Aalto University
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The Effect of ESG Factors on Corporate Credit Rating

Master's Thesis

Miika Kousa
Aalto University School of Business

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School of Business

Aalto University, P.O. BOX 11000, 00076 AALTO
www.aalto.fi

Abstract of master's thesis

Author Miika Kousa	
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Abstract

Since their establishment in the late 19th century, credit rating agencies have played a pivotal role in society by assessing the credit risk possessed by companies, securities, and sovereign states (Investopedia, 2022). This has further enhanced the transparency and reliability of the business world as several conclusions can be drawn by just looking at the assigned credit rating. In the 20th century, more and more research began to focus on analysing the constituents of credit risk and what factors affect the credit risk assessment process (Ubarhande and Chandadi, 2021). Along with credit rating-related research came the importance of understanding corporate sustainability and how it might affect the credit rating assigned to a company. Following the adoption of ESG factors in the early years of the 21st century, corporate sustainability was given concrete measures to look at when analysing it. Since then, an increasing number of studies have tried to examine the connection between ESG factors and credit risk.

This thesis aims to complement previous literature by studying the effect different ESG (environmental, social and governance) dimensions have on a corporate credit rating. Compared to earlier literature, this thesis has used non-listed companies. By conducting a quantitative study using data given by Suomen Asiakastieto Oy, I have tried to test whether ESG factors are positively associated with an improved credit rating. Following the modifications on the dataset, the final set of data consisted of 20 590 credit ratings from the year 2021 as well as the corresponding ESG scores. In addition, control variables of EBIT margin, current ratio, equity ratio, industry code and size of revenue were used. By computing correlation coefficients and running five different regressions in Stata statistical software, the regression results showed that all ESG factors were positively associated with the credit rating by having a p-value between 0.01-0.05. In other words, the inclusion of ESG factors to credit rating assessment improved the assigned credit rating. Furthermore, control variables of industry codes, current ratio and equity ratio were also found to affect the credit rating. However, unlike many previous papers have discovered, such as Altman (1968), EBIT margin and size of revenue did not affect the credit ratings used in this thesis.

The author acknowledges the limitations present in the study and the need for further research by using a larger set of different company types as well as by having a wider geographical and timely focus. This would help in discovering whether ESG factors' effect on a credit rating is prone to e. g. geopolitical tensions, economic cycles, or natural disasters.

Keywords ESG, credit rating, credit risk, corporate sustainability

Aalto-yliopisto
Kauppakorkeakoulu

Aalto-yliopisto, PL 11000, 00076 AALTO
www.aalto.fi

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Tiivistelmä

Siitä lähtien kun luottoluokitusyritykset perustettiin 1800-luvun lopulla, on niiden yhteiskunnallinen rooli ollut erittäin merkittävä. Tämä rooli korostuu luottoluokitusyritysten luokittaessa niin yrityksiä, arvopapereita kuin valtioita (Investopedia, 2022). Luokitusten ansiosta liike-elämän läpinäkyvyys ja luotettavuus ovat parantuneet, sillä luottoluokituksesta on kyetty tekemään erilaisia päätelmiä yrityksen taloudellisesta tilasta. 1900-luvun alusta lähtien yhä useammat tutkimukset alkoivat tutkimaan luottoluokitukseen ja luottoriskiin vaikuttavia tekijöitä (Ubarhande and Chandadi, 2021). 1900-luvun edetessä myös yrityksen kestävyysasiat alkoivat herättämään kasvavaa kiinnostusta ja kestävyysasioiden vaikutusta yrityksen luottoluokitukseen alettiin tutkia. Yrityksen kestävyysasiat saivatkin konkreettiset mittarit, joita analysoida, kun ympäristölliset, sosiaaliset ja hallinnolliset tekijät (ESG) otettiin käyttöön 2000-luvun alkupuolella. Lukuisat tutkimukset ovat tämän jälkeen tutkineet ESG-tekijöiden vaikutusta yrityksen luottoluokitukseen.

Tämän tutkielman tavoitteena on täydentää olemassa olevaa tutkimusta tutkimalla yksittäisten ESG-tekijöiden vaikutusta listaamattomien yritysten luottoluokitukseen. Tätä kvantitatiivista tutkimusta varten tarvittava data saatiin Suomen Asiakastieto Oy:ltä ja tavoitteena oli testata, ovatko ESG-tekijät positiivisessa yhteydessä parantuneeseen luottoluokitukseen. Lopullinen, muokattu data sisälsi 20 590 luottoluokitusta vuodelta 2021 sekä ESG-luokitukset. Kontrollimuuttujina empiirisessä analyysissä käytettiin liikevoittomarginaalia, current ratiota, omavaraisuusastetta, toimialakoodeja sekä yrityksen liikevaihdon kokoa. Statan tilastollisessa ohjelmassa tehtyjen viiden eri regressioanalyysin perusteella voitiin todeta, että kaikilla ESG-tekijöillä oli yhteys yrityksen parantuneeseen luottoluokitukseen p-arvoilla, jotka olivat välillä 0.01-0.05. Kontrollimuuttujista toimialakoodit, current ratio ja omavaraisuusaste vaikuttivat myös yrityksen luottoluokitukseen. Vastoin aikaisempia tutkimuksia, kuten esim. Altman (1968) osoitti, liikevoittomarginaali sekä liikevaihdon koko eivät vaikuttaneet tutkimuksessa käytettyihin luottoluokituksiin.

Tämän tutkimuksen rajoitteet ovat kuitenkin tunnistettavissa ja tutkimusta onkin mahdollista jatkaa kasvattamalla käytettyjen yritysmuotojen määrää sekä hyödyntämällä laajempaa maantieteellistä ja ajallista ulottuvuutta. Tämä mahdollistaa esimerkiksi geopoliittisten, taloudellisten tai ilmastonmuutokseen liittyvien muutosten mahdollisen vaikutuksen havaitsemisen yrityksen luottoluokitukseen.

Avainsanat ESG, luottoluokitus, luottoriski, yrityksen kestävyys

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1 Introduction

A credit rating as a concept stands for a “quantified assessment of a borrower’s creditworthiness” (Investopedia, 2022). Creditworthiness itself can relate to a debt or financial obligation. Since credit rating expresses the probability of one being able to survive from its obligations, managing credit risk is vital for a company’s success. Although credit ratings are assigned to various companies, they can also be given to individual securities, municipalities, or even sovereign states. This is where credit rating agencies (later also referred to as “CRAs”) play a major role as they assign credit ratings upon request. The three largest credit rating agencies in the world are: Standard & Poor’s, Moody’s, and Fitch (Investopedia, 2022).

Regardless of the work of credit rating agencies being widely recognised as of great importance and their outputs being generally trusted, they have still faced a fair amount of criticism. For example, CRAs have been accused of being biased towards borrowers or too slow in reacting to the changes in credit quality of the borrowers. This issue is elaborated further by Manso (2012) in his study of ‘Feedback Effects of Credit Ratings’. By employing a performance-sensitive-debt (PSD) model, he finds that CRAs should not only focus on providing accurate ratings but also on how the ratings affect the probability of survival of the borrower. Furthermore, small shocks to the rating-agency equilibrium, that is whether a CRA assigns high or low ratings, may result in multi-notch downgrades or even a default. Similar consequences are recognised if competition exists between credit rating agencies. Manso (2012) provides a solution for the issue as he suggests that by collecting a small fee from the firms being rated, CRAs are incentivised to assign more accurate and better ratings which then lead to lower interest rates, lower cost of financing and a lower probability of defaulting.

As for corporate sustainability, it has been an important and timely topic for companies, shareholders, and investors for years. In return, it has led to the need for quantifying performance in corporate sustainability matters. Thanks to the introduction of environmental, social and governance factors (ESG) in the early years of the 21st century, sustainability in it various forms became more concrete (Preqin, 2020). As a result, more and more studies also began to study the importance of embedding ESG factors into credit risk assessment. For instance, the study by Devallo, Fiandrino and Cantino (2017) found out that variables measuring performance in social and governance matters were strongly associated with an improved credit rating. In addition, Weber, Scholz and Michalik's (2010) use of ESG factors in their discriminant analysis was able to correctly classify 80,6 per cent of the defaulted loans.

This thesis aims to supplement previous research by studying the effect ESG factors have on a corporate credit rating. Although the relationship between corporate sustainability and credit risk has been subject to a number of studies over the past decades, the relationship between environmental, social and governance (ESG) factors and actual credit ratings is rather recent and of growing interest. Futhermore, this thesis provides a new perspective to the existing literature by solely using non-listed companies. Given the increased importance of companies' sustainability matters as well as intensified both global and local regulation, this topic offers an intriguing opportunity to examine the effect individual ESG components have on a corporate credit rating.

The data for the thesis was provided by Suomen Asiakastieto Oy. It contained credit ratings for companies of various types between years 2000-2021. As ESG scores were only provided for the latest year, that being 2021, credit ratings could also be used only for the same year. The final cleaned set of data consisted of 20 590 observations for both non-listed public companies and limited liability companies. For the purpose of analysis, credit ratings and ESG scores were given numerical values and ranked between best and worst.

After that, correlation coefficients were computed and five regressions were run in Stata statistical software. As for the correlation, the results showed that all ESG factors and financial ratios were in a small correlation with the credit rating and each other. As for the regressions, all ESG factors, environmental, social and governance, had a positive association with the credit rating while expressing strong statistical significance by having a p-value between 0.01-0.05. In other words, enhanced performance in environmental, social and governance practices improved the credit rating. Similar to the findings of Devallo, Fiandrino and Cantino (2017), which discovered that social and governance matters such as shareholders and community associated with an improved credit rating, the findings of this thesis are also in line with other previous studies. As for the influence of control variables, different industries were found to have possible connection with the credit rating. However, contrary to previous research, the only financial ratios that were statistically significant in improving the credit rating were current ratio and equity ratio. EBIT margin and the size of revenue did not improve the rating.

The rest of the thesis is organised as follows. Chapter two reviews the existing literature on credit risk and credit ratings, explains the historical timeline of ESG and its components. The role of ESG factors in credit risk assessment as well as scientific literature on the relationship between ESG factors and credit ratings is also covered in chapter two. Section three presents the data and hypothesis used in the thesis and the statistical models used in the past as well as in this paper. Chapter four presents the findings of the empirical analysis and how they relate to previous literature. Chapter five explains the limitations for research. Chapter six ponders upon ideas for future research. The last chapter concludes the study.

2 Literature review

2.1 Overview

The plausibility of ESG factors and corporate credit risk having a relationship has been subject to a number of studies over the last years, more increasingly during the last decade. However, to understand the relationship between ESG factors and corporate credit ratings, we must first study the fundamental determinants included in the assessment of credit risk and the importance of selecting suitable and relevant factors for the credit rating model. As mentioned, credit ratings can be assigned to e. g. corporations, financial institutions, securities, loans, or even sovereign states. Although credit ratings can also be issued by other parties than traditional credit rating agencies, this thesis utilises the methodology published by the two largest CRAs in the world: Standard & Poor’s (S&P) and Moody’s Investors Service.

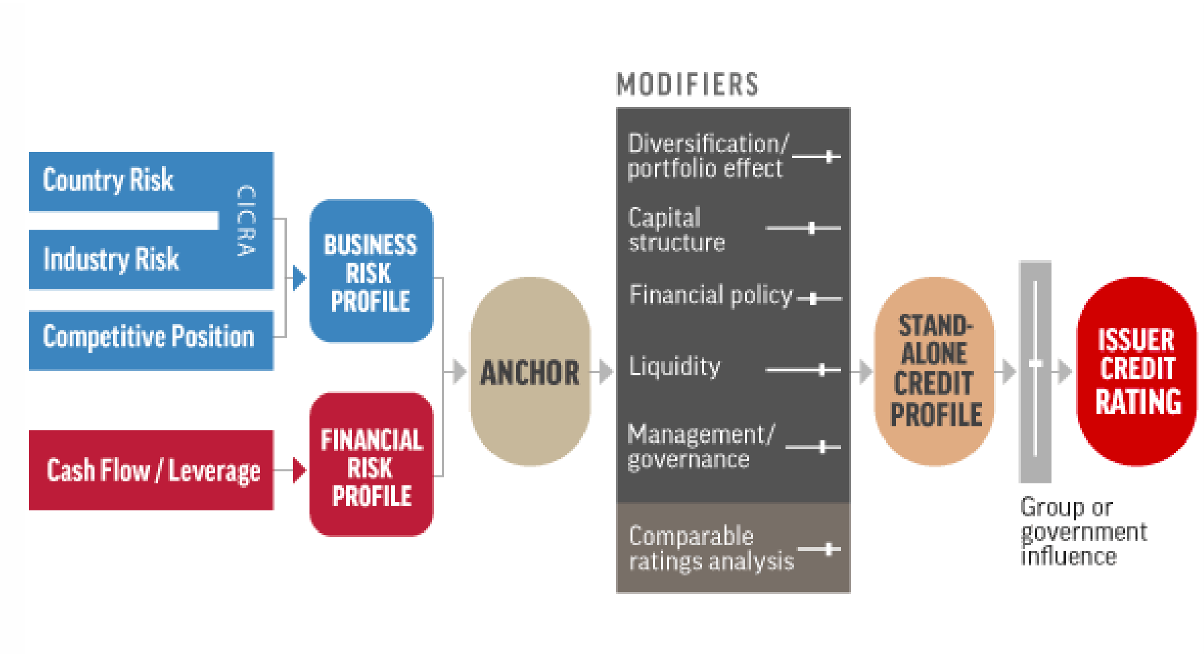
To limit the scope to a manageable extent, I will use general rating methodologies published by both S&P and Moody’s Investors Service since they’re easy to access. Furthermore, rating methodologies will be covered on a general level as sector specific methodologies are not found online for free. As my thesis is focused on analysing credit ratings that are already assigned, I will not too much into the actual credit rating assignment process; instead, I will aim to cover the fundamental elements S&P and

Moody's look at when performing credit risk analyses. After that, the thesis discusses some of the most relevant studies conducted over the years about credit ratings and the determinants of a credit risk analysis. This is followed by the analysis of environmental, social and governance factors (ESG), what they are, and which elements affect each individual component. Finally, relevant scientific papers are discussed to shed light on the effect ESG factors have on credit ratings and in the assessment of credit risk.

2.2 Determinants of a credit rating and credit risk analysis

Standard & Poor's (2013) approach to credit risk assessment comprises of various elements all of which help in determining a reliable stand-alone credit profile and an issuer credit rating. Both financial and non-financial determinants are considered when analysing the credit risk profile of a corporation. Their analysis is divided into three components all of which affect credit risk: business risk profile, financial risk profile and other factors. The following graph depicts the process of determining a credit rating in more detail.

Picture 1. Credit Rating Assessment Framework (S&P, 2022)



Note 1. The picture above depicts the credit rating assessment process applied by Standard & Poor's.

The business risk profile accounts not only for the competitive position the firm has on the market, but also takes into account the advantages and disadvantages the firm has. Furthermore, it considers the wider macroeconomic factors affecting the industry as well as the risks posed by the country itself. In essence, the business risk profile captures the risk and return potential the company possesses. Both quantitative and qualitative information is used in the assessment of the business risk profile. As for the competitive position and industry risk, historical cyclicality of revenues and profitability levels is analysed to strengthen the assessment. The components, industry risk, competitive position, and country risk, are evaluated individually on a scale from one to six, one representing the lowest risk.

The financial risk profile strongly relates to the business risk profile by presenting the financial decisions taken by the management on the basis of the business risk profile. S&P uses cash flow and leverage analysis to determine the financial risk carried by the company. The main financial ratios, both core and supplemental, include e. g. funds from operations (FFO) to debt, debt to EBITDA, cash flows from operations (CFO) to debt, and EBITDA to interest. Like the business risk profile, the financial risk profile is also measured on a scale from one to six, one representing the lowest amount of leverage. The results of the financial and business risk profiles are then combined to form the "anchor" of the analysis.

In the next step the anchor is modified by applying the following modifiers: diversification, capital structure, financial policy, liquidity, governance, and comparable ratings analysis. This modification results in a potential notching of the rating, meaning the probable rating could be either upgraded or downgraded by a certain number of notches. The output of the modification represents the stand-alone credit profile of the company and when assessed against the influence of a group or government, a final issuer credit rating is created. Credit ratings issued by Standard & Poor's vary between AAA and D, AAA being the highest possible rating. Ratings above BBB are considered investment grade.

Like S&P, Moody's (2021) also analyses both financial and non-financial factors when performing credit risk analyses. The degree of using quantitative or qualitative factors varies across industries; financial sectors are often rated by conducting more advanced financial modelling while traditional sectors are assessed with more simplified scorecards embedded with both financial and non-financial ratios. The qualitative factors include among others industry sector, market position, product mix, business strategy, financial policy, ownership structure and corporate governance. The quantitative factors, on the other, include e. g. level of sales or assets, growth rates, cash flows, leverage ratios, working capital ratios, capital expenditure levels and liquidity ratios. The credit rating process and selected factors used by Moody's bear strong resemblance to the ones used by other CRAs. The only notable difference is in the actual rating classification which ranges between Aaa and C, Aaa representing the highest possible rating. A rating of Baa3 corresponds to the S&P's rating of BBB, the lowest rating in the investment grade category.

2.3 Studies on credit ratings and credit risk assessments

Research conducted on credit ratings and credit risk-related topics dates back to the early 1900s when first prominent studies on credit ratings were performed. Although the assessment of creditworthiness goes as far back as the late 19th century when the first credit rating agencies (CRA) were established, the importance of unbiased credit ratings grew significantly post the Great Depression as Ubarhande and Chandadi (2021) point out. They studied the key components of credit ratings by analysing previous studies conducted on topics related to credit ratings. They found out that between 1934 and 2020, 1886 research papers were added on databases of Scopus and Web of Science under the name "credit rating". Of these, only 62 were added before 2001, implying that the majority of credit ratings-related research is fairly new. Their study also revealed that research on credit ratings increases post crises due to tightened regulation and wider credit risk awareness.

Since credit ratings reflect the creditworthiness of a company and the probability of a default, most studies have focused on understanding the determinants of credit risk and what factors predict it the best. Beaver's (1966) study on 'Financial ratios as predictors of failure' is widely considered a precursor that set the tone for subsequent studies of modelling credit risk. Since then, studies have more or less focused on which model can assess the credit risk the best and what the constituent elements of credit risk are. Trujillo-Ponce, Samaniego-Medina and Cardone-Riportella's (2014) study on the ability of accounting-based versus market-based models to predict corporate credit risk strongly suggests that by combining accounting and market-based data, the estimation of credit risk improves. In other words, the authors acknowledged the inadequacy of solely using either accounting or market-based models because accounting-based models rely on historical information while market-based models might suffer from prediction errors due to the inefficiencies of the capital markets. Therefore, both accounting and market-based data was used to construct a set of independent variables. Credit Default Swaps (CDS) and their spreads were used as dependent variables to represent credit risk. As for CDS, it stands for a derivative contract where the seller sells credit protection against periodic payments while the buyer hedges against his/her asset's future default (Pimco, 2022).

Next, 10 accounting variables were used to account for the liquidity, capital structure, debt service, cash flow generation, profitability, and firm size. Market-based data consisted of a distance-to-default model and P/E ratio. The final sample of 2186 observations consisted of 51 firms listed on the FTSEuroFirst100 Index as well as CDS spreads from the Markit database between years 2002-2009. By regressing the natural logarithm of CDS spreads and running multiple linear regressions for both of the models, Trujillo-Ponce, Samaniego-Medina and Cardone-Riportella (2014) found out that by combining accounting and market-based models to measure credit risk, predictivity and accuracy is improved. Therefore, their study positively complements previously conducted research and justifies the use of multiple different variables.

Following the pioneering work of Beaver (1966) on credit risk assessment, researchers began to focus more on the quantitative tools of credit risk modelling by using both accounting and market-based data. Edward I. Altman (1968) studied the use of financial ratios as a predictor of bankruptcy by using a multiple discriminant analysis (MDA). The use of multiple variables was to mitigate the risk of faulty interpretations that are characteristic to univariate analyses. Five ratios were selected based on the categories of liquidity, profitability, leverage, solvency, and activity ratio. Previous studies underpinned the efficiency of using working capital/total assets, retained earnings/total assets, EBIT/total assets, market equity value/book value of total debt and sales/total assets as predictors of bankruptcy. 66 sample companies were selected and divided into two groups: bankrupt and non-bankrupt. Financial data was then collected from the preceding five years prior to bankruptcy. The results from Altman's study showed that the discriminant analysis predicted correctly 94 per cent of the initial sample of bankrupted firms since companies with a higher probability to default showed lower discriminant scores. The study also revealed that the ability to predict a bankruptcy is extremely accurate for up to two years.

Altman's work was elaborated further by Ohlson (1980) in his paper of 'financial ratios and the probabilistic prediction of bankruptcy'. By using the conditional logit model, Ohlson widened the sample size of companies significantly compared to previous studies and took 2163 firms as observations: 105 bankrupt firms and 2058 non-bankrupt firms. Another distinctive difference in Ohlson's study was his use of 10-K financial statements as a basis for data instead of Moody's Manual utilised in all previous research. The use of 10-K reports allowed Ohlson to determine whether the financial data was released to the public prior to or after the bankruptcy. This made a difference to the classification of the companies as bankrupt or non-bankrupt firms affected the dynamics of the sample size. The impact of timing on the classification was largely let non-discussed in previous studies, hindering their scientific relevance. Combined with a much larger sample size, Ohlson improved the credibility of predicting bankruptcy with financial ratios.

Ohlson's study revealed four major factors that were statistically significant in determining the probability of a bankruptcy: the size, the financial structure, the performance, and the current liquidity of the company. Despite using a much larger sample size and more accurate data, Ohlson's findings are mostly in line with the results from Altman's study (1968), especially in terms of the ability of financial ratios to predict the default of a company. Both of these studies justify the decision to use financial ratios as reliable predictors in credit risk assessment while corroborating the applicability of accounting-based models.

Subsequent studies have tried to fix the shortcomings present in accounting-based credit risk models. In their study of "Accounting data and the credit spread: an empirical investigation", Demirovic, Tucker and Guermat (2015) explain how accounting-based models lack in having no forward-looking data by only providing predictions based on historical information. They also point out the limitations for measuring credit risk if accounting-based models are solely used. Reflecting on the use of market-based credit risk models, Merton (1973) is often considered the trailblazer of research on market-based credit risk. His study analyses the credit risk expressed by the market price of securities that contain all possible information. Debt and equity are used as derivatives, the price of which depend on the value of the firms' assets. According to Merton (1973), default occurs when the market value of firm's assets decreases to the value of firm's debt. Thus, changes in the firm's leverage and values of accounting assets determine the probability of a default. Conversely, an increase in the value of equity lowers the firm's credit risk.

Elaborating on the market-based models of credit risk by Merton and subsequent researchers, Demirovic, Tucker and Guermat (2015) studied "the relevance of accounting data in explaining variations in the credit spread". Their analysis consisted of US firm-level equity, bond, and accounting variables from 349 firms and 11 632 quarterly observations. Their findings are largely in line with previous research, concluding that while market-based measures outperform accounting-based measures, they are not solely sufficient in capturing all relevant information in accounting data. The best outcomes were reached when accounting variables were combined with market-based measures. Of used accounting variables, profitability ratios were the most incrementally informative, which is in line with previous studies of Altman (1968) and Ohlson (1980) that emphasised the significance of profitability, liquidity, and leverage as predictors of default risk. However, Demirovic, Tucker and Guermat concluded that profitability was the only statistically significant variable in terms of the credit spread and the leverage ratio did not depict the financial risk in the balance sheet well enough.

2.4 The historical timeline of ESG

Before dwelling deeper into the constituents of ESG, let's take a more detailed look into the history of ESG and its emergence. The roots of ESG date back to the 1700s when ESG was not known under its current name. Back then, religion, moral norm and cultural values were the denominating factors of code of conduct and slave labour was often excluded from responsible investment practices. The 1980's and 90's saw the emergence of premature sustainability legislation, e. g. in the form of the concept of people, planet, and profit. The adoption of the United Nations Framework Convention on Climate Change (UNFCCC) in 1994 aimed at the stabilisation of greenhouse gas emissions. Sustainability as a theme was further extended in the beginning of the 2000s when the UN's Global Compact policy was launched. This new framework that promoted sustainable and responsible business practices added human rights, labour, and anti-corruption to the sustainability spectrum. In 2006, ESG factors in their current form were added to the investment analysis and decision-making processes, following the United Nations' Responsible Investment- initiative (Preqin, 2020).

The last decade has seen an increasing amount of ESG-related regulation and policies being initiated e. g, the introduction of the United Nations' 17 Sustainable Development Goals (SDG) and the Task Force on Climate-Related Financial Disclosures (TCFD) in 2015. Sustainable financing was further enhanced in 2021 when the Sustainable Finance Disclosure Regulation (SFDR) was launched. The SFDR is focused on the wider promotion of ESG values and their disclosures. Investment funds are mandated to disclose whether their products fall under article 6, 8 or 9, depending on the level of ESG incorporation (Preqin, 2020). The upcoming years will see an adoption of more detailed EU sustainability reporting standards when the planned Corporate Sustainability Reporting Directive (CSRD) becomes mandated. The directive is aimed at harmonising sustainability reporting by promoting timely and transparent disclosure practices in more detail. All large and listed companies, as well as permanent establishments operating in the EU will be subject to the clauses of the CSRD (European Commission, 2022).

2.5 Identifying the core elements of environmental, social and governance (ESG) factors

ESG is an abbreviation of the words Environmental, Social and Governance. They stand for non-financial metrics deemed for the purpose of disclosing a company's approach to environmental, social and governance matters in their operations. As CFA Institute (2022) puts it "there is no definitive taxonomy of ESG factors. ESG factors are often interlinked, and it can be challenging to classify an ESG issue as only an environmental, social, or governance issue". However, distinctive elements can still be found when ESG factors are examined one by one.

Environmental factors (E)

The environmental factors concern the conservation of the natural world and actions towards the mitigation of the climate change. Common areas of interest include the firm's actions towards the climate, the reduction of emissions, especially CO2, and the overall pollution of air and water. Environmental factors often include the fostering of biodiversity, deforestation and the efficient use of energy and water. In addition, waste management and recycling are also of heightened importance as topics of sustainable performance (CFA Institute, 2022).

Social factors (S)

Social factors of the ESG relate to the sphere of people and relationships. Companies often explore this area both inside and outside the company. External social factors can concern customer satisfaction and community relations. Internal social factors, on the other, can emphasise human and labour rights as well as employee engagement and gender diversity. Data protection and privacy usually concern the responsible management of both employee and customer data (CFA Institute, 2022).

Governance factors (G)

Governance factors account for the standards and rules in running a company. Examples include for example the composition of the board or audit committee, compensation systems for executives, political contributions, and the firm's ability to tackle bribery and corruption. Strongly related to the social factors are also whistle-blower schemes that allow everyone's voice and opinions to be heard (CFA Institute, 2022).

ESG approach in practice

Since my thesis is focused on the analysis of ESG factors on credit risk assessment of Finnish limited liability and public limited liability companies, I took Cargotec as an example to study ESG factors in a real-life setting. Cargotec's (2022) sustainability section on their website explains their sustainability approach from all three ESG perspectives. In terms of the environment, Cargotec is e. g. committed to following the Science Based

Targets Initiative to limit the global warming to 1.5 degrees. The most important sustainable strategic focus areas relate to the mitigation of climate change and the development and manufacturing of low carbon products. Automation, robotics, and digitalisation are all leveraged to secure an eco-friendly production cycle. Cargotec's concrete targets include among others the reduction of GHG emissions by 50 per cent by 2030.

In the social dimension, Cargotec pays strong attention to the safety, engagement, diversity, and inclusion of its employees. Operational safety is measured by using an Industrial Incident Frequency Trend (IIFT) that measures the number of incidents per million hours worked. Employee engagement is studied and enhanced with the help of annual surveys. Diverse and inclusive environment, complemented by a working atmosphere promoting equality, plays a pivotal role in Cargotec's operations.

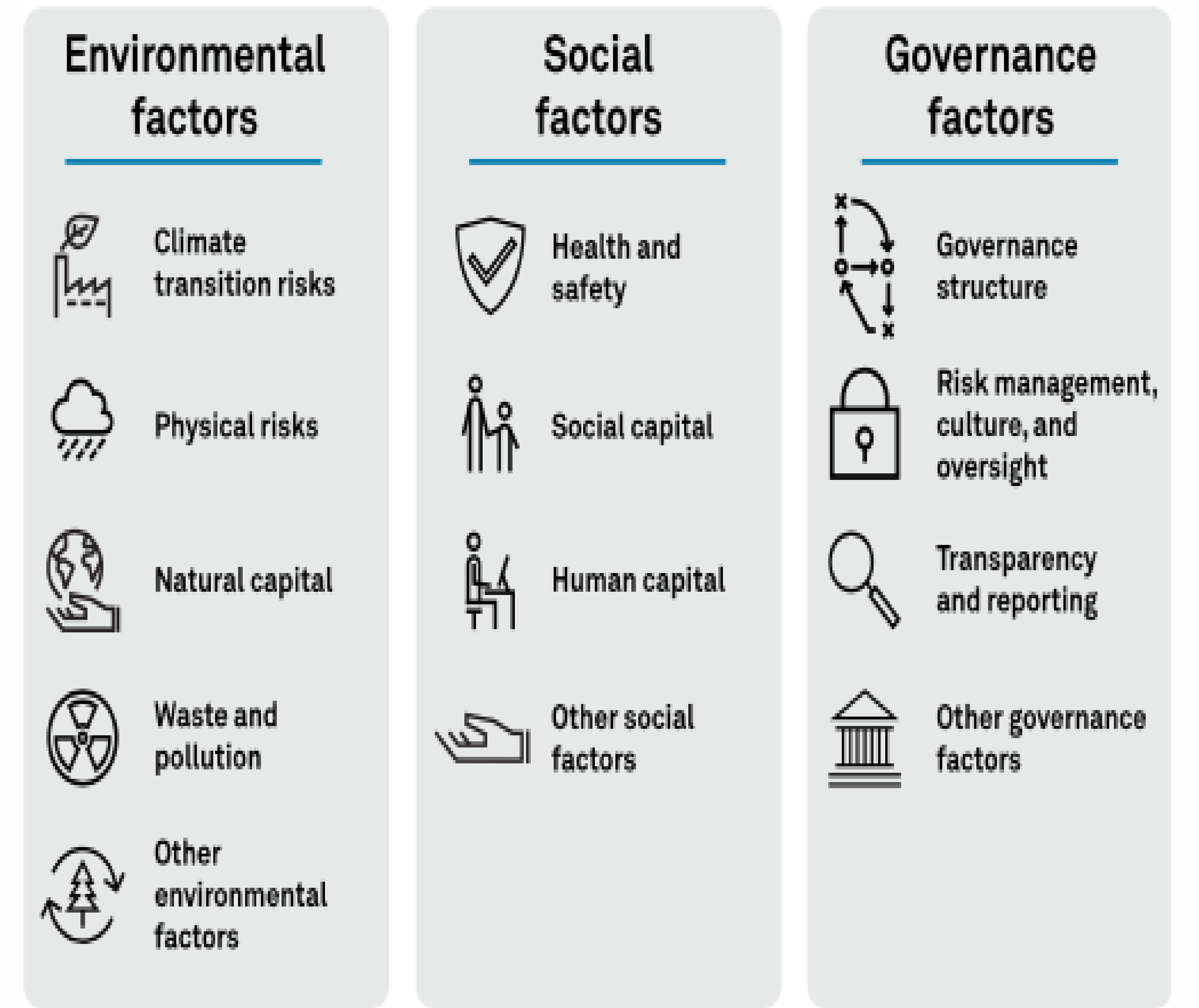
From a governance point of view, the current governance structure of Cargotec composes of eight members in the Board of Directors, ten members in the Leadership Team, complemented by the Audit and Risk Management Committee and the Nomination and Compensation Committee. In terms of misconduct or misbehaviour including harassment, bribery, corruption etc., Cargotec has implemented a "SpeakUp Line" for its employees to report on suspicious and inappropriate conduct (Cargotec, 2022).

2.6 ESG factors as part of credit risk assessment

The following two sections aim to incorporate ESG factors and credit risk into the analysis by studying their possible relationship. Recent years have seen an increase both in the adoption of ESG matters into credit rating assessments and in credit risk related research. As for the purpose of this thesis, the following sections are of particular interest as they provide a solid foundation for the empirical, quantitative part of the thesis. Furthermore, the notion of incorporating ESG and credit rating as a relevant and timely topic is hopefully strengthened.

Standard & Poor’s (2022) methodology on which ESG factors influence credit rating assessment analyses the possible effects of environmental, social and governance factors on corporate credit rating. Since not all ESG factors are material in their potential to influence the creditworthiness of a company and the degree of influence can vary by industry or geographical region, Standard & Poor’s defines the relevant factors as “ESG Credit Factors”. These factors may affect credit ratings through e. g. operating costs, profitability, liquidity, risk management and governance structure. The following chart depicts ESG credit factors that are material in the credit risk assessment and ultimately affect the final credit rating assignment.

Picture 2. ESG Credit Factors (Standard & Poor’s, 2022)



Note 2. The picture shows the relevant ESG factors analysed by Standard & Poor’s in their credit rating assessment.

In terms of environmental factors' effect on credit ratings, Standard & Poor's (2022) mentions risks related to climate change and waste and pollution to have a potential effect on firm's credit rating. This could be materialised e. g. in the form of fines imposed when the company's operations are in breach of climate-related regulation and laws. As a result, non-compliance can also affect the firm's financial profitability. As for social factors, compromising the health and safety of employees can result in shortages of staff which then hinders the performance of the company. On the other hand, aging population provides positive business opportunities for old age homes and pharmaceutical companies, while lowering the industry risk of companies operating in such sectors.

As for governance factors, poor management of risks, culture and their oversight can result in reputational damages for the company and its brand, weakening its competitive position and attractiveness. Legal or tax infringements can have similar outcomes. It must be born in mind that though ESG factors can have a positive or negative effect on firm's credit rating, a strong creditworthiness doesn't necessarily correlate with strong ESG performance and vice versa.

2.7 Research on ESG factors' effect on corporate credit risk

The 21st century has seen an increasing amount of research conducted on corporate social performance (CSP) and its impact on financial performance. Furthermore, the last decade has more or less focused on the implications ESG factors have on companies' financial risk. Though my thesis is focused on the relationship between ESG and credit risk, rather than financial risk, supporting evidence can still be derived from several previously conducted studies. After all, financial risk is just one part of the credit risk assessment as mentioned earlier.

The study of "Impact of ESG Factors on Firm Risk in Europe" by Sassen, Hinze and Hardeck (2016) examines the effect Corporate Social Performance (CSP) has on firm risk. The CSP is operationalised by the ESG dimensions that analyse three different forms of risk: total risk, idiosyncratic, and systematic. Total risk measures the firm's stock's volatility whereas idiosyncratic and systematic risk measure the company-specific and overall market risk respectively. The dataset used in the study consists of 8752 firm-year observations covering European companies between 2002-2014.

In terms of the correlation between ESG and firm risk, the study by Sassen, Hinze and Hardeck (2016) provides some interesting findings. By conducting fixed effects regressions, they found out that the higher the aggregated ESG score, the lower the total and idiosyncratic risk. As for the three dimensions of ESG, strong social performance resulted in a lower score in all three risk measures. A company with a strong public image accompanied by a strong, ethical style of management and fair work practices lowers the overall firm risk. Furthermore, strong environmental performance was found to decrease idiosyncratic risk but only lowered total and systematic risk in environmentally sensitive industries. Surprisingly, strong performance in terms of governance did not have any effect on firm's risk level. Their study, however, corroborates the notion that by integrating ESG measures into company's strategy and operations, one can lower the firm's risk. In addition, strong emphasis on solid social and environmental performance, especially in terms of external stakeholders, provides the best possibility to alter the firm's risk level.

Although the study by Sassen, Hinze and Hardeck (2016) is not explicitly applicable to my thesis and study of ESG on credit risk, it still provides relevant supporting evidence. The research question of my thesis is better supported by the study of Razak, Ibrahim and Ng (2020) on "Which Sustainability Dimensions Affect Credit Risk? Evidence from Corporate and Country-Level Measures". Their study focuses on identifying empirical evidence of the relationship between sustainability measures and credit risk. By using Credit Default Swaps (later also referred to as "CDS") and their spreads as a measure of market-based credit risk as well as Morgan Stanley Capital International's (MSCI) ESG data, a dynamic panel data model was constructed to test the correlation between CDS and ESG dimensions. As mentioned earlier, CDS stands for a derivative contract where the seller sells credit protection against periodic payments while the buyer hedges against his/her asset's future default (Pimco, 2022). The purpose behind using the MSCI's ESG data was that it allowed for the assessment of industry specific ESG materiality.

A wide array of variables was utilised in the empirical analysis, the data of which was based on 2094 observations of 592 global non-financial firms between years 2013-2016. The study of Razak, Ibrahim and Ng (2020) came with several noteworthy findings. First, strong sustainability performance across all ESG dimensions was related to lower credit risk manifested by the credit default swaps. As an example, particular risk reducing potential was possessed by the following areas of interest: climate change, use of natural resources, human capital, and corporate governance. However, one must bear in mind that the level of risk reducing potential may vary between industries. Second, the financial benefits of strong corporate social responsibility were greater in economies with a lower level of sustainability performance. In essence, economies as such can benefit from lower transaction costs when the access of capital is facilitated. Finally, the study revealed that the best way to reduce credit risk is to foster strong corporate governance practices by strengthening internal resources and other intangible benefits. The primacy of focusing on corporate governance principles prior to the other dimensions is also emphasised in the paper.

In comparison to the study by Sassen, Hinze and Hardeck (2016), Razak, Ibrahim and Ng (2020) found corporate governance to be of great importance. As the latter focused on analysing the relationship of ESG and credit risk, rather than sole firm risk, the opposing results could be explained by the difference in the scopes of the studies. Respectively, strong social performance was discovered to reduce both firm and credit risk, underpinning its importance as a risk-affecting factor.

Another study by Weber, Scholz and Michalik (2010) examines the incorporation of various sustainability criteria into credit risk management. By analysing commercial debtor's economic, environmental, and social performance in terms of their impact on credit risk, Weber, Scholz and Michalik (2010) tried to identify whether sustainability factors affect the predictability of a firm's financial performance. 180 different loans classified between non-default and default loans were analysed to test the predictability of credit risk by using sustainability criteria.

First, a regression analysis was conducted followed by a discriminant analysis that tested whether the sustainability criteria combined with traditional financial criteria enhanced the validity of discriminating non-default loans from default loans. In the first step, a significant positive correlation was found between traditional criteria and environmental criteria for non-defaults but no significant correlation for defaulted loans. The discriminant analysis in the second step was able to correctly classify 78.9 % of the loans, with 80.6%

correct classification for the defaults and 77.9% correct classification for the non-defaults. Consequently, the study corroborates the preceding studies in terms of the positive correlation between a firm's financial performance and sustainability performance (Weber, Scholz and Michalik, 2010).

Considering the goal of my thesis, which is to analyse the effect of ESG factors on corporate credit risk, the study of "The Linkage Between ESG Performance and Credit Ratings: A Firm-Level Perspective Analysis" by Devallo, Fiandrino and Cantino (2017) is perhaps the one with the best comparability. In terms of the scope and objective, their study has plenty of similarities, from the application of European-wide company data to the use of actual credit ratings and ESG variables. As they point out, the analysis of ESG factors' effect on credit ratings, and especially the role of the environmental dimension is rather recent given that most research has previously focused on corporate social responsibility (CSR) or efficient governance practices. Devallo, Fiandrino and Cantino (2017) studied the effect of ESG performance on credit ratings by using 56 Italian and Spanish companies from the manufacturing industry and accompanied ESG data from the year 2015. 840 items were analysed, comprising of 15 variables for 56 observations. The authors proposed three different hypotheses which argued that strong environmental and social performance along with sound corporate governance practices would all be positively associated with a credit rating: higher performance in any of these dimensions would lead to a better credit rating.

Ordered Logistic Regression was selected as the empirical model because it has the ability to "estimate relationships between an ordinal dependent variable and a set of independent variables" (Devallo, Fiandrino and Cantino, 2017). Credit rating was selected as the dependent variable while environmental, social and governance variables such as resource use, workforce and management were used as independent variables. Credit ratings were ordered from 1 to 7, one being the highest rating (AAA) and seven the lowest (CCC). The analysis revealed that variables in the social and governance dimensions such as community score and shareholder score were highly significant by having a p-value of less than 0.001. Furthermore, CSR strategy also proved to be of high significance in terms of its positive association with the credit rating by having a p-value of less than 0.005. Surprisingly, environmental scores like product responsibility or environmental innovation were not positively associated with a better credit rating. However, the authors acknowledge the need for further research by using a larger scope and more years to draw any clear-cut conclusions (Devallo, Fiandrino and Cantino, 2017).

The studies described above provide interesting yet differing results in terms of the ESG factors' effect on credit risk, firm risk, and credit rating. Although they share many commonalities, many questions remain regarding the contradicting discoveries. In terms of the environmental dimension's effect on credit and firm risk, the studies by Sassen, Hinze and Hardeck (2016) and Devallo, Fiandrino and Cantino (2017) strengthened the perception that environmental matters have an inconsistent effect on risk levels. While the environmental dimension of the ESG was discovered to decrease idiosyncratic firm risk in the study of Sassen, Hinze and Hardeck (2016), it lacked the potential to improve a credit rating as was discovered by Devallo, Fiandrino and Cantino (2017). In addition, corporate governance was not seen as a risk-reducing factor according to Sassen, Hinze and Hardeck (2016) although their study focused on analysing firm risk rather than credit risk. However, the study by Razak, Ibrahim and Ng (2020) found out that by fostering strong corporate governance practices in terms of e. g. internal resources, one can effectively reduce credit risk.

These contradicting results could be explained by the difference in the research question: Sassen, Hinze and Hardeck (2016) studied ESG factor's effect on firm risk while Razak, Ibrahim and Ng (2020) focused on Credit Default Swaps. As firm risk is just one part of the credit risk assessment, opposing results can occur. Furthermore, the number of observations used by Sassen, Hinze and Hardeck (2016) was more than four times the number of observations used by Razak, Ibrahim and Hardeck (2020). A wider geographical focus accompanied by a longer time period can both explain the variance of the results.

As shown by the aforementioned studies, the social dimension is often the most relevant part of the ESG function as to its effect on credit risk assessment. Sassen, Hinze and Hardeck (2016) found out that strong social performance is linked to lower firm risk in all three measures: idiosyncratic, systematic, and total risk. Fair work practices along with ethical management style can be seen as effective contributors according to their study. Similarly, emphasis on efficient human capital utilization was seen as a risk reducing factor as manifested by their effect on the credit default swaps in the study of Razak

Ibrahim and Ng (2020). Variables measuring social performance such as community score and CSR strategy had a strong, positive association with an improved credit rating as was discovered by Devallo, Fiandrino and Cantino (2017).

Therefore, it seems that if companies focus on solid and fair labour practices while acknowledging the importance of harnessing human capital effectively, they can with a reasonable assurance positively affect their credit risk level. In terms of my thesis and its goal, the study by Devallo, Fiandrino and Cantino (2017) offers the best foundation to continue building on. By extending and delimiting the scope of the thesis to include both public and non-public limited liability companies in Finland as well as their credit ratings from the past 20 years, I will be able to examine the effect individual ESG dimensions have on corporate credit ratings on a general yet geographically restricted level. Furthermore, as I won't be delineating my thesis to include any specific industry, the results can hopefully provide answers and intriguing opportunities for future research.

2.8 The hypothesis of the thesis

Considering the historical studies on the effect ESG factors have on corporate credit ratings, a following hypothesis was decided to be tested in the study:

H1: ESG factors are positively associated with a credit rating

The validity of the hypothesis is supported by the historical studies on the effect ESG factors have on a corporate credit rating as was discussed earlier in the thesis. Since most of the studies focused on both aggregated and individual ESG scores and their relationships with a credit rating, I was able to make reliable and credible conclusions on the possible connection between the results of my thesis and prior research. The hypothesis of this thesis is supported e. g. by Razak, Ibrahim and Ng (2020) as they studied the relationship between credit default swaps and MSCI ESG data. Their study revealed that strong sustainability performance across all ESG dimensions was related to a decreased credit risk as displayed by the credit default swaps. In the study by Weber, Scholz and Michalik (2010), discriminant analysis was able to correctly classify 80.6 per cent of the defaulted loans when the sustainability criteria were combined with financial criteria. This further highlights the importance of embedding sustainability criteria into credit risk assessment.

Providing the best comparability, the study by Devallo, Fiandrino and Cantino (2017) examines the relationship between European-wide credit ratings and ESG data. Their study covered 56 Italian and Spanish companies in the manufacturing industry for which the authors had credit ratings and ESG data from 2015. Their hypothesis was similar to the one used in this thesis, stating that all ESG dimensions would be positively associated with an improved credit rating. They too set the credit rating as the dependent variable and numerated them from 1-7. However, their ESG data consisted of matters such as resource use or management as opposed to the actual ESG ratings that were used in this thesis.

Their study revealed that social and governance dimensions were highly significant with an improved credit rating by having a p-value of less than 0.001. The environmental dimension, however, did not positively correlate with a better credit rating. These results provide supporting argumentation in terms corroborating my hypothesis and the overall validity of the thesis.

3. Data and methods used in the thesis

3.1 Empirical data

Before dwelling deeper into the statistical model used in the thesis, I will first describe the rationale behind the selection of empirical data for the thesis, it's structure and the crucial modifications that needed to be done to utilise the data accordingly.

The dataset used in the study was provided by Suomen Asiakastieto Oy (later also referred to as "Asiakastieto"). As one of Finland's leading digital providers of financial and company-specific information for both corporates and consumers, Suomen Asiakastieto collects and refines data to form analysed data models that are used between the interaction of consumers, companies, and society. They provide services and tools to help in the everyday decision-making as well in finance, sales, and marketing processes. Financial, retail and wholesale sectors are among the biggest clients of Suomen Asiakastieto Oy (Suomen Asiakastieto Oy, 2023).

The dataset created by Suomen Asiakastieto initially consisted of datapoints for more than a million different companies operating solely in Finland, ranging from unlisted public companies to mutual real estate companies. Categorised into columns that contained labels such as business ID, name, starting date, expiration date, ESG environmental score, ESG social score and ESG governance score, the dataset also contained annual credit ratings for each company from 2000 to 2021. ESG scores were only provided for one year and therefore it was assumed, that the ESG scores were the most recent ones available.

Unnecessary information regarding merged or acquired companies and expiration dates was removed as I wanted to utilise companies that were still in operation. Furthermore, firms with incomplete information or mere blank cells were also removed. For the sake of simplicity, only unlisted public companies and limited liability companies were left for further analysis as their governance structure and operative elements are easier to understand. In addition, most research on credit ratings has historically focused on either listed or unlisted companies, so narrowing the scope and aligning it with previous studies helped to improve the comparability of my thesis. The cleaned set of data consisted of 20 590 companies for which Suomen Asiakastieto has been performing credit rating assessments between 2000-2021. An illustrative picture of the modified dataset is provided below.

Picture 3. ESG scores and credit ratings between 2000-2021 (Suomen Asiakastieto Oy, 2022)

Company name	Environmental	Social	Governance	Rating 2000
Tokimoto Oy	No comments	Consider	Pay attention	AA
Tikkurilan Hammaslääkäriasema Oy	No comments	Consider	No comments	A+
Urakointi J. Pääkkönen Oy	No comments	Positive	No comments	AA
Autohuolto T & M Reini Oy	No comments	Consider	No comments	A
Rakennusliike Mustonen Oy	No comments	Positive	Positive	AA
Rent Driving Oy	No comments	Consider	No comments	A+
Oy Artira Ab Ltd	No comments	Consider	No comments	A+
Peartek Oy	No comments	Consider	No comments	A+
KK-Neliöt Oy	No comments	Consider	No comments	B
OakGlen Systems Oy	No comments	Consider	No comments	A+
e-tilit Finland Oy	No comments	Consider	Pay attention	A+

Note 3. The table above shows a fraction of the modified dataset that was used in this thesis.

As shown above, Asiakastieto classifies the ESG scores it assigns to the assessed companies between categories of positive, no comments, consider and pay attention. As these scores were initially described in Finnish, I translated them to English for the purpose of being compatible with the thesis. In terms of the order of superiority, Asiakastieto discloses no further explanation of the requirements needed to be met to reach a certain

ESG score. To get some clarity on the ranking of the ESG scores, I used one of their reports as an example of their ESG assessment on Kiilto Oy. An illustrating picture is provided below.

Picture 4. Kiilto Oy- ESG Report (Suomen Asiakastieto Oy, 2022)

Note 4. The picture above shows an example of an ESG report published by Suomen Asiakastieto Oy.

The picture above depicts Asiakastieto's ESG assessment on Kiilto Oy's sustainability. Environmental, social and governance dimensions are all analysed individually, each receiving a score of either "positiivinen" (positive), "ei huomautettavaa" (no comments), "harkitse" (consider) or "huomioitavaa" (pay attention). Since Asiakastieto provides no information on the order of superiority of the scores, I decided to proceed with the ESG information found in Kiilto Oy's report. As positive matters are marked with a green mark and matters requiring attention with a red exclamation point, I reckoned these would represent the best and worst scenarios. The middle categories of "no comments" and "consider" are marked with a yellow exclamation point and a grey minus sign, giving the assumption that matters in these categories are not directly good or bad but require consideration.

As for the credit ratings, Asiakastieto has assigned the following credit ratings to the companies: AAA, AA+, AA, A+, A, B and C. Running from best to worst, their credit rating scale is similar to that of Standard & Poor's.

To perform a descriptive statistical analysis of the previously mentioned dataset, both the annual credit ratings from 2000-2021 and the ESG scores needed to be converted to numerical values. As ESG scores were only provided for the latest year, that being 2021, credit ratings from that year could solely be used.

Consequently, the ESG scores were ranked from 1 to 4, "positive" representing the best category and receiving a value of four. The following values were given to the rest of the ESG scores: no comments (3), consider (2) and pay attention (1). The numerical sequence of the categories of "no comments" and "consider" was chosen based on the characteristics of these categories: matters in category 3 are more positive in terms of sustainability and require less improvement than matters in category 2.

As for the annual credit rating, a ranking of similar type was performed and AAA as the best category was given a value of seven. The rest of the credit ratings were ranked as follows: AA+ (6), AA (5), A+ (4), A (3), B (2) and C (1). This was done to ease the analysis of the empirical results as the interpretation of the results is more intuitive if better ratings receive larger numbers.

Following the conversion of ESG scores and credit ratings to numerical values, the output was tested with descriptive statistics. Measures such as mean, median and standard deviation were computed to see the distribution of data. These were computed for the year 2021. As for the ESG scores, each category of either environmental, social or governance received its own set of results. The two tables below present the most significant findings.

Picture 5. Descriptive statistics for the credit rating (Suomen Asiakastieto Oy, 2022)

Credit rating 2021	
Mean	5,11
Standard Error	0,01
Median	5
Mode	6
Standard Deviation	1,42
Sample Variance	2,02
Kurtosis	0,17
Skewness	-0,76
Range	6
Minimum	1
Maximum	7
Sum	105169
Count	20590

Note 5. The table above shows the descriptive statistics for the credit rating of 2021.

Picture 6. Descriptive statistics for the ESG scores (Suomen Asiakastieto Oy, 2022)

Environmental score		***Social score***		***Governance score***	
Mean	2,87	Mean	2,52	Mean	2,95
Standard Error	0,00	Standard Error	0,01	Standard Error	0,00
Median	3	Median	2	Median	3
Mode	3	Mode	2	Mode	3
Standard Deviation	0,35	Standard Deviation	0,88	Standard Deviation	0,46
Sample Variance	0,12	Sample Variance	0,77	Sample Variance	0,21
Kurtosis	2,84	Kurtosis	-0,80	Kurtosis	11,81
Skewness	-1,88	Skewness	1,08	Skewness	-2,81
Range	3	Range	3	Range	3
Minimum	1	Minimum	1	Minimum	1
Maximum	4	Maximum	4	Maximum	4
Sum	59124	Sum	51844	Sum	60738
Count	20590	Count	20590	Count	20590

Note 6. The picture above shows the descriptive statistics for the individual ESG scores.

The descriptive statistics performed for the numerated credit ratings in 2021 show interesting results in terms of the distribution of the observations. The average assigned value of the credit ratings in 2021 is 5.11, implying a credit rating of AA. With a median of 5 and a standard deviation of 1.42, there's only little variance between the observations. In addition, the negative skewness of -0.76 implies that the data is left-skewed and most of the companies receive better than average ratings, in other words larger numerated ratings than the average 5.11. The negative skewness is due to the fact that better ratings receive larger numbers, e. g. the rating of AAA receives a value of seven. On the X-axis, most observations lie on the right-hand side.

In terms of the ESG scores, their means range between 2.52-2.95 implying that on average the companies' performance in environmental, social and governance matters falls within the "no comments" -category. Both the median and the mode for the environmental and governance dimensions are 3, meaning that most of the companies operate in a sustainable manner in their environmental and governance matters. However, the median and mode of the social score are worse than those of the other dimensions and therefore, fall in the "consider" -category. No apparent reason can be found for the discovery. Finally, the standard deviation of the three ESG scores is relatively small, between 0.35-0.88, implying that most observations receive scores close to their means.

In order to avoid the omitted variable bias, which occurs when one or more variables are left out of the equation that would have otherwise affected the coefficients of the independent or dependent variable, a set of control variables was chosen to strengthen the credibility of the analysis (Statology, 2020). Control variables stand for variables that are held constant or limited in the study to test whether or not they influence the outcome of the analysis. They are not of interest to the study's objective but are controlled to e. g. avoid the omitted variable bias (Scribbr, 2022).

Industry codes describing the industries the companies under analysis belong to as well as three financial ratios and the size of the company were chosen as control variables. Ranging from food product manufacturing to mining, various industries were represented. The size of revenue represented the size of the company and it ranged from one thousand euros to more than 20 million euros. As for the financial ratios, they were chosen on the grounds of how they depict the credit risk of the company. The following ratios were chosen: EBIT margin, current ratio and equity ratio. As shown by the historical studies on credit risk described in this thesis, profitability, liquidity, and leverage are one of the most substantial factors affecting credit risk.

Suomen Asiakastieto Oy has defined the methods of calculation for their computed financial ratios. As for the EBIT margin, it is calculated by dividing the operating profit of the year by the operating revenue. The current ratio is calculated by dividing the sum of financial assets and inventory by the short-term interest-bearing debt. Finally, the equity ratio is computed by dividing the sum of equity and provisions by the total sum of debt and equity, from which received advances have been deducted.

For the purpose of the analysis, all financial ratios were divided by 100 to convert the percentages into decimal values. Since overly large or small ratios can affect the outcome of the regression analysis, a winsorisation was performed for the financial figures. A winsorisation means that extreme outliers, small or large, are set equal to a specified percentile of data (Statology, 2021). As for this thesis, 99 per cent winsorisation was selected. To clarify, all observations less than the 1st percentile of data were set to equal the value at the 1st percentile. In addition, all observations greater than the 99th percentile of data were set to equal the value at the 99th percentile. A picture below shows a snapshot of the winsorised data.

Picture 7. The winsorised financial ratios (Suomen Asiakastieto Oy, 2022)

Company name	**Industry code**	**Winsorised EBIT margin**	**Winsorised current ratio**	**Winsorised equity ratio**
Rakennusliike Mustonen Oy	41	0,834	1,25022	1
Rent Driving Oy	77	0,834	1,25022	1
Oy Artira Ab Ltd	70	0,834	1,25022	-6,23309
Peartek Oy	27	0,834	1,25022	1
KK-NeliÖt Oy	68	0,834	1,25022	1
e-tilit Finland Oy	69	0,834	1,25022	1
Nord-Marin Småbåtsvarvet Ab	47	0,834	1,25022	1
Refrak Oy	43	0,834	1,25022	1
Pravocon O/Y	69	0,834	1,25022	1
Suomen Viljava Oy	52	0,834	1,25022	1
Kymen Paviljonki Oy	56	0,834	1,25022	1

Note 7. Above is an example of the winsorised financial ratios that were used as control variables.

To test whether the control variables influence the outcome of the regression analysis, five different regressions were run. The first one only tested for the possible association between the ESG scores and credit rating from 2021. The second regression included the aforementioned financial ratios, company size and industry codes as control variables. The third regression was run without the industry codes. The fourth regression was run with financial ratios and company size as sole predictors. The fifth and final regression contained the three ESG factors and the company size.

The next chapter discusses the statistical tool used in the empirical part of the thesis and provides some reasons behind choosing the specific model. Previous studies on credit ratings and credit risk assessment have used various models for testing the possible association between credit ratings and different independent variables. Some of the models are described next, followed by an explanation of the OLS (Ordinary Least Squares) regression and how it was structured to serve the purpose of this thesis.

3.2. Statistical tools used in the past

Historically, studies on credit ratings and credit risk assessments have utilized multiple different models to test for the association between credit risk, as displayed by e. g. credit ratings, and other independent variables. The papers described in this thesis have used models such as fixed effects regression as was used by Sassen, Hinze and Hardeck (2016) in their study. A fixed effects regression model is a statistical model where the group means are fixed, meaning that "each group mean is a group-specific fixed quantity". In case panel data is used, fixed effects refer to subject-specific means (Wikipedia, 2022a).

Weber, Scholz and Michalik (2010) utilized discriminant analysis as their tool when they analysed the effect ESG factors have on the predictability of a firm's financial performance in terms of discriminating non-default loans from defaulted loans. Discriminant analysis stands for a technique where the dependent variable is divided into a number of categories such as A, B and C and the independent variables are interval in nature. The goal of the discriminant analysis is to "develop discriminant functions that are nothing but the linear combination of independent variables that will discriminate between the categories of the dependent variable in a perfect manner" (Statistics Solutions, 2023). In the study by Weber, Scholz and Michalik (2016), the categories of defaulted and non-default loans represented the categorical dependent variable that was discriminated by the ESG factors as independent variables.

Finally, Devallo, Fiandrino and Cantino (2017) applied ordered logistic regression to test the possible association between ESG factors and credit ratings of 56 Italian and Spanish manufacturing companies. Ordered logistic regression refers to a model in which dependent variables are ordered, such as "good, "very good" and "excellent" and the response to a question is predicted by the response to other questions in the study (Wikipedia, 2022b). In Devallo, Fiandrino and Cantino's case (2017), ordered logistic regression was an excellent choice for a research method as their credit ratings as dependent variables were categorised numerically from 1 to 7, one representing the best rating.

3.3 OLS regression as a statistical tool

For the purposes of this thesis, I decided to proceed with the ordinary least squares regression (OLS). Although the empirical part of my thesis could have also been done by using the ordered logistic regression like Devallo, Fiandrino and Cantino (2017) did, the OLS regression is still more widely used in credit rating- related research and therefore offers better comparability and credibility. In addition, the application of the multiple regression is simple yet reliable. Since credit ratings are not perfectly ordered in terms of the intervals being vague, the use of OLS regression removes this issue.

The OLS model estimates the "coefficients of linear regression equations which describe the relationship between one or more independent quantitative variables and a dependent variable" (Xlstat, 2023). The regression itself can therefore be simple or multiple. As for the least squares, it stands for the minimum square error (SSE) that aims to minimize the prediction error between the predicted and real values. In terms of my study on ESG factors' effect on corporate credit rating, and the ratings and ESG scores of which are provided by Asiakastieto, the multiple regression model is a simple yet credible way to test for the linear association between individual ESG scores and annual credit ratings.

The formula below depicts the constituents of the simple regression model.

$\boldsymbol{y} = \beta_0 + \beta_1 \boldsymbol{x}_i + \varepsilon$

Where:

$\boldsymbol{y}$ = dependent variable

β_0 = constant

β_1 = regression coefficient

$\boldsymbol{x}_i$ = independent variable, regressor

ε = error term

In the regression model, the dependent variable is the variable to be explained by the independent variables, also knowns as regressors. The regression coefficient depicts the slope of the independent variable, in other words the degree or strength of the linear association between the independent and dependent variable. The error term, on the other, captures all the factors affecting the dependent variable but not the independent variable. The ultimate "objective of regression analysis is to estimate or predict the average value of one variable on the basis of the fixed value of the other variable" (Research Methods in Accounting, 2022).

As for my thesis, the formula for the multiple regression model follows the structure used by Devallo, Fiandrino and Cantino (2017). In the model of the thesis, the dependent variable is the numerated assigned value of the annual credit rating (from AAA to C) published by Suomen Asiakastieto Oy. However, in this thesis better ratings receive higher values, and the order of superiority is from 7-1, AAA receiving a value of seven. The numerated independent variables of environmental, social and governance, the levels of which range from "positive" to "pay attention", explain the changes in the credit rating. The error factor tries to capture all other factors affecting the annual credit rating by disregarding the firm's ESG performance.

An example of the multiple regression model used in this thesis is depicted and described below.

Deloitte Oy = $\beta_0 + \beta_1$ environmental score $+ \beta_2$ social score $+ \beta_3$ governance score $+ \varepsilon$

Where:

$\boldsymbol{y}$ = annual credit rating of a company

β_0 = constant

β_n = regression coefficient

$\boldsymbol{x}_1$ = environmental score

$\boldsymbol{x}_2$ = social score

$\boldsymbol{x}_3$ = governance score

ε = error term

The dependent variable in the example above is the credit rating of Deloitte Oy in 2021. The corresponding numerated credit rating for Deloitte Oy in 2021 would be 6, implying a credit rating of AA+. The numerated environmental score would be 3, referring to a score of "no comments". The respective scores for both social and governance factors would be 4 and 3, corresponding to scores "positive" and "no comments". To illustrate the model more clearly, two examples are provided underneath.

$6 = \beta_0 + \beta_1 3 + \beta_2 4 + \beta_3 3 + \varepsilon$

Or

$\text{AA+} = \beta_0 + \beta_1 \text{"no comments"} + \beta_2 \text{"positive"} + \beta_3 \text{"no comments"} + \varepsilon$

As mentioned earlier, five regressions were run to test for the possible influence of the control variables on the outcome. The formulas of the regressions are described below.

1. Credit rating 2021 = $\beta_0 + \beta_1$ environmental score + β_2 social score + β_3 governance score + ε
2. Credit rating 2021 = $\beta_0 + \beta_1$ environmental score + β_2 social score + β_3 governance score + β_4 EBIT-% + β_5 current ratio + β_6 equity ratio + β_7 industry code + β_8 company size + ε
3. Credit rating 2021 = $\beta_0 + \beta_1$ environmental score + β_2 social score + β_3 governance score + β_4 EBIT-% + β_5 current ratio + β_6 equity ratio + β_7 company size + ε
4. Credit rating 2021 = $\beta_0 + \beta_1$ EBIT-% + β_2 current ratio + β_3 equity ratio + β_4 company size + ε
5. Credit rating 2021 = $\beta_0 + \beta_1$ environmental score + β_2 social score + β_3 governance score + β_4 company size ε

The next chapter describes the results of the multiple regression analysis conducted in Stata statistical software in more detail.

4. The results of the empirical analysis

4.1 The results

Before running the regressions, Pearson's correlation coefficients were computed for the credit rating, ESG scores and financial ratios to test for their possible linear relationship with each other. Similar to the correlation coefficients, the multiple regressions were also run in Stata statistical software. In addition to ESG scores, control variables including industry codes, EBIT margin, current ratio and equity ratio were embedded in the regression to test for their possible influence on the outcome. In total, five different regressions were run to get a thorough view of the phenomenon, each providing a set of interesting results.

Table 1. Correlation coefficients for the data

	Credit rating	Environmental	Social	Governance	EBIT margin	Current ratio	Equity ratio	Size of revenue
Credit rating	1.00							
Environmental	0.01	1.00						
Social	0.15***	-0.11***	1.00					
Governance	0.42***	0.01	0.06***	1.00				
EBIT margin	0.00	-0.01*	0.06***	-0.00	1.00			
Current ratio	-0.04***	-0.02**	0.05***	-0.01*	0.03***	1.00		
Equity ratio	0.07***	-0.03***	0.12***	-0.02**	0.04***	0.04***	1.00	
Size of revenue	0.01	0.02**	-0.00	-0.00	-0.01	0.00	-0.00	1.00
N	20590							

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The correlation coefficients computed for the data show that most of the ESG scores and financial ratios correlate slightly, either positively or negatively, with each other. As for the correlation with the credit rating, social and governance scores as well as current and equity ratios show statistically significant relationship with the rating. However, all of the coefficients are extremely small, implying a rather vague linear relationship exists within the data.

As for the results of the regressions, the first results are provided in the table below.

Table 2. The first regression- Credit rating and ESG scores

	Credit rating
Environmental score	0.064^{**}
	(2.50)
Social score	0.198^{***}
	(19.44)
Governance score	1.276^{***}
	(66.30)
Constant	0.662^{***}
	(6.82)
N	20590
adj. R^2	0.194

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The results of the first regression analysis indicate that all three dimensions, environmental, social and governance, have a positive association with the credit rating in 2021. For example, one unit increase in the governance score, from e. g. 1 (pay attention) to 2 (consider) results in a 1.276-unit increase in the credit rating. Respectively, one unit increase in the environmental score results in a 0.064-unit increase in the credit rating. In terms of statistical significance, both the social and governance scores have a p-value of less than 0.01 (1%), indicating that the results are statistically extremely significant as the possibility of the association being chance-only is 1 per cent or less. In statistics, a p-value less than 0.05 (5%) is often considered significant, allowing for the null hypothesis to be rejected (Simplilearn, 2023). To clarify, a null hypothesis states that there is no association between the dependent and the independent variable.

As for the environmental score, its p-value is less than 5 per cent, indicating that it's statistically significant although less than the social and governance scores. In terms of the goodness of fit, the R-Squared of 0.194 shows that the proportion of variance in the dependent variable that is explained by the independent variables is 19.4 per cent.

As for the second regression, winsorised EBIT margin, current ratio, equity ratio as well as industries and size of revenue were added as control variables to test whether they might influence the outcome of the results. The results are presented below.

Table 3. The second regression- Credit rating, ESG scores and control variables

	Credit rating
Environmental score	-0.152
	(-1.62)
Social score	0.253***
	(22.33)
Governance score	1.270***
	(66.86)
0.Industrycode	0.000
	(.)
1.Industrycode	0.197
	(0.99)
2.Industrycode	0.032
	(0.16)
3.Industrycode	-0.139
	(-0.48)
7.Industrycode	-0.814
	(-0.90)
8.Industrycode	0.248
	(1.01)
10.Industrycode	0.432*
	(1.90)
11.Industrycode	0.078
	(0.22)

13.Industrycode	0.095
	(0.36)
14.Industrycode	0.074
	(0.28)
15.Industrycode	0.422
	(1.16)
16.Industrycode	0.067
	(0.33)
17.Industrycode	0.561**
	(2.01)
18.Industrycode	-0.067
	(-0.28)
19.Industrycode	0.570
	(0.45)
20.Industrycode	0.579**
	(2.17)
21.Industrycode	1.002*
	(1.94)
22.Industrycode	0.653***
	(2.76)
23.Industrycode	0.548**
	(2.48)
24.Industrycode	0.119
	(0.35)
25.Industrycode	0.282
	(1.32)
26.Industrycode	0.738***
	(2.98)
27.Industrycode	0.570**
	(2.21)
28.Industrycode	0.530**
	(2.36)
29.Industrycode	0.367
	(1.32)

30.Industrycode	-0.269
	(-0.88)
31.Industrycode	-0.062
	(-0.26)
32.Industrycode	0.247
	(1.06)
33.Industrycode	0.317
	(1.40)
35.Industrycode	0.415*
	(1.89)
36.Industrycode	0.951***
	(3.21)
37.Industrycode	-0.059
	(-0.13)
38.Industrycode	0.500**
	(2.08)
39.Industrycode	0.280
	(0.43)
41.Industrycode	-0.171
	(-0.81)
42.Industrycode	0.246
	(0.96)
43.Industrycode	0.021
	(0.10)
45.Industrycode	0.227
	(1.07)
46.Industrycode	0.320
	(1.53)
47.Industrycode	0.265
	(1.26)
49.Industrycode	-0.187
	(-0.99)
50.Industrycode	-0.183

	(-0.72)
51.Industrycode	-0.257
	(-0.67)
52.Industrycode	0.300
	(1.33)
53.Industrycode	0.007
	(0.02)
55.Industrycode	0.011
	(0.05)
56.Industrycode	-0.061
	(-0.28)
58.Industrycode	0.120
	(0.52)
59.Industrycode	-0.127
	(-0.55)
60.Industrycode	1.227**
	(2.48)
61.Industrycode	-0.136
	(-0.43)
62.Industrycode	0.352
	(1.64)
63.Industrycode	0.339
	(1.20)
64.Industrycode	0.757***
	(3.50)
66.Industrycode	0.597***
	(2.77)
68.Industrycode	0.530**
	(2.53)
69.Industrycode	0.503**
	(2.37)
70.Industrycode	0.234
	(1.10)

71.Industrycode	0.132
	(0.62)
72.Industrycode	0.346
	(1.27)
73.Industrycode	0.078
	(0.35)
74.Industrycode	-0.044
	(-0.20)
75.Industrycode	0.551
	(1.44)
77.Industrycode	-0.000
	(-0.00)
78.Industrycode	-0.217
	(-0.83)
79.Industrycode	-0.198
	(-0.87)
80.Industrycode	-0.273
	(-0.94)
81.Industrycode	0.016
	(0.07)
82.Industrycode	-0.014
	(-0.06)
84.Industrycode	-0.036
	(-0.08)
85.Industrycode	0.244
	(1.10)
86.Industrycode	0.667^{***}
	(3.07)
87.Industrycode	0.558^{**}
	(2.19)
88.Industrycode	0.342
	(1.19)
90.Industrycode	-0.378
	(-1.55)

91.Industrycode	-0.138
	(-0.28)
92.Industrycode	0.543
	(0.82)
93.Industrycode	0.309
	(1.41)
94.Industrycode	0.669
	(1.12)
95.Industrycode	0.126
	(0.50)
96.Industrycode	0.074
	(0.33)
EBIT margin	0.012
	(0.47)
Current ratio	-0.414^{***}
	(-5.85)
Equity ratio	0.058^{***}
	(10.39)
Size of revenue	0.000
	(0.90)
Constant	1.404^{***}
	(4.99)
N	20590
adj. R^2	0.223

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The results of the second regression show interesting results. Out of the 96 different industries present in the regression, I will analyse a few in more detail. Industry codes 66 (Financial and Insurance Services) and 86 (Healthcare) have decent regression coefficients, depicting positive association with the 2021 credit rating. In addition, industry codes 66 and 86 are statistically significant by having a p-value of less than 0.01 (1%). In total, the coefficients of the 96 industry codes were diverse and varied from having no association to having a strong association with the credit rating. It can, therefore, be concluded that various industries can affect the outcome of the regression, implying that the risk levels between different industries vary.

As for the financial ratios and the company size in terms of its revenue, current ratio and equity ratio show strong association with the 2021 credit rating by having a p-value of less than 0.01 (1%). The results are mostly in line with previous research, as liquidity and leverage are among the factors affecting the credit risk level and further the credit rating the company receives. As pointed out by Altman (1968) and Ohlson (1980), profitability, liquidity and leverage as financial predictors have a substantial effect on the firm's credit risk. However, in contradiction with the aforementioned studies, EBIT margin and the size of revenue are not statistically significant as their p-values are larger than 0.05 in this thesis. As for the coefficient of determination, the inclusion of industries, financial ratios and company size into the regression improved the R-Squared by 0.029 percentage points to 0.223 (22.3%).

To test whether the exclusion of industries would improve the possible association of the control variables with the credit rating, a third regression was run. A table below presents the results.

Table 4. The third regression- Credit rating, ESG scores, financial ratios and size

	Credit rating
Environmental score	0.065^{**}
	(2.54)
Social score	0.190^{***}
	(18.55)
Governance score	1.278^{***}
	(66.61)
EBIT margin	-0.017
	(-0.67)
Current ratio	-0.516^{***}
	(-7.24)
Equity ratio	0.054^{***}

	(9.60)
Size of revenue	0.000
	(1.02)
Constant	1.287^{***}
	(9.70)
N	20590
adj. R^2	0.199

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The results of the third regression follow a similar pattern as shown by the second regression. Both the current ratio and equity ratio are again strongly statistically significant by having a p-value of less than 0.01. In addition, EBIT margin and size of revenue are not statistically significant. Surprisingly, the exclusion of industry codes did not improve the coefficient of determination as it decreased to 0.199 (19.9%).

As for the fourth regression, ESG factors and industry codes were excluded from the regression to see whether the financial ratios and company size as sole predictors would indicate any association with the credit rating. The results are provided below.

Table 5. The fourth regression- Credit rating, financial ratios, and size

	Credit rating
EBIT margin	0.005
	(0.18)
Current ratio	-0.521^{***}
	(-6.56)
Equity ratio	0.060^{***}
	(9.58)
Size of revenue	0.000
	(0.82)
Constant	5.706^{***}
	(56.69)
N	20590
adj. R^2	0.006

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The fourth regression shows interesting results as the R-Squared decreased dramatically, from 0.199 to 0.006. The p-values of current ratio and equity ratio being less than 0.01, the results can be considered significant and reliable. Once again, the EBIT margin and size of revenue show no statistically significant association with the credit rating.

The fifth and final regression only included the ESG factors as independent variables as well as the size of revenue as the sole control variable. The results are shown in a table below.

Table 6. The fifth regression- Credit rating, ESG scores and size

	Credit rating
Environmental score	0.063^{**}
	(2.48)
Social score	0.198^{***}
	(19.44)
Governance score	1.276^{***}
	(66.30)
Size of revenue	0.000
	(0.99)
Constant	0.659^{***}
	(6.78)
N	20590
adj. R^2	0.194

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The results show little surprises when compared to the previous regressions. The individual ESG scores of the environmental, social and governance dimensions are still strongly associated with the annual credit rating of 2021. As for the company's size as a possible influencer of the outcome, its coefficient is still not statistically significant to associate with the credit rating.

As a result of the five regressions that were run in Stata, several conclusions can be drawn, especially in terms of the validity of the hypothesis. The hypothesis stated that "all ESG factors would be positively associated with a credit rating". As we can conclude from the above-described regressions, the hypothesis is true. Each score, environmental, social and governance, was highly statistically significant by having a p-value of either 0.01 (1%) and less or 0.05 (5%) and less.

As for the effect of control variables that was tested in four different regressions, the results were intriguing yet a bit contradictory. The effect of different industries varied a lot, ranging from having a strong association to having a weak association. For example, financial and insurance services displayed strong statistical significance with a regression coefficient of 0.597 and a p-value of 0.01 (1%). On the other, not all industries were statistically significant. Manufacturing of furniture, for instance, had a regression coefficient of -0.062 but a p-value of more than 0.1 (10%).

The association of current ratio and equity ratio and the non-association of EBIT margin and size of revenue with the credit rating were among the most intriguing and contradictory discoveries that were made from the regressions. In contradiction with most of the previous studies conducted on credit ratings and credit risk, EBIT margin and size of revenue showed no statistically significant association with the 2021 credit rating. This is quite odd given the fact that profitability, liquidity, and leverage are among the most important factors affecting credit risk and the overall risk profile the company possesses. The significance of using financial ratios as predictors of credit risk and bankruptcy was analysed by e. g. both Ohlson (1980) and Demirovic, Tucker and Guermat (2015), the latter emphasising the importance of profitability as the best predictor. The findings of my thesis are therefore surprising, yet they corroborate the results of the positive association that was found between ESG factors and the credit rating as well as the possible influence different industries, current ratio and equity ratio can have on the credit rating.

Given the limitations of the research, it can be concluded that all ESG factors, environmental, social and governance, are positively associated with an improved credit rating by having a p-value between 0.01-0.05. In addition, different industries, current ratio, and equity ratio can influence the degree to which the ESG factors affect the credit rating. However, EBIT margin and the size of the company do not associate with the credit rating as the association is not statistically significant. No apparent reason can be found for this.

The following two chapters discuss the results of the regression in the light of previous studies as well as outline the limitations for the research conducted in this thesis.

4.2 The empirical results in the light of previous studies

The historical studies explained in this thesis on ESG factors, credit risk determinants and the relationship between them provide both supporting and disapproving arguments in terms of the empirical results of the thesis. As all the ESG factors, environmental, social and governance, were discovered to be strongly statistically significant and had a positive association with the credit rating, this result is largely in line with the findings done by e. g. Devallo, Fiandrino and Cantino (2017). They studied the credit ratings of 56 Italian and Spanish companies from the manufacturing industry and accompanied ESG data from 2015. By ranking the credit ratings from 1-7, one representing the best rating, the association between ESG factors and 2015 credit rating was tested with ordered logistic regression. Similar to the results of my thesis, they too found both social and governance factors to be of statistical significance as this was displayed by the high regression coefficients of both community and shareholder scores. The positive association between the environmental factors and credit rating of 2021 that was found statistically significant in my thesis, was discovered to be non-existent in the study of Devallo, Fiandrino and Cantino (2017). Their results revealed that e. g. both product responsibility and environmental innovation were not associated with an improved credit rating. Their results support the findings made in this thesis as to the strong association of the social and governance factors but contradict the statistically significant effect displayed by the environmental factors.

The study by Razak, Ibrahim and Ng (2020) on which ESG dimensions affect credit risk provides contradicting results in terms of the findings done from the regression analyses conducted in this thesis. Credit Default Swaps (CDS) and their spreads, consisting of 2094 observations of 592 global non-financial firms, were utilized to depict the level of credit risk the firm possesses. In addition, Morgan Stanley Capital International’s (MSCI) ESG data was utilized as independent variables to test for the possible effect of the ESG factors on the spreads of the CDS. Similar to the findings of my thesis which found the effect of all ESG factors on the credit rating to be of high significance, Razak, Ibrahim and Ng (2020) too found strong sustainability practices across all ESG dimensions to positively affect the credit risk levels as manifested by the lower credit spreads of the CDSs. Strong performance in areas such as climate change, use of natural resources, human capital, and corporate governance resulted in a lower credit risk. However, the authors also emphasise the primacy of focusing on strong governance practices prior to other dimensions which can be seen as supporting argumentation with regards to the results of my thesis. The strong association of the social and governance factors as was displayed by the results is further corroborated by the fact that the number of observations used in the thesis was 10 times larger than the number of observations used by Razak, Ibrahim and Ng (2020). Receiving similar results with a much larger scope strengthens the credibility of my thesis and provides strong evidence on the importance of solid social and governance practices as contributors to lower credit risk.

As for the strong association shown by the current and equity ratios and the non-association shown by the EBIT margin and size of revenue, previous research seems to be partly in contradiction with the results of my thesis. As described earlier and supported by the historical studies on credit risk and credit ratings, financial indicators for profitability, liquidity and leverage should predict and affect credit risk levels inevitably. However, this was not supported by the results of the thesis's empirical analysis which showed that only financial ratios of current ratio and equity ratio were statistically significant and in association with the credit rating by having a p-value of 0.01.

From Beaver's (1966) pioneering study of 'Financial ratios as predictors of failure' to Trujillo-Ponce, Samaniego-Medina and Cardone-Riportella's (2014) study on the ability of accounting-based versus market-based models to predict credit risk, each of the studies described in this thesis have more or less emphasised the importance of various accounting and market-based metrics as relevant and reliable predictors of credit risk. Altman (1968) discovered that by using liquidity, profitability, leverage, solvency, and activity ratio as financial ratios in his multiple discriminant analysis, he was able to correctly predict 94 per cent of the bankrupted firms in his initial sample. In addition, he deduced that bankruptcy could be predicted accurately for up to two years in advance. In line with Altman's (1968) study that found out lower liquidity and solvency are related to a higher probability of defaulting, the results of this thesis show that stronger current ratio and equity ratios affect the credit rating positively.

Altman's work (1968) was later elaborated further by e. g. Merton (1973) who concluded that changes in the firm's leverage and values of accounting assets determine the probability of a default. Conversely, an increase in the value of equity lowers the firm's credit risk.

By using 10-K financial statements as a basis for data instead of Moody's Manual, Ohlson (1980) improved the credibility of predicting bankruptcy with financial ratios. His study revealed that the following four factors were statistically significant in determining the probability of a bankruptcy: the size, the financial structure, the performance, and the current liquidity of the company. The ratios analysed by Ohlson (1980) are also present in the regression analysis of this thesis. However, the only statistically significant financial ratios in the thesis were current and equity ratios, corroborating the importance of ensuring companies focus on their liquidity and level of leverage.

Finally, Demirovic, Tucker and Guermat's study (2015) revealed that in order to predict credit risk accurately, the use of market-based models should be combined with accounting-based models. The use of market-based metrics in predicting credit risk is among factors missing from the empirical analysis of my thesis. This and other limitations of this thesis are described next.

5. Limitations of the study

Although the scope of this thesis covers a large number of unlisted public and limited liability companies, namely 20 590 observations, several limitations still exist for the study. To begin with, the data provided by Suomen Asiakastieto Oy that was used as in the empirical part of the thesis contained several different company types, from limited partnerships to registered foundations. Of these, only unlisted public companies and limited liability companies were chosen for the study's sample. This narrowed down the scope to 20 590 observations. Had more company types been included in the scope, the results of the empirical analysis on the ESG factors' effect on the credit rating could have been different. Furthermore, Asiakastieto's data did not include stock-listed companies.

In terms of the time period and geographical focus, only one year was used in the regression analyses as ESG data was only provided for the latest year, that being 2021. Although credit ratings were provided for years 2000 to 2021, only the latest year could be used to be compatible with the ESG data. This limited the number of observations and made it difficult to draw any conclusions on possible trends. As for the geographical focus, all the companies in scope were Finnish companies operating in Finland. Similar to the study by Devallo, Fiandrino and Cantino (2017), which used Italian and Spanish manufacturing companies, my thesis also lacked in having a wider geographical focus.

As for the use of certain financial ratios and company size as control variables, a different set of variables could have resulted in a different outcome. Various metrics for measuring profitability, liquidity and leverage exist although the set of variables used in this thesis aimed to predict credit risk as reliably as possible. As the thesis focuses on testing for the possible association between different ESG factors and a credit rating, the use of market-based metrics was not seen relevant. Having said that, an alternative set of market-based and accounting-based metrics could have resulted in an outcome where the control variables had an influence, as previous research has shown.

6. Avenues for further research

As research on the relationship between ESG factors and credit ratings is fairly new and narrow, plenty of new perspectives are left to be discovered around this topic. Considering the topic and scope of this thesis, a number of new research ideas come to mind. First, a larger variety of different company types could offer an interesting opportunity to explore the relationship of ESG and credit risk on a much broader and deeper level. Combined with a wider geographical focus, such as the Nordics or Europe, the results would provide a better view of the European business landscape, the current credit risk levels and how various companies pay attention to their sustainability efforts.

Second, by extending the time frame to include more years for both ESG data and actual credit ratings, possible trends, or shocks in the development of the credit risk levels and ESG scores could be noticed and analysed further. This would allow us to discover whether the relationship of ESG factors and credit ratings is subject or prone to the influence of other external factors such as climate change, environmental crises, economic shocks, geopolitical tensions and so on. Smaller ESG scores or worse credit ratings during turbulent and unsecure times would emphasise the importance of having a fruitful and sound operating environment as well as indicate the possibility of the influence surroundings can exert.

Third, the use of alternative financial ratios in addition to other control variables could lead to different outcomes in terms of the financial ratios having an influence on the association of ESG and credit ratings. Although the financial ratios applied in this thesis correspond to the ones used or suggested by previous research, similar ratios do exist that measure the same focal matters affecting credit risk: profitability, liquidity, and leverage. As an example, EBIT could be substituted with EBITDA or operating profit, current ratio could be changed to quick ratio or equity ratio could be replaced with gearing. Furthermore, limiting the size of the companies under scope could also provide interesting results on the role the number of personnel or the amount of revenue play in the credit risk assessment. Needless to say, countless of more dimensions and perspectives exist from which one can examine the effect ESG factors have on a corporate credit rating.

7. Conclusion

This thesis has focused on studying the effect different ESG factors have on a corporate credit rating. Though previous research on the role corporate sustainability plays in credit risk assessment exists, studies on the relationship between various ESG dimensions and assigned credit ratings are few and far between and the number of studies has just begun to increase during the last decade or so. Since the level of credit risk the company bears is related to its ability to survive from its liabilities, identifying the influence individual environmental, social or governance (ESG) matters have on the credit risk is crucial for the firm’s survival. Furthermore, corporate sustainability is subject to increased amount of regulation with a number of new rules and directives set to come into effect in the upcoming years. The thesis has tried to fill in this gap.

The data used in the study was provided by Suomen Asiakastieto Oy. It contained credit ratings for companies of various types between years 2000 to 2021. As ESG scores were only provided for the latest year, that being 2021, only ratings from that year could be used. Following the modifications, the final cleaned set of data consisted of 20 590 observations for both non-listed public companies and limited liability companies. For the purpose of analysis, credit ratings and ESG scores were given numerical values and ranked between best and worst. As the best rating, credit rating of AAA was given a value of seven and C as the worst rating, was given a value of one. As for the ESG scores, “positive” as the best rating was given a value of four, followed by “no comments” receiving a value of three, “consider” a value of two and “pay attention” as the worst score a value of one. In addition, several control variables were selected to avoid the omitted variable bias. These were: industry codes, company size, EBIT margin, current ratio, and equity ratio.

The multiple regression analysis was selected as the statistical method to test for the possible association between ESG factors and credit rating. As a simple yet reliable method, it allowed for the input of several different variables. The final formula for the regressions constituted of a credit rating as the dependent variable and ESG factors as the independent variables, combined with a set of control variables. By first computing the correlation coefficients for the data and then running five different regressions in Stata Statistical Software, the correlation results showed that all the ESG factors as well as financial ratios were in a small correlation with the credit rating and with each other. As for the regressions, all the ESG factors, environmental, social and governance had a positive association with the credit rating while expressing strong statistical significance by having a p-value between 0.01-0.05. Similar to the findings of Devallo, Fiandrino and Cantino (2017), who discovered that social and governance matters such as community and shareholders associate with an improved credit rating, the findings of my analysis are also in line with other previous studies.

As for the influence of control variables, different industries were found to have possible connection with the credit rating. However, contrary to previous research, the only financial ratios that had a statistically significant association with the credit rating were current ratio and equity ratio. The importance of various financial ratios depicting profitability, liquidity, and leverage, that was emphasised by e. g. Altman (1968) and

Ohlson (1980), was partly left uncaptured in the results of the thesis. The results can be held credible, as the p-value for current and equity ratios was less than 0.01.

Despite the confounding non-association between the some of the financial ratios and credit ratings, avenues for future research exist. By enlarging the timely and geographical focus of the analysis, interesting results may arise on the international aspect of companies' current credit risk levels as well as on how climate change, economic cycles and geopolitical tensions affect firms' sustainability efforts and therefore, the association with its credit rating. In an increasingly global world of business, opportunities and threats for sustainability are limitless and navigating through it takes time and precision, but most importantly dedication.

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