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ESG Scores and Credit Risk

Master's thesis

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Declaration of Authorship

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Abstract

This thesis investigates the impact of ESG scores on default risk and profitability. In order to facilitate the analysis of financial data provided by a Czech banking institution, which comprises anonymised financial indicators and ESG scores, models for credit risk and profitability of non-financial companies were constructed. The former are estimated using ordinary least squares and binary choice methods, while the latter are estimated using a first-differenced estimator and a generalised method of moments. The findings of the thesis indicate that firms with superior and inferior ESG scores exhibit different behaviours. Companies with worse ESG scores demonstrate a more pronounced effect of changes in profitability and solvency on default probability, while liquidity appears to be a more significant factor for the other group. The analysis of profitability revealed higher persistence of returns for firms with superior ESG performance.

JEL Classification	C23, G32, F23, L25, Q58
Keywords	ESG, credit risk, profitability, panel data analysis
Title	ESG Scores and Credit Risk

Abstrakt

Tato práce zkoumá vliv skóre ESG na riziko bankrotu a ziskovost. Pro použití na datech poskytnutých českou bankou, které obsahují anonymizovány finanční ukazatele a ESG skóre firem byly zestaveny modely pro kreditní riziko a ziskovost nefinančních podniků. První jmenované byli odhadnuty metodami nejmenších čtverců a metodami pro binární veličiny, druhé metodou prvních rozdílů a zobecněné metody momentů. Zjištění práce naznačují, že firmy s lepším a horším ESG skóre vykazují odlišné chování. Společnosti s horším ESG skóre vykazují výraznejší vliv změn ziskovosti a solventnosti na pravděpodobnost selhání, zatímco u druhé skupiny se zdá být silnejším faktorem likvidita. Analýza ziskovosti odhalila vyšší stálost výnosů u firem s lepší výkonností ESG.

Klasifikace JEL	C23, G32, F23, L25, Q58
Klíčová slova	ESG, kreditní risk, ziskovost, panelová analýza dat
Název práce	ESG Skóre a Kreditní Risk

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Acronyms

APE Average Partial Effect

ASRF Asymptotic Single Risk Model

AT1 Additional Tier 1

BCBS Basel Committee for Banking Supervision

BIS Bank for International Settlements

CET1 Common Equity Tier 1

CFCR Cashflow Coverage RAtio

DE Debt-to-Equity

EAD Exposure at Default

EL Expected Losses

ESG Environmental Social and Governance

FE Fixed Effects

FGLS Feasable Generalised Least Squares

GMM Generalised Method of Moments

ICAAP Internal Capital Adequacy Assessment Process

LGD Loss Given Default

LPM Linear Probability Model

MA Maturity Adjustment

MLE Maximum Likelihood Estimator

PEA Partial Effect on Average

RE Random Effects

ROA Return on Assets

ROE Return on Equity

OLS Ordinary Least Squares

RWA Risk-Weighted Assets

UL Unexpected Losses

Chapter 1

Introduction

In recent years, there has been a notable increase in the significance attributed to corporate responsibility. It is no longer sufficient for a company to demonstrate economic results; it is now essential to understand the manner in which these results are achieved. The measurement of these means is commonly achieved through the monitoring of environmental, social, and governance indicators, which are typically abbreviated as ESG. Although the European Union mandated the reporting of these issues for large and listed enterprises as of 1 January 2024, many of them have been fulfilling their obligation in environmental, social, and governance spheres for years. During that time, there has been no consensus reached on the outcomes and impacts of the issue. Some experts argue that corporate responsibility leads to greater engagement and trust of both shareholders and stakeholders (Cornell & Shapiro 1987; Jensen 2010). In contrast, others claim that funds spent on such activities are a waste of resources with no tangible effect on matters outside the corporate sector (Barnea & Rubin 2010; Friedman 1970). This paper aims to contribute to the ongoing debate by examining the case of the Czech Republic.

The objective of this thesis is to identify and examine the eventual discrepancies between the determinants of credit risk and the profitability of firms engaged in ESG issues and those with worse ESG performance. In pursuing this objective, we were granted access to two datasets from an anonymous Czech bank. The first dataset comprises anonymised financial data regarding the condition of a number of companies that have been granted loans by our data provider. The second dataset contains a variety of information regarding the environmental, social, and governance (ESG) behaviour of the firms in question, as well as the assigned score for each of these criteria and the overall ESG score. The two aforementioned datasets are combined to create a new, unique dataset, which is employed in this thesis. We construct models for default risk and profitability and employ appropriate estimation techniques to evaluate them.

In the majority of cases, other researchers investigating the effects of corporate social responsibility on credit rating or profitability have included the ESG scores directly in their model (Chodnicka-Jaworska 2021; Henisz & McGlinch 2019; Kim & Li 2021; Li *et al.* 2022). However, this may prove problematic due to the potential for endogeneity and causality issues (see Abdallah *et al.* 2015). Accordingly, the ESG scores have been employed to divide the dataset into subsets based on the ratings of the firms.

Our findings support the hypotheses about the link between ESG, credit risk and profitability. Regarding the credit risk model, the results suggest that companies with inferior ESG scores react more extensively to changes in profitability and solvency, whereas the default probability of superior performers appears to react more strongly to changes in liquidity. With regard to the profitability analysis, the outcomes of the thesis indicate higher persistence of returns for companies with better ESG ratings. The incorporation of macroeconomic variables into the model resulted in an enhanced fit, although only the changes in the harmonised CPI were found to be statistically significant.

The rest of the thesis is structured as follows: First half of Chapter 2 maps the history and the present of the corporate social responsibility and ESG. Second half is dedicated to the development of credit risk. In Chapter 3 we introduce our dataset and approach the dataset used in this study. Chapter 4 presents the model structure and estimation method chosen as a framework for this thesis. Chapter 5 displays the estimates of our models together with analysis of the results. Chapter 6 summarises our findings and observations.

Chapter 2

Literature review

2.1 ESG and its predecessors

The origins of responsible investing can be traced back to the turn of the 1960s and 1970s (Brown *et al.* 2009; Eccles *et al.* 2020; Schueth 2003). The participation of the US in the Vietnam War and the rise of antiwar sentiments among part of its population resulted in the creation of Pax World Funds in 1971, the first mutual fund that took social criteria into consideration (Impax 2024). The trend persisted in the 1980s with the movement against the Apartheid regime in the South African Republic (Brown *et al.* 2009).

In March 1989, the Exxon Valdez tanker crash off the coast of Alaska caused an ecological catastrophe. In response, the Coalition for Environmentally Responsible Economies (CERES) was formed by various groups, including corporations, social investors, religious and environmental groups. The aim of CERES was to change corporate standards regarding the environment. In September of the same year, a set of rules was published to give consolidate these demands. These 10 rules are commonly known as the CERES principles (sometimes referred to as Valdez principles, see Schuck 1990). The aim of these rules was to promote sustainable use of resources, reduction of waste and energy consumption, public disclosure and management commitment. The severity of the situation is highlighted by the fact that these standards are perceived as something common and self-evident nowadays. Enterprises might choose to voluntarily comply with these rules to demonstrate their concerns about the approach to the environment and commitment to change (Brown *et al.* 2009; Smith III 1993).

At the same time, the global warming issue has been discussed at the international level. The formation of the Intergovernmental Panel on Climate Change within the United Nations in 1988 laid the foundations for worldwide solutions. The First Assessment Report addressed the issues of changing climate, mapping the scientific evidence and impact of climate change, and outlining response strategies (IPCC 1992). The report prompted the adoption of the United Nations Framework Convention on Climate Change (UNFCCC) at the Earth Summit in Rio de Janeiro in 1992. The signatory countries pledged to maintain the level of greenhouse gases in the atmosphere at levels that would prevent human-induced disruption of the climate system. The treaty became effective as of 1994 (United Nations Framework Convention on Climate Change. Secretariat 1992).

The goals of UNFCCC progressed further with the formulation of the Kyoto Protocol in 1997. States that ratified the protocol obligated themselves to decrease their greenhouse gases emissions by a certain amount between 2008 and 2012. Despite being signed in December 1997, the protocol did not come into effect until 2005 and was valid until 2020. The Kyoto Protocol was not universally accepted. Critics have pointed out that its implementation is extremely costly and the strategy is highly cost-ineffective with possibility of an actual increase in greenhouse gasses emissions (Copeland & Taylor 2005; Nordhaus & Boyer 1999). These concerns have been proven to be justified. Aichele & Felbermayr (2015) documented the presence of carbon leakages under the Kyoto Protocol, i.e. that enterprises transferred their production to countries with less strict environmental policies. Almer & Winkler (2017) found little evidence for the effect of Kyoto Protocol restrictions on greenhouse gasses emissions from high emitters. It is worth noting that the protocol was replaced by the Paris Agreement only in 2020.

In 2005, the Global Reporting Initiative (GRI) was established by CERES and Tellus Institute as a non-governmental organization to create and develop sustainability reporting standards. This was in response to the need for standardized reporting, which arose after the signing of the Kyoto Protocol. The guidelines were first issued in June 2000, and work on the second version began at the same time. The rules have been regularly updated and 78% of the world's 250 largest companies used GRI reporting standards as of 2022 (Adams *et al.* 2022; Brown *et al.* 2009; KPMG 2022).

Similar initiatives were carried out at the governmental level too. In January 1999, at the World Economic Forum in Davos, Switzerland, UN Secretary-General Kofi Annan invited the present representatives to join a global compact for setting standards that would humanise the global market (United Nations 1999). The pact was established in 2000 and is not legally binding. The Compact is based on nine principles that cover human rights, labour, and the environment. The human rights principles require respecting and protecting human rights and not being an accomplice in their abuse. The labour principles aim to eliminate discrimination, forced and child labour. The environmental principles require stepping forward to support environmental responsibility and development in this area (United Nations Global Compact 2000). In 2004, the Compact added a tenth principle that covers corruption, which requires the prohibition and active suppression of bribery and extortion (De Jonge & Tomasic 2017; United Nations 2004).

In 2004, once again on the initiative of the United Nations, a report titled *Who cares wins* was published by UNGC. The paper was produced as a joint project by a group of banks and investment companies. The ultimate aims of the rules and guidelines presented were to enhance the resilience and trustworthiness of financial markets and promote further sustainable development. The report outlined contemporary issues such as the vague definition of ESG issues and quality and the quantity of information. Noteworthily, the term *environmental, social and governance issues* and its abbreviation *ESG* were used for the first time in a document of such significance. The paper argued for the usefulness of ESG criteria for business and encouraged stakeholders to require compliance with these rules in order to ensure the long-term prosperity of the financial sector (United Nations 2004).

Another initiative by UN Secretary-General Kofi Annan led to the creation of Principles for Responsible Investment in 2005. Representatives of the largest institutional investors, supported by experts from various industries and intergovernmental organisations, established a network to shape yet another set of rules for responsible investment. Their efforts crystallised into the creation of six principles, which include implementing ESG issues into their own decision-making processes and reporting on their application, actively seeking ESG reports from companies in their portfolios and integrating them into their investment decisions. Furthermore, they should promote the principles and collaborate to improve compliance with them (PRI 2005). Note that these rules resemble an updated version of the CERES rules from the early 90s.

In 2011, Jean Rogers founded the non-profit organization, the Sustainability Accounting Standards Board (SASB), to improve sustainability reporting rules. Previous sets of rules were too general and did not consider the unique aspects of individual industries. The aim of SASB was to introduce rules that would allow for industry-specific reporting whilst maintaining a certain level of uniformity. SASB developed key performance indicators for sustainability based on the principles of simplicity, materiality, and transparency (Lydenberg *et al.* 2010). In November 2018, the organization released the first set of guidelines for 77 industries (SASB 2024a;b).

In 2015, significant changes were made to ESG and sustainability reporting, as well as climate protection as a whole. The UNFCCC made efforts to replace the Kyoto Protocol, resulting in the formulation of the Paris Accord. The main objective of this treaty is to limit the increase of the average global temperature to below 2°C and actively seek to keep the rise below 1.5°C compared to pre-industrial levels. The Paris Agreement differs from the Kyoto Protocol in that it applies to all signatory parties, rather than just a select group of developed countries. Each country is required to outline and document its contribution to the goal. Although no specific levels were set for the countries, it is expected that the emission targets will progressively surpass themselves. The Accord attempts to help mobilise sufficient financial means for this as well as aid in adapting to climate change (United Nations Environment Programme 2015).

In addition to emissions restrictions, the United Nations initiated the creation of another guideline for human development on a broader scale. Following on from the Millennium Development Goals, the United Nations has published Sustainable Development Goals (SDGs), a set of 17 objectives aimed at achieving greater peace and prosperity on Earth. Although these are not directly focused on the financial sector like ESG, it is evident that the SDGs promote very similar objectives: equality of sexes, decent work and economic growth, reduced inequalities and responsible consumption and production to name a few (United Nations 2015). The SDGs are to be met by 2030. The progress of fulfilling these aims is quite heterogeneous. While some have seen promising advances (particuraly those related to economic issues), others have experienced rather worse outcomes and are unlikely to be completed on time (Halkos & Gkampoura 2021; Affairs, D.E.S. 2020).

At the end of 2015, the Financial Stability Board (FSB) established the Task Force for Climate Related Financial Disclosure (TCFD) at the request of the G20 Group. The TCFD's mandate was to create recommendations for disclosing information on climate change risks to investors and stakeholders. The first set of disclosure recommendations, published in 2017, revolves around 4 thematic areas: risk management, governance, strategy, and metrics and targets. In 2023, the TCFD was disbanded and its activities were taken over by the International Financial Reporting Standards (IFRS) Foundation, as it was deemed successful in achieving its purpose (TCFD 2023).

In 2019, the European Council launched a new agenda to create a carbon-neutral European Union. The initiative resulted in the creation of the European Green Deal, a set of policies initiated by the European Commission. Its main aim is to sequentially lower the GHG emissions in the European Union to achieve a zero-carbon footprint of the member states until 2050. The policies encompass changes for a number of aspects of living in the European Union with wide-ranging impacts on everyday life. Although only some of the policies are directly focused on financial sector, others affect all sectors of the economy. Moreover, the target of achieving climate neutrality has become one of the top priorities and supersedes all sectors of the economy to this goal.

The European Council (2023) lists the following initiatives under the Green Deal programme: Fit for 55 and European Climate Law propose 55% cut in GHG emissions in the EU by 2030. The EU strategy to on adaptation to climate change and EU biodiversity strategy for 2030 intend to prepare Europe for the inevitable change in climate, recovery and preservation of European nature. Farm to Fork and Forest Strategy and Deforestation focus on agriculture and nature respectively. The former aspires to create a plan for a healthy and nutritious diet with sustainable production, while the latter is one of the key elements in the efforts to reduce the GHG emissions and form sustainable policies for forestry. The European Industrial Strategy invigorates the role of industry in growth and innovation. The EU Chemicals Strategy for Sustainability aims to protect human health and create an environment free of toxic substances. Clean Affordable and Secure Energy stresses the development of clean energy sources and the promotion of renewable energy usage, as 75% of GHG emissions in the EU originate from the power industry. The Circular Economy Action Plan supports a shift towards circular production and consumption, which involves extending the life cycle of products to the maximum. Financial support for these policies will be provided by the Just Transition Mechanism and Fund, with a total of €55 billion reserved to cover the costs associated with the transition of European economies to the Green Deal (European Council 2023).

To effectively monitor the progress of implemented measures, the European Union has placed several rules related to ESG reporting. Firstly, in 2021, the Sustainable Finance Disclosure Regulation (SFDR) was introduced. This regulation requires financial market participants to disclose sustainability information to assist investors in making informed decisions about green investment opportunities (European Commission 2023). In 2023, The Corporate Sustainability Reporting Directive (CSRD) was introduced, requiring large companies and listed small and medium enterprises to include ESG details in their annual reports. This is supposed to provide both stakeholders and investors with additional information to assess the company's risk in relation to climate change. According to the directive, the ESG reports must be included from 2024 annual reports onwards (European Commission 2024).

2.2 ESG and CSR currently

Even though the mandatory ESG reporting became firstly effective in the European Union in 2024, companies around the world have included the reports on their corporate responsibility for a longer time, although the extent of this practice is heterogeneous. Thorne *et al.* (2014) investigated Canadian companies for their CSR disclosure practices and motivations. They claim that larger companies are more likely to issue standalone CSR reports due to their public visibility and governmental supervision. Contrarily, family companies are more prone to issue less transparent ESG reports, especially in the social subsection. This is due to the high value attached to virtues such as privacy and legacy, which are highly esteemed in such companies. Moreover, it has been proven that institutional investors may enhance corporate responsibility disclosure in the family companies (Arduino *et al.* 2024).

The relationship between ESG, corporate responsibility and decision-making can be viewed from two competing perspectives. The stakeholder value maximisation perspective argues that a company should consider interests of not only the bond- and stockholders, but also other participants involved in the firm's activity, such as employees, customers or government workers. The central concept is the discrepancy between explicit and implicit contractual claims. In the former, the concepts such as warranties and wage contracts are understood. The latter can be represented by an improvement in working conditions or employment security. A contemporary example of implicit contract could be a season pass in a videogame. The game developer undertakes to continue providing new content for the game for some time after the release, thus the buyers were sold (apart from the game itself) an implicit claim that the new content be provided. However, the exact nature of this content is unknown.

A company that has proven its trustworthiness in implicit contracts will provide incentives to stakeholders to contribute to its efforts, thereby positively affecting the shareholder wealth (Cornell & Shapiro 1987; Jensen 2010).

In contrast, the shareholder expense approach asserts that the primary responsibility of management is to generate profit and raise the value of the company for its shareholders. From this point of view, a company is not a person and thus cannot have any responsibility. The corporate executives are employees of the owners of the business, with responsibility to conduct operations in a manner that aligns with their objectives. These objectives often include the maximisation of the profits (unless the company in the question is a non-profit or governmental organisation) while complying with relevant laws and social norms. In this sense, spending the money provided by the shareholders for a general social interest and thus diverting from their role can be considered a form of misappropriation (Friedman 1970). Furthermore, the executives may gain utility from their role within a corporate entity that behaves responsibly and as a "good citizen". Given that they bear only a fraction of the costs, they are susceptible to excessive expenditure on CSR issues. Empirical evidence indicates that both insiders' ownership and leverage have a negative effect on firm's social rating, meaning that once insiders have acquired a significant stake in the company, they tend to restrict this type of spending (Barnea & Rubin 2010).

The composition of the corporate executive team is an important factor influencing corporate responsibility issues and spending within the firm. Harjoto *et al.* (2015) investigated the influence of board of directors' diversity on CSR performance of US companies. The results suggest that a more diverse board of directors is associated with higher CSR level of the company. Namely, the variety in sex, tenure and experience of the members reduces the corporate social responsibility concerns. On the other hand, the effect of race, age, power or outside directorship was found to be insignificant. Li & Kong (2024) focused on the executives in Chinese companies and detected a negative link between financial background of executives and CSR spending. The effect was amplified in privately-owned companies and in highly competitive markets. In a study focused on French listed companies between 2006 and 2017, Miloud (2024) found that companies with efficient governance issue more informative reports and adhere to GRI standards more rigidly.

The implementation of corporate responsibility practices creates or influences a range of different types of risk. Mandas *et al.* (2024) identified a negative effect of ESG reputational risk on market value in a sample of European banks. Furthermore, banks with a greater ESG exposure are more vulnerable during unstable periods and tend to respond more strongly to reputational risk shocks. Zhang *et al.* (2024) uncovered ESG performance having a reducing effect on litigation risk via internal control in a sample of more than 6,000 listed companies from Shanghai and Shenzhen between 2016 and 2022.

As a result, the companies that proactively address social issues and maintain high ESG scores tend to obtain more favourable loan conditions than their counterparts with lower social responsibility levels (Alves & Meneses 2024; Huang *et al.* 2024; Goss & Roberts 2011). Goss & Roberts (2011) discovered in a sample of US firms that those with inferior CSR received less favourable loan maturity and spread (approximately 7 to 18 basis points) compared to those conducting their business in a more socially responsible manner. In a similar vein, Eliwa *et al.* (2021) observed a correlation between higher ESG performance and a reduction in the cost of debt for companies in European countries. In addition, Alves & Meneses (2024) claim that data substantiates the hypothesis that ESG is overall a more relevant factor for companies with higher indebtedness. The authors have observed a disparity based on geographical context as well. In the US market and countries with a bank-based financial system, ESG is a more significant factor.

Another area of interest for researchers was the cost of equity. El Ghoul *et al.* (2011) conducted a study on 13,000 US companies over the period of 1992-2007. Enterprises with higher levels of CSR exhibited a significantly lower cost of equity. The study revealed that employee relations, environmental policies and product strategies contribute to a reduction in debt cost, whereas human rights, diversity and community relations do not.

The effect on mergers and acquisitions is debatable. Deng *et al.* (2013) investigated mergers on the US market between 1992 and 2007. The findings indicate that mergers by higher CSR acquirers take less time and are more likely to be finished successfully. Moreover, the increase in long-run operating performance is more noticeable and merger announcement returns, in conjunction with long-run stock returns, are higher as well when compared to lower CSR acquirers. This suggests that corporate responsibility plays an important part of merger performance and supports the stakeholder value maximisation view. In contrast, Brunner-Kirchmair & Wagner (2024) examined mergers and acquisitions in the European market between 2005 and 2019. The findings imply no significant effect of the acquiring company's CSR on operating performance. In addition, the stock performance appears to be negatively affected in both the short and long term for the acquirers with higher CSR levels. The authors notice this contrast between the US and the European areas and argue that CSR reporting in Europe is heavily regulated by laws and institutional frameworks. In America, reporting is based more on a voluntary principle, with a lower proportion of companies reporting on CSR compared to Europe (see KPMG (2022)). The authors posit that CSR investments above the regulatory framework are not appreciated positively by European shareholders, but rather perceived as an overinvestment and a value-decreasing factor. The regional disparities in the impact of environmental, social, and governance factors on European and US markets are also discussed in other papers (see Alves & Meneses (2024)).

The research suggests important implications of corporate social responsibility in times of crises. In periods of uncertainty, trust and social capital are important determinants of performance. Firms with superior CSR tend to perform better and various announcements have a less disruptive effect on them than on their competitors with inferior CSR (Lins *et al.* 2017; Rupp & Limpaphayom 2024).

What is more, the implementation of ESG practices has significant implications for the broader economy. In normal times, both the best and the worst ESG performers have an impact on the financial system. However, in times of crisis, companies with high levels of ESG have greater spillover effects, highlighting the importance of ESG in systematic risk assessment and insinuating policy measures to prevent these effects (Bax *et al.* 2024).

2.2.1 Controversies

The objective of ESG reporting is to facilitate the identification and assessment of various risks within an enterprise, enhance transparency, and assist potential investors in their decision-making processes. Consequently, companies may be inclined to embellish the reality of their circumstances in order to persuade investors and supervisors that the state of affairs within the company is more favourable than it actually is. This practice in terms of ESG is usually referred to as "greenwashing". It was first employed in an essay by Jay Westerveldt in 1986 when he exposed the dubious practice in the hospitality industry, where hotels promoted repetitive towel use to save the environment. In reality, the accommodators made minimal to no effort to actually address the environmental issue and utilised the aforementioned practice solely to decrease laundry costs (Orange & Cohen 2010).

In the wake of this, a problem of correct identification of greenwashing has arisen. It has been found that customers are usually able to identify greenwashed products when cautioned about their presence. However, when unsuspecting any dishonest product labelling, most of them succumb to it (Fella & Bausa 2024). A similar abuse is present on financial markets. Eliwa *et al.* (2021) argued that the market is unable to differentiate between ESG performance (engagement in social and ecological activities) and disclosure (the presentation of information designed to directly influence stakeholders' perceptions). According to the findings of Teti *et al.* (2024), the market appears not to react to greenwashing revelations. Such announcements appear to have little to no effect on the company's cumulative abnormal returns, implying that the market itself is not fully capable of identifying and punishing such behaviour, calling for governmental oversight.

Nevertheless, the governmental interventions may have unintended consequences. The impact of environmental regulations on green innovations in low-polluting firms is negligible, whereas they significantly decrease the number of such innovations in the case of heavy polluters. Furthermore, more stringent restrictions may encourage unsustainable businesses to towards greenwashing practices (Zhang 2022b). A similar consequence of regulation can be observed in product quality. While it might assist low-polluters in raising the quality of their products, their non-ecological competitors lean towards product quality deterioration. The latter corporations are also constrained by financial limitations, which is not the case for the former ones (Zhang 2022a). It has been identified that enhanced credit accessibility reduces the prevalence of greenwashing behaviour, particularly for highly leveraged and large, financially constrained firms (Sun 2024).

The social environment and its behavioural patterns belong to important determinants that influence the actions of businesses in terms of morality. Evidence was uncovered indicating a strong positive relationship between societal trust and the conduct of corporations, which partially explains cross-country variations in ESG practices (Chkir *et al.* 2023). A study conducted in the United States revealed relationship between religiosity and greenwashing. Companies based in counties with a stronger religious sentiment among their residents were found to be less prone to undertake greenwashing, and even if they did, the extent of such activities was relatively limited (Gomes *et al.* 2024).

One of the issues connected to greenwashing is constituted by the ESG scores themselves. These are based on the reports of the firms and issued by independent third-party rating agencies. The absence of a standardised framework (as illustrated in the previous chapter) leads to varying methodologies and approaches for the computation of the individual components and the overall ESG score. Rating agencies have the option to select from a range of E, S and G measures and employ different weighting methods. This in turn may (and often does) result in heterogeneity in ESG scores issued by various agencies for the same company (Billio *et al.* 2021; Gibson Brandon *et al.* 2021; Lee *et al.* 2023; Lopez *et al.* 2020). This also provides firms with opportunities for greenwashing, particularly by manipulating the S and G factors that can be viewed more subjectively as the E factor (Lee *et al.* 2023).

2.3 History and development of credit risk

This section provides insight into the evolution of credit risk and associated matters. The emphasis is placed on the development of related Basel rules set by Bank for International Settlements (BIS) which are generally accepted standards in contemporary financial world. Additionally, a short synopsis of PD models is presented.

Every loan has two counterparties: the lender and the borrower. The borrower, also known as the creditor, provides amount of money to lender, or obligor, with the expectation of its return. There is always a chance that the lender will not be able to return the money back, and the borrower usually requires a bonus amount to offset it. This risk is commonly referred to as credit risk. Basel Committee on Banking Supervision defines credit risk as follows:

> Credit risk is most simply defined as the potential that a bank borrower or counterparty will fail to meet its obligations in accordance with agreed terms. The goal of credit risk management is to maximise a bank's risk-adjusted rate of return by maintaining credit risk exposure within acceptable parameters. Banks need to manage the credit risk inherent in the entire portfolio as well as the risk in individual credits or transactions. Banks should also consider the relationships between credit risk and other risks. The effective management of credit risk is a critical component of a comprehensive approach to risk management and essential to the long-term success of any banking organisation (BCBS 2000).

Nevertheless, credit risk is not a recent phenomenon, as borrowing and lending of money (and the risk associated with it) have existed since the introduction of money itself. The earliest coins, as we understand them today, are believed to be issued during the ancient period, specifically in the Kingdom of Lydia around in 7th century BC (Mitchiner 2004). Gibbon (1840) described the customs of borrowing and lending of (not only) money in the ancient Roman Empire, where an important part of the compliance with obligations was the Roman goddess of faith and honesty Fides. This was reflected in the honouring of financial obligations. Moreover, formal rules were incorporated into Roman law system that punished dishonesty and usury. Smith (1776) mentions a predecessor of risk management: due to insufficient law enforcement in the barbaric kingdoms that appeared on the map of Europe after the fall of the Western Roman Empire, the interest rates on borrowing money were extremely high, even usurious. This was a result of the borrowers protecting themselves against expected losses. Noticeable are also authorâ€™s remarks about the contemporary credit market: while bank has to review number of loan application submitted by many different people and thus has restricted information, a private lender is prone to lend money only to person with reasonable judgement whom he trusts to return the lent amount.

Today, the vast majority of the financial transactions, including borrowing, is carried out through banks. The European Union defines bank (or 'credit institution' to be specific) as *an undertaking the business of which is to take deposits or other repayable funds from the public and to grant credits for its own account* (European Union 2013). Půlpán *et al.* (1998) defines bank as *a financial provider, credit institution, or deposit institution collecting free money and offering loans to different subjects as well as services (mainly connected to a payment system).*

The aforementioned definitions highlight the most important roles of the banking sector which in turn is one of the crucial components of the financial system (Mejstřík *et al.* 2015). Therefore, governments endeavour to regulate and protect the banking sector to establish sound and secure environment. Hull (2012) claims that the main reason for banks regulation is to ensure the sufficient level of capital for its respective risk appetite. For the first half of 20th century, the regulation of banks happened mostly on the national level. The internationalisation of regulatory rules in the world began in 1970s with the progressing globalisation and the resulting pressure on unification of rules and standards. Besides, more sophisticated types of transactions (interest rate swaps, currency swaps...) have been created, which made the situation regarding the different national regulations even blinder (Mejstřík *et al.* 2015).

2.3.1 Basel I

The final catalyst for a resolute action was the failure of Bank Herstatt in Germany. In the 1973 and 1974, Bank Herstatt became involved in German Mark (DEM) - US Dollar foreign exchange market and accumulated large losses - approximately 470 million DM, while the capital of the bank was only 44 million DM. These problems did not initially attract the attention of German authorities, as reporting on forward exchange transactions was not required and the bank assured the supervisory authorities that everything was in order. The problems became apparent in June 1976 (Schenk 2011). On 26 June 1976, the German authorities ordered the liquidation of the bank. The bank was closed at 16:30 CEST, which was equal to 10:30 EDT in New York. Due to this discrepancy, Bank Herstatt had already received the payments in DEM, but had not released USD payments due, which affected several financial institutions in the United States (European Central Bank 2007; Schenk 2011).

In response, the Basel Committee on Banking Supervision (BCBS) was established by the BIS at the end of 1974 (Bank for International Settlements 1975). The founding countries were members of the G10 group (USA, Canada, the United Kingdom, France, West Germany, Italy, Belgium, the Netherlands, Sweden, Japan, Switzerland) and Luxembourg. The goal of the committee was to strengthen financial stability through upgraded rules for banking regulation and to serve as a forum for cooperation among members. The initial efforts culminated in 1988 with the issue of set of rules and recommendations known as the 1988 BIS Accord (also called the Basel Accord, the Basel Capital Accord and later colloquially as Basel I). The main objective was to set the standards for credit risk and capital adequacy. The Accord defined capital tiers and risk weights for assets of internationally active banks. Tier 1 capital consisted of common equity and disclosed reserves. Tier 2 capital (or supplementary capital) comprised hybrid capital instruments, subordinated debt and other instruments (BCBS 1988). Risk weights were created to reflect the hazard of the distinct types of obligors, ranging from 0% to 100% . Another important innovation was the introduction of the so-called Cook Ratio (named after Peter Cooke of Bank of England), also known as the Capital Adequacy Ratio. This ratio compares the capital of a bank and its risk-weighted assets (BCBS 1988; Hull 2012):

$$CAR = \frac{Tier\ 1\ Capital + Tier\ 2\ Capital}{Risk - Weighted\ Assets} \geq 8\%.$$

Risk weigths	*Asset category*
0%	Cash, claims on OECD central governments and central banks
20%	Claims on banks incorporated in the OECD, non-domestic OECD public-sector entities
50%	Loans fully secured by mortgage on residential property
100%	Claims on private sector, commercial companies, real estate investments, banks and governments outside OECD

Table 2.1: Risk weights according to Basel I.

According to the Accord, the ratio should be at minimum 8%. At least 50% of the regulatory capital held had to be Tier 1 capital. The changes introduced by the Accord were to be implemented until the end of 1992. In addition to the basic principles proposed in 1988, a supplement to these rules was issued eight years later as the 1996 Amendment, which presented modifications to calculation of capital requirements for market risk.

2.3.2 Basel II

The First Basel Accord was highly successful, with more than 100 countries implementing the rules. Nonetheless, certain problems arose after the implementation of the rules. Universal risk weights for an asset category (e.g. corporate loans) and the resulting capital requirements without distinguishing the actual risk were deemed as a major weakness of the rules. Chatterjee (2015) argues that it led to risk-shifting of banks, incentivising them to hold riskier assets as they were expected to yield higher returns. Jablecki (2009) supports this claim (securitisation of assets in the US banking sector) and adds that banks trying to properly comply with the regulations might reduce their lending due to capital requirements. This led to the proposal of new rules by the BCBS in 1999 (Hull 2012). The final version of the Basel II rules was approved in 2004 and was to be implemented in 2008. The main objectives that the Committee wanted to achieve included more risk-sensitive capital requirements, greater utilisation of internal systems in capital calculations and a wider choice of approaches for financial institutions to credit and operational management that better reflect their operations and financial market infrastructure (BCBS 2006). The Accord was built around three pillars: Pillar I - minimum capital requirements, Pillar II - supervisory review of capital adequacy and Pillar III - effective use of disclosure.

The First Pillar brought about the most far-reaching changes. This thesis focuses on credit risk, so only the adjustments to the computation of market and operational risk will be briefly mentioned. Three approaches were presented for operational risk: the Basic Indicator Approach (BIA), the Standardised Approach (SA) and the Advanced Measurement Approach (AMA), from the simplest to the most complex. It is important to note that the AMA is subject to supervisory approval. Regarding the market risk, the Value at Risk (VaR) approach had become the preferred model. The most extensive changes have been aimed at credit risk. Three frameworks for calculation of credit risk had been specified: Standardised, Foundation Internal Rating Based and Advanced Internal Rating Based.

The Standardised Approach was the simplest one and was intended for less sophisticated banks. Although it retained the rationale of the First Accord in the form of risk-weighted assets, the system of risk weights altered significantly.

	AAA to AA-	*A+ to A-*	*BBB+ to BBB-*	*BB+ to B-*	*Below B-*	*Unrated*
Sovereigns	0%	20%	50%	100%	150%	100%
Banks	20%	50%	50%	100%	150%	50%
Corporates	20%	50%	100%	150%	150%	100%

Table 2.2: Risk weights according to Basel II.

As can be seen in table 2.2, creditors from the same segment were no longer considered as equally risky in order to better reflect the actual risk associated with the borrower. The Internal Rating Based (IRB) Approaches introduced new principles for calculating of regulatory capital for credit risk and introduced numerous new definitions and terms. Losses were divided into two categories: expected and unexpected. Expected loss (EL) is computed as the product of probability of default (PD), exposure at default (EAD) and loss given default (LGD):

$$EL = PD * EAD * LGD.$$

While PD is an entity characteristic, EAD is a parameter of transaction. The regulatory minimum for PD was set at 0.03%. Banks and other financial institutions were not required to hold capital to cover expected losses as these should be covered by margins and provisions. Unexpected losses (UL) were computed as the complement of expected loss to credit value-at-risk, i.e. extreme (stressed) credit loss. The latter is calculated using asymptotic single risk factor (ASRF) model proposed by Merton (1973). This model estimates the probability of a single borrower defaulting within a one-year period, assuming normal distribution of the risk. A 99.9% one-tail confidence level was set by Accord to simulate the extreme loss situations. The formula is as follows:

$$PD_s = N\left(\frac{N^{-1}(PD) + N^{-1}(0.999)\rho^{1/2}}{(1-\rho)^1/2}\right)$$

where PD is the probability of default of the borrower, N denotes the normal cumulative distribution function and ρ stands for the correlation coefficient. Basel II assumed a relationship between the correlation coefficient and the probability of default in the following form:

$$\rho = 0.12 * \frac{1 - exp(-50 * PD)}{1 - exp(-50)} + 0.24 * \left[1 - \frac{1 - exp(-50 * PD)}{1 - exp(-50)}\right]$$

The capital requirement for credit risk (expressed as a percentage of EAD) was then computed as

$$CR = (LGD * PDs - LGD * PD) * MA,$$

where

$$MA = \frac{1 + (M - 2.5) * b}{1 - 1.5 * b}$$

is the maturity adjustment that accounts for one-year credit exposure of an instrument with longer maturity, M is maturity of exposure and

$$b = [0.11852 - 0.05478 * ln(PD)]^2.$$

Finally, the RWA is calculated as

$$RWA = 12.5 * CR * EAD.$$

The coefficient 12.5 is the inverse value of the regulatory minimum of 8% (BCBS 2006). In the Foundation IRB approach, the bank computes the PD, while EAD and LGD are determined by Basel II. In the Advanced IRB approach, the bank is expected to calculate all components, but still has to abide by certain rules and set values - for instance, the 0.03% minimum for PD (Hull 2012).

An important addition was the exact definition of default as this was only defined in an indirect way in Basel I. According to the document, a *default is* *considered to have occurred with regard to a particular obligor when either or both of the two following events have taken place.*

- *The bank considers that the obligor is unlikely to pay its credit obligations to the banking group in full, without recourse by the bank to actions such as realising security (if held).*

- *The obligor is past due more than 90 days on any material credit obligation to the banking group. Overdrafts will be considered as being past due once the customer has breached an advised limit or been advised of a limit smaller than current outstandings* (BCBS 2006).

Last but not least, new Tier 3 capital was introduced to support market risk. Tier 3 mainly comprised of short-term subordinated debt (Hull 2012).

The purpose of Pillar II was to encourage banks to align their capital position and strategy were consistent with their risk profile and to implement more sophisticated risk management processes within the bank. Banks were mandated to implement processes to assess overall risk adequacy in relation to risk. Operating above minimum regulatory capital ratios was promoted. Supervisory review and evaluation of banks were established together with supervisory intervention in order to prevent capital from falling below minimum levels. Pillar II measures led to the introduction of the Internal Capital Adequacy Assessment Process (ICAAP), which formalised a framework for overall governance and supervision. Pillar III required banks to disclose more information about capital allocation and risk appetite to enhance shareholder awareness and potential shareholder foreknowledge (BCBS 2006; Hull 2012).

2.3.3 The Great Recession and Basel III

The urge for a modification of rules became fully apparent in 2007, before the Basel II Accord was fully implemented. The year-long financial crisis was one of the most severe ones in recent history, thereof the name The Great Recession. One of its major causes was the subprime mortgage crisis: financial inflows into the US led to relatively cheap loans and subsequent housing boom. Problems emerged in early 2007 due to subprime mortgages. These mortgages were granted to clients with low credit scores who were unable to repay (Bernanke 2009; Taylor 2009). According to the report by US Financial Crisis Inquiry Commission (2010), the crisis was avoidable and was caused by failures in financial supervision and regulation, corporate governance and risk management, excessive borrowing combined with risky investments and lack of transparency.

Concerns about the calculation of market risk emerged during the crisis. The series of adjustments to Basel II were published in 2009 and later became known as Basel II.5 (BCBS 2009). Nevertheless, the crisis exposed other problematic parts of Basel II. Risk weights depended on external ratings from rating agencies, which proved to be problematic and were part of the contributed to the contagion of the crisis (US Financial Crisis Inquiry Commission 2010). Their questionable quality was addressed by the Dodd & Frank (2010), which made credit rating agencies more accountable for their ratings. However, the impact of this legislation has not been as expected. Dimitrov *et al.* (2015) argued that the ratings were not more accurate or informative but rather artificially lowered, resulting in more false warnings.

Nevertheless, the Committee was aware of the deficiencies of Basel II and began work on an entirely new set of rules. The new Accord aimed to improve the ability to absorb shocks, further enhance risk management and corporate governance and strengthen transparency and disclosures at both the microprudential and macroprudential levels. The proposals for the new Basel III Accord were first published in December 2009 and after incorporating comments and suggestions from banks, the final version was published a year later (Hull 2012). Implementation was originally scheduled for 2013-2015, but had been gradually postponed and finally took effect on 1st of January 2023.

Extensive changes were made to the classification of capital. Tier 3 capital was abolished. Tier 1 capital was split into two categories. The first category, Common Equity Tier 1 (CET1) capital, is built up from common stock and retained earnings, while excluding goodwill and deferred tax assets. The second, Additional Tier 1 (AT1) capital, consists of assets that were previously classified as Tier 1 but were not common equity. Tier 2 capital has been retained (Hull 2012).

2.3.4 Probability of default models

The first efforts to conduct a more comprehensive analysis of default detection (with the integration of financial ratios) can be traced back to the late 1930s (see Merwin 1942; Smith 1935). Significant contributions to the field were published in the 1960s. Beaver (1966) used various financial ratios to determine the creditworthiness of debtors. These included cashflow ratios, net income ratios, debt-to-total assets ratios, liquid assets-to-total assets ratios, liquid assets-to-current debt ratios and turnover ratios. The author also pointed out a very interesting remark that should be considered when using these ratios. The ratios are used to assess the health of a company. Poor values of these ratios may indicate illness and malfunctioning in the company, but on the other hand, they may help to detect it and start the recovery process to restore good financial condition. It is therefore important to remember that the ratios may not only act as a predictor of failure, but also as a warning to the company's management that it is time for change.

Two years later, Altman (1968) published another significant work, in which he examined a sample of 66 US manufacturing medium-sized companies. The sample comprised 33 bankrupt companies and 33 operating companies, and spanned the period from 1946 to 1965. The author employed a range of ratios, including those covering liquidity, solvency, leverage, profitability and activity, to compute a coefficient using multiple discriminant analysis (MDA). This coefficient later became known as the Altman Z-score. The original form of the score is as follows:

$$\boldsymbol{Z = 1.2x_1 + 1.4x_2 + 3.3x_3 + 0.6x_4 + 1.0x_5},$$

where x_1 = working capital to total assets, x_2 = retained earnings to total assets, x_3 = EBIT to total assets, x_4 = market value of equity to book value of total liabilities and x_5 = sales to total assets. A company was deemed to be in a healthy financial position if its score was above 2.99. Conversely, a score below 1.8 indicated a serious risk of default. Corporates scoring between these two values were regarded as being of some doubt as to their financial viability.

The original model had an accuracy of 95%. The model's drawbacks included a relatively small and specific sample (middle-sized US manufacturing firms). However, over time, the model coefficients and interpretation of the score itself have been adjusted on multiple occasions (see Altman 2013; 2018). Consequently, the z-score continues to be a valuable tool in this context.

In the following years, other researchers continued the work of Beaver and Altman, further developing MDA in the field of bankruptcy prediction (Deakin 1972; Edmister 1972; Wilcox 1971). In the late 1970s, works discussing the drawbacks and limitations of the discriminant analysis in default prediction appeared (Altman & Eisenbeis 1978; Joy & Tollefson 1975). As a result of these shortcomings of MDA, the logit/probit approach became more popular and was utilised in the field. The early pioneers of this technique were Martin (1977) and Santomero & Vinso (1977), who applied logit regression to model the bankruptcy of financial institutions, while Chesser (1974) and Ohlson (1980) examined the bankruptcy of commercial companies. Zmijewski (1984) employed a probit model on a sample of non-financial firms. Despite the limitations of both the logit and probit methods, they remain widely used in the field. Empirical evidence suggests that they have superior predictive power compared to DA models (Gurnỳ *et al.* 2013; Lennox 1999). In addition to the aforementioned methods, other techniques employed for bankruptcy prediction include generalised additive models (Berg 2007), deep learning models (Mai *et al.* 2019), neural network models (Tam 1991; Yang *et al.* 1999; Zhang *et al.* 1999) and hazard models (Bauer & Agarwal 2014).

While some of the models investigating the default probability utilise macroeconomic data, others rely on microeconomic data, and there are also models that combine these two approaches. Jakubík & Teplỳ (2008) employed data from the Czech Capital Information Agency to identify the factors influencing bankruptcy in the Czech Republic between 1993 and 2005. In their model, the most influential factors for default were identified as interest coverage, cash ratio and financial leverage. Kovacova & Kliestik (2017) employed a similar model on 2015 Slovak corporate data. The results indicate that rentability, liquidity and capital structure are significant predictors of bankruptcy. Westgaard & Van der Wijst (2001) conducted a study of small and medium-sized enterprises in Norway, and reached similar conclusions to those of the aforementioned researchers. Another finding by Cherkasova & Kurlyanova (2019) was the identification of a U-shaped relationship between default probability and research and development expenditure. While the aforementioned analysts employed microeconomic data, Virolainen (2004) investigated bankruptcies in various industrial sectors using quarterly data from Finland over the period of 1986 to 2003 at the macroeconomic level. The paper found a significant relationship between macroeconomic variables (GDP, interest rate, corporate indebtedness) and default rates.

Analogous models were employed to investigate the financial sector and the probability of bank default. Gurnỳ *et al.* (2013) compared logit, probit and linear discriminant methods in determining US bank bankruptcies between 2007 and 2010. The logit model exhibited the best predictive power out of the three employed methods. The study found that size (total assets), profitability (return on average equity) and assets quality (problem loans to gross loans) had a significant effect on default probability. Peresetsky *et al.* (2004) built a similar model for Russian banks and demonstrated that the addition of macroeconomic variables improved the overall quality of the model. Another work by Peresetsky & Karminsky (2011) showed that using a model with publicly available data could approximate the rating of the banks by Moody's. The study identified four key determinants of default: size, capital adequacy, profitability and efficiency. The issue of determining the appropriate lag structure of the model remains unresolved. Some researchers employ a static contemporaneous model with no lags (Chodnicka-Jaworska 2021; Kim & Li 2021), while Westgaard & Van der Wijst (2001) concluded that a two-year period between accounting data and status is optimal. In their study on the default of Russian banks, Peresetsky *et al.* (2004) estimated the optimal lag to be between one and one and a half years, while Gurnỳ *et al.* (2013) suggested a one-to-two-year delay.

Another issue connected to PD modelling stems from the Basel rules and the possibility of internal models for default probability. Although the Basel III Accord addressed the issue of internal ratings-based (IRB) models, there are still incentives for banks to obtain more favourable results that are not in line with the intention of the regulators. Consequently, the estimation of the probability of default (PD) for the same company by different banks and their respective models can yield markedly disparate results, exhibiting a pronounced downward bias when compared to third-party estimates (e.g. rating agencies). Furthermore, Stepankova & Teply (2023) demonstrated that differences based on location, industry, and type of firm are present in these estimates.

2.4 ESG, default and financial performance

In their meta-analysis, Friede *et al.* (2015) examined over 2000 studies dealing with corporate social responsibility and profitability published from the 1970s. The majority of these papers suggest a positive relationship between CSR and corporate financial performance. The study also highlights potential for ESG outperformance in North America, emerging markets and non-equity assets classes. Kim & Li (2021) conducted a more detailed investigation into the relationship between ESG practices and corporate finance, examining a sample of over 4,700 companies from the S&P database. The paper identifies a positive effect of overall ESG scores on corporate profitability and further investigates the influence of the individual factors. While all factors positively affect the profitability, amplified for companies with large total assets, the governance category appears to be the most influential, with the effect being particularly strengthened for firms with weak governance. Pu (2023) identified a non-linear relationship between ESG activities and firm performance in a Chinese sample of companies. The inverted U-shaped relationship indicates the existence of an optimal volume of ESG actions that maximise a company's financial performance.

The financial sector was also the subject of research. Azmi *et al.* (2021) examined the impact of corporate social responsibility (CSR) on the value of banks in emerging economies. The results indicated that low levels of ESG have a positive effect on bank value in developing markets, with diminishing returns to scale when increased. While efficiency and cash flow are positively influenced by ESG activities, there is evidence of a negative effect on the cost of equity.

A higher ESG scores also leads to higher price targets set by financial analysts. In this case, the most influential component is the environmental performance (Roger 2024).

In recent years, the significance attributed to ESG scores and their predecessors as a contributing factor in determining default risk has increased. Incorporating ESG factors into credit risk assessment significantly increases the accuracy of the rating models (Bonacorsi *et al.* 2024; Michalski & Low 2024; Weber *et al.* 2010).

Nonetheless, the particular effect of individual factors and ESG scores as a whole is questionable since researchers have obtained assorted results. Chodnicka-Jaworska (2021) used Moody's and Fitch credit ratings for European companies as a regressand. A significance of ESG factors and scores was present in a simple model, however, after adding control variables, only the environmental score was statistically significant at the 1% level with a positive effect in a model with Fitch ratings. Governance and the overall score were significant at the 10% level with both having a positive on rating. The study also identifies the industrial, energy and utilities sectors as the most sensitive to ESG measures.

The results of Kim & Li (2021) demonstrated the effect of all subfactors and the overall score on the credit rating, with the social dimension being the most influential factor and environmental having negative effect on credit rating. Li *et al.* (2022) exposed an inverse relationship between ESG scores and default risk.

One of the most crucial aspects of examining the impact of ESG is the accurate identification of causality. This is a matter that has been somewhat overlooked in the field of business analysis. A failure to consider the potential for endogeneity may result in inaccurate estimates and misleading inferences (Abdallah *et al.* 2015). It was demonstrated that CSR was positively correlated with both prior and future financial efficiency. This indicates that the availability of surplus resources that can be allocated to ESG and good management expressed in the form of ESG affect the corporate financial performance (Waddock & Graves 1997).

Chapter 3

Data description

3.1 ESG dataset

The data utilised in this paper was provided by an anonymous Czech bank in the form of two principal datasets. The first dataset contains information on the environmental, social and governance ratings of companies. It comprises a total of 4,897 companies, each distinguished by a unique identifier. The measured variables are available for 4,637 of them. For these companies, we have obtained numerous indicators of environmental, social and governance performance. In total, there are 364 variables that characterise the company's environmental, social and governance performance. The source data for the variables in the ESG dataset was predominantly collected between 2017 and 2022. However, the final score itself lacks a time dimension. The data provider aggregated the variables and employed them for the calculation of the score for each subsection. The score is a categorical integer variable, taking values from one (the best possible result) to five (the worst possible outcome). However, the precise process of subscore calculation was not disclosed to the author of this thesis.

3.1.1 Environmental components

The majority of the indicators fall within the environmental category. The category comprises 240 indicators, 160 of which are specific to each firm, while one indicator is based on the industry in which the company operates. The majority of the data was sourced from government agencies, including the Energy Regulatory Office and the Czech Environmental Inspectorate. These variables reflect a range of environmental metrics, including emissions, waste production,

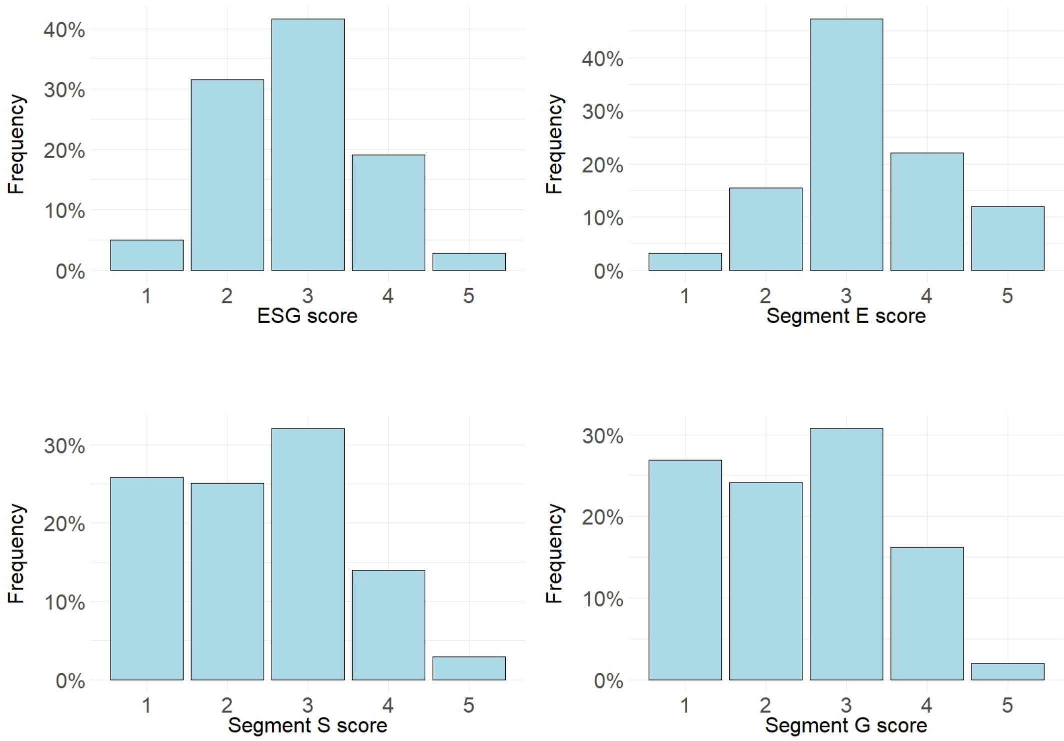

Figure 3.1: The distribution of ESG score and segment subscores in the ESG dataset. One denotes the best result, five the worst result.

environmental hazards, and energy efficiency. A portion of these indicators are binary variables that identify the utilization of distinct energy sources (biogas, hydro, wind, etc.), gas and heat production. The dataset also contains information on infringements of environmental legislation (e.g. waste or control legislation). The other part of the data consists of numerical variables that measure the magnitude of the indicators. For instance, if a company has violated water laws, the variable would indicate the amount of fines paid. Similarly, if the company uses biomass for energy production, the variable would indicate the number of kilowatt-hours produced. Additionally, various ratios are employed to assess the environmental impact of the enterprise.

The data on the industrial level were provided by the Czech Statistical Office and pertain to the total waste production in tons for the industry company in question. The remaining 79 indicators are based on the geographical location of the company - four at regional (NUTS3), 42 at provincial (NUTS4) and 33 at municipal (ORP) level. The data for these variables were also gathered from government sources: in addition to the Energy Regulatory Office also the Czech Environmental Information Agency, the Fire Service and the Ministry of Transport. The data reveals information about the environmental features and performance of the local area: from the number of different types of cars and buses, through the amount of different types of waste produced and the percentage of recycled waste, to the damage caused by forest fires.

3.1.2 Social components

The social score is determined using 100 variables affiliated to customers and own employees' relationship. Only 40 are individually based, four are conditional on industrial sector and 56 are bind to the provincial level. The individual data mostly apprise about the amount of various donations and governmental subsidies drawn on projects connected to improvement of workplace environment and labour standards, including safety, cybersecurity, digitalisation or disabled employees. The local data from Ministry of Labour and Social Affairs and Czech Statistical Office describe the situation in terms of criminality in the area as well as miscellaneous information about the workforce in the region. We have data about number of foreign workers, economically active inhabitants, accidents and diseases incapacity to name a few. This section also includes information about gender gap and female corporate ownership in the observed company as well as in the province and region.

3.1.3 Governance components

In order to assess the performance of the governance section, 24 indicators were engaged. These indicators are all firm-unique. The data for these indicators is derived from a variety of sources, including financial statements and company registers, as well as the number of Czech ministries. The largest proportion of this section is composed of binary/categorical variables that examine general governance (presence of protest in the firm, presence of prejudicial and registrar deeds), transparency (consolidation and certification of balance sheet, publishing of Sustainable Report) and ethical consideration (cooperation with public/state institutions, traceable code of conducts and ethics). The remaining elements of this category are comprised of risk and strategy management (dividends, payment delays), and inclusiveness (average age of representatives, presence of family ties, etc.). In addition to the ESG variables, the dataset also contains measurements of physical risk. A total of 18 variables have been identified as representing acute and chronic menaces to businesses in the near future. To illustrate, these include territorially extensive changes such as alterations to long-term temperatures, wind patterns and rising sea levels, as well as local climate transformations comprising droughts, heat waves, floods and soil erosion that may impact businesses by the year 2040. A score between 1 and 10 has been attributed to each risk.

The aforementioned information was utilised in the calculation of a score for each of the three subcategories, as well as for the overall ESG score. The score is expressed as an integer within the range of one to five, with one representing the optimal result and five indicating the least favourable outcome. Similarly to the calculation of the subscores, the exact procedure for the final score calculation is unknown; presumably, it is a weighted average of the subscores.

3.2 Financial dataset

The second dataset comprises information on the financial performance of firms that obtained a loan from the bank. The original raw dataset encompasses 12,615 observations of 30 variables, spanning the period from 2015 to 2023. The data are collected on an annual basis. The observations in question belong to 2,334 individual companies. It should be noted that information is not available for each company in every year. The data include information from each company's income statement and balance sheet. From the balance sheet we gathered information on current and non-current assets, liabilities, equity, cash and cash equivalents, total debt, nominal capital and inventories. From the profit and loss account, the following figures have been extracted: total turnover, gross sales, EBITDA, pre-tax earnings, capital expenditures, operating cashflow and net profit/loss. For each entry, the date of the statement and the currency in which the items were recorded are provided. Firstly, all values are converted to Czech koruna (CZK) in order to ensure the comparability of the resulting figures. Secondly, a series of financial ratios are calculated, which we believe to be significant variables in the models that explain default probability and profitability, as well as their relationship with ESG scores. The selection of ratios is based on both our own perspective and expert judgement, mainly following the guidelines of Fraser (2016). Furthermore, the financial data available for the companies in question imposes additional constraints.

In order to evaluate the profitability of a given company, it is necessary to consider two key ratios: return on equity (ROE) and return on asset (ROA). Both ratios link the initial deployment of resources to the final profitability outcome. ROE is a measure of the primary objective of a company, namely the

Condition	*Metric*	*Abbreviation*
Profitability	Return on Equity	ROE
Operating efficiency	Return on Asset	ROA
Solvency	Debt-to-Equity	D/E
Liquidity	Cashflow coverage ratio	CFCR
Size	Total assets	Assets
Sales performance	Volatility of net sales	NSVol
Investment	Capital expenditures to total sales	Capex/Sales

Table 3.1: Financial indicators and representing variables.

value created for the owners. In addition to its role in measuring profitability, ROA is also regarded as a reference for operating efficiency. This is because it takes into account all of the resources employed by the firm in its value-creation activities.

The ability of a company to raise funds for the purpose of covering both short-term and long-term obligations is regarded as one of the key indicators of financial health. In order to assess solvency, we adopt the debt-to-equity ratio (D/E), which compares a firm's own funds to those borrowed. In the absence of a distinction between current and non-current liabilities in the dataset, it is not possible to compute standard liquidity indicators such as current ratio, cash ratio or quick ratio. Consequently, we have opted to utilise the cash flow coverage ratio (CFCR), which is calculated as the proportion of operational cash flow to total debt of the company. This ratio provides insight into the ability of the company to meet its financial obligations through funds received from operating activities.

In order to account for the size of a company, we designate total assets as an indicator of dimension. To capture the market conditions that the firm is facing, the volatility of net sales (NSVol) is selected as the appropriate indicator. Finally, to apprehend the internal investment towards future growth, the capital expenditures-to-total sales ratio (Capex/Sales) is employed as the relevant indicator. All variables are listed in Table 3.1.

The subsequent phase of the data processing involves the elimination of erroneous or highly anomalous values from our variables. The proportion of observations recorded for the years 2015, 2016 and 2023 is negligible. Therefore, these observations are excluded from the subsequent analysis. The cleaning process reduced the dataset to 5,481 observations for 1,572 companies.

Table 3.2 presents statistical overview of the original financial data. The

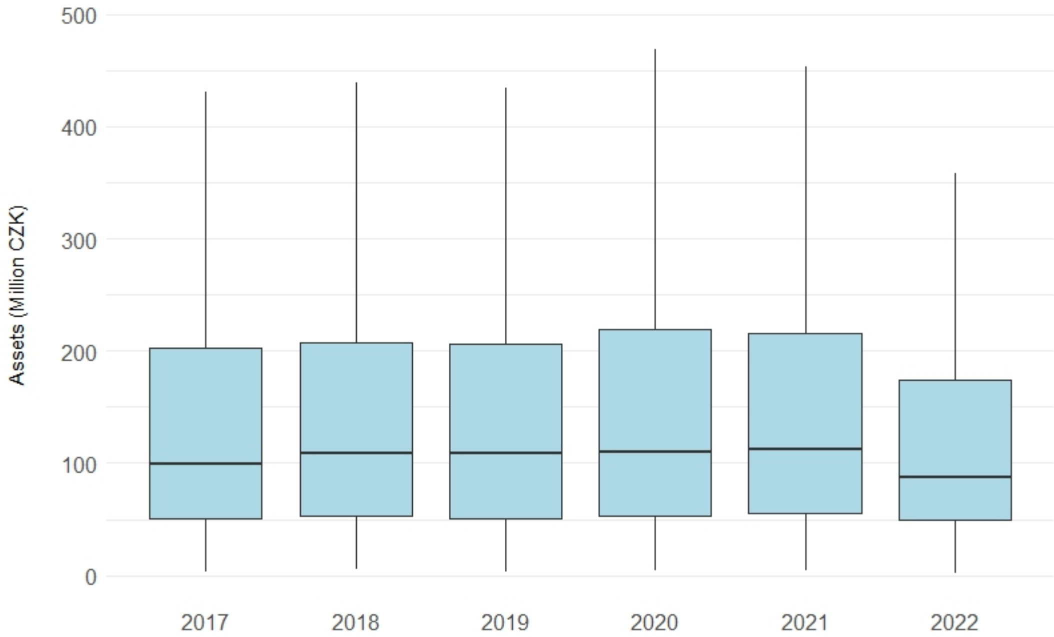

Figure 3.2: Total assets of companies, 2017-2022.
The middle line in the box represents median value. The endpoint of a whisker on a box plot represents the furthest point from the first and third quartiles, respectively, that falls within 1.5 times the interquartile range.

	Assets	*Liabilities*	*Equity*	*Debt*	*EBITDA*	*Profit/Loss*
Min. :	2,084,000	789,000	145,000	73,000	-154,574,000	-76,729,000
1st Qu.:	56,825,000	28,206,000	21,930,000	11,671,000	4,937,000	1,001,000
Median :	125,796,000	60,538,000	52,473,000	29,986,000	11,684,000	3,734,000
Mean :	233,748,743	115,171,540	118,111,996	66,719,634	21,519,948	8,582,668
3rd Qu.:	277,612,000	132,170,000	134,213,000	72,341,000	25,886,000	10,246,000
Max.:	11,841,414,000	6,659,399,000	5,904,932,000	5,354,883,000	634,993,000	330,528,000

Table 3.2: Summary statistics of chosen variables (CZK)

companies represented in our dataset include small ones with total assets worth of millions of CZK to multibillion colossi. However, most of the companies can be described as medium-sized with assets worth of hundreds of millions of CZK. The debt also varies greatly, from a few thousands to billions of CZK. Although the majority of firms included in the dataset are profitable, it is evident that dataset contains information on companies that have recorded losses. The size of the companies remained relatively stable from 2017 to 2021, with a slight decline emerging in 2022 (Figure 3.2).

Table 3.3 summarises the statistical data for the ratios and variables envisaged for employment in our models. A more careful examination of the data reveals that some companies experience minimal fluctuations in net sales,

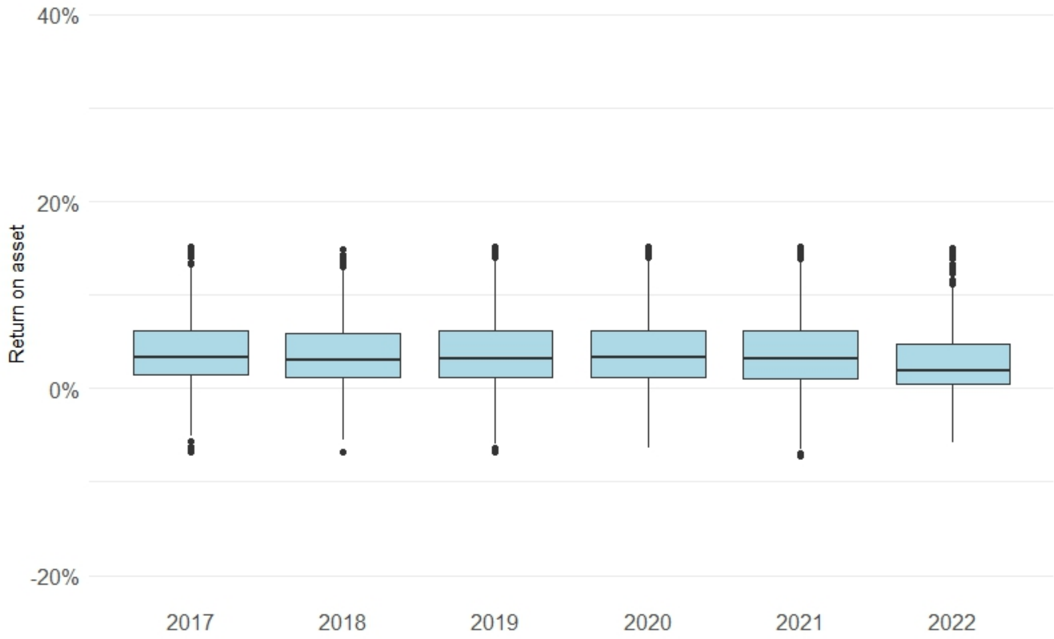

Figure 3.3: ROA of companies, 2017-2022.

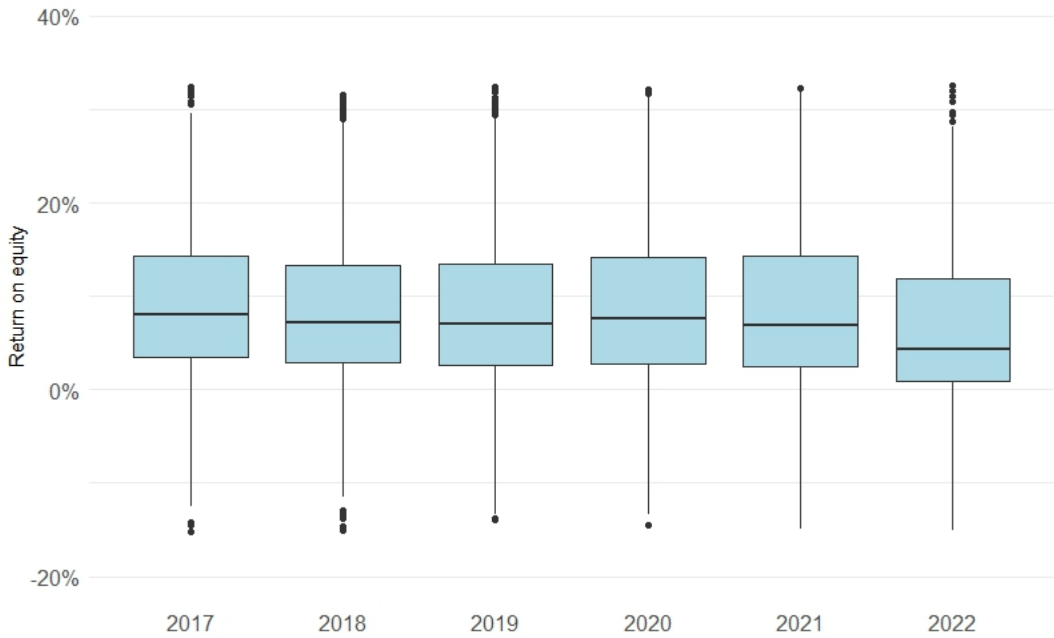

Figure 3.4: ROE of companies, 2017-2022.

	ROE	*ROA*	*CFCR*	*D/E*	*NSVol*	*Capex/Sales*
Min. :	-0.15261	-0.07258	-0.8106	0.000959	1.000	0.0000014
1st Qu.:	0.02582	0.01076	0.2086	0.292156	1.060	0.0140209
Median :	0.07064	0.03061	0.3698	0.609417	1.100	0.0422497
Mean :	0.08561	0.03788	0.6448	0.810633	1.144	0.0976689
3rd Qu.:	0.13839	0.06058	0.7243	1.153915	1.190	0.1204565
Max.:	0.32505	0.15203	4.9977	2.998791	1.790	0.9810120

Table 3.3: Summary statistics of chosen variables

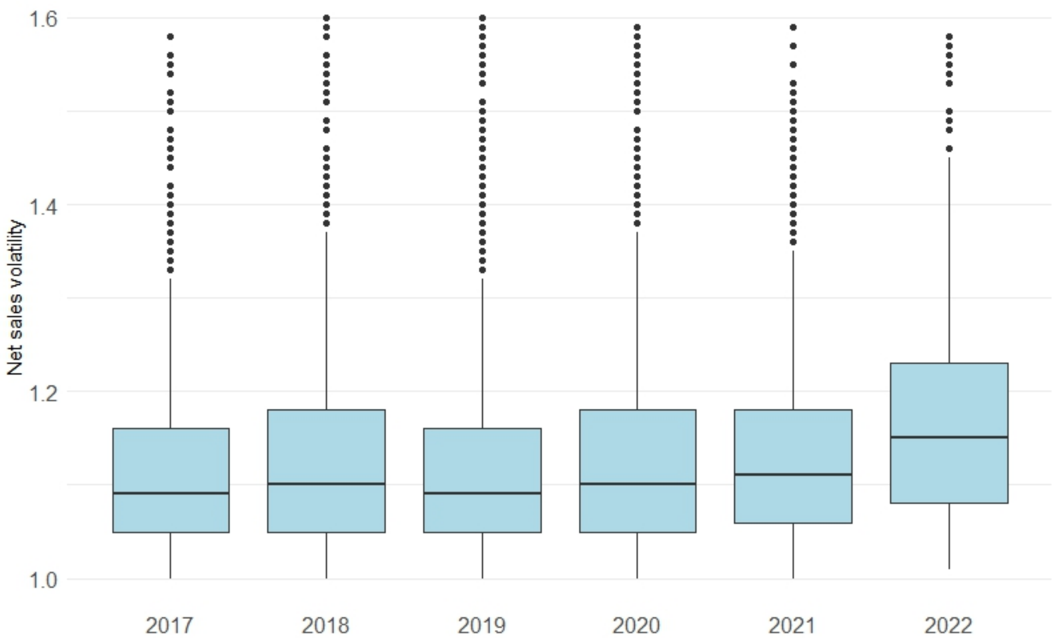

Figure 3.5: Net sales volatility of companies, 2017-2022.

whereas others contend with significantly volatile sales. It is notable that the majority of the companies recorded in our dataset have positive returns. The median value of ROE is approximately 7%, while the median value of ROA is roughly 3.1%. The maximum recorded return in the dataset is equal to 32.5% (ROE) and 15.2% (ROA), respectively. Figures 3.3 and 3.4 manifest pattern akin to that one described in the preceding paragraph: a relatively stable period with little fluctuations from 2017 to 2021, followed by a fall in 2022 parallel to that of total assets.

The liquidity ratio (CFCR) and the solvency ratio (D/E) demonstrate no noteworthy fluctuations over the course of the study period, as illustrated in Figures A.2 and A.3). The ratio of capital expenditures-to-sales remained relatively stable, with a slight decrease observed in 2022 (Figure A.4). Contrarily, the volatility of net sales exhibited a distinct increase in 2022, potentially attributable to the outbreak of the Russo-Ukrainian war (Figure 3.5).

3.3 Merged dataset

A merged dataset is created by combining the information from the ESG and financial datasets, with the client identification code serving as the merge key. As the ESG data set lacks a time dimension, the ESG information for each company is identical across all observations. It should be noted that the information on ESG performance is not available for every firm for which the financial data is available. Conversely, the financial statements and data are not accessible for each company for which we possess the ESG rating.

Frequencies of partial and overall ESG scores are displayed in Table 3.4. Approximately one quarter of all companies included in the dataset after cleansing are not rated in regards to ESG. The majority of the companies with assigned ESG ratings have overall scores that fall in the *good* or *very good* category. While in the social and governance categories, the vast majority of the firms scored 3 or higher, only approximately 11% of the evaluated firms scored *great* or *very good* in the environmental section. The distribution of ratings in the merged dataset exhibits a relatively minor divergence from that observed in the ESG dataset (Figure 3.1).

Value	*ESG score*	*E score*	*S score*	*G score*
1 (great)	79	32	422	451
2 (very good)	422	141	305	324
3 (good)	477	521	344	314
4 (poor)	144	254	74	45
5 (bad)	41	215	18	29
NA	409	409	409	409

Table 3.4: ESG characteristics of the dataset.

Figure 3.6 displays the default probabilities with respect to the overall ESG rating. With the exception of the third quartile for firms with an overall ESG score of *good*, all parts are found to be relatively identical.

Inspection of the size of firms in relation to their ESG performance (Figure 3.7) reveals that the companies with the highest overall scores are of a smaller size than those with the lowest ratings. The median size of the best-rated enterprises is approximately half that of those with a bad overall ESG

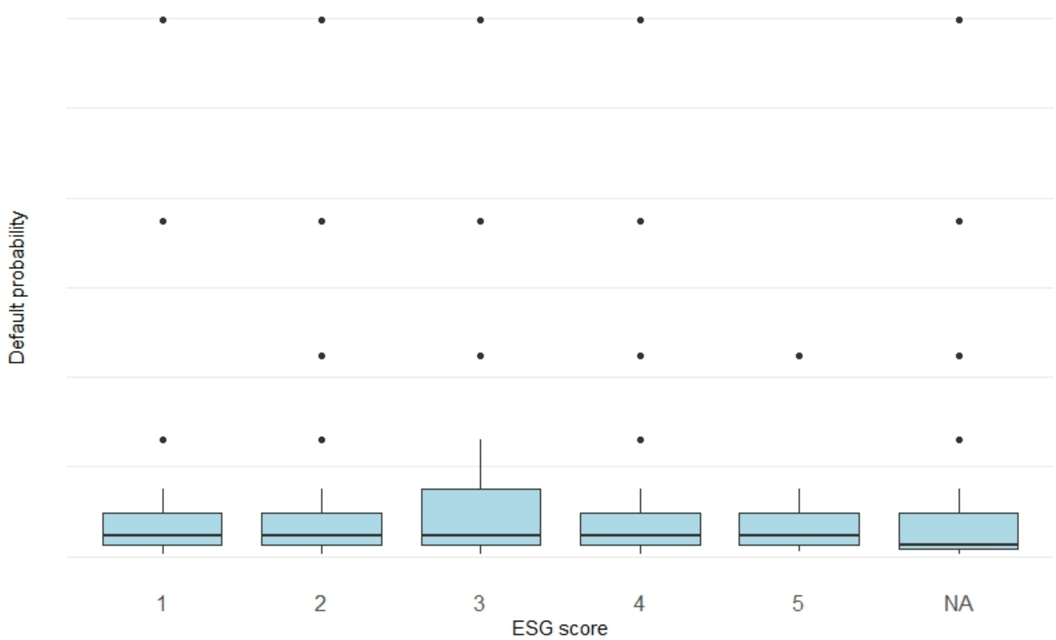

Figure 3.6: Probability of default with respect to ESG score.

rating. The differences between the two aforementioned groups of businesses are relatively minor, although the median size of firms with a poor overall score is slightly higher than that of those with a *very good* or *good* ESG score. While accounting for approximately a quarter of the entire dataset, the total assets of unrated companies are significantly lower in comparison to those of rated companies. This suggests that, despite the ESG reporting becoming mandatory for large enterprises in the European Union since 1 January 2024, it has become a standard practice for medium and large companies prior to this formal regulation.

The distribution of firm size with respect to E and G score is somewhat ambiguous (Figure 3.8). In contrast to the overall score distribution, the size of the firms grouped by their social score exhibits an inverse relationship. The highest possible score was predominantly earned by larger firms within the dataset. The median value does not vary significantly with worsening score until the penultimate group, although a slight decline in the value of the third quartile is evident. However, the median size of companies with the worst social score is remarkably lower than the rest.

The narrow range might be accountable to small proportion of the firms scoring *bad* in social category (only 18 companies). The low score of small companies might be explained by the firm-specific factors employed for the

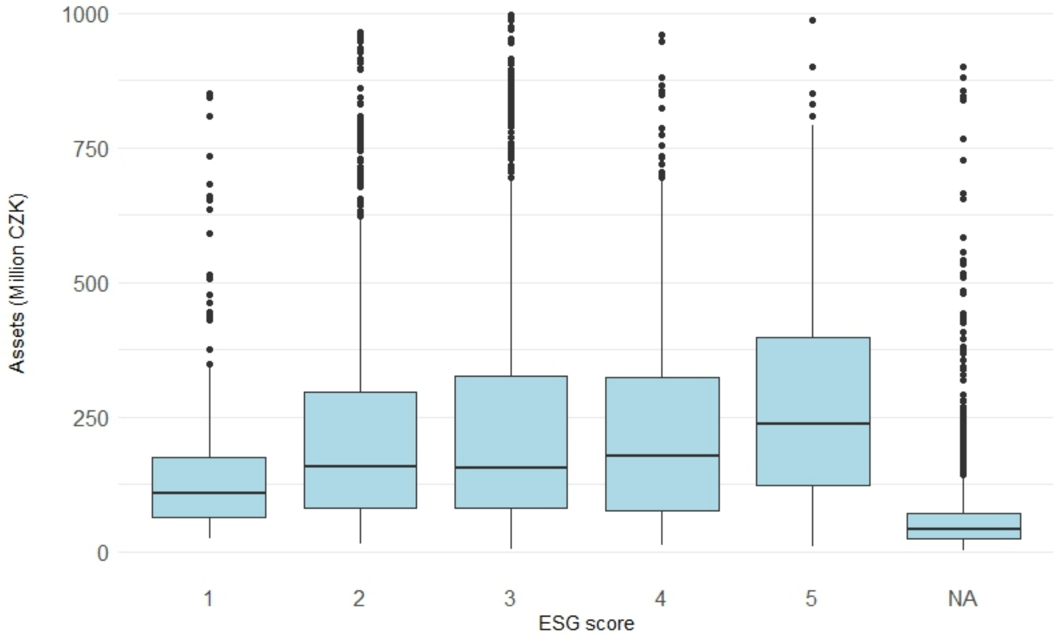

Figure 3.7: Size of companies with respect to ESG score.

estimation of the social impact.

Firstly, the social subscore considers the utilisation of state subsidies and the amount drawn for various purposes, including cybersecurity and the support of disabled employees. It is typically the case that smaller recipients of the aforementioned support are unable to utilise the subsidies to the same extent as larger corporations, which have a higher number of employees and greater exposure to cyberthreats.

Secondly, the social score takes into account the proportion of women in the workforce and in corporate governance. Multinational conglomerates are keen to demonstrate their commitment to achieving a variety of sustainability goals, including gender equality. In some countries, there are legal requirements in place to ensure that a minimum percentage of women are employed. For instance, in France, the legal minimum share of women in corporate management bodies is set at 40%. Smaller firms do not face such obstacles, but this may be reflected in their lower social score if they do not adhere to these regulations.

A comparison of the returns of companies with varying ESG scores reveals a high degree of similarity (Figure 3.9). The same is seen when the data is divided into individual subsegments, where only minimal differences are observed (see Figure A.7 in Appendix A).

The variation in leverage with respect to the overall ESG score is min-

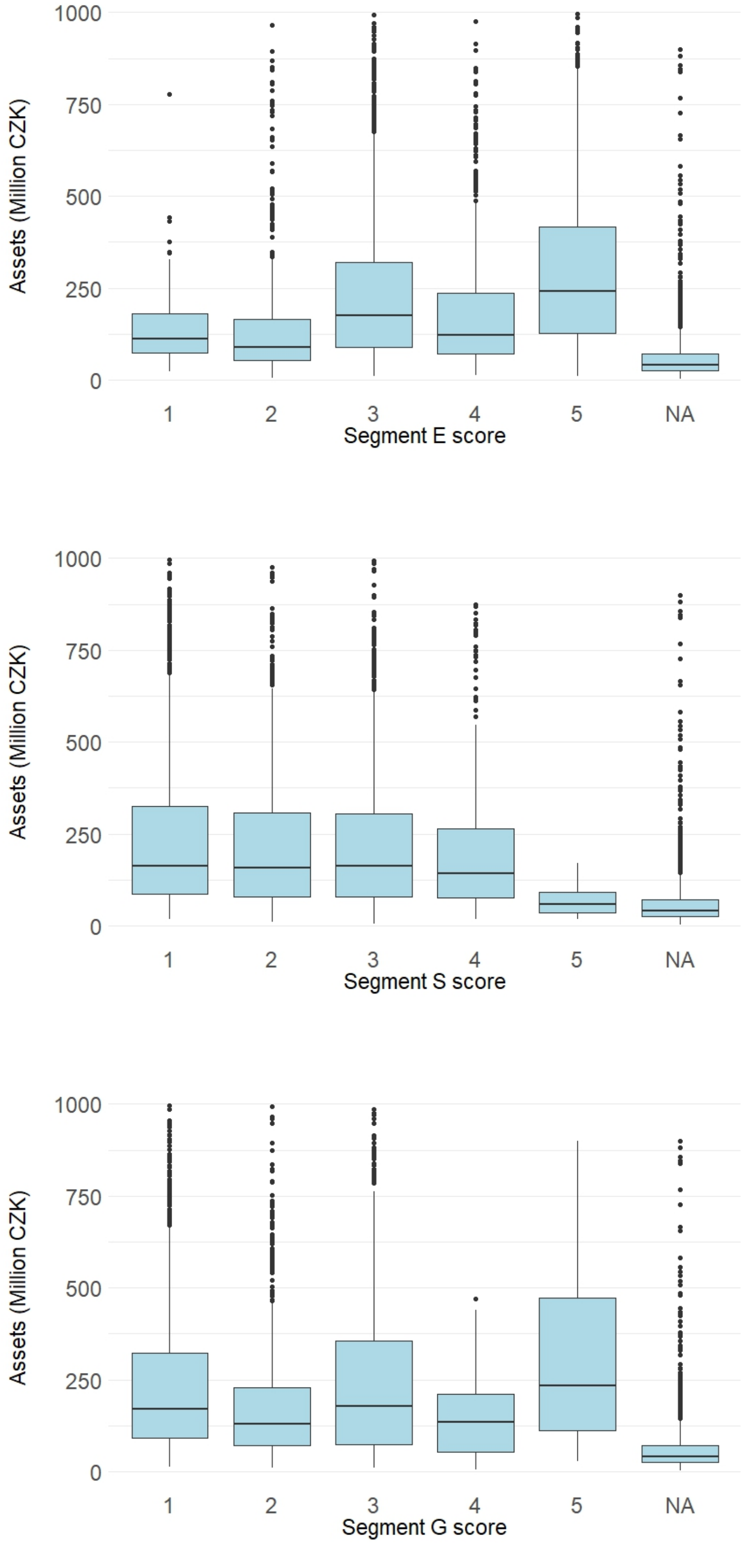

Figure 3.8: Size of companies with respect to ESG subscores.

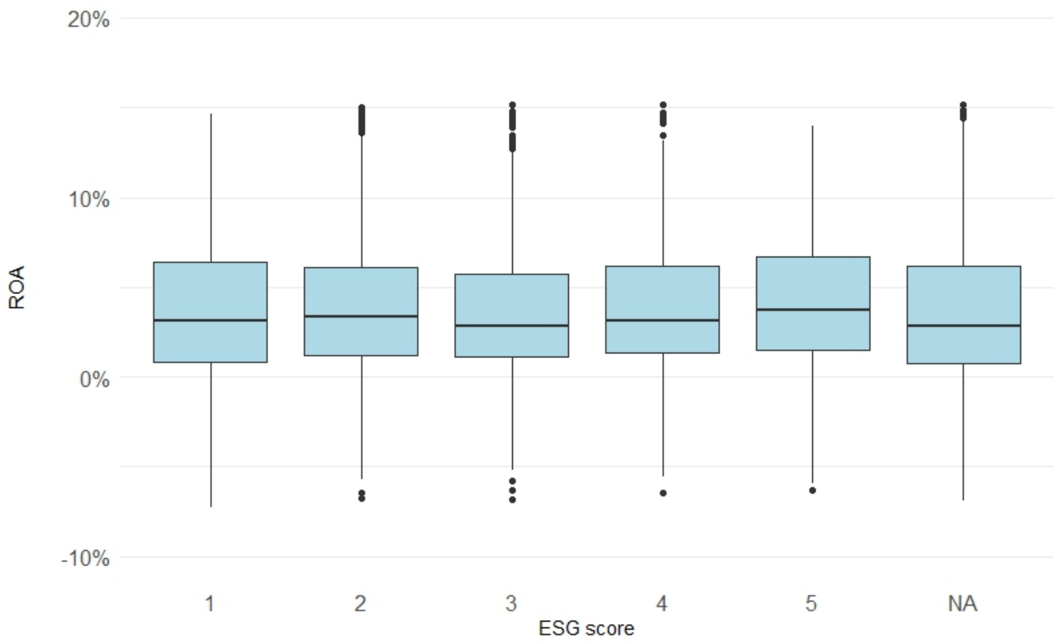

Figure 3.9: ROA of companies with respect to ESG score.

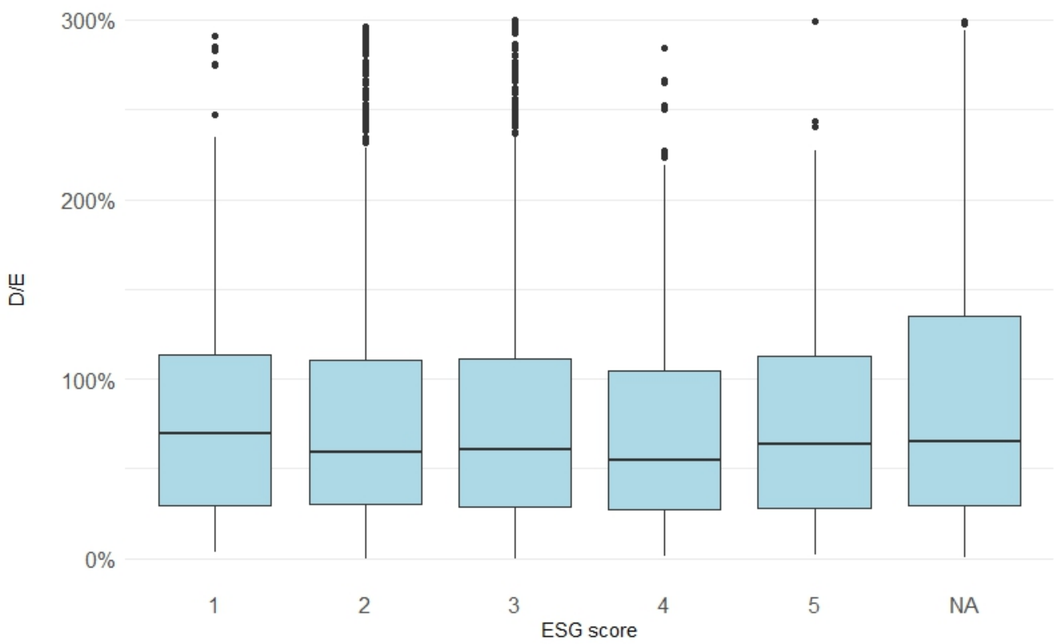

Figure 3.10: Debt-to-equity of companies with respect to ESG score.

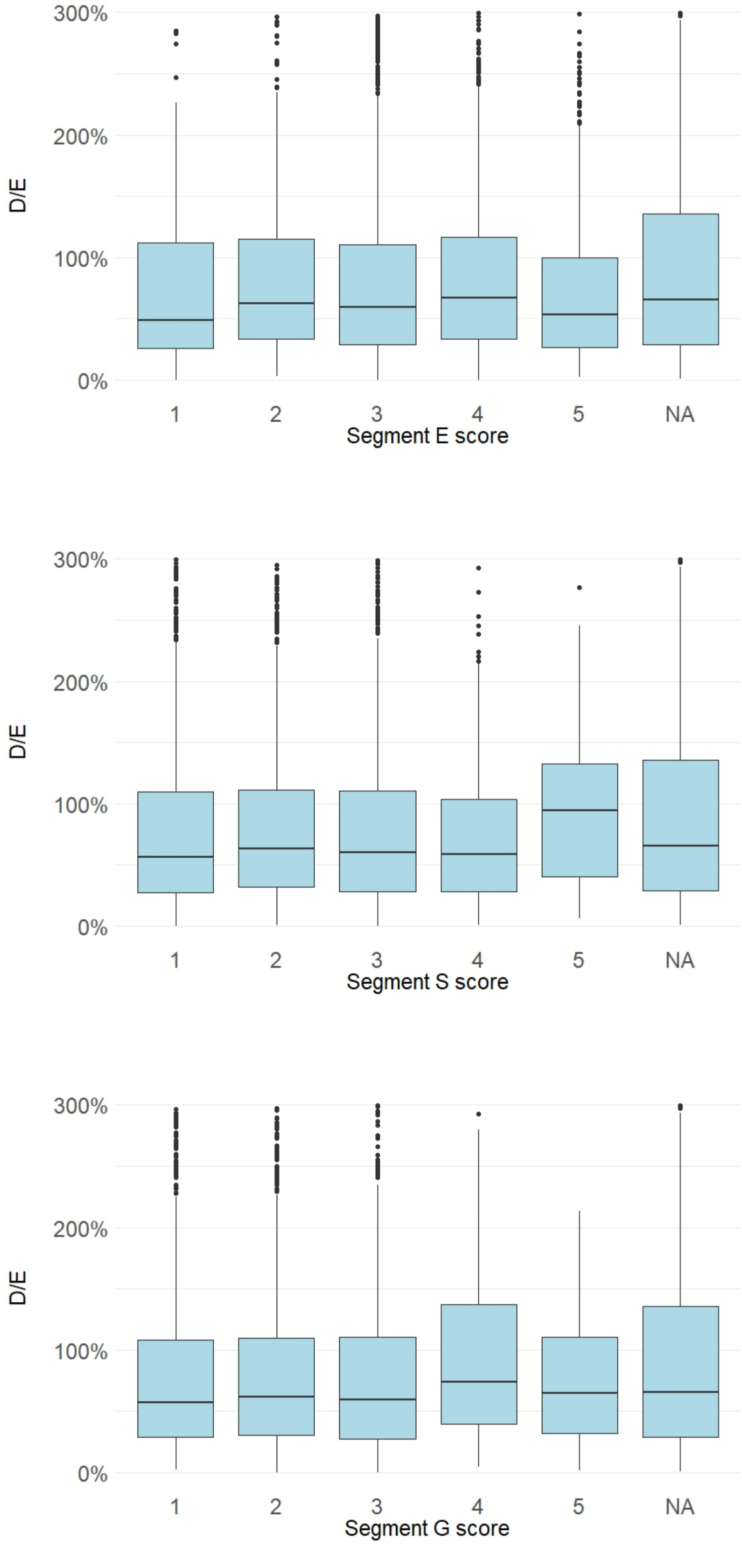

Figure 3.11: Debt-to-equity of companies with respect to ESG sub-scores.

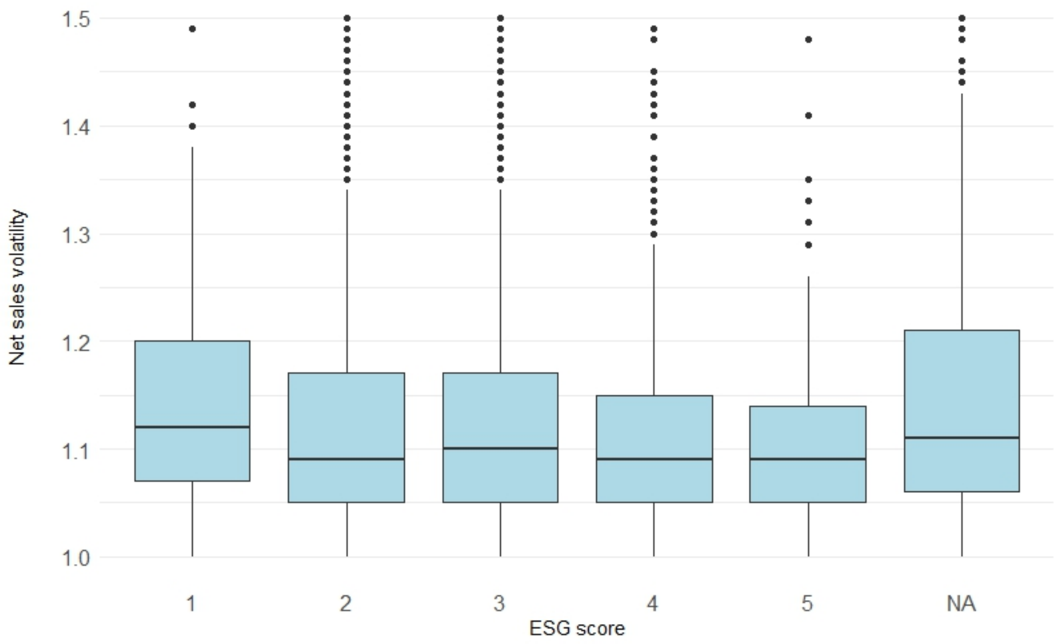

Figure 3.12: Net sales volatility of companies with respect to ESG score.

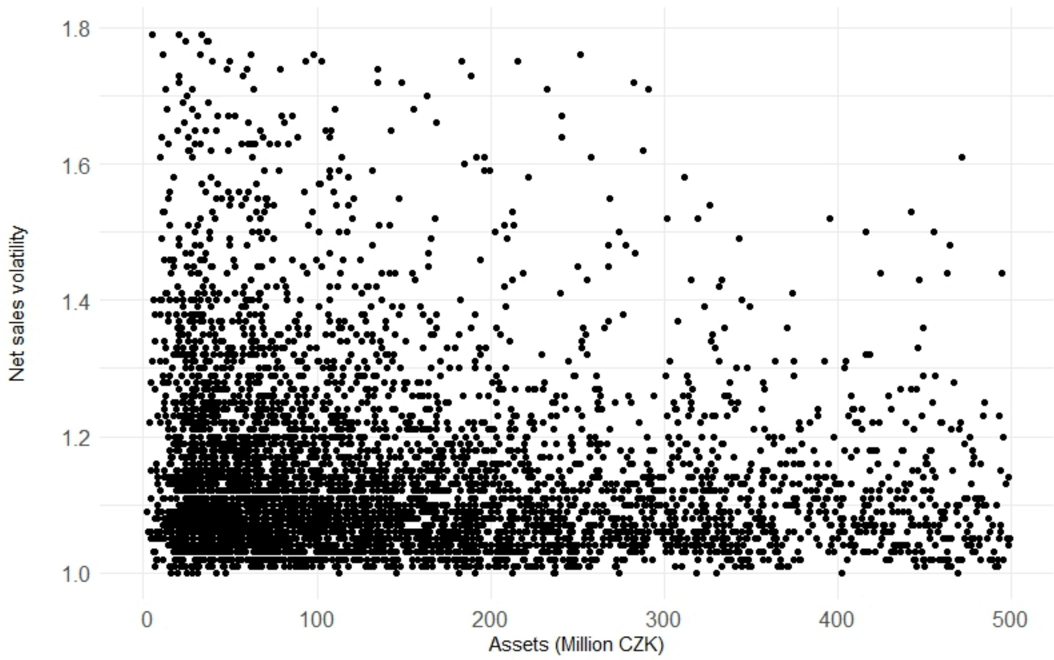

Figure 3.13: Net sales volatility of the companies with respect to size.

imal (Figure 3.10). The median value, as well as the 1st quartile, exhibit minimal fluctuations. Only the 3rd quartile is slightly higher for the unrated companies. It is also noteworthy that the median value and overall shift for the worst-performing companies in the social sub-rating (Figure 3.11) have increased. This may indicate that companies with a low social score face greater challenges in attracting potential investors, thereby leading to a greater reliance on debt financing. A comparable incidence is observable for governance subscores. Firms with an unfavourable governance rating appear to be more heavily indebted than those with superior governance practices. It is pertinent to note that the impact is more pronounced in companies with *poor* ratings than in those with *bad* ratings. This may suggest that firms with poor governance are less attractive to potential investors and therefore have to rely on creditors instead.

Figure 3.12 illustrates the relationship between net sales volatility and the overall ESG score. The median value is observed to be higher for unrated firms and those with a *great* overall score. Despite the fact that enterprises with a high overall rating are, on average, larger than those that have not been rated, the difference in net sales volatility between the two groups is not particularly pronounced. It is important to note that both firms in both groups are of a smaller size than the rest in our dataset (Figure 3.7) and therefore this discrepancy may not be caused by the ESG performance but rather by the size of the companies. Figure 3.13 supports this view.

3.3.1 Macroeconomic variables

A set of macroeconomic variables has been incorporated into the dataset in order to capture potential economy-wide effects in the models. The macroeconomic data were sourced from the Czech Statistical Office. In order to gain an accurate overview of the current state of the Czech economy, it is vital to consider the real GDP growth rate. The Harmonised Consumer Price Index is employed as the control variable for inflation within the country.

3.4 Hypotheses for testing

Based on the data description and available research in the field, we formulate the following hypotheses we aim to test in this thesis:

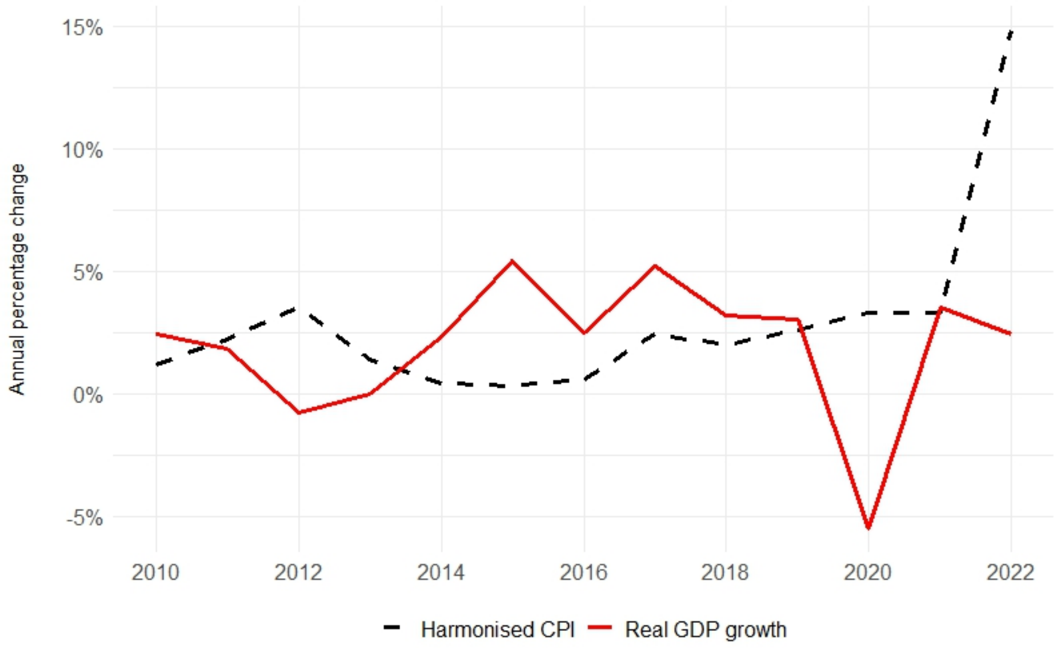

Figure 3.14: Real GDP and harmonised CPI, 2010-2022.

Hypothesis 1: Profitability, solvency and liquidity are the main factors determining a firm's probability of default.

Hypothesis 2: The ESG scores have an impact on the sensitivity of the determinants of profitability and probability of default.

Hypothesis 3: In addition to traditional borrower-based ratios, macroeconomic variables play a significant role in determining profitability.

Chapter 4

Methodology

4.1 Probability of default model

The dependent variable in our main model, the probability of default, is a binary variable that takes value 0 if the company could not meet its obligations and 1 otherwise. The focus is on estimating the response probability, which is the value of the dependent variable for different values of explanatory variables. Therefore, we employ the linear probability model (LPM), which is defined by Wooldridge (2016) as

$$P(y = 1|x) = \beta_0 + \beta_1 x_1 + ... + \beta_k x_k \tag{4.1}$$

where y is our binary dependent variable, x_i is regressor and β_i is coefficient for variable i to be estimated. To evaluate the model, there are several methods available, including OLS, logit/probit and rare event logit model. In the following sections, we discuss the principles, advantages and drawbacks of these estimation methods.

4.1.1 Ordinary Least Squares

Using OLS to estimate a LPM is the most straightforward way. Beta coefficients $\beta_i = \partial P(y = 1|\boldsymbol{x})/\partial x_i$ can be interpreted as a change in the probability of success with the one-unit change in the explanatory variable (Wooldridge 2010). On the other hand, this method is restrained with certain limitations. Wooldridge (2010) notes that while the estimators of the betas should be unbiased and consistent, the variance of the model is not constant, indicating a presence of heteroscedasticity (unless all betas are zero). To address this issue, one can employ heteroscedasticity-robust standard errors and t-statistics. Another matter to consider is the predicted value of dependent variable. The regressand usually represents a probability of success and should therefore fall between 0 and 1. Fitted values from the model might yield results outside of this interval, particularly for extreme regressor values. Wooldridge (2010) stresses that OLS estimation for LPM model is useful when the aim is to approximate partial effects of independent variables. However, as mentioned before, this approach might not yield accurate estimates for wide range of covariate values.

4.1.2 Binary response model

To address the aforementioned limitations of the OLS approach, a transformation is necessary to restrict the outcome to fall between 0 and 1. Let us consider binary response model defined by Wooldridge (2016) in the following form:

$$P(y = 1|x) = G(\beta_0 + \beta_1 x_1 + ... + \beta_k x_k) = G(\beta_0 + \boldsymbol{x\beta}) \tag{4.2}$$

where G(z) is a transformation function that takes values strictly between 0 and 1. Wooldridge (2010) uses term index models for such functions due to the way in which the dependent variable depends on the independent ones: through the index $\boldsymbol{x\beta} = \beta_1 + \beta_2 x_2 + ... + \beta_K x_K$. There is a wide range of functions that can be used as the G(z) function for the model. For the purpose of econometric analysis, there are two functions commonly used. For a probit model, the function G(z) is equal to the cumulative normal distribution function, i.e.:

$$G(z) = \phi(z) \equiv \int_{-\infty}^{z} \phi(v)\, dz \tag{4.3}$$

where $\phi(z)$ is the standard normal density:

$$\phi(z) = 2\pi^{-1/2} exp(-z^2/2) \tag{4.4}$$

. The logit model uses cumulative logistic distribution as a function G(z). Both logit and probit models should yield the same signs and significance of coefficients.

Due to the nonlinear nature of $E(y|x)$, the usage of OLS to estimate the coefficients is limited. Wooldridge (2016) suggests using Maximum Likelihood

Estimator (MLE) instead. To obtain MLE, we need to identify y_i given x_i:

$$f(y_{|}\boldsymbol{x_i};\boldsymbol{\beta}) = [G(\boldsymbol{x_i\beta})]^y[1 - G(\boldsymbol{x_i\beta})]^{y-1}, y = 0, 1. \tag{4.5}$$

We can then obtain the log-likelihood function for the i-th observation by taking the logarithm of the function above:

$$\ell_i(\boldsymbol{\beta}) = y_i log[G(\boldsymbol{x_i\beta})] + (1 - y_i) log[1 - G(\boldsymbol{x_i\beta})] \tag{4.6}$$

Finally, we sum the functions for all observations to get the log-likelihood function that we need to maximise in order to obtain MLE of β: $\boldsymbol{\mathcal{L}}_i(\boldsymbol{\beta}) = \sum_{i=1}^{n} \ell_i(\boldsymbol{\beta})$. For G(.) as the standard logistic cumulative distribution function, $\hat{\boldsymbol{\beta}}$ is the logit estimator, for G(.) as the standard normal cumulative distribution function, $\hat{\boldsymbol{\beta}}$ is the probit estimator. Under general conditions, MLE is consistent, asymptotically normal and asymptotically efficient, which allows us to derive asymptotic standard errors (Wooldridge 2016).

The difficult aspect of the logit/probit models is interpretation of coefficients. Due to the transformation via G(z), the unit increase in x_i does not correspond to β increase in probability of y_i, but rather $g(\beta_0 + \boldsymbol{x\beta})\hat{\beta}_i$. Unlike LPM models, the effects cannot be interpreted directly due to scaling factor $g(\beta_0 + \boldsymbol{x\beta})$. Wooldridge (2016) suggests two basic techniques to deal with this issue when reporting the results of index models. In the first one the explanatory variables are replaced with sample averages:

$$\Delta\hat{P}(y = 1|\boldsymbol{x}) \approx [g(\hat{\beta}_0 + \boldsymbol{x}\hat{\boldsymbol{\beta}})\hat{\beta}_j]\Delta x_j \tag{4.7}$$

.

Thus, the partial effect at the average (PEA) is obtained using this method. However, two notable problems may arise when using PEA. Firstly, it may not be meaningful to look at the average, since it does not represent anyone (for example by discrete variables). Secondly, when dealing with non-linear transformations of variables, it might be challenging to determine the right phase to use the average during the process. To tackle these issues, it might be reasonable to consider the average effect across all observations. This is known as average partial effect (APE) and can be expressed as

$$\Delta\hat{P}(y=1|\boldsymbol{x}) \approx [[n^{-1}\sum_{i=1}^{n} g(\hat{\beta}_0 + \boldsymbol{x}\hat{\boldsymbol{\beta}})]\hat{\beta}_j]\Delta x_j \tag{4.8}$$

.

To check the goodness-of-fit of index models, the use of R^2 is inappropriate. Recall that R^2 measures the proportion of variance in the dependent variable that can be explained by the independent variable(s) in a model, indicating how well the model fits the data. In case of a binary dependent variable, the real values are limited to 0 or 1, whereas fitted values of the regressand can fall anywhere on the interval [0;1]. Therefore, other measurements are necessary to determine the goodness-of-fit of the model. One method is to use percentage of correctly predicted values of explained variable. A binary predictor of y_i equal to 1 if the predicted value of dependent variable by the model is higher than 0.5 and equal to 0 otherwise is an option. This can be also achieved by defining variable $\hat{y}_i = 1$ if $G(\boldsymbol{x_i}\hat{\boldsymbol{\beta}}) \geq 0.5$ and $\hat{y}_i = 0$ if $G(\boldsymbol{x_i}\hat{\boldsymbol{\beta}}) < 0.5$. The percentage of correct predictions is then the percentage of cases when y_i=$\hat{y}_i$ (Wooldridge 2010). Although the percentage of correct predictions might be a useful goodness-to-fit measure, it might lead to some misleading results, particularly when the values of dependent variable are extremely unbalanced. Wooldridge (2010) also critises the practice of using the threshold of 0.5 (or 50%). McFadden (1974) proposed a variant of pseudo-R^2, nowadays known as McFadden-R^2, equal to $1 - \mathcal{L}_{LM}/\mathcal{L}_0$, where $\mathcal{L}_{LM}$ represents log-likelihood function for the estimated model and $\mathcal{L}_0$ stands for log-likelihood function for the model with intercept only.

A further alternative is the Akaike Information Criterion (AIC). The criterion is employed for the purpose of comparison between disparate models. The value of AIC is calculated as $AIC = 2k - 2\hat{L}$, where k is the number of parameters and $\hat{L}$ is the maximised likelihood function of the model. In consideration of the set of models, the one with the lowest score is to be esteemed as the optimal choice (Akaike 1974).

4.1.3 Rare events logit

Another issue that requires attention is the proportion of the values in the dependent variable. If the proportion is in favour of one side, i.e. the number of cases of success is much greater than the number of fails (or vice versa), it influences the results of the estimation. King & Zeng (2001) argue that using a logit model with rare events data causes complications: firstly, $\hat{\beta}$ is a biased estimate of β and even if $\hat{\beta}$ was unbiased, it would still be an inferior estimator of $Pr(Y_0 = 1|X)$. They proposed a solution to this issue in form of rare events logit regression, also known as relogit. The procedure is based on estimating the bias of β and correcting the estimate of β in the following way: firstly, the following weighted least-square equation is estimated:

$$bias(\hat{\beta}) = (\boldsymbol{X'WX})^{-1}\boldsymbol{X'W}\xi, \tag{4.9}$$

where $\xi = 0.5Q_{ii}[(1 + w_1)\hat{\pi}_i - w_1]$, Q_{ii} are the diagonal elements of

$$\boldsymbol{Q = X(X'WX)^{-1}X'},$$

$\boldsymbol{W} = diag\{\hat{\pi}_i(1 - \hat{\pi}_i)w_i\}$ and $w_i = y/\tau$ are weights for offsetting the difference between the sample (y) and population (τ) fractions of rare events. The equation is estimated by weighted least-square regression with $\boldsymbol{X}$ as the explanatory variable, ξ as explained variable and $\boldsymbol{W}$ as weights. The bias of $\hat{\beta}$ is then subtracted from the $\hat{\beta}$ estimate to get the bias-corrected estimate $\tilde{\beta} = \hat{\beta}$ - bias($\hat{\beta}$).

4.2 Profitability model

It is acknowledged by the author that the options for analysing credit risk with the available dataset are limited and insufficient for the work of the extent of a diploma thesis. Furthermore, it is suspected that profitability plays a pivotal role in determining credit risk. The nature of the dataset should provide a suitable platform for further investigation. Thus, an analysis of profitability determinants and an examination of ESG influence on them will be conducted in addition to the analysis of the credit risk and ESG.

In our second model, we seek to explain determinants of profitability and their relationship with ESG. In this case we do not encounter issues with dependent variable as in our first model and we are able to employ standard econometric methods.

4.2.1 Linear estimators

Due to the nature of our dataset (unbalanced panel) and the purpose of this paper, there are three methods we consider: Pooled Ordinary Least Squares (POLS), Fixed Effects and Random Effects model. As per Wooldridge (2016), the main difference of these approaches lies in the treatment of individual effects. Let

$$y_{it} = \beta_0 + \beta_1 x_{it1} + ... + \beta_k x_{itk} + \alpha_i + \epsilon_{it}$$

be the model, where α_i denotes the unobserved, time-constant effect, also called unobserved heterogeneity. If there are no such effects (or if we are able to actually observe them), then it is possible to include them in the model and use the POLS estimator that is the best among the aforementioned ones in this case. However, once those effects are present, the error terms of POLS estimators became biased and the inference is thus invalid. In presence of unobserved heterogeneity, a_i might be correlated with the explanatory variables. In this case, we are dealing with fixed effects and thus employment of a fixed effects model is recommended. When unobserved heterogeneity is uncorrelated with explanatory variables, it is appropriate to use a random effects model (Wooldridge 2016).

To decide between POLS and FE model, Baltagi (2008) suggests using F-test to detect the unobserved effects. Under the null hypothesis, there are no unobserved effect in the model and POLS is consistent estimator. Under alternative hypothesis, POLS is inconsistent.

For further test of correlation between regressors and residuals, we employ Hausman test proposed by Hausman (1978). Under the null hypothesis, both FE and RE estimators are consistent, but FE estimators is not efficient and therefore it is better to use RE estimator. Under alternative hypothesis, the unobserved heterogeneity is correlated with predictors and thus RE estimator is inconsistent and biased and only FE estimator remains consistent (Baltagi 2014).

Furthermore, we will test our model for possible heteroskedasticity and autocorrelation in residuals. For the former, Wooldridge (2016) recommends using Breusch-Pagan test. This test was firstly introduced in 1979 and its null hypothesis assumes constant variance or residuals. Under alternative, the variance is not constant and heteroskedasticity is present in the error term (Breusch & Pagan 1979).

For the latter, we employ the Breusch-Godfrey test for autocorrelation. The test was firstly developed by Breusch (1978) and Godfrey (1978). The test is able to uncover higher order serial correlation in residuals. The null hypothesis of this test claims no autocorrelation.

In case our suspicions of heteroskedasticity and/or autocorrelation turn correct, we employ heteroskedasticity and autocorrelation robust (HAC) standard errors to achieve valid inference from our estimates.

4.2.2 Generalised method of moments estimators

Regarding the profitability model, one of our concerns is normality of the residuals due to the distribution of our dependent variable (Figure A.8). Although the non-normal distribution of dependent variable does not automatically induce non-normal distribution of residuals, the residuals are from definition differences between observed and predicted values of the model and thus non-normal dependent variable increase the chance of error term to be non-normal as well. This would invalidate the test statistics and the inference from the model would be incorrect.

The methods mentioned previously also require exogeneity of independent variables, i.e. independent variable must not be correlated with the error term. Among sources of endogeneity is dynamic relationship between regressor and regressand. Endogeneity might also arise as a consequence of omitting an important variable (Wooldridge 2016).

Another concern of us is dealing with lagged variables, as some researchers (see for example Li *et al.* 2022) include the lag of dependent variable in their profitability models. However, Verbeek (2017) explains how the inclusion of lagged variable makes the OLS estimation inconsistent. Barros *et al.* (2020) further proves that that OLS, FE or RE methods may be inconsistent and suggest using Generalised Method of Moments (GMM) estimator. Roodman (2009) also mentions the good fit for data with low number of time periods but many cross-sectional observations and suitability for cases when the regressand depends on its own lagged values.

This thesis considers two methods from the GMM framework for the purpose of this study. The first method was first proposed by Arellano & Bond (1991). It is therefore sometimes referenced as the Arellano-Bond estimator. However, in this thesis, it is referred to as the difference GMM. The goal of this method is to eliminate unobserved heterogeneity via first differencing of the model equation. In order to address the potential endogeneity of the lagged dependent variable on the right-hand side of the equation, instruments in the form of further lags of the dependent variable are employed.

Despite its effectiveness, the difference GMM may yield unsatisfactory results when the relationship between the dependent variable and its lagged value approximately follows a random walk process. To address this issue, Arellano & Bover (1995) and Blundell & Bond (1998) built upon the work of Arellano & Bond (1991) and developed a method that is known by several names. This technique is also known as the Arellano-Bover/Blundell-Bond estimator; however, the author of this thesis prefers the notation system GMM. In addition to the difference GMM, the system GMM utilises the level equation in addition to the differenced one, and introduces additional moment conditions.

In this thesis, we estimate the model with both aforementioned types of GMM. Based on the test statistics and overall fit, we select the method that is more appropriate for our data. To assess the validity of the used instruments, Roodman (2009) recommends to embrace the Hansen-Sargan test developed by Hansen (1982) and Sargan (1958). The null hypothesis of this test states that the instruments used for the endogenous variable are valid.

4.3 Model specification

4.3.1 PD model specification

The objective of the first model is to clarify the influence of diverse financial elements on the probability of default. The dependent variable is the probability of default. Various model specifications of the probability of default are considered. Primarily, the default probabilities calculated by our data source are transformed into a binary 0/1 variable based on the calculated PD. The threshold is set at 15%. Henceforth, the aforementioned variable will be designated as *default*.

Additionally, the models are estimated using the calculated PDs directly. For use in the OLS model, the PD is transformed using a logit transformation: $log(\frac{y}{1-y})$. The variable is represented as *transformed_pd* throughout this thesis.

As independent variables, we employ various financial ratios and measures described in section 3.2. The model equation looks following:

$$\begin{aligned} PD_i = \alpha + \beta_1 ROE_i + \beta_2 CFCR_i + \beta_3 DE_i + \\ \beta_4 nsvol_i + \beta_5 capex\_sales_i + \beta_6 assets_i + \epsilon_i \end{aligned} \tag{4.10}$$

where ROE stands for return on equity, DE for debt-to-equity, $CFCR$ for cashflow coverage ratio, $assets$ for total assets, $nsvol$ for net sales volatility and $capex\_sales$ for capital expenditure to sales ratio. α is the constant and ϵ_i is the error term. Given that the information regarding the default probability is not subject to change over time, we posit that it represents the most recent data concerning the default probability of the company in question. To determine the optimal lag between a company's default and its financial performance, we employ a range of lags for the independent variables. In doing so, we seek to offer a comparison with existing research in this field.

4.3.2 Profitability model specification

In our second model, we intend to detect the factors that influence the profitability of the companies in our dataset. In this case, we opt for return on assets as the dependent variable. Our base equation for the profitability model is as below:

$$\begin{aligned} ROA_{it} = \alpha + \beta_1 CFCR_{it} + \beta_2 DE_{it} + \\ \beta_3 nsvol_{it} + \beta_4 capex\_sales_{ti} + \beta_5 assets_{it} + \\ \nu_i + \phi_t + \epsilon_{it} \end{aligned} \tag{4.11}$$

As in the PD model, DE stands for debt-to-equity, $CFCR$ for cashflow coverage ratio, $assets$ for total assets, $nsvol$ for net sales volatility and $capex\_sales$ for capital expenditure to sales ratio.

In order to estimate the parameters of the model using OLS, fixed and random effects methods, we adjust the formula to by taking the logarithms of variables with non-negative values and adding time and individual effects. The adjusted equation assumes the following form: equation, where ν_i denotes the individual effect and ϕ_t the time effect.

The next specification of the model includes the addition of macroeconomic variables. If the specification of the model remains unchanged, the time effects would remain perfectly correlated with the macroeconomic variables, since our dataset only contains information on Czech firms or Czech subsidies to firms. To account for changes in the Czech economy, we can simply omit the time effects (as per Huang *et al.* 2022) and adjust the model equation as follows:

$$\begin{aligned} ROA_{it} = \alpha + \beta_1 CFCR_{it} + \beta_2 DE_{it} + \\ \beta_3 nsvol_{it} + \beta_4 capex\_sales_{ti} + \beta_5 assets_{it} + \\ \delta_1 GDPg_t + \delta_2 \Delta CPI_t + \nu_i + \epsilon_{it} \end{aligned} \tag{4.12}$$

In the equation, $GDPg$ stands for growth of real GDP of the Czech republic and ΔCPI denotes annual changes in harmonised consumer price index. The time-invariant effect is omitted from the equation in order to capture the impact of the aforementioned macroeconomic variables.

Based on the preceding research on this topic, we consider a model with lagged value of the dependent variable. The updated equation form then looks as follows:

$$\begin{aligned} ROA_{it} = \alpha + \gamma_1 ROA_{it-1} + \beta_1 CFCR_{it} + \beta_2 DE_{it} + \\ \beta_3 nsvol_{it} + \beta_4 capex\_sales_{ti} + \beta_5 assets_{it} + \\ \delta_1 GDPg_t + \delta_2 \Delta CPI_t + \nu_i + \epsilon_{it} \end{aligned} \tag{4.13}$$

4.3.3 Detection of the ESG impact

The central objective of this study is to elucidate the impact of corporate responsibility, as reflected in ESG scores, on the factors that influence the probability of default and profitability. As previously stated in Chapter 3, the ESG scores provided lack a temporal dimension. This makes their inclusion in our models problematic, particularly given the questionable causality between ESG on one side and default and profitability on the other. Therefore, we propose using ESG scores as a reference. After running a regression on the entire dataset and selecting the optimal model, we divide it into multiple subsets based on the company scores.

Chapter 5

Results

5.1 Default model results

As a preliminary step, we intend to examine the prepared dataset for any evidence of multicollinearity prior to running any regression analysis. Table 5.1 presents the matrix of correlation coefficients between the variables included in our models. Apart from the highly correlated ROA and ROE, the only noteworthy value is the correlation between the cash flow coverage ratio and the debt-to-equity ratio. The aforementioned variables manifest a moderate negative correlation, which is not an insurmountable obstacle. Therefore, it is plausible to proceed with the regressions in accordance with the desired specification.

	ROE	ROA	CFCR	D/E	NS vol	Capex/Sales	Assets
ROE	1.00	0.84	0.21	0.10	0.13	-0.10	-0.09
ROA	0.84	1.00	0.37	-0.16	0.07	-0.06	-0.05
CFCR	0.21	0.37	1.00	-0.45	0.03	-0.10	-0.09
D/E	0.10	-0.16	-0.45	1.00	0.10	0.02	-0.06
NS vol	0.13	0.07	0.03	0.10	1.00	-0.06	-0.08
Capex/Sales	-0.10	-0.06	-0.10	0.02	-0.06	1.00	0.17
Assets	-0.09	-0.05	-0.09	-0.06	-0.08	0.17	1.00

Table 5.1: Correlation analysis of variables.

Table 5.2 presents the results of the estimates of the PD model. The first column displays the results of the OLS estimation, with the transformed probability of default serving as the dependent variable. The remaining three columns feature estimates for models with a binary dependent variable indicating default, and (from left to right) estimated via probit, logit and rare events logit (relogit). The majority of coefficients have the expected sign, with the exception of the size coefficient for the logit and relogit methods. Nevertheless, the coefficient is not statistically significant at the 10% level. The financial statement and company's status are concurrent, with no lags included.

	Dependent variable:			
	transformed_pd	default		
	OLS	*probit*	*logit*	*rare events logit*
	(1)	(2)	(3)	(4)
ROE	-0.974^{***}	-1.458	-3.369	-3.587^{*}
	(0.281)	(0.904)	(2.154)	(2.144)
CFCR	-0.226^{***}	-0.233	-0.688	-0.500
	(0.031)	(0.175)	(0.485)	(0.483)
DE	0.499^{***}	0.245^{**}	0.544^{**}	0.579^{**}
	(0.038)	(0.102)	(0.229)	(0.228)
nsvol	0.766^{***}	0.285	0.773	0.919
	(0.162)	(0.461)	(1.041)	(1.037)
capex_sales	-0.383^{**}	-1.233	-2.918	-2.546
	(0.174)	(0.759)	(1.926)	(1.917)
assets	-0.0001^{*}	-0.00000	0.00001	0.0004
	(0.00005)	(0.0001)	(0.0003)	(0.0003)
Constant	-5.281^{***}	-2.290^{***}	-4.515^{***}	-5.098^{***}
	(0.194)	(0.566)	(1.296)	(1.290)
Observations	1,572	1,572	1,572	1,572
R^2	0.235			
Adjusted R^2	0.232			
Log Likelihood		-152.934	-152.861	-152.861
Akaike Inf. Crit.		319.869	319.722	319.722
Residual Std. Error	0.945 (df = 1565)			
F Statistic	80.293^{***} (df = 6; 1565)			
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 5.2: Estimates for default models.

In the first model, all variables are statistically significant at the 1% level, with the exception of the size variable. A negative relationship is observed between credit risk and profitability, liquidity (as proxied by the cashflow coverage ratio) and development/investment expenses. Conversely, an increase in indebtedness and volatility of net sales results in an increased possibility of default.

Inspection of the results of binary choice models reveals a rapid decline in the number of statistically significant variables. In the case of the probit and logit models, only the intercept and indebtedness appear to be statistically significant at the 1% and 5% levels, respectively. In the relogit model, the sole additional significant variable is profitability, represented by ROE. However, the level of significance is only 10%. The Akaike Information Criterion is slightly lower for the logit/relogit model. As previously discussed in Chapter 4, the coefficients of the OLS and binary choice models are not directly comparable, nor are the goodness-of-fit statistics. Based on the theoretical and practical foundations, the binary models are considered to be more appropriate, with the relogit model being the preferred option in this case.

5.1.1 Optimal lag of financial data

One of the interests of this thesis is to identify the optimal number of lags for our credit risk model. In order to ensure the comparability of the data, the dataset was filtered in such a way that only individuals with up to two preceding periods were retained. The aforementioned procedure resulted in a final sample size of 1,072 individuals. The results of the regression analysis conducted on this dataset with the base specification of the model are presented in Table 5.3. The first column shows the estimates for the model in which the default variable and the financial data are from the same period. The second model presents the results of a regression where the financial data is lagged by one period (i.e. one year) with respect to the default variable. The final model is estimated with financial data lagged by two years. The first model, which does not include a lag, does not yield a statistically significant coefficient; only the intercept is significant. The model with a one-year lag has, apart from the intercept, only solvency and size as significant variables, both at the 10% level. The final model, which lags the financial data by two years behind the default variable, yields significant coefficients for ROE at the 10% level and for capital expenditures-to-sales at the 5% level. Furthermore, the intercept is also found to be significant for this model.

The results of the final estimation, with a two-year lag, appear to be the most meaningful. The Akaike Information Criterion reaches its lowest value for this model, indicating that it is the most optimal of the three estimated

	Dependent variable: default		
	Model		
	contemporaneous	one lag	two lags
ROE	−3.288	−2.919	−6.607*
	(3.510)	(3.456)	(3.520)
CFCR	−0.414	−0.093	0.314
	(0.745)	(0.816)	(0.394)
DE	0.366	0.680*	0.534
	(0.409)	(0.391)	(0.416)
nsvol	1.753	1.101	2.254
	(1.624)	(1.959)	(1.856)
capex_sales	−1.067	−1.145	2.456**
	(2.407)	(2.427)	(1.219)
assets	0.001	0.001*	0.001
	(0.0004)	(0.0004)	(0.0005)
Constant	−5.948***	−5.621**	−7.192***
	(2.012)	(2.346)	(2.138)
Observations	1,072	1,072	1,072
Log Likelihood	−75.539	−75.184	−74.374
Akaike Inf. Crit.	165.077	164.368	162.747
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5.3: Estimates for various lags of the default model - relogit.

	Dependent variable: transformed_pd		
	Model		
	contemporaneous	one lag	two lags
ROE	-1.002^{***}	-0.761^{**}	-1.085^{***}
	(0.336)	(0.359)	(0.371)
CFCR	-0.220^{***}	-0.221^{***}	-0.089^{**}
	(0.039)	(0.044)	(0.042)
DE	0.554^{***}	0.490^{***}	0.446^{***}
	(0.050)	(0.052)	(0.054)
nsvol	0.748^{***}	0.884^{***}	0.861^{***}
	(0.206)	(0.229)	(0.247)
capex_sales	-0.406^{**}	-0.078	-0.531^{**}
	(0.201)	(0.198)	(0.221)
assets	0.0001	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)
Constant	-5.387^{***}	-5.534^{***}	-5.485^{***}
	(0.246)	(0.267)	(0.279)
Observations	1,072	1,072	1,072
R^2	0.233	0.193	0.120
Adjusted R^2	0.228	0.189	0.115
Residual Std. Error (df = 1065)	0.891	0.913	0.954
F Statistic (df = 6; 1065)	53.797^{***}	42.505^{***}	24.286^{***}
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5.4: Estimates for various lags of the default model - OLS.

models. This finding is consistent with those reported in previous studies of Gurný *et al.* (2013) and Westgaard & Van der Wijst (2001). However, all three models under comparison demonstrate a relatively poor performance. This may be attributed to the relatively low number of defaults observed in the entire dataset, which was further reduced in the subset used for lag comparison.

One potential way to justify these results would be through the use of beta regression. The method was developed by Ferrari & Cribari-Neto (2004) as a tool for the analysis and estimation of models whose dependent variable is defined on an interval from zero to one (e.g. various ratios). The estimation method is based on the assumption that the dependent variable follows a beta distribution. It is unfortunate that this is not the case for our dependent variable, as illustrated in Figure A.1 in Appendix A.

Estimating the model with the transformed default as the dependent variable using OLS produces more convincing results. With the exception of Capex/Sales in the second model and size in all models, all variables are statistically significant at the 5% level or below. Furthermore, all variables have identical signs across all three models.

In contrast with our previous findings, based on R^2 the best fitting model is the contemporaneous one, followed by the one-year lag model and the model with two-period lags (Table 5.4).

5.1.2 Credit risk and ESG results

In order to examine the impact of ESG on credit risk, the entire dataset is divided into two subsets. The first subset comprises firms that have been rated as either 'great' or 'very good' in terms of their overall ESG performance, while the second subset includes the remaining rated firms. It is unfortunate that this process limits the dataset to such an extent that the estimation with a binary choice model is no longer applicable due to the extremely low number of defaults in both groups (Table B.1). As a result, we are constrained to rely on the OLS contemporaneous model, the results of which are presented in Table 5.5.

In both models, CFCR and D/E are statistically highly significant at the 1% level. The former exhibits a greater magnitude for the subset of superior ESG performers, while the latter displays a slightly higher magnitude for companies with inferior ESG ratings. The coefficient for profitability is statistically significant at the 10% level for the first subset, whereas for the second subset,

	Dependent variable: transformed_pd		
		Overall ESG score	
	All firms	1,2	3,4,5
ROE	-0.974^{***}	-1.097^{**}	-1.653^{***}
	(0.281)	(0.482)	(0.413)
CFCR	-0.226^{***}	-0.272^{***}	-0.150^{***}
	(0.031)	(0.055)	(0.045)
DE	0.499^{***}	0.532^{***}	0.588^{***}
	(0.038)	(0.066)	(0.058)
nsvol	0.766^{***}	0.956^{***}	0.529^{**}
	(0.162)	(0.293)	(0.243)
capex_sales	-0.383^{**}	-0.208	-0.291
	(0.174)	(0.374)	(0.229)
assets	-0.0001^{*}	-0.0001	-0.0001^{*}
	(0.00005)	(0.0001)	(0.0001)
Constant	-5.281^{***}	-5.448^{***}	-4.963^{***}
	(0.194)	(0.345)	(0.292)
Observations	1,572	501	662
R^2	0.235	0.273	0.255
Adjusted R^2	0.232	0.264	0.248
Residual Std. Error	0.945 (df = 1565)	0.917 (df = 494)	0.879 (df = 655)
F Statistic	80.293^{***} (df = 6; 1565)	30.876^{***} (df = 6; 494)	37.383^{***} (df = 6; 655)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5.5: Credit risk OLS model estimates for subsampled data - total ESG score.

the coefficient for ROE is significant at the 1% level and is also moderately higher than for the first dataset. This indicates that a decline in profitability represents a more severe and threatening event for companies with lower ESG scores. Conversely, a decline in liquidity is deemed a more significant concern for companies with high ESG standards. The volatility of net sales also appears to be a significant determinant of credit risk for companies with superior ESG scores. In contrast, for the subset of inferior ESG performers, the volatility appears to be insignificant. Furthermore, the capital expenditure-to-sales ratio is significant at the 10% level, indicating that an increase in development and investment spending within a firm with a lower overall ESG score might contribute to a decrease in default probability.

These findings are largely consistent with those of Chodnicka-Jaworska (2021) and Kim & Li (2021). Both studies identified evidence of a reverse effect of ESG alteration on credit risk, specifically in the form of a credit rating. That is, an improved ESG score is associated with an enhanced credit rating. Our findings essentially support this conclusion, indicating that for firms with superior ESG scores, changes in their financial performance influence default probabilities to a lesser extent than in firms with inferior ESG scores.

5.2 Profitability model results

5.2.1 Linear model estimates

In the initial phase of profitability analysis, the base specification of the profitability model using OLS, FE (within estimator with individual and time effects), first-differenced (FD) and RE (FGLS) method is estimated. The results are presented in Table B.2. Thereafter, a series of tests is conducted in order to determine the optimal method for the analysis of the dataset.

F test for twoway effects
Data: Profitability model F = 3.4372, df1 = 1576, df2 = 3899, p-value < 2.2e-16 Alternative hypothesis: significant effect

Table 5.6: F-test result.

Firstly, an F-test is carried out in order to select the superior model between the OLS and FE methods. The results of the test (see Table 5.6) indicate presence of significant individual and time effects. Thus, the fixed effects approach appears to be a superior method in comparison to the ordinary least squares.

Hausman test
Data: Profitability model
$\chi^2 = 97.681$, df = 5, p-value < 2.2e-16
Alternative hypothesis: one model is inconsistent

Table 5.7: Hausman test result.

We proceed to undertake a comparison of the outcomes yielded by the FE and RE methods, utilising the Hausmann test (Table 5.7). The low p-value allows us to reject the null hypothesis, which states that the unobserved heterogeneity is uncorrelated with the predictors. This result indicates that the FE model is the superior of the two models under consideration.

Breusch-Godfrey/Wooldridge test for serial correlation in panel models
Data: Profitability model
$\chi^2 = 117.17$, df = 1, p-value < 2.2e-16
Alternative hypothesis: serial correlation in idiosyncratic errors

Table 5.8: Result of the Breusch-Godfrey test.

The next step is to examine the presence of autocorrelation and heteroskedasticity in the model. To ascertain whether the error term in the model is serially correlated, the Breusch-Godfrey test (Table 5.8) is performed. The low p-value in the test allows the null hypothesis to be rejected and autocorrelation in the residuals to be admitted. In order to detect heteroskedasticity, we utilise the Breusch-Pagan test. The findings of this test (Table 5.9) enable us to conclude that there is evidence of heteroskedasticity of the residuals.

Based on the results of the conducted tests, it can be concluded that the FD and FE methods are the most appropriate for the purpose of this thesis. The question that we must now address is that of choosing between the two models. Wooldridge (2016) states that in the presence of serial correlation in residuals (as is the case with our model), the FD model is more efficient. On the other hand, the FD estimator does not utilise all the information in the dataset due to first-differencing data, whereas the FE estimator is able to make use of all the observations available. The same is valid for the extended model with macroeconomic variables. As can be seen in Table 5.10, the results show only marginal differences. The R^2 is slightly higher for the FD model in both the base and extended specification. The model with macroeconomic variables added exhibits a somewhat higher R^2 compared to its counterpart in the case of FD model and slightly lower R^2 in the case of FE model.

Studentized Breusch-Pagan test
Data: Profitability model
BP = 350.22, df = 5, p-value < 2.2e-16
Alternative hypothesis: heteroskedasticity in idiosyncratic errors

Table 5.9: Result of the Breusch-Pagan test.

Furthermore, the variance inflation factor is calculated in order to rule out the possibility of multicollinearity (Table 5.11). The critical value of the statistic is five. In our model, none of the values exceed two, which is entirely satisfactory.

5.2.2 GMM estimates

In order to perform the Generalised Method of Moments (GMM) estimation, the specification which includes macroeconomic variables is used directly. Table B.4 presents the results for both estimation methods, namely system GMM and difference GMM. With the exception of D/E and Capex/Sales ratios, the estimated coefficients exhibit identical signs. Notably, the magnitude varies considerably for the majority of individual variables. The Hansen-Sargan test for overidentification in instruments allows us to reject the null hypothesis in the case of system GMM, but not in the case of difference GMM. The rejection of null hypothesis implies that the instruments are not exogenous. This suggests a presence of an issue related to the model. The autocorrelation tests indicate the presence of first-order autocorrelation in the residuals of both models. The null hypothesis of second-order autocorrelation cannot be rejected, and thus, it can be concluded that no second-order correlation is present. The Wald test for coefficients yields evidence of at least one significant variable with a non-zero coefficient. In the context of the aforementioned test results, it is preferable to select the difference GMM method as the superior and more appropriate of the two.

Table 5.12 enables a direct comparison of the selected GMM and linear (with robust standard errors) models. The results of the estimation methods exhibit minimal discrepancies. The FE model, however, is the most divergent.

	Dependent variable: ROA			
	Model			
	base FE	base FD	extended FE	extended FD
CFCR	0.016***	0.017***	0.016***	0.017***
	(0.001)	(0.001)	(0.001)	(0.001)
DE	−0.011***	−0.013***	−0.010***	−0.013***
	(0.002)	(0.003)	(0.002)	(0.003)
nsvol	0.018***	0.009	0.018***	0.011
	(0.005)	(0.009)	(0.005)	(0.009)
capex_sales	0.003	0.004	0.004	0.004
	(0.004)	(0.004)	(0.004)	(0.004)
log(assets)	0.022***	0.033***	0.018***	0.034***
	(0.003)	(0.006)	(0.003)	(0.006)
GDPg			0.0002*	−0.0001
			(0.0001)	(0.0001)
ΔCPI			−0.001***	−0.001***
			(0.0002)	(0.0001)
Constant		−0.004***		−0.003***
		(0.001)		(0.001)
Observations	5,481	3,909	5,481	3,909
R^2	0.131	0.141	0.128	0.144
Adjusted R^2	−0.222	0.140	−0.225	0.142
F Statistic	117.144***	128.309***	81.658***	93.636***
	(df = 5; 3899)	(df = 5; 3903)	(df = 7; 3902)	(df = 7; 3901)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 5.10: Comparison of FD and FE estimates of the profitability model.

CFCR	D/E	NS vol	Capex/Sales	Assets	GDPg	ΔCPI
1.1328	1.2458	1.0138	1.0807	1.1698	1.0044	1.0094

Table 5.11: Variance inflation factor (extended FD model).

	Dependent variable: ROA		
	panel linear		*panel GMM*
	FE	*FD*	
ROA_{t-1}			0.392***
			(0.069)
$CFCR_t$	0.016***	0.017***	0.020***
	(0.001)	(0.001)	(0.002)
DE_t	−0.010***	−0.013***	−0.013***
	(0.002)	(0.003)	(0.003)
$nsvol_t$	0.018***	0.011	0.002
	(0.005)	(0.009)	(0.008)
$capex\_sales_t$	0.004	0.004	0.002
	(0.004)	(0.004)	(0.006)
$\log(assets)_t$	0.018***	0.034***	0.048***
	(0.003)	(0.006)	(0.006)
$GDPg_t$	0.0002*	−0.0001	−0.0001
	(0.0001)	(0.0001)	(0.0001)
ΔCPI_t	−0.001***	−0.001***	−0.001***
	(0.0002)	(0.0001)	(0.0003)
Constant		−0.003***	
		(0.001)	
Observations	5,481	3,909	2,737
R^2	0.128	0.144	
Adjusted R^2	−0.225	0.142	
F Statistic	81.658*** (df = 7; 3902)	93.636*** (df = 7; 3901)	
Note:		*p<0.1; **p<0.05; ***p<0.01	

Table 5.12: Comparison of chosen profitability model estimates.

Unlike the other two models, the FE model identified net sales volatility and GDP growth as significant variables at the 1% and 10% levels, respectively.

All models demonstrate a comparable significance in terms of liquidity and solvency ratios. As anticipated, the CFCR exhibits a positive correlation with profitability - a higher operational cashflow to total debt is indicative of better performance. The sign of the debt-to-equity ratio is negative, as anticipated. In general, a lower D/E ratio is preferred.

In light of the findings obtained from the models and the conducted tests, it was determined that the most suitable baseline for further analysis of ESG impact would be a difference GMM model. In the case that the GMM model is deemed to be ineffective, the FD approach will be employed as a backup methodology.

As previously stated, both solvency and liquidity ratios appear to have statistically highly significant influence on profitability. Nevertheless, the impact is economically marginal, with a 100 percentage points increase of the D/E ratio resulting in an decrease of only 1.3 percentage point in the return on assets.

The size of the company also appears to have a positive and significant effect. A 100% increase in the size of the firms would result in a 4.8 percentage point increase in profitability.

The model also indicates a persistent effect of profitability. An increase of 10 percentage points in the ROA in the current year should lead to growth of more than 3.92 percentage points in the following year. Conversely, changes in the harmonised consumer price index have a negative impact on profitability. A 10 percentage point change in CPI would result in a one percentage point drop in ROA.

5.2.3 Profitability and ESG results

As previously stated, the analysis of ESG impact on profitability determinants is conducted by dividing the dataset into multiple subsets, which are then compared with the estimates of the original model. The division into groups is undertaken in a manner that ensures the functionality of the model.

In this manner, the dataset is split into two subsets. The first subset comprises all companies that received an overall score of either *great* or *very good*, representing a total of 501 firms. The second subset contains 661 enterprises whose overall ESG rating was classified as *good* or worse. The results of the estimation are presented in Table 5.13. The first column of the results displays the estimates for the entire dataset. All models are estimated using the difference GMM method. The two subset models exhibit a satisfactory fit. The two subsampled models display no second-order autocorrelation, and the results of the Wald test permit the rejection of the null hypothesis that none of the coefficients is different from zero. The results of the Hansen-Sargan test for the first subsample suggest the validity of the null hypothesis that the overidentifying restrictions are valid. The results for the second subsample are less conclusive, but the null hypothesis remains unrejected at the 1% significance level.

The significance and direction of coefficients diverge from those of the original model in few cases. Although changes in CPI are of considerable significance in the original model, no meaningful relationship is identified in either subset model. The Capex/Sales ratio is not statistically significant at the 10% level for both the original model and the subset of companies with inferior ESG ratings. On the other hand, for companies with superior overall scores, the ratio is significant at the 10% level.

The coefficients measuring the impact of past profitability are found to be highly significant in all three models. In the case of the subset of firms with a worse scores, the coefficient is equal to 0.312, which is lower than in the model estimated for all data. Meanwhile, the estimate for companies with superior overall ESG scores reaches 0.459, a higher estimate than the 0.392 for the entire dataset. These outcomes suggest that companies with higher ESG ratings tend to maintain more stable profitability than companies that do not engage proactively with ESG issues.

Similar results can be observed for the liquidity in the form of CFCR. The estimated coefficient for the full dataset is 0.02, while the value for companies with a good overall score is 0.024. The estimate for the second subset is lower than that of the aforementioned models, equalling 0.018. This indicates that enterprises with higher ESG scores tend to generate higher returns from improved liquidity than those with weaker ESG performance.

The solvency, represented by the D/E ratio, appears to be more impactful on superior performers, while showing a slight reduction in impact on firms with inferior ESG rating. In the latter case, the result is also significant only at the 5% significance level.

The estimated coefficients for size differ only marginally. While the model with the whole dataset employed yielded a value of 0.048, the estimated values for the first and second subsets were 0.049 and 0.048, respectively.

	Dependent variable: ROA		
	All firms	*Overall ESG score*	
		1, 2	3, 4, 5
ROA_{t-1}	0.392^{***}	0.459^{***}	0.312^{***}
	(0.069)	(0.096)	(0.119)
$CFCR_t$	0.020^{***}	0.024^{***}	0.018^{***}
	(0.002)	(0.005)	(0.003)
DE_t	-0.013^{***}	-0.018^{***}	-0.009^{**}
	(0.003)	(0.005)	(0.004)
$nsvol_t$	0.002	0.005	0.009
	(0.008)	(0.015)	(0.010)
$capex\_sales_t$	0.002	0.025^{*}	-0.004
	(0.006)	(0.014)	(0.007)
$\log(assets)_t$	0.048^{***}	0.049^{***}	0.048^{***}
	(0.006)	(0.009)	(0.009)
$GDPg\ _t$	-0.0001	0.0003	0.00004
	(0.0001)	(0.0002)	(0.0002)
ΔCPI_t	-0.001^{***}	-0.001	0.0003
	(0.0003)	(0.0004)	(0.0004)
Observations	2,737	908	1,237
Sargan test	$\chi^2(9) = 12.451$	$\chi^2(9) = 11.217$	$\chi^2(9) = 17.35$
p-value	0.189	0.261	0.044
Autocorr. test (1)	-8.567	-5.447	-4.627
p-value	<0.001	<0.001	<0.001
Autocorr. test (2)	1.059	0.279	0.009
p-value	0.289	0.78	0.993
Wald test for coefficients	$\chi^2(8) = 205.795$	$\chi^2(8) = 102.825$	$\chi^2(8) = 82.661$
p-value	<0.001	<0.001	<0.001
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5.13: Estimates of the profitability model for subsampled data - total ESG score.

	Dependent variable: ROA		
	All firms	*Social subscore*	
		1, 2	3, 4, 5
ROA_{t-1}	0.392***	0.463***	0.216*
	(0.069)	(0.094)	(0.115)
$CFCR_t$	0.020***	0.021***	0.018***
	(0.002)	(0.003)	(0.003)
DE_t	−0.013***	−0.015***	−0.011**
	(0.003)	(0.004)	(0.005)
$nsvol_t$	0.002	−0.004	0.016
	(0.008)	(0.012)	(0.013)
$capex\_sales_t$	0.002	0.019*	−0.001
	(0.006)	(0.011)	(0.009)
$\log(assets)_t$	0.048***	0.057***	0.041***
	(0.006)	(0.009)	(0.008)
$GDPg_{\ t}$	−0.0001	0.0003	0.0001
	(0.0001)	(0.0002)	(0.0002)
ΔCPI_t	−0.001***	0.0001	0.0001
	(0.0003)	(0.0004)	(0.0004)
Observations	2,737	1,331	814
Sargan test	$\chi^2(9) = 12.451$	$\chi^2(9) = 12.824$	$\chi^2(9) = 12.234$
p-value	0.189	0.171	0.2
Autocorr. test (1)	-8.567	-6.086	-4.133
p-value	<0.001	<0.001	<0.001
Autocorr. test (2)	1.059	0.441	-0.412
p-value	0.289	0.659	0.681
Wald test for coefficients	$\chi^2(8) = 205.795$	$\chi^2(8) = 98.32$	$\chi^2(8) = 65.522$
p-value	<0.001	<0.001	<0.001
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5.14: Estimates of the profitability model for subsampled data - social subscore.

	Dependent variable: ROA		
	All firms	*Governance subscore*	
		1, 2	3, 4, 5
ROA_{t-1}	0.392^{***}	0.333^{***}	0.463^{***}
	(0.069)	(0.082)	(0.147)
$CFCR_t$	0.020^{***}	0.019^{***}	0.020^{***}
	(0.002)	(0.003)	(0.004)
DE_t	-0.013^{***}	-0.016^{***}	-0.008
	(0.003)	(0.004)	(0.006)
$nsvol_t$	0.002	0.006	0.014
	(0.008)	(0.012)	(0.014)
$capex\_sales_t$	0.002	0.004	0.009
	(0.006)	(0.011)	(0.009)
$\log(assets)_t$	0.048^{***}	0.050^{***}	0.050^{***}
	(0.006)	(0.008)	(0.012)
$GDPg_{\ t}$	-0.0001	0.0004^{**}	-0.0002
	(0.0001)	(0.0002)	(0.0003)
ΔCPI_t	-0.001^{***}	-0.001	0.001^{***}
	(0.0003)	(0.0004)	(0.0004)
Observations	2,737	1,410	735
Sargan test	$\chi^2(9) = 12.451$	$\chi^2(9) = 15.138$	$\chi^2(9) = 10.542$
p-value	0.189	0.087	0.308
Autocorr. test (1)	-8.567	-6.378	-3.525
p-value	<0.001	<0.001	<0.001
Autocorr. test (2)	1.059	0.394	0.634
p-value	0.289	0.694	0.526
Wald test for coefficients	$\chi^2(8) = 205.795$	$\chi^2(8) = 101.489$	$\chi^2(8) = 56.987$
p-value	<0.001	<0.001	<0.001
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5.15: Estimates of the profitability model for subsampled data - governance subscore.

The theory of higher persistence of the superior ESG performers is further supported by the findings in Table 5.15. In this case, the companies represented in our dataset are divided into groups based on the social section score. The first subset contains firms with *very good* and *good* social score. The second one includes the rest of the rated enterprises. The null hypothesis for the Hansen-Sargan test cannot be rejected at 10% level in both cases.

Similarly, as observed in the case of ESG subsets, the changes in liquidity and solvency are more pronounced for firms with superior scores. In contrast to the preceding case, the coefficients for size exhibit variation among the social subgroups and in comparison to the entire dataset. The impact is particularly amplified for firms with superior scores.

The estimation for environmental subsets produces a somewhat different result. The Hansen-Sargan test for the subset of firms with inferior environmental subscores can only be rejected at the 5% significance level. In the case of the first subset, the p-value of the second-order autocorrelation test is equal to 0.05, which is also a slightly inconclusive result. The aforementioned test outcomes suggest that the model does not behave very well for the environmental subsets. Therefore, we consider this outcome too weak to draw an inference from it. The results can be seen in Table B.5 in Appendix B.

The results for the subsamples based on governance subscores appear to demonstrate better performance. The Hansen-Sargan test for the companies with superior governance subscores yields a p-value of 0.087, which is sufficient to reject the null hypothesis at the 5% level. For other significant tests, the null hypothesis cannot be rejected at the 10% level of significance. Of particular interest are the estimated coefficients for returns in the previous period. In contrast to the results observed for the remaining models, the coefficient for past returns is significantly lower in the subsample of firms with superior governance ratings than in the subsample of firms with poorer ratings. In the latter subsample, the estimate is larger than in the full dataset (0.463 to 0.392). The rationale behind this unexpected outcome is debatable. It is possible that firms with poor governance are prioritising short-term profit over long-term financial health. However, the exact reason for this phenomenon is beyond the scope of this study.

Although the aforementioned results may appear peculiar at first glance, the findings of Kim & Li (2021) yielded highly analogous outcomes. The aggregate ESG score within their model exhibited a positive relationship with the profitability of the examined companies. Furthermore, the positive impact of the governance subsection was discernible exclusively for firms with inadequate governance, a phenomenon that aligns with our observations.

5.2.4 Robustness check

In order to justify the findings of the preceding section, a further set of estimations was conducted with ROE as the dependent variable. The results presented in the Tables B.6 and B.7 in Appendix B are comparable to those presented in the main body of the thesis.

Chapter 6

Conclusion

The growing significance of corporate social responsibility (CSR) among enterprises in developed countries creates a challenging situation for analytics in credit risk departments and investors alike. While ESG scoring has become a standard practice in the current millennium, the research on this topic remains disparate and inconsistent. The objective of this thesis is to contribute to this field of research.

This thesis employs using two datasets provided by an anonymous Czech bank. These datasets were combined to create a unique dataset combining information from financial statements with the evaluation of the companies in terms of their environmental, social and governance spheres. Two separate models were created for the analysis of credit risk and profitability of non-financial enterprises. The former was analysed using the OLS and rare events logit methods. The latter was estimated primarily with difference GMM.

The results for the default model indicate a reduction in the variation in default probability for firms with superior ESG ratings with respect to changes in profitability and solvency. In contrast, the fluctuations in terms of liquidity appear to affect the superior ESG performers to a greater extent than their counterparts with poorer corporate responsibility practices.

Furthermore, we seize the opportunity provided by the credit model to investigate the optimal lag of financial data in relation to the status of the firm. The results of this section are inconclusive. While the outcome of the OLS estimation suggests that the contemporaneous (no lags included) model is the optimal choice, the rare events logit results (which we deem to be more credible) indicate that a two-year lag is the best fit. The results of the relogit method are consistent with those reported in previous studies of Peresetsky *et al.* (2004) and Gurný *et al.* (2013).

With regard to the profitability model, the base model for the entire dataset indicates that past profitability, liquidity, solvency, size and inflation (as represented by the CPI) are significant determinants of returns. Upon examination of the subset of the dataset based on the obtained ESG rating, it becomes evident that there are notable differences in the response of superior and inferior performers. It appears that past profitability is a more persistent factor for firms with an overall ESG score that is more favourable. Similarly, the impact of liquidity and solvency on profitability is more pronounced for firms that demonstrate greater engagement with ESG issues. The impact of size on profitability is consistent with the base model for both subsets.

Similar results were obtained for the subsets based on social score, with the exception of coefficients for size. Companies with superior performance in social issues appear to benefit more from size than their counterparts with inferior social subscores. On the other hand, the profitability of companies with inferior governance scores appears to be more influenced by its past values than the returns of enterprises with superior governance ratings.

This study is not without its shortcomings. Firstly, the ESG data lacks a time dimension, which restricted the available options for model construction. With regard to the financial dataset, the lack of certain essential variables, such as current liabilities or interest expense, compelled us to employ alternative ratios that may not be as effective in capturing the financial condition as the traditional ones. The absence of information on default or default probability for each observation (year) of individual company further reduced the range of options for analysis and is likely to have contributed to the inability to utilise a binary response model for ESG impact analysis in this section of the thesis.

Nevertheless, it is our belief that this work makes a valuable contribution to the field of research. In contrast to the majority of studies in this field, which have focused on large listed companies in the US, Western Europe and China, our study employs a dataset encompassing firms from the relatively small Czech economy, with representation of smaller, medium, and large enterprises. Our approach differs from that of the majority of studies on this topic, which directly include ESG scores in the model equation. Additionally, we aim to contribute to the existing literature by providing an extensive overview of the development of credit risk measurement, as well as the history and evolution of corporate social responsibility (CSR) and environmental, social, and governance (ESG) ratings. It would be of interest to other researchers to confirm the results presented here with a dataset that would allow them to utilise the ratios that are considered more appropriate, for example the quick or current ratio for liquidity. An additional area of investigation would be the examination of the ESG effect with default information available for all observations of individual firms over a number of years.

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Appendix A

Figures

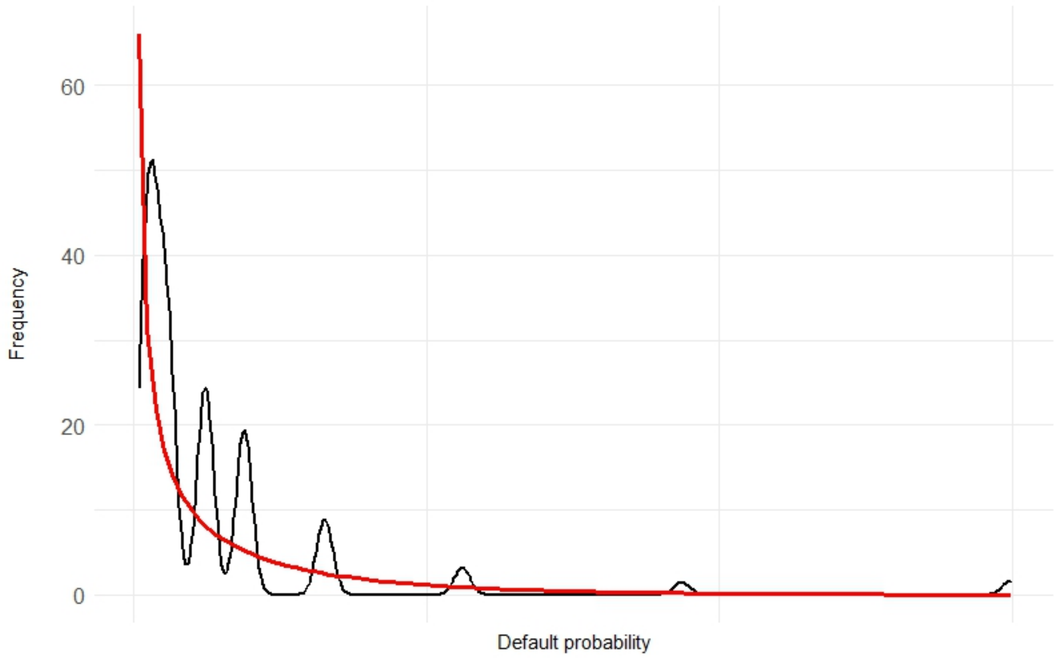

Figure A.1: Distribution of the dependent variable in the PD model.

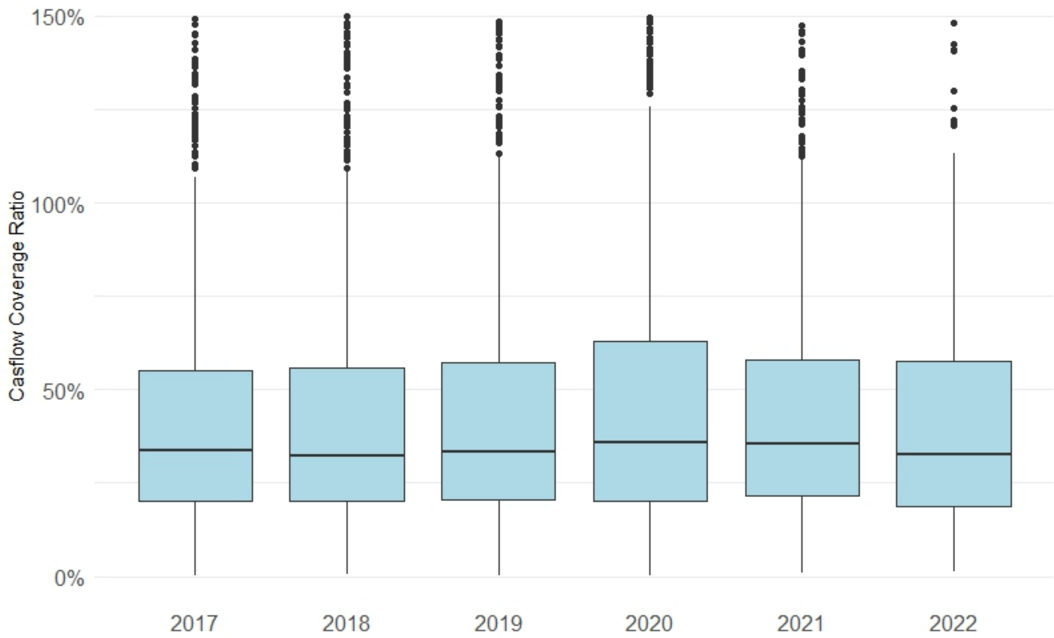

Figure A.2: Cashflow coverage ratio of companies, 2017-2022.

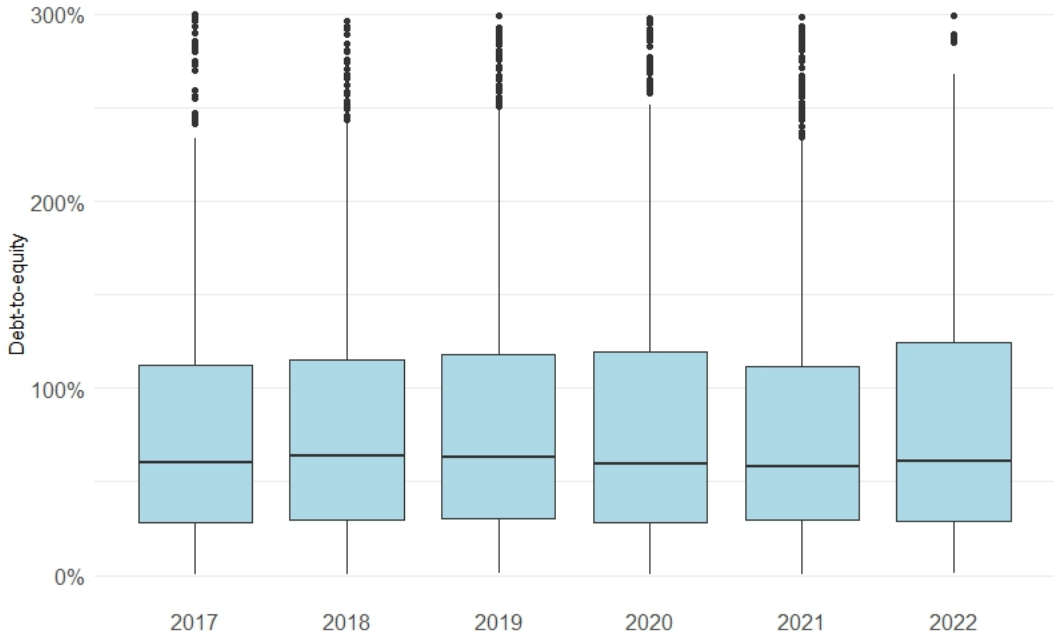

Figure A.3: Debt-to-equity of companies, 2017-2022.

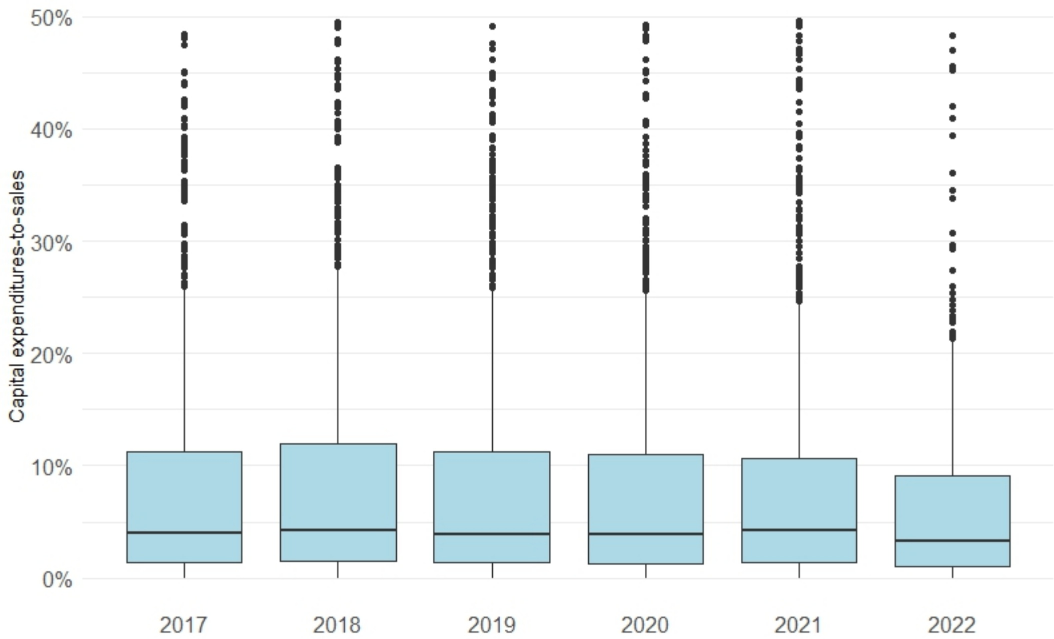

Figure A.4: Capital expenditure-to-sales ratio of companies, 2017-2022.

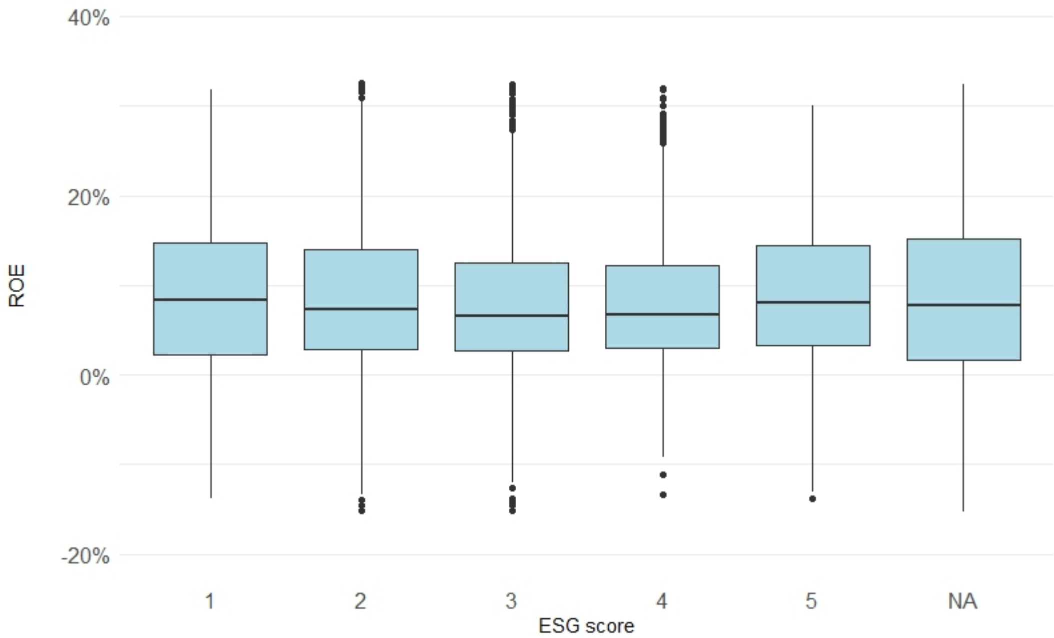

Figure A.5: ROE of companies with respect to ESG score.

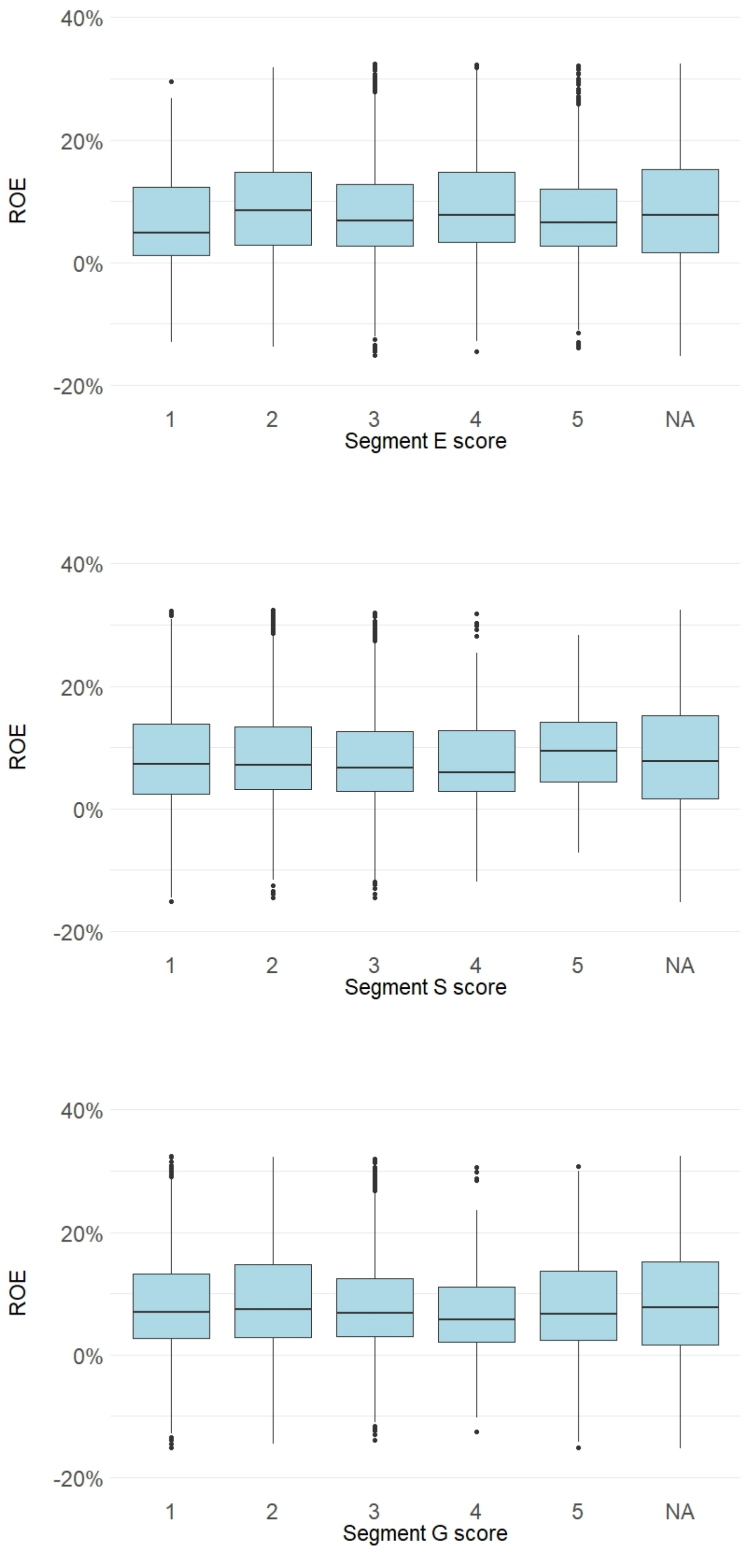

Figure A.6: ROE of companies with respect to ESG subscores.

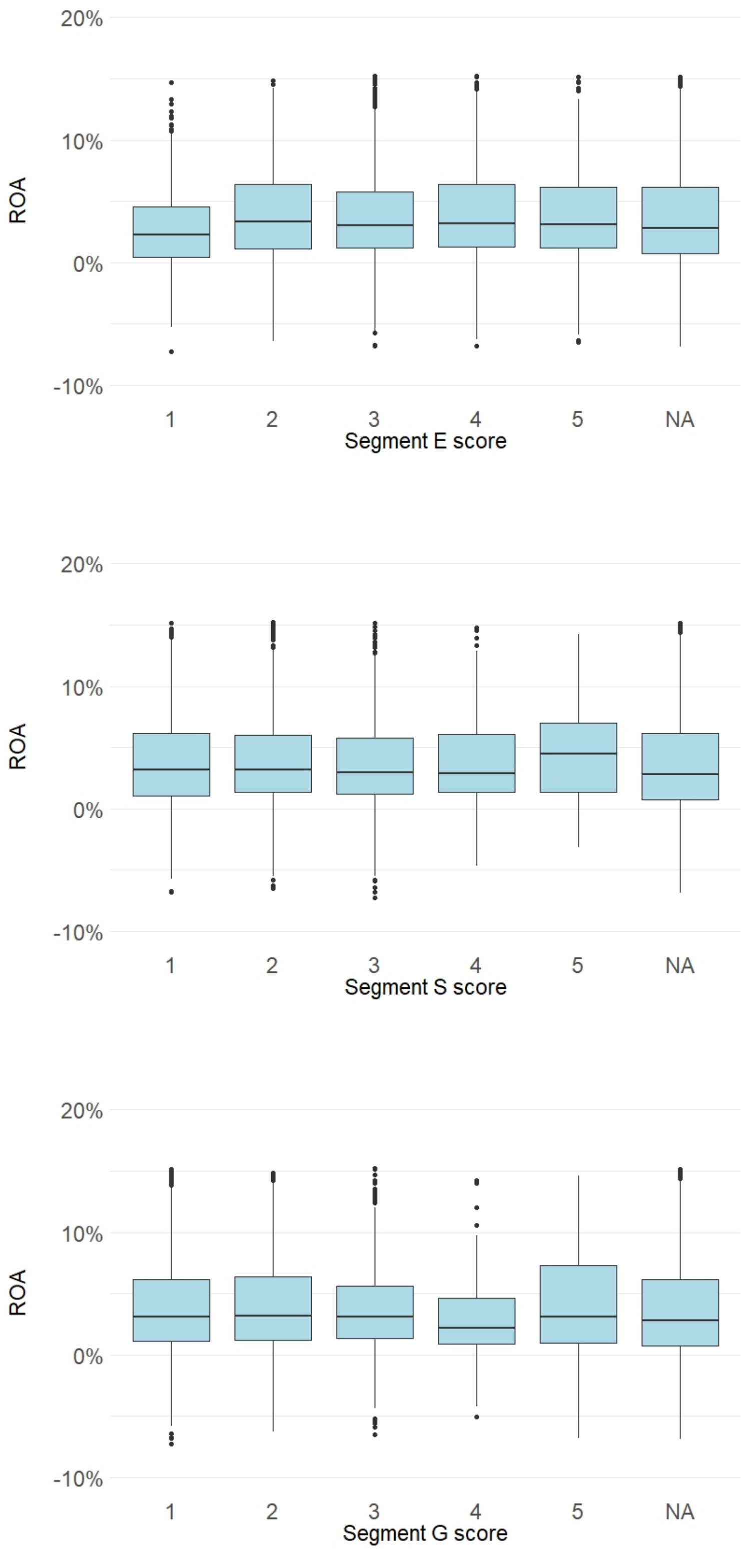

Figure A.7: ROA of companies with respect to ESG subscores.

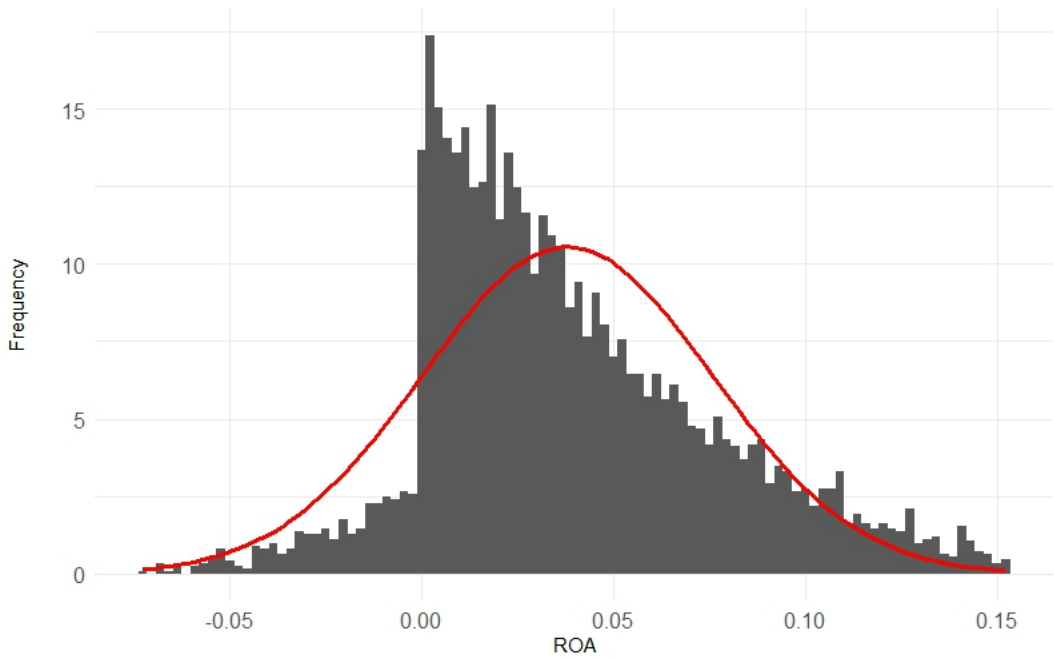

Figure A.8: Histogram of ROA.

Appendix B

Tables

	Dependent variable: default	
	Overall ESG score	
	1, 2	3, 4, 5
ROE	4.638	−10.057
	(7.019)	(7.473)
CFCR	−2.078	−3.676
	(1.432)	(3.492)
DE	−1.083	0.940
	(1.437)	(0.888)
nsvol	4.470	2.510
	(2.915)	(4.207)
capex_sales	2.509	3.650^{*}
	(4.033)	(1.986)
assets	0.001	−0.0002
	(0.001)	(0.004)
Constant	-7.814^{**}	−6.515
	(3.706)	(4.720)
Observations	355	485
Log Likelihood	−19.713	−13.726
Akaike Inf. Crit.	53.426	41.452
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table B.1: Credit risk binary model estimates for subsampled data - total score.

	Dependent variable: ROA			
	Method			
	OLS	FE	FD	RE
CFC	0.017***	0.016***	0.017***	0.016***
	(0.001)	(0.001)	(0.001)	(0.001)
DE	0.00001	-0.011***	-0.013***	-0.002*
	(0.001)	(0.002)	(0.002)	(0.001)
nsvol	0.016***	0.018***	0.009**	0.018***
	(0.004)	(0.004)	(0.005)	(0.004)
capex_sales	-0.006*	0.003	0.004	-0.0004
	(0.004)	(0.004)	(0.004)	(0.004)
log(assets)	0.0004	0.022***	0.033***	0.001
	(0.0005)	(0.003)	(0.003)	(0.001)
Constant	0.002		-0.004***	-0.009
	(0.010)		(0.001)	(0.013)
Observations	5,481	5,481	3,909	5,481
R^2	0.138	0.131	0.141	0.144
Adjusted R^2	0.138	-0.222	0.140	0.144
F Statistic	175.906***	117.144***	128.309***	771.486***
	(df = 5; 5475)	(df = 5; 3899)	(df = 5; 3903)	
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table B.2: Estimates of the profitability model - base specification.

	Dependent variable: ROA			
	Method			
	OLS	FE	FD	RE
CFCR	0.017***	0.016***	0.017***	0.016***
	(0.001)	(0.001)	(0.001)	(0.001)
DE	0.00005	-0.010***	-0.013***	-0.002*
	(0.001)	(0.002)	(0.002)	(0.001)
nsvol	0.018***	0.018***	0.011**	0.020***
	(0.004)	(0.004)	(0.005)	(0.004)
capex_sales	-0.006*	0.004	0.004	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)
log(assets)	0.0003	0.018***	0.034***	0.001*
	(0.0005)	(0.002)	(0.003)	(0.001)
GDPg	-0.0001	0.0002*	-0.0001	0.00003
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ΔCPI	-0.001***	-0.001***	-0.001***	-0.001***
	(0.0001)	(0.0001)	(0.0002)	(0.0001)
Constant	0.004		-0.003***	-0.012
	(0.010)		(0.001)	(0.013)
Observations	5,481	5,481	3,909	5,481
R^2	0.144	0.128	0.144	0.148
Adjusted R^2	0.142	-0.225	0.142	0.147
F Statistic	131.066***	81.658***	93.636***	797.032***
	(df = 7; 5473)	(df = 7; 3902)	(df = 7; 3901)	
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table B.3: Estimates of the profitability model with macroeconomic variables.

	Dependent variable: ROA	
	Method	
	System GMM	Difference GMM
ROA_{t-1}	0.165^{***}	0.392^{***}
	(0.045)	(0.069)
$CFCR_t$	0.016^{***}	0.020^{***}
	(0.001)	(0.002)
DE_t	0.0003	-0.013^{***}
	(0.001)	(0.003)
$nsvol_t$	0.015^{***}	0.002
	(0.004)	(0.008)
$capex\_sales_t$	-0.004	0.002
	(0.004)	(0.006)
$\log(assets)_t$	0.0003	0.048^{***}
	(0.0003)	(0.006)
$GDPg\ _t$	-0.0002	-0.0001
	(0.0001)	(0.0001)
ΔCPI_t	-0.001^{***}	-0.001^{***}
	(0.0002)	(0.0003)
Observations	7,284	2,737
Sargan test	$\chi^2(20) = 122.344$	$\chi^2(9) = 12.451$
p-value	<0.001	0.189
Autocorr. test (1)	-8.102	-8.567
p-value	<0.001	<0.001
Autocorr. test (2)	0.415	1.059
p-value	0.678	0.289
Wald test for coefficients	$\chi^2(8) = 2839.839$	$\chi^2(8) = 205.795$
p-value	<0.001	<0.001
Note:		*p<0.1; **p<0.05; ***p<0.01

Table B.4: GMM estimates of the profitability model.

	Dependent variable: ROA		
	All firms	*Environmental subscore*	
		1, 2	3, 4, 5
ROA_{t-1}	0.392^{***}	0.478^{**}	0.403^{***}
	(0.069)	(0.211)	(0.083)
CFCR_t	0.020^{***}	0.025^{***}	0.020^{***}
	(0.002)	(0.006)	(0.002)
DE_t	-0.013^{***}	-0.007	-0.014^{***}
	(0.003)	(0.009)	(0.004)
nsvol_t	0.002	-0.019	0.011
	(0.008)	(0.019)	(0.010)
$\mathrm{capex\_sales}_t$	0.002	0.027	0.005
	(0.006)	(0.021)	(0.008)
$\log(\mathrm{assets})_t$	0.048^{***}	0.048^{***}	0.055^{***}
	(0.006)	(0.016)	(0.007)
$\mathrm{GDPg}_{\ t}$	-0.0001	0.0004	0.0001
	(0.0001)	(0.0005)	(0.0002)
$\Delta\mathrm{CPI}_t$	-0.001^{***}	-0.001	0.0001
	(0.0003)	(0.001)	(0.0003)
Observations	2,737	292	1,853
Sargan test	$\chi^2(9) = 12.451$	$\chi^2(9) = 11.047$	$\chi^2(9) = 15.647$
p-value	0.189	0.272	0.075
Autocorr. test (1)	-8.567	-2.316	-6.955
p-value	<0.001	0.021	<0.001
Autocorr. test (2)	1.059	-1.964	0.902
p-value	0.289	0.05	0.367
Wald test for coefficients	$\chi^2(8) = 205.795$	$\chi^2(8) = 30.848$	$\chi^2(8) = 127.863$
p-value	<0.001	<0.001	<0.001
Note:			*p<0.1; **p<0.05; ***p<0.01

Table B.5: Estimates of the profitability model for subsampled data - environmental subscore.

	Dependent variable: ROE	
	Method	
	System GMM	Difference GMM
ROE_{t-1}	0.193^{***}	0.331^{***}
	(0.043)	(0.061)
$CFCR_t$	0.030^{***}	0.041^{***}
	(0.003)	(0.004)
DE_t	0.025^{***}	-0.036^{***}
	(0.003)	(0.009)
$nsvol_t$	0.060^{***}	0.016
	(0.010)	(0.020)
$capex\_sales_t$	-0.026^{***}	0.010
	(0.008)	(0.013)
$\log(assets)_t$	-0.002^{***}	0.076^{***}
	(0.001)	(0.015)
$GDPg_{\ t}$	-0.0004	-0.0002
	(0.0003)	(0.0003)
ΔCPI_t	-0.002^{***}	-0.003^{***}
	(0.0004)	(0.001)
Observations	7,284	2,737
Sargan test	$\chi^2(20) = 107.241$	$\chi^2(9) = 10.708$
p-value	<0.001	0.296
Autocorr. test (1)	-8.14	-9.012
p-value	<0.001	<0.001
Autocorr. test (2)	0.458	1.148
p-value	0.647	0.251
Wald test for coefficients	$\chi^2(8) = 3300.654$	$\chi^2(8) = 168.084$
p-value	<0.001	<0.001
Note:		*p<0.1; **p<0.05; ***p<0.01

Table B.6: GMM estimates of the profitability model (ROE as dependent variable).

	Dependent variable: ROE		
	All firms	*Overall ESG score*	
		1, 2	3, 4, 5
ROE_{t-1}	0.331^{***}	0.355^{***}	0.317^{***}
	(0.061)	(0.083)	(0.106)
CFCR_t	0.041^{***}	0.052^{***}	0.037^{***}
	(0.004)	(0.009)	(0.005)
DE_t	-0.036^{***}	-0.041^{**}	-0.031^{**}
	(0.009)	(0.016)	(0.012)
nsvol_t	0.016	0.012	0.034
	(0.020)	(0.032)	(0.026)
capex_sales_t	0.010	0.059^{**}	0.0002
	(0.013)	(0.028)	(0.017)
$\log(\text{assets})_t$	0.076^{***}	0.097^{***}	0.077^{***}
	(0.015)	(0.024)	(0.024)
$\text{GDPg}\ _t$	−0.0002	0.001	0.00000
	(0.0003)	(0.001)	(0.0005)
ΔCPI_t	-0.003^{***}	-0.002^{**}	0.0001
	(0.001)	(0.001)	(0.001)
Observations	2,737	908	1,237
Sargan test	$\chi^2(9) = 10.708$	$\chi^2(9) = 7.261$	$\chi^2(9) = 9.597$
p-value	0.296	0.61	0.384
Autocorr. test (1)	-9.012	-5.462	-5.075
p-value	<0.001	<0.001	<0.001
Autocorr. test (2)	1.148	0.366	0.182
p-value	0.251	0.714	0.856
Wald test for coefficients	$\chi^2(8) = 168.084$	$\chi^2(8) = 80.312$	$\chi^2(8) = 63.489$
p-value	<0.001	<0.001	<0.001
Note:			*p<0.1; **p<0.05; ***p<0.01

Table B.7: Estimates of the profitability model for subsampled data - total ESG score (ROE as dependent variable).