 2020). The ESG-ratings provide the investors a quick approximation of the enterprise's ESG quality. However, there are some issues concerning the reliability of ESG-ratings. First, ESG-ratings are too general and do not focus on the material issues, which are the issues relevant to the investee enterprise (Khan et al., 2016). Enterprises with a focus on material sustainability issues tend to outperform enterprises with low ratings on material issues, while a focus on immaterial issues does not show this out-performance. Another problem that arises when not focusing on material issues, is that a negative score on a material issue can be cancelled out by high scores on immaterial issues. Combined with an 'industry neutral' approach, this leads to high ratings for the least bad companies in very unsustainable industries (Schoenmaker & Schramade, 2019b). Second, the rating agencies are not capable of interpreting huge data sets and are prone to certain biases. Per analyst, as many as 70 enterprises are covered which limits them to asses the enterprises in-depth. Furthermore, the scores are biased, for example, on size where bigger enterprises receive better scores as they have the resources for example a sustainability management team (Schoenmaker & Schramade, 2019b). Finally, the ESG-ratings of different rating agencies do not converge on average meaning they differ significantly per agency (Berg et al., 2019; Semenova & Hassel, 2015). Berg et al. (2019) find three main sources for the divergence based on data of six rating agencies. The two most important are divergence in scope, where raters include diverging attributes, and divergence in measurement, where raters measure the same attribute with a different measurement. The divergence leads to market inefficiencies, mixed signals for enterprises and challenges for empirical research. For these reasons, other metrics, like carbon emissions, could provide more accurate and less subjective results.

2.2.2 Carbon Emissions

Carbon emissions offer a metric that is more easily quantifiable and less prone to biases. Furthermore, measuring carbon emissions, increasingly makes sense as it is linked with certain risks. The most general form of risk related to environmental performance is 'environmental risk'. A subset of environmental risk is 'carbon risk' or 'climate risk' which refers to 'any corporate risk related to climate change or the use of fossil fuels (Hoffmann & Busch, 2008). Over-reliance on fossil fuels, newly imposed regulations and changes in consumer preferences are examples of the risks associated with the transition to a low- carbon economy. Labatt and White (2011) break climate risk down to three components which are regulatory, physical and business risks. Regulatory risk are risks associated with emission related regulations. An example of regulations directly linked to emissions are carbon taxes, which are already introduced in some countries. Physical risk are risks associated with extreme weather events and temperature rises which can harm assets or resources. Finally, business risk are associated with potential harm to reputation and consumer demand. Bolton et al. (2020) increase the urgency by claiming that the traditional backward-looking risk assessments cannot capture the magnitude climate-related risks will take. These unprecedented risks are called 'green swan' risks, which entail potentially extreme financial disruptive events which could trigger the next financial crisis. With temperatures increasing and sea levels rising, enterprises' overall exposure to climate risk will grow accordingly.

2.3 Climate Change

Climate change is a danger for all life on this planet and therefore we have to act accordingly. On 12 December 2015, 196 parties adopted the Paris Agreement which formed a framework for a collective approach to undertake the biggest threats the climate is facing. The framework contains several actions to be taken with the aim to hold global warming well below 2 degrees Celsius and the ambition to limit it at 1.5 degrees Celsius. Furthermore, a goal was set for global emissions to peak as soon as possible after which years of decline would follow ultimately leading to net-zero emissions by 2050 (United Nations, 2020). The willingness to contribute to a carbon neutral world is an important step, but actions will have to follow. Over the last years, the United Nations Environment Program (UNEP) provides a yearly report about the current level of carbon emissions and what the gap is with the goals set in the Paris Agreements. The Emissions Gap Report of 2020 provides information that despite a reduction in emissions caused by COVID-19, the world is still on a path to a rise in temperature of over 3 degrees Celsius. Why are enterprises not transitioning towards a low carbon economy? It seems that market constraints and the pervasiveness of short-termism block significant actions taken in the near future. Moreover, as weak economic incentives and ambiguous relations between sustainable and financial performance persist, enterprise and governmental endeavors in the transition towards a revised economic model remain misaligned (Schoenmaker & Schramade, 2019a).

2.4 Environmental Performance in Corporate Finance

Despite increasing efforts and progress in climate-related policies and regulations, carbon emissions are growing annually. As stated earlier, managing carbon emissions can reduce carbon risks (Hoffmann & Busch, 2008; Labatt & White, 2011). Being less exposed to these risks can have benefits and may incentivise enterprises to manage their carbon emissions. In the next section, studies are analysed which study the effect of CSR and environmental performance on financial performance and cost of capital. As carbon risk is a vital part of CSR and environmental risks, studies concerning CSR and environmental performance are relevant for this study.

2.4.1 Environmental Performance and Financial Performance

In accordance with Friedman (1970) the only responsibility of an enterprise is to maximise shareholder value and profit. Focusing on environmental issues could lead to a conflict of interest with achieving this main goal. However, an enterprise has to comply to environmental regulations, which can be costly. Managers can therefore experience a trade-off between environmental and financial performance (Walley & Whitehead, 1994). Contradicting this trade-off, Klassen and McLaughlin (1996) find a positive relation between financial performance, measured by stock market performance, and environmental performance. Environmental rewards would result in positive stock returns where bad environmental news was associated with negative stock returns. The study shows that investors anticipate on environmental news in the short-run. Other studies test the long-term performance of environmental stocks by applying regression analysis instead of event studies. Overall, the results are not uniform. Cohen et al. (1997) find no penalty nor a premium for investing in greener enterprises based on a portfolio analysis of S&P enterprises. Derwall et al. (2005) on the other hand find that eco-efficient enterprises provide significantly higher returns than enterprises that score lower on eco-efficiency. Another stream of literature tests whether environmental performance influences enterprise value measured by Tobin's q. Overall, the results are uniform and suggest a positive relation between environmental performance and enterprise value. King and Lenox (2002) and Konar and Cohen (2001) find that enterprises with better environmental management, in the form of waste disposal management and fewer environmental lawsuits, experience a higher Tobin's q. The results of Konar and Cohen (2001) show that a 10% decrease in the emissions of toxic chemicals for manufacturing enterprises belonging to the S&P500, results in a $34 million increase in enterprise value. Matsumura et al. (2014) use carbon emissions as metric for environmental performance and find a negative relationship between carbon emissions and enterprise value. Furthermore, they conclude that not disclosing carbon emissions leads to an extra penalisation. When using carbon emissions or carbon intensity as proxy for environmental performance, an opposite association compared to performance scores is desired as a decrease in emissions should be strove for. To avoid confusions, environmental performance will be replaced by emission performance when emissions data is used. Another body of research focuses on operating performance, in the form of accounting metrics. Russo and Fouts (1997) find that environmental performance is positively related to operating performance by regressing the Return on Assets (RoA) of 477 enterprises. Hart and Ahuja (1996) complement this theory by finding a negative relation between carbon emission reductions and operating performance. Return on Sales (RoS) and RoA significantly benefit in the year after a reduction initiative was implemented where the effect on Return on Equity (RoE) was visible after two years. The effect was larger for enterprises with the highest emission levels. Overall, multiple financial performance metrics were used over the years, Guenster et al. (2011) concludes that environmental performance, measured as eco-efficiency, relates positively to both operating performance as well as market value. Trinks et al. (2020) employ a productive efficiency model to test enterprises' carbon emission levels compared to those of best performing peers which helps to quantify enterprises' relative dependence on carbon. In an international sample of 1572 enterprises they find that 1 basis point increase in carbon efficiency is associated with a 1.0% increase in profitability and a 0.6% decrease in systematic risk. Friede et al. (2015) perform a review analysis of over 2,200 individual studies. Approximately 90% of the studies find a non-negative relation between CSR performance and financial performance with a majority finding positive relationships which were stable over time. Overall, the studies conclude that good environmental performance can benefit enterprises' financial performance. Therefore, instead of testing 'whether' environmental performance positively affects financial performance, the question should be 'when' according to Busch and Lewandowski (2018). By conducting a meta-analysis on 32 empirical studies that focus on corporate carbon performance they analyse whether differences in measurements of carbon performance and financial performance determine the outcomes. The results indicate that relative emissions produce more statistically significant results compared to absolute emissions. Furthermore, carbon performance is more positively related to market based compared to accounting based measures of financial performance.

2.4.2 Environmental Performance and Cost of Equity

To introduce the relationship between environmental performance and cost of capital without seeking for empirical results, Heinkel et al. (2001) provide a theoretical framework to grasp the relation. The study includes investors which solely invest in 'green' enterprises and investors that are indifferent. Reforming a highly polluting enterprise requires at least 25% of the investors to be green, with only 10% of all the investors having green preferences at the time. Not reforming would result in stock price reductions because of relatively lower demand for polluting enterprises' stock. As a result, cost of capital increases. One of the first to test the empirical relationship between environmental performance and cost of equity were Sharfman and Fernando (2008). For a sample of 267 publicly listed U.S. enterprises, they find a significantly negative relationship between environmental management and cost of equity, estimated with the use of CAPM. Next to the asset pricing model approach used by Sharfman and Fernando (2008), the greater extend of literature regressed cost of equity on a measure of environmental performance. El Ghoul et al. (2011) regress cost of equity on corporate social responsibility, where they examine six qualitative issues from the KLD database. Three issues have a statistically negative effect on cost of equity where environmental policies is one of them. Ng and Rezaee (2015) find similar results as the relationship between ESG and cost of equity is negative, where only environmental and governance metrics contribute to this effect. On top of that, they extend the literature by concluding that disclosing sustainability is negatively related to cost of equity, especially for enterprises with strong ESG performance. Gupta (2018) tested the relationship in a sample containing 43 countries and found that the negative relationship is stronger where country-level governance is weak. A reduction of unnecessary waste and carbon emissions led to the most significant effect on cost of equity. Several studies focused specifically on the relation between emission performance and cost of capital or equity. Bolton and Kacperczyk (2020) test whether emission performance, measured by total carbon emissions, affect U.S. stock returns and find that stocks of enterprises with higher absolute carbon emissions earn higher returns. They interpret that investors are expecting higher returns for their increased carbon risk exposure. However, the results are insignificant when testing carbon intensity instead of absolute carbon emissions. Similarly, Li et al. (2014) study the relationship between emission performance, measured by carbon intensity, and cost of equity in an Australian sample. However, they also found no evidence to support their hypothesis that there is a positive relation between the two variables. On the other hand, Kim et al. (2015) do find a positive relation between carbon intensity and cost of equity in a sample of 379 enterprises in Korea. These results are indifferent for enterprises that disclose emissions voluntarily or by law.

2.4.3 Environmental Performance and Cost of Debt

Significant attention was given to the effect of environmental performance on financial performance and cost of equity where the effect on cost of debt has received considerably less attention. One of the first articles to include cost of debt in their analysis were Sharfman and Fernando (2008). They hypothesised that environmental risk management reduces an enterprise's cost of debt as risk management would lower the cost of financial distress and lessen the possibility of extreme environmental events. Unlike the effect on cost of equity, they find a significantly positive effect between environmental risk management and the cost of debt. Next to cost of debt on enterprise level, studies focused on bond spreads as metric variable. Menz (2010) tested a sample of Euro corporate bonds and hypothesises that issuers with higher CSR scores, experience lower bond spreads. But like Sharfman and Fernando (2008), he does not find a statistically negative effect. Furthermore, Magnanelli and Izzo (2017) tested the relation between CSR performance and cost of bank debt in an international sample of 332 enterprises and find a significantly positive relation, implying banks consider positive CSR performance not as risk reduction but as cost driver. An important note to make, is that both Menz (2010) as Magnanelli and Izzo (2017) use RobecoSAM as measure for environmental performance which could impact the results as mentioned in section 2.2.1. Schneider (2011) on the contrary finds a highly significant negative effect between environmental performance, measured by the toxic release inventory, and bond spreads in a sample of U.S. enterprises operating in the pulp and paper and chemical industries. Toxic releases being a material issue to the examined industries could have impacted the results (Khan et al., 2016). Polbennikov et al. (2016) complement the findings of Schneider (2011) where sustainable performance, measured by MSCI ESG scores, has a significantly negative effect on bond spread in a U.S. sample. An interesting finding is that the effect is substantially stronger for bonds with low credit ratings. Ge and Liu (2015) explicitly test the relation between environmental performance, measured by the KLD scores, and credit ratings. They find that environmental performance is positively associated with credit ratings which suggests that environmental risks are at least partly already integrated in credit ratings. Delis et al. (2019) specifically test whether banks price in the risk of possible stranded fossil fuel reserves by matching corporate fossil fuel reserves to syndicated loans. Subsequently, the loan rates between fossil fuel enterprises and other enterprises are compared to test the exposure to climate risks. They find that before 2015, therefore before the Paris Agreement, banks did not price in climate risks. After 2015, fossil fuel enterprises did experience a significantly higher cost of debt as banks began to take climate risks into account. A few studies test emission performance as independent variable. Unlike the insignificant results for the effect on cost of equity, Li et al. (2014) do find a significantly positive effect between carbon intensity and cost of debt. They identify three key aspects to justify the relation between carbon risk and debt capital cost: a higher default premium, a negative effect on market asset value leading to a higher probability of covenant breach and an increase in litigation and reorganisation costs which reduce financial resources. Several papers studied the effect in particular countries or regions, Maaloul (2018) in Canada, Kumar and Firoz (2018) in India and Caragnano et al. (2020) in Europe which all resulted in a significantly positive effect. Jung et al. (2018) tests carbon risk awareness as mitigating factor between an enterprise's historical carbon emissions and cost of public debt. The results indicate that enterprises with higher carbon emissions and lower risk awareness experience significantly higher costs of debt than enterprises with demonstrated carbon awareness. Awareness is measured with three separate metrics which all come to the same conclusion. To conclude, they find that the effect is more prominent in high emitting industries.

2.5 Green Bonds

A recent development in financial instruments was the emergence of the Green Bond which has the same basic features as a conventional bond, but with a 'green' purpose. While the use of corporate Green Bonds has skyrocketed in the past years, it may seem unclear that enterprises choose to issue Green Bonds over conventional bonds, as the proceeds are devoted to green projects, restricting investment policies. Moreover, to issue a certified bond, third parties like the Climate Bonds Initiative, have to approve the issue which involves administrative and compliance costs. What is the incentive of issuing a Green Bond over a conventional bond? Flammer (2021) proposed three potential rationales, a signalling argument, the greenwashing argument and the cost of capital argument. The issuance of a Green Bond signals an enterprises' commitment towards a greener future. Studies have shown that capital markets responds positively to enterprises' pro-environmental behaviour (Jung et al., 2018; Klassen & McLaughlin, 1996). Flammer (2021) and Tang and Zhang (2020) find that issuers' stock prices increased significantly as a result of announcing a Green Bond. On the contrary, issuing a Green Bond can also be considered as an attempt of greenwashing (Lyon & Montgomery, 2015). This concern stems from the absence of public governance on Green Bonds. The Green Bond market relies on private certifying parties which do not posses the same enforcement mechanisms as public regulation. On top of that, a company could issue a Green Bond with the purpose of financing a 'green' project while increasing pollution with their regular business activities. The cost of capital rationale states that investors are willing to accept lower yields for a reduction in carbon risk exposure. Opposed to the finding on stock markets, Flammer (2021) and Tang and Zhang (2020) do do not find evidence that Green Bonds have lower bond spreads compared to regular bonds. Testing the green premium is a popular topic among researches over the last years with contradicting results. Zerbib (2019) finds evidence that there is a significant negative premium, the Green Bond spread is lower than the conventional bond spread which is according to them related to investors' pro-environmental preferment. However, the effect is only -2 basis points on average. Gianfrate and Peri (2019) find a greater effect in a sample of Euro bonds, where Green Bonds issued by enterprises have a significant premium of -21 basis points. Larcker and Watts (2020) on the other hand, find economically identical spreads for green and conventional issues by comparing Green Bonds to nearly identical conventional bonds by the same issuers. Next to answering whether issuing Green Bonds could result in lower bond spread, the broader benefits of the Green Bond market were explored. There are more financial incentives for issuers like improved access to capital and also business incentives like increased customer demand (Maltais & Nykvist, 2020). However, Maltais and Nykvist (2020) also conclude that currently the emphasis of Green Bond impact is on the interaction between issuer and investor and not on the actual impact the bond made on the environment. Therefore, there is still the risk that investors perceive the bond to be more effective than they actually are. The study concludes that Green Bonds do not make green projects financially possible as they could be replaced by conventional debt.

2.6 Hypotheses Development

To summarise, the effect of environmental performance on financial performance indicators has received significant attention in recent years. A range of metrics for environmental performance was used in the variety of literature. A discrete and objective measure for environmental performance are absolute carbon emissions or relative carbon emissions in the form of carbon intensity (Hart & Ahuja, 1996; Kim et al., 2015; Li et al., 2014; Matsumura et al., 2014). Measuring carbon emission becomes increasingly relevant with the climate changing as a result of excessive pollution. Ignoring carbon emission could make an enterprise more prone to so-called 'climate risks' (Hoffmann & Busch, 2008; Labatt & White, 2011). Focusing on the effect of environmental performance on cost of debt, results in contradicting outcomes where there are studies which result in positive (Magnanelli & Izzo, 2017; Menz, 2010; Sharfman & Fernando, 2008) and negative (Ge & Liu, 2015; Polbennikov et al., 2016; Schneider, 2011) effects between environmental performance and cost of debt. Differences in metrics could contribute to these inconsistencies. Nevertheless, the results when measuring emission performance still leads to inconclusive results (Li et al., 2014). Therefore, the question how environmental performance, and in particular emissions performance, is affecting borrowing costs remains unanswered. However, if environmental performance does positively affect financial performance (Friede et al., 2015; Klassen & McLaughlin, 1996; Russo & Fouts, 1997) and reduces the sensitivity to climate risk, then intuitively environmental performance should equally have a favourable effect on cost of debt, assuming not all the benefits are captured by the cost of equity. By measuring environmental performance with the objectivity and relevance of carbon intensity, the first hypothesis of this paper holds:

Hypothesis 1:
Carbon Intensity has a positive relationship with Cost of Debt

Second, Jung et al. (2018) find that enterprises which are unaware of the risks involved with emitting experience a significant positive relationship between carbon intensity and the cost of debt. The effect of carbon intensity on cost of debt can be mitigated by demonstrating awareness of the involved climate risks. El Ghoul et al. (2011) regress cost of equity on corporate social responsibility, and conclude that among other issues, environmental policies have a statistically negative effect on cost of equity. Solely looking at past carbon intensity levels ignores future intentions of enterprises to change their emission performance. Therefore, combining the two studies, enterprises which have demonstrated carbon reduction policies in place can be considered as aware of the risks involved with polluting which should positively influence debt capital markets. Accordingly, this paper studies the following hypothesis:

Hypothesis 2:
Enterprise's emission reduction policy mitigates the positive relationship of Carbon Intensity and Cost of Debt

Third, a stream of literature tested the effect of environmental performance on bond spreads (Ge & Liu, 2015; Menz, 2010; Polbennikov et al., 2016). As stated earlier, environmental performance can have an effect on risks and therefore on credit ratings. Ge and Liu (2015) find that environmental performance is positively related to credit ratings which result in lower bond spreads. However, the reduction in cost of debt is not fully captured by credit ratings according to them. Therefore, bondholders perceive environmental performance as an extra risk feature not included in credit ratings. To mitigate the transition towards a low-carbon economy, a new financial instrument was introduced with the same basic features as a conventional bond, the Green Bond. Gianfrate and Peri (2019) and Zerbib (2019) find that Green Bonds trade at a significant negative premium. However, it is unclear whether this effect would hold if the issuer scores low on environmental performance. It could be perceived as a form of greenwashing when enterprises with low environmental performance, in the form of carbon emissions, issue a Green Bond (Lyon & Montgomery, 2015). If the investors would be suspicious about potential greenwashing attempts, this could result in unfavourable effects for the bond spread. On the other hand, Flammer (2021) and Tang and Zhang (2020) find that Green Bond issuance can be perceived as a signal for environmental risk awareness and willingness to change which resulted in increased stock prices. Studies have shown that capital markets responds positively to enterprises' pro-environmental behaviour (Jung et al., 2018; Klassen & McLaughlin, 1996). Therefore, issuing a Green Bond could signal a pro-environmental attitude towards the market despite the issuer's historic carbon intensity. In accordance with the second hypothesis, the 'Green' label on a bond could mitigate the positive effect of carbon intensity on cost of debt. Hence, the third hypothesis of this paper is:

Hypothesis 3:
The 'Green' label on a bond mitigates the positive relationship between Carbon Intensity and Bond Spread

3 Methodology & Data

This section will explain the applied methodologies in testing the hypotheses. Furthermore, the intuition behind the chosen variables and their expected effects are interpreted. Lastly, the data collection process is elaborated on and summary statistics are provided.

3.1 Methodology - Carbon Intensity on Cost of Debt

The first empirical model is constructed to test whether carbon intensity has a positive effect on cost of debt. Similar to Jung et al. (2018), Li et al. (2014) and Magnanelli and Izzo (2017), the data collected will have a panel structure as it combines cross-sectional and time-series data. The panel structure increases the estimation accuracy and allows controlling for enterprise heterogeneity. To prevent regression variables to correlate with excluded factors, the panel structure provides the possibility to include fixed effects in the form of year, country and industry effects. Similarly to Jung et al. (2018), this study applies an ordinary least squares (OLS) regression:

$$CoD_{i,t} = \alpha + \beta CI_{i,t} + \gamma Y_{i,t} + \Lambda + \epsilon_{i,t} \tag{1}$$

Where $CoD_{\mathrm{i,t}}$ is Cost of Debt of enterprise i in year t, $CI_{\mathrm{i,t}}$ is the Carbon Intensity of enterprise i in year t, $Y_{\mathrm{i,t}}$ are the enterprise-level control variables and Λ denotes the year, country, and industry fixed effects. $\epsilon_{\mathrm{i,t}}$ is the error term of enterprise i in year t to take heteroscedasticity into account.

The second empirical model is constructed to capture the incremental effect that an enterprise's carbon policy has on the relation between carbon intensity and cost of debt. To test this mitigation the binary variable Carbon Policy (CP) and an interaction term, Carbon Intensity * Policy, are included in model (2). The effect of carbon intensity on the cost of debt for enterprises without a carbon policy is captured by β_1 whereas $\beta_1 + \beta_3$ captures the effect for enterprises with a carbon policy. Since the second hypothesis predicts that the effect will be smaller for enterprises with a carbon policy compared to the enterprises that do not have one, $\beta_1 + \beta_3$ is expected to be smaller than β_1. Hence, hypothesis 2 predicts that β_3 will be negative ($\beta_3 < 0$). In line with Jung et al. (2018), the model is constructed as:

$$CoD_{i,t} = \alpha + \beta_1 CI_{i,t} + \beta_2 CP_{i,t} + \beta_3 CI_{i,t} * CP_{i,t} + \gamma Y_{i,t} + \Lambda + \epsilon_{i,t} \tag{2}$$

3.1.1 Dependent variable - Cost of Debt

Dependent variable Cost of Debt for the first two empirical models measures the level of interest expense on an enterprise level. In line with Jung et al. (2018) Cost of Debt is measured as the enterprise's interest expense in year t divided by the average of its interest-bearing debt for year t and $t-1$. By measuring all interest bearing debt, interest on public and private debt is included in contrast to studies testing bond spreads (Ge & Liu, 2015; Polbennikov et al., 2016).

3.1.2 Independent variable - Carbon Intensity

In line with Jung et al. (2018) and Li et al. (2014), Carbon Intensity is measured as independent variable which relates enterprises' carbon emissions to an enterprise performance metric (e.g. Sales or Assets). By using Carbon Intensity instead of absolute carbon emissions the extent to which the enterprises' business activities are based on carbon usage is measured. In this study, Carbon Intensity indicates the enterprises' carbon efficiency in generating sales. Carbon Intensity is measured by enterprises' scope 1 (direct) and 2 (indirect) carbon emissions in Tonnes divided by total sales ($000).

3.1.3 Moderating variable - Carbon Policy

Jung et al. (2018) measure an enterprise's willingness to respond to a Carbon Disclosure Project (CDP) questionnaire as proxy for carbon risk awareness. The CDP questionnaire covers enterprises' activity with regard to climate change extensively where enterprises responding to the questionnaire are likely to have greater awareness and policies in place. El Ghoul et al. (2011) find that enterprises demonstrating superior performance with respect to environmental policies experience lower equity financing costs. This study tests whether a demonstrated carbon policy can function as a moderating variable between the carbon intensity and cost of debt relationship. The Thomson Reuters' ASSET4 database contains data of enterprises' carbon policies. The variable ENERDP0051 measures whether 'the enterprise describes, claims to have or mention processes in place to improve emission reduction'. For the purpose of this study, based on variable ENERDP0051 a binary variable is formed where enterprises without an emission reduction policy are denoted by zero and enterprises with an emission reduction policy are denoted by one.

3.1.4 Independent variable - Control Variables

Other factors potentially affect the cost of debt and therefore should be controlled for to prevent biased results. In order to do this, this study examines literature that implements cost of debt as dependent variable and carbon performance as independent variable. This study also considers controls used in literature testing ESG performance, given that many studies focused on ESG-ratings as proxy for environmental performance. The following control variables based on model specifications by El Ghoul et al. (2011), Jung et al. (2018), and Li et al. (2014) are included:

- *Size:* Measured as the enterprise's natural logarithm of total assets in year t. Larger enterprises are more stable in their cash generating ability and are expected to benefit from economies of scale in debt costs. Hence, larger enterprises are perceived as less risky and therefore size is expected to be negatively associated with cost of debt.
- *Leverage:* Measured as the enterprise's total debt to total assets in year t. A higher leverage ratio is perceived with greater risk of default. Therefore, leverage is expected to be positively associated with cost of debt.
- *Profitability:* Measured as the enterprise's net income to total assets (ROA) in year t. Profitable enterprises are more likely to better service their future debt obligations and face a lower probability of financial distress. Hence, a higer ROA is negatively associated with cost of debt.
- *Market to Book (MtB):* Measured as the enterprise's natural logarithm of market capitalization to book value of equity in year t. MtB value is an indicator for growth opportunities. Therefore, MtB is expected to be negatively associated with cost of debt.
- *Interest Coverage Ratio (ICR):* Measured as the operating income to the total interest expense of the enterprise in year t. A higher ICR indicates that the enterprise has greater operating income to cover the interest payments. Therefore, a higher ICR is negatively associated with cost of debt.
- *Z-Score:* The Z-score is an indicator of an enterprise's likelihood of bankruptcy designed by Altman (1968). The equation to calculate the Z-score is:

  $$Z - score = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$$

  Where X_1 = working capital / total assets, X_2 = retained earnings / total assets, X_3 = earnings before interest and tax / total assets X_4= market value of equity / total liabilities X_5= sales / total assets. A score below 1.8 suggests increased risk of bankruptcy. Hence, Z-score is negatively associated with cost of debt.

An overview of the variable construction and definitions can be found in Appendix A.

3.2 Methodology - Carbon Intensity on Bond Spread

The third empirical model is constructed to test whether the 'Green' label on a bond can mitigate the positive effect of carbon intensity on bond spread. For this model, an OLS regression with panel data is constructed similar to Ge and Liu (2015), Goss and Roberts (2011), and Schneider (2011). Their studies were aimed on finding a relationship between environmental or CSR performance and bond or loan spreads. For the purpose of this regression model, also literature concerning Green Bond performance should be analysed.

Zerbib (2019) constructs a sample of green and conventional bonds with similar characteristics. For each Green Bond, two conventional bonds are matched based on characteristics. The conventional bond has to be, among other things, from the same issuer and with a maturity close to the Green Bond. Ehlers and Packer (2017) use a similar matching approach, however they only match based on issuer, currency and maturity structure. Gianfrate and Peri (2019) use a propensity score matching technique which matches Green to conventional bonds based on similar propensity scores. The approach of these studies is to match vital bond characteristics from Green Bonds to conventional bonds up to a point where the only difference remains is the spread of the bond. Consequently, they can test whether Green Bonds trade at a premium. However, the aim of this study is to test the effect of carbon intensity on Green Bond spreads. Nevertheless, the matching techniques from Ehlers and Packer (2017), Gianfrate and Peri (2019), and Zerbib (2019) can be used to eliminate the issuers' credit risk effect. Matching bonds from the same issuers allows for a focus on bond level specific features as explanatory variables. The difference of bond-specific effects are mitigated by matching the green and conventional bonds by similar characteristics and including control effects. In section 3.4 the matching is further clarified. The empirical model to test the third hypothesis is constructed in a similar way as the second model, with the Green label as proxy for carbon policy. To do so, a dummy variable is added, 'Green'. This variable functions as a binary variable to distinguish between a conventional bond (0) and a Green Bond (1). Similar to the second empirical model, an interaction term is constructed, Carbon Intensity * Green. The effect of carbon intensity on the bond spread for conventional bonds is captured by β_1 whereas $\beta_1 + \beta_3$ captures the effect for Green Bonds. Since the third hypothesis predicts that the effect of carbon intensity on bond spreads is smaller for Green Bonds compared to conventional bonds, $\beta_1 + \beta_3$ is expected to be smaller than β_1. Hence, hypothesis 3 predicts that β_3 will be negative ($\beta_3 < 0$). The model is constructed as:

$$Spread_{i,t} = \alpha + \beta_1 CI_{i,t} + \beta_2 Green_{i,t} + \beta_3 CI_{i,t} * Green_{i,t} + \gamma Y_{i,t} + \epsilon_{i,t} \tag{3}$$

Where $Spread_{\mathrm{i,t}}$ is the spread of bond i in year t, $CI_{\mathrm{i,t}}$ is the Carbon Intensity of enterprise i in year t, $Y_{\mathrm{i,t}}$ are the bond-level control variables and $\epsilon_{\mathrm{i,t}}$ is the error term.

3.2.1 Dependent variable - Bond Spread

For the purpose of this study, primary bond spreads will be analysed as I want to test the effect of the initial carbon intensity profile of the issuer on bond spreads. In line with Ge and Liu (2015), bond spreads are measured as the difference between the bond yield at issuance and a Treasury bond yield with comparable maturity expressed in basis points.

3.2.2 Independent variable - Control Variables

The impact of enterprise specific effects, like the probability of default, are controlled for through the sample matching method. However, bond specific factors impacting spreads can still remain. Gabbi and Sironi (2005) test the most important factors impacting primary market bond spreads in Europe. They find that bond ratings have the biggest impact on spreads where in contrast to their hypothesis, liquidity measured by issue size, resulted to be irrelevant in the variability of bond spreads. However, Wang and Zhang (2009) find in their research on institutional ownership and credit spreads that issue size is positively related to spreads. The control variables for this study are included based on a combination of the methodologies of Ge and Liu (2015) and Schneider (2011) which both have a similar research setting on the impact of environmental or CSR performance on bond issue spreads.

- *Issue size:* Measured as the natural logarithm of the issued amount. As stated earlier, larger issues are associated with higher liquidity. Furthermore, larger issue size can lower the associated risk premium as a result of economies of scale in size of underwriting (Sengupta, 1998). Hence, despite the contrasting results for liquidity, I expect issue size to be negatively associated with bond spread.
- *Maturity:* Measured as the number of years to maturity starting from the issuance date. Bond issues with longer maturities can be considered riskier than issues with shorter maturities. On the other hand, bonds of longer duration may only be issued by enterprises with stronger fundamentals (Schneider, 2011). Therefore, no prediction on the association between maturity and bonds spreads is made.
- *Redeem:* Measured as binary variable whether the bond is callable. It equals one for bonds that possess a call option and zero if not. A callable bond provides issuers the opportunity to repurchase the bond before maturity. This increases the associated interest risk for bondholders. Hence, redeemable bonds are positively associated with bond spreads.

- *Security:* Measured as binary variable for the collateralisation status of the bond. It equals one for bonds that are secured and zero if the bond is unsecured. Unsecured bonds carry more risk as they are not backed by collateral. Hence, secured bonds are negatively associated with bond spreads.

An overview of the variable construction and definitions can be found in Appendix A.

3.3 Data - Carbon Intensity on Cost of Debt

The carbon emission and the carbon policy data is extracted from the Thomson Reuters ASSET4 database. The data is obtained for the period from 2013 to 2019 as Green Bond data before 2013 is limited. To avoid measuring the hypotheses for different time periods, data before 2013 is excluded. Furthermore, the emission data for 2020 is for the majority of enterprises still unavailable and therefore not incorporated in this study. First, the complete universe of public enterprises incorporated in Europe and the United States with at least one year of emission data available are collected resulting in 4,882 enterprises. To improve the validity of the results, enterprises with less than 3 consecutive years of carbon data are removed from the sample, resulting the sample to decrease to 3,907 enterprises. Enterprises belonging to the financial sector are excluded since they are incomparable with regards to the cost of debt financing (Caragnano et al., 2020; Jung et al., 2018). The remaining variables are extracted from the CompuStat Global and CompuStat North America databases. The data for variables containing local currencies are converted to US$. Observations with no debt and negative interest expense are excluded resulting in a final sample of 2,737 enterprises and 10,711 enterprise-year observations.

The tested variables are further adjusted for outlier observations by winsorizing at the 1st and 99th percentile. Moreover, to test whether the fixed effects model is preferred over a random effects model, the Hausman test is conducted. The results show that the use of the selected fixed effects are preferred stated by the rejection of the null hypothesis (Chi=1133.82, $p<0.000$). Lastly, the OLS regression model presumes homoskedasticity which states that the variance of the error terms is constant. By performing the Breusch-Pagan test, heteroskedasticity is identified (Chi= 10535.45, $p<0.000$). Therefore, the variance of the error term is not constant (White, 1980). Hence, all tested models are run on White's robust standard errors to account for heteroskedasticity.

Table 1 presents the summary statistics for the dependent and independent variables. Variables Carbon Intensity, MtB and Size are in normal form, rather than in natural logarithms which are used for the regression models, to improve data interpretation. The mean of 4.99% for the cost of debt is similar to previous research. For example, Magnanelli and Izzo (2017) find a mean of 4.9% in a global sample of 332 enterprises. The Carbon

Intensity mean of 2.91 suggests that this sample emits on average 2910 kg CO2 to produce 1000$ worth of sales. Furthermore, this number is also in line with previous research where Bolton and Kacperczyk (2020) find in their global research a mean of 1.92 for scope 1 and and a mean of 0.34 for scope 2 emissions, both being winsorized at 2.5%. Appendix B presents the summary statistics divided between enterprises with and without the carbon policy. The enterprise-year observations with a policy have a lower cost of debt, a higher carbon intensity and are larger in size compared to the the observations without a policy.

Table 1: Descriptive statistics - enterprise level

	N	mean	s.d.	min	max
Dependent Variable					
Cost of Debt (%)	10575	4.99	3.06	0.70	22.72
Independent Variable					
Carbon Intensity	10682	2.91	7.86	0.01	50.95
Control Variables					
Size ($ Millions)	10711	15792	32085	198	208690
Leverage	10711	0.29	0.16	0.00	0.72
Profitability	10697	0.04	0.09	-0.42	0.23
Market to Book	10699	3.90	5.12	0.26	37.40
ICR	10550	11.34	15.73	-26.13	59.62
Z-score	10674	6.30	7.30	-0.49	31.10
Policy	10711	0.65	0.48	0.00	1.00

This table shows descriptive statistics for the entire enterprise sample. The first column reports the total observations for each variable. The second column reports the mean and the third column the standard deviation. The fourth and fifth column report the minimum and maximum value for each variable. The data is obtained from Thomson Reuters ASSET4, Compustat and Datastream. All variables are winsorised at the 1st and 99th percentiles.

Griffin and Heede (2017) and Taylor and Watts (2019) found that the 100 most polluting enterprises are responsible for over 70% of the emissions. Figure 1 shows the distribution of carbon emissions divided in percentiles. The top 4% emitters, which are the top 100 emitting enterprises in this sample measured in 2018, are accountable for nearly 75% of the total emissions while their market cap only sums up to 11.9% of the total. In contrast, the 80% lowest emitting enterprises are only responsible for 3.9% of the total emissions. Therefore, also in this sample it appears that only a small number of enterprises is responsible for the majority of the emissions.

To understand the selected variables' interaction and to verify whether the variables are not too correlated, the correlation matrix is presented in Table 2. Importantly, none of the pairwise correlations among the independent variables in the model exceed 0.6. Nevertheless, A Variance Inflated Factor (VIF) test is performed to assure that multicollinearity is absent. Reconfirming initial expectations, the VIF test result suggest multicollinearity is not an issue as all variables score below 5. (Appendix C)

Table 2: Correlation matrix - enterprise level

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CoD	(1)	1								
CI	(2)	0.055***	1							
Policy	(3)	-0.138***	0.181***	1						
Size	(4)	-0.212***	0.168***	0.422***	1					
Leverage	(5)	-0.124***	0.133***	-0.034***	0.124***	1				
Profit	(6)	-0.210***	-0.097***	0.139***	0.147***	-0.170***	1			
MtB	(7)	-0.092***	-0.291***	-0.063***	-0.135***	0.131***	0.231***	1		
ICR	(8)	-0.013	-0.159***	0.033***	-0.088***	-0.383***	0.356***	0.164***	1	
Z-score	(9)	0.373***	-0.090***	-0.026**	-0.125***	-0.292***	0.119***	0.121***	0.578***	1

This table shows the pair-wise correlation statistics for the entire enterprise sample. The data is obtained from Thomson Reuters ASSET4, Compustat and Datastream. All variables are winsorised at the 1st and 99th percentiles. (***) (**) (*) indicate significance at the (1%) (5%) (10%) level respectively.

3.4 Data - Carbon Intensity on Bond Spread

To test the third hypothesis, bond data is extracted from the Bloomberg database. The sample includes bonds issued from 2013 to 2019. The initial dataset consists of 1,402 Green Bonds, which are all the Green Bonds issued in the sample period documented by Bloomberg. Excluding bonds issued outside Europe and the U.S. resulted in 608 Green Bonds remaining. Moreover, bonds with missing bond spreads and carbon emissions data at issuance are excluded resulting in a total sample of 57 Green Bonds. These 57 Green Bonds are matched with conventional bonds which are similar on a fixed set of characteristics. First of all, all the bonds issued by the issuers of the Green Bond sample are collected resulting in 476 conventional bonds. In line with Gianfrate and Peri (2019), the propensity score matching technique is used to pair the Green Bonds to the conventional bonds in order to control for biases in the causal effect. Rosenbaum and Rubin (1983) describe how to bundle characteristics of the sample in a single-index variable, the propensity score, which makes achieving consistent estimates of the treatment effect possible similar to matching on all covariates. By doing so, differences in spread of this well selected and thus adequate control group and of the treated group can be attributed to the treatment, in this case, to the Green label. Two main conditions will have to be satisfied in order to correctly and effectively implement this matching technique. The first condition is the “common support”, which holds that there must be presence of comparability. The Green Bond must be matched with a conventional bond with similar propensity scores in order to avoid comparison of incomparable bonds. The second condition is that the propensity score accurately balances the covariates. This is tested by performing a covariate imbalance test. For this study, the nearest neighbours matching with 5 matches is applied as main testing model. By using nearest neighbours matching, 5 conventional bonds are chosen as matching partners for a single Green Bond which are closest in terms of propensity score. It is allowed for conventional bonds to be included more than once in the matching procedure to enhance the overall quality of the matching. Again, by performing the Breusch-Pagan test, heteroskedasticity is identified (Chi= 35.78, $p<0.000$), therefore, the variance of the error term is not constant (White, 1980). Hence, all tested models are run on White's robust standard errors.

Appendix D presents the summary statistics for the variables of the entire sample pre-balancing. Variables Carbon Intensity and Size are in normal form, rather than in natural logarithms which are used for the regression models, to improve data interpretation. To understand the interaction and verify whether the variables are not too correlated, the correlation matrix is presented in Table 3. Again, none of the pairwise correlations among the independent variables in the model exceed 0.6. The Variance Inflated Factor (VIF) test is performed to assure that multicollinearity is absent. The VIF test result suggest multicollinearity is not an issue as all variables score below 5. (Appendix C)

Table 3: Correlation matrix - bond level

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Spread	(1)	1						
Carbon Intensity	(2)	0.145**	1					
Green Label	(3)	0.023	0.224***	1				
Size	(4)	0.007	0.084	-0.044	1			
Maturity	(5)	0.235***	0.306***	-0.087	0.062	1		
Security	(6)	0.175***	0.171***	0.150***	-0.040	-0.082	1	
Redeem	(7)	-0.029	0.512***	0.149**	0.080	0.112*	0.059	1

This table shows the pair-wise correlation statistics for the entire bond sample. The data is obtained from Thomson Reuters ASSET4, Compustat and Bloomberg. (***) (**) (*) indicate significance at the (1%) (5%) (10%) level respectively.

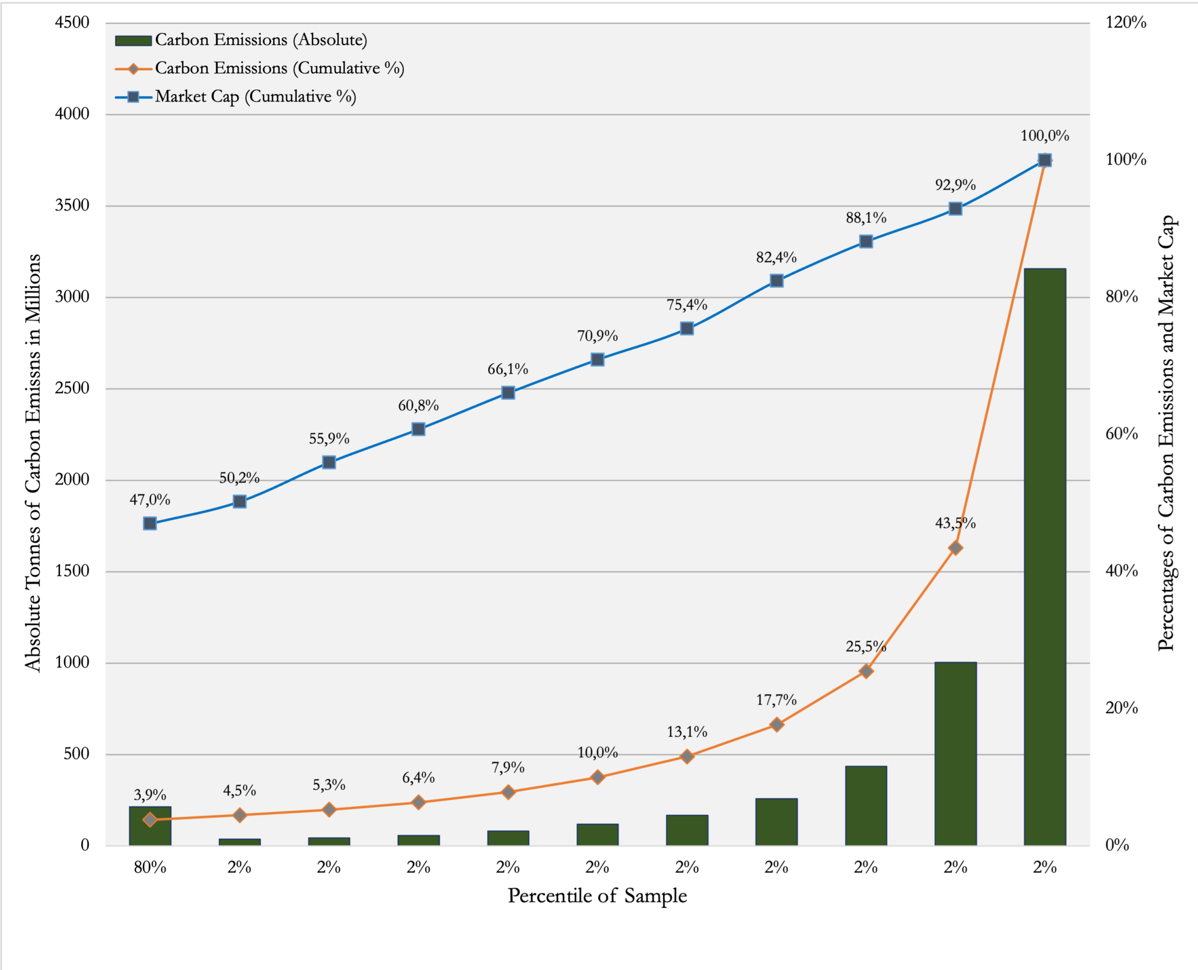
The outcomes of the balancing procedure based on the nearest neighbours matching with 5 matches is summarized in Table 4. To conclude whether the matching procedure is correctly applied, there should be no systematic differences between the treated and control group. This is done by running a covariate imbalance test. Indicated by the p-values in the last column, for all the variables included, the null hypothesis about the equality of the means between the treated and control groups cannot be rejected. This suggests a sensibly high quality of the balancing process (Gianfrate & Peri, 2019).

Table 4: Covariate Imbalance test

	Mean			t-test	
	Treated	Control	%bias	t	|p|>t
Size (log)	20.66	20.70	0.2	0.47	0.64
Maturity	8.30	8.65	4.2	0.43	0.67
Security	0.15	0.13	-13.3	-0.35	0.72
Redeem	0.54	0.48	-11.1	-0.71	0.48

This table provides an overview of the results of the covariate imbalance test based on the nearest neighbours matching with 5 matches. Included are the means for the variable of the treated and control group and the bias between the groups. The t-test result illustrates whether there are remaining significant differences between the treated and control group.

Figure 1: Carbon Emissions distribution



This figure shows the distribution of absolute carbon emissions for the year 2018, as emission data coverage is the most optimal in that year, across 2549 enterprises. The green bars visualise 50 enterprises (i.e. 2% of 2549 enterprises), except for the far left bar, which shows the absolute carbon emissions for the lowest emitting 80% of the sample. Furthermore, the cumulative share of total carbon emissions and the cumulative share of total market capitalization in 2018 are presented. The data is obtained from Thomson Reuters ASSET4 and Datastream.

4 Results

4.1 Primary results

4.1.1 Analysis of enterprises' Carbon Profile on Cost of Debt

To test the first two hypotheses of this study, multiple regressions variants are presented in Table 5. Column 1 and 2 present the results of the first regression model where column 1 excludes fixed effects and column 2 includes year, industry and country fixed effects. Column 3 and 4 present the results of the second regression model where the Policy and the interaction variable are introduced. Again, in column 3 the fixed effects are excluded and in column 4 they are included. For both models the full specification containing the fixed effects results in the highest model fit determined by a large adjusted R^2 of 0.359. In combination with the earlier conducted Hausman test, the results will be interpreted based on column 2 and 4. As the test for heteroskedasticity affirmed non-constant volatilities in the error terms of the enterprise-level variables over time, all tested models are run on White's robust standard errors.

The first hypothesis predicts a positive effect of carbon intensity on cost of debt. The results in column 2 confirm the first hypothesis with a significantly positive Carbon Intensity coefficient (0.0519, p = 0.015) at the 5% confidence level. The coefficient implies that an increase of 10% in carbon intensity results in a 0.21 basis point increase in cost of debt (0.0519 * log(1.1)). This is economically a rather small effect. However, the deviation in carbon intensity can be quite large (mean of 2.91 with a s.d. of 7.86). The penalty on debt financing costs for heavy emitters can therefore still be considerable. The results strengthens the empirical evidence on the assumption that superior carbon performance could result in reduced financing costs. Furthermore, the findings are consistent with earlier research conducted testing the relationship of emission performance and the cost of debt (Caragnano et al., 2020; Kumar & Firoz, 2018).

The second hypothesis predicts that an emission reduction policy can mitigate the positive relationship of carbon intensity and cost of debt. Specifically looking at column 4, it provides evidence for both the first and second hypothesis. Consistent with the first hypothesis, the Carbon Intensity coefficient is positive and significant at the 1% confidence level (0.107, p = 0.001) indicating that for enterprises without a carbon policy, an increase of 10% in carbon intensity leads to a 0.43 basis points increase in cost of debt. This is more than double the effect compared to the full sample, revealing that enterprises without a carbon policy are more exposed to the positive effect. Furthermore, the significantly negative Carbon * Policy coefficient (-0.0679 p = 0.038) at the 5% confidence level confirms the second hypothesis. The results imply that a demonstrated emission reduction policy

Table 5: Regression results - Carbon Profile on Cost of Debt

Dependent variable	CoD (1)	CoD (2)	CoD (3)	CoD (4)
Carbon Profile				
Carbon Intensity	0.104***	0.0519**	0.194***	0.107***
	(0.0150)	(0.0218)	(0.0310)	(0.0340)
Policy			-0.468***	-0.161**
			(0.0684)	(0.0697)
Carbon * Policy			-0.0983***	-0.0679**
			(0.0338)	(0.0324)
Control Variables				
Size	-0.336***	-0.325***	-0.284***	-0.311***
	(0.0179)	(0.0190)	(0.0200)	(0.0213)
Leverage	-1.661***	-1.748***	-1.757***	-1.758***
	(0.235)	(0.244)	(0.235)	(0.244)
Profitability	-5.092***	-5.507***	-4.975***	-5.494***
	(0.543)	(0.543)	(0.542)	(0.543)
MtB	-0.239***	-0.183***	-0.232***	-0.177***
	(0.0346)	(0.0371)	(0.0346)	(0.0375)
ICR	-0.0241***	-0.0226***	-0.0240***	-0.0226***
	(0.00162)	(0.00161)	(0.00162)	(0.00161)
Z-score	0.0239***	0.0234***	0.0239***	0.0234***
	(0.00142)	(0.00140)	(0.00142)	(0.00140)
Country fixed effects	No	Yes	No	Yes
Industry fixed effects	No	Yes	No	Yes
Year fixed effects	No	Yes	No	Yes
Adjusted R^2	0.284	0.359	0.287	0.359
Observations	10473	10473	10473	10473

This table shows the results of the first two regression models with Cost of Debt as dependent variable and Carbon Intensity and Carbon * Policy as main independent variables. Variables Carbon Intensity, Size and MtB are presented as natural logarithm. The data is obtained from Thomson Reuters ASSET4, Compustat and Datastream. All variables are winsorised at the 1st and 99th percentiles. Standard errors are displayed in parentheses, and are adjusted for heteroskedasticity using White's robust standard errors. (***) (**) (*) indicate significance at the (1%) (5%) (10%) level respectively.

effectively mitigates the effect of carbon intensity on cost of debt. The net coefficient for enterprises with a carbon policy is 0.0391 (0.107-0.0679). Overall, the results presented in Table 5 consistently reveal carbon intensity to be a relevant indicator of cost of debt, but notably more relevant for enterprises that have no carbon policy in place. Enterprises with a demonstrated carbon policy appear to mitigate the impact of their historical carbon intensity level. As such, complementary to Jung et al. (2018), evidence is provided that debt markets not only incorporate enterprises' historical carbon performance but also include forward-looking indicators into their investment decisions.

The included control variables in the model impact cost of debt mostly as expected. As predicted, enterprise size, profitability, MtB ratio and ICR all have a significantly negative effect on cost of debt at the 1% confidence level. Leverage on the other hand surprisingly has a positive effect on cost of debt suggesting that it could point towards better financing conditions for enterprises with a more pronounced debt track record. The counter-intuitive results on Z-score may also simply indicate a rather weak suitability of Z-scores in predicting financial distress for enterprises not operating in the manufacturing sector, from which the actual score originally stems from.

4.1.2 Analysis of the 'Green' Label on Bond Spread

The main purpose of the third regression model is to test whether the 'Green' label on a bond mitigates the positive effect of carbon intensity on bond spread. However, the model will also test whether there is supporting evidence on the identified significant impact of carbon intensity on the cost of debt. The bond-level analysis is conducted on the propensity matched bond sample of 57 Green Bonds issued in the period between 2013 and 2019. Similar to the regression design of Gianfrate and Peri (2019), the analysis is performed with multiple matching techniques, where neighbouring matching with 3, 5 and 8 matches is conducted. Like the enterprise-level analysis, all tested models are run on White's robust standard errors. The results are presented in Table 6. Column 1 presents the results for 3 matches, column 2 for 5 matches and column 3 for 8 matches. Column 2 presents the initial test with 5 matches and will therefore be used to interpret the results. The other columns test the robustness of the results.

The third hypothesis predicts that the Green label can mitigate the positive relationship of carbon intensity and bond spreads. The significantly positive Carbon Intensity coefficient (5.340, $p = 0.012$) at the 5% confidence level provides additional support for the first hypothesis. Accordingly, carbon intensity positively impacts the initial spread on conventional bonds, therefore increasing financing costs. An increase of 10% in carbon intensity is associated with an increase of 0.22 basis points ($5.340 * \log(1.1)$) in bond spread. Supporting the third hypothesis, the significantly negative Carbon * Green coefficient

(-6.277, p = 0.055) at the 10% confidence level suggests that the 'Green' label on a bond can fully mitigate the positive relationship. Hence, carbon intensity has no effect on Green Bond spreads. Therefore, the results suggests that lenders perceive issuance of a Green bond as signal of a pro-environmental attitude unaffected by the issuer's historic carbon intensity. The similar findings in column 1 and 3 provide evidence for the robustness of the results. For most of the control variables, no statistically significant impact on spread is found. This is in line with the expectations as the propensity matching approach balances the differences in treatment and control group on Size, Maturity, Security and Redeem for which both groups are alike on these characteristics. Only a weakly statistically significant negative effect of the indicator Redeem is observed which is unexpected and contrary to other studies (Ge & Liu, 2015).

Table 6: Regression results - Carbon Profile on Bond Spread

	NN = 3	NN = 5	NN = 8
Dependent variable	Spread	Spread	Spread
	(1)	(2)	(3)
Carbon Profile			
Carbon Intensity	5.526**	5.340**	6.128***
	(2.455)	(2.094)	(1.799)
Green Label	0.955	0.310	0.0208
	(0.873)	(0.373)	(0.0223)
Carbon * Green	-6.631*	-6.277*	-6.932**
	(3.355)	(3.246)	(3.232)
Control Variables			
Size	-11.32	-10.08	-7.813
	(12.34)	(10.34)	(9.213)
Maturity	-2.997**	-1.681	-0.741
	(1.336)	(1.116)	(0.978)
Security	27.89	27.15	24.02
	(21.53)	(20.79)	(20.25)
Redeem	0.250	-17.22*	-29.54***
	(12.09)	(10.32)	(9.203)
Adjusted R^2	0.406	0.386	0.428
Observations	145	189	239

This table shows the results of the third regression model with Bond Spread as dependent variable and Carbon Intensity and Carbon * Green as main independent variables. Variables Carbon Intensity and Size are presented as natural logarithm. The data is obtained from Thomson Reuters ASSET4, Compustat and Bloomberg. All variables are winsorised at the 1st and 99th percentiles. Standard errors are displayed in parentheses, and are adjusted for heteroskedasticity using White's robust standard errors. (***) (**) (*) indicate significance at the (1%) (5%) (10%) level respectively.

4.2 Robustness tests

4.2.1 Alternative model measurements

Similarly to Jung et al. (2018), a different measure for carbon policy in the form of a carbon target (ENERDP0161) is tested for sensitivity purposes. This variable from the Thomson Reuters ASSET4 database measures whether an enterprise has set targets or objectives to be achieved on emission reduction. This measurement differs from the current proxy for policy which measures if there are processes in place to improve emission reduction. In column 2 of Table 7 the model with dummy variable 'Target' and interaction term Carbon * Target is tested. The effect of carbon intensity on cost of debt presented in the first column remains the same as in the primary model. Adding the dummy 'Target' in the second column still leads to a significantly positive Carbon Intensity coefficient (0.0452, $p = 0.073$) at the 10% confidence level. However, the Carbon Intensity coefficient is smaller compared to the coefficient in column 1 suggesting enterprises without a carbon target do not experience a greater effect of carbon intensity compared to the full sample. The insignificant Carbon * Target coefficient (0.0126, $p = 0.628$) concludes that having a carbon reduction target does not mitigate the positive effect of carbon intensity on cost of debt. The results suggests that lenders consider enterprises implementing an emission reduction target not to be sufficient for a viable and active policy for carbon reductions.

Instead of measuring carbon intensity, studies tested absolute carbon emissions as carbon performance measurement (Bolton & Kacperczyk, 2020). By measuring relative emissions the extent to which the enterprises' business activities are based on carbon usage is measured, which should produce more statistically significant results compared to absolute emission (Busch & Lewandowski, 2018). However, when measuring the effect on stock returns, Bolton and Kacperczyk (2020) found a significant effect with absolute emissions and no effect with carbon intensity. The reason could be that regulations are assumably to target operations where the absolute level of emissions is the highest. In column 3 of Table 7, the results show that there is no significant impact of absolute carbon emissions on cost of debt. However, the positive Carbon Emissions coefficient (0.0890, $p = 0.005$) at the 1% confidence level in column 4 shows that enterprises without a carbon policy do experience the impact of absolute carbon emissions on their financing costs. The significantly negative Carbon * Policy coefficient at the 10% confidence level (-0.0581, $p = 0.070$) implies that a carbon policy can still effectively mitigate this effect.

4.2.2 Time and region analysis

To test whether the effect of the relationship differs for certain geographic areas or time frames, extra tests are conducted dividing the sample in sub-samples. By doing so,

Table 7: Regression results - Alternative Model Measurements

Dependent variable	CoD	CoD	CoD	CoD
	(1)	(2)	(3)	(4)
Carbon Profile				
Carbon Intensity	0.0519**	0.0452*		
	(0.0218)	(0.0253)		
Carbon Emissions			0.0289	0.0890***
			(0.0238)	(0.0311)
Target		0.0553		
		(0.0560)		
Policy				-0.157**
				(0.0706)
Carbon * Target		0.0126		
		(0.0259)		
Carbon * Policy				-0.0581*
				(0.0318)
Control Variables				
Size	-0.325***	-0.332***	-0.349***	-0.392***
	(0.0190)	(0.0211)	(0.0291)	(0.0335)
Leverage	-1.748***	-1.737***	-1.638***	-1.701***
	(0.244)	(0.245)	(0.248)	(0.245)
Profitability	-5.507***	-5.506***	-5.173***	-5.662***
	(0.543)	(0.543)	(0.559)	(0.542)
MtB	-0.183***	-0.186***	-0.203***	-0.186***
	(0.0371)	(0.0373)	(0.0380)	(0.0374)
ICR	-0.0226***	-0.0226***	-0.0216***	-0.0226***
	(0.00161)	(0.00161)	(0.00166)	(0.00161)
Z-score	0.0234***	0.0234***	0.0224***	0.0235***
	(0.00140)	(0.00140)	(0.00144)	(0.00140)
Country fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.359	0.359	0.348	0.359
Observations	10473	10473	10499	10473

This table shows the results of alternative measurements for the first two regression models with Cost of Debt as dependent variable and Carbon Intensity, Carbon Emissions, Carbon * Policy and Carbon * Target as main independent variables. Variables Carbon Intensity, Carbon Emissions, Size and MtB are presented as natural logarithm. The data is obtained from Thomson Reuters ASSET4, Compustat and Datastream. All variables are winsorised at the 1st and 99th percentiles. Standard errors are displayed in parentheses, and are adjusted for heteroskedasticity using White's robust standard errors. (***) (**) (*) indicate significance at the (1%) (5%) (10%) level respectively.

it allows for extra analysis in when and where debt capital markets adjust for carbon performance. The time frames are from 2013 to 2015 and 2016 to 2019 which divides the sample in periods before and after the Paris Agreement. In line with Delis et al. (2019), there should be more environmental awareness from both the enterprises as well as the financiers after the Paris Agreement. Secondly, the sample is divided between Europe and the United States. Gupta (2018) tested the relationship between emission performance and the cost of equity and found that the negative relationship is stronger in countries where country-level governance is weaker. Furthermore, with Donald Trump neglecting the importance and even exiting the Paris Agreement, there could be a far less focus in the United States on emission performance compared to Europe. Lastly, enterprises in the United States are more shareholder centered compared to in Europe, which are making more progress towards a stakeholder model incorporating other stakeholders in corporate and investing policy (Schoenmaker & Schramade, 2019b).

Table 8 provides the results of the analysis. The insignificant Carbon Intensity coefficient in column 2 and 4 implies that for both time periods there is no significant impact of carbon intensity on cost of debt in the United States. In Europe on the other hand, there is a strong significant effect for the period from 2016 to 2019 displayed in column 3. The effect of carbon intensity on cost of debt for enterprises without a carbon policy is significantly positive (0.278 p = 0.004) at the 1% confidence level. The significantly negative Carbon * Policy coefficient (-0.236 p = 0.012) at the 5% confidence level suggests that a carbon policy can effectively mitigate the effect. The effect is considerably larger compared to the effect on the full sample. The results suggests that lenders in Europe incorporate climate risk in their investment decisions triggered by the Paris Agreements (Delis et al., 2019). Overall, European enterprises can benefit more from managing their carbon performance, especially with increased focus over the years.

4.2.3 ***Emission based sample analysis***

Khan et al. (2016) found that enterprises with a focus on material sustainability issues outperform enterprises which score low on material issues. Therefore, investors should focus on performance in material issues concerning that industry. On the other hand, Kim et al. (2015) found a positive relationship between carbon risk and cost of equity which was greater for enterprises belonging to industries with lower environmental sensitivity. They conclude that enterprises in a sector with lower carbon emissions are encouraged to keep emissions at a low level. To test whether there are differences among industries, the sample is split in high emitting (Mining, Manufacturing, Transport and Gas & Electric) and low emitting industries (Construction, Communications, Trade and Services). Appendix E shows an overview of the carbon emissions per industry. The significantly positive Carbon

Table 8: Regression results - Time and Region

	2013 - 2015		2016 - 2019	
	Europe	U.S.	Europe	U.S.
Dependent variable	CoD	CoD	CoD	CoD
	(1)	(2)	(3)	(4)
Carbon Profile				
Carbon Intensity	0.0976	0.0538	0.278***	0.0399
	(0.107)	(0.0699)	(0.0967)	(0.0458)
Policy	-0.0714	-0.143	0.0976	-0.0616
	(0.215)	(0.119)	(0.223)	(0.0888)
Carbon * Policy	-0.0863	-0.0599	-0.236**	-0.00320
	(0.106)	(0.0601)	(0.0935)	(0.0389)
Control Variables				
Size	-0.182***	-0.383***	-0.163***	-0.424***
	(0.0529)	(0.0571)	(0.0446)	(0.0296)
Leverage	-3.291***	-0.935*	-3.912***	-0.485
	(0.555)	(0.554)	(0.552)	(0.345)
Profitability	-4.297***	-1.879*	-2.073	-6.174***
	(1.629)	(1.035)	(1.297)	(0.677)
MtB	-0.225**	-0.253***	-0.359***	-0.146***
	(0.104)	(0.0851)	(0.0888)	(0.0494)
ICR	-0.0273***	-0.0331***	-0.0238***	-0.0177***
	(0.00339)	(0.00410)	(0.00244)	(0.00290)
Z-score	0.0261***	0.0348***	0.0262***	0.0172***
	(0.00259)	(0.00779)	(0.00198)	(0.00265)
Country fixed effects	Yes	No	Yes	No
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.435	0.417	0.445	0.314
Observations	1928	1287	2784	4474

This table shows the results for the first two regression models with Cost of Debt as dependent variable and Carbon Intensity and Carbon * Policy as main independent variables on multiple sub-samples. Variables Carbon Intensity, Carbon Emissions, Size and MtB are presented as natural logarithm. The data is obtained from Thomson Reuters ASSET4, Compustat and Datastream. All variables are winsorised at the 1st and 99th percentiles. Standard errors are displayed in parentheses, and are adjusted for heteroskedasticity using White's robust standard errors. (***) (**) (*) indicate significance at the (1%) (5%) (10%) level respectively.

Intensity coefficient (0.141 p = 0.007) in column 1 of Table 9 implies that enterprises without a carbon policy operating in high emitting industries experience the impact of carbon intensity on their financing costs. The significantly negative Carbon * Policy coefficient (-0.115 p = 0.026) suggests that a carbon policy effectively mitigates the effect. This effect is invisible in low emitting industries suggesting that lenders focus on sustainability issues material to the industry (Khan et al., 2016).

As displayed in figure 1, a small set of enterprises is responsible for the majority of carbon emissions. Therefore, it is interesting to examine these enterprises in detail. To do so, the top 100 emitting enterprises of 2018 are analysed separately resulting in 579 enterprise-year observations. The insignificant Carbon Intensity coefficient (-0.820 p = 0.282) in column 3 shows that in a sample of the top 100 emitters, there is no significant effect of carbon intensity on cost of debt. The results on the rest of the sample do provide significant effects. Therefore, the top 100 emitting enterprises are not rewarded nor punished for increasing or reducing their carbon intensity.

4.2.4 Addressing endogeneity

Similar to other studies, a Granger Causality test is performed to address the potential likeliness of endogeneity between the cost of debt and carbon intensity (Du et al., 2017). The Granger test is described by equation 4 and 5. Equation 4 entails lag terms of carbon intensity and cost of debt to test whether cost of debt depends on carbon intensity in the previous year with lagged cost of debt as controlling variable. Equation 5 tests if carbon intensity depends on cost of debt in the previous year with lagged carbon intensity as controlling variable. Furthermore, both regressions are controlled for the same lagged extra control variables and fixed effects are included. A significant Carbon Intensity coefficient in equation 4 and an insignificant Cost of Debt coefficient in equation 5 would decrease the likeness of reverse causality between carbon intensity and cost of debt.

$$CoD_{i,t} = \alpha + \beta_1 CI_{i,t-1} + \beta_2 CoD_{i,t-1} + \gamma Y_{i,t-1} + \Lambda + \epsilon_{i,t} \tag{4}$$

$$CI_{i,t} = \alpha + \beta_1 CoD_{i,t-1} + \beta_2 CI_{i,t-1} + \gamma Y_{i,t-1} + \Lambda + \epsilon_{i,t} \tag{5}$$

The results of the tests are presented in Appendix F. The results of equation 4 are presented in column 1 which shows a significantly positive Carbon Intensity coefficient (0.0357, p = 0.092) when controlled for lagged Cost of Debt. Column 2 presents the results of equation 5 where the Cost of Debt coefficient is insignificant. Hence, there is no effect of lagged cost of debt on carbon intensity. Therefore, these results decrease the likeliness of reverse causality.

Table 9: Regression results - Emission based sample

	Industries		Top 100 Emitting	
	High Emitting	Low Emitting	Top Emitting	Rest of Sample
Dependent variable	CoD	CoD	CoD	CoD
	(1)	(2)	(3)	(4)
Carbon Profile				
Carbon Intensity	0.141***	0.0655	-0.820	0.0943***
	(0.0523)	(0.0432)	(0.762)	(0.0351)
Policy	-0.107	-0.153	-4.456	-0.155**
	(0.0929)	(0.100)	(2.981)	(0.0714)
Carbon * Policy	-0.115**	-0.0155	1.210	-0.0764**
	(0.0515)	(0.0418)	(0.791)	(0.0338)
Control Variables				
Size	-0.393***	-0.198***	-0.321**	-0.311***
	(0.0283)	(0.0315)	(0.136)	(0.0227)
Leverage	-1.780***	-1.806***	1.395	-1.704***
	(0.348)	(0.343)	(1.534)	(0.249)
Profitability	-5.788***	-4.077***	-0.401	-5.542***
	(0.655)	(0.912)	(2.279)	(0.551)
MtB	-0.137**	-0.210***	-0.777***	-0.187***
	(0.0546)	(0.0505)	(0.248)	(0.0384)
ICR	-0.0224***	-0.0233***	-0.0822***	-0.0226***
	(0.00212)	(0.00252)	(0.0145)	(0.00163)
Z-score	0.0230***	0.0237***	0.472***	0.0234***
	(0.00162)	(0.00274)	(0.110)	(0.00140)
Country fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.380	0.324	0.401	0.365
Observations	6202	4271	579	9894

This table shows the results for the first two regression models with Cost of Debt as dependent variable and Carbon Intensity and Carbon * Policy as main independent variables on multiple sub-samples. Variables Carbon Intensity, Carbon Emissions, Size and MtB are presented as natural logarithm. The data is obtained from Thomson Reuters ASSET4, Compustat and Datastream. All variables are winsorised at the 1st and 99th percentiles. Standard errors are displayed in parentheses, and are adjusted for heteroskedasticity using White's robust standard errors. (***) (**) (*) indicate significance at the (1%) (5%) (10%) level respectively.

5 Discussion

This study finds that carbon intensity positively impacts the cost of debt for enterprises. The Granger Causality test strengthens the causal interpretation of this relationship. Furthermore, this study finds evidence that lenders incorporate forward-looking indicators in their assessment of carbon risk exposure. The effect of carbon intensity on cost of debt appeared to be more prominent for enterprises without a carbon policy where a demonstrated carbon policy could effectively mitigate the positive effect. Lastly, the results on the bond sample indicate that the 'green' label on a bond functions similarly to having a carbon policy. The green label can fully mitigate the positive effect of carbon intensity on bond spread. Hence, historic emission performance does not affect Green Bond spread.

Contrary to Magnanelli and Izzo (2017), Menz (2010), and Sharfman and Fernando (2008), the results provide evidence that pro-environmental behaviour has a favourable effect on cost of debt. Magnanelli and Izzo (2017) argued that banks recognise pro-environmental performance not as a reduction of risk exposure but as a cost driver. They imply that lenders are only interested in the enterprise's financial ability to service the debt obligations. Investing in improved carbon performance, which is outside the core operations of the enterprise, will negatively impact the cash flows left to pay down the debt. However, there are some vital differences between this study and their studies. First of all, there are measurement differences, where Magnanelli and Izzo (2017) and Menz (2010) use CSR performance scores from the RobeccoSAM database. Second of all, and more important is the difference in sample period. Their research was conducted on a sample period before the Paris Agreement, where in line with this study, the favourable effect on cost of debt was invisible.

The favourable effect of carbon performance on cost of debt complements earlier findings of Caragnano et al. (2020) and Li et al. (2014) and suggests that climate risks like, over-reliance on fossil fuels, newly imposed regulations and changes in consumer preferences are priced in by lenders.

The second finding of this study, is that the penalty of historic emitting performance can be effectively mitigated by a demonstrated carbon reduction policy. These results are in line with Jung et al. (2018) who tested whether enterprises' awareness of carbon risks could mitigate the effect of carbon intensity on cost of debt. Consequently, implementing carbon reduction policies, is encouraged by lenders. Therefore, it is important for enterprises to effectively channel incremental information to investors about their future carbon risk profile which goes beyond their historical carbon intensity level. Although the economic impact of reductions may be small, the penalty for high emitting enterprises can be significant. Hence, the benefits on financing costs for heavy emitters seeking to adapt their operations to a carbon-constrained future can be substantial.

To test for robustness, other measurements of emission performance and carbon policy are tested. When replacing carbon policy for a carbon target, the mitigating effect disappears. Dahlmann et al. (2019) test whether carbon targets actually impact emissions and find no overall significant effect. Accordingly, lenders interpret carbon targets not as a viable action to reduce their climate risk exposure. Moreover, a possible concern when testing relative emissions instead of absolute emissions, is that carbon intensity can be affected by financial performance through the scalar, sales, instead of the actual emissions (Clarkson et al., 2015). Replacing carbon intensity by absolute carbon emissions results in a significantly positive effect on cost of debt suggesting the results to be robust to the choice of measurement of carbon performance.

For further analysis and robustness of the results, sub-samples of enterprises are examined separately. In line with Delis et al. (2019), carbon risks are only priced in after the Paris Agreement and not before. A result of the Paris Agreement was that governmental climate policy became stricter. McGlade and Ekins (2015) already estimated that implementation of the proposed climate policies will leave fossil fuel reserves stranded leading to a loss in their economic value thereby increasing enterprises' risks. The trend of internalisation of climate risks by lenders and enterprises in Europe is increasing. However, in the U.S. the effect even after the agreement remained invisible. This could be partly explained by the presidency of Donald Trump who is a big sceptic of the human role in climate change. Therefore, the risk of governmental intervention was substantially smaller for the U.S. than in Europe. With new leadership, it will be interesting to test whether this will favourably influence lenders and enterprises.

The other tested sub-samples are based on the emission profile of the enterprises and the industry they are operating in. Testing the sub-sample of enterprises operating in high emitting industries, results in a significantly positive relation between carbon intensity and cost of debt which can be mitigated by carbon policy. This effect is invisible for enterprises in low emitting industries. In line with Khan et al. (2016), investors and enterprises should focus on issues material to the industry. On the contrary, this study finds that carbon intensity does not increase cost of debt in a sample of the top 100 emitting enterprises. This is unfortunate as these are the enterprises which should be triggered to reduce their emissions as they are responsible for nearly 75% of the total emissions. Debt markets can play an important role in the transition towards a more sustainable world by allocating its capital to the most efficient needs (Schoenmaker & Schramade, 2019b). A more widespread awareness by investors of the risks associated with heavy emissions, like stranded assets and physical risks, will be key to rightly incorporate these risks into future financing decisions.

Lastly, this study finds a similar significantly positive effect between carbon intensity and bond spread in a sample of conventional and Green Bonds. More interestingly, in line with the third hypothesis, the green label on a bond can similarly to a carbon policy mitigate this positive effect. Hence, carbon intensity has no effect on Green Bond spreads. Therefore, lenders perceive the issuance of a Green Bond as a signal of commitment towards a greener future instead of an attempt of greenwashing (Flammer, 2021). The results do not inevitably conclude that Green Bond issuers will benefit from reduced financing costs, as there are additional costs associated with the issuance of a Green Bond. Moreover, although the proceeds of the bonds are devoted to green projects, they are not ring-fenced. In addition, undertaking a green project does not mean that the overall enterprise becomes greener. Therefore, it is still uncertain whether issuing a Green Bond effectively reduces the exposure to climate risks (Maltais & Nykvist, 2020). A new instrument overcoming these shortcomings are so called sustainability linked loans or bonds, which adapts the interest costs to the current performance of the linked metric, for example carbon performance (Schoenmaker & Schramade, 2019b).

6 Conclusion

6.1 Summary

This study aims to measure the impact of carbon performance on cost of debt. With temperatures increasing and sea levels rising, enterprises and investors play an important role in reducing emissions and accurately pricing the risks associated with emitting. This study analyses panel data of 2,737 enterprises operating in Europe and the United States from the period between 2013 and 2019. First, the effect of enterprises' historic carbon intensity (direct and indirect emissions to sales) on cost of debt across the full sample is tested. The results show a significantly positive effect suggesting that lenders incorporate climate risks into their pricing. Second, a demonstrated carbon reduction policy is found to be a statistically mitigating factor on the relationship of carbon intensity and cost of debt. Therefore, lenders incorporate forward-looking indicators of carbon performance not visible yet in historic emission intensities into their risk assessment. Furthermore, the effects appear to be invisible before the Paris Agreement and in the United States and are stronger in Europe post the Paris Agreement compared to the results on the full sample. Moreover, the effect is only visible for enterprises where emissions are a material issue (high emitting industries). Lastly, this study finds that the 'green' label on a bond can mitigate the positive effect between carbon intensity and bond spreads in a sample of 57 Green Bonds and matching conventional bonds from the same issuers. The results suggest that lenders perceive the issuance of a Green Bond as a signal of commitment towards a greener future independent of their historic carbon intensity. As Green Bonds are a recently new instrument, it is still unclear whether they will effectively contribute to a greener planet.

6.2 Limitations and future research

In this study several limitations are embedded which potentially disclose ideas for future research. First of all, contractual mechanisms like covenants and other mechanisms to mitigate agency problems and carbon risk are not considered. Therefore, lenders could substitute a more stringent contract for a higher cost of debt for enterprises with high carbon risk. This substitution could disguise the actual effect of carbon intensity on the cost of debt. Secondly, enterprises that did not disclose carbon emissions or the carbon emissions were not obtained or calculated by Thomson Reuters Asset4 are excluded from the sample, which could have led to certain prospective bias. Third, the study is based on large listed enterprises, therefore not providing evidence about the investor perspective in capital markets for small to medium enterprises. With a statistically significant effect of enterprise size in this study, it shows additionally to other studies an economically meaningful effect on enterprises' cost of debt. Hence, the results of this study may be biased towards large enterprises making the results not applicable to the financing of smaller non-listed companies. Despite data availability being an issue, the significance of enterprise size increases the urge for additional research on the effect of carbon intensity for small and medium sized enterprises. This can provide valuable insights for both financial institutions as SMEs. Fourth, the tests are based on a sample region of the modern western world. With cultural and governance differences among countries and regions affecting the relationship between environmental performance and cost of capital (Gupta, 2018), the results may not be applicable to other geographical regions. As global warming is not limited to the western world, future attention by scholars should be on emerging markets given their rapid economic growth which led to excessive emissions in the western world. Financial institutions and investors can play a key role in allocating the capital to the right needs. Fifth, despite the massive growth in Green Bonds over the last years, the available data remains limited. Therefore, the matching procedure could still cause bias in the results. Green Bonds for which no emission data is available are excluded, which again could have led to prospective bias. With the issuance of Green Bonds rising every year, data quality is increasing. Future research should carefully monitor the interaction between issuer and investor, but more importantly, it should test the actual impact on the environment. Finally, only scope 1 and 2 emissions are included in the analysis as data availability for scope 3 is still limited. The largest enterprises increasingly incorporate scope 3 emissions into their reporting and therefore investors may also include them in their lending considerations. With increased integrated reporting and stricter regulations, data may become more easily available in the future which provides opportunities for incorporating scope 3 emissions in research.

Appendices

A Variables description

Table 10: Variable specifications - Enterprise level

Variable	Database	Definition
Dependent variable		
Cost of Debt	CompuStat	Interest expense in year t divided by the average of interest-bearing debt for year t and $t-1$
Carbon Profile		
Carbon Intensity	ASSET4/CompuStat	Scope 1 (direct) and 2 (indirect) carbon emissions divided by total sales.
Emissions	ASSET4	Scope 1 (direct) and 2 (indirect) carbon emissions
Carbon Policy	ASSET4	Dummy variable that equals 1 if an enterprise claims to have or mention processes in place to improve emission reduction and 0 if this is not the case
Carbon Target	ASSET4	Dummy variable that equals 1 if an enterprise has set targets or objectives to be achieved on emission reduction and 0 if this is not the case
Control variables		
Size	CompuStat	Measured as the natural logarithm of total assets in year t
Profitability	CompuStat	Measured as total debt to total assets in year t
Leverage	CompuStat	Measured as net income to total assets (ROA) in year t
Market to Book	CompuStat/Datastream	Measured as the natural logarithm of market capitalization to book value of equity in year t
Interest Coverage Ratio	CompuStat	Measured as the operating income to the total interest expense in year t
Z-score	CompuStat/Datastream	The score is computed as: 1.2 * (working capital/total assets) + 1.4 * (retained earnings/total assets) + 3.3 * (earnings before interest and taxes/total assets) + 0.6 * (market value of equity/total liabilities) + (sales/total assets)

Table 11: Variable specifications - Bond level

Variable	Database	Definition
Dependent variable		
Bond Spread	Bloomberg	The difference between the bond yield at issuance and a Treasury bond yield with comparable maturity
Carbon Profile		
Carbon Intensity	ASSET4/CompuStat	Scope 1 (direct) and 2 (indirect) carbon emissions divided by total sales.
Green Label	ASSET4	Dummy variable that equals 1 if the bond is labeled as 'Green' 0 if this is not the case
Control variables		
Issue size	Bloomberg	Measured as the natural logarithm of the amount issued
Maturity	Bloomberg	Measured as the number of years to maturity starting from the issuance date
Redeem	Bloomberg	Dummy variable that equals 1 if the bond is callable and 0 if this is not the case
Security	Bloomberg	Dummy variable that equals 1 if the bond is secured and 0 if this is not the case

B Summary statistics sorted by policy

Table 12: Descriptive statistics - enterprise level

With Policy	N	mean	s.d.	min	max
Dependent Variable					
Cost of Debt (%)	6880	4.67	2.86	0.70	22.31
Independent Variable					
Carbon Intensity	6929	3.19	8.00	0.01	50.95
Control Variables					
Size ($ Millions)	6934	17575	33614	198	208690
Leverage	6934	0.28	0.15	0.00	0.72
Profitability	6926	0.05	0.07	-0.42	0.23
Market to Book	6932	3.61	4.57	0.26	36.91
ICR	6861	12.11	14.87	-25.66	59.62
Z-score	6929	5.81	6.70	-0.49	31.01
Without Policy	N	mean	s.d.	min	max
Dependent Variable					
Cost of Debt (%)	3695	5.56	3.31	0.70	22.72
Independent Variable					
Carbon Intensity	3753	2.44	5.78	0.01	48.67
Control Variables					
Size ($ Millions)	3777	12979	22164	198	199951
Leverage	3777	0.29	0.18	0.00	0.72
Profitability	3771	0.02	0.11	-0.39	0.21
Market to Book	3767	4.42	5.97	0.29	37.40
ICR	3689	10.09	17.13	-26.13	57.97
Z-score	3745	7.21	8.22	-0.45	31.10

This table shows descriptive statistics split between the enterprise-years with and without a carbon policy. The first column reports the total observations for each variable. The second column reports the mean and the third column the standard deviation. The fourth and fifth column report the minimum and maximum value for each variable. The data is obtained from Thomson Reuters ASSET4, Compustat and Datastream. All variables are winsorised at the 1st and 99th percentiles. Standard errors are displayed in parentheses, and are adjusted for heteroskedasticity using White's robust standard errors. (***) (**) (*) indicate significance at the (1%) (5%) (10%) level respectively.

C VIF tests

Table 13: Variance Inflated Factor (VIF) test - enterprise level

	(1) VIF
Carbon Intensity	1.17
Policy	1.26
Size	1.32
Leverage	1.31
Profitability	1.28
MtB	1.27
ICR	1.85
Z-score	1.55

Table 14: Variance Inflated Factor (VIF) test - bond level

	(1) VIF
Carbon Intensity	1.61
Green Label	1.10
Size	1.02
Maturity	1.16
Security	1.07
Redeem	1.37

D Summary statistics bonds

Table 15: Descriptive statistics - bond level

	N	mean	s.d.	min	max
Dependent Variable					
Spread (bp)	533	140.31	81.43	30.00	693.00
Independent Variable					
Carbon Intensity	489	1.48	3.66	0.00	29.34
Control Variables					
Size ($ Millions)	524	1177	646	150	5500
Maturity	533	10.76	9.55	2.99	100.00
Security	533	0.11	0.31	0.00	1.00
Redeem	533	0.38	0.49	0.00	1.00

This table shows descriptive statistics for the entire bond sample. The first column reports the total observations for each variable. The second column reports the mean and the third column the standard deviation. The fourth and fifth column report the minimum and maximum value for each variable. The data is obtained from Thomson Reuters ASSET4, Compustat and Bloomberg.

E Carbon emissions per industry

Table 16: Carbon Emissions per industry

Industries	SIC Codes	N	Carbon Emissions Mean
Mining	1000-1499	704	3.15
Construction	1500-1799	488	0.49
Manufacturing	2000-3999	4092	2.88
Transport	4000-4799	612	4.50
Communications	4800-4899	626	0.47
Gas & Electric	4900-4999	794	12.90
Trade	5000-5999	1451	1.08
Services	7000-8999	1706	0.22

This table shows descriptive carbon emission statistics per industry. The first column reports the industry. The second column reports the associated SIC Code and the third column the number of enterprise-year observations. The last column reports the carbon emission mean in Tonnes (Millions) per industry from 2013 to 2019. The data is obtained from Thomson Reuters ASSET4.

F Granger Causality test

Table 17: Granger Causality test

Dependent variable	CoD		CI	
	(1)		(2)	
Independent				
Carbon Intensity	0.0357*	(0.092)	0.953***	(0.000)
Cost of Debt	0.599***	(0.000)	0.000416	(0.824)
Control Variables				
Size	-0.138***	(0.000)	0.00256	(0.453)
Leverage	0.190	(0.400)	0.0747*	(0.071)
Profitability	-1.856***	(0.001)	0.171*	(0.069)
MtB	-0.162***	(0.000)	-0.0321***	(0.000)
ICR	-0.00346*	(0.065)	0.000195	(0.271)
Z-score	0.00324*	(0.078)	-0.0000346	(0.638)
Country fixed effects	Yes		Yes	
Industry fixed effects	Yes		Yes	
Year fixed effects	Yes		Yes	
Adjusted R^2	0.543		0.954	
Observations	8036		8054	

This table shows the results of the Granger Causality test with two regression models with Cost of Debt as dependent variable and with the lag term of Carbon Intensity as main independent variables in column 1. In column 2, Carbon Intensity as dependent variable with the lag term of Cost of Debt as main independent variable. Variables Carbon Intensity, Size and MtB are presented as natural logarithm. The data is obtained from Thomson Reuters ASSET4, Compustat and Datastream. All variables are winsorised at the 1st and 99th percentiles. P-values are displayed in parentheses. Standard errors are adjusted for heteroskedasticity using White's robust standard errors. (***) (**) (*) indicate significance at the (1%) (5%) (10%) level respectively.

References

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, *23*(4), 589–609. http://www.jstor.org/stable/2978933

Amel-Zadeh, A., & Serafeim, G. (2018). Why and how investors use esg information: Evidence from a global survey. *Financial Analysts Journal*, *74*(3), 87–103. https://doi.org/10.2469/faj.v74.n3.2

Barnea, A., & Rubin, A. (2010). Corporate social responsibility as a conflict between shareholders. *Journal of business ethics*, *97*(1), 71–86.

Berg, F., Koelbel, J. F., & Rigobon, R. (2019). *Aggregate confusion: The divergence of esg ratings*. MIT Sloan School of Management. https://doi.org/http://dx.doi.org/10.2139/ssrn.3438533

Bolton, P., Despres, M., Da Silva, L. A. P., Samama, F., Svartzman, R., et al. (2020). The green swan. *BIS Books*.

Bolton, P., & Kacperczyk, M. (2020). Do investors care about carbon risk? (26968). https://doi.org/10.3386/w26968

Busch, T., & Lewandowski, S. (2018). Corporate carbon and financial performance: A meta-analysis. *Journal of Industrial Ecology*, *22*(4), 745–759.

Caragnano, A., Mariani, M., Pizzutilo, F., & Zito, M. (2020). Is it worth reducing ghg emissions? exploring the effect on the cost of debt financing. *Journal of Environmental Management*, *270*, 110860. https://doi.org/https://doi.org/10.1016/j.jenvman.2020.110860

Clarkson, P. M., Li, Y., Pinnuck, M., & Richardson, G. D. (2015). The valuation relevance of greenhouse gas emissions under the european union carbon emissions trading scheme. *European Accounting Review*, *24*(3), 551–580.

Cohen, M., Fenn, S., & Konar, S. (1997). Environmental and financial performance: Are they related? http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.498.9820&rep=rep1&type=pdf

Dahlmann, F., Branicki, L., & Brammer, S. (2019). Managing carbon aspirations: The influence of corporate climate change targets on environmental performance. *Journal of business ethics*, *158*(1), 1–24.

Delis, M. D., de Greiff, K., & Ongena, S. (2019). Being stranded with fossil fuel reserves? climate policy risk and the pricing of bank loans. *Climate Policy Risk and the Pricing of Bank Loans (April 21, 2019). Swiss Finance Institute Research Paper*, (18-10).

Derwall, J., Guenster, N., Bauer, R., & Koedijk, K. (2005). The eco-efficiency premium puzzle. *Financial Analysts Journal*, *61*(2), 51–63. http://www.jstor.org/stable/4480656

Du, X., Weng, J., Zeng, Q., Chang, Y., & Pei, H. (2017). Do lenders applaud corporate environmental performance? evidence from chinese private-owned firms. *Journal of Business Ethics*, *143*(1), 179–207.

Ehlers, T., & Packer, F. (2017). Green bond finance and certification. *BIS Quarterly Review September*. https://ssrn.com/abstract=3042378

El Ghoul, S., Guedhami, O., Kwok, C. C., & Mishra, D. R. (2011). Does corporate social responsibility affect the cost of capital? *Journal of Banking & Finance*, *35*(9), 2388–2406.

Elkington, J. (1998). Accounting for the triple bottom line. *Measuring Business Excellence*, *2*(3), 18–22. https://doi.org/https://doi.org/10.1108/eb025539

Flammer, C. (2021). Corporate green bonds. *Journal of Financial Economics*. https://doi.org/https://doi.org/10.1016/j.jfineco.2021.01.010

Freeman, R. E. (1984). *Strategic management: A stakeholder approach*. Cambridge University Press. https://doi.org/10.1017/CBO9781139192675

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

Friedman, M. (1970). A Friedman doctrine - The Social Responsibility of Business Is to Increase Its Profits. *New York Times Magazine*.

Gabbi, G., & Sironi, A. (2005). Which factors affect corporate bonds pricing? empirical evidence from eurobonds primary market spreads. *The European Journal of Finance*, *11*(1), 59–74.

Ge, W., & Liu, M. (2015). Corporate social responsibility and the cost of corporate bonds. *Journal of Accounting and Public Policy*, *34*(6), 597–624. https://doi.org/https://doi.org/10.1016/j.jaccpubpol.2015.05.008

Gianfrate, G., & Peri, M. (2019). The green advantage: Exploring the convenience of issuing green bonds. *Journal of Cleaner Production*, *219*, 127–135. https://doi.org/https://doi.org/10.1016/j.jclepro.2019.02.022

Goss, A., & Roberts, G. S. (2011). The impact of corporate social responsibility on the cost of bank loans. *Journal of Banking & Finance*, *35*(7), 1794–1810. https://doi.org/https://doi.org/10.1016/j.jbankfin.2010.12.002

Griffin, P., & Heede, C. (2017). The carbon majors database. *CDP carbon majors report 2017*, *14*.

Guenster, N., Bauer, R., Derwall, J., & Koedijk, K. (2011). The economic value of corporate eco-efficiency. *European financial management*, *17*(4), 679–704.

Gupta, K. (2018). Environmental sustainability and implied cost of equity: International evidence. *Journal of Business Ethics*, *147*(2), 343–365.

Hart, S. L., & Ahuja, G. (1996). Does it pay to be green? an empirical examination of the relationship between emission reduction and firm performance. *Business strategy and the Environment*, *5*(1), 30–37.

Hartzmark, S. M., & Sussman, A. B. (2019). Do investors value sustainability? a natural experiment examining ranking and fund flows. *The Journal of Finance*, *74*(6), 2789–2837.

Heinkel, R., Kraus, A., & Zechner, J. (2001). The effect of green investment on corporate behavior. *The Journal of Financial and Quantitative Analysis*, *36*(4), 431–449. http://www.jstor.org/stable/2676219

Hoffmann, V. H., & Busch, T. (2008). Corporate carbon performance indicators. *Journal of Industrial Ecology*, *12*(4), 505–520. https://doi.org/https://doi.org/10.1111/j.1530-9290.2008.00066.x

Jung, J., Herbohn, K., & Clarkson, P. (2018). Carbon risk, carbon risk awareness and the cost of debt financing. *Journal of Business Ethics*, *150*(4), 1151–1171. https://EconPapers.repec.org/RePEc:kap:jbuset:v:150:y:2018:i:4:d:10.1007_s10551-016-3207-6

Khan, M., Serafeim, G., & Yoon, A. (2016). Corporate sustainability: First evidence on materiality. *Accounting Review*, *91*(6), 1697–1724.

Kim, Y.-B., An, H. T., & Kim, J. D. (2015). The effect of carbon risk on the cost of equity capital. *Journal of Cleaner Production*, *93*, 279–287. https://doi.org/https://doi.org/10.1016/j.jclepro.2015.01.006

King, A., & Lenox, M. (2002). Exploring the locus of profitable pollution reduction. *Management Science*, *48*(2), 289–299.

Klassen, R. D., & McLaughlin, C. P. (1996). The impact of environmental management on firm performance. *Management Science*, *42*(8), 1199–1214. http://www.jstor.org/stable/2634452

Konar, S., & Cohen, M. A. (2001). Does the market value environmental performance? *Review of economics and statistics*, *83*(2), 281–289.

Krueger, P., Sautner, Z., & Starks, L. T. (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies*, *33*(3), 1067–1111.

Kumar, P., & Firoz, M. (2018). Impact of carbon emissions on cost of debt-evidence from india. *Managerial Finance*, *44*, 1401–1417. https://doi.org/10.1108/MF-03-2018-0108

Labatt, S., & White, R. R. (2011). *Carbon finance: The financial implications of climate change* (Vol. 362). John Wiley & Sons.

Larcker, D. F., & Watts, E. M. (2020). Where's the greenium? *Journal of Accounting and Economics*, *69*(2-3), 101312.

Li, Y., Eddie, I., & Liu, J. (2014). Carbon emissions and the cost of capital: Australian evidence. *Review of Accounting and Finance*, *13*, 400–420. https://doi.org/10.1108/RAF-08-2012-0074

Lyon, T. P., & Montgomery, A. W. (2015). The means and end of greenwash. *Organization & Environment*, *28*(2), 223–249.

Maaloul, A. (2018). The effect of greenhouse gas emissions on cost of debt: Evidence from canadian firms. *Corporate Social Responsibility and Environmental Management*, *25*(6), 1407–1415.

Magnanelli, B., & Izzo, M. F. (2017). Corporate social performance and cost of debt: The relationship. *Social Responsibility Journal*, *13*, 250–265. https://doi.org/10.1108/SRJ-06-2016-0103

Malik, M. (2015). Value-enhancing capabilities of csr: A brief review of contemporary literature. *Journal of Business Ethics*, *127*(2), 419–438.

Maltais, A., & Nykvist, B. (2020). Understanding the role of green bonds in advancing sustainability. *Journal of Sustainable Finance & Investment*, 1–20.

Matsumura, E. M., Prakash, R., & Vera-Munoz, S. C. (2014). Firm-value effects of carbon emissions and carbon disclosures. *The accounting review*, *89*(2), 695–724.

McGlade, C., & Ekins, P. (2015). The geographical distribution of fossil fuels unused when limiting global warming to 2 c. *Nature*, *517*(7533), 187–190.

Menz, K. M. (2010). Corporate social responsibility: Is it rewarded by the corporate bond market? a critical note. *Journal of Business Ethics*, *96*(1), 117–134. http://www.jstor.org/stable/40836192

Moneva, J. M., & Cuellar, B. (2009). The value relevance of financial and non-financial environmental reporting. *Environmental and Resource Economics*, *44*(3), 441–456.

Ng, A. C., & Rezaee, Z. (2015). Business sustainability performance and cost of equity capital. *Journal of Corporate Finance*, *34*, 128–149. https://doi.org/https://doi.org/10.1016/j.jcorpfin.2015.08.003

Polbennikov, S., Desclée, A., Dynkin, L., & Maitra, A. (2016). Esg ratings and performance of corporate bonds. *The Journal of Fixed Income*, *26*(1), 21–41. https://doi.org/10.3905/jfi.2016.26.1.021

Porter, M. E., & Kramer, M. R. (2006). The link between competitive advantage and corporate social responsibility. *Harvard business review*, *84*(12), 78–92.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1), 41–55.

Russo, M. V., & Fouts, P. A. (1997). A resource-based perspective on corporate environmental performance and profitability. *Academy of management Journal*, *40*(3), 534–559.

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

Schoenmaker, D., & Schramade, W. (2019a). Investing for long-term value creation. *Journal of Sustainable Finance & Investment*, *9*(4), 356–377. https://doi.org/10.1080/20430795.2019.1625012

Schoenmaker, D., & Schramade, W. (2019b). *Principles of sustainable finance*. Oxford University Press.

Semenova, N., & Hassel, L. G. (2015). On the validity of environmental performance metrics. *Journal of Business Ethics*, *132*(2), 249–258. http://www.jstor.org/stable/24703538

Sengupta, P. (1998). Corporate disclosure quality and the cost of debt. *The Accounting Review*, *73*(4), 459–474. http://www.jstor.org/stable/248186

Sharfman, M. P., & Fernando, C. S. (2008). Environmental risk management and the cost of capital. *Strategic Management Journal*, *29*(6), 569–592. http://www.jstor.org/stable/20142042

Tang, D. Y., & Zhang, Y. (2020). Do shareholders benefit from green bonds? *Journal of Corporate Finance*, *61*, 101427.

Taylor, M., & Watts, J. (2019). Revealed: The 20 firms behind a third of all carbon emissions. *The Guardian*, *9*(10), 2019.

Trinks, A., Mulder, M., & Scholtens, B. (2020). An efficiency perspective on carbon emissions and financial performance. *Ecological Economics*, *175*, 106632.

United Nations (Ed.). (2020). *7. d paris agreement*. https://treaties.un.org/Pages/ViewDetails.aspx?src=TREATY&mtdsg_no=XXVII-7-d&chapter=27&clang=_en#4

van Marrewijk, M. (2003). Concepts and definitions of csr and corporate sustainability: Between agency and communion. *Journal of Business Ethics*, *44*(2/3), 95–105. http://www.jstor.org/stable/25075020

Walley, N., & Whitehead, B. (1994). It's not easy being green. *Harvard Business Review*, *72*(3), 46–51. https://search-ebscohost-com.eur.idm.oclc.org/login.aspx?direct=true&db=buh&AN=9406231651&site=ehost-live&scope=site

Wang, A. W., & Zhang, G. (2009). Institutional ownership and credit spreads: An information asymmetry perspective. *Journal of Empirical Finance*, *16*(4), 597–612. https://doi.org/https://doi.org/10.1016/j.jempfin.2009.04.002

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica: journal of the Econometric Society*, 817–838.

Zerbib, O. D. (2019). The effect of pro-environmental preferences on bond prices: Evidence from green bonds. *Journal of Banking & Finance*, *98*, 39–60.