Timur Galiullin

Assessing the Predictive Power of ESG Scores on Company Default Probability.

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Author: Timur Galiullin
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ABSTRACT :

For many investors risk avoidance is a feature they build their portfolios upon. Investing in a solvent company with prudent governance and fair practices over a longer term can make these investors feel secure about their future profits. A key principle of selecting a sustainable company is through ESG. ESG ratings evaluate Environmental Social and Governance practices of a business to be compared and recent research suggests that ESG ratings affect company performance. Treating the probability of default as a key measure of company performance, the research questions arise: Does ESG affect the probability of default, and can it be a significant predictor of insolvency?

To address these questions, the study first turns to the key theories. Legitimacy theory is examined to see how companies may use sustainable reporting to legitimize their own activities for more favorable investor sentiment. The modern Stakeholder theory is reviewed against the more classical Shareholder theory to view the arguments of both sides to understand whether a business should actively promote corporate social performance. These theories help to understand the background behind ESG frameworks and the push for business to do good. The research also shows that ESG influences corporate performance and firm value in particular.

This paper views the probability of default as the main metric of company performance and solvency. The probability of default is measured employing the methodology developed by Altman, a widely used Z score. The Z score focuses on several key financial ratios to evaluate the default risk of a company. The research approach is to treat Z scores as dependent variables and ESG scores as independent ones, employing the Ordinary Least Squares regression method. The second part is to take the same data and use machine learning, specifically gradient boosting, to evaluate the feature impact of ESG scores on default probabilities. Financial data and ESG scores come from the Refinitiv database. Using this data Z scores are calculated independently. The data focuses on the financial metrics of 346 companies from 12 countries from 2001 until 2022.

The results show that ESG scores affect the probability of default negatively and significantly, although the magnitude of this effect is close to zero. The second part of the research using the Xgboost functions shows that ESG can be an impactful factor in predicting insolvency. The results demonstrate that inclusion of ESG in the probability of default models can significantly improve the accuracy of these models. This research suggests that although ESG participation alone does not reduce insolvency risk, its inclusion improves predictive power, offering valuable insights for investors, companies, and policymakers.

KEYWORDS: Probability of default, ESG, Altman Z score, Xgboost, CSR, Solvency

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Abbreviations

CSR: Corporate Social Responsibility

CSP: Corporate Social Performance

ESG: Environmental Social Governance

ML: Machine Learning

PD: Probability of Default

1. Introduction

Insights into the probability of default estimation can be crucial for investors and policymakers. According to Besley et al. (2020), “a firm’s probability of default is a sufficient statistic for capital allocation”. The probability of default estimation is closely tied to bankruptcy prediction. Traditionally, bankruptcy prediction models have relied on financial metrics and economic indicators to assess a company's solvency and risk of default. However, recent developments in the field suggest that Environmental, Social, and Governance (ESG) factors hold untapped potential in enhancing the predictive power of bankruptcy models. The integration of ESG scores into bankruptcy prediction models represents a growing area of research within the finance domain. The inclusion of ESG metrics in the probability of default and bankruptcy prediction models reflects a broader acknowledgment of the interconnectedness between corporate behavior, societal impact, and financial outcomes.

In the finance literature, several probability of default models have gained prominence for their ability to assess the financial health and viability of firms. The Altman’s Z Score Model, introduced by Altman (1968), utilizes a combination of financial ratios including working capital, retained earnings, EBIT, market value of equity, and total assets to compute the Z score, effectively predicting default risk. Merton's Model, developed by Merton (1974), applies option pricing theory to evaluate the probability of default, factoring in asset value volatility and liabilities. Ohlson's O-Score Model, proposed by Ohlson (1980), employs logistic regression analysis, considering accounting variables such as earnings and book value of equity to forecast bankruptcy. None of these models integrate any corporate social performance factors.

The demand for businesses to be more socially responsible was announced as early as 1984 by Freeman (1984) with the proposition of the stakeholder theory, in the contrary to popular view of Friedman (1970) suggesting that businesses should only be concerned with profits. Before the concept of ESG emerged, it was not clear how can the social performance of a business be rationally quantified. Social expenditure, employee wellbeing, and other potential factors do not show the whole picture. Such metrics are much more nuanced than traditional financial ratios, so they are not as straightforward in their implementation.

Considering the evolving regulatory landscape and increasing investor demand for socially responsible investment strategies, the integration of ESG scores into the probability of default models holds significant implications for financial practitioners, policymakers, and corporate stakeholders. There is ambiguity in evaluation of the effect of CSP on solvency and this study aims to contribute to closing this research gap. By providing a comprehensive analysis of the potential benefits and challenges associated with this approach, this thesis aims to advance understanding of how ESG considerations can enhance the predictive accuracy of default risk modeling, ultimately contributing to more informed investment decision-making and risk management practices in the financial industry.

2. Study Structure and Development

2.1 The Purpose of the Study

The purpose of this study is to contribute to narrowing the gap in understanding the impact of ESG on default risk. The question asked is: “Can ESG be used as a predictor of insolvency or potential financial problems of a company?” The literature review in the later sections suggests there is mixed evidence when it comes to ESG and bankruptcy prediction. Many studies suggest that there is a positive relationship between CSR and company performance, but it does not necessarily imply improved financial stability scores or metrics. Taking 12 high-income economies with strong information efficiency, this study aims to find out if ESG ratings influence the risk of default. The objective is to study if companies' ESG ratings can impact insolvency and to evaluate if ESG is a significant factor in estimating default probability.

Financial and ESG data is obtained from the Refinitiv database and calculations are performed independently. This is a widely used database in financial research, but the scope of countries’ data and a unique mix of industries, aims to provide a broader understanding of the subject, contributing to existing literature. Should ESG scores have a significant influence or be a relevant predictor of default it will complement a range of relevant studies highlighting the importance of integration of non-financial metrics into default risk models. In case of mixed results, it may pinpoint a research opportunity to expand upon in the future.

2.2 Hypothesis Development

Previous literature supports the idea that ESG and CSR lower the risk of financial distress during times of crisis, but the shielding effect on potential insolvency is yet to be investigated. Godfrey et al. (2009) argue that ESG and CSR activities may act as insurance-like protection in times of crisis for some firms that engage in ESG practices. According to Fatemi et al. (2014), CSR investing can under certain circumstances create value for the firm's shareholders. To understand these findings and relationships better, a literature review of relevant studies is conducted. The research shows that improved ESG and CSR can be beneficial for a company in multiple ways, especially during times of financial crises (Lins & Tamayo, 2017). Citterio and King (2022) find that including ESG metrics improves information efficiency in evaluating companies' financial health. Taking previous research into account and attempting the evaluate financial stability with ESG metrics, the following hypotheses are proposed:

H_1 = High ESG scores reduce the probability of default.

H_2 = ESG scores are an impactful default risk prediction metric.

2.3 Structure of the study

Having presented the topic in the introduction, stated the purpose, and developed hypotheses, the next sections will focus on presenting the most relevant theories as well as reviewing critical literature. First, legitimacy, shareholder, and stakeholder theories are introduced, then connected with the interpretation of ESG and CSR frameworks, introducing default probability later. The literature review in the following chapter aims to examine the studies that explore the materiality of ESG and CSR while discussing their effects on term value and finally default probability.

The data description and methodology section explores ESG as a variable and discusses the selected data along with integration of ESG scores into the probability of default models. The chapter continues with introducing the machine learning model for evaluating feature importance and ends with a comprehensive section demonstrating descriptive statistics of selected data. The final three chapters focus on presenting the empirical research results, their discussion, and interpretation with the very last chapter giving the conclusion for the whole paper.

3. Theoretical Framework

3.1 Legitimacy Theory

To get more insights into sustainability, reporting and ultimately explore the concept of ESG further, it is important to investigate the Legitimacy Theory. It is related to the Stakeholder theory, however with an emphasis on reporting. According to Cho and Patten (2007), public pressure in the political and social environment determines the extent of financial reporting on environmental exposure. It is how businesses aim to maintain legitimacy and uphold social approval within society. Achieving financial success in a way that is socially acceptable is part of this theory.

Enterprises aiming to acquire or uphold legitimacy are motivated to employ communication tactics, such as financial report disclosures, to possibly shape societal perceptions. Nevertheless, the inclusion of environmental information in financial reports does not necessarily signify its sole purpose as a tool for legitimacy (Deegan, 2002). Vice versa, financial performance may not only be achieved by strategic activities, but also by engagement in ethical behavior and sustainability efforts.

Finally, it is relevant to keep in mind that companies do use financial reports as legitimizing tools (Cho & Patten 2007). In turn, environmental performance is inversely proportional to financial disclosure, meaning the poorer the performance the more disclosure is to be expected. Important to note that when evaluating disclosure one must keep in mind that only the extra disclosure presented by companies that is not required to be presented by regulators is of interest in the scope of Legitimacy Theory. If something is required to be reported or disclosed it would have been done anyway, whether the company is aiming to improve its reputation or not.

3.2 Friedman vs Freeman

There are two prominent theories that explore corporate social performance: Stakeholder theory and Shareholder theory. Both focus on value maximization and managerial responsibility but use different approaches. Shareholder theory was developed by Milton Friedman, a famous 20th-century economist, and a free market advocate. He states that the only social responsibility a business may have is to maximize its profits within the given legal framework (Friedman, 1970). In 1984 Edward Freeman proposed a new theory calling for a focus on a broader group of stakeholders, diverging from traditional economic roots and defining stakeholders as all individuals who affect or are potentially affected by the business activities of an organization (Freeman, 1984).

The main debate here is about the purpose and responsibility of corporations. Friedman argues that broadening this concept of conformity of businesses to major social causes would create a “fundamentally subversive doctrine” (Friedman, 1970), leading to collectivist ends achieved by collectivist means. It is important to understand that due to the context of the Cold War, radical pressure on businesses to uphold social causes could have been seen as an attack on democracy (to which Friedman unequivocally hints in his article). On the contrary, Stakeholder theory promotes the idea of actively exploring relationships with all stakeholders (employees, clients, partners) to achieve success (Freeman, 1984). Comparing these two theories at “face value” they demonstrate two distinct managerial approaches towards corporate governance.

According to the International Monetary Fund, government spending as a percentage of GDP has been growing steadily since Friedman posted his famous article (International Monetary Fund, n.d.) in the USA and in the world. Regulations have also been on the rise since, as well as regulatory agency budgets (Regulatory Studies Center, 2024). This can indicate a paradigm shift in running the free market economy, where governments not only more heavily regulate, but enhance and incentivize certain types of business behavior,

highlighting a stakeholder instead of a shareholder approach. It seems more acceptable to forfeit profit maximization to increase the benefits of all stakeholders, gain a better reputation, and avoid bad publicity with tools like ESG score.

Despite the paradigm shift in the management theory of value maximization, Jensen (2002) argues that there is no specific need for alternative approaches. “We are asking them to maximise in more than one dimension at a time with no idea of the tradeoffs between the measures. As a result, purposeful decisions cannot be made” (Jensen, 2002). This ties in with the argument that the stakeholder theory cannot provide a specific objective function for a corporation, while the straightforward method of value maximization promoted by the shareholder theory solves this issue, making everyone better off. There is no action guide. Phillips and Wicks (2003) argue the opposite. They admit that the stakeholder theory is not a complete guide for decision-making, however, this is a known and understood limitation. “It is only when the primary beneficiary of this profitability is constantly and exclusively a single stakeholder (e.g., equity share owners) that there is conflict between the theories” (Phillips & Wicks, 2003). This is supported by the idea that a corporation’s success or failure will be distributed among all the stakeholders. The authors note that material results are not the only subjects of distribution.

The research shows that the two theories do not have to be contradictory. Friedman proposed his ideas in an economic environment that was different from today’s where corporations are expected to be contributing to society in more ways than just making a profit (and it does not have to be in the form of profit redistribution). Freeman’s stakeholder theory achieves a broader view of corporate managers’ roles in society. The theory does not prioritize stakeholders over shareholders, just making sure that the former do not benefit at the expense of the latter. ESG as a concept can potentially help managers to mitigate conflicts of interest while maximizing shareholder value.

3.3 Stakeholder theory and ESG framework

This section is intended to examine stakeholder theory along with the concepts of CSR and ESG. There is an examination of CSR, the concepts of materiality, and the distinction between CSR and ESG. ESG is introduced and given critical evaluation with its' impact and shortcomings.

Stakeholder theory is an important concept, interlinked with CSR and ESG. Weitzner and Deutsch (2022) state that the theory is designed to offer a conceptual framework that redirects the focal point of management discussions. Instead of historically prioritizing the needs of shareholders, the theory advocates for a shift towards recognizing the ethically and strategically crucial relationships that a firm maintains with a wide array of stakeholders. In order for the theory to take hold among decision-makers it was reformulated as "Doing well by doing good" (Weitzner & Deutsch, 2022). This way it is directly related to CSR activities, with the mindset that companies must not only seek maximization of shareholder value but to account for all stakeholders: customers, governments, environment, etc. It makes the stakeholder theory appear like a broad concept, so for the purpose of this research, stakeholder theory will be examined from the prisms of CSR and ESG.

In the context of this paper, it is important to clearly distinguish two terms: CSR and ESG. The former is Corporate Social Responsibility, and the latter is Environmental Social Governance. Sometimes these terms can be used interchangeably, and although they are related, research within these two contexts must be clearly differentiated. According to Jo and Harjoto (2011), CSR is "an extension of firms' efforts to foster effective corporate governance, ensuring firms' sustainability via sound business practices that promote accountability and transparency". Hill et al. (2007) identify it as "Economic, legal, moral, and philanthropic actions of firms that influence the quality of life of relevant stakeholders". Generally, the practices that are beneficial for all stakeholders at the expense of none that

follow moral guidelines and strictly obey the law are a part of CSR. So Corporate Social Responsibility can be seen as either just philanthropy or a company trying to do well, avoiding unethical decisions to benefit the shareholders in the long term.

Sometimes ESG and CSR are treated as synonyms because there are several areas where they overlap. Environmental Social Governance factors are three distinct areas that can be evaluated on a company level. ESG is an important investment trend. According to the Global Sustainable Investment Alliance (n.d.) as of 2020, there are more than $30 trillion of assets under management, selected using sustainable strategies, the most prominent one being the selection of ESG-rated companies according to the report. There are several rating agencies such as MSCI ESG Research or S&P Global ESG Scores and others. ESG investments have been growing steadily and the industry promotes itself for investors as a tool for earning money, while doing good by investing into companies that have high ESG scores.

There is a problem when it comes to ESG ratings by different agencies. Christensen et al. (2022) prove that the greater the ESG disclosure of a company, the greater there is disagreement on the specific ESG rating of that company by rating agencies. Using ESG disclosure to measure the impact on ESG rating disagreement, the authors show that the relationship between these factors is positive and significant. Just like CSR, ESG affects materiality and solvency. Serafeim and Yoon (2021) investigate if ESG ratings predict future ESG news and the corresponding market reactions. Taking unique firm-day observations with ESG news over eight years and constructing long/short portfolios of firms with the highest disagreements, the authors find that companies with high ESG ratings experience a moderate market response to positive news, suggesting that information may already be incorporated into the stock prices. Conversely, firms with consistently high average ESG ratings exhibit more pronounced reactions and heightened sensitivity to negative ESG news, resulting in more significant negative returns. It corresponds with the idea stated earlier in

research on CSR, that avoiding “bad” actions is materially preferable, to seeking “good” ones.

The problems with ESG lay in materiality and more importantly ratings disagreements. There is a pressing requirement for greater standardization in ESG data reporting. It is crucial for stakeholders, including companies, exchanges, investors, and regulators, to collaborate on defining specific and comparable metrics. This consensus is essential to minimize discrepancies and misunderstandings, alleviating the burden on companies inundated with survey requests (Kotsantonis & Serafeim, 2019). Another problem is peer groups. Kotsantonis and Serafeim (2019) argue that certain industries, such as oil compared to banks, are inherently predisposed to underperform on environmental issues. When determining success within the same peer group, consider the example of an industry where the second-best performer in diversity has 15% women in the workforce, while the leader has only a marginal increase at 16%. Thus, the leader would be considered the best performer, but the overall performance of the industry may be lacking. This scenario underscores the need to reconsider the methodology applied in evaluating success. Finally, a significant problem with ESG ratings is filling the gaps. The agencies are forced to use predictive models or industry averages when some information is lacking. This could be potentially misleading.

ESG is supposed to be a world-changing concept, but it fails to do that. Instead, we see companies just ticking the “right boxes” when it comes to regulation, but real-world impact is lacking. Porter et al. (2019) point out that companies featured on Fortune magazine's annual Change the World list do not necessarily attain the highest ESG rankings within their industries, nor do they command a significant share in Socially Responsible Investment (SRI) funds. Despite this, these companies consistently generate superior shareholder value. ESG practices are not primarily perceived as future value drivers, instead, they are viewed as means to mitigate regulatory risks and attract investors. In contrast, companies focused on

values make distinctive choices compared to their competitors, incorporating a unique social impact into their business models. Consequently, these companies yield superior returns for their shareholders.

Edmans (2023) argues that there is nothing special about ESG and focusing too much on this concept can distract from more relevant metrics, “We want great companies, not just companies that are great at ESG” (Edmans, 2023). Considering the long-term factors is not special to ESG investing only, in fact, it is the common sense of investing. “I took the “100 Best Companies to Work For in America” and found that they delivered higher shareholder returns than their peers over a 28-year period” (Edmans, 2023). The companies mentioned by the author were not leaders by ESG metrics. The author notes, however, that the only case where ESG investing can be considered special, is when social goals are achieved at the expense of shareholder returns. ESG can be harmful in misleading investors. Cooper et al. (2005) find that funds that altered their names to align with current market trends, such as appending "Cautious" during a downturn or "Growth" during an upswing, experienced a significant increase in inflows by 28% over the following year, irrespective of any changes in their actual holdings. Too much focus on ESG can lead to similar name manipulations. Edmans (2023) supports the claim on ESG disagreements by stating that ESG rating is not a fact, it's an opinion. Finally, the whole concept of ESG can be controversial with different pillars standing for opposing objectives, for example, closing a plant is good for the environment (E) but damaging to the employees (S).

Stakeholder theory promotes care not only for the investors of a business but also for all the parties affected by its activities. In this regard, Corporate Social Responsibility is an important concept to keep companies accountable. Environmental Social Governance is a more specific, rating-based approach, motivating companies to do better, however, it still has many flaws and shortcomings that have been addressed.

3.4 Insolvency and Default Risk Prediction

It is important to discuss the overall notion of default risk, what it is, and how a company can be seen as solvent or insolvent. The section will consider solvency, first of all from the point of view of creditor rights with relation to jurisdictions where the companies are located and risk-taking of these companies, and most importantly the likelihood of default. Then there is an examination of corporate disclosure and analyst behavior, mainly the informativeness of disclosure policy and the accuracy of analysts' earnings forecasts. To consider a different perspective there is also a discussion on firms' leverage and endogeneity of corporate tax status, which develops a discussion of default probability further.

Researchers look at solvency, probability of default, financial stability, and other similar metrics for companies to analyze if the entities will be able to function sustainably, depending on indebtedness, capital structure, balance sheet, and other characteristics. Oxford University Press (n.d.) defines "default" as the failure to pay a debt. Default or insolvency is the opposite of solvency, where solvency can be defined as a firm having healthy levels of debt in its capital structure, acceptable creditor ratings by agencies, and an overall low probability of default. The terms insolvency risk or default risk may be used interchangeably.

Acharya et al. (2011) examine what effects creditor rights have on corporate risk-taking, specifically in the realm of mergers and acquisitions. They examine if enhanced creditor rights in different countries lead companies to take on less risk. The primary focus is on minimizing risk through diversified acquisitions, thereby reducing the chances of default (Acharya et al. 2011). The authors use regression analysis with Creditor rights as the main independent variable. They find that first of all stronger creditor rights decrease the financial leverage of a company, imposing more responsibility for taking on debt, while the opposite is true for weaker creditor rights because the cost of financial distress is therefore

lower. This, in turn, means that: “having strong creditor rights in a country leads firms to reduce risk” (Acharya et al., 2011). The panel data also shows that there is no significant relation between shareholder rights and creditor rights, nor the relationship is inverse i.e. strong creditor rights mean weak shareholder rights and vice versa. Finally, it shows that shareholder rights overall tend to be stronger on average across all 38 examined countries compared to creditors' rights. Creditors' rights alone, can not be seen as a predictor of financial stability.

Lang and Lundholm (1996) consider another relevant approach to solvency looking at corporate disclosure and analyst behavior. Information availability is critical to examining the market pricing of stocks. If the price is mismatched, then the company can either be overvalued or undervalued, both leading to financial distress in lack of capital or overvaluation and consequential corrections on the secondary market. According to Brealey et al. (2009), all levels of market efficiency are determined by the degree of information reflected in security prices. Firm disclosure is an integral part of ensuring an adequate amount of information to maintain market efficiency.

Lang and Lundholm (1996) take US firms to test the first set of hypotheses examining the relationship between the number of analysts following a firm and the informativeness of its disclosure policy, as well as the correlation between the dispersion of analysts' earnings forecasts and the policy's informativeness. The second set posits a positive association between the accuracy of analysts' earnings forecasts and the informativeness of a firm's disclosure policy, alongside a negative correlation between the volatility of analyst earnings forecast revisions and the firm's disclosure policy. According to the results, the number of analysts following the company has a negative correlation with earnings surprise and is highly positively correlated with market value, confirming that large companies tend to get most of the following and their earnings forecasts are accurate. In turn, firms that disclose more have a larger pool of potential investors, as such reducing the probability of default

and potential volatility. It implies that in order to get the highest quality of information it is suitable to look into the largest publicly traded companies, especially when examining the area where information efficiency is still lacking, such as ESG.

The next two studies build upon each other focusing on trade-off theory, corporate taxation, and cost of financial distress. The trade-off theory is "the firm's debt-equity decision as a trade-off between interest tax shields and the costs of financial distress" (Brealey et al., 2009). The theory rationalizes moderate debt ratios, stating that all else equal, some level of debt may even be beneficial, rather than no debt at all. Graham et al. (1998) go on to prove that low-tax firms lease more than high-tax firms, with relation to corporate taxation it means that high-tax firms tend to take on more debt to take advantage of tax shields as per stakeholder theory. One of the independent variables is the Z score, which is positively and significantly correlated with Marginal Tax Rate. On the surface level it can be counterintuitive as high levels of debt should reduce the Z score and a higher Z score corresponds with a company being more financially stable. Z score will be discussed in detail in later sections. The main result presented by Graham et al. (1998) also states that companies anticipating elevated marginal tax rates typically exhibit increased levels of debt ratios.

Another study by Hovakimian et al. (2011) disputes the claim that if the rationale behind a heightened debt ratio is the reduction of bankruptcy costs, it will imply a greater likelihood of large firms facing bankruptcy, contradicting their research outcomes. Hovakimian et al. (2011) examine the robustness of the trade-off theory, considering novel measures of default probability. They use two measures: firm-level S&P credit ratings and Moody's KMV Expected Default Frequency. The findings reveal that companies with minimal bankruptcy and financial distress costs, such as larger firms and those with more tangible assets, exhibit the lowest likelihood of bankruptcy. Interestingly, firms with the lowest marginal tax rates (and in theory the lowest debt) tend to have the highest probability of default. This suggests

that sizable firms with tangible assets can potentially raise their debt ratios, leveraging tax shields without significantly escalating their bankruptcy probabilities.

Default risk is mitigated by solvency. Solvency is being able to continuously service debts, maintain sufficient ratings, and a potentially solid reputation. Creditor rights alone, are not a determinant of company stability, ensuring that if a company will be forced to pay all its debts, the management would have to be more financially prudent. However, in countries with strong creditor rights, the companies tend to be more financially stable. Solvency is also related to information efficiency, namely company disclosure and consequential analyst following, minimizing earnings surprises and fluctuations. Finally, the relationship between debt levels and bankruptcy prediction is not always straightforward. Some companies facing high bankruptcy risk can have low levels of debt, while more stable bigger companies can be just seen as underleveraged losing the advantage of utilizing the benefits of tax shield.

4. Literature Review

4.1 CSR and firm value

This section examines the effect of CSR on access to finance, shareholder value, and corporate governance mechanisms, and unlike ESG CSR is not quantifiable (there is no specific metric), it is important to understand that even this intangible concept can impact financial performance demonstrating relevancy.

Does CSR affect firm value? According to the analysis by Jo and Harjoto (2011), they lean toward an affirmative answer. The research reveals a positive correlation between the adoption of CSR and various internal and external corporate governance and monitoring mechanisms. These mechanisms encompass board leadership, board independence, institutional ownership, analyst following, and antitakeover provisions. This is valuable notice that CSR even as a broad subject in financial literature has a positive effect on the solvency of a firm.

Cheng et al. (2014) make a strong argument that CSR is not just philanthropy, but a business practice that can yield tangible results. The aim of the examination is to check if CSR strategies can influence a firm's access to finance in capital markets. Taking 10000 firm-year observations from different countries over the span of seven years and regressing the KZ index, with CSR ratings as the dependent variable. The KZ or Kaplan-Zingales Index shows that firms with elevated KZ-Index scores are prone to encountering challenges during periods of financial constraint, as they may face obstacles in securing the necessary funds for their day-to-day operations. Cheng et al. (2014**)** show that the KZ index and CSR scores in their research have a negative and significant relationship, therefore, companies involved in CSR have better access to finance in general.

There is an evident impact of CSR in producing shareholder value. Fatemi et al. (2014) show that under certain circumstances a firm's commitment to socially responsible expenditures leads to value for its shareholders. For this analysis, the firm value as a function of CSR and probability of survival is taken. Oikonomou et al. (2014) however raise some doubts about the materiality of firms' Corporate Social Performance. They conduct a study to examine if social performance can reduce market and financial risks, to see what relationship exists between social/environmental strength and concerns, and financial risk, and finally, what is the relationship between social performance and financial risk during high volatility periods. Aggregate strengths and concerns are assigned weights to create indicators, each based on averages derived from five mirrored strength and concern factors. The risk assessment involves the beta of returns for a company's shares, employing factor models that integrate aggregated strengths and concerns. This process involves regression analysis to provide a comprehensive evaluation. They find that social strengths are negatively but not significantly associated with systemic risks, but social concerns are much stronger and positively related to systemic risks. The authors admit that it yields no specific investment approach, although it is clear that avoiding "bad" actions is much more preferable than doing "good" actions.

The research shows that valuing governance and other intangible factors can lead to superior returns and reduced risks even with mixed evidence. It is important to avoid bad publicity to remain solvent. Seeing that CSR has tangible effects, the next step is to see how ESG impacts financial performance more specifically.

4.2 ESG and firm performance with relations to governance

This section is purposed to analyze the relationship between ESG, governance, and performance. Taking a step back, it is necessary to give more evidence on firm governance in general, especially what other factors may affect governance. As a related concept, CSR and governance relations are also examined in order to create a more comprehensive picture. Finally, a broad examination of ESG influence on financial stability.

To establish a clear relationship between financial stability, governance, and Corporate Social Responsibility, there is a need to discuss corporate governance first. Research on governance practices has been going on for decades. Rights and responsibilities distributed to shareholders are part of Governance criteria in ESG (S&P Global, 2020). Gompers et al. (2003) construct a governance index, based on provisions of shareholders' rights. Companies with the weakest shareholders' rights are labeled "Dictatorships" and countries with the strongest rights are "Democracies". The strategy according to which "Democracy" firms are purchased and "Dictatorship" firms sold (long/short strategy) would have earned abnormal returns of 8.5% per year. Significant evidence of internal governance on materiality.

Shareholder rights and corporate governance depend on managers. Based on the study of UK firms from 2006 to 2017, the social capital of managers of the FTSE 350 index has a negative effect on corporate risk-taking (Al-Bataineh et al., 2022). The study also focuses on the cognitive social capital of firms' managers using CSR as a proxy. Engaging in Corporate Social Responsibility (CSR) is linked to a favorable correlation with a company's inclination for risk-taking. On the other hand, structural social capital exhibits a negative connection with both idiosyncratic and total risk metrics, underscoring the economic significance of this impact. A related idea can be seen in a US-focused study by Amin et al. (2020). They examine if board connections affect Corporate Social Responsibility, using a novel CSR score as a

dependent variable. They find that the association between board connections and CSR performance is positive. The more connected the managers are, including connections to shareholders, the more probable it is that the company will perform well in CSR.

Going back to CSR performance and stakeholder value, a study by Godfrey et al. (2009) proposes to examine if CSR activities may lead to positive attributions from shareholders who in turn would mitigate their judgments and forfeit potential sanctions because of the goodwill. This is checked via an event study treating stock price fluctuations around the negative event as the independent variable and the CSR variable as a dependent one. The authors find that engaging in CSR activities appears to provide a form of insurance-like protection for several companies. The findings suggest that managers of firms involved in CSR can, at times, generate value for their shareholders by establishing this insurance-like safeguard.

What kind of CSR actions are valued and what kind of actions do shareholders pay the most attention to? Hawn and Ioannou (2016) rephrase the question and ask: what is the interconnection between internal and external CSR actions on the share price of a firm? Treating ESG variables as independent and Tobin's Q (ratio of market value of an asset and its replacement cost) as dependent they find that altogether the sum of external and internal actions positively influences market value. However, a wide gap between these actions can lead to unrealized potential. “In other words, firms do not realize the full benefits of their internal actions when such actions are not externally communicated to key stakeholders, and to the investment community in particular” (Hawn & Ioannou, 2016). In other words, talking about doing good is as important as actually doing good in terms of shareholder value.

A firm might realize tangible gains and retain shareholder confidence by investing in sustainability, but what kind of issues should be focused on? Mozaffar et al. (2015) dive into

distinguishing between investing in material and immaterial sustainability issues. Using two databases, SASB and KLD, mapping the sustainability issues with each other, the researchers classify the issues that were closely matched with others are material while those that were only present in the KLD database are immaterial. Using the Fama-French five-factor model, Mozaffar et al. (2015) find that investing in material sustainability issues can enhance value for shareholders, whereas investments in immaterial sustainability issues generally have minimal, if any, positive or negative, value implications. The authors find that the best strategy is to invest in material issues while ignoring the immaterial ones. For example, according to the methodology for every industry, the materiality of the issues will vary, as such for the financial sector the most material issues are fair marketing and advertising, while for non-renewable resources it is air quality.

From previous sections, it is evident that the companies are eager to take part in sustainability activities specifically in ESG to be rated and more visible within the investment universe. Taking into account the ESG performance of European banks Toth et al. (2021) examine the rate of non-paying loans to see if there is a positive relationship. They find that ESG performance reduces the rate of non-paying loans and that each of the three main ESG factors positively affect the profits of the studied financial institutions. To continue with the financial sector, Baselga-Pascual et al. (2023) examine the effect of CSR on bank credit ratings. They show that exemplary Corporate Social Responsibility practices correlate with favorable credit ratings within the banking sector. However, Di Tommaso and Thornton (2020) also focus on the European banks but show that the book value is negatively affected by ESG. Conversely, they also note that the risk of bankruptcy denoted by the Z score is reduced with higher ESG performance.

To finalize and establish a relation between CSR and ESG-related actions and corporate financial performance, a comprehensive study review is conducted by Friede et al. (2015). The authors aim to analyze and combine the results from 2200 individual studies spanning

from 1982 until 2015. To do this, they apply a two-step research approach for analyzing existing reviews and primary studies. First, they conduct a vote-count analysis to identify the prevailing outcomes (positive, negative, or nonsignificant) based on the number of studies. Second, perform a second-order meta-analysis by aggregating findings from econometric review studies to provide a summary of evidence from multiple meta-analyses on the same topic. Approximately 50% of the studies in the vote-count sample show a positive relation, while around 10% indicate a negative one. In the 25 meta-analyses, positive findings are 74.9%, but negative results remain at 0%, with the lowest effect being -0.003. Emphasizing a long-term commitment to responsible investing is crucial for rational investors of all types (Friede et al., 2015).

This section shows that governance affects firm performance and managerial social capital affects governance. CSR can offer insurance-like protection to various firms and firms should focus on communicating their CSR activities, specifically the material ones. In the European financial sector, ESG is associated with a lower quantity of non-paying loans and overall ESG has a positive effect on corporate financial performance.

4.3 ESG and financial relationships during crisis and non-crisis periods

This section explores ESG as a factor of solvency in the scope of relationships between various firms. These relationships are also examined in the context of crisis and non-crisis periods. The review leads to a further understanding of ESG as an input.

Issues of trust often come up when examining governance and social performance. It has been mentioned before that Social Responsibility and Firm Governance can act as insurance-like protection (Godfrey et al., 2009). Examining the crisis periods first, looking at the dependence of ESG and financial relationships during crisis periods, Lins et al. (2017) take a sample of 3000 US companies over the period from 2001 until 2009. Despite strong

market growth during this period, it is suitable as it accommodated two major financial crises: the Burst of the Dotcom Bubble in 2001 and the Global Financial Crisis in 2008. The authors posit that a company's social capital, in fostering trust and collaboration among stakeholders, is likely to yield greater returns when the significance of trustworthiness is heightened, as seen in periods of unexpectedly low trust like during a crisis. Lins et al. (2017) employ different regression models to estimate stock returns during the crisis period, considering firms' pre-crisis CSR ratings and several control variables as factors. The results show that companies with higher CSR ratings surpassed those with lower CSR ratings by a minimum of four percentage points during the crisis. However, there is no discernible difference in stock return performance between high- and low-CSR firms during the recovery period following the crisis.

Li et al. (2023) examine if Environmental and Social (ES) activities influence default risk. Namely, if banks with high ES maintain lower credit and liquidity risk and pose higher market value. With 244 banks from 52 countries and a period of examination of 18 years, the authors take the banks' ratios of non-performing loans to total loans treating this as credit risk. Liquidity risk is average loans minus average deposits divided by average total assets. Using OLS to test the hypotheses, the authors show that the banks focusing on stakeholders and those possessing substantial social capital tend to have reduced exposures to credit and liquidity risks. It can be practical for investors to pay attention to banks' CSR activities (Li et al., 2023).

Testing the European banks against ESG scores specifically, Chiaramonte et al. (2021) examine several hypotheses. First, if banks with higher ESG scores are less risky and if environmental activism reduces banks' risk-taking. Second, if bank instability is inversely related to the level of social engagement and if fair government practices affect stability positively. And finally, if the EU 2014 Non-Financial Reporting Directive rewarded banks more engaged in CSR. Multiple regressions and estimators are used, but the key dependent

variable is Merton's distance to default. The overall ESG score, along with its individual components, plays a role in diminishing bank fragility, with the social dimension exhibiting a particularly pronounced impact (Chiaramonte et al., 2021). This influence is evident during periods of crises and remains robust against concerns of selection bias and endogeneity. The findings align with the tenets of stakeholder theory, underscoring the notion that moral capital contributes to the creation of value and resilience in firms, resembling an insurance-like mechanism. This evidence from European banks is in alignment with the findings by Li et al. (2023).

Access to capital can be the most critical factor during a crisis for a company to survive. When discussing financial stability and trying to tie ESG as a factor, it is relevant to determine if Environmental Social Governance has any effect on access to capital. Houston and Shan (2022) examine whether banks influence firms' ESG policies. With more than 2400 borrowers and 116 lenders over the period of 11 years, the authors come to insightful conclusions. Banks tend to be more inclined to extend loans to borrowers whose ESG profiles align with their own, exerting a positive impact on the borrowers' subsequent ESG performance. This influence is particularly heightened under two conditions: firstly, when banks possess markedly superior ESG ratings compared to borrowers, and secondly, when borrowers rely significantly on the banks. It can also imply that banks tend to influence the ESG-related behavior of the firms if these banks have more bargaining power.

The research shows that ESG can be an input factor when evaluating solvency. First of all, during crisis periods companies with higher CSR ratings do much better due to trust from the stakeholders and intermediaries, however in normal circumstances the difference is not so pronounced. Within the financial sector, banks that outperform on Social and Environmental issues, demonstrate less liquidity and credit risk. These issues also have a significant impact during crisis periods demonstrating resilience of the firms. Finally, in crises and non-crisis periods, banks tend to lend capital to companies with ESG performance

similar to their own. Sometimes these banks can influence the performance of borrowers depending on the situation.

4.4 Estimating probability of default

This part focuses on estimating the probability of default. For the purpose of the study, default refers to the inability of a company to service even short-term obligations. There are no specific chapters of bankruptcy (as per US law), nor distinctive characteristics that these definitions will focus on. Bankruptcy is not the reason for the decrease in company value but the result of it (Brealey et al., 2009). This is why preventing or at least predicting bankruptcy, insolvency, or default (once again to be used interchangeably for the purpose of the study) can be critical in company evaluation.

There are many models and variations on measuring default probability. Some professionals may use Bloomberg's default risk models or KMV or Merton's distance to default models. One of the classical bankruptcy prediction methodologies is Altman's (1968) Z score, which is frequently cited in finance literature. Altman introduced a statistical method known as the Altman Z score, which is a formula for predicting the likelihood of default for publicly traded manufacturing companies. The Z score is a combination of five financial ratios (and associated coefficients) that are believed to be effective indicators of a company's financial health and solvency. The higher the Z score, the lower the default risk. This methodology can not be applied to all companies unilaterally to achieve quality results, as such in some industries companies can have low Z scores but feel financially healthy.

Another notable approach to bankruptcy prediction is demonstrated by Ohlson (1980). The author uses 10-K statements reported prior to the bankruptcies of companies. This procedure offers a significant benefit: the reports specify the time of their release to the public, allowing one to verify whether the company declared bankruptcy before or after this

date. Using probability functions with unknown variables the author shows that the statistically significant factors predicting insolvency within a year are size, performance, and liquidity. Ohlson (1980) notes that some previous studies have overstated the predictive power of some models. Interestingly, the author removes financial companies from his analysis.

Charalambous et al. (2019) demonstrate another way of predicting bankruptcy. With the Leland-Toft (LT) framework, first, they argue that LT is a better alternative to the Black - Scholes - Merton (BSM) model. Second, they state that Altman's Z score predictive ability can be improved by incorporating LT into it and that this methodology is superior to augmenting Altman's Z score with BSM. Studying 5460 firms, 333 of which filed for bankruptcy in the US over a 19-year period, the authors prove that LT improves all of the prediction models. In fact, based on the research, the authors' methodology yields an interesting note on the Z score methodology, as the bank that was applying it showed the worst results out of the sample of 5. However, the authors use this mostly for comparison of LT to BSM and that it could be due to differences in discriminating abilities and that the findings may not serve to discredit the methodology.

Another study by Oikonomou et al. (2014) is notable because it incorporates both Altman's Z score and Corporate Social Performance into analyzing corporate performance. The study proposes that firms with more social and environmental strengths have superior bond ratings (lower default risk), while the opposite is true for firms with social and environmental concerns. The authors use regression analysis to test the relationship between CSP and corporate debt costs and credit ratings. They run several regression models to control for other factors that may affect the results, such as firm size, profitability, and industry. The results support the hypothesis that firms with higher CSP had lower debt costs, which is also consistent with several studies examined previously.

Overall, the Z score is a widespread methodology applied in researching and estimating default risk. Default, insolvency, or low credit rating (high insurance spreads) mean the same thing in the context of this paper. The current research focuses on the Z score as the main estimator and metric for to identify insolvency.

4.5 Integration of ESG factors into the probability of default models

ESG has been explored as a material factor in a company's value. It has been proven to affect stock prices, investor sentiments, and credit. Due to clear evidence on the materiality of ESG, it is necessary to examine the ways corporate social performance can be integrated into various models. Looking at solvency of a company, the key aspect or a result of such stability will be solvency. This section focuses on ESG integration into the probability of default models.

Yu et al. (2018) propose integrating ESG disclosure as a factor in firms' value, aiming to establish if ESG transparency can influence Tobin's Q. Tobin's Q is a sum of market capitalization, liabilities, preferred equity, and minority interests divided by total assets. Initially, the authors set up two functions. The first one is a function of ESG disclosure as a positive factor on firms' performance and the second one is viewing disclosure level as a cost with a negative function. Then an equation combines the two weighting benefits against costs. Taking an international perspective with 47 developed and emerging countries over the period of 4 years, the authors set up an equation where Tobin's Q is a dependent variable on ESG disclosure. Enhanced ESG transparency contributes positively to value, as gauged by Tobin's Q, with a non-linear correlation between ESG factors and Tobin's Q. The findings indicate that ESG transparency serves as supplementary nonfinancial data, offering valuable insights to investors. Additionally, the results affirm that an uptick in ESG disclosure can mitigate information asymmetry and reduce agency costs for investors.

Companies exhibiting larger size, fewer insider holdings, a lower proportion of institutional investors, superior liquidity (current ratio), and higher R&D intensity are inclined to provide more comprehensive disclosures on ESG and environmental matters.

ESG as an insurance-like strategy, or ESG performance as an investor confidence boost, has been examined in prior sections and shown that there are benefits of improved CSP during times of crisis. It is feasible to look into ESG as a distress aid during the times of economic upswing. Habermann and Fischer (2021) hypothesize that in times of economic upswing, the level of a firm's CSP (overall as well as in each respective ESG pillar) does not affect its likelihood of bankruptcy. The data involves firm-year observations with firms listed in the US over a nine-year period. The regression is set up with Altman's Z score as a dependent variable and Corporate Social Performance as an independent one. Before interpreting the results, it is important to note that in descriptive statistics, the mean Z score is 6.8 with a standard deviation of 8.2, which indicates a very high degree of variability and outliers with a minimum of -24.7 and a maximum of 71. Considering that a Z score above 3 indicates that the company is financially healthy (Altman, 1968) some of the scores may indicate that the results can be potentially skewed. Nevertheless, the results demonstrate that in line with the proposed hypothesis high CSP has no effect on the likelihood of bankruptcy during economic upswing. In fact, the study also shows that an increase in CSP levels can lower the Z score in the following years.

The results above, however, are contradicted by statements presented by Badayi et al. (2021). The authors ask directly if CSR influences a firm's probability of default. Looking at 17 developing nations, constituting a total of 3,968 firm-year observations over a seven-year period, the authors apply the two-step system Generalized Method of Moments (GMM). The first part is the calculation of the Z score, which is then substituted to an equation as a dependent variable treated as probability of default. Firm-level ESG performance is treated as CSR. Utilizing several types of models, the authors claim that

participation in CSR lowers the likelihood of default for firms in developing countries (Badayi et al., 2021).

The role of Environmental, Social, and Governance (ESG) factors in shaping companies' value has been explored, with demonstrated effects on stock prices, investor sentiments, and credit. The study by Yu et al. (2018) focuses on integrating ESG transparency into models, particularly examining its impact on Tobin's Q. Results indicate that enhanced ESG transparency positively contributes to firm value, with a non-linear correlation between ESG factors and Tobin's Q. The study also highlights the role of ESG disclosure in reducing information asymmetry and agency costs for investors. Contrarily, Habermann and Fischer (2021) investigate ESG as an insurance-like strategy during economic upswings, finding that high CSP has no effect on the likelihood of bankruptcy, and increased CSP levels may even lower financial health indicators. However, these findings are challenged by Badayi et al. (2021), who directly assess the impact of Corporate Social Responsibility (CSR) on the probability of default for firms in developing countries. The studies show that ESG can be integrated into models in various ways.

Analyzing the predictive power of ESG in computing bank financial distress models Citterio and King (2022) take ESG and Z score observations. They theorize that from the stakeholder theory perspective, a strong commitment to ESG may suggest enhancements in bank transparency and increased backing for stakeholders. Conversely, poor ESG performance might indicate a disregard for minority stakeholders, such as bondholders. The authors show that the inclusion of ESG strongly reduces the likelihood of misclassifying distressed banks as healthy.

4.6 Evaluating importance features using machine learning

To comprehensively evaluate the importance of different features influencing the probability of default Machine Learning (ML) algorithms can be implemented. Although the study is not built around utilizing machine learning to achieve the main results, there are clear benefits of running the data through these algorithms. Following the concepts outlined by Citterio and King (2022), it makes sense to use ML for significance and the impact some factors may have on the investigated model. To keep the analysis simple and relevant, Xgboost, a gradient-boosting algorithm will be introduced in the methodology section.

Xgboost is relevant as this approach helps researchers to identify feature importance in their models as research by Hoang et al. (2023) shows. Machine learning algorithms have the potential to not only evaluate the models but also improve their predictive power (Zhang et al., 2023) and are already effective in default prediction (Shetty et al., 2022). Finally, feature importance in default prediction using machine learning is explored by Muslim and Dasril (2021) and by Carmona et al. (2022) who specifically focus on Xgboost classifier.

5. Data Description and Methodology

5.1 Data Selection

To find out if ESG can impact solvency by predicting probability of default, a large set of data is required. This study has an international focus, so the companies chosen are from various countries and regions across the world. When it comes to country selection, the focus is on developed economies with high absolute GDP per capita figures. Developed economies are also chosen due to them having the highest information efficiency, resulting in more efficient markets and higher transparency of accounting data required for estimations. Developed economies are the high-income economies according to the World Bank (2023). Not all developed countries are chosen to be represented because due to the study limitations of selecting publicly traded companies only, the country must have a large and well-developed stock market with enough companies to be considered for representation.

In total, there are 12 high-income developed economies to investigate the companies from. These economies are the USA, United Kingdom, Canada, Australia, New Zealand, Japan, South Korea, Germany, France, Denmark, Sweden and Italy. The United States can be considered an outlier, because it is the largest economy in the world, with the largest and most developed stock market, the US enjoys an “exorbitant privilege” in the form of excess returns over its external assets compared to liabilities, but for that provides global insurance to the rest of the world (Gourinchas et al., 2017). To mitigate that, a much smaller proportion of US companies are to be selected out of the key indices compared to other countries. This is also due to many other selected economies having a much smaller pool of companies to choose from.

Financial companies are excluded from this research due to their unique capital structure and other difficulties in comparability, especially in the scope of environmental performance. Therefore, in all countries' banks, insurance companies, funds, pension funds, REITs, investment companies, and other financial service providers are excluded. The firms that provide financing may demonstrate their CSP through exclusion of certain stocks from their portfolio or activist management practices in the companies they invested, but not so much through own ESG scores of the investor.

There are in total 346 companies selected that fit the above-mentioned criteria. All the companies in one country would roughly equal 6-7% of the total sample. This should provide more unbiased results when evaluating companies from different countries and regions. The timeline of evaluation is from 2001 until 2022, although the first estimation results are expected to be from 2003 because according to the methodology it requires data inputs from the previous two years.

5.2 ESG as a variable

When it comes to evaluating ESG performance, the Refinitiv database is chosen as it provides scores across all the pillars and is popular in academic research. ESG scores offer an assessment of companies' ESG performance, commitment, and effectiveness across ten key themes, leveraging publicly reported data. Comprising a framework, these scores integrate over 630 company-level ESG measures, with a subset of 186 meticulously selected for their comparability and materiality within each industry (Refinitiv, 2024). These measures are chosen based on considerations such as impact, data availability, and industry relevance, ensuring a comprehensive evaluation tailored to specific industry groups. The resulting ESG scores, grouped into ten categories, contribute to the computation of three pillar scores: environmental, social, and corporate governance. While category weights vary

across industries for the environmental and social pillars to accommodate industry-specific nuances, governance weights remain consistent across all sectors. This approach ensures that the final ESG score accurately reflects a company's ESG performance based solely on publicly available information, offering stakeholders a reliable measure of its sustainability efforts.

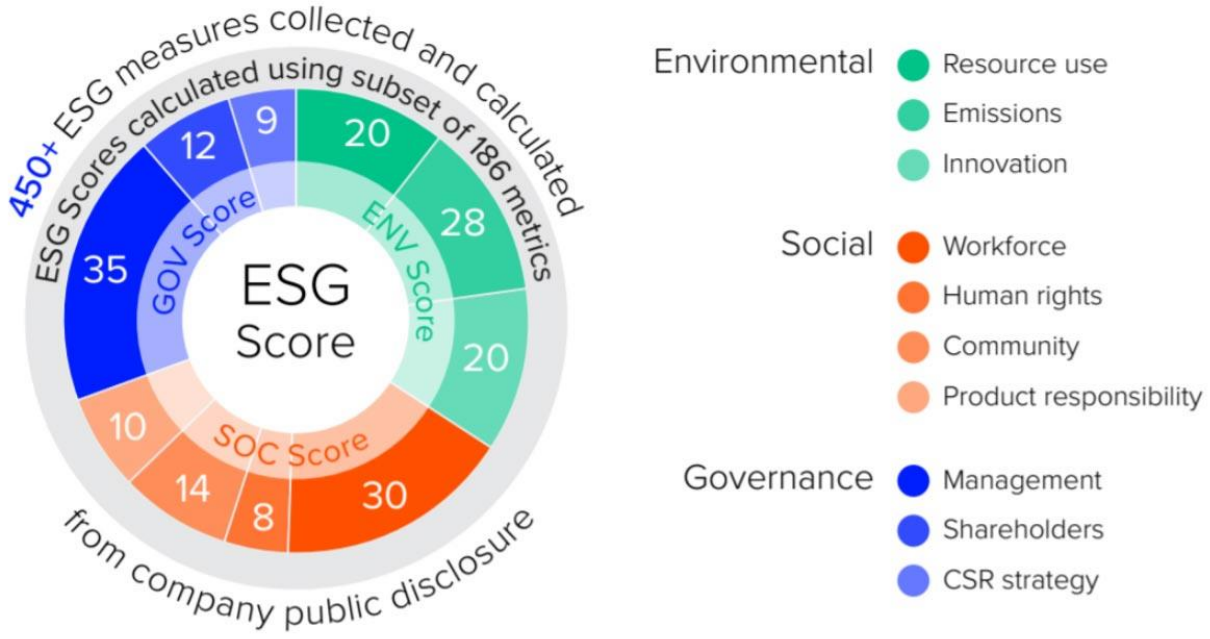

Figure 1. Refinitiv ESG score (Refinitiv.com, 2022).

The score for each category is calculated by equally weighing all the indicators utilized within it, with normalized weights computed after excluding indicators lacking public domain data. The weight of each category is determined by the number of measures it encompasses. The final ESG Score is obtained by computing a weighted average of the ten underlying category scores, ensuring a comprehensive reflection of a company's sustainability performance (Refinitiv, 2022). Due to this methodology and the quantifiability of ESG performance, ESG scores can be used as input data into predictive models.

5.3 Probability of default model

There have been various studies examining the probability of default. It has already been stated that Altman's (1968) Z score is a valid measure for bankruptcy prediction. In line with studies by Badayi et al. (2021) and Habermann & Fischer (2021) Z score is to be treated as probability of default. This is a two-step methodology, where the first step is Z score calculation. This measure is to be calculated as follows in Equation 1:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.64X_4 + 1.05X_5 \quad (1)$$

where Z is the overall measure, X_1 is the Working capital/total assets, X_2 is the Retained earnings/total assets, X_3 is the Earnings before interest and taxes/Total assets, X_4 is the Market value of equity/Book value of total debt, and X_5 is the Sales/Total assets. The second equation will take the Z score calculated in the first step and use it as a dependent variable to estimate the effect of ESG scores on the probability of default. Continuing the methodology of Badayi et al. (2021), adjusted for ESG the second equation - Equation 2 will be the following:

$$PD = \beta_0 + \beta_1 ESG_t + \beta_2 PD_{av} + \beta_3 LEV_t + \beta_4 SIZE_t + \beta_5 CR_t + \beta_6 NDTS_t + \emptyset + \alpha_t + \mu_t \quad (2)$$

Where:

PD = Default probability calculated using the Z score.

ESG = Environmental Social Governance

PD_{av} = Average probability of default for two previous years

LEV = Debt/Total assets

$SIZE$ = Firm size

CR = Current assets/Current Liabilities

$NDTS$ = Non-debt tax shield

∅ = Volatile industry dummies

α_t = Crisis Year dummies

μ_t = Error term

There is a possibility that the probability of default in previous years will influence this year's probability, this is why the average Z score of two previous years will be employed. The main variable of interest is β_1.

The second equation has been slightly adjusted because Ordinary Least Squares (OLS) regression will be employed instead of the Generalized Method of Moments (GMM) used in the article by Badayi et al. (2021). OLS is one of the most popular methods for this type of analysis as it will give robust and reliable results. This is also why the number of variables is slightly reduced as some of them are already similar to the original model, which can cause endogeneity problems. Another difference with the original model is adding Crisis year and Volatile industry dummy variables. Crisis years are years where significant market crashes occurred, for this sample there are the years 2001, 2008, and 2020. Volatile industry accounts for industries in which market values tend to change rapidly and industries that suffer more during crises. In this case, industries like Airlines, Leisure and Travel, Real Estate, and Entertainment.

5.4 Evaluating Feature Importance

Traditional models provide significance and impact of certain factors on dependent variables, but there is a possibility to use more innovative methods, building upon existing models and evaluating the impact of ESG on bankruptcy predictions. Taking the variable from Equation 2, the proposed principle could be evaluated from the scope of machine learning in estimating default probabilities. One such model that can aid with this task is Xgboost.

Xgboost, an abbreviation for eXtreme Gradient Boosting, is a machine learning algorithm renowned for its efficacy in handling structured data. Utilizing a boosting technique, Xgboost sequentially trains decision tree models to correct errors made by preceding ones, ultimately amalgamating them into a robust learner. A distinctive feature of Xgboost is its capability to quantify feature importance. By assessing how frequently features are utilized across decision trees and their contribution to minimizing the loss function, Xgboost generates feature importance scores. Such insight facilitates a deeper understanding of the underlying data dynamics and enhances the interpretability and performance of Xgboost models. Figure 2 shows a simplified example of such a decision tree model used to evaluate house prices.

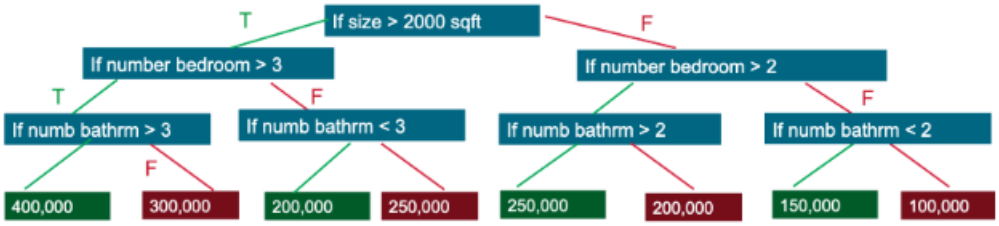

Figure 2. Example of Decision Tree Model (Nvidia, 2024).

The structure of Equation 2 will be used as an input. Z score will be predicted based on the same independent variables used in OLS. In the context of feature importance, grid search in Xgboost involves systematically exploring various combinations of hyperparameters to optimize the model's ability to assess feature importance accurately. Hyperparameters such as tree depth, learning rate, and regularization strength can significantly impact how Xgboost evaluates feature importance. By conducting a grid search over a range of hyperparameter values, researchers can identify the configuration that maximizes the model's ability to distinguish the most influential features from the less important ones. Setting parameters and applying the method described will yield a better understanding of the importance of input factors in the model and evaluate its potential for machine learning in bankruptcy prediction, evaluating ESG as an input. Two methods will be utilized.

In the first method, XGBRegressor is employed to build an Xgboost regression model. The model is trained on data derived from a linear regression analysis, which includes features such as ESG score, average PD, LEV, SIZE, CR, and NDTS. The Xgboost model is configured with default hyperparameters. Once trained, the model is capable of capturing interactions and relationships between the input features and the target variable, which is the PD. The “plot_importance” function provided by Xgboost will be utilized to visualize the relative importance of each feature in predicting the PD. This method offers a straightforward approach to model training and feature importance analysis, suitable for cases where hyperparameter tuning is not a primary concern and default settings suffice.

The second method opts for a more hands-on approach using the lower-level functions provided by the Xgboost library. DMatrix object is created from the training data and then employs the “xgboost.train” function to train the model. This method allows for greater flexibility in hyperparameter tuning, as the parameters can be specified such as the number of boosting rounds (num_boost_round), maximum tree depth (max_depth), learning rate

(eta), and others. By performing hyperparameter tuning, the model's performance is fine-tuned and potentially shows improved predictive accuracy. Additionally, the plot_importance function is utilized to visualize feature importances, providing insights into which features have the most significant impact on PD prediction. This is the most important idea in testing the second hypothesis by demonstrating the importance of parameter features in the model.

The second Xgboost model inputs will be the following as per Table 1. These values should be optimal to test the performance and evaluate the impact of all factors. The are 1500 boosting rounds to have enough depth. Gamma is chosen to be 0.6 for the most optimal loss reduction. Others are default parameters for this type of model.

Table 1. Xgboost grid-search with custom DMatrix model parameters.

b_rounds	1500
m_depth	4
eta	0.1
ssample	0.8
col_tree	0.8
m_child_w	2
gam	0.6

b_rounds-Number of Boosting Rounds, m_depth - Maximum Depth of Trees, eta-Learning Rate, ssample-Subsample, col_tree - Colsample bytree, m_child_w-Minimum Child Weight, gam -Gamma. N=5220

5.5 Descriptive Statistics

Table 2. Descriptive Statistics.

	Z score	ESG Score	Z score av	LEV	SIZE	CR	PROF	NDTS
mean	7.910	57.544	8.959	0.260	17.577	1.610	0.090	0.041

std	10.949	20.231	13.973	0.152	3.002	1.825	0.087	0.024
min	0.000	0.400	0.929	0.000	0.000	0.000	-0.974	0.000
25%	2.319	44.220	2.311	0.158	15.738	0.963	0.047	0.026
50%	4.042	59.360	4.111	0.247	17.199	1.294	0.079	0.037
75%	7.568	73.710	7.752	0.358	18.733	1.806	0.123	0.051
max	47.332	95.910	60.462	1.653	26.170	56.975	0.543	0.298

Z score – the probability of default, Z score av – average Z score for previous 2 years, LEV – Leverage, SIZE - natural logarithm of total assets, CR – Current assets/Current Liabilities, PROF – EBIT/Total assets, NDTS – Depreciation/Total Assets. N = 5220.

Table 2 presents descriptive statistics of all the input variables in Equation 2. Equation 1 is used to calculate Z score and Z score av (average value of 2 previous years). Habermann and Fischer (2021) note that Z score data may have huge outliers that may skew the results, so the Z score data went through winsorizing to remove extreme outliers. When calculating Z scores if a company had 0 debt, regularization was used to avoid dividing by zero in the X4 parameter of Equation 1. All company data that corresponded to zero values is also removed. The table's purpose is to demonstrate the scale and scope of the input data. Notably Z score for the previous 2 years tends to be higher and more volatile than the current Z score on average.

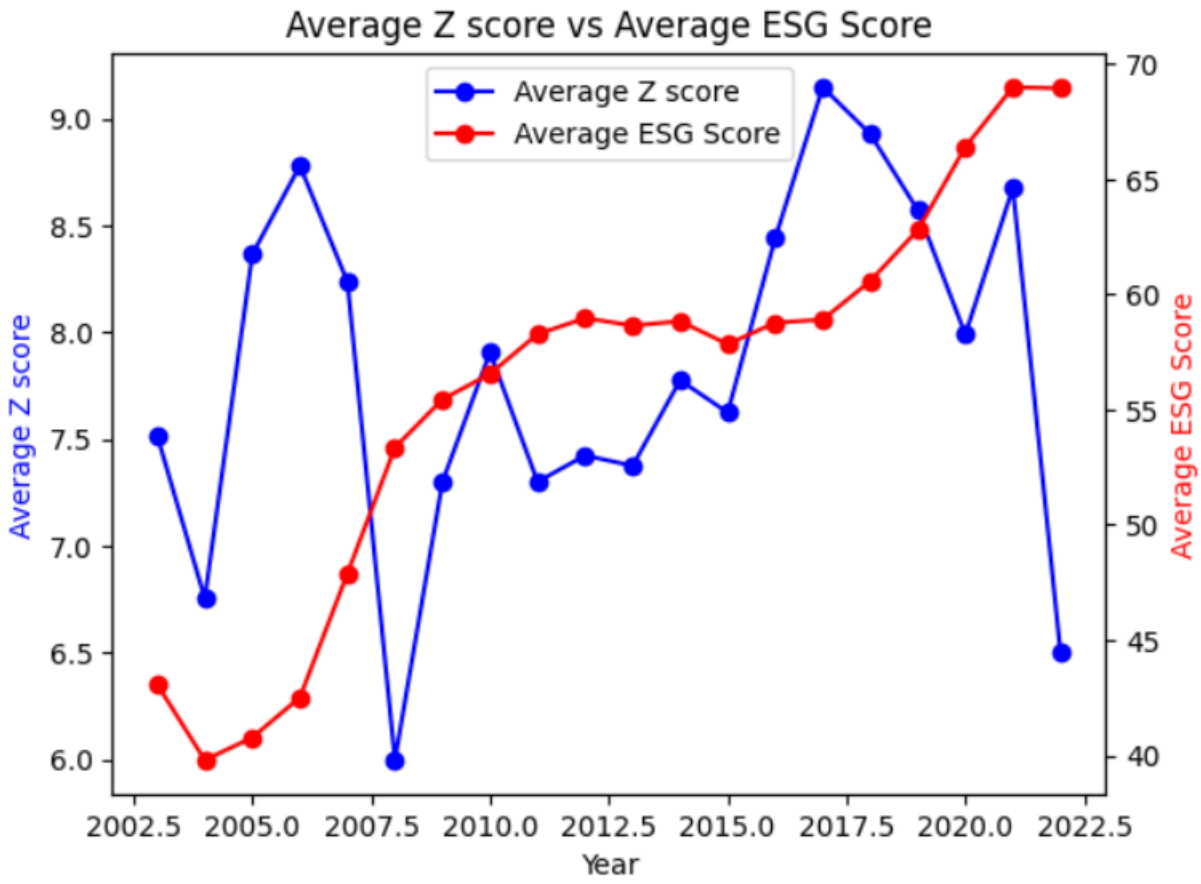

Figure 3. ESG score vs Z score over time period.

Figure 3 shows the dynamic of ESG scores and Z scores over the time period. Average Z scores overall seem to follow market sentiment, which is evident from the crisis drops in 2008, 2020, and 2022. ESG score averages steadily increase over the 20-year period. It is sensible to believe that a lot of this growth is due to the recognition and growth of the popularity of the concept and the submission of metrics by companies. For example, in 2003 there were only 101 companies with ESG scores assigned in the data sample, while in 2022 there are 251 companies with ESG scores.

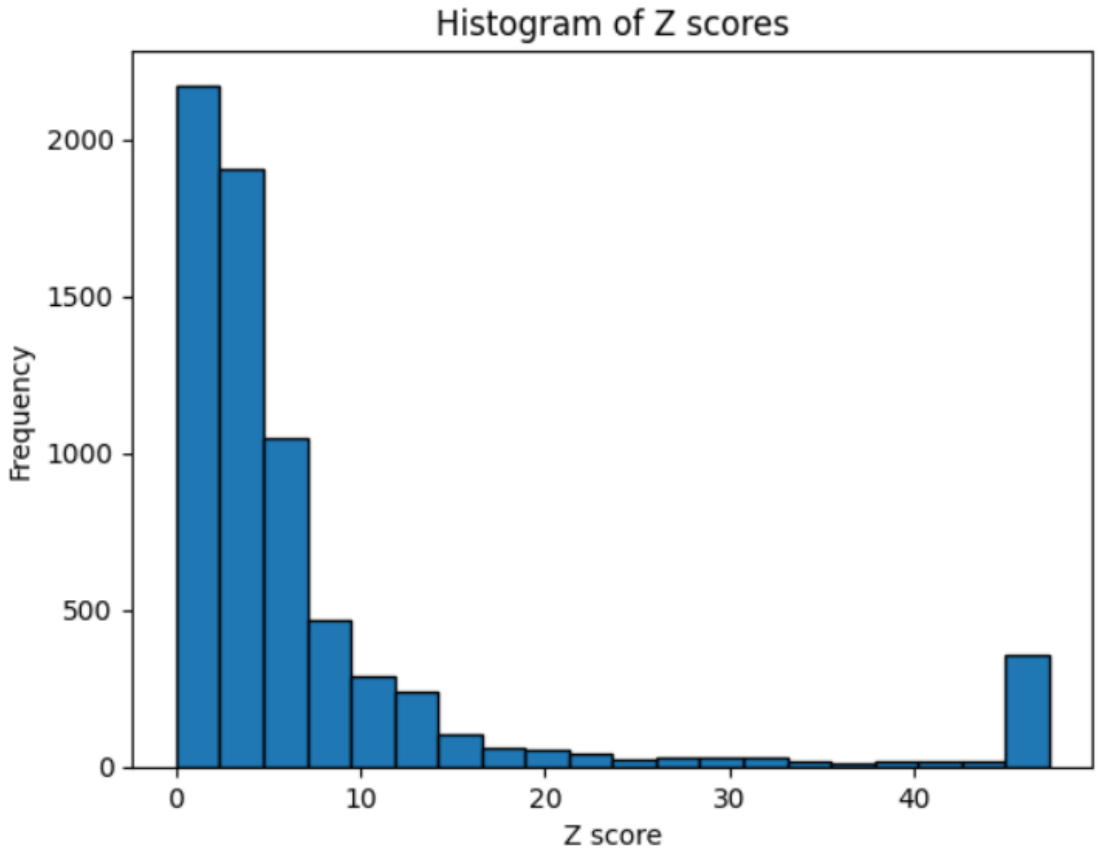

Figure 4. Histogram of Z scores.

Figure 4 shows the distribution of calculated Z scores. The majority of the scores are clustered between 0 and 10 with the notable exception of a group of companies having values above 40. Naturally, they are not normally distributed. This could be due to high market values or the absence of debt. This table also results from removing extreme outliers. Negative values could artificially skew potential results and decrease the predictive power of the model. A Z score above 3 constitutes that the company is financially healthy.

Table 3. Correlation Matrix.

	Z score	ESG Score	Z score av	LEV	SIZE	CR	PROF	NDTS
Z score	1							
ESG Score	-0.123	1						
Z score av	0.119	0.017	1					
LEV	-0.568	0.104	-0.060	1				
SIZE	-0.050	0.180	0.033	0.115	1			
CR	0.310	-0.100	0.031	-0.290	-0.028	1		
PROF	0.347	-0.017	-0.026	-0.250	-0.141	0.043	1	
NDTS	-0.027	0.085	-0.025	0.105	0.026	0.015	0.053	1

Z score – the probability of default, Z score av – average Z score for previous 2 years, LEV – Debt/total assets, SIZE - natural logarithm of total assets, CR – Current assets/Current Liabilities, PROF – EBIT/Total assets, NDTS – Depreciation/Total Assets

Table 3 shows correlations between different variables. ESG scores have a small yet negative correlation with default probability. It makes sense that the average Z score of the previous 2 years is highly correlated with the Z score variable. Leverage has a noticeable inverse relationship with the Z score, as debt increases so does the probability of bankruptcy lowering Z scores. The bigger the company, the more financially stable it is, and bigger current assets help companies meet their short-term financial obligations.

Table 4. Display of Industries.

Industry	**Z score**	**ESG Score**	**Share**
Consumer Cyclicals	8.963	43.413	23.41%
Industrials	6.610	43.695	15.61%
Natural Resources Extraction	5.956	49.361	13.29%
Utilities	3.845	41.359	8.09%
Health Care	9.348	35.586	7.51%
Technology Services	11.814	45.788	6.65%
Communication Services	7.032	54.014	4.62%
Electronic Technology & Equipment	7.585	50.969	3.47%
Construction & Building Materials	6.673	46.407	2.31%

Industry – the industry where the company operates, Z score – average z score in that industry, ESG score – average ESG score in that industry, Share – percentage of studied companies in that industry.

Table 4 shows average Z scores calculated using Equation 1 and ESG scores from the database attributable to each industry. The last column shows the share of the specific industry within the dataset Only the top 9 industries are shown, so they do not add up to 100%. Each company is assigned an industry based on primary activity. The idea is to approach each individual company on a case-by-case basis to classify it upon the main activity it conducts. Naturally, some industries tend to outweigh the others in the sample, because more companies belong to industries such as Retail and Industrial, with other industries having smaller presence in the selected countries. Technology services tend to have the highest Z scores with ESG scores being around average (43). Healthcare companies on average have the lowest ESG scores while being financially stable.

6. Empirical Results

6.1 Regression Results

Table 5. Regression Results.

Variable	Coefficient	T-statistics	Standard error
Constant	3.7209***	6.738	0.552
ESG score	-0.0150***	-3.768	0.004
Z score av	0.5381***	81.080	0.007
LEV	-14.0738***	-23.002	0.612
SIZE	0.1176***	4.374	0.027
CR	0.3206***	7.006	0.046
PROF	13.5089***	14.038	0.962
NDTS	4.7190	1.436	3.287
R2	0.735		
Durbin-Watson:	1.377		
Observations	5220		

The numbers in parentheses show p-values. *, **, and *** denote significance at the 10, 5, and 1% levels.

The results of Equation 2 presented in Table 5 show that ESG is negatively associated with the probability of default. This means that holding all other variables constant, a one-unit increase in the ESG score is associated with a 0.015 unit decrease in the Z score. Leverage has a strong inverse relationship with default probability also. Size positively impacts the Z score. The R-squared value of 0.735 indicates that the model tends to explain a substantial portion of the variability observed in the dependent variable using the predictors included.

6.2 Xgboost Models

6.2.1 PD estimation using XGBRegressor

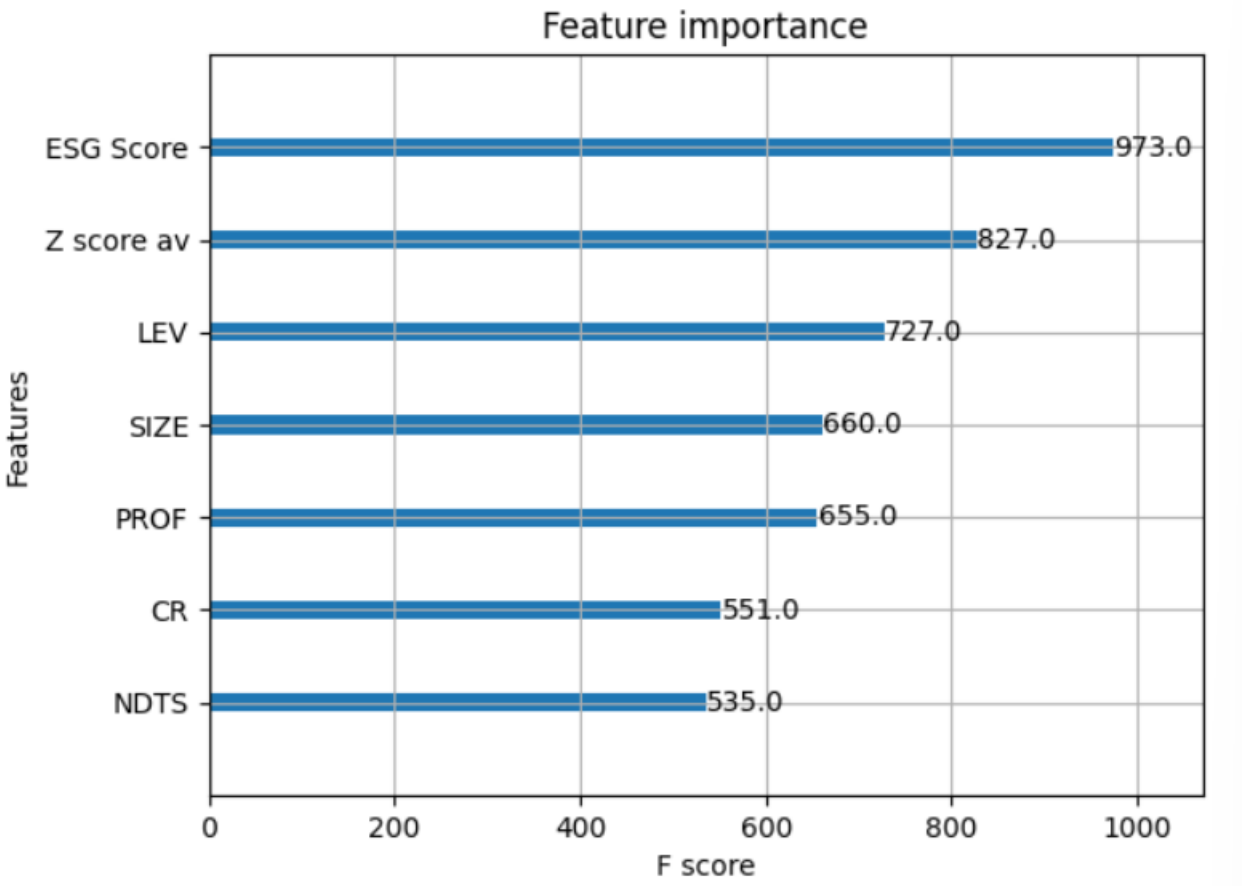

Figure 5. XGBregressor model feature importance.

The first model's results based on XGBregressor are presented in Figure 5. It demonstrates that ESG is the most relevant predictor followed by average Z score and leverage based on F score. In Xgboost, the F-score is a measure of feature importance, and it is calculated based on the number of times each feature is used to split the data across all boosting rounds (iterations). Essentially, the higher the F-score of a feature, the more important it is in contributing to the overall predictive power of the Xgboost model. The model derives its

data and set up from Equation 2 and the result is surprising considering the low coefficient of ESG score.

6.2.2 PD estimation with DMatrix model feature importance

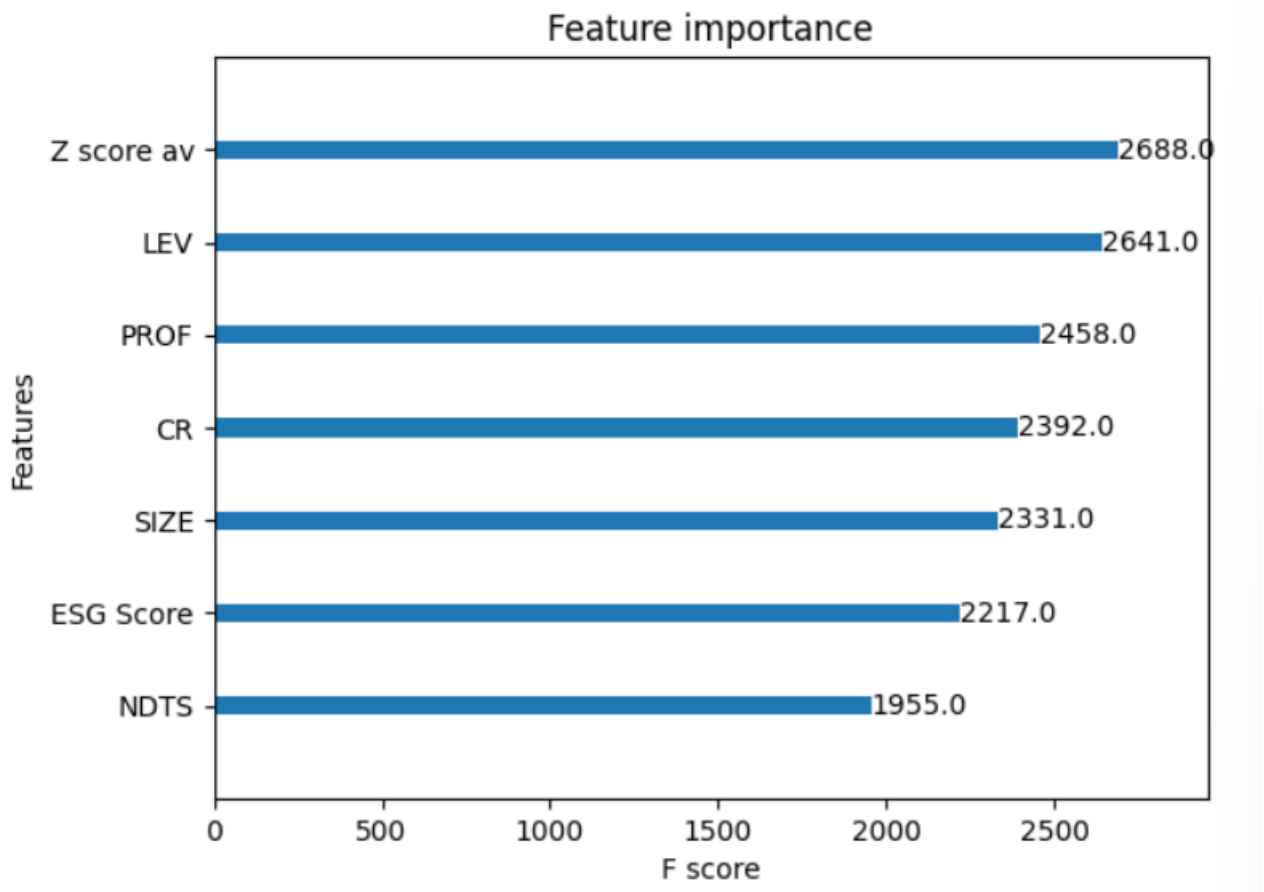

Figure 6. DMatrix model feature importance.

Figure 6 helps to evaluate the impact of different chosen factors on the results. The DMatrix model is set up using the input features in Table 1. Unlike in the linear model, and similar to the previous model, the previous year's Z score tends to be an influential factor, followed closely by Leverage. ESG score tends to have the second least predictive power among all

variables, however, based on the F score points it is only 17% less impactful than Leverage or previous year's Z scores.

7. Discussion and further research possibilities

7.1 Discussion of the results

Based on the OLS regression there is a very slight negative effect of ESG ratings on Z score, very close to zero. The first hypothesis states that: High ESG scores reduce the probability of default. The results show that hypothesis number 1 should be rejected because the result is significant and the coefficient of ESG is negative, although very close to 0. These results are partially in line with the legitimacy theory as companies might report more on their environmental endeavors using this as a legitimizing tool. More importantly, the results support the shareholder theory, which states that businesses should focus on profit maximization within the given legal framework.

Evaluating ESG as a relevant predictor of default probability presents mixed results. Xgbregressor demonstrates ESG to be the most significant factor drawn upon when predicting the probability of default. The more comprehensive DMatrix model shows that ESG can be impactful, however, it is not the most relevant factor in the chosen setup. The second hypothesis states that ESG scores are impactful factors in PD estimations. This hypothesis can be accepted because based on the machine learning models ESG is an impactful but can not be treated as a sole default estimator.

The examination of the impact of ESG factors on the probability of default yields mixed evidence, aligning with previous studies that have addressed related issues. For instance, Oikonomou et al. (2014) raise concerns regarding the materiality of CSR performance, albeit not directly addressing default probabilities. Similarly, Habermann and Fischer (2021) find limited evidence supporting a significant effect of Corporate Social Performance on bankruptcy probabilities. The authors also find that increasing CSP participation lowers

companies' Z scores in the following years. These findings suggest that while ESG considerations may play a role in corporate sustainability and reputation management, their direct influence on default risk may be less pronounced than initially anticipated.

Interestingly, the analysis reveals that ESG scores demonstrate little effect on the Altman Z score. However, the inclusion of ESG scores as predictors in the model, particularly in conjunction with advanced machine learning techniques such as Xgboost, reveals their potential significance in predicting default probabilities. This observation is consistent with recent research by Citterio and King (2022), which highlights the importance of ESG factors in enhancing the predictive power of bankruptcy models.

While the results suggest that ESG scores alone may not serve as strong predictors of potential corporate distress, they underscore the importance of incorporating ESG considerations into predictive models. Traditional models like Altman's Z score often overlook enterprises' social and environmental performances, which can be critical determinants of long-term viability and resilience. The findings promote investigation into hybrid bankruptcy prediction models and challenge claims made by some studies highlighting only the positive effect of ESG on company financial performance. Decision makers can benefit from adding non-financial metrics to their prediction models and these metrics do not have to be ESG scores only, however further analysis on specific metrics to choose may be needed.

In summary, while ESG scores may not independently drive default probabilities, their inclusion in predictive models offers valuable insights into the broader risk landscape facing corporations. Moving forward, further research is warranted to explore the relationships between ESG factors and financial distress.

7.2 Further Research Possibilities

One avenue for further investigation involves identifying alternative proxies for ESG performance, considering the limitations of traditional ESG scores highlighted in previous sections. For instance, researchers could explore the use of novel data sources or metrics that better capture the nuanced aspects of sustainability and social responsibility relevant to bankruptcy prediction.

Furthermore, a promising research direction is to develop industry-specific bankruptcy prediction models by focusing solely on ESG pillars that are particularly relevant to certain industries. Building on the insights from Kotsantonis and Serafeim (2019), who demonstrate industry-specific variations in ESG-related issues, researchers could tailor bankruptcy prediction models to account for the unique challenges and opportunities faced by different sectors. For instance, certain industries may be more susceptible to environmental risks, while others may prioritize social or governance factors. By customizing ESG integration to specific industries, researchers can enhance the relevance and accuracy of bankruptcy prediction models.

Additionally, there is potential to refine ESG evaluation frameworks by excluding irrelevant metrics that may distort comparisons across industries. For instance, in the case of technology companies, metrics related to environmental pollution within the ESG 'Environment' pillar may be less relevant compared to other industries. By removing such irrelevant metrics, researchers can ensure a more equitable assessment of ESG performance and improve the predictive power of bankruptcy models within specific sectors.

8. Conclusion.

ESG and CSR are firmly established concepts in the world of finance. Environmental disclosure, sustainable practices, and fair governance are the trends in which more and more companies are eager to participate, if not to change the world, but to at least legitimize themselves as decent business practitioners. The stakeholder theory approach is prioritized over the shareholder theory, as businesses are now expected to do well while doing good. ESG scores hold the potential to be an unbiased qualifier, which along with traditional financial metrics, can be utilized to analyze a company most comprehensively. There are, however, shortcomings and limitations from lack of proper and comparable information, hyperfocus on the scores themselves and not the results by company managers, and disagreements by rating agencies.

The literature review section of this thesis shows that CSP and consequently ESG scores can be material and the companies engaged in CSR practices enjoy higher trust and potentially greater access to finance. Logically, financially stable companies would face a lower risk of insolvency or the probability of default on their debts. Adapting the methodology presented by Badayi et al. (2021) this paper investigates the impact of ESG scores on default probability. It is a three-step process of calculating the Z scores from raw financial data, putting the scores as inputs to the adjusted model, and then implementing the same model, running it through novel ML algorithms to test the significance of ESG scores' input and influence on default probability of non-financial international companies.

The results of the OLS model show that ESG scores impact solvency negatively and significantly, albeit the impact itself is not major. This research is advanced further by using a similar setup to run the data through decision tree-based ML models which yield mixing

results. The OLS results support the viewpoint of the shareholder theory where businesses should not engage in CSR in the way promoted by the stakeholder theory. Negative impacts of ESG scores on default probability may seem counterintuitive to the expectations set by the results of some of the academic literature reviewed. This could be explained by significant differences in the research setup, the number of variables, and the data used. A definitive result of this research suggests that ESG scores are a beneficial input into the probability of default models.

There are several limitations to be acknowledged. First, ESG scores may not always be the most representative metrics of CSP and therefore stating unequivocally that corporate social performance increases the likelihood of default is not correct. Second, the range of industries in this study is wide, which limits the precision of the predictive power of the implemented models. Future research may focus on specific industries where the variability in significance of different ESG pillars is minimized. It can also be beneficial to include a wider range of countries, including some developing economies with available ESG data.

Decision makers can benefit from including more non-financial metrics to their predictive models and trend-setters need to look beyond just ESG scores to evaluate the impact a company may have on the environment and the stakeholders. The study highlights that depending on the research set up ESG scores and firm values may behave differently. Although the proposed researched gap is not closed, but the major contribution can be seen in the ESG scores having almost no effect on PD, meaning that companies should be encouraged to experiment with ways to deliver CSP value proposition to their stakeholders.

References

Acharya, V. V., Amihud, Y., & Litov, L. (2011). Creditor rights and corporate risk-taking. *Journal of Financial Economics, 102, 150-166*. https://doi.org/10.1016/j.jfineco.2011.04.001

Amin, A., Chourou, L., Kamal, S., Malik, M., & Zhao, Y. (2020). It's who you know that counts: Board connectedness and CSR performance. *Journal of Corporate Finance, 64, 929-1199.* https://doi.org/10.1016/j.jcorpfin.2020.101662

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

Al-Bataineh, O., Iqbal, A., & King, T. (2022). Managerial Social Capital and Firm Risk [Unpublished manuscript]. University of Kent. Retrieved from https://kar.kent.ac.uk/id/eprint/93811

Badayi, S. A., Matemilola, B. T., Bany-Ariffin, A. N., & Theng, L. W. (2021). Does corporate social responsibility influence firm probability of default? *International Journal of Finance & Economics, 26 (3), 3377–3395.* https://doi.org/10.1002/ijfe.1966

Baselga-Pascual, L., Dimic, N., & Vähämaa, E. (2023). Corporate Social Responsibility and Bank Credit Ratings. Springer. Retrieved from https://osuva.uwasa.fi/handle/10024/16141

Brealey, R. A., Myers, S. C., & Allen, F. (2009). Principles of corporate finance (10th ed.). McGraw-Hill/Irwin.

Besley, T. J., Roland, I. A., & Van Reenen, J. (2020, June). The Aggregate Consequences of Default Risk: Evidence from Firm-Level Data (ECB Working Paper No. 2425). European Central Bank. https://www.ecb.europa.eu/pub/pdf/scpwps/ecb.wp2425~12ba0e10e6.en.pdf

Carmona, P., Dwekat, A., & Mardawi, Z. (2022). No more black boxes! Explaining the predictions of a machine learning XGBoost classifier algorithm in business failure. *Research in International Business and Finance, 61*, 101649. https://doi.org/10.1016/j.ribaf.2022.101649

Cheng, B., Ioannou, I., & Serafeim, G. (2014). Corporate social responsibility and access to finance. *Strategic Management Journal, 35*, 1–23. https://doi.org/10.1002/smj.2131

Charalambous, C., Martzoukos, S. H., & Taoushianis, Z. (2019). Predicting corporate bankruptcy using the framework of Leland-Toft: evidence from U.S. *Quantitative Finance, 20(2), 329–346.* https://doi.org/10.1080/14697688.2019.1667519

Christensen, D. M., Serafeim, G., & Sikochi, A. (2022). Why is Corporate Virtue in the Eye of The Beholder? The Case of ESG Ratings. *The Accounting Review, 97, 147-175.* https://doi.org/10.2308/TAR-2019-0506

Chiaramonte, L., Dreassi, A., Girardone, C., & Piserà, S. (2021). Do ESG strategies enhance bank stability during financial turmoil? Evidence from Europe. *The European Journal of Finance, 28(12), 1–39.* https://doi.org/10.1080/1351847x.2021.1964556

Cho, C. H., & Patten, D. M. (2007). The role of environmental disclosures as tools of legitimacy: A research note. *Accounting, Organizations and Society,* 32(7-8)*,* 639–647. https://doi.org/10.1016/j.aos.2006.09.009

Citterio, A., & King, T. (2022). The role of Environmental, Social, and Governance (ESG) in predicting bank financial distress. *Finance Research Letters,* 51, 103411. https://doi.org/10.1016/j.frl.2022.103411

Cooper, M. J., Gulen, H., & Rau, P. R. (2005). Changing Names with Style: Mutual Fund Name Changes and Their Effects on Fund Flows. *The Journal of Finance*, *60*(6), 2825–2858. https://doi.org/10.1111/j.1540-6261.2005.00818.x

Deegan, C. (2002). The legitimizing effect of social and environmental disclosures: a theoretical foundation. *Accounting, Auditing and Accountability Journal*, 15, 282–311. https://doi.org/10.1108/09513570210435852

Di Tommaso, C., & Thornton, J. (2020). Do ESG scores effect bank risk taking and value? Evidence from European banks. *Corporate Social Responsibility and Environmental Management*, 27(5). https://doi.org/10.1002/csr.1964

Edmans, A. (2023, January 4). The End of ESG. Papers.ssrn.com. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=422199

ESG Scores. (n.d.). Www.lseg.com. https://www.lseg.com/en/data-analytics/sustainable-finance/esg-scores#methodology

Fatemi, A., Fooladi, I., & Tehranian, H. (2014). Valuation effects of corporate social responsibility. *Journal of Banking & Finance*, *59*, 182-192. https://doi.org/10.1016/j.jbankfin.2015.04.028

Freeman, R. E. (1984). A Stakeholder Approach to Strategic Management. *SSRN Electronic Journal*, 1(1). https://doi.org/10.2139/ssrn.263511

Friede, G., Bucsh, T., & Bassen, A. (2015). ESG and financial performance: Aggregated evidence from more than 2000 empirical studies. *Journal of Sustainable Finance & Investment*, *5*(4), 210-233. https://doi.org/10.1080/20430795.2015.1118917

Friedman, M. (1970, September 13). The social responsibility of business is to increase its profits. *The New York Times.* https://www.nytimes.com/1970/09/13/archives/a-friedman-doctrine-the-social-responsibility-of-business-is-to.html

Graham, J. R., Lemmon, M. L., & Schallheim, J. S. (1998). Debt, Leases, Taxes, and the Endogeneity of Corporate Tax Status. *The Journal of Finance*, *53*(1), 131–162. https://doi.org/10.1111/0022-1082.55404

Global Sustainable Investment Alliance. (n.d.). Global sustainable investment review finds US$30 trillion invested in sustainable assets. Global Sustainable Investment Alliance. Retrieved March 26, 2024, from https://www.gsi-alliance.org/global-sustainable-investment-review-finds-us30-trillion-invested-in-sustainable-assets/

Godfrey, P. C., Merrill, C. B., & Hansen, J. M. (2009). The Relationship Between Corporate Social Responsibility And Shareholder Value: An Empirical Test Of The Risk

Management Hypothesis. *Strategic Management Journal, 30*, 425-445. https://doi.org/10.1002/smj.750

Gompers, P. A., Ishii, J. L., & Metrick, A. (2003). Corporate Governance and Equity Prices. *SSRN Electronic Journal, 118*(1). https://doi.org/10.2139/ssrn.278920

Gourinchas, P.-O., & Rey, H. (2022, January 1). Exorbitant Privilege and Exorbitant Duty. *Social Science Research Network*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4026850

Habermann, F., & Fischer, F. B. (2021). Corporate Social Performance and the Likelihood of Bankruptcy: Evidence from a Period of Economic Upswing. *Journal of Business Ethics, 182*, 243–259. 10.1007/s10551-021-04956-4

Hawn, O., & Ioannou, I. (2016). Mind The Gap: The Interplay Between External And Internal Actions In The Case Of Corporate Social Responsibility. *Strategic Management Journal, 37*, 2569–2588. https://doi.org/10.1002/smj.2464

Hill, R. P., Ainscough, T., Shank, T., & Manullang, D. (2006). Corporate Social Responsibility and Socially Responsible Investing: A Global Perspective. *Journal of Business Ethics, 70*(2), 165–174. https://doi.org/10.1007/s10551-006-9103-8

Hoang Hiep Nguyen, Viviani, J.-L., & Sami Ben Jabeur. (2023). Bankruptcy prediction using machine learning and Shapley additive explanations. *Review of Quantitative Finance and Accounting.* https://doi.org/10.1007/s11156-023-01192-x

Hovakimian, A., Kayhan, A., & Titman, S. (2011). Are Corporate Default Probabilities Consistent with the Static Trade-off Theory? *Review of Financial Studies, 25*(2), 315–340. https://doi.org/10.1093/rfs/hhr101

Houston, J. F., & Shan, H. (2022). Corporate ESG Profiles and Banking Relationships. *The Review of Financial Studies, 35*, 3373–3417. https://doi.org/10.1093/rfs/hhab125

International Monetary Fund. (n.d.). FvsFr. In IMF DataMapper. Retrieved February 26, 2024, from https://www.imf.org/external/datamapper/exp@FPP/USA

Jensen, M. C. (2002). Value Maximization, Stakeholder Theory, and the Corporate Objective Function. *Business Ethics Quarterly, 12*(2), 235–256. doi:10.2307/3857812

Jo, H., & Harjoto, M. A. (2011). Corporate Governance and Firm Value: The Impact of Corporate Social Responsibility. *Journal of Business Ethics, 103*, 351–383. https://doi.org/10.1007/s10551-011-0869-y

Kotsantonis, S., & Serafeim, G. (2019). Four Things No One Will Tell You About ESG Data. *Journal of Applied Corporate Finance, 31*(2), 50–58. https://doi.org/10.1111/jacf.12346

Lang, M., & Lundholm, R. (1996). Corporate disclosure policy and analyst behavior. *The Accounting Review, 71*(4), 467-492. https://ssrn.com/abstract=2646

Li, T., Trinh, V. Q., & Elnahass, M. (2023). Drivers of Global Banking Stability in Times of Crisis: The Role of Corporate Social Responsibility*. British Journal Of Management, 34*, 595–622. https://doi.org/10.1111/1467-8551.12631

Lins, K. V., & Tamayo, A. (2017). Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *The Journal of Finance, 72*(4), 1785-1824. https://doi.org/10.1111/jofi.12505

LSEG Data & Analytics | Financial Technology & Data. (2023, November 20). Www.lseg.com. https://www.lseg.com/en/data-analytics

Merton, R. C. (1974). On the Pricing of Corporate Debt: The Risk Structure of Interest Rates. *The Journal of Finance, 29*(2), 449. https://doi.org/10.2307/2978814

Mozaffar, K., Serafeim, G., & Yoon, A. (2015). Corporate sustainability: First evidence on materiality (Harvard Business School Working Paper No. 15-073). https://doi.org/10.1002/smj.2464

Muslim, M. A., & Dasril, Y. (2021). Company bankruptcy prediction framework based on the most influential features using XGBoost and stacking ensemble learning. *International Journal of Electrical and Computer Engineering (IJECE), 11*(6), 5549. https://doi.org/10.11591/ijece.v11i6.pp5549-5557

Ohlson, J. A. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research, 18*(1), 109–131. https://doi.org/10.2307/2490395

Oikonomou, I., Brooks, C., & Pavelin, S. (2014). The Effects of Corporate Social Performance on the Cost of Corporate Debt and Credit Ratings. *The Financial Review, 49*(1), 49–75. https://doi.org/10.1111/fire.12025

Oikonomou, I., Brooks, C., & Pavelin, S. (2014). The impact of corporate social performance on financial risk and utility: A longitudinal analysis. *Financial Management, 41*(1), 483-515. https://doi.org/10.1111/j.1755-053X.2012.01190.x

Oxford Dictionary. (n.d.). Oxford learner's dictionaries. Oxfordlearnersdictionaries.com; Oxford University Press. https://www.oxfordlearnersdictionaries.com/

Phillips, R., Freeman, R. E., & Wicks, A. C. (2003). What Stakeholder Theory Is Not. *Business Ethics Quarterly, 13*(4), 479–502. https://www.jstor.org/stable/3857968

Porter, M. E., Kramer, M., & Serafeim, G. (2019, October 16). Where ESG fails. Institutional Investor. https://www.institutionalinvestor.com/article/2bswdin8nvg922puxdzwg/opinion/where-esg-fails

Regulatory Studies Center. (n.d.). Reg Stats. Regulatory Studies Center, Trachtenberg School of Public Policy & Public Administration, Columbian College of Arts & Sciences, The George Washington University. Retrieved March 26, 2024, from https://regulatorystudies.columbian.gwu.edu/reg-stats

Serafeim, G., & Yoon, A. (2021). Stock Price Reactions to ESG News: The Role of ESG Ratings and Disagreement. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3765217

Shetty, S., Musa, M., & Brédart, X. (2022). Bankruptcy Prediction Using Machine Learning Techniques. *Journal of Risk and Financial Management, 15*(1), 35. https://doi.org/10.3390/jrfm15010035

S&P Global. (2020, February 24). What is the "G" in ESG? *S&P Global*. https://www.spglobal.com/en/research-insights/articles/what-is-the-g-in-esg

Tóth, B., Lippai-Makra, E., Szládek, D., & Kiss, G. D. (2021). Why is Corporate Virtue in the Eye of The Beholder? The Case of ESG Ratings. *Public Finance Quarterly, 3*, 429-450. https://doi.org/10.35551/PFQ_2021_3_7

Weitzner, D., & Deutsch, Y. (2022). Harm Reduction, Solidarity, and Social Mobility as Target Functions: A Rortian Approach to Stakeholder Theory. *Journal of Business Ethics*. https://doi.org/10.1007/s10551-022-05248-1

What is XGBoost? (n.d.). NVIDIA Data Science Glossary. https://www.nvidia.com/en-us/glossary/xgboost/

World Bank Open Data. (2023). *World Bank Open Data*. https://data.worldbank.org/income-level/high-income?view=chart

Yu, E. P., Guo, C. Q., & Luu, B. V. (2018). Environmental, social and governance transparency and firm value. *Business Strategy and the Environment, 27*(7), 987–1004. https://doi.org/10.1002/bse.2047

Zhang, T., Zhu, W., Wu, Y., Wu, Z., Zhang, C., & Hu, X. (2023). An explainable financial risk early warning model based on the DS-XGBoost model. *Finance Research Letters, 56*, 104045. https://doi.org/10.1016/j.frl.2023.104045

Appendices

Appendix 1. Company names and identifiers.

Number	Company Name	ISIN
1	3M	US88579Y1010
2	A2 Milk Company Ltd	NZATME0002S8
3	A2A SPA	IT0001233417
4	Adidas AG	DE000A1EWWW0
5	AGC Inc	JP3112000009
6	Agnico-eagle mines	CA0084741085
7	Air New Zealand Ltd	NZAIRE0001S2
8	Aisin Corp	JP3102000001
9	Alfa Laval AB	SE0000695876
10	Alstom SA	FR0010220475
11	Ambu A/S	DK0060946788
12	Amgen Inc	US0311621009
13	Amorepacific Corp	KR7090430000
14	Amplifon SPA	IT0004056880
15	Anglo American PLC	GB00B1XZS820
16	APA Group	AU000000APA1
17	Apple Inc	US0378331005
18	Aristocrat Leisure	AU000000ALL7
19	Arvida GR	NZARVE0001S5
20	Assa Abloy AB	SE0007100581
21	Associated British	GB0006731235
22	Astrazeneca PLC	GB0009895292
23	Atlas Copco	SE0017486889
24	Auckland International Airport Ltd	NZAIAE0002S6
25	BAE Systems	GB0002634946
26	Barrick Gold Corporation	CA0679011084
27	Basf SE	DE000BASF111
28	Bayer AG	DE000BAY0017
29	Bayerische Motoren Werke AG	DE0005190003
30	BCE Inc	CA05534B7604
31	Beiersdorf AG	DE0005200000
32	BHP Group Ltd	AU000000BHP4
33	Boeing Co	US0970231058
34	Boliden AB	SE0020050417
35	Bouygues	FR0000120503

36	BP PLC	GB0007980591
37	Brambles Ltd	AU000000BXB1
38	Brenntag SE	DE000A1DAHH0
39	British American Tobacco	GB0002875804
40	BT Group	GB0030913577
41	Bunzl	GB00B0744B38
42	Burberry	GB0031743007
43	Buzzi SPA	IT0001347308
44	Cameco Corp	CA13321L1085
45	Canadian National Railway Company	CA1363751027
46	Canadian Natural Resources Limited	CA1363851017
47	Canadian Pacific Railway Limited	CA13646K1084
48	Capgemini	FR0000125338
49	Carlsberg - Class A Shares	DK0010181759
50	Carrefour	FR0000120172
51	Carsales.com Ltd	AU000000CAR3
52	Caterpillar Inc	US1491231015
53	CELLTRION	KR7068270008
54	CELLTRION HEALTHCARE	KR7091990002
55	Cenovus Energy Inc.	CA15135U1093
56	Centrica	GB00B033F229
57	CGInc.	CA12532H1047
58	Channel Infrastructure	NZNZRE0001S9
59	Chevron Corporation	US1667641005
60	Chorus	NZCNUE0001S2
61	Chr. Hansen Holding	DK0060227585
62	Chubu Electric Power	JP3526600006
63	Cisco Systems, Inc	US17275R1023
64	Coca-Cola Company (The)	US1912161007
65	Cochlear Ltd	AU000000COH5
66	Coles Group Ltd	AU0000030678
67	Coloplast AS	DK0060448595
68	Compagnie de Saint-Gobain	AU000000CPU5
69	Computershare Ltd	CA21037X1006
70	Constellation Software Inc.	NZCENE0001S6
71	Contact Energy	DE0005439004
72	Continental AG	GB00BD3VFW73
73	Convatec	DK0010201102
74	Copenhagen Airport	DE0006062144
75	Covestro AG	GB00BYZWX769
76	CSL Ltd	AU000000CSL8
77	DAEWOO SHIPBUILDING	KR7042660001
78	Daifuku Co. Ltd	JP3497400006

79	Daito Trust Constructio Co.,Ltd.	JP3486800000
80	Danone	FR0000120644
81	Dechra Pharmaceuticals	GB0009633180
82	Demant A/S	DK0060738599
83	Deutsche Post AG	DE0005552004
84	Deutsche Telekom AG	DE0005557508
85	Deutsche Wohnen SE	DE000A0HN5C6
86	Diageo	GB0002374006
87	Diasorin	IT0003492391
88	Dollarama Inc.	CA25675T1075
89	Doosan Enerbility	KR7034020008
90	Dow Inc.D	US2605571031
91	DS Smith	GB0008220112
92	DSV AS	DK0060079531
93	E. On SE	DE000ENAG999
94	EBOS	NZEBOE0001S6
95	Enbridge Inc.	CA29250N1050
96	Endeavour Mining	GB00BL6K5J42
97	Enel SPA	IT0003128367
98	Engie SA	FR0010208488
99	Eni	IT0003132476
100	ERG SPA	IT0001157020
101	Experian PLC	GB00B19NLV48
102	F.L.Smidth & Co. AS	DK0010234467
103	First Quantum Minerals Ltd.	CA3359341052
104	Fisher & Paykel Healthcare	NZFAPE0001S2
105	Fletcher Building	NZFBUE0001S0
106	Fonterra Shareholders	NZFCGE0001S7
107	Fortescue Metals Group Ltd	AU000000FMG4
108	Fortis Inc.	CA3495531079
109	Franco-Nevada Corporation	CA3518581051
110	Frasers Group	GB00B1QH8P22
111	Freightways	NZFREE0001S0
112	Fresenius Medical Care AG & Co. KG	DE0005785802
113	Fresenius SE & Co. KGaA	DE0005785604
114	Fresnillo plc	GB00B2QPKJ12
115	Genesis Energy	NZGNEE0001S7
116	George Weston Limited	CA9611485090
117	Geox	IT0003697080
118	GFL Environmental Inc.	JE00B4T3BW64
119	Glencore	DK0010272632
120	GN Store Nord A.S.	AU000000GMG2
121	Goodman Group	GB00BN7SWP63

122	GSK plc	GB00BMX86B70
123	H LUNDBECK B	DK0061804770
124	Haleon PLC	NZHLGE0001S4
125	Hallenstein Glasson	JP3771800004
126	Hamamatsu Photonics K.K.	KR7000880005
127	HANWHA AEROSPACE	DE000A161408
128	HelloFresh SE	DE0006048432
129	Henkel AG & Co. KGAA	SE0000106270
130	Hennes & Mauritz AB	IT0003697080
131	Hera	IT0001250932
132	Hermes	FR0000052292
133	Hikma Pharmaceuticals	GB00B0LCW083
134	Home Depot, Inc. (The)D	US4370761029
135	Honeywell International Inc	US4385161066
136	Howdens Joinery	GB0005576813
137	Hybe	KR7352820005
138	Hydro One Limited	CA4488112083
139	Hyundai Glovis	KR7086280005
140	Hyundai Merc Mar	KR7011200003
141	Hyundai Mobis	KR7012330007
142	Hyundai Motor Co	KR7005380001
143	IBM	US4592001014
144	Idemitsu Kosan Co	JP3142500002
145	IMI PLC	GB00BGLP8L22
146	Imperial Brands	GB0004544929
147	Imperial Oil Limited	CA4530384086
148	Infineon Technologies AG	DE0006231004
149	Infrastrutture Wire	IT0005090300
150	Infratil	NZIFTE0003S3
151	Intel Corporation	US4581401001
152	Interpump Group	IT0001078911
153	Intertek	GB0031638363
154	ISS A/S	DK0060542181
155	Isuzu Motors Ltd	JP3137200006
156	J SAINSBURY PLC	GB00B019KW72
157	Japan Airlines	JP3705200008
158	JFE Holdings, Inc.	JP3386030005
159	Johnson & Johnson	US4781601046
160	Kakao	KR7035720002
161	KANSAI ELEC. POWER	JP3228600007
162	KAWASAKI KISEN	JP3223800008
163	KDDI CORP	JP3496400007
164	KEPCO PLANT	KR7051600005

165	KIA CORP	KR7000270009
166	KINGFISHER PLC	GB0033195214
167	KMD BRANDS LTD	NZKMDE0001S3
168	KONAMI GROUP CORP	JP3300200007
169	KOREA ZINC INC	KR7010130003
170	KRAFTON INC	KR7259960003
171	KT & G CORP	KR7030200000
172	KT CORP	KR7033780008
173	L'Air Liquide	FR0000120073
174	LEGRAND S.A.	FR0010307819
175	LEONARDO SPA	IT0003856405
176	LG CHEM LTD	KR7051910008
177	LG CORP	KR7003550001
178	LG ELECTRONICS INC	KR7066570003
179	LG ENERGY SOLUTION L	KR7373220003
180	LIXIL CORP	JP3626800001
181	LOBLAW COMPANIES	CA5394811015
182	L'OREAL SA	FR0000120321
183	LOTTE CHEMICAL CORP	KR7011170008
184	LOTTERY CORP	AU0000219529
185	LVMH MOET HENNESSY	FR0000121014
186	Maersk	DK0010244508
187	MAGNA INTERNATIONAL	CA5592224011
188	MAINFREIGHT LIMITED	NZMFTE0001S9
189	MAKITA CORPORATION	JP3862400003
190	MCDONALD'S CORP	US5801351017
191	MEIJI HOLDINGS	JP3918000005
192	MELROSE	GB00BNGDN821
193	MERCEDES-BENZ	DE0007100000
194	MERCK & CO INC	US58933Y1055
195	MERCURY NZ LTD	NZMRPE0001S2
196	MERIDIAN ENERGY	NZMELE0002S7
197	Michelin	FR001400AJ45
198	MICROSOFT CORP	US5949181045
199	MINEBEA MITSUMI INC	JP3906000009
200	MINERAL RESRCS	AU000000MIN4
201	MISUMI GROUP INC	JP3885400006
202	MITSUBISHI CHEM	JP3897700005
203	MONCLER SPA	IT0004965148
204	MTU AERO ENGINES AG	DE000A0D9PT0
205	NAVER CORP	KR7035420009
206	NEWCREST MINING LTD	AU000000NCM7
207	NEXT PLC	GB0032089863

208	NIKE INC.	US6541061031
209	NISSAN CHEMICAL CORP	JP3670800006
210	NISSIN FOODS HOLD	JP3675600005
211	NKT A/S	DK0010287663
212	NORTHERN STAR RESR'S	AU000000NST8
213	NOVOZYMES A/S	DK0060336014
214	NUTRIEN LTD	CA67077M1086
215	OCADO GROUP PLC	GB00B3MBS747
216	OCEANIA HEALTH	NZOCAE0002S0
217	ORANGE SA	FR0000133308
218	ORIGIN ENERGY LTD	AU000000ORG5
219	OSAKA GAS CO., LTD.	JP3180400008
220	PACIFIC EDGE	NZPEBE0002S1
221	PANDORA	DK0060252690
222	PEARSON PLC	GB0006776081
223	PERNOD RICARD SA	FR0000120693
224	PILBARA MINERALS	AU000000PLS0
225	PIRELLI & C	IT0005278236
226	PORT OF TAURANGA	NZPOTE0003S0
227	POSCO DX	KR7022100002
228	POSCO FUTURE	KR7003670007
229	POSCO HOLDINGS INC	KR7005490008
230	POSCO INTERNATIONAL	KR7047050000
231	PROCTER & GAMBLE	US7427181091
232	PRYSMIAN SPA	IT0004176001
233	PUMA SE	DE0006969603
234	RAMSAY HEALTH CARE	AU000000RHC8
235	REA GROUP LTD.	AU000000REA9
236	RECORDATI	IT0003828271
237	REECE LTD	AU000000REH4
238	RENAULT Ã‚REGIE	FR0000131906
239	RENTOKIL INITIAL PLC	GB00B082RF11
240	RESTAURANT BRAND	CA76131D1033
241	RIO TINTO LIMITED	AU000000RIO1
242	ROCKWOOL A/S	DK0010219153
243	ROGERS COMMUNICATION	CA7751092007
244	ROHM CO LTD	JP3982800009
245	ROLLS-ROYCE	GB00B63H8491
246	ROYAL UNIBREW A/S	DK0060634707
247	RS GROUP PLC	GB0003096442
248	RWE AG	DE0007037129
249	RYMAN HEALTHCARE	NZRYME0001S4
250	SAFRAN	FR0000073272

251	SAGE GROUP PLC	GB00B8C3BL03
252	SAIPEM SPA	IT0005495657
253	SALESFORCE INC	US79466L3024
254	SAMSUNG BIOLOGICS	KR7207940008
255	SAMSUNG C&T	KR7028260008
256	SAMSUNG HEAVY IND	KR7010140002
257	SAMSUNG SDI CO LTD	KR7006400006
258	SAMSUNG SDS CO LTD	KR7018260000
259	SANDVIK AB	SE0000667891
260	SANFORD LIMITED	NZSANE0001S0
261	SANOFI	FR0000120578
262	SANTOS LIMITED	AU000000STO6
263	SAP SE	DE0007164600
264	SARTORIUS	DE0007165631
265	SCALES CORP LTD	NZSCLE0002S8
266	SCENTRE GROUP	AU000000SCG8
267	SCHNEIDER ELECTRIC	FR0000121972
268	SERKO LTD	NZSKOE0001S7
269	SEVERN TRENT PLC	GB00B1FH8J72
270	SHOPIFY INC	CA82509L1076
271	SIEMENS	DE0007236101
272	SIEMENS AG	DE000ENER6Y0
273	SIEMENS HEALTHI	DE000SHL1006
274	SIMCORP AS	DK0060495240
275	SK ENERGY	KR7000660001
276	SK HYNIX INC	KR7096770003
277	SK TELECOM CO LTD	KR7017670001
278	SKANSKA AB	SE0000113250
279	SKELLERUP HOLDINGS	NZSKXE0001S8
280	SKF AB	SE0000108227
281	SKY CITY ENTER	NZSKTE0001S6
282	SKY NETWORK TV LTD	NZSKCE0001S2
283	SMITHS INDUSTRIES	GB00B1WY2338
284	SNAM SPA	IT0003153415
285	SONIC HEALTHCARE LTD	AU000000SHL7
286	SOUTH32 LTD	AU000000S320
287	SPARK NEW ZEALAND	NZTELE0001S4
288	SPIRAX-SARCO ENGIN.	GB00BWFGQN14
289	SSAB SVENSKT STAL AB	SE0000171100
290	SUMITOMO CHEMICAL CO	JP3401400001
291	SUMITOMO ELECTRIC	JP3407400005
292	SUNCOR ENERGY	CA8672241079
293	SVENSKA CELLULOSA	SE0000112724

294	SYMRISE AG	DE000SYM9999
295	SYNLAIT MILK	NZSMLE0001S9
296	TC ENERGY CORP	CA87807B1076
297	TECK RESOURCES	CA8787422044
298	TELE2 AB	SE0005190238
299	TELECOM ITALIA	IT0003497168
300	TELEFONAKTIEBOLAGET	SE0000108656
301	TELEPERFORMANCE SE	FR0000051807
302	TELUS CORP	CA87971M1032
303	TERNA SPA	IT0003242622
304	TESCO PLC	GB00BLGZ9862
305	THALES SA	FR0000121329
306	TOKYO ELECTRON LTD.	JP3571400005
307	TOKYO GAS CO., LTD.	JP3573000001
308	TOKYU CORPORATION	JP3574200006
309	TORAY INDUSTRIES	JP3621000003
310	TOTALENERG	FR0000120271
311	TOURISM HOLDINGS LTD	NZHELE0001S9
312	TOURMALINE OIL CORP	CA89156V1067
313	TRANSURBAN CITY LINK	AU000000TCL6
314	TREND MICRO INCORP.	JP3637300009
315	UNIBAIL-RODAMCO	FR0013326246
316	UNILEVER PLC	GB00B10RZP78
317	UNITE GROUP PLC	GB0006928617
318	UNITEDHEALTH GROUP	US91324P1021
319	VECTOR LTD	NZVCTE0001S7
320	VEOLIA ENVIRONNEMENT	FR0000124141
321	VERIZON COMMUNICATNS	US92343V1044
322	VINCI	FR0000125486
323	VISA INC.	US92826C8394
324	VIVENDI SE	FR0000127771
325	VODAFONE GROUP PLC	GB00BH4HKS39
326	VOLKSWAGEN AG	DE0007664005
327	VOLVO AB	SE0016844831
328	VOLVO CAR AB	SE0000115446
329	WALGREENS BOOTS	US9314271084
330	WALMART INC	US9311421039
331	WALT DISNEY	US2546871060
332	WAREHOUSE GROUP LTD	NZWHSE0001S6
333	WASTE CONNECTIONS	CA94106B1013
334	WESFARMERS LIMITED	AU000000WES1
335	WEST JAPAN RAILWAY	JP3659000008
336	WHEATON PRECIOUS	CA9628791027

337	WISETECH GLOBAL	AU000000WTC3
338	WOODSIDE ENERGY	AU0000224040
339	WOOLWORTHS	AU000000WOW2
340	WSP GLOBAL INC	CA92938W2022
341	YAKULT HONSHA CO.	JP3931600005
342	YAMAHA CORP	JP3942600002
343	YAMAHA MOTOR CO.	JP3942800008
344	ZALANDO SE	DE000ZAL1111
345	ZEALAND PHARMA A/S	DK0060257814
346	ZOZO INC	JP3399310006

Appendix 2. XGBRegressor code.

```
Import xgboost as xgb

from sklearn.model_selection import train_test_split

from sklearn.metrics import mean_squared_error

X1 = df1[['ESG Score', 'Z score av', 'LEV', 'SIZE', 'CR', 'PROF',
'NDTS']]

y1 = df1['Z score']

X_train, X_test, y_train, y_test = train_test_split(X1, y1,
     test_size=0.2, random_state=42)

xgb_model = xgb.XGBRegressor(objective='reg:squarederror')

xgb_model.fit(X_train, y_train

y_pred = xgb_model.predict(X_test)

import xgboost as xgb

import matplotlib.pyplot as plt

xgb_model = xgb.XGBRegressor(objective='reg:squarederror')

xgb_model.fit(X_train, y_train)

xgb.plot_importance(xgb_model)

plt.show()
```

Appendix 3. DMatrix code.

```
import xgboost

import os

import pandas as pd

import matplotlib.pyplot as plt

y_df = df1['Z score']

x_df = df1[['ESG Score', 'Z score av', 'LEV', 'SIZE', 'CR', 'PROF',
     'NDTS']]

dtrain = xgboost.DMatrix(x_df, label=y_df)

b_rounds = 1500

subsample = 0.8

colsample_bytree = 0.8

from sklearn.model_selection import GridSearchCV

[i/5.0 for i in range(0,11)]

param_values     =     {'learning_rate':[i/10.0     for     i     in
     range(1,5)],'max_depth':range(1,5,1),

                 'gamma':[i/5.0          for          i          in
     range(0,5)],'min_child_weight':range(1,3,1)}

gsearch            =            GridSearchCV(estimator            =
     xgboost.XGBRegressor(n_estimators  =  b_rounds,  subsample  =
     subsample,                  colsample_bytree                  =
     colsample_bytree,objective='reg:squarederror',seed = 12),

                      n_jobs  =  -1,  param_grid  =  param_values,
     cv=5)

gsearch.param_grid

gsearch.fit(x_df,y_df)

gsearch.best_params_

gsearch.best_score_

b_rounds = 1500

m_depth = 4

eta = 0.1

ssample = 0.8

col_tree = 0.8
```

```
m_child_w = 2

gam = 0.6

param = {'max_depth': m_depth, 'eta': eta, 'subsample': ssample,
     'colsample_bytree': col_tree, 'min_child_weight' : m_child_w,
     'gamma' : gam}

dtrain = xgboost.DMatrix(x_df,y_df,nthread=-1)

bst_model = xgboost.train(param,dtrain,num_boost_round=b_rounds)

xgboost.plot_importance(bst_model,grid=False)
```