SCHOOL OF ECONOMICS AND MANAGEMENT

The impact of environmental performance on credit ratings

Master Thesis in Economics

NEKN01

Department of Economics, Lund University

23.05.2023

Author:

Marta Celina Brejwo

Supervisor:

Hossein Asgharian

Abstract

This paper aims to investigate the relationship between environmental performance and credit ratings on the Asian, European, and North American market in the context of the ESG framework over a period of ten years through 2013-2022. Through the usage of primarily POLS and POLS with a fixed year effect model, 242 firms across the different regions are studied on an aggregate level, in terms of being consumer oriented and manufacturing intensive as well as on a regional level in order to explore said relationship. The findings speak in favor of better environmental performance leading to higher credit ratings, however what precise components of the environmental performance lead to this effect is shown to be circumstantial and vary across industries and regions. The largest effects could be found for the manufacturing intensive industries, as well as for the North American region.

Keywords: ESG, CSR, Environmental performance, Credit ratings, Credit risk

Table of contents

Abbreviations

CDS	Credit Default Swap
CE	Circular Economy
CRA	Credit Rating Agency
CSR	Corporate Social Responsibility
ESG	Environmental, Social and Governance
FEM	Fixed Effects Model
GMM	Generalized Method of Moments
OLS	Ordinary Least Squares
POLS	Pooled Ordinary Least Squares
REM	Random Effects Model
SRI	Socially Responsible Investment

1. Introduction

The aim of this essay is to investigate the effect of environmental performance on credit ratings with regard to firms in Europe, North America, and Asia. The research is conducted in the context of the environmental, social and governance (ESG) framework, using global data. With its findings, this essay hopes to clarify what relationship environmental performance has with credit ratings, as well as what specific aspects of it could be of more critical importance.

ESG has throughout the recent years become an increasingly important topic for companies that wish to thrive in the modern world's social setting. The work that a company performs in terms of environmental and social responsibility, as well as good governance, is continuously experiencing growing prominence. Investments in sustainable funds have grown more than tenfold between 2005 and 2021, and by 2022 over 90% of S&P 500 companies have started publishing ESG reports (Pérez, Hunt, Samandari, Nuttall & Biniek, 2022) to meet the growing demand from various stakeholders. With the increased interest in ESG and the way that it is incorporated into firms' business practices it is interesting to examine the effect that ESG activities have on financial performance and creditworthiness. It has been shown that good ESG performance in most cases tends to lead to better return on equity (ROE), better return on assets (ROA) and increased stock price (Whelan, Atz & Clark, 2021). Hence, increased disclosure on ESG performance can help to attract investors, especially in terms of the environmental and governance components (Chen & Xie, 2022). However, activities linked to ESG performance also have a tendency of leading to high operating costs and can, as a result of this, lead to lower financial performance (Chen, Kuo & Chen, 2022). This would essentially entail that ESG activities can in some cases to be too costly to atone for the positive aspects of them. A positive correlation between ESG and a firm's financial performance may also often be explained by other factors, such as positive conditions in the industry (Pérez et.al., 2022), suggesting its dependence on other factors.

With regard to ESG and credit risk, existing studies focus largely on the relationship between ESG metrics and credit default swaps (CDS). While it has been shown that there is a negative relationship between ESG and CDS spreads, it is important to note that this effect varies with each firm's level of ESG performance, making it the largest in those firms that perform modestly in terms of ESG rather than exceptionally high or low (Barth, Hübel & Scholz, 2022).

Similarly, research studying the mitigation effects of corporate social responsibility (CSR) levels on CDS spreads showed that a higher corporate sustainability level leads to lower spreads and thereby lower credit risk (Caiazza, Galloppo & La Rosa, 2023). Another way to help assess the credit risk within a firm is with the use of credit ratings, as it has been done in studies conducted by Stellner, Klein & Zwergel (2015) or Zanin (2020). Credit ratings can be used as a tool to assess the credit risk of a firm by stakeholders such as investors or regulators (Piccolo & Shapiro, 2022). Due to their ease of comparison, they are advantageous in terms of deciding between investment choices.

As existing studies are inconclusive on whether increased ESG activity leads to an increase in financial performance, as well as what effect it has on credit risk, the topic requires deeper investigation. Although the majority of studies up to date focus on ESG ratings in general, this study focuses specifically on the environmental component of ESG to give a better insight on the relationship of this constituent with credit ratings. This study will reflect on past financial performance and the correlating environmental metrics to capture a potential future effect that might be realized in terms of environmental performance and credit ratings. This being rooted in the idea of expectations of environmental performance having an impact on reputational risk, and in turn the level of trust that stakeholders have in the company (Teor, Ilyina & Kulibanova, 2022). Investors are now more aware on topics regarding climate change and related environmental issues and, although further studies are needed, it has already in several cases been reported that these factors may have both a negative and positive effect on credit ratings (S&P Global Ratings, 2017).

While it would be particularly interesting to examine this relationship on the European market, as studies doing so are scarce, lack of sufficient data makes it harder to do so. The study therefore includes a broad sample of firms in Europe, North America as well as Asia using a panel data approach. To distinguish between the three markets and examine them independently, both aggregate and separate regressions are run on the dataset. In addition to regressions being separately run for each of the three regions, the study also controls for two groups that distinguish firms from one another based on the sector that they belong to. These groups consider whether the firm is consumer-oriented or manufacturing intensive; in some cases, both. This to examine whether there are large variations in the relationship between environmental metrics and credit ratings depending on the type of industry. The findings ultimately show that there is supporting evidence in favor of better environmental performance leading to higher credit ratings, however that what components of it weigh the heaviest can be highly circumstantial and vary in their significance depending on the context.

This study has the following structure. Chapter two introduces a literature review, with explanations of the terms used as well as a review of existing studies regarding the aforementioned topic. Chapter three thereafter presents an overview of the data as well as the chosen methodology for the subsequent analysis. This is followed by an empirical analysis in chapter four, where results and findings are presented, as well as a discussion where the implications of the results are debated. The study concludes in chapter five with final remarks and suggestions for potential future research that could complement the findings.

2. Literature review

This section aims to give an overview on existing literature regarding the topic studied. It begins with the history of ESG, where the concept is introduced and explained. This is followed by a subsection explaining the connection between ESG and credit risk, and thereby credit ratings. Subsequently, ESG and its relation to reputational risk and industry is discussed. The section ends with a presentation of hypotheses based on the literature review.

2.1 History of ESG

Although ESG is a term often used interchangeably with corporate social responsibility (CSR), it has been noted that while CSR tends to focus more on social contribution ESG focuses on corporate governance and investors (Jun, 2023). It is however worth noting that since social metrics are included in the scope of ESG this study will treat ESG as an extension of CSR.

The concept of ESG is said to originate in as early as the 1960s as a concept of socially responsible investing, or SRI (MSCI, n.d.). With time the term evolved into CSR, defined as 'a commitment that an organization must have towards society, expressed through acts and attitudes that affect it positively.' (Anholon, Quelhas, Filho, Pinto & Feher, 2016, p. 740). This in terms of social, environmental, and economic aspects. CSR therefore puts pressure on firms towards their stakeholders, to work beyond strict financial gain and embrace the socio-ecological obligations that they are faced with (Anholon et.al., 2016). Ultimately, increased efforts in CSR-related activities are often introduced to increase stakeholder satisfaction, even though doing so may lead to decreased profits (Valiente, Ayerbe & Figueras, 2012). With a shift in investors' interest into environmental, social and governance issues the term ESG was coined and introduced for the first time by the United Nations (UN) in their report '*Who Cares Wins: Connecting Financial Markets to a Changing World*' (Eccles, Lee & Stroehle, 2020). Since then, the demand for ESG data and its presence in the corporate sphere has been continuously growing. There is today a wide variety of agencies offering ESG ratings in terms of a wide range of metrics, that may differ in both content and ways of measurement across different CRA's. The biggest providers include MSCI, providing ESG ratings for over 6 000 companies and 400 000 securities, as well as Sustainlytics, with ratings for over 7 000 companies (Atkins, 2020). As each agency may have their own methods in the collection of data there is no universal scale range that determines how well the corporation performs in terms of the assigned ratings.

Although it is acknowledged that environmental, social and governance are three pillars that make up the base for ESG, there is no definition specifying the components that each pillar should include or how they should be measured (Eccles et.al., 2020). The lack of a harmonized way to measure and report their metrics remains a large issue. Valiente et.al. (2012) identify the lack of an interdisciplinary measurement approach as a problem, highlighting that although corporate responsibility is a global term there are few guidelines or standards that can unify results between different organizations. This poses an obstacle when it comes to intercorporate comparisons, as differing methods may lead to divergent results. Berg, Kölbel & Rigobon (2022) examined the divergence of ESG ratings across six different agencies and found that how the ratings are measured account for 56% of the divergence in the scores, with the underlying data being the main reason. Furthermore, the authors argued that more transparency is needed from the rating agencies in terms of measurement and method assigned to their scoring. The discrepancy has also shown to be larger in cases where there is more disclosure from the firms' side, ultimately juxtaposing the pressuring need for increased reporting with the offsetting effect of diverging ESG scores between credit rating agencies (CRA's) (Liu, 2022). Similar results were found by Dorfleitner, Halbritter & Nguyen (2015) concluding that complexity of assessment and transparency in terms of ESG measurements, as well as differing methods in terms of quantitative and qualitative judgments lead to different results. It was also found that larger firms tend to have higher ESG scores as well, which may be due to the fact that they have larger reporting and disclosure on their activities as compared to smaller firms. Although more information on ESG related activities is something that stakeholders look positively upon, the current lack of regulations surrounding the reporting of these actions is becoming problematic (Arvidsson & Dumay, 2021). It is therefore important to note that the way in which firms across different industries report their ESG performance is not harmonized. This entails that the conclusions drawn on the topic in academic research are at risk of large variations depending on the source of said metrics. Ultimately, these issues may lead to greenwashing practices (Martini, 2021) since the lack of unanimous reporting may lead investors and stakeholders astray in terms of the actions that the corporation is undertaking.

Hence, while ESG reporting may increase because of the pressure from stakeholders there may be reason to believe that actual ESG performance does not (Arvidsson & Dumay, 2021).

2.2 ESG in relation to credit risk

Credit risk can be defined as the risk that a company may not be able to repay the obligation that it took upon i.e., the risk of an unpaid debt. It can be divided into three components: probability of default (PD), loss given default (LGD) and exposure at default (EAD) (Spuchl'akova & Cug, 2014). A common way to examine the credit risk of a company in relation to other relevant factors is credit default swaps (CDS), that are used as a way to hedge against credit risk, this as in the case of Subrahmanyam, Tang & Wang (2014) that studied the impact CDS has on corporate risk and liquidity management. Along with CDS, studies investigating credit risk advocate for the use of credit ratings as a tool as well. Zanin (2020) chose to do precisely this when investigating the relationship between ESG effects and credit ratings. Credit ratings take probability of default into account in terms of both qualitative and quantitative criteria, i.e., they act as an accurate assessment of the creditworthiness of the company (Weissova, Kollar & Siekelova, 2015). Credit ratings are therefore an effective way for investors to assess the financial standing of a company and determine the risk of a potential investment from a stakeholder's point of view. Fabozzi, Breemen, Vink, Nawas & Gengos (2022) found this to be especially applicable in the United States, with weaker evidence for Europe. The authors used credit ratings from Moody's as well as S&P and examined the weight that investors put on credit ratings when it comes to funding collateral loan obligations (CLO's). They concluded that the reliance is high and highlighted the fact that the divergence between the US and European markets increased with the global financial crisis. Regarding regional differences when it comes to credit risk, Choi (2022) found that when it comes to interdependence in credit risk Asia, North America and Europe seem to be highly connected when considered together. Additionally, the author also found that particularly Asia and North America display significant relationships when it comes to credit risk when analyzed in the long run.

As the significance of ESG performance is on the rise there is a growing interest in when it comes to studies related to ESG and financial performance, including aspects of credit risk. As recently as in 2019 the CRA Fitch announced that they will begin including ESG metrics in their credit rating processes (Chalamish, 2019). By doing so they are not an exception. S&P, that is also a provider of credit ratings, maintains that ESG metrics have a large impact on the creditworthiness of companies. The CRA therefore assesses ESG credit indicators as important factors when it comes to analyzing credit ratings (S&P Global Ratings, 2023a). S&P also maintains that environmental factors have a large negative influence on debt, with climate transition risks being the largest contributing component because of its correlation with carbon emissions. This provides firms with a need to meet expectations and environmental regulations by 'modify[ing] its production processes, supply chain, or product lines to adapt to stricter regulations, taxonomy, or pressure from its stakeholders, including financers.' (S&P Global Ratings, 2022, p. 5).

Existing studies examining the relationship between credit ratings and ESG or CSR related metrics present varying outcomes. Stellner, Klein & Zwergel (2015) conducted a study where they examined the relationship between CSR and credit ratings based on bonds in twelve countries within the European Monetary Union. Although the authors found no statistically significant correlation between the two variables, they concluded that companies will generally enjoy higher credit ratings given that the ESG levels of the country are above average. Zanin (2020) further examined the relationship between ESG and credit ratings and found that the environmental metrics play a larger role in terms of credit ratings than social and governance scores. The author used scores from two different CRA's and showed that the effect of ESG on credit ratings was the largest in mining and quarrying industries, whilst no such unanimous results could be obtained for social and governance metrics as the results differed between the agencies. It is therefore reasonable to assume that the findings of each study conducted might differ not only depending on the methodology used but also depending on the CRA chosen to provide the ratings as well as the source of the ESG metrics. It is also important to note that results will differ depending on the chosen ESG variables.

When it comes to studies focusing on what effect environmental metrics in particular have on credit ratings, the results are scarcer. Agliardi, Alexopolous & Karvelas (2023) researched the relationship between the environmental pillar of ESG and financial performance, the authors found that companies with a low environmental score tend to have better financial performance and are associated with higher returns - thereby decreasing the credit risk. Youngtae (2021) examined the impact of environmental strategy, organization, management, and performance on credit ratings in South Korea and found that environmental performance along with stakeholder communications had the biggest impact on credit ratings. The author therefore concluded that companies with a high level or corporate environmental responsibility are deemed more reliable when perceived by creditors. However, as the literature covering the topic of environmental metrics and their relation to credit ratings has not been widely covered more studies on the subject are needed.

2.3 ESG in relation to industries

The value of a company's ESG performance, creditworthiness aside, lies largely in the perception that its stakeholders hold. ESG performance has a positive effect on corporate value, since it may attract media attention and act in favor of how the company is perceived (Zheng, Wang, Sun & Li, 2022). Reputational risk is thus decreased the better the companies perform in terms of ESG related activities. These findings are supported by Teor et.al. (2022) as they found that ESG is an essential part when it comes to shaping your corporate reputation and gaining trust. A failure of incorporating ESG metrics into the operations of a firm can hence be detrimental with regards to reputational risk. A study conducted by Fafaliou, Giaka, Konstantios & Polemis (2022) conducted on the US market showed that the longevity of a firm is strongly impacted by ESG reputational risk, suggesting that it is beneficial for firms to embrace ESG best practices and incorporate these into their businesses. An increase in ESG related reputational risk is also proven to lead to 'increased information asymmetry between stakeholders and managers, which leads to adverse selection and increased cost of equity and financial underperformance.' (Agoraki, Giaka, Konstantios & Patsika, 2023, p. 16). This is largely due to uncertainty amongst stakeholders that grows when their perception of the trustworthiness of the company diminishes. Additionally, it is shown that ESG controversies are correlated with lower credit ratings in the European banking industry, which may be explained by a high reputational risk since the industry is active in what is deemed a 'trust-based sector' and is therefore largely dependent on its consumers and their perception of the organization (Samaniego-Medina & Giráldez-Puig, 2022). Because of its effect on reputational risk, ESG performance may have a large impact on stakeholders, their investment and in turn the financial performance of the company. The reason for why credit ratings could diminish with increased reputational risk might also be connected to the issue of ESG related technological innovation. High-technology firms are becoming more committed to ESG related activities (Teor et.al., 2022) and green technology, which has its focus on combating environmental issues, is becoming increasingly important to drive ESG performance forward and thereby improve reputational risk (Zhang & Jin, 2022). Better technology may essentially lead to improvements in ESG activities and create positive spillover effects.

A risk related to the subject of reputational risk in relation to ESG is that of greenwashing. Yu, Luu & Chen (2020) conducted a study where they examined greenwashing behavior by identifying firms that report high scores of ESG activities that are not reflected in practice. The authors found that the risk of greenwashing decreases when stakeholders demand greater transparency on how actual ESG performance is connected to what is being reported. However, it is also mentioned that due to a lack of common regulations ESG reporting often remains unaudited which can serve as a barrier for overcoming this issue.

When it comes to ESG and portfolio debt management Verheyden, Eccles & Feiner (2016) acknowledge that ESG metrics can help investors assess the future performance of firms and act as value creating. This especially in a setting where the social pressure regarding environmental matters is substantial. It was also found that excluding certain companies based on ESG criteria, so called ESG screening, had a positive effect on annual performance of the investor portfolio with an average of 0,16% added regardless of the investment strategy chosen (Verheyden et.al., 2016). Martini (2021) similarly found that increased work with ESG is closely related to SRI, as retail investors increasingly demand that the behavior of firms aligns with that which is deemed socially responsible.

Yet another indicator or how well a firm performs in terms of ESG can be closely associated with the type of industry it belongs to. Naeem, Cankaya & Bildik (2022) examined the relationship between ESG performance and financial performance in what they deemed to be environmentally sensitive industries - meaning industries with a large environmental impact in their production processes. The authors found that the ESG performance had a positive relationship with profitability, and in turn on the market value, of the corporations included in the study. Companies belonging to so called ‘sensitive industries’, i.e. those ‘more likely to cause social and environmental damage.’ have shown to perform better in terms of ESG (Garcia, Mendes-Da-Silva & Orsato, 2017, p. 135). Furthermore, companies belonging to manufacturing intensive industries will tend to disclose more on their environmental actions (Garcia et.al., 2017). Thereby, when a company faces more reputational risk because of the industry it finds itself in it may be actively working towards improving its environmental processes and overall ESG performance to meet public pressure and be perceived in a more positive light.

Additionally, the value of SRI - and thereby the value of a firm's environmental performance - can vary between regions as proved by Badía, Cortez & Ferruz (2020). The authors found that ESG disclosure, and CSR in general, is highly valued in North America in comparison to Europe, Japan, and Asia Pacific. It was also highlighted that the regional differences may occur due to the fact that 'different regions may be in different stages of development with regard to investor awareness and understanding of the valuation impact of CSR practices.' (Badía et.al., 2020, p. 2760). The value of ESG, and thereby environmental performance, is therefore shown not only to depend on reputational risk and industry, but also on the geographical location of the firms.

2.4 Hypotheses

The literature review largely revolves around the idea of all three pillars of ESG metrics being prominent and influential when it comes to the assessment of firms' creditworthiness and credit ratings. However, few studies treat the topic of environmental metrics exclusively in relation to credit ratings, and thereby a firm's financial standing. Based on the theoretical framework described above, the following hypotheses have been formed.

Hypothesis 1:
Better environmental performance leads to higher credit ratings.

With its steadily increasing presence in firms' annual reports and increasing interest for stakeholders, ESG metrics have proven to be a topic of importance when assessing the prosperity of firms. Additionally, studies such as those conducted by Youngtae (2021) and Zanin (2020) emphasize the importance of environmental performance and metrics when it comes to assessing credit ratings. Their arguments speak in favor of this hypothesis.

Hypothesis 2:

Better environmental performance leads to higher credit ratings in consumer-oriented industries.

This being due to increased exposure to public pressure and higher reputational risk. Industries having a closer relationship to their investors and other stakeholders run a larger reputational risk if they choose not to comply with actions and values deemed to be socially desirable. A failure to meet these expectations may thereby act detrimentally on the reputation of the firm and have a negative impact on its financial performance, as supported by studies conducted by Fafaliou et. al. (2022) as well as Agoraki et.al. (2023). A negative public perception may impact market share, and in turn credit ratings, as investors could turn to a competitor if the company's values do not align with their own.

Hypothesis 3:
Better environmental performance leads to higher credit ratings in manufacturing intensive industries, whereas the impact tends to be lower in capital intensive industries.

Firms in manufacturing industries and industries that are associated with having a negative environmental impact tend to actively work against this bad reputation and thereby perform better in terms of environmental scoring and ESG ratings, as proven by Naeem et.al. (2022) and Garcia et.al. (2017). Because manufacturing intensive industries produce greater emissions and therefore stand at risk of higher pollution, they bear a greater risk of facing lower ratings when it comes to the environmental aspect of their performance which they need to counteract.

Hypothesis 4:
There are cross-regional differences regarding the relationship between environmental performance and credit ratings.

As the degree of environmental awareness may differ between regions, and thereby the exposure to reputational risk, it is reasonable to assume that environmental performance has differing effects on credit ratings between them. This as supported by the findings of Badía, Cortez & Ferruz (2020) who concluded that North America was the most mature market for valuation of ESG practices. There is also reason to believe that Asia and North America could display a close relationship in this study, as their credit risks have shown to be significantly related in the long run (Choi, 2022).

3. Data and methodology

This section begins by presenting the data used in this study along with its sources as well as information on distribution. Thereafter, the methodology is introduced where the choice of models is presented and evaluated.

3.1 Data Selection

The data used in the study consists of observations for 242 companies over the period of ten years between 2013 and 2022. All companies chosen for the study have their country of exchange in Europe, Asia, or North America. The main reasoning in the choice of regions was the availability of relevant data. Specifically, critical criteria in the study were the availability of credit rating data over the chosen period of years, as well as accessibility to environmental metrics and firm-specific control variables. This resulted in discardment of companies lacking significant amounts of data for the above-mentioned criteria. Companies were also discarded for the years where no credit rating data was available. Each company was divided into one of the eleven Global Industry Classification Standard (GICS) sectors, presented in Appendix A, Table A.1. The division into GICS sectors was sourced from Refinitiv Eikon. In the appendix, the relevant sectors were also categorized as consumer-oriented and manufacturing intensive in alignment with hypotheses two and three.

Each year for each company is treated as a separate observation, resulting in a total of 2 013 observations. Out of these observations 821 were collected for Asia, 601 for Europe, and 591 for North America. All monetary variables were collected and analyzed in USD.

3.1.1 Credit Rating data

Credit ratings are treated as a measure of credit risk in this study. The credit ratings used for the study were those reported as long-term credit ratings as well as long term counterparty risk ratings by Moody's Investors Service at the end of each fiscal year between 2013 and 2022. These serve to assess a firm's credit quality and ability to 'meet its financial commitments'

(S&P Global Ratings, 2023b.). Essentially, credit ratings are a way for investors and shareholders to assess the safety of their investment in relation to the likelihood of the firm defaulting and the ability of the firm to manage their finances. It has also been shown that credit ratings tend to influence CDS spreads and credit spreads (Daniels & Jensen, 2005), making them an important determinant in investment related decisions.

Although credit ratings can be a good indicator of the creditworthiness of a firm, they also comes with drawbacks. A fundamental critique is the lack of objectivity when it comes to measuring the ratings (Rafailov, 2011). As there is no universal regulation advocating on the way that credit rating should be measured, various CRA's can produce ratings that may differ and thereby be misleading towards their recipients. Moreover, Luitel, Vanpée & De Moor (2016) found that CRA's tend to be biased in the way they assess credit ratings of their home countries as compared to international financial markets. The authors also found that credit ratings in emerging markets often need to be based on subjective judgement on a larger scale than in established markets, as there may be a lack of quantitative data to accurately assess them. This may further increase the bias.

The scale of Moody's credit ratings ranges from Aaa as the highest rating representing minimal risk, down to C as the rating representing an obligation that potentially might be in default and having low chance of recovery (Moody's Investors Service, n.d.). The following figure illustrates the distribution of credit ratings for the chosen companies over a period of ten years ranking from the lowest to the highest rating, the frequency can also be found in Appendix A, Table A.2.

As the credit rating data consists of categorical string variables, these are converted to numeric variables in a manner proposed by Ferri, Liu & Majnoni (2000). This to correctly incorporate the data into the performed regressions. Since a higher credit rating indicates a lower risk, the conversion assigns a higher value to the variable the better the credit rating. The conversion chart of the credit ratings to numerical variables can be found in Appendix A, Table A.2.

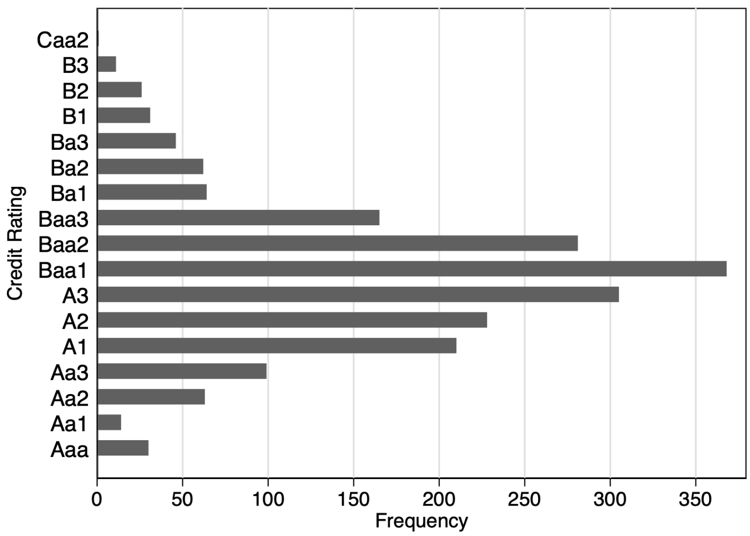

Figure 1: Distribution of credit ratings

The figure presents the frequency of credit rating grades sourced from Moody's Investor Service.

3.1.2 Data on environmental metrics

The data on environmental metrics used in this study was extracted from the Refinitiv Eikon database. The study includes five variables that focus on the environmental metrics of firms: the environmental pillar score grade, the emissions score grade, waste recycled to total waste, total energy used as well as water use to revenue. Refinitiv has developed their own system of calculating ESG related performance in their scores. The company describes their ESG performance calculations being based on reports provided by firms discounted by any ESG related controversies, using their 23 controversy measures which are not specified or disclosed. All the data provided by Refinitiv is based on public reports and thereby on what is disclosed by the companies and by media (Refinitiv Eikon, n.d.).

The environmental pillar score grade takes three categories into account. The first category considers the resource use of the company, and the possibility of incorporating more environmentally efficient solutions in the supply chain. The second category considers the emission reduction that the company works towards. Lastly, the third category includes the innovation of the company in terms of reducing 'the environmental costs and burdens for its customers' (Refinitiv, 2022, p. 25). This environmental pillar score is, along with the social pillar score and the governance pillar score, one of the three components of a total ESG score that Refinitiv assigns in its ratings. The emissions score grade is a component used in the environmental pillar score and will therefore not be included in regressions where the environmental pillar score is used. Because of the risk that the remaining environmental variables are encompassed in the environmental pillar score, they will not be regressed together with it either.

The environmental pillar score grade and the emissions score grade data were collected as string variables, these are converted to numerical variables in a manner similar to that of the conversion of credit ratings. The scores range from D- to A+, with D- denoting a company's performance in the area as poor whereas A+ indicates performance that is exceptionally good with the firm having a high level of transparency (Refinitiv, 2022). The conversion was based on the maximum percentile score for each grade that Refinitiv assigned in their metric calculations, which is then rounded up. For example, the environmental pillar score grade of D- is assigned a firm from 0 up to the 0.083333rd percentile. The score of D- is thereby assigned the value of 8.33 in this study. The conversion enables a regression of the scores with credit ratings in mind whilst also following the logic of Refinitiv's scoring system. The conversion chart of the scores of the environmental pillar score grade and the emissions score grade can be found in Appendix A, Table A.3 and the distribution of the environmental pillar score grade is shown in figure 2 below.

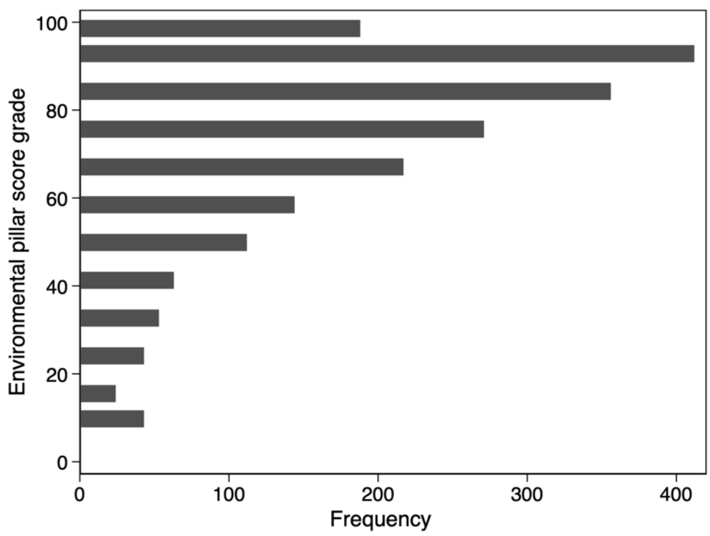

Figure 2: Distribution of the environmental pillar score grade

The figure presents the frequency of the environmental pillar score grade sourced from Refinitiv Eikon.

To take further environmental metrics into account the study also includes data on the waste recycled to total waste ratio, as an additional measure of the actions taken by the firm to account for their environmental impact. Because of its accessibility, waste management data tends to be a large component of the Circular Economy (CE) monitoring framework, intending 'to promote the responsible and cyclical use of resources.' (Moraga, Huysveld, Mathieux, Blengini, Alaerts, Acker, Meester & Dewulf, 2019, p. 452). It can therefore be an indicator of how a firm works with responsible resource management. However, it is important to keep in mind that the recycled waste does not necessarily entail conversion into recycled material, which is essentially what the environmental aspect of it requires (Moraga et.al., 2019). The study also includes total energy used by the companies to indicate how production intensive the firm is. Energy consumption is closely connected to environmental issues such as pollution, climate change and the emission of greenhouse gases (EEA, n.d.) and is therefore an important component of a firm's environmental performance. Additionally, this study also takes the water used to revenues into account. With increased water use we are at risk of lower water levels, which may have an impact on the environment in the form of 'higher concentrations of natural and human pollutants.' (EPA, n.d.).

3.1.3. Firm-specific control variables

To avoid the occurrence of research bias this study also includes firm-specific control variables that may affect both credit rating and the environmental scores. The control variables are collected from the Refinitiv Eikon database as well as S&P Capital IQ.

Net profit margin is used as a measure of the profitability of the firm, which is often negatively correlated with credit risk as a high level of profitability most likely entails good financial standing. According to Andriana & Anisykurlillah (2019, p. 143) the profit margin 'has a significant effect on financial performance through environmental disclosure as the intervening variable', due to the affordability to disclose more information on environmental performance that a higher profit margin leads to. Total debt to total equity is used as a measure of leverage, indicating how much of the firms' equity is composed of liabilities. A high ratio may indicate higher credit risk, as it indicates a high level of funding by debt. The measure is also linked to environmental performance, as with increasing pressure on firms to act sustainably it has been shown that although environmental strategies can increase financial debt, the cost of debt decreases with increased and better environmental performance (Fernández-Cuesta, Castro, Tascón & Castaño, 2019). The market-to-book ratio is used as a measure of market value and has been calculated as the share price over the book value per share at the end of each year 2013-2022. It is a good indicator of the value of the company and may therefore be positively correlated with credit ratings, as a higher market-to-book ratio also often indicates that a firm faces lower debt costs (Chen & Zhao, 2006). The environmental performance of a firm can at times have positive or negative effects on the market value of a firm, depending on the type of environmental announcement (Jacobs, Singhal & Subramanian, 2010). Lastly, total assets of the firm are included as a measure of the size of the company, since larger companies may often present better credit ratings and have a larger possibility of financing environmental activities. It may be the case that firms exert more environmental effort and have better environmental policies when they perform well financially (Hidayah, Wahyuningrum, Yanto, Suryandari, Suryarini, Dinassari & Rahayu, 2022).

A summary description of all variables used, and their various sources can be found in Appendix A, Table A.4.

3.2 Methodology

3.2.1 Choice of models

Previous studies examining the correlation between ESG metrics and credit ratings have focused on a variety of models. Chao, Mian, Xi & Wenli (2022) chose to explore the relationship between the two variables with both the instrumental variable method and the GMM method whilst examining this dynamic on the Chinese market. On the other hand, Zanin (2022) chose to use a multivariate ordinal logistic regression and instead examine the effect on credit ratings from two different types of CRA's. There is therefore no unanimous view on which model should be applied in similar studies. As this study uses panel data, it may be wise to consider the usage of regression models commonly deemed suitable for its analysis - pooled ordinary least squares model (POLS), fixed effects model and random effects model. Because the models may experience problems with autocorrelation and cointegration, all variables will be lagged by one period to reduce the risk of this occurring (Enders, 2014). It is also reasonable to assume that the credit ratings of a certain year are based on the information reported the year before, which further justifies the use of lagged variables. Additionally, variables that are not expressed as a score or ratio are logged to normalize them and improve the fit of the model. This applies to total energy used, water used to revenues and total assets.

3.2.2 Estimation approach

Pooled OLS (POLS) is a model in which you apply an OLS regression on to panel data without accounting for its structure, meaning that the individual effects are not explicitly accounted for but rather that each point in time with its associated variables will be treated as a separate entity (Vomberg, Wies, Homburg & Klarmann, 2022). The advantage of using this approach is that it provides consistent estimates if the error term has no correlation with the independent variables. However, the disadvantage with POLS is that its efficiency depends on whether the error terms are homoscedastic and not autocorrelated. To partially account for the potential problem with heteroskedasticity, robust standard errors are used in the regression (Hoechle, 2007). To account for the possibility of autocorrelation, the independent variables are lagged by one period.

Two other commonly used models fit for regressions performed on panel data include the fixed effects (FEM) and the random effects model (REM), which are also two types of OLS models. Both these models allow for heteroscedasticity and autocorrelation within a sample over time (not cross-sectionally) and are therefore a rational choice when it comes to models used on panel data. Gelman (2005) examined the different definitions of fixed and random effects and specified that fixed effects as those that are constant across all individuals in a sample and can be estimated with the least squares or the maximum likelihood model, while random effects are those that vary across all individuals and should be estimated with shrinkage - thereby, random variables are treated as non-random in the FEM. However, the author further argues that the definitions of fixed and random effects can often be conflicting and bear different definitions depending on the source. Demir & Doğuyurt (2022) expand the definitions onto fixed effects modelling and random effects modelling. The authors describe the fixed effects model as one characterized by homogeneous distributions where outcomes from the same population have the same effect. The authors also describe the random effects model as one with a heterogenous distribution, where the effect of the outcome in one population is random. I.e., whether a random effects model should be included in the study lies in the potential correlation or non-correlation between the regressor and the error term. When it comes to determining whether FEM or REM should be used Wooldridge (2002) advocates for the use of the Hausman test to examine the data for endogeneity. Under the null, the Hausman test dictates that the data is steered by random effects, and we should therefore use the random effects model in addition to the fixed effects model. If we can reject the null, the fixed effects model is the most appropriate choice and the random effects model will not be included. The results of the Hausman test performed on the chosen dataset resulted in the rejection of the null hypothesis, thereby choosing to discard the random effects model. It should however be kept in mind that the fixed effects model estimates its effects on mean adjusted values for all individual companies, it cannot differ between them.

4. Empirical Analysis and Findings

This section begins with a subsection discussing the descriptive statistics of the variables included in the study. It is thereafter continued with a subsection presenting the aggregate regression results, followed by the sectoral regression results and the regional regression results. The section concludes with a discussion of the implications of the results found in the study.

4.1 Descriptive statistics

Table 1 describes the summary statistics of all variables included in the study. Credit ratings, the environmental pillar score grade and the emissions score grade all range from the lowest to the highest possible score. All variables were tested for normality using the Shapiro-Francia test, as it was deemed suitable for variables having less than 5 000 observations. The null hypothesis of the data being normally distributed was rejected for all included variables. This will however not pose as a problem as robust standard errors are used.

Sector	Obs.	Mean	Sd.	Min.	Max.
Credit rating	2 013	66.66	13.72	5	100
Env. pillar score grade	1 926	73.34	21.85	8.33	100
Emissions score grade	1 926	79.36	24.18	8.33	100
Total energy used (logged)	1 645	15.38	2.21	3.33	20.11
Waste recycled to total waste	1 419	0.66	0.28	1.05e-5	1
Water use to revenues (logged)	1 671	6.13	2.66	-0.74	15.59
Net profit margin	2 013	0.17	0.23	1.881e-4	3.37
Total debt to total equity	2 008	1.13	1.37	6.923e-4	15.85
Market-to-book ratio	1 993	2.73	3.19	0.07	49.07
Total assets (logged)	2 013	24.23	1.46	20.15	28.78

Table 1: Summary statistics

The table presents summary statistics for all variables included in the study. It includes the number of observations, mean value, standard deviation, minimum value, and maximum value.

As mentioned in section 3.1, Asia is the region holding the largest number of observations, followed by Europe and lastly North America. Table 2 shows the frequency that the observations had across the range of GICS sectors. We can see that the Financials, Materials, and Industrials sectors have the largest representation in this study while the Energy, Communication Services and Health Care sectors have the smallest. Additionally, each sector in the study is categorized as consumer oriented, manufacturing intensive or both, to account for hypothesis two and three and be included in separate regressions as dummy variables. The division into the two categories is based on the following reasoning. Consumer oriented industries are those that stand a higher risk of reputational damage if choosing not to display good environmental performance. This typically entails that the firm is a provider of a product or service intended for personal use. The consumer oriented industries were also identified based on sectors in which consumers have substitution opportunities and therefore the freedom to change between companies if loss of trust occurs. I.e., industries where the firm is at particular risk of gaining a bad reputation if they choose not to engage in ESG performance. Manufacturing intensive industries, on the other hand, are those that have a large environmental impact because of their production processes, often with the transformation of raw materials into a final product. They were also identified based on those industries which, due to their production processes, might have a significant environmental impact, as described by Naeem et.al. (2022)

GICS Sector	Frequency
Communication Services*	72
Consumer Discretionary* **	185
Consumer Staples* **	186
Energy**	34
Financials*	427
Health Care*	133
Industrials**	252
Information Technology*	125
Materials**	255
Real Estate*	159
Utilities**	185
Total	2013

Table 2: Sectoral distribution of firms

The table displays the frequency distribution of the firms in the study, based on the GICS sector they belong to. It also presents the division of firms into consumer oriented and manufacturing intensive according to the following notation:
*Consumer oriented
**Manufacturing intensive
(Note that some sectors are categorized as both)

The correlation between all variables is presented in table 3. We observe that the environmental pillar score grade and emissions score grade are highly and positively correlated, reaching 81.12% amongst themselves. It may be asserted that the outcome at hand is foreseeable as the emissions score is a component of the environmental pillar score in the Refinitiv Eikon grading. Both the environmental pillar score grade and the emissions score grade show a positive and significant correlation with credit ratings, with the environmental pillar score grade having a slightly higher value. This may be due to the reason that the environmental pillar score takes resource use and innovation into account as well and thereby covers a larger scope of the environmental impact of the firms (Refinitiv, 2022). The water use to revenues presents a negative correlation with credit ratings, which is expected as the two should evolve in separate directions. We can also observe that waste recycled to total waste and total energy used presents a significant positive correlation to credit ratings which further suggests that environmental metrics overall may have a positive effect on credit rating. There may also be a possibility that the remaining environmental metrics serve as components in the environmental pillar score grade as well. To avoid issues with multicollinearity the regressions will be separated between those only including the environmental pillar score grade and the firm-specific control variables, as well as those including the remaining environmental variables as well as firm-specific control variables.

Expectedly, net profit margin and market-to-book ratio portray a significant and positive correlation with credit ratings as well. This largely due to the company's financial standing having and influence over the risk of default that the company might face. The total assets variable also presents a statistically significant correlations with credit ratings, while a significance level of 5% could not be confirmed for the total debt to total equity variable. In general, the firm-specific control variables are deemed a good fit for the following regressions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Credit rating (1)	1.0000									
Env. pillar score grade (2)	0.2418* (0.0000)	1.0000								
Emissions score grade (3)	0.2400* (0.0000)	0.8112* (0.0000)	1.0000							
Water use to revenues (4)	-0.1746* (0.0000)	-0.0642* (0.0087)	-0.0065 (0.7912)	1.0000						
Total energy used (5)	0.0851* (0.0006)	0.2161* (0.0000)	0.2532* (0.0000)	0.4881* (0.0000)	1.0000					
Waste recycled to total waste	0.1635* (0.0000)	0.1402* (0.0000)	0.2141* (0.0000)	-0.0013 0.9623)	0.2126* (0.0000)	1.0000				
Net profit margin (7)	0.1667* (0.0000)	-0.0109 (0.6312)	-0.0268 (0.2390)	-0.1111* (0.0000)	-0.2936* (0.0000)	-0.1115* (0.0000)	1.0000			
Total debt to total equity (8)	0.0120 (0.5919)	0.0455* (0.0460)	-0.0092 (0.6878)	-0.2278* (0.0000)	-0.2360* (0.0000)	-0.0761* (0.0042)	0.0008 (0.9728)	1.0000		
Market-to-book ratio (9)	0.1540* (0.0000)	0.0369 (0.1068)	0.0657* (0.0041)	-0.0503* (0.0403)	0.0264 (0.2859)	0.1313* (0.0000)	-0.0285 (0.2042)	0.0309 (0.1684)	1.0000	
Total assets (10)	0.4805* (0.0000)	0.3962* (0.0000)	0.3132* (0.0000)	-0.3972* (0.0000)	-0.0362 (0.1426)	0.0277 (0.2979)	0.1114* (0.0000)	0.2465* (0.0000)	-0.1570* (0.0000)	1.0000

Table 3. Correlation matrix (p-value in parentheses)
The table presents the correlation matrix for all variables included in the study.
* Indicates significance level of 5%

4.2 Results

The remainder of the chapter presents results for, as well as a discussion of, regressions ran using the OLS and fixed effects. This subsection begins with an aggregate analysis using the POLS and fixed effects models, and their implications for the study, thereafter moving on to the sectoral and regional regressions. Each independent variable was lagged with one time period i.e., one year. This was done so that the credit ratings of one particular year can be explained by the financial state of the company and its ESG reporting from the year before. The lagging resulted in a decrease in the number of observations.

4.2.1 Aggregate results

Testing the first hypothesis will be based on regressions of the aggregate data, no division into sectors nor regions is made.

For the POLS regressions we have models (1) and (2). The first model accounts for no fixed effects, while the second one accounts for a year fixed effect. On an aggregate level we can see that the environmental pillar score does have a significant effect on the credit ratings of a company according to both POLS models. A one unit increase in the environmental score leads to a 3.24% increase in credit ratings the following year in model (1), and similarly a 3,61% increase in credit ratings the following year in model (2). This is in accordance with results by Youngtae (2022) that spoke in favor of a positive relationship between environmental metrics and credit ratings. It is also important to note that all control variables taking into account size, profitability, leverage, and market value were deemed as highly significant by the POLS, making them a good fit for the regressions performed. It is also reasonable that the total debt to total equity ratio presented a negative relationship with credit ratings, as a larger debt relative to money in a firm reasonably leads to lower creditworthiness.

The FE model is presented in two ways, model (3) accounts for the year fixed effects, and model (4) accounts for both individual and yearly fixed effects. We can observe that in the FE models no statistically significant influence of the environmental pillar score grade on credit ratings could be proven, this may imply that the cross-sectional effects are more significant than the effects over time within one firm when applied to these variables specifically. This entails that in the FE model the influence environmental metrics have on credit ratings is limited, which could be due to the environmental pillar score grade and credit rating being relatively stable over time in one firm but varying across firms. The FE model is unable to capture these cross-sectional variations. We can also observe that the R-squared value is significantly lower for both FE models as compared to the POLS models, suggesting that POLS serves as a better fit for the regression of this data. For the firm-specific control variables model (3) finds all control variables excluding the total assets of being significant whilst model (4) excludes the net profit margin. This as well indicates that the FE model may not be a particularly good fit for the data.

	(1)	(2)	(3)	(4)
Environmental pillar score	0.0324**	0.0361**	-0.0191	-0.0174
	(0.0142)	(0.0143)	(0.0138)	(0.0134)
Net profit margin	6.537***	6.955***	0.998*	0.811
	(1.376)	(1.456)	(0.601)	(0.642)
Total debt to total equity	-2.149***	-2.070***	-0.859**	-0.907**
	(0.394)	(0.396)	(0.375)	(0.392)
Market-to-book ratio	1.053***	1.052***	0.226**	0.260***
	(0.120)	(0.119)	(0.0890)	(0.0960)
Total assets	4.765***	4.804***	0.449	1.745*
	(0.233)	(0.235)	(0.637)	(0.981)
Constant	-52.35***	-53.73***	58.01***	26.43
	(5.232)	(6.275)	(15.15)	(23.31)
Observations	1,669	1,669	1,669	1,669
R-squared	0.311	0.320	0.026	0,053
Individual fixed effect	No	No	Yes	Yes
Year fixed effect	No	Yes	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Aggregate regression results using the environmental pillar score grade

The table presents the results for the aggregate POLS and FE regressions using the environmental pillar score grade and firm specific variables as the independent variables.

Table 5, seen below, presents the results for the regression for the entire sample using the different measures of environmental performance and excluding the environmental pillar score grade. Although the emissions score grade is a component of the environmental pillar score grade, which had a positive and significant relationship with credit ratings, is does not portray any statistical significance in the POLS nor the FE cases. The reason for this is that the emissions may be more relevant on the industry level and be more relevant in environmentally sensitive industries, as suggested by Naeem, Cankaya & Bildik (2022). I.e., it may be more relevant for firms that have a larger environmental impact and thereby face a larger reputational risk if this is not accounted for. The same reasoning could be applied to water used to revenues, as firms that are more manufacturing intensive tend to use more resources that affect the environment negatively. Furthermore, both POLS models (1) and (2) showed that energy used, and waste recycled to total waste, influence credit ratings positively. Although higher energy use might be correlated with environmental issues (EEA, n.d.), it may also be an indicator of higher production levels and thereby higher operating profits for the firm – thereby explaining the positive relationship with credit ratings. It is important to note that while waste recycled to total waste is highly significant it is also accompanied by a high standard error of 1.313, meaning that the results have a wide spread around the mean and may not necessarily be a fair estimation of what we are regressing upon – in this case the credit ratings. For the FE cases in models (3) and (4) the only variable that is highly significant and has a positive effect on credit ratings is the market-to-book ratio. This may be due to the FE model being a poor fit for the aggregate data. However, it may also suggest that the variables are more important cross-sectionally i.e., that the values change mostly across firms rather than within one firm over time.

The firm-specific control variables behaved as expected in the cases where they held statistical significance.

	(1)	(2)	(3)	(4)
Emissions pillar score	0.0243	0.0265	0.00429	0.0134
	(0.0200)	(0.0200)	(0.0145)	(0.0137)
Water used to revenues	-0.0548	-0.0578	-0.0218	-0.0485
	(0.137)	(0.137)	(0.160)	(0.144)
Total energy used	0.430**	0.362*	-0.290	-0.361
	(0.194)	(0.194)	(0.262)	(0.247)
Waste recycled to total waste	4.920***	4.657***	0.690	0.559
	(1.313)	(1.294)	(0.606)	(0.631)
Net profit margin	5.403***	5.567***	0.636	0.350
	(1.373)	(1.442)	(0.561)	(0.612)
Total debt to total equity	-1.841***	-1.791***	-0.850	-0.875
	(0.509)	(0.514)	(0.527)	(0.569)
Market-to-book ratio	0.831***	0.838***	0.221**	0.267**
	(0.123)	(0.122)	(0.110)	(0.124)
Total assets	4.545***	4.557***	-0.327	1.247
	(0.295)	(0.301)	(0.840)	(1.210)
Constant	-55.47***	-53.89***	80.71***	43.13
	(6.714)	(6.783)	(19.85)	(28.85)
Observations	1,090	1,090	1,090	1,090
R-squared	0.318	0.327	0.034	0.073
Individual fixed effect	No	No	Yes	Yes
Year fixed effect	No	Yes	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Aggregate regression results using remaining environmental variables

The table presents the results for the aggregate POLS and FE regressions using different measures of environmental performance, excluding the environmental pillar score grade, and firm specific variables as the independent variables.

In terms of hypothesis one we can observe that the environmental pillar score grade has a statistically significant effect on credit ratings in the POLS model. Additionally, in terms of other environmental components we observe total energy used as well as waste recycled to total waste displaying statistical significance as well. No such conclusions could be drawn for the remainder of the environmental metrics. On an aggregate level we may also draw the conclusion that environmental metrics have the largest effect on credit ratings when accounted for across firms rather than within one firm over a closed interval of time, as the FE model did not provide significant results.[1] As the environmental pillar score grade and two additional environmental components, proved to have a statistically significant effect on credit ratings on an aggregate level in the POLS, the first hypothesis will be confirmed.

4.2.2 Results based on sector

Whilst an aggregate approach might give a fundamental overview of the effect that ESG metrics have on credit ratings, it may also be partly misleading. Different industries may differ in areas such as the environmental footprint that they have due to their manufacturing processes, closeness with consumers as well as the reputational risk that they are exposed to. These factors can all influence the interaction between ESG and credit ratings and should be accounted for in analyses.

The results of the sectoral regressions can be found in Tables 6, and 7. This subsection will begin with an analysis of the consumer oriented industries, and thereafter move on to the manufacturing intensive industries. The division of industry sectors into the two categories can be found in Table 2 as well as in the Appendix A, Table A.1. As some industries could be classified as both consumer-oriented and manufacturing-intensive, separate regressions for both categories were run.

4.2.2.1 Consumer-oriented industries

The consumer oriented industries included the following sectors: communication services, consumer discretionary, consumer staples, financials, health care, information technology and real estate. Models (1) and (2) present the POLS regression results for consumer oriented and non-consumer oriented industries, whilst models (3) and (4) present the POLS regression results with year fixed effect for the same groups in both table 6 and 7. We observe that both POLS models show no statistically significant relationship between the environmental pillar score grade and credit ratings when it comes to consumer oriented industries. This is not the case for the remainder of the companies. Both models in non-consumer oriented industries deemed the environmental pillar score grade to be statistically significant, with similar strength

[1] As the FE model showed little to no significance in the aggregate, as well as following regression results, it is omitted in the following regressions. The study will therefore focus on POLS and POLS with a year fixed effect.

in effect. Model (4) with the fixed year effect shows a slightly stronger impact on credit ratings, suggesting that the invididual differences being controlled for by the year are important for the regression. Addidionally, since the R^2 is higher it suggests that the year fixed effect model is a better fit for the data and can be deemed more reliable.

When it comes to the different environmental variables in table 7, we can observe that model (1) deemed the water used to revenues to have a negative effect on credit ratings and the total energy used a positive one in consumer oriented industries. Model (3) however found all environmental variables, excluding the environmental pillar score and waste recycled to total waste, to be significantly related to credit ratings. As previously mentioned, consumer-oriented industries are those being at greater risk of reputational damage. It is therefore reasonable to assume that the less water a firm uses and the less emissions it produces has a positive effect on the reputation of that firm, granting it the benefits of lower reputational risk as discussed by Fafaliou et.al. (2022). The result that might stand out in this case is once more the positive relationship between energy used and credit ratings portrayed. It may however not only be due to the energy use by itself but also the company's size. It is reasonable to assume that larger firms exert more energy to keep up with high production levels to meet growing demand, as proved by the large and significant effect that total assets have on credit ratings. Larger production may in turn lead to larger revenues, which will have a positive impact on the creditworthiness of a firm as well. As model (3) presented the largest number of significant environmental variables when it comes to the consumer oriented industries, and presented results in accordance with the theory of Verheyden et.al. (2016) in terms of ESG acting as value creating, this may again suggest that the environmental performance of a firm is best captured through a POLS with a fixed year effect.

For the remainder of the firms not categorized as consumer oriented, we can observe that waste recycled to total waste showed to be an important variable when it comes to its effect on credit ratings. The relationship is large and positive, and as it also displayed the same pattern in the aggregate regression, waste recycled could therefore be a variable of importance when measuring the effect of environmental performance on credit ratings. We also observe negative relationship with total energy used as well as the emissions pillar score grade with credit ratings in model (4). The negative relationship of the emissions pillar score grade with credit ratings can be explained by the fact that firms operating in non-consumer oriented industries are at less of a risk to suffer from reputational damage and thereby may not necessarily need to focus as much on the emission component. The environmental pillar score grade however was deemed to be significant in these industries, which could imply that the remaining two components of the grade are more important for these types of firms.

These diverging results speak for the rejection of hypothesis two, if not considered strictly with a fixed year effect. Although a relationship between credit ratings and the emissions score grade as well as water used could be established in table 7 model (3), the results seem to be lacking for the remaining regressions. Additionally, no significant effect on credit ratings could be found when it comes to the environmental pillar score grade, that encompasses several important environmental metrics. We can therefore draw the conclusion that reputational risk may not be as important of a factor when it comes to assessing environmental performance relative to credit risk.

4.2.2.2. Manufacturing intensive industries

The manufacturing intensive industries consisted of the following sectors: consumer discretionary, consumer staples, energy, industrials, materials as well as utilities. The POLS regressions without fixed year effect for manufacturing intensive and non-manufacturing intensive industries are shown in models (5) and (6), while the POLS regressions with the fixed year effect are shown in models (7) and (8) in tables 6 and 7 below. Unlike in the consumer oriented industry case we can confirm a positive relationship between the environmental pillar score grade and credit ratings in both POLS models for manufacturing intensive industries, and not for the firms outside of this category. A one unit increase in the environmental pillar score grade is shown to lead to a 3.26% respectively 3.64% increase in credit ratings, thereby confirming the findings of Naeem et.al. (2022) and Garcia et.al. (2017) who found that companies in environmentally sensitive industries, i.e., those that could be categorized as manufacturing intensive, enjoy a positive relationship between ESG performance and market value.

For the remaining environmental measures in manufacturing intensive industries, we observe that the total energy used has a large positive relationship with credit ratings, suggesting once more that although high levels of energy used can be associated with increased pollution and climate change it may have positive effects if it is brought along by higher production and sales levels which ultimately leads to a chance of increasing the creditworthiness of a firm. The waste recycled to total waste presents itself as an important component of the regression once more, with its high influence on credit ratings.

In the non-manufacturing intensive industries, we observe a negative relationship between waste recycled to total waste and credit ratings within both models (6) and (8), suggesting that recycling becomes less important for industries that are not deemed environmentally sensitive. We also observe that total energy used has a statistically significant and negative relationship with credit ratings in model (8) with the fixed year effect in place, which could be explained by the fact that non-manufacturing intensive firms simply need to be more wary of the levels of energy used in terms of their relationship with credit ratings, as their production levels may not lead to as high profits as in the case of manufacturing intensive firms.

Acceptance or rejection of hypothesis three is harder to determine. Although the individual environmental variables did not show any significance with regard to the emissions pillar score grade or water used, we see a high dependence on total energy used and waste recycled to total waste in terms of the manufacturing intensive industries. Additionally, the environmental pillar score grade also proved to be statistically significant in terms of its positive effect on credit ratings. The latter may entail that there is a larger significant relationship between credit ratings and other environmental metrics not used in this study. As a result of this, hypothesis three will be weakly confirmed.

	(1) Consumer oriented=1	(2) Consumer oriented = 0	(3) Consumer oriented=1	(4) Consumer oriented = 0	(5) Manufacturing intensive = 1	(6) Manufacturing intensive = 0	(7) Manufacturing intensive = 1	(8) Manufacturing intensive = 0
Environmental pillar score	0.0270	0.0379*	0.0279	0.0489**	0.0326**	0.135	0.0364**	0.122
	(0.0186)	(0.0200)	(0.0188)	(0.0197)	(0.0146)	(0.0981)	(0.0147)	(0.114)
Net profit margin	6.008***	17.82***	6.404***	18.46***	6.622***	3.427	7.020***	9.719
	(1.285)	(2.755)	(1.374)	(2.712)	(1.405)	(9.946)	(1.483)	(13.48)
Total debt to total equity	-1.686***	-4.808***	-1.593***	-4.860***	-2.079***	-12.48***	-2.003***	-12.07***
	(0.412)	(0.860)	(0.414)	(0.830)	(0.393)	(2.927)	(0.395)	(3.450)
Market-to-book ratio	1.077***	1.522***	1.075***	1.556***	1.066***	2.234***	1.067***	1.973**
	(0.144)	(0.268)	(0.143)	(0.263)	(0.126)	(0.838)	(0.125)	(0.896)
Total assets	5.126***	4.691***	5.169***	4.689***	4.645***	8.589***	4.687***	8.519***
	(0.278)	(0.481)	(0.281)	(0.476)	(0.233)	(1.495)	(0.235)	(1.548)
Constant	-62.09***	-49.54***	-62.06***	-48.32***	-49.50***	-148.0***	-49.60***	-144.6***
	(6.409)	(10.75)	(6.498)	(10.73)	(5.225)	(38.36)	(5.316)	(39.63)
Observations	1,056	613	1,056	613	1,605	64	1,605	64
R-squared	0.328	0.306	0.336	0.323	0.308	0.624	0.316	0.633
Individual fixed effect	No	No	No	No	No	No	No	No
Year fixed effect	No	No	Yes	Yes	No	No	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6. Sectoral regression results using the environmental pillar score grade

The table presents the results for the sectoral POLS regressions using the environmental pillar score grade and firm specific variables as the independent variables.

	(1) Consumer oriented = 1	(2) Consumer oriented = 0	(3) Consumer oriented = 1	(4) Consumer oriented = 0	(5) Manufacturing intensive = 1	(6) Manufacturing intensive = 0	(7) Manufacturing intensive = 1	(8) Manufacturing intensive = 0
Emissions pillar score	0.0391	-0.0447	0.0436*	-0.0485*	0.0215	0.0727	0.0248	-0.111
	(0.0256)	(0.0290)	(0.0256)	(0.0294)	(0.0205)	(0.146)	(0.0205)	(0.146)
Water used to revenues	-0.632*	0.139	-0.667**	0.135	-0.0691	-3.664	-0.0804	-2.460
	(0.330)	(0.159)	(0.333)	(0.159)	(0.140)	(2.533)	(0.140)	(2.619)
Total energy used	1.070***	-0.845***	0.988***	-0.853***	0.455**	-5.804	0.396**	-8.854**
	(0.280)	(0.284)	(0.278)	(0.280)	(0.195)	(3.761)	(0.195)	(3.755)
Waste recycled to total waste	2.153	6.777***	1.878	6.722***	5.357***	-23.06***	5.074***	-23.71***
	(2.072)	(1.688)	(2.031)	(1.675)	(1.352)	(5.328)	(1.334)	(5.774)
Net profit margin	6.525***	13.04**	6.747***	13.79**	5.476***	-25.93	5.638***	10.44
	(1.613)	(6.301)	(1.694)	(6.018)	(1.386)	(16.35)	(1.452)	(19.08)
Total debt to total equity	-1.254**	-5.920***	-1.230**	-5.863***	-1.772***	-22.11***	-1.727***	-19.28***
	(0.514)	(1.202)	(0.529)	(1.164)	(0.504)	(3.661)	(0.510)	(3.792)
Market-to-book ratio	0.860***	0.956***	0.869***	1.018***	0.818***	3.964*	0.823***	1.866
	(0.145)	(0.356)	(0.145)	(0.353)	(0.124)	(2.162)	(0.123)	(2.323)
Total assets	4.165***	5.644***	4.182***	5.691***	4.501***	17.32***	4.504***	19.73***
	(0.357)	(0.533)	(0.364)	(0.542)	(0.293)	(2.035)	(0.298)	(2.189)
Constant	-53.44***	-53.52***	-52.30***	-52.34***	-54.77***	-226.7***	-53.20***	-222.7***
	(7.966)	(12.31)	(8.028)	(12.76)	(6.700)	(31.78)	(6.805)	(39.40)
Observations	722	368	722	368	1,045	45	1,045	45
R-squared	0.318	0.396	0.325	0.416	0.319	0.864	0.327	0.906
Individual fixed effect	No	No	No	No	No	No	No	No
Year fixed effect	No	No	Yes	Yes	No	No	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Sectoral regression results using remaining environmental variables

The table presents the results for the sectoral POLS regressions using different measures of environmental performance, excluding the environmental pillar score grade, and firm specific variables as the independent variable.

4.2.3 Results based on region

Tables 8 and 9 present results of POLS and POLS with fixed year effect regressions for the three regions this study included. Models (1) and (2) display the results for the Asian market, models (3) and (4) display the results for the European market and models (5) as well as (6) display the results for the North American market.

The Asian region had the largest number of observations in the study, it however bears little resemblance with the aggregate results in tables 4 and 5. This could mean that the largest region is not the core driving source of the aggregate regression, but that each region has an important impact on the aggregate result. The environmental pillar score grade is not associated with any statistically significant results in the region, and the emissions score grade shows an inverse relationship between the variable and credit ratings in the POLS. This is an unexpected result, as China is the world's biggest CO2 emission producer which would make the Asian region a large contributor to pollutions today (Khan & Ozturk, 2019). An explanation for the atypical result of an inverse relationship between the emissions score grade and credit ratings may be rooted in environmental performance displaying diminishing marginal utility, meaning that firms can enjoy the positive effects of their environmental performance on credit ratings up to a certain point after which it starts having the opposite effect. The negative relationship could also be due to the firms benefiting from spending less on ESG related activities and focusing more on financially enhancing performance, and thereby confirm the results of Agliardi et.al. (2023) as they saw a positive correlation between lower environmental scores and good financial performance. Similarly to previous regressions, there is a large and significant relationship between waste recycled to total waste and credit ratings.

For the European region we observe similar results as in the previous regression. Models (5) and (6) show no statistically significant relationship between credit ratings and the environmental pillar score grade. The models do however present a negative relationship of the dependent variable with water used to revenues, which may be due to the European Union's active work in terms of sustainable water management (Tsani, Koundouri & Akinsete, 2020). A positive relationship could be established with credit ratings and total energy used, similarly to the aggregate case where total energy used also displayed a positive relationship with credit ratings.

Lastly, although it bears the smallest number of observations in this study, the North American region showed the largest effects of the independent variables on credit ratings out of all three regions. This might be due to higher degrees of freedom in the regression, as the smaller sample size results in fewer parameters to estimate which in turn results in lower standard errors. All environmental variables excluding total energy used showed statistical significance and behaved as theoretically expected. These results therefore suggest that North American firms reap the biggest benefits of displaying good environmental performance in terms of the effect on their credit ratings. This is in accordance with the results presented by Badía et.al. (2020), who concluded that ESG performance bore the largest value in North America.

We could observe significant differences between North America and the remaining two regions, Asia, and Europe; however, the results seem volatile. The differing results may be due to the differences in sample size; they may also be due to parameters not included in this study. Based on the regional results solely it is difficult to determine what environmental variables weigh the heaviest in terms of positive effects on credit ratings. The emissions pillar score grade shows large significance with a positive effect in North America, yet no significance at all in Europe and a significant negative effect in Asia. Similarly, waste recycled to total waste has the expected positive effect in North America and Asia, yet no such effect in Europe. The variables showing statistical significance in the European region are water used to revenues and total energy used, however these variables showed no significance in the remaining two regions.

Based on the reasoning above we can conclude that there are cross-regional differences in the effect that environmental performance has on credit ratings, although a minor resemblance between North America and Asia is found in terms of waste recycled to total waste. Hypothesis four can therefore be confirmed.

	(1)	(2)	(3)	(4)	(5)	(6)
	Asia		Europe		North America	
Environmental pillar score	0.0294	0.0427	0.0379	0.0363	0.0541***	0.0606***
	(0.0286)	(0.0282)	(0.0264)	(0.0266)	(0.0161)	(0.0165)
Net profit margin	12.32***	14.03***	3.985***	3.815***	3.838	5.020**
	(2.474)	(2.316)	(1.067)	(1.055)	(2.469)	(2.470)
Total debt to total equity	-3.685***	-3.307***	0.0163	-0.0256	-2.372***	-2.338***
	(0.837)	(0.817)	(0.367)	(0.374)	(0.356)	(0.365)
Market-to-book ratio	2.401***	2.446***	0.877***	0.885***	1.050***	1.070***
	(0.517)	(0.491)	(0.101)	(0.100)	(0.187)	(0.189)
Total assets	4.823***	5.084***	4.466***	4.442***	4.841***	4.755***
	(0.496)	(0.489)	(0.339)	(0.345)	(0.374)	(0.380)
Constant	-54.21***	-58.47***	-47.96***	-48.32***	-55.59***	-52.72***
	(11.72)	(11.59)	(7.710)	(7.902)	(8.181)	(8.355)
Observations	673	673	506	506	490	490
R-squared	0.226	0.256	0.343	0.346	0.603	00.612
Individual fixed effect	No	No	No	No	No	No
Year fixed effect	No	Yes	No	Yes	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Regional regression results using the environmental pillar score grade

The table presents the results for the regional POLS regressions using the environmental pillar score grade and firm specific variables as the independent variables.

	(1)	(2)	(3)	(4)	(5)	(6)
	Asia		Europe		North America	
Emissions pillar score	-0.0765*	-0.0671*	0.0405	0.0400	0.105***	0.109***
	(0.0393)	(0.0387)	(0.0344)	(0.0333)	(0.0278)	(0.0283)
Water used to revenues	0.307	0.318	-0.458**	-0.489**	-0.718**	-0.728**
	(0.316)	(0.309)	(0.194)	(0.197)	(0.286)	(0.285)
Total energy used	0.672	0.654	0.684**	0.725***	0.195	0.159
	(0.442)	(0.437)	(0.273)	(0.275)	(0.247)	(0.247)
Waste recycled to total waste	9.034***	8.195***	-1.412	-1.474	6.892***	6.688***
	(2.186)	(2.102)	(1.881)	(1.889)	(2.139)	(2.162)
Net profit margin	20.81***	24.01***	3.845***	3.662***	-1.195	-0.219
	(6.057)	(6.106)	(1.043)	(1.034)	(3.016)	(3.016)
Total debt to total equity	-2.141	-1.770	-0.0974	-0.140	-3.337***	-3.301***
	(1.422)	(1.375)	(0.509)	(0.522)	(0.461)	(0.472)
Market-to-book ratio	2.162***	2.169***	0.785***	0.797***	0.921***	0.939***
	(0.682)	(0.623)	(0.109)	(0.112)	(0.178)	(0.180)
Total assets	4.169***	4.421***	4.399***	4.362***	4.878***	4.744***
	(0.758)	(0.749)	(0.462)	(0.473)	(0.460)	(0.473)
Constant	-48.66**	-50.21***	-52.79***	-54.44***	-62.22***	-58.80***
	(19.36)	(19.08)	(10.61)	(10.91)	(9.759)	(10.44)
Observations	427	427	374	374	289	289
R-squared	0.213	0.258	0.367	0.375	0.640	0.650
Individual fixed effect	No	No	No	No	No	No
Year fixed effect	No	Yes	No	Yes	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Regional regression results using remaining environmental variable

The table presents the results for the regional POLS regressions using different measures of environmental performance, excluding the environmental pillar score grade, and firm specific variables as the independent variables

4.3 Discussion

It may be interesting to note that the fixed effects model did not provide any statistical significance to the environmental variables used in the study. As previously mentioned, this may be due to the FE model being unable to capture cross-sectional variations thereby making the POLS a better fit, which is confirmed by its higher R^2 value in the aggregate regressions.

Volatile results could be found regarding the total energy used variable. It was shown to have a positive relationship with credit ratings in the aggregate POLS models in terms of consumer oriented and manufacturing intensive industries, and a negative one in non-consumer oriented and non-manufacturing intensive industries. Additionally, it was only statistically significant in the European region, suggesting that it is highly circumstantial. Although the results could be partly explained, the source of the variable does not make the distinction between different types of energy the variable encompasses. It would therefore be interesting to see if the same study with that distinction would result in different outcomes. Whether a variable was statistically significant and had a positive or negative effect on credit ratings was also shown to be circumstantial when it comes to the remaining environmental variables as well, especially considering the emissions pillar score grade and the water used to revenues variables. This makes it more difficult to determine what variable bears the largest influence on credit ratings, as results may differ across the regressions.

With the above results in mind, specific environmental drivers in terms of their influence on credit ratings may be highly dependent on the circumstances and the settings under which they are analyzed, since the results differ across industries and geographical regions of the firm. Additionally, as credit ratings tend to be stable over time - given external circumstances not changing drastically – it may be difficult to estimate core environmental drivers that lead to their improvement.

5. Conclusion

This section summarizes the findings of the study and the implications of them. It also discusses the limitations of the study and presents possibilities for further research.

5.1 Summary

This study aimed to explore the relationship between environmental performance and credit ratings for 242 firms in Asia, Europe, and North America over the years 2013-2022 with the data chosen being obtained at the end of each fiscal year. All firms were categorized into one of the eleven GICS sectors. Although many studies up to date choose to focus on credit risk and its relationship with ESG holistically, this study focuses strictly on the environmental component of the framework as research doing so is scarce. As previously mentioned ESG metrics and credit rating score are faced with problems in the way that they might differ between different CRA's. Because of this there is no unanimous way to make concluding remarks on the type of relationship that ESG may have with other factors, as results may differ depending on the source of the data and the agency that assigned it. It is therefore important to be aware of these differences whilst drawing conclusions related to the topic.

To examine the relationship between environmental performance and credit ratings four hypotheses were formed. These focused on the relationship from an aggregate point of view, on the importance of environmental performance when it comes to consumer oriented and manufacturing intensive industries as well as on whether any regional differences can be found. The regressions used for the testing of these hypotheses mainly consisted of the POLS model and the POLS with a fixed year effect, with the FE model being deemed as insignificant after being regressed on the aggregate data. On an aggregate level, the results for the POLS models showed to be highly significant in terms of the environmental pillar score grade, as well as the firm-specific control variables. This suggested that a higher environmental pillar score is positively correlated with larger credit ratings. It is also showed that total energy used, and waste recycled to total waste have a statistically significant effect on credit ratings. Hypothesis one was thereby confirmed. When it comes to the effect within consumer oriented industries, hypothesis two could not be confirmed as the regression results were diverging between the models and presented the strongest results with a fixed year effect – however, as some of the variables proved to be statistically significant in both POLS models it is difficult to determine whether a full rejection of this hypothesis should be made. In terms of the manufacturing intensive industries, hypothesis three could be weakly confirmed as a statistically significant relationship between credit ratings and the environmental pillar score grade, total energy used and waste recycled to total waste could be established. Lastly, in the regional regressions all three regions displayed varying results which confirms hypothesis four of there being cross-regional differences in terms of the relationship studied.

Although further research on the topic is needed, the implications of this study that environmental performance does have a positive influence on credit ratings, however determining the components that lead to this positive relationship is to a large degree circumstantial.

5.2 Limitations and further research

A large limitation that this, and similar studies face, is that of the lack of harmonization across different rating agencies when assessing ESG scores of firms. Since there is no universal way of assessing a firms ESG performance, results of studies may display inconsistencies and spurious results in comparison to one another. Additionally, there may be other environmental variables, or external circumstances, influencing credit ratings that were not included in this study. As mentioned in section 3.1.3. the environmental pillar score grade also encompasses innovation and resource use, that would be important aspects for future studies to include.

In future research it may also be important to incorporate the effects of impactful global events, such as the Covid-19 pandemic, into the analysis as well as it may prove to be impactful. It would also be interesting to investigate the topic from the perspective of a longer time period exceeding ten years, however data that reaches further back in time could be more difficult to obtain and display higher levels of imbalance. More studies are also needed with regards the influence of environmental metrics on credit ratings in distinct separate regions, such as the European region – where the difficulty to obtain relevant data poses as an obstacle once more.

References

Agliardi, E., Alexopolous, T., Karvelas, K. (2023). The environmental pillar of ESG and financial performance: A portfolio analysis, *Energy Economics*.

Agoraki, M., Giaka, M., Konstantios, D. & Patsika, V. (2023). Firms' sustainability, financial performance, and regulatory dynamics: Evidence from European firms, *Journal of International Money and Finance*, vol. 131.

Andriana, A. & Anisykurlillah, I. (2019). The Effects of Environmental Performance, Profit Margin, Firm Size, and Environmental Disclosure on Economic Performance, *Accounting Analysis Journal*, vol. 8.

Anholon, R., Quelhas, O., Filho, W., Pinto, J. & Feher, A. (2016). Assessing corporate social responsibility concepts used by a Brazilian manufacturer of airplanes: A case study at Embraer, *Journal of Cleaner Production*.

Arvidsson, S. & Dumay, J. (2022). Corporate ESG reporting quantity, quality and performance : Where to now for environmental policy and practice?, *Business Strategy and the Environment*, vol. 33, iss. 3, pp. 1091-1110.

Atkins, B. (2020). Demystifying ESG: Its History & Current Status. *Forbes* [online]. Available at:
https://www.forbes.com/sites/betsyatkins/2020/06/08/demystifying-esgits-history--current-status/?sh=39754e132cdd. [Accessed 28 March 2023].

Badía, G., Cortez, M. & Ferruz, L. (2020). Socially responsible investing worldwide: Do markets value corporate social responsibility?, *Corporate Social Responsibility Management and Environmental Management,* vol. 7, pp. 2751-2764.

Barth, F., Hübel, B. & Scholz, H. (2022). ESG and corporate credit spreads, *Journal of Risk Finance*.

Berg, F., Kölbel, J. & Rigobon, R. (2022). Aggregate Confusion: The Divergence of ESG Ratings, *Review of Finance*, vol. 26, iss. 6, pp. 1315-1344.

Caiazza, S., Galloppo, G. & La Rosa, G. (2023). The mitigation role of corporate sustainability: Evidence from the CDS spread, *Finance Research Letters*.

Chalamish, E. (2019). Fitch Adds Sustainable Metrics To Credit Rating., *Global Finance*, vol. 33, iss. 2, p. 10.

Chao, L., Mian, W., Xi, C. & Wenli, H. (2022). Environmental, social and governance performance, corporate transparency, and credit rating: Some evidence from Chinese A-share listed companies, *Pacific-Basin Finance Journal*.

Chen, H., Kuo, T. & Chen, J. (2022). Impacts on the ESG and financial performances of companies in the manufacturing industry based on the climate change related risks, *Journal of Cleaner Production*, vol. 380.

Chen, L. & Zhao, X. (2006). On the relation between the market-to-book ratio, growth opportunity, and leverage ratio, *Finance Research Letters*, vol. 3

Chen, Z. & Xie, G. ESG disclosure and financial performance: Moderating role of ESG investors, *International Review of Financial Analysis,* vol. 83.

Choi, S. (2022). Credit risk interdependence in global financial markets: Evidence from three regions using multiple and partial wavelet approaches, *Journal of International Financial Markets, Institutions & Money*, vol. 80.

Daniels, K. & Jensen, M. (2005). The Effect of Credit Ratings on Credit Default Swap Spreads and Credit Spreads, *Journal of Fixed Income*.

Demir, S. & Doğuyurt, M. (2022). A comparison of fixed and random effect models by the number of research in the meta-analysis studies with and without an outlier, *African Educational Research Journal*, vol. 10, pp. 277-290.

Dorfleitner, G., Halbritter, G. & Nguyen, M. (2015). Measuring the level and risk of corporate responsibility – An empirical comparison of different ESG rating approaches, *Journal of Asset Management*, vol. 16, pp. 450-466.

Eccles, R., Lee, L. & Stroehle, J. (2020). The Social Origins of ESG: An Analysis of Innovest and KLD, *Organization & Environment*, vol. 33, iss. 4.

EEA: European Environment Agency. environmental impact of energy. Available online: https://www.eea.europa.eu/help/glossary/eea-glossary/environmental-impact-of-energy#:~:text=The%20environmental%20problems%20directly%20related,cause%20of%20urban%20air%20pollution. [Accessed 16 April, 2023].

Enders, W. (2014). *Applied Econometric Time Series*, 4th ed, John Wiley & Sons, New Jersey, NJ.

EPA: United States Environmental Protection Agency. (n.d.). How We Use Water. Available online: https://www.epa.gov/watersense/how-we-use-water#:~:text=water%20during%20droughts-,Less%20Water%20Affects%20the%20Environment,of%20natural%20and%20human%20pollutants. [Accessed 16 April, 2023].

Fabozzi, F., Breemen, V., Vink, D., Nawas, M. & Gengos, A. (2023). How much do Investors Rely on Credit Ratings: Empirical evidence from the U.S. and E.U. CLO primary market, *Journal of Financial Services Research*, vol. 63, pp. 221-247.

Fafaliou, I., Giaka, M., Konstantios, D. & Polemis, M. (2022). Firms' ESG reputational risk and market longevity: A firm-level analysis for the United States, *Journal of Business Research*, vol. 149, pp. 161-177.

Fernández-Cuesta, C., Castro, P., Tascón, M. & Castaño, F. (2019). The effect of environmental performance on financial debt. European evidence, *Journal of Cleaner Production*, vol. 207.

Ferri, G., Liu, L. & Majnoni, G. (2000). How the Proposed Basel Guidelines on Rating-Agency Assessments Would Affect Developing Countries. Available online: https://ssrn.com/abstract=630741. [Accessed 4 April 2023].

Garcia, A., Mendes-Da-Silva, W. & Orsato, R. (2017). Sensitive industries produce better ESG performance: Evidence from emerging markets, *Journal of Cleaner Production*, vol. 150, pp. 135-147.

Gelman, A. (2005). ANALYSIS OF VARIANCE—WHY IT IS MORE IMPORTANT THAN EVER, *The Annals of Statistics*, vol. 33.

Hidayah, R., Wahyuningrum, I., Yanto, H., Suryandari, D., Suryarini, T., Dinassari, R. & Rahayu, R. (2022). Environmental Performance with Firm Size as an Intervening Variable, *Jurnal Presipitasi*, vol. 19, pp. 363-372.

Hoechle, D. (2007). Robust standard errors for panel regressions with cross-sectional dependence, *The Stata Journal*, vol. 7, pp. 281-312.

Jacobs, B., Singhal, V. & Subramanian, R. (2010). An empirical investigation of environmental performance and the market value of the firm, *Journal of Operations Management*, vol. 28.

Jun, H. (2023). One in the Same? Unpacking Corporate Social Responsibility (CSR) and ESG in South Korea., *Korea Observer*, vol. 54, iss. 1, pp. 59-80.

Khan, M. & Ozturk, I. (2019). Examining foreign direct investment and environmental pollution linkage in Asia, *Environmental Science and Pollution Research*, vol. 27.

Liu, M. (2022). Quantitative ESG disclosure and divergence of ESG ratings, *Frontiers in Psychology*. Available online: https://search-ebscohost-com.ludwig.lub.lu.se/login.aspx?direct=true&AuthType=ip,uid&db=edselc&AN=edselc.2-52.0-85136488311&site=eds-live&scope=site. [Accessed 22 March 2023].

Luitel, P., Vanpée, R. & De Moor, L. (2016). Pernicious effects: How the credit rating agencies disadvantage emerging markets, *Research in International Business and Finance*, vol. 38, pp. 286-298.

Martini, A. (2021). Socially responsible investing: from the ethical origins to the sustainable development framework of the European Union, *Environment, Development and Sustainability: A Multidisciplinary Approach to the Theory and Practice of Sustainable Development*.

Moraga, G., Huysveld, S., Mathieux, F., Blengini, G., Alaerts, L., Acker, K., Meester, S. & Dewulf, J. (2019). Circular economy indicators: What do they measure?, *Resources, Conversation & Recycling*, vol. 146, pp. 452-461.

Moody's Investors Service (n.d.). Moody's Rating System in Brief. Available online: https://www.moodys.com/sites/products/productattachments/moody%27s%20rating%20system.pdf. [Accessed 16 April, 2023].

MSCI. (n.d.). The Evolution of ESG Investing. Available online: https://www.msci.com/esg-101-what-is-esg/evolution-of-esg-investing#:~:text=The%20practice%20of%20ESG%20investing,the%20South%20African%20apartheid%20regime. [Accessed 28 March 2023]

Naeem, N., Cankaya, S. & Bildik, R. (2022). Does ESG performance affect the financial performance of environmentally sensitive industries? A comparison between emerging and developed markets, *Borsa Istanbul Review*, pp. S128-S140.

Pérez, L., Hunt, V., Samandari, H., Nuttall, R. & Biniek, K. (2022). Does ESG really matter - and why?, *McKinsey Quarterly*. Available online: https://www.mckinsey.com/capabilities/sustainability/our-insights/does-esg-really-matter-and-why#/. [Accessed 22 March 2023].

Piccolo, A. & Shapiro, J. (2022). Credit Ratings and Market Information, *The Review of Financial Studies,* vol. 35, iss. 10, pp. 4425-4473.

Rafailov, D. (2011). The Failures of Credit Rating Agencies during the Global Financial Crisis - Causes and Possible Solutions, *Economic Alternatives*, iss. 1, pp. 34-45.

Refinitiv. (2022). ENVIRONMENTAL, SOCIAL AND GOVERNANCE SCORES FROM REFINITIV. Available online: https://www.refinitiv.com/content/dam/marketing/en_us/documents/methodology/refinitiv-esg-scores-methodology.pdf. [Accessed 4 April 2023]

S&P Global Market Intelligence | MSCI. (2018). GICS. Available online: https://www.spglobal.com/marketintelligence/en/documents/112727-gics-mapbook_2018_v3_letter_digitalspreads.pdf. [Accessed 5 April 2023].

S&P Global Ratings. (2017). How Environmental And Climate Risks And Opportunities Factor Into Global Corporate Ratings - An Update. Available online: https://www.spglobal.com/_assets/documents/ratings/research/how-environmental-and-climate-risks-and-opportunities-factor-into-global-corporate-ratings-an-update.pdf. [Accessed 10 April 2023].

S&P Global Ratings. (2022). ESG in Credit Ratings Newsletter April 2022. Available online: https://www.spglobal.com/_assets/documents/ratings/research/101518080.pdf. [Accessed 27 March 2023]

S&P Global Ratings. (2023a.). ESG in Credit Ratings. Available online: https://www.spglobal.com/ratings/en/research-insights/special-reports/esg-in-credit-ratings. [Accessed 27 March 2023]

S&P Global Ratings (2023b.). Credit Ratings. Available online: https://www.spglobal.com/ratings/en/products-benefits/products/credit-ratings. [Accessed 28 March 2023]

Samaniego-Medina, R. & Giráldez-Puig, P. (2022). Do Sustainability Risks Affect Credit Ratings? Evidence from European Banks, *Amfiteatru Economics*, vol. 24, iss. 61, pp. 720-738.

Spuchl'akova, E. & Cug, J. (2015). Credit Risk and LGD Modelling, *Procedia Economics & Finance*, vol. 23, pp. 439-444.

Stellner, C., Klein, C. & Zwergel, B. (2015). Corporate Social Responsibility and Eurozone Corporate Bonds: The Moderating Role of Country Sustainability, *Journal of Banking & Finance*, vol. 59, pp.538–549

Subrahmanyam, M., Tang, D. & Wang, S. (2014). Does the Tail Wag the Dog?: The Effect of Credit Default Swaps on Credit Risk, *The Review of Financial Studies*, vol. 27, iss. 10, pp. 2927-2960.

Teor, T., Ilyina, I. & Kulibanova, V. (2022). The Influence of ESG-concept on the Reputation of High-technology Enterprises, *Communication Strategies in Digital Society Seminar (ComSDS) Communication Strategies in Digital Society Seminar (ComSDS)*.

Tsani, S., Koundouri, P. & Akinsete, E. (2020). Resource management and sustainable development: A review of the European water policies in accordance with the United Nations' Sustainable Development Goals, *Environmental Science and Policy,* vol. 114, pp. 570-579.

Valiente, J., Ayerbe, C. & Figueras, M. (2012). Social responsibility practices and evaluation of corporate social performance, *Journal of Cleaner Production*.

Verheyden, T., Eccles, R. & Feiner, A. (2016). ESG for All? The Impact of ESG Screening on Return, Risk, and Diversification, *Journal of Applied Corporate Finance*, vol. 28, iss. 2, pp. 47-55.

Vomberg, A., Wies, S., Homburg, C. & Klarmann, M. (2022). *Panel Data Analysis: A Non-technical Introduction for Marketing Researchers*, Springer International Publishing, New York City.

Weissova, I., Kollar, B. & Siekelova, A. (2015). Rating as a Useful Tool for Credit Risk Measurement, *Procedia Economics and Finance*, vol. 26, pp. 278-285.

Whelan, T., Atz, U. & Clark, C. (2021). ESG AND FINANCIAL PERFORMANCE: Uncovering the Relationship by Aggregating Evidence from 1,000 Plus Studies Published between 2015 – 2020, NYU Stern & Rockefeller Asset Management, Available online: https://sri360.com/wp-content/uploads/2022/10/NYU-RAM_ESG-Paper_2021-2.pdf. [Accessed 22 May 2023]

Wooldridge, J. (2002), Econometric Analysis of Cross Sectional and Panel Data, MIT Press.

Youngtae, Y. (2021). Non-Financial Environmental Responsibility Information, Information Environment, and Credit Ratings: Evidence from South Korea, *Sustainability*, vol. 13, iss. 1315.

Yu, E., Luu, B. & Chen, C. (2020). Greenwashing in environmental, social and governance disclosures, *Research in International Business and Finance*, vol. 52.

Zanin, L. (2020). Estimating the effects of ESG scores on corporate credit ratings using multivariate ordinal logit regression, *Empirical economics*, vol. 62, iss. 6, pp. 3087-3118.

Zhang, C. & Jin, S. (2022). What Drives Sustainable Development of Enterprises? Focusing on ESG Management and Green Technology Innovation, *Sustainability (Switzerland)*.

Zheng,Y., Wang, B., Sun X. & Li, X.(2022). ESG performance and corporate value: Analysis from the stakeholders' perspective, *Frontiers in Environmental Science*, vol. 10.

Appendix

GICS Sector	Industry
Communication Services*	Diversified Telecommunication Services, Wireless Telecommunication Services, Media, Entertainment, Interactive Media & Services
Consumer Discretionary* **	Auto Components, Automobiles, Household Durables. Leisure Products. Textiles, Apparels & Luxury Goods, Hotels, Restaurants & Leisure, Diversified Consumer Services, Distributors, Internet & Direct Marketing Retail, Multiline Retail, Specialty Retail
Consumer Staples* **	Food & Staples Retailing, Beverages, Food Products, Tobacco, Household Products, Personal Products
Energy**	Energy, Equipment & Services, Oil, Gas & Consumable Fuels
Financials*	Banks, Thrifts & Mortgage Finance, Diversified Financial Services, Consumer Finance, Capital Markets, Mortgage REITs, Insurance
Health Care*	Health Care Equipment & Supplies, Health Care Providers & Services, Health Care Technology, Biotechnology, Pharmaceuticals, Life Sciences Tools & Services
Industrials**	Aerospace & Defence, Building Products, Construction & Engineering, Electrical Equipment, Industrial Conglomerates, Machinery, Trading Companies & Distributors, Commercial Services & Supplies, Professional Services, Air Freight & Logistics, Airlines, Marine, Road & Rail, Transportation Infrastructure
Information Technology*	IT Services, Software, Communications Equipment, Technology Hardware, Storage & Peripherals, Electronic Equipment, Instruments & Components, Semiconductors & Semiconductor Equipment
Materials**	Chemicals, Construction Materials, Containers & Packaging, Metals & Mining, Paper & Forest Products
Real Estate*	Equity REITs, Real Estate Management & Development
Utilities**	Electric Utilities, Gas Utilities, Multi-Utilities, Water Utilities, Independent Power, and Renewable Electricity Producers

Table A.1. Industry classification (S&P Global Market Intelligence | MSCI. (2018))

The table displays the eleven GICS sectors that the firms used in this study were categorized into, and the industries that they include. It also presents the division of firms into consumer oriented and manufacturing intensive according to the following notation:
*Consumer oriented
**Manufacturing intensive
Note that some sectors are categorized as both.
Sector descriptions sourced from S&P Global Market Intelligence | MSCI. (2018)

Moody’s Credit Rating	Numerical equivalent	Frequency
Aaa	100	30
Aa1	95	14
Aa2	90	63
Aa3	85	107
A1	80	210
A2	75	228
A3	70	305
Baa1	65	368
Baa2	60	281
Baa3	55	165
Ba1	50	64
Ba2	45	62
Ba3	40	46
B1	35	31
B2	30	26
B3	25	11
Caa1	20	0
Caa2	15	1
Caa3	10	0
Caa/Ca/C	5	1

Table A.2. Conversion chart of credit scores to numerical data | Ferri, Liu & Majnoni (2000)

The table presents the range of credit rating scores offered by Moody’s Investors Service, their numerical equivalent as converted by Ferri, Liu & Majnoni (2000), as well as the frequency distribution of their occurrence in this study.

Refinitiv Score	Numerical equivalent
A+	100
A	91.67
A-	83.33
B+	75
B	66.67
B-	58.33
C+	50
C	41.67
C-	33.33
D+	25
D	16.67
C-	8.33

Table A.3. Conversion of Refinitiv Eikon scores

The table presents the range of Refinitiv rating scores used for the environmental pillar score grade and the emissions score grade along with their numerical equivalent.

Variable	Source
Credit Rating	Moody’s Investors Service
Environmental Pillar Score Grade	Refinitiv Eikon
Emissions Score Grade	Refinitiv Eikon
Energy Use, Total	Refinitiv Eikon
Waste recycled to Total Waste (%)	Refinitiv Eikon
Water used to revenues	Refinitiv Eikon
Net profit margin	Refinitiv Eikon
Total debt to total equity	Refinitiv Eikon
Market-to-book ratio	S&P Capital IQ
Total assets	Refinitiv Eikon

Table A.4. Variable source and description

The table displays all variables used in this study along with their sources.