THE EFFECT OF ESG PERFORMANCE ON CREDIT RISK AMONG THE TOP 100 PUBLICLY LISTED COMPANIES IN ASIA

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BY

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A research project submitted in partial fulfilment of the requirement for the degree of

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DECLARATION

I hereby declare that:

(1) This undergraduate research project is the end result of my own work and that due acknowledgement has been given in the references to ALL sources of information be they printed, electronic, or personal.

(2) No portion of this research project has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.

(3) The word count of this research report is 23021 words.

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DEDICATION

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LIST OF ABBREVIATIONS

ESG	Environmental, Social, and Governance
E	Environment
S	Social
G	Governance
RES	Resource Use (Environmental Sub-Dimension)
EMIS	Emissions (Environmental Sub-Dimension)
INNOV	Innovation (Environmental Sub-Dimension)
WORK	Workforce (Social Sub-Dimension)
HUM	Human Rights (Social Sub-Dimension)
COMM	Community (Social Sub-Dimension)
PROD	Product Responsibility (Social Sub-Dimension)
MAN	Management (Governance Sub-Dimension)
SHAR	Shareholders (Governance Sub-Dimension)
CSR	Corporate Social Responsibility (Governance Sub-Dimension)
ICR	Interest Coverage Ratio
SDG	Sustainable Development Goals
FEM	Fixed Effect Model
Z-Score	A statistical measurement used for financial stability
GFC	Global Financial Crisis
LSEG	London Stock Exchange Group
PDS	Probability of Default
LGD	Loss Given Default
PD	Probability of Default
CDS	Credit Default Swap
D/E	Debt-to-Equity Ratio
EBIT	Earnings Before Interest and Taxes
EBITDA	Earnings Before Interest, Taxes, Depreciation, and Amortization

PREFACE

This thesis represents a personal journey that began my growing interest in how companies are integrating sustainability into their strategies, especially in the context of Asia's diverse markets. The idea of this research emerged from my academic background in finance and a desire to understand how ESG practices affect firms' credit risk.

While the process wasn't without challenges - from analyzing complex ESG data to navigating new territory in research - I'm incredibly grateful for the support of my supervisor, Dr. Lim Boon Keong, whose guidance was invaluable. I'm also thankful for my family, friends, and peers, whose encouragement kept me going during difficult moments.

This thesis reflects not just my academic work but the collective support and insights I've gained along the way. I hope the findings contribute to a better understanding of ESG's role in reducing credit risk, especially in today's rapidly changing world.

ABSTRACT

This thesis explores how Environmental, Social, and Governance (ESG) performance influences the financial stability and credit risk of the top 100 publicly listed companies in Asia between 2017 and 2024. As sustainability has become a central concern for businesses and investors, understanding whether ESG practices strengthen financial resilience has grown increasingly important, particularly when comparing developed and developing countries and considering the disruption caused by the COVID-19 pandemic.

The study draws on data from LSEG/Refinitiv and focuses on three key measures of credit risk: the Altman Z-score as an indicator of financial stability, the Interest Coverage Ratio (ICR) as a measure of debt-servicing capacity, and Credit Ratings (converted into a numerical scale) as a proxy for creditworthiness. Panel multiple linear regression models are employed, with both fixed and random effects specifications considered. The Hausman test is used to determine the appropriate estimator. Firm size and the SDG index are included as control variables, while country and pandemic dummies, together with interaction terms, capture variations across contexts and time periods.

The findings provide evidence that ESG performance can play a meaningful role in reducing credit risk and improving financial resilience. By highlighting differences between countries and before and after the pandemic, this research adds to the growing body of ESG literature and offers practical insights for investors, managers, and policymakers aiming to balance sustainability with financial performance.

CHAPTER 1: INTRODUCTION

1.1 Background of the Study

ESG ratings are intended analyze a company's ability to seek out and put effort into sustainable practices and policies (Postiglione et al, 2025). The term ESG itself was developed by twenty financial institutions in 2004 in response to request from Kofi Annan, the Secretary-General of the United Nations (Wong, 2023). The overall objective of incorporating ESG factors is to direct capital towards highest-performing companies that successfully reduce negative effects on society and the environment (Agosto et al., 2023).

Over the decade, the concept of ESG have shifted from consideration to a focus in both corporate strategy and investment decision-making (Wang, 2025). The growing awareness of critical issues like climate change, environmental damage, social inequality have highlighted the need for business to incorporate sustainable practices (Alam et al., 2022). From the investor's perspective, ESG factors are increasing integrated into their investment strategies, not only for ethical purposes but also due to they believe ESG can enhance portfolio performance, reduce risk, and generate long-term value (Lee et al., 2024). For companies, strong ESG performance can build reputation, foster trust with stakeholders, and obtain capital at a lower cost, thereby enhancing long-term sustainability (Brogi et al., 2022).

In recent years, there's been a clear trend toward stronger integration of Environmental, Social, and Governance (ESG) into credit risk assessments by major global credit rating agencies such as Moody's, S&P, and Fitch. ESG are now widely recognized as one of the essential elements in the credit rating methodologies of these agencies (Chen et al., 2025). This is due to companies experiencing ESG-related controversies can suffer regulatory penalties, operational disruptions, and reputational damage, all of which increase credit risk (Firmo, 2024). For instance, environmental fines, labour disputes, or governance failures can directly impact operational cash flows, thereby affecting creditworthiness and increasing default risk.

In Asia, firms are under growing pressure from international stakeholders and global supply chains to strengthen their ESG practices. For example, China has introduced green finance policies and the Belt and Road Initiative to push companies toward higher sustainability standards (Wang, 2025). Similarly, South Korea is addressing governance challenges in its chaebols while managing the environmental transition to a low-carbon economy (Seo et al., 2024). In Malaysia, the introduction of frameworks like the FTSE4Good Bursa Malaysia Index aims to align with global ESG standards, while in India, companies with stronger ESG performance are experiencing less financial distress (Alam et al., 2022). Despite this progress, ESG adoption remains uneven across sectors and countries, with industries such as airlines facing higher financial strain due to the heavy costs of environmental investments. These differences highlight that, although ESG is gaining ground in Asia, its role in shaping financial stability and credit risk is far from straightforward and deserves closer investigation.

The motivations for ESG adoptions are diverse and are well explained by the theories. Various companies adopt ESG practices to enhance their reputation, reduce risk exposure, and secure long-term resilience in a rapidly evolving business environment (Goss & Roberts, 2011). Regulators in advanced economies, such as the European Union, have also accelerated ESG adoption by imposing sustainability disclosure requirements and integrating ESG into financial regulation (Chen et al., 2025). ESG can also generate competitive advantages by fostering innovation, reducing costs, and enhanced attractiveness as an employer (Choi et al., 2024).

However, ESG implementation is not without barriers. The costs of sustainability initiative can be substantial, especially for firms in developing countries where financial resources and institutional support are limited (Farah et al., 2021). Methodological challenges, including varying measurement frameworks and information asymmetry, make it difficult to access genuine ESG performance and its impact on financial outcomes (Agosto et al., 2023). Additionally, firms often face short-term performance pressures that lead to prioritizing immediate profits over long-term ESG investments (Wang, 2025). In some cases, managers may engage in symbolic measures or disclose information without really improving performance, which can lead to greenwashing concerns that distort the real relationship between ESG and credit risk.

The rising importance of ESG has led to a crucial area of investigation: the relationship between ESG performance and credit risk which defined as the possibility that debtor fails to fulfill contractual debt requirements (Basel Committee on Banking Supervision, 2000). Credit risk commonly measured via both probability of default (PD) and loss given default (LGD), which come together to calculate the anticipated credit loss (Altman & Hotchkiss, 2010). The scope of credit risk assessment includes evaluating a firm's solvency, liquidity, and ability to service debt, using both qualitative and quantitative indicators. Common measures of credit risk includes credit ratings by agencies (e.g. Moody's, S&P, Fitch), and financial ratios like the Altman Z-score as bankruptcy prediction (Altman, 1968) and the interest coverage ratio, which measures a firms' capacity to meet interest payments from operating profits. Majority of the empirical studies claim an inverse relationship between ESG performance and credit risk (e.g. Zhou et al., 2025; Meles et al., 2023; Brogi et al., 2022; Agosto et al., 2023; Bruno & Henisz, 2024; Campanella et al., 2025). While few studies show a positive strength (e.g. Habermann & Fischer, 2021) or no relationship (e.g. Michalski & Low, 2024).

Incorporating ESG performance into credit risk models is critical due to the growing recognition that a company's sustainability practices can have a substantial effect on its capacity to pay debts and maintain financial stability. While ESG factors have been shown as a significant role in long-term business sustainability and risk management. A key challenge is the reliance on aggregated ESG scores, which simplifying the nature of sustainability. Aggregation can hinder the distinct impacts of ESG sub dimensions on credit risk, leading to inconclusive or contradictory results. Empirical findings in Asia remain fragmented, with study in Korea suggesting a strong environmental influence on financial stability (Choi et al., 2024), while in Malaysia results appear mixed or significant (i.e. Alam et al., 2022).

This indicates the need to examine ESG pillar and sub-dimensions more systematically to identify which elements are most vital for credit risk. A deeper exploration of ESG pillar and sub-dimensions necessary because relying solely on aggregate ESG scores can obscure complex, nuanced, and even contradictory effects (Seefloth et al., 2025). Aggregating performance often hides the fact that different components contribute differently to financial outcomes and risk mitigation (Habermann & Fischer, 2021). Disaggregated analysis is essential for company strategy and risk modelling since it helps identify the actual factor (such as environmental innovation over overall environmental spend) that really improve creditworthiness.

In addition, the disparity between developed and developing countries remain unexplored. The global ESG-credit risk relationship is strongly shaped by institutional, cultural, and regulatory contexts, which often vary significantly across economies. In advanced economies, governance factors are found to be more likely to influence creditworthiness; while in developing countries, environmental and social factors may be more material due to agricultural dependence, social development priorities, or weaker institutional framework (Pineau et al., 2022). Furthermore, the maturity of ESG adoption in developing economies is still evolving, with firms facing higher costs, limited financing options, and weaker investor demand for ESG-aligned practices (Broadstock et al., 2021). These differences suggest that ESG factors may have divergent effects on credit risk depending on whether firms operate in developed or developing markets.

Also, the COVID-19 pandemic triggered an unexpected global crisis, impacting economies, industries, and companies across the world. With the lockdowns, disrupted supply chains, economic recessions, businesses faced extreme challenges that tested their financial stability (Shi et al., 2023). It was necessary of considering the difference between pre and post pandemic periods when studying the relationship between ESG performance and credit risk primarily from the observation that economic cycles fundamentally alter the magnitude and direction of ESG's financial impact (Habermann & Fischer, 2021).

1.2 Problem Statement

Many firms still do not view ESG as a strategy for risk management, despite increasing global attention on their importance. This scepticism is arises from divergent theoretical viewpoints and actual results about the relationship between ESG and credit risk. While a significant body of research suggests that strong ESG practices can help mitigate risks and improve financial stability, other asserted that ESG investments may lead to unnecessary costs, increased financial distress, or diminished returns (Nguyen & Nguyen, 2021). Not to mention, the existing literature remains disproportionately focused on developed Western economies, with relatively few studies addressing the Asian context. For example, in a global sample of 3,331 firms, Asia accounted for only 534 (16%), compared with 1,635 firms from the Americas (49%) and 679 from Europe (20%). Similarly, U.S. and European studies often analyse thousands of firm-year observations, while Asian subsamples are comparatively much smaller, highlighting the region's underrepresentation (Brogi et al., 2022).

This creates a knowledge gap, as Asia presents unique regulatory environments, cultural settings, and market dynamics that may shape how ESG performance influences credit risk. For example, while some studies recommend that ESG practices can reduce credit risk through improved risk management and stakeholder trust, others highlight potential drawbacks, such as the higher costs of sustainability initiatives leading to increased financial strain. These mixed findings underscore the need for more systematic analysis of the ESG and credit risk relationship in Asia. In order to overcome the gap, this study investigates how overall ESG performance affects the credit risk of Asia's top publicly listed companies. By focusing on this region, the research provides timely insights for investors, policymakers, and other stakeholders to understand whether ESG practices enhance financial stability in diverse institutional and regulatory contexts.

Second, many existing literatures continues to evaluate ESG as an aggregated score, overlooking the distinct effects of its individual components. Over relying solely on a company's overall ESG performance may not fully reflects how different aspects of sustainability actually affect its credit risk. This is due to different ESG pillar and sub-dimensions can actually impact credit risk differently. This approach creates a knowledge gap because it assumes equal importance across all ESG pillars, even there is evidence that their effects on credit risk may differ**.** For example, a previous study discovered that the effect of each ESG sub-dimension on credit risk isn't equal, with specific dimensions like climate change, resource use, human capital and corporate governance showing risk reduction effects, while other dimensions had insignificant effects (Razak et al., 2020). Therefore, this study address the gap by examining the effect of ESG pillar and ten sub-dimensions on credit risk among top publicly listed companies in Asia to provide more insights on which dimension truly matter for credit risk.

Thirdly, the relationship between ESG performance and credit risk remains inconclusive, possibly due to varying economic, regulatory environments across developed and emerging markets (Verma and Mukhtaruddin, 2023 ; Postiglione et al., 2025). Empirical evidence in Asia show the mixed results regarding the ESG-credit risk relationship. Several studies have reported a negative association, suggesting that stronger ESG practices contribute to reduced credit risk through improved risk management and stakeholder trust (Campanella et al., 2025; Choi et al., 2024). Conversely, other studies have identified a positive association, indicating that ESG adoption may increase credit risk due to higher capital expenditures and operational costs linked to sustainability initiatives (Farah et al., 2021; Habermann & Fischer, 2023). Additionally, there is research has found no statistically significant relationship between ESG factors and credit risk (Veltri et al., 2023). Furthermore, most prior studies focus on either developed or emerging markets, or treat the markets as homogeneous. Therefore, this study aims to examine whether there is any difference in ESG (overall, pillars, and sub-dimensions and credit risk between companies in different countries development level.

Lastly, a limited studies focused on defining the association of ESG and credit risk that compares the pre and post pandemic period. Research has shown that external shocks, such as Global Financial Crisis (GFC), can significantly affect how effective ESG factors are in managing credit risk (Lee et al., 2024). With the disruption caused by the COVID-19 pandemic, it raising question about whether ESG performance still helps reduce risk during such dramatic market shifts. Most existing studies haven't fully examined how the association between ESG and credit risk differs before and after the pandemic, leaving a gap in understanding. Therefore, this study aims to examine whether the association between ESG (overall, pillars, and sub-dimensions) and credit risk differs between pre and post-pandemic periods.

1.3 Research Objectives

This study aims to explore the relationship between ESG performance and credit risk among the top 100 publicly listed companies in Asia. Specifically, it seeks to:

(1) To assess the effect of overall ESG performance on the credit risk of the top 100 publicly listed companies in Asia, measured by Altman Z-Score, Interest Coverage Ratio (ICR), and Credit Ratings.

(2) To assess the effect of Environmental (E), Social (S), and Governance (G) pillars on the credit risk of the top 100 publicly listed companies in Asia, , measured by Altman Z-Score, Interest Coverage Ratio (ICR), and Credit Ratings.

(3) To assess the effect of ESG 10 sub-dimensions on the credit risk of the top 100 publicly listed companies in Asia, , measured by Altman Z-Score, Interest Coverage Ratio (ICR), and Credit Ratings.

(4) To examine whether the relationship between ESG (overall, pillars, and sub-dimensions) and credit risk differs across countries with different developing levels.

(5) To examine whether the relationship between ESG (overall, pillars, and sub-dimensions) and credit risk differs between pre and post-pandemic periods.

1.4 Research Questions

This study aims the address the following research questions:

(1) What is the effect of overall ESG performance on firms' credit risk, as measured by Altman Z-Score, Interest Coverage Ratio (ICR), and Credit Ratings?

(2) What is the effect of the Environmental (E), Social (S), and Governance (G) pillars on the credit risk of the top 100 publicly listed companies in Asia, as measured by the Altman Z-Score, Interest Coverage Ratio (ICR), and Credit Ratings?

(3) What is the effect of the 10 ESG sub-dimensions on the credit risk of the top 100 publicly listed companies in Asia, as measured by the Altman Z-Score, Interest Coverage Ratio (ICR), and Credit Ratings?

(4) Does the relationship between ESG (overall, pillars and its ten sub-dimensions) and credit risk differ between companies in developed and developing Asian countries?

(5) Does the relationship between ESG (overall, pillars and its ten sub-dimensions) and credit risk differ between pre and post-pandemic periods?

1.5 Significance of the Study

The results of the present literature have several important implications for empirical development, policy implementation, and practical uses.

First, in terms of theoretical and empirical contributions, this study enriches the academic literature on ESG and credit risk by focusing on Asia, a region underrepresented in prior research. While most previous studies emphasize developed Western economies, this research provides new evidence from both developed and developing Asian markets. Furthermore, by disaggregating ESG into ten sub-dimensions, the study advances theory by identifying which specific aspects of sustainability—such as emissions, workforce, human rights, or corporate governance—are most influential in shaping firms' credit risk. This contributes to a more thorough comprehension of how ESG operates beyond aggregate scores, offering pathways for future research to refine credit risk models incorporating ESG.

Second, from the perspective of policy implementation, the findings offer important insights for regulators and policymakers. If ESG is found to significantly reduce credit risk, particularly in developing countries, it supports the case for stronger ESG reporting requirements and sustainability-related regulatory frameworks. Governments may use the findings to design policies that incentivize firms to improve ESG performance, thereby enhancing overall financial stability. For example, regulators such as the Securities Commission Malaysia or the Monetary Authority of Singapore could integrate ESG performance into credit assessments, while governments may encourage adoption through tax benefits, preferential lending, or subsidies that reward firms with strong ESG practices.

Third, in terms of practical implications, the results offer insightful information for firm managers, investors, and stakeholders. For managers, understanding which ESG sub-dimensions have the strongest effect on credit risk allows for more strategic allocation of resources for ESG initiative. For investors and shareholders, the study provides useful evidence to incorporate ESG into risk assessment and portfolio design, enabling informed decisions. Finally, for broader stakeholders such as employees, customers, and communities, the study highlights how ESG practices help companies stay financially strong, sustainable, and better prepared for risks and crises.

1.6 Scope of the Study

The present study attempts to examine the effect of ESG performance on credit risk among the top 100 publicly listed companies in Asia, with a focus on both aggregated ESG and its 10 sub-dimensions scores. A distinctive contribution of this study lies in investigating how ESG factors individually and collectively influence firms' credit risk exposure, as well as whether these relationships differ between firms in developed and developing Asian countries. The sample consists of the 100 largest companies by market capitalization across Asia.

Financial institutions are excluded because their balance sheets, capital structures, and risk exposures are differ from non-financial firms. Banks and insurance companies are subject to strict regulatory frameworks that directly influence their credit risk measures. In addition, their ESG disclosure practices often follow different reporting standards, making them less comparable to industrial and service sector firms. Excluding financial firms therefore ensures greater consistency and comparability across the sample.

The study covers an eight-year period from 2017-2024. This timeframe is appropriate as it captures two distinct phases: (i) the pre-pandemic period which representing stable market conditions, and (ii) the post-pandemic period which including the pandemic years and the subsequent recovery phase. By spanning these two phases, the study provide valuable information into how ESG performance interacts with credit risk before and after the pandemic.

Both ESG scores and sub-dimensions and financial data for credit risk proxies are collected from Refinitiv Eikon / LSEG. Credit risk is measured using both market-based indicators, such as credit ratings and Altman Z-scores, and accounting-based indicators, such as interest coverage ratio.

1.7 Limitations of the Study

While this study offer insightful information, there' are limitations ought to be recognized.

First, the analysis depends only on Refinitiv for ESG data. Different databases often use their own scoring methods and disclosure frameworks, so results might vary if another source were used. The findings should therefore be read in the context of Refinitiv's approach rather than as a universal measure of ESG performance.

Second, there's a potential endogeneity concern in the relationship between ESG and credit risk. Firms with stronger ESG practices may indeed face lower credit risk, but it is equally possible that companies with stronger financial positions and lower risk profiles have more resources to invest in ESG activities. This makes it difficult to untangle whether ESG drives risk reduction or whether financially sound firms simply appear more sustainable. Although this study does not fully resolve this issue, future work could apply robustness checks—such as lagging ESG variables, testing alternative model specifications, or using instrumental variables—to help reduce this bias.

Third, the measures of credit risk applied here—Altman Z-Score, Interest Coverage Ratio, and credit ratings—are widely used but still limited. They cannot fully capture the complexity of credit risk in practice, especially when unexpected shocks, regulatory shifts, or global economic disruptions affect firms in ways beyond what the models reflect.

1.8 Organization of the Thesis

This thesis structured into five chapters to guide reader through the theoretical background, empirical analysis, implications of the study.

Chapter 1 mainly presents the research motivation, outline the central questions concerning the relationship between ESG performance and credit risk. Chapter 2 reviews the existing body of work on ESG performance, credit risk. It also highlighted key theoretical perspectives - such as Stakeholder, Agency and Institutional Theory that linked ESG and credit risk, and synthesized prior findings on overall ESG scores, pillar-level effects, and 10 sub-dimensions. This chapter also establishes the research gaps that this thesis addresses.

Chapter 3 will be described the dataset, variable construction, and sample selection procedures. It explains the measures used for ESG performance and credit risk, and introduces the statistical models employed in the analysis- including interaction terms that capture difference between country development levels and pre vs post pandemic periods.

Chapter 4 presents the results and findings, beginning with the descriptive analysis, followed by diagnostic test results and lastly regression results. The final chapter further explained on the findings in Chapter 4 in details, summarized the key findings and reflects on their theoretical and practical implications for firms, investors, and managers. It also discusses the study's weaknesses and makes suggestions for later research.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter provides a literature review on ESG practices and their relationship with firms' credit risk. It begins by discussing the transformation of corporate social responsibility (CSR) into the broader ESG framework and the theoretical foundations underpinning ESG practices. The chapter then reviews empirical studies on ESG, its 10 sub-dimensions, and their effects on firm outcomes, with a particular focus on credit risk. Attention is also given to differences in ESG practices between developed and developing countries, including challenges such as weak standardization and disclosure.

Importantly, the review is structured to address the key research gaps identified in the problem statement. Specifically, it highlights the scarcity of Asian-focused studies, the tendency of prior research to rely on aggregate ESG scores rather than sub-dimensions, and the lack of comparative analysis between developed and developing markets. By doing so, the review not only synthesizes existing knowledge but also demonstrates where further empirical work is needed, thereby justifying the focus of this study. To ensure a comprehensive and balanced review, relevant studies were identified through databases such as Scopus, Web of Science, and Google Scholar, using terms including *ESG, CSR, credit risk, credit ratings, Altman Z-score, interest coverage ratio, emerging markets,* and *Asia*.

Finally, the chapter concludes by identifying the remaining gaps in the literature and presenting the conceptual framework and hypotheses that guide this study.

2.2 The concept of ESG and Credit Risk

Credit risk refers to the possibility that a borrower will default on its financial commitments, which may result in potential losses for lenders or investors. Traditionally, it has been measured using financial ratios, credit ratings, and market-based indicators, but in recent decades, attention has expanded to non-financial factors such as ESG practices.

The concept of ESG has its origins in the broader idea of Corporate Social Responsibility (CSR). In the 1930s, debates about corporate responsibility centered on whether businesses should protect the interests of employees and customers, even if it limits the owners' profits (Berle, 1931). From the early 1970s, there was a growing interest in the association between corporate survival, firm risk, and social responsibility (Shi et al., 2023). Firms started to face increasing pressure to conduct business sustainably.

Public mistrust about shareholder primacy's effectiveness was further triggered by scandals such as the Enron accounting fraud (2001), the subprime mortgage financial crisis (2008), and the BP Deepwater Horizon oil spill (2010), which drew attention to firms' responsibility to their stakeholders and CSR practices (Shin et al., 2021). Institutional investors began taking a more active role in corporate governance, partly because of rules like the USA's ERISA, which requires them to vote responsibly. Regulators also shaped corporate governance worldwide, particularly during privatization efforts. For example, the UK's Cadbury Report (1992) and the OECD Principles of Corporate Governance (1999) helped establish governance codes and guide legal reforms (Becht, 2005).

Whilst ESG is often considered an evolution of CSR, it provides a more structured framework to assess sustainability performance across specific environmental, social, and governance factors (Khalid, 2021). The term "ESG" itself was developed by twenty financial institutions in a 2004 research in response to a request from the United Nations Secretary-General, Kofi Anna (Gillan et al, 2021).

As time goes by, ESG has rapidly evolved from a niche concern to a mainstream business activity. It is now recognized as a major element in evaluating creditworthiness and a crucial component of competitive strategy for businesses (Kitzmueller and Shimshack, 2012; Wong, 2021). It is evident that investors are incorporating ESG more and more into their investment plans, recognizing its potential to identify resilient companies with lower operational risks, better management, and stronger innovation capabilities, leading to better long-term financial prospects (Kaminskyi et al., 2025).

Initially, ESG reporting was largely voluntary. However, particularly in European Union, there has been a shift towards mandatory ESG disclosure requirements (Chen et al., 2025). Directives like Corporate Sustainability Reporting Directive (CSRD), adopted in 2023, have expanded the scope and reporting obligations, requiring all large companies and listed companies to disclose detailed non-financial information (Chodnicka-Jaworska, 2021). The push for regulatory frameworks and standardized ESG reporting aims to enhance transparency and accountability within financial systems. Greater transparency from companies about their ESG practices help investors, creditors, and regulators make informed decisions and better assess evolving risks.

2.2.1 Characteristic of ESG

ESG factors are benchmarks used to evaluate a company’s operations based on its impact on the environments, social responsibility toward various stakeholders, and quality of its corporate governance (Meles et al., 2023). ESG is widely recognized as a method to assess the sustainability practices of corporations. Building on the idea of CSR, ESG is the newest concept used to assess their non-financial performance (Wong, 2021). ESG offers insights beyond conventional financial measurements by representing a company's non-financial performance and risk exposure associated with sustainability (Kiesel & Lücke, 2019).

ESG and CSR share the common objective of promoting sustainability and responsible corporate behaviour by integrating non-financial concerns—environmental, social, and governance—into business practices (Wong, 2023). CSR reflects a company's broader ethical and social commitments, while ESG provides a structured, measurable framework to evaluate how well those commitments are implemented and how they impact financial performance (Meles et al., 2023). In this sense, ESG can be seen as an evolution of CSR, translating its principles into quantifiable standards that are especially relevant for investors and regulators.

2.2.2 Environmental Dimension

The Environmental (E) dimension evaluates how a business affects ecosystems, air, land, and water. It demonstrates how effectively a business can implement best management practices to lower environmental risks and seize environmental opportunities in order to eventually boost shareholder value. Key sub-dimensions include resource use, emissions, innovation.

Resource use measures a company's ability to identify environmentally friendly ways through better supply chain management and to use less energy, water, or materials (Chodnicka-Jaworska, 2021). Businesses that strive to minimize waste production and implement sustainable resource management typically receive higher ratings (Qin et al., 2019).

Emissions, which cover various type of emissions, including carbon emissions (Scope 1,2 and 3), greenhouse gas emissions, and climate change risk (Bonacorsi et al., 2024). Lins et al. (2021) found that firms that reducing emissions can benefit the environment yet enhance financial performance. However, initiative to reduce environmental risks, such as emission reductions, can increase the possibility of financial distress in the short term, potentially resulting from long-term investment costs associated with green transition (Bonacorsi et al., 2024).

Innovation, which measures company's ability to invest in environmentally friendly research and development. Companies' efforts in environmental R&D spending are measured to capture their commitment to developing friendly products or services that reduce emissions and resource consumption. The development of clean energy technologies—such as wind, solar, hydro, geothermal, and biomass power, that assist businesses in making the shift to more environmentally friendly operations is a key area of environmental innovation (Liang & Renneboog, 2017).

Measuring the Environmental (E) dimension of ESG remains difficult due to the absence of standardization, limited data availability, and concerns over reporting credibility. ESG ratings often diverge across providers, and corporate environmental reporting may not accurately reflect actual performance, as disclosure practices are highly variable and sometimes symbolic rather than substantive. Data limitations—such as scarce non-financial reporting, reliance on qualitative rather than quantitative measures, and a heavy focus on developed-country samples—further constrain comparability and generalizability. These challenges, compounded by the risk of greenwashing and the broad, loosely defined notion of "environmental impact," highlight the need for more consistent, transparent, and reliable approaches to assessing environmental performance in ESG research (Eliwa et al., 2021).

2.2.3 Social Dimension

The Social (S) dimensions addresses a company's relationships with its employee, customers, suppliers, and the communities (Esteban-Sanchez et al., 2017).

The workforce sub-dimension evaluates how companies manage their employees to promote satisfaction, diversity, equality, and professional development (Bonacorsi et al., 2024). It includes fair labour practices, health and safety, training, employee benefits, and policies that encourage workforce diversity and reduce the gender gap. Firms that invest in skilled employees, maintain a diverse workforce, and uphold strong labour standards tend to experience better financial performance and reduced credit risk (Pandey, 2020; Bonacorsi et al., 2024). A good management of staff lowers operational and reputational risks, fosters stakeholder trust, and increases productivity.

The human rights sub-dimension examines a company's adherence to ethical labour and social practices, focusing on preventing human trafficking, forced labour, child labour, and other violations. Firms that fail to respect human rights risk legal sanctions, reputational damage, and financial losses. (Wong, 2021). Therefore, maintaining stakeholder relations and long-term company survival depend on ensuring human rights compliance. Businesses more likely able reduce risks and improve overall organizational resilience when they actively monitor and implement human rights standards throughout their supply chains and operations.

The product responsibility sub-dimension evaluates how companies ensure the safety, quality, and ethical integrity of their products and services. This includes chemical safety, privacy and data security, fair trade practices, and management of genetically modified products (Liang & Renneboog, 2017). Strong product responsibility policies protect consumers, reduce liability risks, and enhance corporate reputation. Firms that prioritize product quality and customer safety are less likely to face legal actions, or reputational damage, which in turn lowers operational and financial risk.

Findings from Asia are mixed. Studies in Korea and India show that social performance enhances financial stability, but evidence from Malaysia and the Asia–Pacific airline industry suggests weaker or even adverse effects, with social initiatives sometimes raising financial distress risk. These regional differences suggest that cultural norms, regulatory enforcement, and institutional maturity affect how the Social pillar influences credit risk.

Ethical considerations further complicate the role of the Social dimension. Substantive engagement in workforce well-being, human rights, and community relations generates “moral capital,” which acts as an insurance mechanism in times of crisis, such as the COVID-19 pandemic. However, the “overinvestment view” warns that costly social initiatives—such as extensive workplace safety programs or community projects—can strain resources, reduce competitiveness, and increase bankruptcy likelihood. Moreover, firms may adopt symbolic disclosure or “greenwashing,” reporting extensively on social initiatives without meaningful changes in practice. Such behaviour undermines stakeholder trust and can backfire through reputational damage, increasing financial risk.

2.2.4 Governance dimension

The Governance (G) dimension assesses the internal systems and procedures that guarantee a company's executives and board members operate in the best interests of its long-term shareholders and other stakeholders (Habermann & Fischer, 2021). With an emphasis on board composition, structure, and functions as well as executive remuneration, it includes both formal and informal methods and procedures (Esteban-Sanchez et al., 2017).

Formal governance refers to the codified rules, structures, and systems that regulate how firms are directed and controlled (LIANG & RENNEBOOG, 2017). These include board composition, executive pay policies, shareholder rights, risk management frameworks, and compliance mechanisms. Such mechanisms are measurable, rules-based, and enforceable through legal or regulatory frameworks, ensuring that managers act in the long-term interests of shareholders and other stakeholders.

Informal governance, by contrast, reflects the norms, culture, values, and relationships that shape decision-making beyond formal rules (Altman & Hotchkiss, n.d.). This includes leadership quality, trust, reputation, and societal expectations, which influence how governance structures are applied in practice. While Civil Law countries tend to rely more on formal rules and state intervention, Common Law systems emphasize discretion, reputation, and ex post accountability. For ESG and credit risk, both forms of governance matter: formal mechanisms establish accountability and reduce misconduct risk, while informal mechanisms such as ethical culture and managerial quality determine whether governance translates into sustainable performance or degenerates into symbolic compliance and greenwashing.

Management quality is critical components of the Governance dimensions. This focuses on how well a company's policies and processes ensure that its executives and board members act in the long-term best interests of its shareholders (Chodnicka-Jaworska, 2021). A firm’s performance is seen to be largely dependent on its management practices, and good governance makes sure that management choices put the interests of all stakeholders first (Wong, 2021). It has been demonstrated that managerial skill amplifies the favourable correlation between credit ratings and ESG performance (Yusupova et al., 2025). A firm's financial stability may be enhanced by competent managers who can lessen the influence of credit-related risk factors. The quality of the management team is also seen to be crucial to credit ratings (Bonsall et al., 2017). Board diversity, independence ratios, CEO remuneration measures, risk management frameworks, and audit and compliance procedures are all included in the "management score" of ESG ratings (Wong, 2021).

Shareholder is another key focus of the Governance pillar. The basic rights of shareholders include the ability to vote on CEO compensation packages, elect board members, approve major acts like mergers and acquisitions, and influence corporate decisions. Strong shareholder rights are linked to improved company performance and a decreased risk of misbehaviour and fraud (Becht et al., 2005). In particular, an ESG "shareholder score" assesses these clauses, voting procedures, proxy access guidelines, engagement strategies, and governance information dissemination.

CSR strategy is viewed as an integrated approach that seeks to build partnerships with several stakeholders while balancing social, environmental, and economic goals (SAIDANE & ABDALLAH, 2021). The "business case for CSR" asserts that via enhancing market position, reputation, and maybe creating new opportunities for development and profitability, well-managed CSR can increase value, sustainability, and competitiveness (Esteban-Sanchez et al., 2017). A strong Corporate Social Responsibility (CSR) strategy helps improve credit rating predictability because companies that actively practice CSR are usually more resilient during crises and face less overall financial and market risk (Michalski & Low, 2024). An ESG "CSR strategy score" specifically assesses policies, commitments, board oversight of CSR, stakeholder engagement mechanisms, and the quality of CSR reporting.

2.3 Theories

2.3.1 Stakeholder Theory

Stakeholder theory, initially conceptualized by Freeman in 1984, suggests that a firm's long-term success and sustainability are not only dependent on maximizing the shareholder wealth, but rather on managing good relationships with different stakeholders. These stakeholders include investors, employees, customers, suppliers, creditors, local communities, and the environment (Mahajan et al., 2023). This theoretical framework directly underpins the integration of ESG into corporate strategy. By engaging in responsible environmental and social practices and maintaining sound governance, firm can cultivate stronger relationships with stakeholders, thereby enhancing their reputation (Seefloth et al., 2025).

The connection between stakeholder theory, ESG, and credit risk is primarily explained through the risk mitigation view, which suggests that superior ESG practices reduce financial distress risk (FDR) and default risk (Abdul Razak et al., 2020). Strong ESG performance, indicative of robust stakeholder relationships, can lead to lower borrowing costs and more favourable financing terms for companies, as it reduces perceived uncertainly for lenders and investors (Zhou et al., 2025). This is reflected in enhanced credit ratings, with major agencies increasingly incorporating ESG factors into their assessments, recognizing their influence on a borrower's cash flows and default likelihood. For instance, environmental factors have been consistently found to have a positive and significant influence on credit ratings (Lee et al., 2024). In addition, firms with strong ESG practices often more stable during economic crises, acting as an "insurance-like" buffer against unfavourable events, as stakeholders are more likely to offer support (Shi et al., 2023). However, the relationship is not always straightforward; some studies, aligning with an "overinvestment view", suggest that substantial ESG investments might increase credit risk due to high costs

2.3.2 Agency Theory

Agency theory, established by Jensen and Meckling (1976), defines the relationship between a firm's principals (shareholders) and their agents (managers), focusing on potential conflicts of interest that can arise between them (Yusupova et al., 2025). Conflicts of interest arise when managers, as agents, pursue their self-interest rather than the shareholder or creditor benefits (Wang, 2025). From agency theory perspective, ESG initiatives can be viewed as "additional costs" or "misallocation of scarce resources". Managers might pursue these initiatives not solely for the firm's financial benefit, but due to external pressures from non-investor outsiders, their personal preferences, or for personal gains, which potentially diverges from the goal of maximizing shareholder wealth (Habermann & Fischer, 2021). This can lead to "overinvestment" in ESG activities, which may lead to lower profitability, reduced cash flows, and consequently, increased firm credit risk. This is due to such overinvestment may impose tangible costs on firms: for example, large-scale capital expenditures for green technologies, expensive compliance with environmental regulations, or philanthropic programs that drain cash flows.

The relationship between ESG and credit risk, viewed by agency theory, presents a dual impact. While excessive ESG can arise agency problems by draining resources, good governance ("G" in ESG) can actually help align interests and reduce credit risk. Strong corporate governance practices can be consistently linked to higher credit ratings, as they promote transparency and effective decision-making (Eliwa et al., 2021). From a creditor's viewpoints, ESG is increasingly seen as a crucial tool for risk assessment, offering an opportunity to identify resilient borrowers and contribute to sustainable lending practices (Veltri et al., 2023). Yet, the empirical findings are quite mixed. For example, a study found that stronger environmental and social activities in European firms sometimes correlated with deteriorated credit ratings, supporting agency-cost interpretation (Bannier et al., 2022). While other researches have indicated that ESG can increase credit risk (i.e.

Seefloth et al., 2025) or show no significant association at all (i.e. Veltri et al., 2023).

2.3.3 Institutional Theory

Institutional theory, notably articulated by scholars like DiMaggio & Powell (1983) and referenced by Campbell (2007) provided a framework to explain why organizations conform to external rules and norms. This theory posits that organizations align their structures, behaviors, and processes with external rules, norms, laws, and best practices to gain and maintain legitimacy within their operating context (Eliwa et al., 2021). These institutional pressures can be coercive, stemming from formal regulations and laws (e.g., climate disclosure rules, UN 2030 Agenda for Sustainable Development); normative, arising from professional standards, industry benchmarks, and expert expectations; and mimetic, where organizations copy peers perceived as more legitimate or successful (Wong, 2023). Consequently, organizations integrate ESG practices as an "embedded social phenomenon" to align with these broader institutional demands, ensuring their reputation, business viability, and social acceptance.

Most studies have found that compliance with institutional pressures, such as increasingly stringent ESG regulations (coercive pressure) and industry practices (normative pressure), can reduce a firm's exposure to fines, legal risks, or exclusion from capital markets, thereby lowering credit risk, thus supporting institutional theory (e.g., Zhou et al., 2025; Bertelli et al., 2025; Farah et al., 2021). However, a negative link emerges if compliance with ESG initiatives requires high costs, or if the engagement is perceived as insincere, potentially weakening financial performance, reducing liquidity, and raising credit risk (Seefloth et al., 2025). A neutral outcome suggests that the impact of ESG on credit risk is highly variable: in weak institutional environments characterized by low regulations or limited ESG awareness; thus, ESG might have little to no bearing on credit risk (Bannier et al., 2022).

The Asian context offers clear examples of how coercive institutional mechanisms shape ESG adoption. In Korea, continuous governance reforms since the 2000s have sought to restructure chaebols and improve transparency in financial institutions, reflecting pressures from G20 guidelines and global competitiveness goals (Seo et al., 2024). In China, regulatory interventions such as green finance policies and requirements for digital governance demonstrate coercive pressures, as firms are compelled to adopt formal structures to mitigate risks of false disclosure and financial misconduct. Beyond domestic regulation, Asian firms also face coercive pressure from international standards, such as the EU's Corporate Sustainability Reporting Directive (CSRD), which indirectly forces companies to expand ESG disclosures to maintain legitimacy and access to global capital markets (Chodnicka-Jaworska, 2021). These examples highlight how coercive institutional mechanisms shape corporate ESG practices across the region.

To conclude, this theory explain that firms implement ESG practices in order to adhere to external pressures, which can reduce credit risk by enhancing legitimacy and minimizing regulatory exposure. Yet, ESG may instead increase risk when compliance is costly, while the effect may be minimal in weak institution environments.

2.4 Empirical Literature Review and Identification of Gaps

2.4.1 ESG and firms' credit risk

The relationship between ESG and credit risk have drawn increasingly scholarly attention in recent as creditors frequently incorporate sustainability considerations into their risk assessments. The main goal of thid literature review is to evaluate existing empirical findings on the relationship between ESG and credit risk. Many of the previous literatures studied the relationship between ESG and firm's credit risk by measuring their financial distress scores (i.e. Altman Z-score, Ohlson O-score, and Zmijewski X-score), market-based default probabilities (i.e. Merton's Distance to Default (MDD), Probability of Default (PD), and Credit Default Swaps (DFS)) or agency-issued credit ratings (i.e. Moody's, S&P, Fitch, and Bloomberg). Collectively, these measures demonstrates how ESG influence firms' credit risks. Based on Table 1, prior studies have reported mix evidence, with some finding that ESG reduces credit risk, others suggesting ESG may increase credit risk, and yet others reporting no significant relationship.

Several factors explain why prior studies report conflicting results on the relationship between ESG and credit risk. One of the reasons is the lack of standardization in ESG scores provided by various agencies, such as Bloomberg, Refinitiv, S&P, and MSCI (Agosto et al., 2023). These providers often use distinct methodologies and scopes, leading to inconsistency about a company's true ESG standing (LI et al., 2024). From another point of view, previous researchers used different proxies to measure credit risk, including the Altman Z-Score, Merton Distance to Default (MDD), Credit Default Swap (CDS) spreads, Probability of Default (PD), and credit ratings. There is disagreement on the causal relationship as well, with studies questioning if ESG affects credit risk or vice-versa

(Postiglione et al., 2025). Geographical differences across regions like Western versus Asian markets, or even within Europe, play a significant role due to variations in regulatory standards, disclosure requirements, and cultural priorities regarding ESG (Liang & Renneboog, 2017; Hail & Leuz, 2006).

The conflicting results across prior studies highlight two important research gaps. First, most of existing empirical evidence on ESG and credit risk has focused heavily on firms in Europe and the United States (e.g. Postiglione et al., 2025; Agosto et al., 2023; Seefloth et al., 2025), while Asian firms remain underexplored despite their distinct ESG dynamics, regulatory environments, and market structures. This lack of region-specific evidence makes it difficult to accurately evaluate the impact of ESG on creditworthiness in Asia, potentially limiting firms' access to sustainable financing. Second, prior research tends to rely on single proxies of credit risk, such as agency-issued ratings (Chen et al., 2025; Yusupova et al., 2025) or financial-based indicators like the Altman Z-score or Merton's Distance-to-Default (Postiglione et al., 2025; Bertelli et al., 2025; Meles et al., 2023). This fragmented approach restricts a holistic understanding of the ESG–credit risk relationship, as each proxy captures only part of the risk dimension. To address these gaps, the present study focuses on the top 100 publicly listed companies in Asia and adopts a comprehensive, multi-dimensional credit risk framework by integrating Credit Ratings, Altman Z-score, and Interest Coverage Ratio, thereby providing both a long-term and short-term perspective on firms' creditworthiness.

Based on above, which highlights the inconsistencies in prior research, the significant under-exploration of Asian market, and the limitations of single-proxy credit risk measures, we can therefore hypothesize that:

H1: Higher ESG performance will reduce firms' credit risk.

Table 1: Literature on the relationship between ESG and credit risk

Author	ESG measures	Credit risk measures	Country	Relationship
Postiglione, M., Carini, C., & Falini, A. (2025).	Aggregate ESG score	Altman Z-Score (Z-Score) & Merton Distance to Default (MDD)	Europe	Mixed relationship
Agosto, A., Cerchiello, P., & Giudici, P. (2023).	MSCI ESG score, Refinitiv ESG score, S&P Global ESG rank	Bloomberg credit ratings	Europe	Negative relationship
Seefloth, M., Siedler, F., Kayser, C., Retsch, B. T., & Zülch, H. (2025)	ESG score	Altman Z-score, Ohlson O-score, Zmikewski X-score	Europe	Positive relationship
Bannier, C. E., Bofinger, Y., & Rock, B. (2022)	ESG score	Credit default swap(CDS), Distance to default (DTD), Probability of Default (PD)	U.S and Europe	Mixed relationship
Michalski, L., & Low, R. K. Y. (2024)	ESG variables	S&P long- term issuer credit rating	Global	Negative relationship
Cubas-Díaz, M., & Martínez	ESG scores	S&P and Fitch credit ratings	Global	Mixed relationship

Sedano, M. Á. (2018)				
Stefania Veltri, Maria Elena Bruni, Gianpaolo Iazzolino, Donato Morea, Giovanni Baldissarro (2023)	ESG factors	Total debt, Profitability of Default (PD), and credit ratings	Europe	No relationship
Francesco Campanella, Antonio Meles, Luana Serino, Vincenzo Verdoliva (2025).	ESG performance	Fitch's credit rating	Europe	Mixed relationship
Laura Bonacorsi, Vittoria Cerasi, Paola Galfrascoli, Matteo Manera (2024).	ESG factors	Altman's Z-score	Europe	Negative relationship
Chodnicka-Jaworska, Patrycja. (2021).	ESG score	Moody and Fitch's credit ratings	Europe	Negative relationship

Bruno, Christopher C., and Witold J. Henisz. (2024).	ESG index	Moody's, S&P, and Fitch credit ratings	U.S	Negative relationship
Brogi, Marina, Valentina Lagasio, and Pasqualina Porretta. (2022).	ESG awareness score	Altman Z-score, Probability of Default (PD)	Global	Negative relationship
Fuyuan Zhou, Hanlong Chen, Shiyu Tang, Chuan Lee, Chin-Tsai Lin (2025)	ESG factors	Financial Distress (FD), measured by Altman's Z-score, Ohlson O-score	China	Negative Relationship

2.4.2 Environment rating and firms' credit risk

While ESG performance is broadly evaluated across ESG dimensions, many studies tend to focus on aggregate ESG scores, which tends to hinder the distinct effect of the ESG pillars. For instance, research indicates that the Governance (G) dimensions often behave differently form the Environmental (E) and Social (S) ones, sometimes showing weaker or non-significant associations with financial stability or credit risk (i.e., Postiglione et al., 2025; Bannier et al., 2022; Eliwa et al., 2021). As a result, this research aims to disaggregate ESG into its three main dimensions (E, S, G) and further into ten sub-dimensions, allowing a more comprehensive analysis of how each pillar independently and collectively influences credit risk and financial outcome.

Environment rating, often referred to as the “Environmental (E) pillar” within the ESG framework, evaluate a firm’s ability to implement sustainable environmental practices (Postiglione et al., 2025). This pillar assesses how a business affects both living and non-living environmental systems, such as the air, land, water, and entire ecosystems. (Habermann & Fischer, 2021). It evaluates how well a business applies best management practices to minimize environmental risks and take advantage of environmental opportunities in order to create long-term shareholder value (Chodnicka-Jaworska, 2021).

Empirical findings showed a significant relationship between environmental ratings and credit risk, with a general consensus that stronger environmental performance is associated with lower credit risk. Companies with good environmental performance tend to receive higher credit ratings (Cubas-Díaz & Martínez Sedano, 2018). This positive link between environmental components and credit ratings indicates a lower default risk for firms with high environmental performance (Dorfleitner & Grebler, 2020). Hence, we can propose that:

H2: Higher environment rating will reduce firms’ credit risk.

The environmental pillar typically encompasses several sub-dimensions, including resource use, emissions, and environmental innovation.

Firstly, resource use, this sub-dimension evaluates a company's dedication to making effective use of natural resources in its manufacturing process. (Dorfleitner & Grebler, 2020). The resource use score is identified as an important determinant for credit risk, measuring a firm’s ability to reduce resource consumption and find eco-efficient solutions (Michalski & Low, 2024). For instance, a study on energy firms in Asian-Pacific countries reported that greater resource use efficiency is associated with a reduction in default probability (Bertelli et al., 2025). Similarly, study on the "natural resource use" dimension of corporate social performance showed that firms with stronger resource management practices experience lower credit risk, particularly in countries with weaker sustainability standards (Abdul Razak et al., 2020). These findings suggest that effective management of environmental resources can mitigate credit risk by enhancing operational efficiency, reducing regulatory exposure, and improving stakeholder trust, and hence we can propose that:

H2a: Resource efficiency will reduce firms' credit risk.

Secondly, emissions, this sub-dimension evaluates a company's dedication to reducing emissions from its production operations. Reducing pollutant emissions not only benefits to environment but also has implications for firms' credit risk. A study had found that companies with a large portion of revenues tied to carbon-intensive activities tend to face higher credit risk, indicating that emission-related operations carry financial exposure (Bonacorsi et al., 2024). Empirical evidence also showed that the emissions score is a top predictive factor for firms' credit risk (Michalski & Low, 2024). Another study reported that emissions, is particularly significant in sectors such as energy, basic materials, industrial, technology, and utilities, as observed in Fitch and Moody's credit ratings, often due to stricter pollution reduction regulations (Chodnicka-Jaworska, 2021). These findings indicate that effective emissions management can enhance financial resilience and mitigate credit risk, especially in environmentally regulated sectors, and hence we can propose that:

H2b: Emissions reduction will reduce firms' credit risk.

Thirdly, innovation, measures a company's capacity to reduce its customers' environmental costs and burdens. Environmental innovation has emerged as a critical driver of firms' creditworthiness. By developing green technologies and optimizing production processes, firms can enhance their reputation and image, strengthen stakeholder relationships, improve access to capital, and enhance market positioning (Wong, 2023). Empirical studies across North America, Europe and Asia consistently identify environmental innovation as a dominant predictor firms credit ratings. Furthermore, environmental innovation is negatively associated with credit risk, with the mitigating effect being stronger in market-oriented countries. This reduction in credit risk is largely driven by enhanced profitability and market value (Meles et al., 2023). Together, these findings suggest that environmental innovation not only strengthen environmental performance but also serves as an effective mechanism to reduce firms' credit risk, and hence we can propose that:

H2c: Environmental innovation will reduce firms' credit risk.

2.4.3 Social rating and firms' credit risk

Social ratings, often referred to as the "Social (S) pillar" within the ESG framework, measure a company's impact on society and its relationships with various stakeholders (Agosto et al., 2023). This dimension is considered crucial for a company's reputation and its long-term license to operate, influencing its ability to generate shareholder value (Habermann & Fischer, 2021).

The social dimension of ESG has been identifed as a key factor influence firms' credit risk. Several studies report a negative correlation between strong social performance and credit risk indicators such as the Altman Z-score (Postiglione et al., 2025; Brogi et al., 2022). Similarly, the social dimension of ESG is generally associated with a lower cost of debt (Eliwa et al., 2021). Beyond financial metrics, strong social performance enhances stakeholder trust and firm reputation, indirectly reducing risk by signalling responsible management and long-term resilience (Agosto et al., 2023).

However, findings are mixed: in some cases, the short-term costs of social initiatives appear to outweigh immediate financial benefits, leading to weaker credit ratings (Chen et al., 2025). Despite some mixed evidence, the overall literature suggests that strong social performance can improve financial stability and reduce credit risk over the long term. Based on this reasoning and the theoretical underpinnings of stakeholder perspective, hence we can propose that:

H3: Higher social rating will reduce firms' credit risk.

The social pillar typically encompasses several sub-dimensions, including workforce, human rights, community, and product responsibility.

Firstly, workforce sub-dimension includes factors like employee satisfaction, diversity, equality, gender equity, protection, workplace safety, training, labour rights (Agosto et al., 2023). Effective management of these workforce aspects can enhance a firm's operational stability and reduce credit risk. For example, a study had found that companies that treat employees fairly, invest in their development, and maintain a safe and production work environment tend to achieve higher engagement and productivity, which supports stronger financial performance and lower credit risk (Wong, 2023). Another empirical evidence indicates that, in Europe, better employment quality and greater workforce diversity tends to positively influence corporate credit ratings (Dorfleitner & Grebler, 2020). Based on the evidences, we can propose that:

H3a: Strong workforce will reduce firms' credit risk.

The human rights dimension is closely tied to credit risk, as firms that fail to respect fundamental labour rights or are linked to child or forced labor often face legal penalties, reputational damage, and stakeholder distrust, which can elevate their risk of default (Wong, 2023). Conversely, companies with strong human rights practices tend to enjoy higher stakeholder confidence, reduced exposure to litigation, and greater long-term financial stability, which translates into lower credit risk and borrowing costs. With these, we can propose that:

H3b: Strong human rights performance will reduce firms' credit risk.

Community dimension, where research reported that firms that actively engage with their communities, whether through donations, social initiatives, or ethical practices, tend to strengthen stakeholder relationships and enhance consumer loyalty, which contributes to reduced risk exposure (Dorfleitner & Grebler, 2020). While a study found no significant relationship between community strengths and credit risk (Meles et al., 2023), others studies suggest community relations are linked to credit risk, highlight that higher community engagement are associated with decreased credit risk (i.e. Abdul Razak et al., 2020; Dorfleitner & Grebler, 2020). Thus, strong community performance is expected to reduce firms' credit risk, and we can propose that:

H3c: Strong community performance will reduce firms' credit risk.

Research indicates that companies with superior product safety and quality lower the risk premiums related to corporate bonds, thereby lowering cost of debt (Abdul Razak et al., 2020). Strong performance in this area not only improves financial outcomes through customer loyalty, brand equity and market share but also signals reliability and long-term stability to investors and credit rating agencies (Auger et al., 2008). Accordingly, product responsibility is expected to reduce firms' credit risk.

H3d: Product responsibility will reduce firms' credit risk.

2.4.4 Governance and firms' credit risk

Governance rating, often referred to as the "Governance (G) pillar" within the ESG framework, focuses on the quality of a company's corporate governance (Agosto et al., 2023). It evaluates the procedures and mechanisms a business has in place to make sure its executives and board members behave in the shareholders' best long-term interests (Habermann & Fischer, 2021). Historically, shortcomings in governance have been linked to major corporate scandals and financial crises such as Enron crisis in the USA, Volkswagen in Germany, and the banking crisis of 2007-2008 (Shin et al., 2021; Soltani, 2013). As a result, strong governance is seen as crucial for navigating risks, maintaining financial stability, and contributing to sustainable firm growth and broader economic development (Adams & Mehran, 2012; Esteban-Sanchez et al., 2017).

The past empirical studies presented mixed and sometimes contradictory findings about the association between governance and firms' credit risk. Studies suggest that good governance is a positive driver of credit ratings. (Abdul Razak et al., 2020) found that stronger governance frameworks are robustly linked to mitigating credit risk. This can be explained by the fact that the high managerial ownership, market power, and independent boards – often considered indicators of good governance, can lead to more transparent decision-making process, lower downside and default risk (Wang et al., 2015).

However, several literatures have found no significant between governance and firms' credit risk. For example, (Bannier et al., 2022) examined for European firms, the governance score doesn't display significant coefficients in any regression model, suggesting no significant relationship between stronger governance activity and credit risk. Similarly, (Seefloth et al., 2025) found that for firms in financial distress, there was no association between governance performance and the Z-Score.

In light of these observations, we can propose the following hypothesis to examine the relationship between corporate governance and firms credit risk:

H4: Higher governance rating will reduce firms' credit risk.

The governance pillar typically encompasses several sub-dimensions, including management, shareholders, and corporate social responsibility (CSR) strategy.

Effective governance at the management level is often reflected in superior financial performance, stronger risk management, and enhanced resilience during economic downturns (Cuong & Lan, 2021). Research suggests that managerial capability can magnify positive effects of ESG performance on credit ratings, particularly when managers successfully intergrate ESG considerations into strategic decision-making (Yusupova et al., 2025).

H4a: Management will reduce firms credit risk.

The literature highlights that shareholder rights are generally associated with better firm performance and a lower likelihood of fraud and misconduct (Becht et al., 2005). Stronger shareholder rights are associated with higher firm valuation, profitability, and lower agency costs (Paskelian and Bell, 2009).

H4b: Shareholder will reduce firms credit risk.

Empirical evidence shows that firms with strong CSR engagement often enjoy superior financial performance, greater resilience during crises, lower debt costs, and reduced default risk, as CSR acts as a form of "insurance" that builds trust and transparency (Chodnicka-Jaworska, 2021). However, the relationship is not always linear; (Wong, 2023) found that excessive CSR investments may lead to resource overuse, increased risk, or negligible benefits if the costs outweigh the returns. Despite these mixed findings, the prevailing view suggests that effective CSR strategies enhance firm stability and reduce exposure to financial distress. In light of this, we can propose that:

H4c: CSR strategy will reduce firms' credit risk.

2.4.5 ESG and firms' credit risk between Developed and Developing countries

Over the past decade, many researchers have investigated the relationship between ESG performance and credit risk. Despite these efforts, the empirical evidence remains inconclusive. Stronger ESG practices may lower credit risk through better risk management and stakeholder trust, according to a number of studies that have found a negative correlation (Campanella et al., 2025; Choi et al., 2024). Conversely, other studies have identified a positive association, indicating that ESG adoption may increase credit risk due to higher capital expenditures and operational costs linked to sustainability initiatives (Farah et al., 2021; Habermann & Fischer, 2023). Additionally, there is research has found no statistically significant relationship between ESG factors and credit risk (Veltri et al., 2023). These conflicting results highlight a gap and the need for more research, especially in Asian emerging markets.

Empirical studies exploring the relationship between ESG performance and firms' credit risk, particularly distinguishing between developed and developing countries, are growing area of interest, though consensus on certain aspects remains elusive. For example, research in China showed that ESG performance can significantly reduce financial distress among firms (Zhou et al., 2025). Similarly, study in Korea show that ESG activities, particularly in the environmental dimension, contribute to enhance the firm's financial stability, leading to lower credit risk (Choi et al., 2024). However, study in Malaysia found no significant relationship between a company ESG' performance and credit risk (Atan et al., 2018). Furthermore, most existing studies focus on either developed or emerging markets, or treat the markets as homogeneous. Therefore, this study aims to examine whether there is any difference in ESG and credit risk between companies in different country development level.

The classification of developed and developing countries in this study follows the World Bank's World Development Indicators, which group economies into high-income (developed) and low- or middle-income (developing) categories. Under this framework, countries such as Japan, Singapore, and South Korea are classified as developed, while Malaysia, China, India, and Indonesia fall under developing. This distinction is critical because institutional environments, financial systems, and regulatory pressures differ sharply across these categories.

The relationship between ESG performance and firms' credit risk appears to be context-dependent when comparing developed economies to emerging and developing markets (Meles et al., 2023). In Emerging Market and Developing Economies (EMDEs), several studies report a stronger risk-reducing effect of ESG/CSR because responsible practices can partially substitute for institutional voids – improving access to financing, encouraging investment, lowering default risk, and lengthening trade credit (Abdul Razak et al., 2020). Yet evidence is mixed: after the 2008 crisis, non-ESG fundamentals often dominated creditworthiness in EMDEs, and regional heterogeneity is pronounced – social factors are noted as important in Middle East and North Africa (Pineau et al., 2022). Conversely, some African firms show a reverse causality, where higher firm stability leads to higher ESG scores, rather than ESG driving stability (Saidane & Abdallah, 2021).

In developed countries, ESG integration tends to be more advanced, with institutional investors having a greater influence on ESG investment practices (Shi et al., 2023). Governance factors are identified as a primary driver of credit ratings in developed countries , while environmental factors, though increasingly important, are less determinative of creditworthiness given greater resilience to climate exposures (Pineau et al., 2022). Moreover, market-oriented systems in these countries exhibit stronger market discipline, where green innovation more visibly reduce default risk through pricing mechanisms (Meles et al., 2023).

Taken together, these findings highlight that the ESG performance on credit risk is not uniform across developed and developing countries. Accordingly, we can propose that:

> **H5: There is a difference in the relationship of ESG (overall, pillars, sub-dimension) and firms' credit risk between the developed and developing countries.**

2.4.6 ESG and firms' credit risk between Pre and Post pandemic

The relationship between ESG performance (including overall scores, pillars, and sub dimensions) and firms' credit risk is strongly dynamic and contingent upon the prevailing economic cycle. The past literatures showed that the relationship between ESG and credit risk differs between periods of economic upswing (pre-pandemic) and period of downturn (post-pandemic).

During the period characterized as an economic upswing (e.g., 2010-2019), exisiting evidence suggests that the protective effect of overall ESG performance is attenuated. In fact, increasing ESG performance was found to raise the likelihood of bankruptcy (BL) because the additional costs incurred outweighed the immediate benefits derived from satisfying stakeholders in a flourishing environment (Habermann & Fischer, 2021). Conversely, when market-wide financial crises occur (like the 2008 GFC or COVID-19), high-ESG portfolios perform better than low-ESG portfolios. (Broadstock et al., 2021). Firms with superior ESG are judged to exhibit greater financial resilience and stability.

The impact of the individual ESG pillars varies based on whether their costs or benefits are recognized within the specific economic phase. For example, the Social pillar often acts as the main driver for negative financial effects during economic upswings because social investment impose upfront costs However, this pillar switches function during a crisis; when firms are in financial distress, a high Social pillar status shows a beneficial, risk reducing effects, supporting its use as an effective turnaround measure (Habermann & Fischer, 2021).

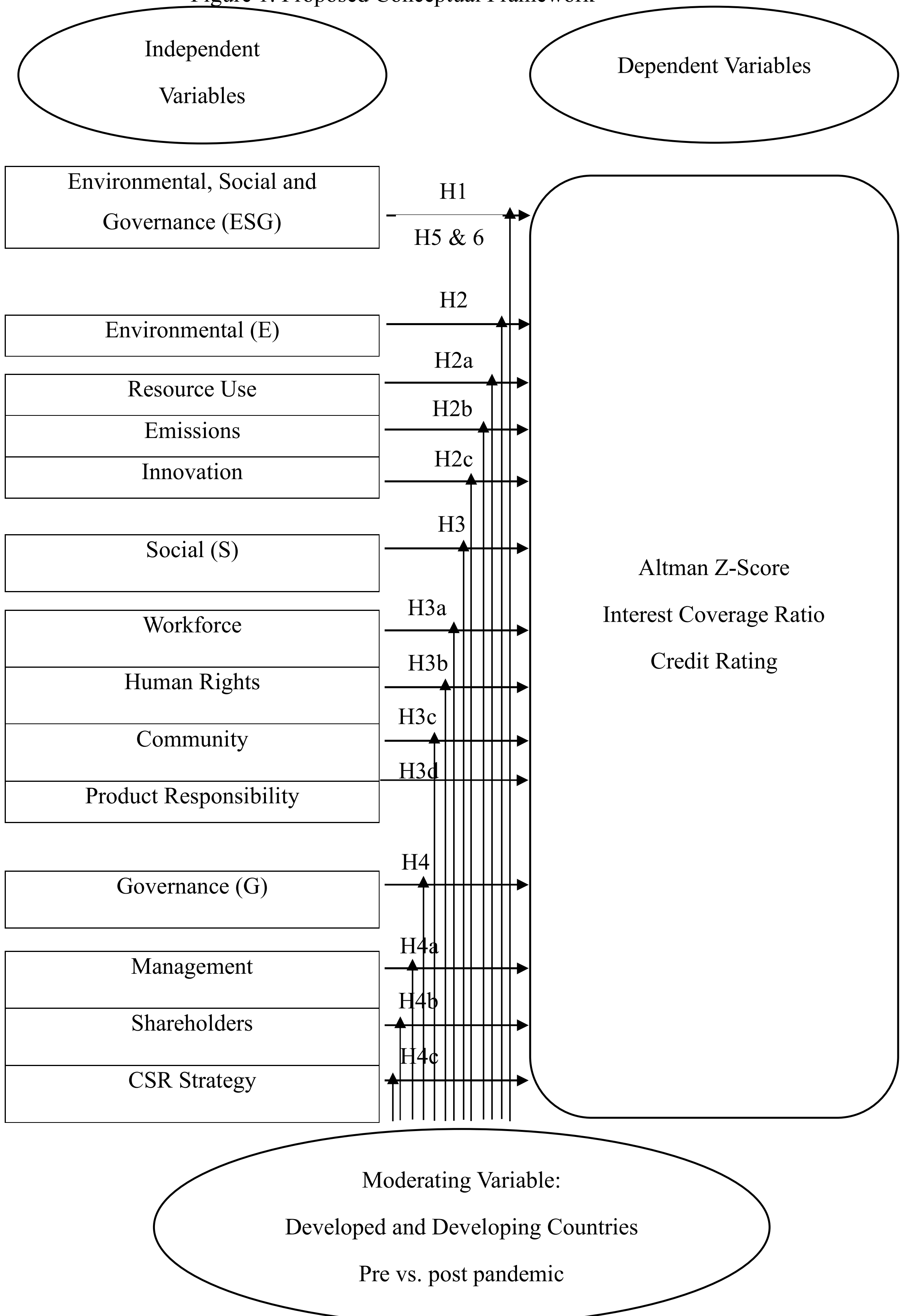
The literature also suggested that the effect of credit rating concerns on strategic ESG activities becomes pronounced and strengthens further in the post-crisis period (Lee et al., 2024). This highlights that managers are motivated to strategically increase ESG engagement as a signalling mechanism to improve credit perception and secure financing during times of high market uncertainty.

Taken together, these findings highlight that the ESG performance on credit risk is not uniform across pre and post pandemic periods. Accordingly, we can propose that:

> **H6: There is a difference in the relationship of ESG (overall, pillars, sub-dimension) and firms' credit risk between the pre and post pandemic periods.**

2.5 Conceptual Framework

Figure 1: Proposed Conceptual Framework



CHAPTER 3: METHODOLOGY

3.1 Introduction

Research methodology refers to the structured process of addressing research problems, which involves defining and refining the research topic, formulating hypotheses, collecting and analysing data, and drawing valid conclusions. A rigorous methodology ensures that findings are reliable, meaningful, and connected to both the theoretical foundation and earlier empirical findings.

The main objective of this study is to examine the relationship between ESG practices (including their pillars and sub-dimensions) and firms' credit risk. A further aim is to assess whether this relationship differs between developed and developing countries, as well as before and after the COVID-19 pandemic.

To achieve these objectives, the study's methodological framework is presented in this chapter. It started by describing the research design and justifying the use of quantitative panel data approach. This is followed by a discussion of data sources, sample selection, and the operationalization of variables. The chapter then outlines the formulation of hypotheses, the statistical models used, and the data analysis plan, including diagnostic tests to ensure robustness. Finally, ethical considerations are addressed, and the chapter concludes with a summary linking the methodology to the study's expected outcomes.

3.2 Research Design

This study uses a quantitative research design to examine the effect of ESG performance on firm credit risk across developed and developing countries. A quantitative approach is appropriate because the research questions require hypothesis testing and statistical evaluation of measurable variables, such as ESG scores, Altman Z-scores, Interest Coverage Ratios (ICR), and Credit Ratings. A quantitative framework allows for objective measurement, comparison among firms, and generalizability of results, in contrast to qualitative or mixed-methods techniques, which are more suited for investigating perceptions and narratives.

A panel data design is adopted, which combines cross-sectional and time-series elements by observing the same firms over the period 2017–2024. Panel data offers several advantages for ESG research: it controls for unobserved firm-level heterogeneity (e.g., governance structures, disclosure practices), improves efficiency of estimation by exploiting both firm- and time-level variation, and captures dynamic changes such as the impact of the COVID-19 pandemic.

A country dummy distinguishes developed from developing countries, with interaction terms between ESG variables and the dummy to capture potential differences in ESG effects across contexts. Another dummy variable is used to distinguish between the pre and post pandemic periods, with interaction terms between ESG variables and this dummy to capture potential differences in the effects of ESG performance on credit risk before and after the pandemic.

Firm size, leverage and SDG index are included as control variables. For all three dependent variables—Altman Z-score, Interest Coverage Ratio (ICR), and Credit Ratings (converted into a numerical scale)—panel multiple linear regression models are estimated using fixed and random effects specifications. This unified approach ensures consistency across models while enabling a systematic assessment of the impact of ESG performance on firms' financial stability and credit risk, taking into account both country-level heterogeneity and firm-level characteristics, as well as structural shifts such as the COVID-19 pandemic.

3.3 Data Source and Sample Selection

The sample of this study consists of the Top 100 publicly listed firms in Asia, selected based on market capitalization rankings (2017-2024). The sample size of the top 100 publicly listed firms is supported by previous researches (i.e., Wong, 2021; He & Loftus, 2014; Hassan & Gup, 2017; Cho & Patten, 2007). Usually, firms with larger market capitalization tend to engage more actively in ESG initiative (Boyd et al., 2006). Focusing on the largest firms also ensure the selection of companies with significant visibility in capital markets, relatively high levels of disclosure, and consistent availability of ESG data. Also, studying Asian region firms not only addresses the geographical gap in the literature but also accounts for crucial cultural and regulatory differences, and provide valuable insights within the region.

Also, financial firms are not included from the sample due to their business models, regulatory environments, and disclosure practices differ substantially from those of non-financial companies. Including them could bias the analysis and reduce comparability across industries. By focusing only on non-financial firms, this study achieves greater consistency in evaluating ESG practices.

The data for both independent and dependent variables were obtained from LSEG (Refinitiv Eikon/Datastream). ESG performance measures, including the overall ESG score, the three ESG pillars, and the ten sub-dimensions, were sourced from Refinitiv's ESG database, which provides standardized and widely used firm-level ESG ratings. Refinitiv ESG scores are the most widely adopted in economic literatures (e.g., Postiglione et al., 2025; Seefloth et al., 2025; Habermann & Fischer, 2021; Veltri et al., 2023; Shi et al., 2023; Yusupova et al., 2025; Wong, 2023). Also, researchers frequently utilize this database, assuming its ESG scores accurately reflect firms' sustainability performance, and its use in over 1000 academic articles over the past 15 years further underscores its prominence and acceptance (Veltri et al., 2023). As for the financial stability indicators—Altman Z-scores, Interest Coverage Ratios (ICR), and Credit Ratings—were also collected through Refinitiv, ensuring consistency across firms and countries. This integrated database allows for comprehensive coverage of both ESG characteristics and financial outcomes, making it well suited for cross-country and pre- versus post-pandemic comparisons.

This study will cover the period from 2017-2024, which is chosen for two reasons. Firstly, consistent and comprehensive ESG data from Refinitiv is only reliably available from 2017 onwards. Second, this period captures both pre-pandemic conditions (2017-2019) and the pandemic and recovery phases (2020-2024), allowing a meaning comparison of ESG effects before and after COVID-19 (Kaminskyi et al., 2025).

To ensure data quality, missing data is handled systematically. Firms with significant missing values across ESG or dependent variables are removed from the sample. For firms with few missing values, interpolation or mean substitution methods are applied, maintaining the integrity of the balanced panel. After data cleaning, only 73 out of the initial 100 firms remain in the sample, due to data availability constraints.

Based on Appendix 1, the sample consists of top 100 publicly listed companies in Asia. These companies are distributed across five developing countries—China (33), India (13), Saudi Arabia (5), Indonesia (4), Thailand (1), United Arab Emirates (1)—and five developed countries—Japan (29), South Korea (5), Taiwan Province of China (4), Hong Kong SAR (3), and Singapore (2). The classification of developing and developed economies follows the World Economic Outlook Database – Groups and Aggregates Information published by the International Monetary Fund (IMF).

In short, this dataset is highly suitable for the study because it directly supports the three research questions. By focusing on the Top 100 non-financial publicly listed firms in Asia, it provides reliable ESG and credit risk information needed to understand the overall impact of ESG performance. The detailed breakdown of Refinitiv's ESG scores into ten sub-dimensions also makes it possible to see how different aspects of ESG contribute to credit risk, rather than treating ESG as a single measure. Finally, due to the sample includes firms from both developed and developing economies, the dataset allows for meaningful comparisons across different institutional and regulatory settings, helping to reveal whether the ESG–credit risk relationship varies between these contexts.

3.4 Variable Measurement and Operationalization

This section explains how the independent, dependent, and control variables are defined and measured. All variables are sourced from LSEG (Refinitiv Eikon/Datastream) to ensure consistency across firms.

3.4.1 Independent Variables

This study examines the effect of ESG performance on credit risk among the top 100 publicly listed companies in Asia. The independent variable is the ESG score obtained from Refinitv's database. The ESG performance will be measured on a 0-100 scale, with higher scores reflecting stronger ESG performance.

The Refinitiv ESG scores are widely used in academic research and constructed using a standardized methodology based on publicly disclosed sources like annual reports and sustainability disclosure. However, potential biases must be acknowledged, including disclosure bias (firms with more reporting may score higher regardless of actual practices), industry comparability issues (ESG relevance differs across sectors), and time-lag bias (scores may reflect past rather than current performance). To strengthen reliability, this study will conduct descriptive and correlation analyses to confirm consistency across the three main dimensions and the ten sub-dimensions of ESG scores, and robustness will be checked by comparing results across these different measurement levels.

The three main dimensions of ESG and ten sub-dimensions are as follow:

Environmental score: This includes company’s impact on natural environment, including air, land, and water.

Social score: This includes company’s commitment to social responsibilities and ethical dealings.

Governance score: This involves how well a company's procedures and systems guarantee that its executives and board members behave in the long-term shareholders' best interests.

Resource used score: This includes a company’s ability toward reducing environmental resource use in its production and operational processes, such as water and energy efficiency.

Emissions score: This includes a company’s ability toward reducing environmental emissions, also focuses on carbon footprint and CO_2 emissions.

Innovation score: This includes a company’s capacity for environmental innovation to leverage environmental opportunities and develop eco-friendly products and services.

Workforce score: This includes aspects like employee relations, health and safety, workplace diversity, labour standards, training and development, as well as employment quality.

Human right score: This includes a company’s commitment to respect and promote human rights, adherence to human right standards and avoiding controversial sourcing.

Community score: This includes a company’s engagement with local communities like social programs and community relations.

Product responsibility score: This includes a company' responsibility for the quality, safety, and ethical aspects of its products and services.

Management score: This includes the effectiveness of a company's management structure, executive compensation, and overall leadership quality.

Shareholder score: This includes how a company ensure the rights and equitable treatment of its shareholders.

Corporate Social Responsibility (CSR) strategy score: This includes the integration of CSR principles into the company's overall strategy and operations.

3.4.2 Dependent Variables

This study employs three complementary measures of credit risk: the Altman Z-score, the Interest Coverage Ratio (ICR), and Credit Ratings. Each measure captures a different aspect of financial stability. The Altman Z-score evaluates overall bankruptcy risk by combining profitability, leverage, liquidity, and solvency indicators. The ICR measures a firm's ability to service its debt obligations using earnings, while Credit Ratings provide an external, market-recognized assessment of creditworthiness. Using these three indicators in combination strengthens validity, as reliance on a single measure may overlook important dimensions of credit risk.

3.4.2.1 Altman Z-score

The Altman Z-score is a widely recognized multivariate formula used to predict firm bankruptcy or financial distress (Seefloth et al., 2025). Developed by Edward Altman in 1968, it combines several key financial ratios to provide a single score that assesses a firm's financial health and default probability (Habermann & Fischer, 2021). The coefficients (1.2, 1.4, 3.3, 0.6, 1.0) are statistically derived weights from Altman's original discriminant analysis model.

The formula for Altman Z-Score is as follows:

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

Whereas,

$X_1 = Working\ capital\ /\ Total\ assets(as\ a\ percentage)$, measures the net liquid assets of the firm relative to its total capitalization.

$X_2 = Retained\ earnings\ /\ Total\ assets(as\ a\ percentage)$, measure the cumulative profitability of the firm over time.

$X_3 = Earning\ before\ interest\ and\ tax\ /$ $Total\ assets(as\ a\ percentage)$, measures the true productivity of the firm's assets, abstracting from tax or leverage factors.

$X_4 = Market\ value\ of\ equity\ /\ Total\ liabilities\ (as\ a\ percentage)$, represents the debt-to equity ratio at market prices and used for measuring financial leverage.

$X_5 = Sales\ /\ Total\ assets$, measures the ability of the firm's assets to generate sales.

Table 2: Interpretation of Altman Z-score Values

Range of Z-score Values	Description
Below 1.88	High probability of bankruptcy
1.88 to 2.99	Questionable or a "grey zone"
Above 2.99	Low risk of default

Although originally developed for manufacturing firms, the model has since been widely applied to non-manufacturing firms, including service and technology sectors. Nevertheless, one limitation is that the sales-to-assets ratio (X_5) may not fully capture efficiency in non-manufacturing industries. This study acknowledges this limitation and interprets findings cautiously, supplementing Z-score analysis with ICR and Credit Ratings.

3.4.2.2 Interest coverage ratio

A measure of a company's capacity to pay interest on its outstanding debt is called the Interest Coverage Ratio, or Time Interest Earned (Eliwa et al., 2021). It shows the number of times a business may use its operational profits to pay its interest costs.

A higher ICR indicates stronger solvency and lower credit risk, while a low ICR signals limited ability to service debt. In cases where EBIT is negative, the ICR also becomes negative. Instead of excluding such cases, this study retains negative ICR values, as they are highly informative indicators of financial distress and potential insolvency risk. By capturing both positive and negative scenarios, ICR provides a direct measure of a firm’s short-term debt-servicing capacity, complementing the broader perspective of the Altman Z-score and the external assessment of Credit Ratings.

The formula for Altman Z-Score is as follows:

$$Interest\ Coverage\ Ratio = \frac{Earnings\ before\ interest\ and\ taxes}{Interest\ expense}$$

Where:

- EBIT (Earnings Before Interest and Taxes), represents a company’s profit before any interest payments and income taxes are deducted.
- Interest Expense, refers to the total interest paid on a company’s debt obligations over a specific period.

3.4.2.3 Credit ratings

The credit ratings are certified assessments of a firm's creditworthiness, reflecting their underlying credit risk (Lee et al., 2024). These ratings offer insight into an obligor's ability to fulfil certain financial commitments and make promised payments. Credit ratings are commonly expressed as alphanumeric scales (e.g., AAA, AA, A, BBB, …).

For comparability with continuous credit risk measures (Altman Z, ICR) and to permit panel multiple regression analysis, ratings will be transformed into a numeric scale (higher values indicate stronger credit quality)

Table 3: Variables of the Study

Independent Variables	**Description**
ESG	Environmental, social, and governance scores
ESG 10 sub-dimensions	Resources used, emissions, innovation, workforce, human rights, community, product responsibility, management, shareholder and corporate social responsibility strategy
Dependent Variables	**Description**
Altman Z-Score	Accounting-based measure of bankruptcy risk
Interest Coverage Ratio	EBIT divided by interest expenses
Credit Ratings	External assessment of a firm's creditworthiness by rating agencies

3.4.3 Control Variables

Firm size is a fundamental variable commonly included in financial and ESG research to account for differences in firms' resources, maturity, risk exposure, and operational dynamics (Postiglione et al., 2025). It commonly measured by using natural logarithm of total assets. As a result, we control for firm size because bigger companies are more widely known and subject to more public and governmental scrutiny for their disclosure of sustainability information. (de Villiers & Marques, 2015; Haque, 2017).

The link between ESG and credit risk is significantly shaped by institutional factors at the national level in addition to firm-level features. The Sustainable Development Goals (SDG) index is therefore used as a control variable. The overall SDG index of respective home country will be sourced from the United Nations' Sustainable Development Report published yearly from 2017-2024. Controlling for the SDG index ensures that the study distinguishes between firm-specific ESG effects and country-level sustainability influence, thereby providing more accurate insights of how ESG affects credit risk across developed and developing countries.

Also, leverage represents a key control variable in ESG research, as highly leveraged firms often face tighter financial constraints, leaving fewer resources available for investment in ESG initiatives. To account for this effect, leverage will be measured using the debt-to-equity (D/E) ratio (Oware & Mallikarjunappa, 2021).

3.5 Formulation of Hypotheses

Based on the theoretical framework and prior empirical evidence, the following hypotheses are proposed to test the relationship between ESG performance and firms' credit risk.

H1: Higher ESG performance will reduce firms' credit risk.

H2: Higher environment rating will reduce firms' credit risk.

H2a: Resource efficiency will reduce firms' credit risk.

H2b: Emissions reduction will reduce firms' credit risk.

H2c: Environmental innovation will reduce firms' credit risk.

H3: Higher social rating will reduce firms' credit risk.

H3a: Strong workforce will reduce firms' credit risk.

H3b: Strong human rights performance will reduce firms' credit risk.

H3c: Strong community performance will reduce firms' credit risk.

H3d: Product responsibility will reduce firms' credit risk.

H4: Higher governance rating will reduce firms' credit risk.

H4a: Management will reduce firms credit risk.

H4b: Shareholder will reduce firms credit risk.

H4c: CSR strategy will reduce firms' credit risk.

H5: There is a difference in the relationship of ESG (overall, pillars, sub-dimension) and firms' credit risk between the developed and developing countries.

H6: There is a difference in the relationship of ESG (overall, pillars, sub-dimension) and firms' credit risk between the pre and post pandemic periods.

3.6 Statistical Models

This study employs panel multiple regression models to investigate the effect of ESG performance on firms' credit risk, measured through Altman Z-scores, Interest Coverage Ratio (ICR), and Credit Ratings.

3.6.1 Panel Multiple Linear Regression Models

This study employs panel multiple linear regression models to investigate the effect of ESG performance on credit risk among the top 100 publicly listed companies in Asia over the period 2017–2024. Unlike pooled OLS, which treats panel data as a single cross-section and ignores time-specific effects, panel data is a type of dataset that combines cross-sectional and time-series dimensions, meaning it observes multiple firms over multiple period of time (Postiglione et al., 2025). Panel multiple linear regression models is often used in research on corporate finance, governance, and social responsibility. It is well-suited for datasets that combine information across different groups (like firms or countries) and over time (such as years or quarters) (SAIDANE & ABDALLAH, 2021). The primary advantage of panel data models is that they can control for unobserved heterogeneity—that is, hidden factors that vary between companies or across time but aren't directly measured in the model (Esteban-Sanchez et al., 2017). By accounting for these hidden influences, panel models provide more reliable and accurate results compared to simpler approaches.

In order to determine whether to use a random effects or fixed effects model in panel data analysis, this study will employ Hausman test. It is the most commonly statistical test for choosing between fixed and random effect models (Seefloth et al., 2025), compare the consistency and efficiency of the estimators derived from both models (Wang et al., 2025).

3.6.2 Model Equation and Variable Definitions

To investigate the relationship between ESG and firm credit risk, three sets of modes were estimated using three alternative measures of credit risk: Altman Z-score, Interest Coverage Ratio (ICR), and Credit Ratings (CR).

Model 1 investigated the impact of ESG performance on firms' financial stability, measured by Altman Z-scores. Model 1A employed the overall ESG score as the key explanatory variable, Model 1B decomposed ESG into the three ESG pillars, and Model 1C further disaggregated ESG into ten sub-dimensions (RES, EMIS, INNOV, WORK, HUM, COMM, PROD, MAN, SHAR, CSR). To capture heterogeneity between developed and developing countries, a country dummy variable (D_i) and its interactions with ESG measures were included. To examine the differential effects of ESG before and after the COVID-19 pandemic, a post-pandemic dummy variable ($Post_t$) and its interactions with ESG measures were included. Firm size, leverage, and the country-based SDG index were controlled for in all specifications. Model 2 followed the same structure, using the Interest Coverage Ratio (ICR) as the dependent variable, while Model 3 applied the framework to Credit Ratings (CR).

Model 1A: Overall ESG and Altman Z-Score

<u>Country heterogeneity</u>

$$Altman\ Z - score_{it} = \beta_0 + \beta_1 ESG_{it} + \beta_2 D_i + \beta_3 (ESG_{it} \times D_i) + \beta_4 Size_{it} + \beta_5 SDG_{it} + \beta_6 Leverage_{it} + \varepsilon$$

<u>Pre vs post pandemic</u>

$$Altman\ Z - score_{it} = \beta_0 + \beta_1 ESG_{it} + \beta_2 Post_t + \beta_3 (ESG_{it} \times Post_t) + \beta_4 Size_{it} + \beta_5 SDG_{it} + \beta_6 Leverage_{it} + \varepsilon$$

Model 1B: ESG Pillars and Altman Z-Score

<u>Country heterogeneity</u>

$$Altman\ Z - score_{it} = \beta_0 + \beta_1 E_{it} + \beta_2 S_{it} + \beta_3 G_{it} + \beta_4 D_i + \beta_5 (E_{it} \times D_i) + \beta_6 (S_{it} \times D_i) + \beta_7 (G_{it} \times D_i) + \beta_8 Size_{it} + \beta_9 SDG_{it} + \beta_{10} Leverage_{it} + \varepsilon$$

<u>Pre vs post pandemic</u>

$$Altman\ Z - score_{it} = \beta_0 + \beta_1 E_{it} + \beta_2 S_{it} + \beta_3 G_{it} + \beta_4 Post_t + \beta_5 (E_{it} \times Post_t) + \beta_6 (S_{it} \times Post_t) + \beta_7 (G_{it} \times Post_t) + \beta_8 Size_{it} + \beta_9 SDG_{it} + \beta_{10} Leverage_{it} + \varepsilon$$

Model 1C: ESG Sub-Dimensions and Altman Z-Score

<u>Country heterogeneity</u>

$$Altman\ Z - score_{it} = \beta_0 + \sum_{k=1}^{10} \beta_k ESGsub_{k,it} + \beta_{11} D_i + \sum_{k=1}^{10} \beta_{11+k} (ESGsub_{k,it} \times D_i) + \beta_{22} Size_{it} + \beta_{23} SDG_{it} + \beta_{24} Leverage_{it} + \varepsilon$$

<u>Pre vs post pandemic</u>

$$Altman\ Z - score_{it} = \beta_0 + \sum_{k=1}^{10} \beta_k ESGsub_{k,it} + \beta_{11} Post_t + \sum_{k=1}^{10} \beta_{11+k} (ESGsub_{k,it} \times Post_t) + \beta_{22} Size_{it} + \beta_{23} SDG_{it} + \beta_{24} Leverage_{it} + \varepsilon$$

Model 2A: Overall ESG and Interest Coverage Ratio

Country heterogeneity

$$ICR_{it} = \beta_0 + \beta_1 ESG_{it} + \beta_2 D_i + \beta_3 (ESG_{it} \times D_i) + \beta_4 Size_{it} + \beta_5 SDG_{it} + \beta_6 Leverage_{it} + \varepsilon$$

Pre vs post pandemic

$$ICR_{it} = \beta_0 + \beta_1 ESG_{it} + \beta_2 Post_t + \beta_3 (ESG_{it} \times Post_t) + \beta_4 Size_{it} + \beta_5 SDG_{it} + \beta_6 Leverage_{it} + \varepsilon$$

Model 2B: ESG Pillars and Interest Coverage Ratio

Country heterogeneity

$$ICR_{it} = \beta_0 + \beta_1 E_{it} + \beta_2 S_{it} + \beta_3 G_{it} + \beta_4 D_i + \beta_5 (E_{it} \times D_i) + \beta_6 (S_{it} \times D_i) + \beta_7 (G_{it} \times D_i) + \beta_8 Size_{it} + \beta_9 SDG_{it} + \beta_{10} Leverage_{it} + \varepsilon$$

Pre vs post pandemic

$$ICR_{it} = \beta_0 + \beta_1 E_{it} + \beta_2 S_{it} + \beta_3 G_{it} + \beta_4 Post_t + \beta_5 (E_{it} \times Post_t) + \beta_6 (S_{it} \times Post_t) + \beta_7 (G_{it} \times Post_t) + \beta_8 Size_{it} + \beta_9 SDG_{it} + \beta_{10} Leverage_{it} + \varepsilon$$

Model 2C: ESG Sub-Dimensions and Interest Coverage Ratio

Country heterogeneity

$$ICR_{it} = \beta_0 + \sum_{k=1}^{10} \beta_k ESGsub_{k,it} + \beta_{11} D_i + \sum_{k=1}^{10} \beta_{11+k} (ESGsub_{k,it} \times D_i) + \beta_{22} Size_{it} + \beta_{23} SDG_{it} + \beta_{24} Leverage_{it} + \varepsilon$$

Pre vs post pandemic

$$ICR_{it} = \beta_0 + \sum_{k=1}^{10} \beta_k ESGsub_{k,it} + \beta_{11} Post_t + \sum_{k=1}^{10} \beta_{11+k} (ESGsub_{k,it} \times Post_t) + \beta_{22} Size_{it} + \beta_{23} SDG_{it} + \beta_{24} Leverage_{it} + \varepsilon$$

Model 3A: Overall ESG and Credit Ratings

Country heterogeneity

$$CR_{it} = \beta_0 + \beta_1 ESG_{it} + \beta_2 D_i + \beta_3 (ESG_{it} \times D_i) + \beta_4 Size_{it} + \beta_5 SDG_{it} + \beta_6 Leverage_{it} + \varepsilon$$

Pre vs post pandemic

$$CR_{it} = \beta_0 + \beta_1 ESG_{it} + \beta_2 Post_t + \beta_3 (ESG_{it} \times Post_t) + \beta_4 Size_{it} + \beta_5 SDG_{it} + \beta_6 Leverage_{it} + \varepsilon$$

Model 3B: ESG Pillars and Credit Ratings

Country heterogeneity

$$CR_{it} = \beta_0 + \beta_1 E_{it} + \beta_2 S_{it} + \beta_3 G_{it} + \beta_4 D_i + \beta_5 (E_{it} \times D_i) + \beta_6 (S_{it} \times D_i) + \beta_7 (G_{it} \times D_i) + \beta_8 Size_{it} + \beta_9 SDG_{it} + \beta_{10} Leverage_{it} + \varepsilon$$

Pre vs post pandemic

$$CR_{it} = \beta_0 + \beta_1 E_{it} + \beta_2 S_{it} + \beta_3 G_{it} + \beta_4 Post_t + \beta_5 (E_{it} \times Post_t) + \beta_6 (S_{it} \times Post_t) + \beta_7 (G_{it} \times Post_t) + \beta_8 Size_{it} + \beta_9 SDG_{it} + \beta_{10} Leverage_{it} + \varepsilon$$

Model 3C: ESG Sub-Dimensions and Credit Ratings

Country heterogeneity

$$CR_{it} = \beta_0 + \sum_{k=1}^{10} \beta_k ESGsub_{k,it} + \beta_{11} D_i + \sum_{k=1}^{10} \beta_{11+k} (ESGsub_{k,it} \times D_i) + \beta_{22} Size_{it} + \beta_{23} SDG_{it} + \beta_{24} Leverage_{it} + \varepsilon$$

Pre vs post pandemic

$$CR_{it} = \beta_0 + \sum_{k=1}^{10} \beta_k ESGsub_{k,it} + \beta_{11} Post_t + \sum_{k=1}^{10} \beta_{11+k} (ESGsub_{k,it} \times Post_t) + \beta_{22} Size_{it} + \beta_{23} SDG_{it} + \beta_{24} Leverage_{it} + \varepsilon$$

Whereas,

Y_{it}: Dependent variable for $firm_i$ in year t, measured alternatively as:

- $Altman\ Z - score_{it}$: Altman Z-score (Model 1 series)
- ICR_{it}: Interest Coverage Ratio (Model 2 series)
- CR_{it}: Credit Rating (Model 3 series)

ESG_{it}: Overall ESG score of $firm_i$ in year t, ranging from 0 to 100

E_{it}, S_{it}, G_{it}: ESG pillar scores of $firm_i$ in year t, representing the Environmental, Social, and Governance dimensions respectively

$ESGsub_{k,it}$: ESG sub-dimension score for $firm_i$ in year t, where k = 1,2,...,10, representing:

1. RES (Resource Use)
2. EMIS (Emissions)
3. INNOV (Innovation)
4. WORK (Workforce)
5. HUM (Human rights)
6. COMM (Community)
7. PROD (Product responsibility)
8. MAN (Management)
9. SHAR (Shareholders)
10. CSR (CSR strategy)

D_i: country dummy (1 = developed, 0 = developing)

$Post_t$: pandemic period dummy (1 for 2020–2024, 0 for 2017–2019)

$Size_{it}$: Firm size

SDG_{it}: SDG index of firm's home country

$Leverage_{it}$: Debt-to-equity (D/E) ratio of $firm_i$ in year t

β_0: Regression intercept

$\beta_1, \beta_2, \ldots$: Estimated coefficients for independent and control variables

ε_{it}: Error term

3.6.3 Software Used

The statistical analysis will be conducted using EViews (version 14), which provides comprehensive tools for panel data estimation, including fixed effects, random effects, and the Hausman test. EViews also allows for robust standard error estimation and diagnostic testing of panel models. Data collection will rely on ESG and financial variables sourced from LSEG/Refinitiv Datastream, while data pre-processing and basic descriptive statistics will be managed within EViews. For regression modelling and panel data estimation, EViews offers a more user-friendly interface than alternatives like Stata or R, which makes it easier to execute and comprehend the results efficiently. Its strong integration with financial and economic datasets further reinforces its suitability for ESG-related research.

3.7 Data Analysis Plan

Data analysis is the process of using statistical data to define, evaluate, and interpret data using suggested analytical methods (Albers, 2017). All analyses will be conducted in EViews 14, which provides comprehensive tools for descriptive analysis, correlation analysis, panel regression modelling, and diagnostic testing.

3.7.1 Descriptive Analysis

Descriptive analysis is the starting point of data analysis. It's about taking a dataset and simply describing what it looks like—summarizing the main features to get a quick overview (Adams & Mehran, 2012). This step comes before using more advanced methods and helps researchers get familiar with the data, spot patterns, and notice any potential problems that might need attention later.

To achieve this, there are few key tools typically used. Measures of central tendency like mean, median, and mode, show the "average" or typical values in the dataset. Measures of dispersion, such as the standard deviation, minimum, and maximum, indicate how spread out the data is and the range of observed values. Additionally, skewness and kurtosis will be computed to assess the distributional properties of the data, which is essential for evaluating the normality assumption underlying regression analysis. The descriptive statistics will be presented in tabular form, supported by graphical outputs such as histograms, trend plots, or box plots where necessary.

3.7.2 Diagnostic Testing

Diagnostic testing is a crucial step in empirical research, particularly in studies examining complex relationships such as that between ESG and credit risk. These tests help ensure the validity, reliability, and appropriateness of the chosen statistical models by assessing key assumptions about the data and error terms.

3.7.2.1 Hausman Test

A hausman test is employed in econometric analysis, particularly within panel data modelling, to aid in determining the most appropriate model specification between a fixed effects (FE) model and a random effects (RE) model. The null hypothesis suggests that the random effects model is appropriate, assuming these individual effects are not related to the variables. If endogeneity is found, the null hypothesis is rejected, meaning the fixed effects model is a better choice.

3.7.2.2 Unit Root Test

To determine if a time series variable is stationary or non-stationary, a unit root test is applied. Stationarity suggests that the series' statistical characteristics remain constant across time. Spurious regression results, in which associations seem to exist when they don't, can come from non-stationary data. The study will use panel unit root tests, such as the Levin-Lin-Chu (LLC) test, to investigate if unit roots exist across the variables in order to address this. In cases where non-stationarity is detected, appropriate remedies such as first differencing or logarithmic transformation will be undertaken to achieve stationarity. This ensures that only stationary variables are used in the panel regression analysis, thereby improving the reliability of the results.

3.7.2.3 Multicollinearity

The Variance Inflation Factor (VIF) is a simple way to check if there is multicollinearity in a regression model (Campanella et al., 2025). Multicollinearity happens when some of the independent variables are too closely related to each other. When this occurs, it becomes hard to figure out the unique effect of each variable, and the model may produce unstable results with inflated standard errors.

VIF tells us how much a variable's results are being "distorted" by correlations with other variables. In this study, a VIF threshold of less than 5 will be adopted as the acceptable cut-off. Variables exceeding this threshold will be examined, and corrective measures such as removing redundant predictors, combining highly correlated variables, or applying dimension-reduction techniques will be considered to ensure the stability and reliability of the regression results.

3.7.2.4 Heteroscedasticity

When the variance of the error terms (residuals) is not constant across all levels of the independent variables, heteroscedasticity arises (Breusch & Pagan, 1979). This goes against a fundamental tenet of OLS regression and can result in biased standard errors and ineffective coefficient estimates, which make hypothesis tests (p-values) unreliable. The Breusch–Pagan Godfrey Test, also known as the Breusch–Pagan test, will be utilized in this investigation to look for this problem. This test ensures that the results are more reliable and accurate by determining whether heteroscedasticity is present in the regression model.

3.7.2.5 Autocorrelation

Autocorrelation (or serial correlation) happens when the error terms are related to each other, rather than being independent. This problem can lead to inefficient coefficient estimates and unreliable hypothesis tests in Ordinary Least Squares (OLS) regression. In this study, the presence of autocorrelation in panel data will be tested using the Durbin–Watson (DW) statistic, which is commonly applied in time-series and panel regressions. If significant autocorrelation is detected, autoregressive (AR) terms will be added to the model to correct for the serial correlation and ensure the robustness of the regression results.

3.8 Ethical Considerations

This study relies exclusively on secondary data obtained from Refinitiv (LSEG), a reputable provider of standardized financial and ESG information. As the dataset contains only firm-level financial and sustainability indicators, without any personal or sensitive information, risks related to confidentiality and privacy are minimal. Nonetheless, all data will be handled securely and used strictly for academic purposes in line with Refinitiv's licensing and usage policies. Proper attribution and citation practices will be followed to ensure transparency and academic integrity.

Since no human subjects are directly involved, formal approval from an Institutional Review Board (IRB) is not required. However, the study remains committed to upholding ethical research standards by ensuring that the analysis and reporting of results are objective, unbiased, and free from misrepresentation. By adhering to these principles, the research ensures compliance with ethical guidelines while maintaining the validity and credibility of its findings.

3.9 Summary

Chapter 3 has presented the methodology designed to examine how ESG performance influences credit risk among the top 100 non-financial publicly listed firms in Asia between 2017 and 2024. A quantitative panel data approach was adopted, drawing on secondary data from Refinitiv. Credit risk was assessed using three complementary measures—Altman Z-score, Interest Coverage Ratio, and Credit Ratings—while ESG performance was captured at three levels: overall scores, the three pillars, and ten detailed sub-dimensions. Firm size, leverage, and the SDG index were introduced as control variables, with interaction terms included to account for differences between developed and developing countries and to capture pre- and post-pandemic effects.

The analysis follows a structured plan, beginning with descriptive statistics and correlation analysis, followed by diagnostic tests such as hausman test, panel unit root, multicollinearity, heteroscedasticity, and autocorrelation, ensuring the validity and robustness of the panel regression models estimated in EViews. This methodological design is not only rigorous but also tailored to address the research questions directly. It is expected to provide clear academic insights into whether ESG practices mitigate credit risk, how these effects differ across institutional settings, and the extent to which ESG contributes to corporate financial resilience during times of the COVID-19 pandemic.

CHAPTER 4: DATA ANALYSIS

4.1 Introduction

In this chapter, it presents an analysis of the relationship between ESG performance and firms' credit risk. The descriptive analysis highlights significant variation in credit risk indicators, with Interest Coverage Ratio (ICR) and Altman Z-score showing diverse financial stability among firms.

Diagnostic tests confirm the use of the Fixed Effects Model (FEM), addressing issues such as unobserved firm characteristics, stationary, multicollinearity, and autocorrelation, ensuring reliable results.

The regression analysis finds that ESG performance generally doesn't have a significant standalone impact on credit risk, but its effect becomes more pronounced when considering country heterogeneity or post-pandemic periods. The Environmental (E) pillar positively influence ICR, while the Social (S) and Governance (G) pillars show mixed effects, these findings emphasized that the impact of ESG on credit risk is context dependent.

4.2 Descriptive Analysis

Table 4: Descriptive Analysis of the Variables

Variable	Mean	Std. Dev.	Maximum	Minimum
ICR	291.25707	1563.03191	24864.6	-547.99
Credit Rating Score	72.6541096	8.50649335	90	30
Altman Z-Score	38.7125733	303.515278	6002.49893	-0.0208137
ESG	67.2595744	15.1754051	92.69	17.68
E	68.2900669	19.9413046	98.64	0
Resource	77.012438	22.1716217	99.9	0
Emission	76.4654305	21.5076805	99.92	0
Innovation	45.8817621	34.5068005	98.96	0
S	68.5399095	19.051556	95.35	12.05
Workforce	76.3014914	19.0993376	99.93	6.38
Human Rights	59.6973467	28.195947	98.92	0
Community	70.1364114	27.4903508	99.86	3.69
Product Responsibility	69.0066536	26.2263448	99.9	0
G	62.9974804	20.2099125	97.58	6.97
Management	64.286559	27.8418237	98.86	1.04
Shareholders	52.8115093	28.9726663	99.56	0.3
CSR Strategy	71.8700815	24.5513768	99.79	0
SZE	10.5002657	1.28164276	13.4053461	7.25400103

SDG	73.7026884	6.09968704	80.7	57.91
LEVERAGE	0.45388288	0.44418967	0	2.1234

This section provides an overview of the descriptive statistics for the variables used in this study. It summarized the main features of the dataset, including means, standard deviations, and ranges, to help explain the characteristics of the firms before moving into deeper statistical testing.

The credit risk indicators show wide differences across firms. The Interest Coverage Ratio (ICR) has an average of 291.26 but a large standard deviation of 1563.03, with values ranging from -547.99 to 24864.6. This indicates that while some firms are highly capable of meeting their interest expenses, others struggle with negative earnings, showing a sign of financial stress.

A similar trend shows in the Altman Z-Score, which averages 38.71 with a large spread (SD=303.52). The minimum and maximum values (-0.02 to 6002.50) suggest significant differences in financial stability - some firms are financial sound, while other face much higher bankruptcy risk.

In contrast, the Credit Rating Score shows a mean of 72.65 and relatively low variation (SD=8.51), suggesting that most firms in the sample are within the investment-grade category and generally maintain strong credit quality.

The overall ESG score averages 67.26 (SD = 15.18), indicating that most firms demonstrate a solid commitment to sustainability, though performance levels still vary widely. For the Environmental (E) pillar, the mean score of 68.29 suggests that environmental management is a relatively strong area for the sample firms. The Resource Use (77.01) and Emissions (76.47) scores are particularly high, showing that many firms have made progress in improving energy efficiency and reducing emissions. However, Innovation stands out as the weakest environmental sub-dimension, with a mean of 45.88 and a large spread (SD = 34.51), implying that while some companies invest heavily in green innovation, others lag far behind.

The Social (S) pillar has a mean of 68.54, reflecting generally positive social responsibility efforts. Sub-dimensions such as Workforce (76.30) and Community (70.14) show strong performance, suggesting effective employee management and engagement with local communities. In contrast, Human Rights records a lower mean (59.70) and high variability, indicating that some firms still lack consistency in respecting and protecting human rights across their operations and supply chains.

For the Governance (G) pillar, the average score is slightly lower at 62.99 (SD = 20.21). Within governance, Shareholder rights (Mean = 52.81) are relatively weak, implying that not all firms provide equitable treatment and transparency to investors. On the other hand, CSR Strategy shows a higher mean (71.87), suggesting that most companies have integrated corporate responsibility principles into their overall business strategies.

Among the control variables, Firm Size (SZE) averages 10.50 (SD = 1.28), showing that the sample mostly includes large and well-established companies. The SDG Index has an average of 73.70, reflecting moderate progress in sustainable development among the countries represented, though with differences between developed and developing nations. The Leverage ratio averages 0.45 (SD = 0.44), suggesting that firms generally maintain balanced capital structures, though some firms operate with much higher debt levels.

In summary, the descriptive analysis reveals a diverse sample of firms with varying financial conditions and ESG practices. The credit risk indicators show substantial variation, indicating both highly stable and financially distressed firms. ESG performance is generally strong, especially in environmental efficiency and workforce-related practices, but weaker in innovation, human rights, and shareholder governance. The control variables confirm that the dataset represents large, regionally diverse firms with differing sustainability contexts.

4.3 Diagnostic Tests

4.3.1 Hausman Test

Table 5: Hausman Test Results

Model	Country heterogeneity	Decision Rule	Pre vs post pandemic	Decision Rule:
Model 1A	0.0000	FE is preferred	0.0000	FE is preferred
Model 1B	0.0002	FE is preferred	0.0005	FE is preferred
Model 1C	0.0078	FE is preferred	0.0130	FE is preferred
Model 2A	0.0000	FE is preferred	0.0000	FE is preferred
Model 2B	0.0000	FE is preferred	0.0000	FE is preferred
Model 2C	0.0008	FE is preferred	0.0000	FE is preferred
Model 3A	0.0000	FE is preferred	0.0007	FE is preferred
Model 3B	0.0000	FE is preferred	0.0125	FE is preferred
Model 3C	0.0000	FE is preferred	0.0177	FE is preferred

In this study, the choice between Fixed Effects (FE) and Random Effects (RE) models was guided by the nature of the dependent variables and the relationship between unobserved firm characteristics and ESG measures. Referring to Table 5, the Hausman test is performed and its results reveal that all the p-values are less than 0.05, which means that the null hypothesis is rejected and the fixed effects model is then preferred over the random effects model. Conclusively, the fixed effects model is the most appropriate for panel data regression analysis in this research.

4.3.2 Panel Unit Root Test

Table 6: Panel Unit Root Test Results

Variables	Levin, Lin, Chu	Im, Pesaran, Shin
ESG	-12.3564***	1.21395***
E	-35.2386***	-0.12063***
S	-30.3161***	-2.31521***
G	-27.1620***	-0.92309***
Emissions	-18.1539***	0.24271***
Innovation	-585.452***	-90.4611***
Resource Use	-27.2935***	-0.05868***
Community	-47.6494***	-1.92318***
Human Right	-77.6457***	-5.80961***
Product Responsibility	-84.6844***	-2.65692***
Workforce	-61.3683***	-2.38330***
CSR Strategy	-36.7967***	-2.91760***
Management	-13.4561***	0.00552
Shareholders	-18.0938***	-0.26982
Altman Z-Score	-117.925***	-6.91953***
Credit Rating Score	-22.2694***	-3.3E+10***
ICR	-32.7016***	-2.70728***
Leverage	-187.108***	-8.45698***
SDG Score	3.07807	3.72839
SZE	-60.1450***	-0.83010

Note: ***,** and * denote that the test statistic is significant at the 0.01, 0.05, and 0.10 levels, respectively.

The outcomes of the variables' unit root tests are displayed in Table 6. The Levin et al. (2002) test and the Im et al. (2003) test are the two types of unit root tests that are used. The results from the Levin et al. (2002) test indicate that all variables excepts SDG are stationary. On the other hand, the Im et al. (2003) test indicate that Management, Shareholders and SDG are not stationary, suggesting these variables may contain a unit root. The discrepancy between the two tests shows the different assumptions and sensitivity of each method, but overall, most variables appear to be stationary, allowing for valid analysis in subsequent models.

4.3.3 Multicollinearity Test

Table 7: Multicollinearity Test Results

Variables	**VIF**
ESG	1.070776
E	1.481264
S	1.471173
G	1.151848
Emissions	2.531885
Innovation	1.355122
Resource Use	2.196436
Community	1.477156
Human Rights	2.089265
Product Responsibility	1.298481
Workforce	1.670204
CSR Strategy	1.553767
Management	1.174409
Shareholders	1.114510
Leverage	1.080063
SDG Score	1.087338
SZE	1.113513

VIF Value	Interpretation
1–5	Acceptable → No multicollinearity problem
5–10	Moderate → Could be a concern
>10	Severe → Serious multicollinearity

Source: Akinwande et al., 2015

Referring to Table 7, the VIF results show that all the variables in the model are comfortably within safe limits, with values ranging from just 1.07 to 2.53. These numbers are well below the usual thresholds that signal a problem, which means the predictors are not too closely related to each other. In simple terms, each variable is bringing its own unique information to the model, and none are overlapping in a way that would distort the results. Because of this, there's no concern about multicollinearity, and all variables can be confidently kept in the analysis.

4.3.4 Heteroskedasticity Test

Table 8: Breusch-Pagan (BP) Test Result

Model	**Country heterogeneity**	**Decision Rule: If p>0.05, fail to reject H_0**	**Pre vs post pandemic**	**Decision Rule: If p>0.05, fail to reject H_0**
Model 1A	0.2470	Homoscedastic	0.2289	Homoscedastic
Model 1B	0.4889	Homoscedastic	0.4610	Homoscedastic
Model 1C	0.0288	Heteroscedasticity	0.1441	Homoscedastic
Model 2A	0.0000	Heteroscedasticity	0.0000	Heteroscedasticity
Model 2B	0.0000	Heteroscedasticity	0.0000	Heteroscedasticity
Model 2C	0.0000	Heteroscedasticity	0.0000	Heteroscedasticity
Model 3A	0.0106	Heteroscedasticity	0.0077	Heteroscedasticity
Model 3B	0.2255	Homoscedastic	0.0636	Homoscedastic
Model 3C	0.0000	Heteroscedasticity	0.0000	Heteroscedasticity

Referring Table 8, across the models, heteroskedasticity was examined using the Breusch–Pagan (BP) test. Most models showed consistent results; however, Model 3A displayed a borderline case. Under the BP test, the p-values for both the country heterogeneity specification ($p = 0.0106$) and the pre- versus post-pandemic specification ($p = 0.0077$) indicated heteroskedasticity, as both values fall below the 0.05 significance threshold.

For the models where heteroskedasticity was confirmed (Models 2A–2C and Model 3A,3C), Panel-Corrected Standard Errors (PCSE) were employed. PCSE is specifically designed for panel data settings with heteroskedasticity, cross-sectional dependence, and serial correlation. This correction ensures that the parameter estimates remain unbiased and that the standard errors are reliable, thereby addressing the heteroskedasticity problem effectively.

4.3.5 Autocorrelation Test

Table 9: Autocorrelation Test Results

Model	Country heterogeneity	Pre vs post pandemic
Model 1A	0.0000	0.0000
Model 1B	0.0000	0.0000
Model 1C	0.0000	0.0000
Model 2A	0.0000	0.0000
Model 2B	0.0000	0.0000
Model 2C	0.0000	0.0000
Model 3A	0.0000	0.0000
Model 3B	0.0000	0.0000
Model 3C	0.0000	0.0000

Referring to Table 9, the results show that all p-values for the autocorrelation tests across all the models are 0.0000, indicating that the null hypothesis of no autocorrelation is strongly rejected for each model. This suggests that significant autocorrelation exists in the residuals, implying that the models do not fully account for temporal or sequential dependencies in the data. To address this issue, Panel-Corrected Standard Errors (PCSE) is used as a remedy, as PCSE can correct for autocorrelation and heteroscedasticity in panel data, ensuring more robust and efficient coefficient estimates. This adjustment would provide more reliable inferences by accounting for the autocorrelation present in the residuals.

4.4 Model Results

Table 10: Fixed Effect Model (FEM) Regression Results for Model 1A,2A,3A (with Country heterogeneity)

Variables	Altman Z-Score	ICR	Credit Rating Score
ESG score	-0.167267	0.228318	0.032690
D	-0.573655	2.293562***	0.023832
ESG_D	0.121774	-0.408425*	0.003912
Leverage	-0.835886***	-1.808446***	-0.113633***
SDG	0.555192	0.259510	-0.328950***
SZE	-0.271164*	-0.435506***	-0.012078***
C	3.020585	6.561953	5.718952
R-squared	0.160118	0.374290	0.252110
Adjusted R-squared	0.151384	0.360020	0.244333
F-statistic	18.33350	26.22810	32.41732
Prob (F-statistic)	0.000000	0.000000	0.000000

Note: ***,** and * denote that the test statistic is significant at the 0.01, 0.05, and 0.10 levels, respectively.

Table 11: Fixed Effect Model (FEM) Regression Results for Model 1A,2A,3A (with Pre-post pandemic)

Variables	Altman Z-Score	ICR	Credit Rating Score
ESG score	-0.125276	0.014686	0.027798
Pre vs Post	0.653749	2.254337*	0.178248
ESG_P	-0.155691	-0.499260*	-0.036942
Leverage	-0.843708	-0.291502	-0.033724
SDG	0.441848	-4.909199	0.672170
SZE	-0.271373*	0.033848	-0.049204*
C	3.319081	24.18489	1.796730
R-squared	0.160845	0.882101	0.607419
Adjusted R-squared	0.152119	0.863891	0.546783
F-statistic	18.43278	48.44016	10.01743
Prob (F-statistic)	0.000000	0.000000	0.000000

Note: ***,** and * denote that the test statistic is significant at the 0.01, 0.05, and 0.10 levels, respectively.

Referring to Table 10 & 11, presents the results of the three models examining the relationship between ESG and firms' credit risk measured by Altman Z-Score, Interest Coverage Ratio (ICR), and Credit Rating Score. These results are analysed both in terms of country heterogeneity and pre vs post pandemic periods.

Across all three models, ESG alone is not significant. Meaning to say, ESG performance by itself doesn't appear to have a strong, standalone impact on firms' credit risk. Similarly, Seefloth et al. (2025), along with Postiglione et al. (2025), also found an insignificant relationship between ESG performance and credit risk, which aligns with the current findings. This suggest the notion that ESG, when considered in isolation, does not have a significant impact on firms' credit risk, consistent with the conclusions of past research in this area. However, when ESG interacts with country characteristics (country heterogeneity) or the post pandemic periods, its impact become negatively significant. In other word, ESG has a more pronounced negative impact on firms' ICR in developed countries and after the pandemic.

Table 12: Fixed Effect Model (FEM) Regression Results for Model 1B,2B,3B (with Country heterogeneity)

Variables	**Altman Z-Score**	**ICR**	**Credit Rating Score**
E score	0.127904**	0.418530***	-0.016967
S score	-0.091661	-0.295551*	0.060181***
G score	-0.258194***	-0.163165	0.029833**
D	-1.215347	1.932659*	0.038474
E score_D	-0.093761	0.566418***	0.019432
S score_D	0.086541	-1.062055***	0.045650
G score_D	0.289108*	0.189070	0.085435***
Leverage	-0.844605***	-1.835299***	0.111546***
SDG Score	0.562848	-0.064692	0.298550***
SZE	-0.292713**	-0.453480***	0.009807***
C	3.418941	9.247276	5.641358
R-squared	0.169969	0.395303	0.277580
Adjusted R-squared	0.155483	0.377140	0.264972
F-statistic	11.73358	21.76502	22.01675
Prob (F-statistic)	0.000000	0.000000	0.000000

Note: ***,** and * denote that the test statistic is significant at the 0.01, 0.05, and 0.10 levels, respectively.

Table 13: Fixed Effect Model (FEM) Regression Results for Model 1B,2B,3B (with Pre-post pandemic)

Variables	**Altman Z-Score**	**ICR**	**Credit Rating Score**
E score	0.110920**	0.465080***	-0.022137**
S score	-0.073599	-0.286154*	0.050775***
G score	-0.204163**	0.050019	0.008983
Pre vs. Post	0.179706	1.220988	0.185843
E score P	-0.021610	0.721545	-0.029024
S score_P	-0.070169	-0.689258**	0.030059
G score_P	0.047583	-0.340681	-0.040905*
Leverage	-0.848189***	-1.904464***	-0.032268
SDG Score	0.488498	2.051980***	0.646583
SZE	-0.290590***	-0.444834***	-0.046130*
C	3.481191	-0.727339	1.833379
R-squared	0.167643	0.379632	0.615072
Adjusted R-squared	0.153116	0.368806	0.552070
F-statistic	11.54063	35.06456	9.762712
Prob (F-statistic)	0.000000	0.000000	0.000000

Note: ***,** and * denote that the test statistic is significant at the 0.01, 0.05, and 0.10 levels, respectively.

Referring to Table 12 & 13, presents the results of the three models examining the relationship between E, S, G pillars and firms' credit risk measured by Altman Z-Score, Interest Coverage Ratio (ICR), and Credit Rating Score. These results are also analysed both in terms of country heterogeneity and pre vs post pandemic periods.

With a beta value of 0.1279, the Environmental pillar (E score) significantly and favourably influences the Altman Z-Score in Model 1. This indicates that, on average, a 1% rise in the E score corresponds to a 0.1279% increase in the Z-Score. The Altman Z-Score is not significantly affected by the Social pillar (S score). With a beta value of -0.2582, the Governance pillar (G score) significantly and negatively affects the Altman Z-Score. The Z-Score typically decreases by 0.2582% for every 1% increase in the G score. The Altman Z-Score is significantly and favorably impacted by the Governance pillar (G score) in developed nations.

With a beta value of 0.4185, the Environmental pillar (E score) in Model 2 (ICR) has a strong positive and substantial influence on ICR. This indicates that the average increase in the ICR is 0.4185% for every 1% rise in the E score. With a beta value of -0.2956, the Social pillar (S score) significantly and negatively affects ICR. The average ICR decreases by 0.2956% for every 1% rise in the S score. ICR is not significantly impacted by the Governance pillar (G score). With a beta value of 0.5664, the Environmental pillar's influence is much greater in developed nations, while the Social pillar's detrimental effects on ICR are also more noticeable. Additionally, this analysis reveal that the Social pillar (S score) has a stronger negative impact on firms' ICR in the post-pandemic pandemic.

With a beta value of -0.022137, the Environmental pillar (E score) significantly and negatively affects the Credit Rating Score in Model 3. Accordingly, the Credit Rating Score typically drops by 0.022137% for every 1% increase in the E score. The Credit Rating Score is positively and significantly impacted by the Social and Governance pillars (S and G scores). In particular, the beta coefficients for the Governance and Social pillars are 0.02983 and 0.06018, respectively. Additionally, with a beta value of 0.2891, the influence of the Governance pillar (G score) on the Credit Rating Score is more favorable for developed nations. Furthermore, the Governance pillar (G score) impact on the firms' Credit Rating Score shifts from positive to negative after pandemic, with a beta coefficient of -0.0409.

Table 14: Fixed Effect Model (FEM) Regression Results for Model 1C,2C, 3C (with Country heterogeneity)

Variables	**Altman Z-Score**	**ICR**	**Credit Rating Score**
Emissions	0.131782	0.325680*	-0.006582
Innovation	0.011814	0.278310***	0.017361***
Resource Use	0.050167	-0.221238	-0.041712***
Community	-0.140495	0.291162***	0.025039
Human Rights	0.022616	-0.302619***	-0.012131
Product Responsibility	0.032590	-0.033435	0.009303
Workforce	-0.226495	0.172435	0.091591***
CSR Strategy	-0.066640	0.011105	-0.002455
Management	-0.058948	-0.0071381	-0.007648
Shareholders	-0.038047	-0.086644	-0.004773
D	-2.371629*	-0.207641	0.302248**
Emissions D	0.330008	1.894969***	0.027621
Innovation D	-0.005252	-0.232190***	-0.017985***
Resource Use D	-0.504653**	-1.107968***	-0.029801
Community D	0.137473	-0.433985***	-0.037101**
Human Rights D	0.043610	0.564238***	0.047490***
Product Responsibility D	0.002681	-0.195570	-0.014544
Workforce D	0.446424*	0.340779	-0.063708*
CSR Strategy D	0.024563	-0.505030**	0.002933
Management D	0.043230	-0.297653*	0.027197*
Shareholders D	0.033071	0.106875	-0.002512
Leverage	-0.814708	-1.639055***	-0.105915***
SDG Score	0.349899	-0.464017	-0.383600***
SZE	-0.289166	-0.443396***	-0.007784**
C	4.549570	9.138525	5.757015
R-squared	0.188422	0.456864	0.349634
Adjusted R-squared	0.153578	0.433545	0.321712
F-statistic	5.407563	19.59198	12.52151
Prob (F-statistic)	0.000000	0.000000	0.000000

Note: ***,** and * denote that the test statistic is significant at the 0.01, 0.05, and 0.10 levels, respectively.

Table 15: Fixed Effect Model (FEM) Regression Results for Model 1C,2C, 3C (with Pre-post pandemic)

Variables	**Altman Z-Score**	**ICR**	**Credit Rating Score**
Emissions	0.197866**	0.118242	-0.040909***
Innovation	0.015500	0.059400	0.014028**
Resource Use	-0.054710	-0.118557	-0.032406***
Community	-0.116158*	0.002584	-0.024729***
Human Rights	0.028655	-0.003257	0.007436
Product Responsibility	0.036699	0.020354	0.015318*
Workforce	-0.080932	0.328834*	0.133495***
CSR Strategy	-0.014308	0.070016	0.015129*
Management	-0.097231**	-0.163101**	0.008540
Shareholders	0.015812	-0.102003*	-0.014110***
Pre vs Post	-0.091862	2.633841***	0.452922***
Emissions_P	-0.357176	-0.779043***	-0.012261
Innovation_P	0.055195	-0.080402*	-0.003488
Resource Use_P	0.053405	0.246262	-0.017073
Community_P	0.126936	0.061805	0.043218**
Human Rights_P	0.031669	0.118327*	0.013018
Product Responsibility_P	-0.075240	-0.119925	0.000501
Workforce_P	-0.224017	-0.191641	-0.108191***
CSR Strategy_P	0.134940*	0.132246	0.006173
Management_P	0.082466	-0.044908	-0.022629**
Shareholders_P	-0.066112***	0.090820*	0.003055
Leverage	-0.581823***	-0.306179	-0.029559
SDG Score	0.134089	-7.265098*	0.387119
SZE	0.293501*	0.002231	-0.041781*
C	6.079461	33.75259	2.713305
R-squared	0.187643	0.888536	0.661527
Adjusted R-squared	0.152765	0.866563	0.594805
F-statistic	5.380031	40.43864	9.914720
Prob (F-statistic)	0.000000	0.000000	0.000000

Note: ***,** and * denote that the test statistic is significant at the 0.01, 0.05, and 0.10 levels, respectively.

Referring to Table 14 & 15, presents the results of the three models examining the relationship between ESG 10 sub-dimension and firms' credit risk measured by Altman Z-Score, Interest Coverage Ratio (ICR), and Credit Rating Score. These results are also analysed both in terms of country heterogeneity and pre vs post pandemic periods.

With a beta value of 0.1318, Emissions has a strong positive and substantial influence on Altman Z-Score in Model 1 (Altman Z-Score). This means that a 1% rise in Emissions is linked to an average increase in Z-Score of 0.132%. With a beta value of -0.1405, the Community pillar has a negative and substantial influence, meaning that an average 1% increase in community engagement results in a 0.141% fall in the Z-Score. Additionally, with a beta value of -0.0589, management has a negative and substantial influence. With a beta value of 0.4464, the Workforce pillar notably becomes important and positive for developed nations. This means that, on average, a 1% improvement in Workforce practices leads to a 0.446% gain in the Z-Score in developed nations. With a beta value of -0.5047, Resource Use also significantly and negatively affects the Altman Z-Score for developed countries. A beta coefficient of -0.0380 indicates a negative impact on shareholders during the post-pandemic period, but a beta coefficient of 0.0246 indicates a favorable impact on CSR strategy.

In Model 2 (ICR), Emissions (beta coefficient of 0.3257) and Innovation (beta coefficient of 0.2783) show strong positive and significant impacts, indicating that a 1% increase in Emissions results in a 0.326% increase in ICR, and a 1% increase in Innovation leads to a 0.278% increase in ICR on average. Meanwhile, Community (beta coefficient of 0.2912) and Workforce (beta coefficient of 0.3288) also show positive and significant impacts, indicating that a 1% increase in Community or Workforce practices results in a 0.291% and 0.328% increase in ICR on average, respectively. However, Human Rights (beta coefficient of -0.3026) and Management (beta coefficient of -0.1631) show negative impacts on ICR. In developed countries, the effect of Emissions on ICR is more favourable, with a beta coefficient of 1.8949, indicating that a 1% increase in Emissions results in a 1.895% increase in ICR on average. Additionally, Human Rights also shows a favourable impact on ICR in developed countries. But in the post-pandemic period, Emissions and Innovation are linked to less favourable ICR, while Human Rights and Shareholder practices are linked to more favourable ICR.

In Model 3 (Credit Rating Score), Innovation (beta coefficient of 0.0174), Workforce (beta coefficient of 0.1335), and CSR Strategy (beta coefficient of

0.0151) show strong positive and significant impacts, with 1% increases in these factors leading to 0.017%, 0.134%, and 0.015% increases in Credit Rating Scores on average, respectively. Conversely, Emissions (beta coefficient of -0.0409) and Resource Use (beta coefficient of -0.0417) show negative impacts on credit ratings, indicating that higher emissions and inefficient resource use are linked to lower credit ratings. In developed countries, Human Rights (beta coefficient of 0.0475) and Management (beta coefficient of 0.0272) show more favourable impacts on Credit Rating Scores, with a 1% improvement in Human Rights and Management leading to 0.048% and 0.027% increases, on average, respectively. Innovation, Community, and Workforce show unfavourable effects on Credit Rating Scores in developed markets. In the post-pandemic period, Workforce and Management practices become less favourable for Credit Ratings with beta coefficients of -0.1082 and -0.0226, respectively, while Community practices are associated with more favourable Credit Ratings, with a beta coefficient of 0.0432.

CHAPTER 5: DATA ANALYSIS

5.1 Introduction

The study findings are discussed in this chapter with an emphasis on the connection between credit risk and ESG performance among the top 100 publicly traded corporations in Asia. The results of the study will be thoroughly examined and presented, offering a deeper comprehension of the relationship between credit risk and ESG performance, especially in Asia.

The discussion will examine the implications of the findings, significant and impact of ESG pillars and sub-dimensions on credit risk measures such as Altman Z-Score, Interest Coverage Ratio (ICR), and Credit Rating Score. This analysis will emphasize how different aspects of ESG affects firms' credit risk, highlight their impact differences based on country development level and pre-and-post pandemic period.

Additionally, the chapter will acknowledging any limitations or potential biases that may have influenced the findings. Finally, recommendations for future research will be provided, identifying areas for further investigation and exploration. These recommendations will guide future scholars in expanding the understanding of the relationship between ESG practices and credit risk, particularly in the Asian market context.

5.2 Discussion of Key Findings

The existing studies examining the relationship between ESG and credit risk are typically focus on Western or U.S market, and has yielded to inconsistent results. Due to the inconsistent outcomes reported by different scholars, the hypotheses in this study are formulated without a predetermined direction for the relationship.

Before diving into the detailed findings, it's important the understand the direction of below credit risk measures to interpret the results clearly.

- A High Altman Z-score = Low Risk (Good)
- A High Credit Rating = Low Risk (Good)
- A High ICR = Low Risk (Good)

5.2.1 The Effect of Overall ESG on the Credit Risk

The overall ESG performance is not statistically significant in explaining the firms' credit risk. Meaning to say, the overall ESG performance doesn't improve the firms' credit risk. This is aligned with existing literature, particularly the identification of an insignificant general association between ESG and credit risk noted by Seefloth et al. (2025).

One of the possible explanation for the insignificant of ESG could be the overall ESG score often combines Environmental (E), Social (S), and Governance (G) together, which can leads the overall score to insignificant. In other word to say, suppose one dimension lead to lower risk, but others carry risks or costs, these effects may offset each other when combined into the overall score (Postiglione, 2025). Additionally, the insignificant relationship between overall ESG and credit risk observed in this study can also be explained by there's situation where the cost of ESG spending offset the perceived risk mitigation benefits. Thus, ESG is shown no marginal benefits on firms credit risk (Habermann & Fischer, 2021).

This “masking effect” is particularly dangerous for investors who rely on a single ESG as a summary of a company’ s risk profile. As demonstrated in findings, the individual ESG pillars have a significant and direct impact on credit risk, but the overall score shows insignificant impact. Thus, it emphasized that the importance of detailed ESG analysis rather than relying on the headline scores.

5.2.2 The Effect of E,S,G pillars on the Credit Risk

For the Environmental pillar, the positive and significant relationship found with the Altman Z-Score and ICR can be explained by companies engaging in environmental practices tend to face lower legal, regulatory and reputational risks (Agosto et al., 2023). This ensure a steady operational performance and future stability and yield to favourable solvency and liquidity metrics like the Z-Score and ICR. Whilst the negative and significant relationship observed with Credit Rating Score aligned with the overinvestment views, which suggesting that implementing environmental measures require long-term and costly investment. These expenditures can strain short-term financial health, which credit rating agency might interpret as increased credit risk (Chollet and Sandwidi 2018; Orlitzky and Benjamin 2001; Shi et al. 2023).

For the Social pillar, the negative and significant effect on the ICR is likely due to the financial drain of implementing social initiatives. Social initiatives often involve huge upfront costs. For a short-term cash flow metric like the ICR, these costs act as cash outflows that can negatively affect the company’s ability to cover interest (Habermann & Fischer, 2021). Whilst the positive relationship with Credit Rating Score supports the view that strong social performance enhance crisis resilience and foster a strong stakeholder relationships (Vishwanathan et al. 2020). Rating agency view this as a sign of reduced reputational risk, and rewarding it with higher creditworthiness.

For the Governance pillar, the positive and significant relationship with the Credit Rating Score shows that governance is highly valued by external agencies. This is due to strong governance structures reduce information asymmetry and enhance the early detection of financial distress (Cheng et al., 2014). These are seen as a crucial elements of a stable risk management framework that merits a higher credit rating. While the negative association with the Altman Z-Score reflects the overinvestment perspective or agency theory arguments. Maintaining excessive or rigid internal control and reporting structures is costly and may lead to management distraction from their core business (Seefloth et al., 2025). This diversion of resources can increase firms credit risk eventually.

5.2.3 The Effect of ESG 10 Sub-dimension on the Credit Risk

The Emissions performance is positive and significant on Altman Z-Score and ICR, which indicates that superior environmental performance is typically associated with reduced legal, regulatory and reputational risks (Fafaliou et al., 2022). Investment in area like environmental innovation and efficient resource use can lead to improved profitability, operational efficiencies, and sustained stability, enhancing solvency (Altman Z-Score) and cash flow (ICR) metrics (Michalski & Low, 2024). Conversely, Emission and Resource Use are negative on Credit Rating Score, which suggesting that achieving higher environmental standards required substantial initial investments, which can temporarily compromise profitability and lead to lower credit assessments (Shi te al., 2023).

Social initiative often involve direct and immediate operational costs. When costs associated with dimensions like Human Right (as suggested by the negative impact on ICR) and Community (as suggested negative impact on Altman Z-Score and Credit Rating Score), these outflows directly suppress short term liquidity and credit rating score. While dimension like Workforce show positive relationship with credit risk. This can be explained that investing in employee training and development programme can lead to improved labour productivity and firm effectiveness over time, positively influence performance indicators (Delmas & Pekovic, 2012).

Results indicating negative impacts from Management (on Z-Score and ICR) and Shareholders (on ICR) align with the overinvestment view. Excessive governance systems, rules, and regulatory reporting requirements impose additional fixed cost, consequently weakening profitability and raising bankruptcy likelihood (Habermann & Fischer, 2021). Additionally, high Shareholder scores can sometimes imply higher dividend payouts, thereby reducing retained earnings, which is a key component used in the Altman Z-Score calculation. Strong governance frameworks are a reliable indicator of management quality, as evidenced by the favorable correlation between CSR strategy and Credit Rating Score.

5.2.4 The Effect of ESG (Overall, Pillars, and Sub-dimensions) Differs across Developed and Developing Countries

The relationship between ESG (including overall, pillars, and sub-dimensions) and credit risk shows a significant differences when comparing firms operating in Developed versus Developing Countries. These differences are fundamentally driven by varying institutional contexts, regulatory pressures, market maturity (Pineau & Estran, 2022).

In developed countries, ESG performance is generally found to increase credit risk. This is often explained by the overinvestment view; firms in developed countries already operate at high sustainability standards, meaning further marginal ESG investments yield diminishing benefits, expose firms to high compliance and transition costs, potentially accelerating risk (Habermann, 2021)

The difference is most evident when analysing the individual pillars. Governance pillar (G score) is consistently noted as the most important ESG factor in credit risk for developed countries. In mature markets, Governance structures are highly valued as they signal transparency, reduced agency costs, and competent risk management, leading to a stronger and positive impact on credit ratings (Shirin Yusupova et al., 2025).

When a sub-dimension is negatively associated with credit risk (e.g., lower Z-Score, ICR or Credit Rating Score), it suggests that the high expenditures required for these initiative outweigh the short-term financial benefits. Resource Use showing a significant negative impact on Altman Z-Score in developed countries, and being unfavourable for ICR, indicates that effort toward resource reduction or waste disposal - often long-term and costly investments (Seefloth et al., 2025). Similarly, the finding that Innovation, CSR strategy, and Management yield an unfavourable ICR suggests that the resources allocated to these forward-looking investments, which may include R&D expenses, new technology adoption or high compliance costs. All these costs act as significant financial burdens on the ability to cover interest expenses (Farah et al., 2021).

When a sub-dimension is associated with lower credit risk, it indicates that the perceived or actual risk-reduction benefits (e.g., reputational protection, enhance operations) are captured by the metrics. Workforce showing a significant positive impact on the Altman Z-Score suggests that good employee relations translate into enhanced operations and financial resilience, improving solvency (Delmas & Pekovic, 2012). Strong employee satisfaction and motivation reduce turnover and leaf to higher labour productivity. Human Rights and Management yielding a favourable Credit Rating Score signals that external agencies value strong governance structure and ethical supply chains for their role in long-term risk management, transparency, and signalling management competence (Lee et al., 2024). These structures reduce legal liabilities and agency costs.

5.2.5 The Effect of ESG (Overall, Pillars, and Sub-dimensions) Differs across Pre and Post Pandemic

The relationship between overall ESG performance and credit risk varies significantly between pre and post pandemic periods. The result that overall ESG has a more pronounced negative impact on firms' ICR post-pandemic suggests that liquidity-straining cost were either exacerbated or brought into sharp focus by the economic environment. The ICR is highly sensitive to current operating expenses; thus, ESG costs appeared as an uncompensated drain on sort-term cash flow (Habermann & Fischer, 2021).

The shift in market perception regarding the effectiveness of the ESG pillars is clearly demonstrated by the opposing movements of the Social and Governance pillars during the pandemic transition. The finding that the Social pillar (S score) has a stronger negative impact on firms' ICR in the post-pandemic period aligns with the reality that social commitments involve measurable operational costs that strain liquidity when cash flow is tight. The Governance pillar (G score) shift from positive to negative impact on the Credit Rating Score after the pandemic. The change might suggest that rating agencies started to see strict rules and governance structures as too expensive or distracting, especially when the company needed to be flexible during the crisis. Another possibility is that these governance systems didn't do enough to protect the company during the crisis, making people question whether they were really valuable in the long term (Habermann & Fischer, 2021).

The specific sub-dimension results highlight which investments were penalized due to cost visibility and which were rewarded for offering crisis resilience during the downswing. The fact that Emission and Innovation yielded an unfavourable ICR post-pandemic is directly tied to the immediate expense they represent. This is due to in post pandemic, the main focus of the firm should be on recovering their business activities, back to normal operations and sales. Thus, efforts focusing on emission control and innovation is not appropriate as it incurs costly investments, punishing the ICR ratio (Cheng et al., 2014; Servaes & Tamayo, 2013).

Conversely, certain dimensions gained positive significant by offering crisis resilience during the downswing. In time of market turbulence, the overall strong Human Right performance acting as an “insurance-like protection’ for intangible, relationship-based assets (Abdul Razak et al., 2020). This commitment helps firms navigate crises, which improves their ability to attract funds and maintain operations (Shi et al., 2023). The reward associated with Management performance emphasized the necessity of competent leadership and transparent structure for securing stability during pandemic recovery periods. Credit Rating agencies value Management performance highly because it indicates superior management quality and competence, which are critical traits for navigating complexity post-crisis. Firms led by managers with high ability are better positioned to navigate risks and uncertainties and make sound strategic decisions (Chen et al. 2015; Hermalin and Weisbach 2017).

5.3 Implications of the Study

This study offers insightful information on the connection between credit risk and ESG (overall, pillars, and ten sub-dimensions). The results have a number of significant theoretical and practical ramifications.

In term of theoretical implications, this study contributes to the ESG and credit risk literature by providing Asia-specific evidence. The insignificant relationship between overall ESG and credit risk challenges previous assumptions that higher ESG performance universally lead to reduced financial risk. The findings also underscore the importance of distinguishing between ESG pillars and sub-dimensions, as their impacts on credit risk can be varied significantly depending on the country development level and pre and post pandemic period.

In term of practical implications, the study emphasized that ESG performance should be considered with caution when evaluating credit risk, Investors should avoid relying solely on aggregated ESG score instead assess ESG pillars and sub-dimensions to better understand their impact on a firm's creditworthiness. This study also identified which ESG dimensions can drive to lower credit risk and which can lead to increase financial strain. Thus, it allows Managers to help firms adopt targeted yet cost-effective ESG strategies instead of relying on overall ESG score.

5.4 Limitations of the Study

While this study provides useful insights, several limitations should be acknowledged.

First, this study relies solely on Refinitiv for ESG data. Since different databases use their own methods and frameworks for scoring and reporting, the results could vary if another data source were used. So, it's important to view the findings within the context of Refinitiv’s approach, rather than as a general measure of ESG performance.

Second, there's a potential issue with endogeneity (two-way relationship) in the relationship between ESG and credit risk. While companies with stronger ESG practices might have lower credit risk, it’s also possible that financially stronger companies, with lower risk profiles, are simply in a better position to invest in ESG activities. This makes it difficult to figure out whether ESG is truly lead to the reduction of risk or if healthier companies just seem more sustainable.

Third, the data loss incurred during the sample selection process. Originally, 100 firms were considered for the analysis; however, 27 firms were removed due to missing data, reducing the final sample size to 73 firms. This results in the potential risk of survivorship bias, as the firms that reported data may not represent the full spectrum of companies in the region. As a result, this study might be optimistic, as firms that are better managed, more transparent, and have lower credit risk are typically more likely to disclose their ESG data.

Fourth, the measures of credit risk applied here—Altman Z-Score, Interest Coverage Ratio, and credit ratings—are widely used but still limited. They cannot fully capture the complexity of credit risk in practice, especially when unexpected shocks, regulatory shifts, or global economic disruptions affect firms in ways beyond what the models reflect.

Finally, this study uses a Fixed Effects model, which accounts for time-invariant elements but limits the conclusions' generalisability. Because the Fixed Effects model focusses on within-entity fluctuations over time, so the results are limited to the firms included in this research. As a result, the findings may not be applicable to firms outside of this sample or to different situations, which should be considered when interpreting the results.

5.5 Recommendations for Future Research

According to the limitations mentioned, several recommendations can be implemented for future research to better understanding the relationship between ESG (overall, pillar-specific, and 10 sub-dimensions) and credit risk in Asian publicly listed companies.

First, it is recommended to expand the scope of ESG analysis. By incorporating data from multiple sources such as Sustainalytics, MSCI, or Bloomberg, enable researchers compare how different databases' scoring methods and disclosure practices impact the findings, as they have different methodology. This would help to validate the reliability of ESG measures and give a clearer picture of how they relate to credit risk using different data sources.

While this study acknowledge the endogeneity issue, it doesn't fully address it in the analysis. To improve future research, it would be valuable to use lagged variables. For example, comparing 2023 credit risk with 2022 ESG scores, to better determine the direction of causality.

Next, it is also recommended for future researchers to test other additional credit risk measures like Probability of Default (PD), Credit Default Swaps (CDS) or Ohlson O-Score for more comprehensive insights. In order to address the endogeneity issue, advanced method like machine learning techniques can be applied as well in the future research. Meanwhile, future research could explore additional factors such as ownership structure and industry type which may moderate the relationship of ESG and firms' credit risk.

5.6 Concluding Remarks

The essential insights gained from analyzing the link between ESG performance and credit risk among the top 100 publicly listed firms in Asia are summarized in the following closing statements, which are based on the study's results and analysis.

With an emphasis on the biggest publicly traded corporations in Asia, this thesis sought to investigate the relationship between credit risk and ESG performance. It has filled a knowledge gap in the body of current literature. Important insights into how sustainability practices might affect a company's credit risk were obtained from the examination of ESG (including overall, pillars, and sub-dimensions).

Key findings show that the relationship between ESG and credit risk is complex. The Social and Governance aspects exhibited different benefits depending on country-specific circumstances, while the Environmental pillar indicated a considerable reduction in credit risk. The analysis also shows that before and after the COVID-19 epidemic, ESG had a different effect on credit risk. The differences between developed and developing nations were also highlighted in the investigation.

Overall, this study had provided valuable insights for investors and managers. It shows that companies should go beyond just adopting ESG practices. They need to focus on the sustainability dimensions that really help reduce their credit risk.

REFERENCES

Abdul Razak, L., Ibrahim, M. H., & Ng, A. (2020). Which Sustainability Dimensions Affect Credit Risk? Evidence from Corporate and Country-Level Measures. *Journal of Risk and Financial Management*, *13*(12), 316. https://doi.org/10.3390/jrfm13120316

Adams, R. B., & Mehran, H. (2012). Bank board structure and performance: Evidence for large bank holding companies. *Journal of Financial Intermediation*, *21*(2), 243–267. https://doi.org/10.1016/j.jfi.2011.09.002

Agosto, A., Giudici, P., & Tanda, A. (2023). *How to combine ESG scores? A proposal based on credit rating prediction*. https://doi.org/10.1002/csr.2548

Alam, Md. M., Tahir, Y. M., Saif-Alyousfi, A. Y. H., Ali, W. B., Muda, R., & Nordin, S. (2022). Financial factors influencing environmental, social and governance ratings of public listed companies in Bursa Malaysia. *Cogent Business & Management*, *9*(1). https://doi.org/10.1080/23311975.2022.2118207

Albers, M. J. (2017). Quantitative Data Analysis—In the Graduate Curriculum. *Journal of Technical Writing and Communication*, *47*(2), 215–233. sagepub.

Altman, E. I. (1968). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *The Journal of Finance*, *23*(4), 589–609. https://doi.org/10.2307/2978933

Altman, E., & Hotchkiss, E. (n.d.). *Predict and Avoid Bankruptcy, Analyze and Invest in Distressed Debt Third Edition Corporate Financial Distress and Bankruptcy*.

Auger, P., Devinney, T. M., Louviere, J. J., & Burke, P. F. (2008). Do social product features have value to consumers? *International Journal of Research in Marketing*, *25*(3), 183–191. https://doi.org/10.1016/j.ijresmar.2008.03.005

Bannier, C. E., Bofinger, Y., & Rock, B. (2021). Corporate Social Responsibility and Credit Risk. *Finance Research Letters*, *44*, 102052. https://doi.org/10.1016/j.frl.2021.102052

Becht, M., Bolton, P., & Röell, A. A. (2002). Corporate Governance and Control. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.343461

Bertelli, B., Ulpiana Kocollari, Merzi, L., & Torricelli, C. (2025). The role of circular economy in reducing corporate default probability: insights from recent research. *Current Opinion in Environmental Sustainability*, *75*, 101555–101555. https://doi.org/10.1016/j.cosust.2025.101555

Bonacorsi, L., Cerasi, V., Galfrascoli, P., & Manera, M. (2024). ESG Factors and Firms' Credit Risk. *Journal of Climate Finance*, *6*, 100032. https://doi.org/10.1016/j.jclimf.2024.100032

Boyd, J. H., Hu, J. N., & Jagannathan, R. (2003). The Stock Market's Reaction to Unemployment News: "Why Bad News is Usually Good for Stocks." *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.423982

Breusch, T. S., & Pagan, A. R. (1979). A Simple Test for Heteroscedasticity and Random Coefficient Variation. *Econometrica*, *47*(5), 1287–1294. https://doi.org/10.2307/1911963

Broadstock, D. C., Chan, K., Cheng, L. T. W., & Wang, X. (2021). The role of ESG performance during times of financial crisis: Evidence from COVID-19 in China. *Finance Research Letters*, *38*(38), 101716. https://doi.org/10.1016/j.frl.2020.101716

Brogi, M., Lagasio, V., & Porretta, P. (2022). Be good to be wise: Environmental, Social, and Governance awareness as a potential credit risk mitigation factor. *Journal of International Financial Management & Accounting*, *33*(3). https://doi.org/10.1111/jifm.12156

Bruno, C. C., & Henisz, W. J. (2024). Environmental, Social, and Governance (ESG) Outcomes and Municipal Credit Risk. *Business & Society*, *63*(8), 1709–1756. https://doi.org/10.1177/00076503231220541

Campanella, F., Meles, A., Serino, L., & Verdoliva, V. (2025). Driving Credit Access Through ESG Performance: A European Perspective. *Finance Research Letters*, 107296. https://doi.org/10.1016/j.frl.2025.107296

Chen, S.-L., Wang, D., & Chen, H.-W. (2025). The Impact of ESG Factors on Credit Ratings: An Empirical Study of European Banks. *International Review of Economics & Finance*, *99*, 104056. https://doi.org/10.1016/j.iref.2025.104056

Chen, Y., Podolski, E.J., and Veeraraghavan, M., 2015. Does managerial ability facilitate corporate innovative success? Journal of Empirical Finance, 34, 313–326.

Cheng, B., I. Ioannou, and G. Serafeim. 2014. “Corporate Social Responsibility and Access to Finance.” Strategic Management Journal 35, no. 1: 1–23. https:// doi. org/ 10. 1002/ smj. 2131.

Chodnicka-Jaworska, P. (2021). ESG as a Measure of Credit Ratings. *Risks*, *9*(12), 226. https://doi.org/10.3390/risks9120226

Choi, D., Yong Kyu Gam, Min Jung Kang, & Shin, H. (2024). The effect of ESG-motivated turnover on firm financial risk. *the British Accounting Review*, 101373–101373. https://doi.org/10.1016/j.bar.2024.101373

Chollet, P., and B. W. Sandwidi. 2018. "CSR Engagement and Financial Risk: A Virtuous Circle? International Evidence." Global Finance Journal 38: 65–81. https:// doi. org/ 10. 1016/j. gfj. 2018. 03. 004.

Clausing, K. A., & Lahav, Y. (2011). Corporate tax payments under formulary apportionment: Evidence from the financial reports of 50 major U.S. multinational firms. *Journal of International Accounting, Auditing and Taxation*, *20*(2), 97–105. https://doi.org/10.1016/j.intaccaudtax.2011.06.004

Cubas-Díaz, M., & Martínez Sedano, M. (2018). Do Credit Ratings Take into Account the Sustainability Performance of Companies? *Sustainability*, *10*(11), 4272. https://doi.org/10.3390/su10114272

de Villiers, C., & Marques, A. (2015). Corporate social responsibility, country-level predispositions, and the consequences of choosing a level of disclosure. *Accounting and Business Research*, *46*(2), 167–195. https://doi.org/10.1080/00014788.2015.1039476

Delmas, M. A., & Pekovic, S. (2012). Environmental standards and labor productivity: Understanding the mechanisms that sustain sustainability. *Journal of Organizational Behavior*, *34*(2), 230–252. https://doi.org/10.1002/job.1827

Doan, M. H., & Sassen, R. (2020). The relationship between environmental performance and environmental disclosure: A meta-analysis. *Journal of Industrial Ecology*, *24*(5). https://doi.org/10.1111/jiec.13002

Dorfleitner, G., & Grebler, J. (2020). The social and environmental drivers of corporate credit ratings: international evidence. *Business Research*. https://doi.org/10.1007/s40685-020-00127-9

Edmans, A., Fang, V. W., & Lewellen, K. A. (2017). Equity Vesting and Investment. *The Review of Financial Studies*, *30*(7), 2229–2271. https://doi.org/10.1093/rfs/hhx018

Eliwa, Y., Aboud, A., & Saleh, A. (2021). ESG practices and the cost of debt: Evidence from EU countries. *Critical Perspectives on Accounting*, *79*, 102097. https://doi.org/10.1016/j.cpa.2019.102097

Epstein, M. J., & Roy, M.-J. (2001). Sustainability in Action: Identifying and Measuring the Key Performance Drivers. *Long Range Planning*, *34*(5), 585–604. https://doi.org/10.1016/s0024-6301(01)00084-x

Esteban-Sanchez, P., de la Cuesta-Gonzalez, M., & Paredes-Gazquez, J. D. (2017). Corporate social performance and its relation with corporate financial performance: International evidence in the banking industry. *Journal of Cleaner Production*, *162*, 1102–1110. https://doi.org/10.1016/j.jclepro.2017.06.127

Fafaliou, I., Giaka, M., Konstantios, D., Polemis, M.: Firms' ESG reputational risk and market longevity: a firm-level analysis for the united states. J. Bus. Res. 149, 161–177 (2022)

Farah, T., Li, J., Li, Z., & Shamsuddin, A. (2021). The non-linear effect of CSR on firms' systematic risk: International evidence. *Journal of International Financial Markets, Institutions and Money*, *71*, 101288. https://doi.org/10.1016/j.intfin.2021.101288

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

Guest, D. E. (2017). Human Resource Management and Employee Well-being: Towards a New Analytic Framework. *Human Resource Management Journal*, *27*(1), 22–38. Wiley. https://doi.org/10.1111/1748-8583.12139

Gujarati, D. N., & Porter, D. C. (2009). *The McGraw-Hill Series Economics*. https://ucanapplym.s3.ap-south-1.amazonaws.com/RGU/notifications/E_learning/0nline_study/Basic-Econometrics-5th-Ed-Gujarati-and-P.pdf

Habermann, F. 2021. "Corporate Social Performance and Over- Investment: Evidence From Germany." Journal of Global Responsibility 12, no. 3: 347–363. https:// doi. org/ 10. 1108/ JGR- 11- 2020- 0095.

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*. https://doi.org/10.1007/s10551-021-04956-4

Hair, Jr. J., Wolfinbarger, M. C., Ortinau, D. J., & Bush, R. P. (2013). *Essential of Marketing*. New York: Mc Graw-Hill

HAIL, L., & LEUZ, C. (2006). International Differences in the Cost of Equity Capital: Do Legal Institutions and Securities Regulation Matter? *Journal of Accounting Research*, *44*(3), 485–531. https://doi.org/10.1111/j.1475-679x.2006.00209.x

Haque, F. (2017). The effects of board characteristics and sustainable compensation policy on carbon performance of UK firms. *The British Accounting Review*, *49*(3), 347–364. https://doi.org/10.1016/j.bar.2017.01.001

Hermalin, B.E. and Weisbach, M.S. 2017. Assessing managerial ability: implications for corporate governance. In: B. E. Hermalin and M. S. Weisbach, eds. The Handbook of the Economics of Corporate Governance (Vol. 1). North Holland, an imprint of Elsevier. Amsterdam, Netherlands: Elsevier, 93– 176. Available from: https://linkinghub.elsevier.com/retrieve/pii/S2405438017300017

Kaminskyi, A., Osetskyi, V., Almeida, N., & Nehrey, M. (2025). Investigating the Relationship Between ESG Performance and Financial Performance During the COVID-19 Pandemic: Evidence from the Hotel Industry. *Journal of Risk and Financial Management*, *18*(3), 126. https://doi.org/10.3390/jrfm18030126

Kotha, S., Rajgopal, S., & Rindova, V. (2001). Reputation Building and Performance: An Empirical Analysis of the Top-50 Pure Internet Firms. *European Management Journal*, *19*(6), 571–586. https://doi.org/10.1016/s0263-2373(01)00083-4

Lee, J., Lee, K., & Oh, F. D. (2024). Credit ratings and corporate ESG behavior. *The Quarterly Review of Economics and Finance*, *98*, 101938. https://doi.org/10.1016/j.qref.2024.101938

Li, X., Lou, Y., & Zhang, L. (2024). Do Commercial Ties Influence ESG Ratings? Evidence from Moody's and S&P. *Journal of Accounting Research*, *62*(5), 1901–1940. https://doi.org/10.1111/1475-679x.12582

LIANG, H., & RENNEBOOG, L. (2017). On the Foundations of Corporate Social Responsibility. *The Journal of Finance*, *72*(2), 853–910. https://doi.org/10.1111/jofi.12487

Mahajan, R., Lim, W. M., Sareen, M., Kumar, S., & Panwar, R. (2023). Stakeholder Theory. *Journal of Business Research*, *166*(1). https://www.sciencedirect.com/science/article/pii/S0148296323004629

Meles, A., Salerno, D., Sampagnaro, G., Verdoliva, V., & Zhang, J. (2023). The influence of green innovation on default risk: Evidence from Europe. *International Review of Economics & Finance*, *84*, 692–710. https://doi.org/10.1016/j.iref.2022.11.036

Michalski, L., & Rand. (2024). Determinants of corporate credit ratings: Does ESG matter? *International Review of Financial Analysis (Online)/International Review of Financial Analysis*, *94*, 103228–103228. https://doi.org/10.1016/j.irfa.2024.103228

Nguyen, C., & Nguyen, L. (2021). The Relationship Between Corporate Social Responsibility and Financial Performance: Empirical Evidence from Vietnam. *The Journal of Asian Finance, Economics and Business*, *8*(8), 75–83. https://doi.org/10.13106/jafeb.2021.vol8.no8.0075

Orlitzky, M., and J. D. Benjamin. 2001. “Corporate Social Performance and Firm Risk: A Meta- Analytic Review.” Business & Society 40, no. 4: 369–396. https:// doi. org/ 10. 1177/ 00076 50301 04000402.

Oware, K. M., & Mallikarjunappa, T. (2021). Corporate social responsibility and debt financing of listed firms: a quantile regression approach. Journal of Financial Reporting and Accounting, 19(4). https://doi.org/10.1108/JFRA-07-2020-0202

Pineau, E., Le, P., & Estran, R. (2022). Importance of ESG Factors in Sovereign Credit Ratings. *Finance Research Letters*, *49*, 102966. https://doi.org/10.1016/j.frl.2022.102966

Postiglione, M., Carini, C., & Falini, A. (2025). Assessing Firm ESG Performance Through Corporate Survival: The Moderating Role of Firm Size. *International Review of Financial Analysis*, *100*, 103973. https://doi.org/10.1016/j.irfa.2025.103973

Principles for the Management of Credit Risk Basel Committee on Banking Supervision Basel. (2000).

SAIDANE, D., & ABDALLAH, S. B. (2021). African firm default risk and CSR. *Finance Research Letters*, 101964. https://doi.org/10.1016/j.frl.2021.101964

Schaltegger, S., Freund, F. L., & Hansen, E. G. (2012). Business cases for sustainability: the role of business model innovation for corporate sustainability. *International Journal of Innovation and Sustainable Development*, *6*(2), 95. https://doi.org/10.1504/ijisd.2012.046944

Seefloth, M., Siedler, F., Kayser, C., Retsch, Benedikt T., & Zülch, H. (2025). Sustainability Performance and Its Impact on Financial Distress Risk—Evidence From STOXX Europe 600. *Business Strategy and the Environment*. https://doi.org/10.1002/bse.4263

Seo Yun Choi, Ryu, D., & You, W. (2024). ESG activities and financial stability: The case of Korean financial firms. *Borsa Istanbul Review*. https://doi.org/10.1016/j.bir.2024.05.007

Servaes, H., & Tamayo, A. (2013). The impact of corporate social responsibility on firm value: The role of customer awareness. Management Science, 59, 1045–1061. https:// doi. org/ 10. 1287/ mnsc. 1120. 1630

Shi, Y., Li, X., & Asal, M. (2023). Impact of sustainability on financial distress in the air transport industry: the moderating effect of Asia–Pacific. *Financial Innovation*, *9*(1). https://doi.org/10.1186/s40854-023-00506-1

Shin, S., Lee, J., & Bansal, P. (Tima). (2021). From a shareholder to stakeholder orientation: Evidence from the analyses of CEO dismissal in large U.S. firms. *Strategic Management Journal*, *43*(7). https://doi.org/10.1002/smj.3369

Shirin Yusupova, Richardson, G., & Lu, M. (2025). Managerial ability, ESG and credit ratings. *Accounting and Business Research*, 1–39. https://doi.org/10.1080/00014788.2025.2485446

Soltani, B. (2014). The Anatomy of Corporate Fraud: A Comparative Analysis of High Profile American and European Corporate Scandals. *Journal of Business Ethics*, *120*(2), 251–274. https://www.jstor.org/stable/42921335

Veltri, S., Bruni, M. E., Iazzolino, G., Morea, D., & Baldissarro, G. (2023). Do ESG factors improve utilities corporate efficiency and reduce the risk perceived by credit lending institutions? An empirical analysis. *Utilities Policy*, *81*, 101520. https://doi.org/10.1016/j.jup.2023.101520

Verma, M., & Mukhtaruddin, M. (2023). Environmental Responsibilities and Firms Financial Performance: A Systematic Review and Bibliometric Analysis. *Indonesian Journal of Sustainability Accounting and Management*, *7*(1). https://doi.org/10.28992/ijsam.v7i1.770

Vishwanathan, P., H. J. van Oosterhout, P. P. M. A. R. Heugens, P. Duran, and M. van Essen. 2020. "Strategic CSR: A Concept Building Meta- Analysis." Journal of Management Studies 57, no. 2: 314–350. https:// doi. org/ 10. 1111/ joms. 12514 .

Wang, L., Tang, R., & Zhou, X. (2025). Financial Crime Risks in Environmental, Social, and Governance (ESG) Investment: Perspectives on Greenwashing and False Disclosure. *Finance Research Letters*, 107856. https://doi.org/10.1016/j.frl.2025.107856

Wang, L.-H., Lin, C.-H., Fung, H.-G., & Chen, H.-M. (2015). Governance mechanisms and downside risk. *Pacific-Basin Finance Journal*, *35*, 485–498. https://doi.org/10.1016/j.pacfin.2015.09.001

Wang, W. (2025). The Non-Linear Relationship Between ESG Performance and Corporate Financing Costs: Evidence from China's A-Share Listed Companies. *Journal of Economic and Managerial Dynamics*, *1*. https://doi.org/10.54254/3657-4300/1/2025002

Wang, Y., Liu, Y., & Chen, X. H. (2025). Green Technology Innovation, ESG Ratings and Corporate Sustainable Performance: Empirical Evidence from Listed Semiconductor Companies in China. *International Review of Economics & Finance*, 104061–104061. https://doi.org/10.1016/j.iref.2025.104061

Xen Yang, W. (2023). *THE EFFECT OF ESG ON FINANCIAL PERFORMANCE AMONG MALAYSIAN PUBLIC LISTED COMPANIES WONG XEN YANG MASTER OF BUSINESS ADMINISTRATION UNIVERSITI TUNKU ABDUL RAHMAN FACULTY OF ACCOUNTANCY AND MANAGEMENT*.

Zhou, F., Chen, H., Tang, S., Lee, C., & Lin, C.-T. (2025). Integrating ESG into financial distress models: The role of financial report quality and innovation in the Chinese market. *International Review of Economics & Finance*, *101*, 104135. https://doi.org/10.1016/j.iref.2025.104135

APPENDICES

Appendix 1: List of the Sampled Firms

Rank	Name	Sector
1	Saudi Arabian Oil Company	Utilities
2	Taiwan Semiconductor Manufacturing Company Limited	Technology
3	Tencent Holdings Limited	Communication Services
4	Alibaba Group Holding Limited	Technology
5	Samsung Electronics Co. Ltd.	Technology
6	Kweichow Moutai Co. Ltd.	Consumer Staples
7	Toyota Motor Corporation	Consumer Discretionary
8	China Mobile Limited	Communication Services
9	PetroChina Company Limited	Materials
10	Reliance Industries Limited	Consumer Discretionary
11	Xiaomi Corporation	Technology
12	Sony Group Corporation	Communication Services
13	Foxconn Industrial Internet Co. Ltd.	Communication Services
14	BYD Company Limited	Consumer Discretionary
15	Bharti Airtel Limited	Communication Services
16	SK hynix Inc.	Technology
17	Tata Consultancy Services Limited	Technology
18	CNOOC Limited	Energy
19	Hitachi Ltd.	Technology

20	Sea Limited	Technology
21	Nintendo Co. Ltd.	Consumer Discretionary
22	China Shenhua Energy Company Limited	Energy
23	Fast Retailing Co. Ltd.	Consumer Discretionary
24	China Yangtze Power Co. Ltd.	Utilities
25	Keyence Corporation	Technology
26	China Telecom Corporation Limited	Communication Services
27	China Petroleum & Chemical Corporation	Materials
28	Hon Hai Precision Industry Co. Ltd.	Consumer Discretionary
29	Zijin Mining Group Company Limited	Materials
30	Mitsubishi Corporation	Industrials
31	Nippon Telegraph and Telephone Corporation	Communication Services
32	NetEase Inc.	Technology
33	Cambricon Technologies Corporation Limited	Technology
34	Mitsubishi Heavy Industries Ltd.	Industrials
35	Recruit Holdings Co. Ltd.	Communication Services
36	Midea Group Co. Ltd.	Technology
37	ITOCHU Corporation	Materials
38	Midea Group	Technology
39	Meituan	Technology
40	Semiconductor Manufacturing International Corporation	Technology
41	PT Barito Renewables Energy Tbk	Utilities
42	Chugai Pharmaceutical Co. Ltd.	Health Care
43	Nongfu Spring Co. Ltd.	Consumer Staples

44	Hindustan Unilever Limited	Consumer Staples
45	MediaTek Inc.	Communication Services
46	Infosys Limited	Technology
47	Wuliangye Yibin Co.Ltd.	Consumer Staples
48	Mitsui & Co. Ltd.	Materials
49	KDDI Corporation	Communication Services
50	Jiangsu Hengrui Medicine Co. Ltd.	Health Care
51	Tokyo Electron Limited	Technology
52	Zhongji Innolight Co. Ltd.	Communication Services
53	LG Energy Solution Ltd.	Consumer Discretionary
54	Delta Electronics Inc.	Consumer Discretionary
55	Delta Electronics (Thailand) Public Company Limited	Consumer Discretionary
56	ITC Limited	Consumer Staples
57	Shin-Etsu Chemical Co. Ltd.	Materials
58	Japan Tobacco Inc.	Consumer Staples
59	Larsen & Toubro Limited	Industrials
60	Singapore Telecommunications Limited	Communication Services
61	Saudi Telecom Company	Communication Services
62	Saudi Arabian Mining Company (Ma'aden)	Materials
63	Advantest Corporation	Industrials

64	Maruti Suzuki India Limited	Consumer Discretionary
65	Coupang Inc.	Technology
66	Samsung Biologics Co.Ltd.	Health Care
67	Eoptolink Technology Inc. Ltd.	Communication Services
68	Mitsubishi Electric Corporation	Industrials
69	Saudi Basic Industries Corporation	Materials
70	Takeda Pharmaceutical Company Limited	Health Care
71	PT DCI Indonesia Tbk	Communication Services
72	Trip.com Group Limited	Consumer Discretionary
73	WuXi AppTec Co. Ltd.	Health Care
74	HCL Technologies Limited	Technology
75	HOYA Corporation	Consumer Discretionary
76	Honda Motor Co. Ltd.	Industrials
77	Daiichi Sankyo Company Limited	Health Care
78	Luxshare Precision Industry Co. Ltd.	Communication Services
79	JD.com Inc.	Technology
80	Mahindra & Mahindra Limited	Consumer Discretionary
81	Sun Pharmaceutical Industries Limited	Health Care
82	ACWA POWER Company	Utilities
83	PT. Chandra Asri Petrochemical Tbk	Materials
84	UltraTech Cement Limited	Materials
85	Fujitsu Limited	Technology
86	Muyuan Foods Co. Ltd.	Consumer Staples
87	Shenzhen Mindray Bio-Medical Electronics Co. Ltd.	Technology

88	Oriental Land Co. Ltd.	Consumer Discretionary
89	NEC Corporation	Communication Services
90	CMOC Group Limited	Materials
91	Kuaishou Technology	Communication Services
92	DENSO Corporation	Consumer Staples
93	Hangzhou Hikvision Digital Technology Co. Ltd.	Technology
94	Hyundai Motor Company	Consumer Discretionary
95	Marubeni Corporation	Industrials
96	NAURA Technology Group Co. Ltd.	Materials
97	Dubai Electricity and Water Authority (PJSC)	Utilities
98	NTT DATA Corporation	Technology
99	PT Dian Swastatika Sentosa Tbk	Materials
100	NTPC Limited	Energy

Appendix 2: Fixed Effect Model (FEM) Statistical Output

Cross-sections included: 73
Total panel (balanced) observations: 584
Swamy and Arora estimator of component variances
Cross-section SUR (PCSE) standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ESG_SCORE	-0.167267	0.206962	-0.808200	0.4193
D01	-0.573655	1.293113	-0.443624	0.6575
ESG_D	0.121774	0.285562	0.426434	0.6700
LEVERAGE__D_E_	-0.835886	0.151678	-5.510928	0.0000
SDG_SCORE	0.555192	1.428432	0.388672	0.6977
SZE	-0.271164	0.140731	-1.926826	0.0545
C	3.020585	5.788059	0.521865	0.6020

Effects Specification

	S.D.	Rho
Cross-section random	0.931759	0.7736
Idiosyncratic random	0.504060	0.2264

Weighted Statistics

R-squared	0.160118	Mean dependent var	0.270484
Adjusted R-squared	0.151384	S.D. dependent var	0.559500
S.E. of regression	0.515413	Sum squared resid	153.2803
F-statistic	18.33350	Durbin-Watson stat	1.293603
Prob(F-statistic)	0.000000		

Total panel (balanced) observations: 584
Swamy and Arora estimator of component variances
Cross-section SUR (PCSE) standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ESG_SCORE	-0.125276	0.170051	-0.736694	0.4616
PRE_VS_POST	0.653749	1.250276	0.522884	0.6013
ESG_P	-0.155691	0.285942	-0.544484	0.5863
LEVERAGE__D_E_	-0.843708	0.147016	-5.738870	0.0000
SDG_SCORE	0.441848	1.056887	0.418065	0.6761
SZE	-0.271373	0.144371	-1.879695	0.0607
C	3.319081	4.657510	0.712630	0.4764

Effects Specification

	S.D.	Rho
Cross-section random	0.929351	0.7729
Idiosyncratic random	0.503739	0.2271

Weighted Statistics

R-squared	0.160845	Mean dependent var	0.270994
Adjusted R-squared	0.152119	S.D. dependent var	0.559721
S.E. of regression	0.515393	Sum squared resid	153.2687
F-statistic	18.43278	Durbin-Watson stat	1.302344
Prob(F-statistic)	0.000000		

Total panel (balanced) observations: 584
Swamy and Arora estimator of component variances
Cross-section SUR (PCSE) standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
E_SCORE	0.127904	0.064703	1.976771	0.0485
S_SCORE	-0.091661	0.171503	-0.534456	0.5932
G_SCORE	-0.258194	0.092084	-2.803896	0.0052
D01	-1.215347	1.267128	-0.959136	0.3379
E_SCORE_D	-0.093761	0.099775	-0.939729	0.3478
S_SCORE_D	0.086541	0.262940	0.329128	0.7422
G_SCORE_D	0.289108	0.155082	1.864223	0.0628
LEVERAGE__D_E_	-0.844605	0.151789	-5.564336	0.0000
SDG_SCORE	0.562848	1.404353	0.400788	0.6887
SZE	-0.292713	0.143614	-2.038195	0.0420
C	3.418941	5.722161	0.597491	0.5504

Effects Specification

	S.D.	Rho
Cross-section random	0.934329	0.7745
Idiosyncratic random	0.504099	0.2255

Weighted Statistics

R-squared	0.169969	Mean dependent var	0.269787
Adjusted R-squared	0.155483	S.D. dependent var	0.559197
S.E. of regression	0.513889	Sum squared resid	151.3189
F-statistic	11.73358	Durbin-Watson stat	1.302596
Prob(F-statistic)	0.000000		

Cross-sections included: 73
Total panel (balanced) observations: 584
Swamy and Arora estimator of component variances
Cross-section weights (PCSE) standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
E_SCORE	0.110920	0.056162	1.974992	0.0487
S_SCORE	-0.073599	0.134907	-0.545553	0.5856
G_SCORE	-0.204163	0.092534	-2.206364	0.0278
PRE_VS_POST	0.179706	1.129485	0.159104	0.8736
E_SCORE_P	-0.021610	0.226297	-0.095495	0.9240
S_SCORE_P	-0.070169	0.152903	-0.458914	0.6465
G_SCORE_P	0.047583	0.147583	0.322414	0.7473
LEVERAGE__D_E_	-0.848189	0.157533	-5.384209	0.0000
SDG_SCORE	0.488498	1.028807	0.474820	0.6351
SZE	-0.290590	0.089545	-3.245185	0.0012
C	3.481191	4.274873	0.814338	0.4158

Effects Specification

	S.D.	Rho
Cross-section random	0.936191	0.7747
Idiosyncratic random	0.504889	0.2253

Weighted Statistics

R-squared	0.167643	Mean dependent var	0.269675
Adjusted R-squared	0.153116	S.D. dependent var	0.559149
S.E. of regression	0.514564	Sum squared resid	151.7169
F-statistic	11.54063	Durbin-Watson stat	1.303504
Prob(F-statistic)	0.000000		

Cross-sections included: 73
Total panel (balanced) observations: 584
Swamy and Arora estimator of component variances
Cross-section SUR (PCSE) standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMISSIONS	0.131782	0.092672	1.422014	0.1556
INNOVATION	0.011814	0.042220	0.279814	0.7797
RESOURCE_USE	0.050167	0.077790	0.644900	0.5193
COMMUNITY	-0.140495	0.093685	-1.499653	0.1343
HUMAN_RIGHTS	0.022616	0.046847	0.482758	0.6295
PRODUCT_RESPONSIBILITY	0.032590	0.070894	0.459703	0.6459
WORKFORCE	-0.226495	0.181677	-1.246692	0.2130
CSR_STRATEGY	-0.066640	0.073971	-0.900895	0.3680
MANAGEMENT	-0.058948	0.055284	-1.066277	0.2868
SHAREHOLDERS	-0.038047	0.032340	-1.176499	0.2399
D01	-2.371629	1.376594	-1.722824	0.0855
EMISSIONS_D	0.330008	0.203931	1.618232	0.1062
INNOVATION_D	-0.005252	0.068646	-0.076515	0.9390
RESOURCE_USE_D	-0.504653	0.235119	-2.146370	0.0323
COMMUNITY_D	0.137473	0.102599	1.339908	0.1808
HUMAN_RIGHTS_D	0.043610	0.091867	0.474706	0.6352
PRODUCT_RESPONSIBILITY_D	0.002681	0.092504	0.028984	0.9769
WORKFORCE_D	0.446424	0.268832	1.660605	0.0974
CSR_STRATEGY_D	0.024563	0.164248	0.149548	0.8812
MANAGEMENT_D	0.043230	0.090068	0.479969	0.6314
SHAREHOLDERS_D	0.033071	0.050992	0.648546	0.5169
LEVERAGE__D_E_	-0.814708	0.151465	-5.378868	0.0000
SDG_SCORE	0.349899	1.569674	0.222912	0.8237
SIZE	-0.289166	0.156346	-1.849534	0.0649
C	4.549570	6.413433	0.709381	0.4784

Effects Specification

	S.D.	Rho
Cross-section random	0.975011	0.7912
Idiosyncratic random	0.500909	0.2088

Weighted Statistics

R-squared	0.188422	Mean dependent var	0.257315
Adjusted R-squared	0.153578	S.D. dependent var	0.553901
S.E. of regression	0.509596	Sum squared resid	145.1857
F-statistic	5.407563	Durbin-Watson stat	1.369615
Prob(F-statistic)	0.000000		

Cross-sections included: 73
Total panel (balanced) observations: 584
Swamy and Arora estimator of component variances
Cross-section SUR (PCSE) standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMISSIONS	0.197866	0.084680	2.336646	0.0198
INNOVATION	0.015500	0.038112	0.406700	0.6844
RESOURCE_USE	-0.054710	0.089288	-0.612740	0.5403
COMMUNITY	-0.116158	0.069204	-1.678489	0.0938
HUMAN_RIGHTS	0.028655	0.032169	0.890771	0.3734
PRODUCT_RESPONSIBILITY	0.036699	0.049728	0.737994	0.4608
WORKFORCE	-0.080932	0.136155	-0.594411	0.5525
CSR_STRATEGY	-0.083085	0.061125	-1.359273	0.1746
MANAGEMENT	-0.097231	0.048203	-2.017134	0.0442
SHAREHOLDERS	0.011582	0.029222	0.396342	0.6920
PRE_VS_POST	1.259093	1.063137	1.184318	0.2368
EMISSIONS_P	-0.357176	0.230988	-1.546293	0.1226
INNOVATION_P	-0.003262	0.029907	-0.109088	0.9132
RESOURCE_USE_P	0.053405	0.136870	0.390191	0.6965
COMMUNITY_P	0.126936	0.098742	1.285535	0.1991
HUMAN_RIGHTS_P	0.031669	0.047195	0.671023	0.5025
PRODUCT_RESPONSIBILITY_P	-0.075240	0.073743	-1.020290	0.3080
WORKFORCE_P	-0.224017	0.203210	-1.102392	0.2708
CSR_STRATEGY_P	0.143404	0.080167	1.788827	0.0742
MANAGEMENT_P	0.082466	0.092495	0.891571	0.3730
SHAREHOLDERS_P	-0.066112	0.023275	-2.840511	0.0047
LEVERAGE__D_E_	-0.818623	0.150660	-5.433575	0.0000
SDG_SCORE	-0.134089	1.181451	-0.113496	0.9097
SZE	-0.293501	0.152549	-1.923983	0.0549
C	6.074961	5.341722	1.137266	0.2559

Effects Specification

	S.D.	Rho
Cross-section random	0.955172	0.7822
Idiosyncratic random	0.503967	0.2178

Weighted Statistics

R-squared	0.187643	Mean dependent var	0.264033
Adjusted R-squared	0.152765	S.D. dependent var	0.556729
S.E. of regression	0.512443	Sum squared resid	146.7924
F-statistic	5.380031	Durbin-Watson stat	1.326929
Prob(F-statistic)	0.000000		

Dependent Variable: ICR
Method: Panel Least Squares
Date: 11/18/25 Time: 15:17
Sample: 2017 2024
Periods included: 8
Cross-sections included: 73
Total panel (balanced) observations: 584
Cross-section SUR (PCSE) standard errors & covariance (d.f. corrected)
WARNING: estimated coefficient covariance matrix is of reduced rank

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ESG_SCORE	0.228318	0.197347	1.156940	0.2478
D01	2.293562	1.001967	2.289059	0.0224
ESG_D	-0.408425	0.239500	-1.705320	0.0887
LEVERAGE__D_E_	-1.808446	0.162410	-11.13506	0.0000
SDG_SCORE	0.259510	0.565809	0.458653	0.6467
SZE	-0.435506	0.046251	-9.416223	0.0000
C	6.561953	2.208237	2.971580	0.0031

Effects Specification

Period fixed (dummy variables)

R-squared	0.374290	Mean dependent var	3.435375
Adjusted R-squared	0.360020	S.D. dependent var	1.871667
S.E. of regression	1.497311	Akaike info criterion	3.668899
Sum squared resid	1277.905	Schwarz criterion	3.773657
Log likelihood	-1057.318	Hannan-Quinn criter.	3.709728
F-statistic	26.22810	Durbin-Watson stat	0.326468
Prob(F-statistic)	0.000000		

Dependent Variable: ICR
Method: Panel Least Squares
Date: 11/18/25 Time: 15:21
Sample: 2017 2024
Periods included: 8
Cross-sections included: 73
Total panel (balanced) observations: 584
Cross-section SUR (PCSE) standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ESG_SCORE	0.014686	0.179337	0.081890	0.9348
PRE_VS_POST	2.254337	1.192382	1.890616	0.0592
ESG_P	-0.499260	0.288598	-1.729948	0.0843
LEVERAGE__D_E_	-0.291502	0.189496	-1.538302	0.1246
SDG_SCORE	-4.909199	4.093958	-1.199133	0.2310
SZE	0.033848	0.168250	0.201178	0.8406
C	24.18489	16.10182	1.501998	0.1337

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.882101	Mean dependent var	3.435375
Adjusted R-squared	0.863891	S.D. dependent var	1.871667
S.E. of regression	0.690513	Akaike info criterion	2.222442
Sum squared resid	240.7882	Schwarz criterion	2.813576
Log likelihood	-569.9530	Hannan-Quinn criter.	2.452836
F-statistic	48.44016	Durbin-Watson stat	1.251900
Prob(F-statistic)	0.000000		

Dependent Variable: ICR
Method: Panel Least Squares
Date: 11/18/25 Time: 15:24
Sample: 2017 2024
Periods included: 8
Cross-sections included: 73
Total panel (balanced) observations: 584
Cross-section SUR (PCSE) standard errors & covariance (d.f. corrected)
WARNING: estimated coefficient covariance matrix is of reduced rank

Variable	Coefficient	Std. Error	t-Statistic	Prob.
E_SCORE	0.418530	0.111133	3.766038	0.0002
S_SCORE	-0.295551	0.163421	-1.808522	0.0711
G_SCORE	-0.163165	0.122590	-1.330981	0.1837
D01	1.932659	0.999737	1.933167	0.0537
E_SCORE_D	0.566418	0.193646	2.925016	0.0036
S_SCORE_D	-1.062055	0.229117	-4.635425	0.0000
G_SCORE_D	0.189070	0.219218	0.862473	0.3888
LEVERAGE__D_E_	-1.835299	0.174903	-10.49324	0.0000
SDG_SCORE	-0.064692	0.573846	-0.112735	0.9103
SZE	-0.453480	0.051785	-8.756902	0.0000
C	9.247276	2.161696	4.277788	0.0000

Effects Specification

Period fixed (dummy variables)

R-squared	0.395303	Mean dependent var	3.435375
Adjusted R-squared	0.377140	S.D. dependent var	1.871667
S.E. of regression	1.477147	Akaike info criterion	3.648439
Sum squared resid	1234.991	Schwarz criterion	3.783128
Log likelihood	-1047.344	Hannan-Quinn criter.	3.700934
F-statistic	21.76502	Durbin-Watson stat	0.358343
Prob(F-statistic)	0.000000		

Dependent Variable: ICR
Method: Panel Least Squares
Date: 11/18/25 Time: 15:27
Sample: 2017 2024
Periods included: 8
Cross-sections included: 73
Total panel (balanced) observations: 584
Cross-section SUR (PCSE) standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
E_SCORE	0.465080	0.116911	3.978063	0.0001
S_SCORE	-0.286154	0.156200	-1.831976	0.0675
G_SCORE	0.050019	0.166253	0.300858	0.7636
PRE_VS_POST	1.220988	1.733695	0.704269	0.4816
E_SCORE_P	0.721545	0.500636	1.441257	0.1501
S_SCORE_P	-0.689258	0.323717	-2.129200	0.0337
G_SCORE_P	-0.340681	0.214705	-1.586743	0.1131
LEVERAGE__D_E_	-1.904464	0.185648	-10.25849	0.0000
SDG_SCORE	2.051980	0.597942	3.431739	0.0006
SZE	-0.444834	0.048705	-9.133192	0.0000
C	-0.727339	2.361763	-0.307965	0.7582

R-squared	0.379632	Mean dependent var	3.435375
Adjusted R-squared	0.368806	S.D. dependent var	1.871667
S.E. of regression	1.486997	Akaike info criterion	3.650051
Sum squared resid	1266.995	Schwarz criterion	3.732361
Log likelihood	-1054.815	Hannan-Quinn criter.	3.682131
F-statistic	35.06456	Durbin-Watson stat	0.363465
Prob(F-statistic)	0.000000		

Dependent Variable: ICR
Method: Panel Least Squares
Date: 11/18/25 Time: 15:30
Sample: 2017 2024
Periods included: 8
Cross-sections included: 73
Total panel (balanced) observations: 584
Cross-section SUR (PCSE) standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMISSIONS	0.325680	0.166400	1.957215	0.0508
INNOVATION	0.278310	0.071816	3.875305	0.0001
RESOURCE_USE	-0.221238	0.144447	-1.531622	0.1262
COMMUNITY	0.291162	0.105512	2.759525	0.0060
HUMAN_RIGHTS	-0.302619	0.108865	-2.779759	0.0056
PRODUCT_RESPONSIBILITY	-0.033435	0.098419	-0.339723	0.7342
WORKFORCE	0.172435	0.261836	0.658561	0.5104
CSR_STRATEGY	0.011105	0.164449	0.067528	0.9462
MANAGEMENT	-0.071381	0.067927	-1.050850	0.2938
SHAREHOLDERS	-0.086644	0.066163	-1.309558	0.1909
D01	-0.207641	1.739346	-0.119379	0.9050
EMISSIONS_D	1.884969	0.388040	4.857664	0.0000
INNOVATION_D	-0.232190	0.073655	-3.152413	0.0017
RESOURCE_USE_D	-1.107968	0.528462	-2.096589	0.0365
COMMUNITY_D	-0.433985	0.137470	-3.156953	0.0017
HUMAN_RIGHTS_D	0.564238	0.212105	2.660185	0.0080
PRODUCT_RESPONSIBILITY_D	-0.195570	0.120362	-1.624851	0.1048
WORKFORCE_D	0.340779	0.459258	0.742021	0.4584
CSR_STRATEGY_D	-0.505030	0.246476	-2.049007	0.0409
MANAGEMENT_D	-0.297653	0.158449	-1.878535	0.0608
SHAREHOLDERS_D	0.106875	0.100114	1.067539	0.2862
LEVERAGE__D_E_	-1.639055	0.148909	-11.00711	0.0000
SDG_SCORE	-0.464017	0.743382	-0.624197	0.5328
SZE	-0.443396	0.061749	-7.180666	0.0000
C	9.138525	2.663798	3.430638	0.0006

R-squared	0.456864	Mean dependent var	3.435375
Adjusted R-squared	0.433545	S.D. dependent var	1.871667
S.E. of regression	1.408677	Akaike info criterion	3.565044
Sum squared resid	1109.263	Schwarz criterion	3.752111
Log likelihood	-1015.993	Hannan-Quinn criter.	3.637953
F-statistic	19.59198	Durbin-Watson stat	0.460643
Prob(F-statistic)	0.000000		

Dependent Variable: ICR
Method: Panel Least Squares
Date: 11/18/25 Time: 15:33
Sample: 2017 2024
Periods included: 8
Cross-sections included: 73
Total panel (balanced) observations: 584
Cross-section SUR (PCSE) standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMISSIONS	0.118242	0.139881	0.845302	0.3984
INNOVATION	0.059400	0.052803	1.124937	0.2612
RESOURCE_USE	-0.118557	0.098157	-1.207832	0.2277
COMMUNITY	0.002584	0.062080	0.041627	0.9668
HUMAN_RIGHTS	-0.003257	0.055611	-0.058576	0.9533
PRODUCT_RESPONSIBILITY	0.020354	0.073182	0.278125	0.7810
WORKFORCE	0.328834	0.171398	1.918536	0.0556
CSR_STRATEGY	0.070016	0.081143	0.862870	0.3886
MANAGEMENT	-0.163101	0.070236	-2.322165	0.0206
SHAREHOLDERS	-0.102003	0.053910	-1.892111	0.0591
PRE_VS_POST	2.633841	0.986100	2.670968	0.0078
EMISSIONS_P	-0.779043	0.249865	-3.117851	0.0019
INNOVATION_P	-0.080402	0.045055	-1.784542	0.0750
RESOURCE_USE_P	0.246262	0.197616	1.246162	0.2133
COMMUNITY_P	0.061805	0.165742	0.372902	0.7094
HUMAN_RIGHTS_P	0.118327	0.070812	1.670995	0.0954
PRODUCT_RESPONSIBILITY_P	-0.119925	0.094903	-1.263654	0.2070
WORKFORCE_P	-0.191641	0.241073	-0.794949	0.4270
CSR_STRATEGY_P	0.132246	0.147056	0.899288	0.3689
MANAGEMENT_P	-0.044908	0.093045	-0.482642	0.6296
SHAREHOLDERS_P	0.090820	0.050169	1.810306	0.0709
LEVERAGE__D_E_	-0.306179	0.188507	-1.624232	0.1050
SDG_SCORE	-7.265098	3.996052	-1.818069	0.0697
SZE	0.002231	0.165854	0.013451	0.9893
C	33.75259	15.86424	2.127589	0.0339

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.888536	Mean dependent var	3.435375
Adjusted R-squared	0.866563	S.D. dependent var	1.871667
S.E. of regression	0.683701	Akaike info criterion	2.227964
Sum squared resid	227.6469	Schwarz criterion	2.953786
Log likelihood	-553.5654	Hannan-Quinn criter.	2.510853
F-statistic	40.43864	Durbin-Watson stat	1.308849
Prob(F-statistic)	0.000000		

Dependent Variable: CREDIT_RATING_SCORE
Method: Panel Least Squares
Date: 11/18/25 Time: 15:34
Sample: 2017 2024
Periods included: 8
Cross-sections included: 73
Total panel (balanced) observations: 584
Cross-section SUR (PCSE) standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ESG_SCORE	0.032690	0.028079	1.164215	0.2448
D01	0.023832	0.181954	0.130980	0.8958
ESG_D	0.003912	0.041941	0.093269	0.9257
LEVERAGE__D_E_	-0.113633	0.010679	-10.64052	0.0000
SDG_SCORE	-0.328950	0.095755	-3.435320	0.0006
SZE	-0.012078	0.003257	-3.708464	0.0002
C	5.718952	0.381818	14.97822	0.0000

R-squared	0.252110	Mean dependent var	4.278584
Adjusted R-squared	0.244333	S.D. dependent var	0.121245
S.E. of regression	0.105397	Akaike info criterion	-1.650246
Sum squared resid	6.409654	Schwarz criterion	-1.597867
Log likelihood	488.8718	Hannan-Quinn criter.	-1.629831
F-statistic	32.41732	Durbin-Watson stat	1.205338
Prob(F-statistic)	0.000000		

Dependent Variable: CREDIT_RATING_SCORE
Method: Panel Least Squares
Date: 11/18/25 Time: 15:35
Sample: 2017 2024
Periods included: 8
Cross-sections included: 73
Total panel (balanced) observations: 584
Cross-section SUR (PCSE) standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ESG_SCORE	0.027798	0.025371	1.095663	0.2737
PRE_VS_POST	0.178248	0.273566	0.651574	0.5150
ESG_P	-0.036942	0.060584	-0.609771	0.5423
LEVERAGE__D_E_	-0.033724	0.029379	-1.147884	0.2516
SDG_SCORE	0.672170	0.491740	1.366923	0.1723
SZE	-0.049204	0.025857	-1.902902	0.0576
C	1.796730	2.041018	0.880311	0.3791

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.607419	Mean dependent var	4.278584
Adjusted R-squared	0.546783	S.D. dependent var	0.121245
S.E. of regression	0.081624	Akaike info criterion	-2.048184
Sum squared resid	3.364542	Schwarz criterion	-1.457050
Log likelihood	677.0698	Hannan-Quinn criter.	-1.817790
F-statistic	10.01743	Durbin-Watson stat	2.117657
Prob(F-statistic)	0.000000		

Dependent Variable: CREDIT_RATING_SCORE
Method: Panel Least Squares
Date: 11/18/25 Time: 15:37
Sample: 2017 2024
Periods included: 8
Cross-sections included: 73
Total panel (balanced) observations: 584
Cross-section SUR (PCSE) standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
E_SCORE	-0.016967	0.011625	-1.459561	0.1450
S_SCORE	0.060181	0.016376	3.674953	0.0003
G_SCORE	-0.029833	0.014621	-2.040508	0.0418
D01	-0.038474	0.148680	-0.258771	0.7959
E_SCORE_D	-0.019432	0.017763	-1.093964	0.2744
S_SCORE_D	-0.045650	0.030417	-1.500829	0.1340
G_SCORE_D	0.085435	0.028838	2.962616	0.0032
LEVERAGE__D_E_	-0.111546	0.010604	-10.51884	0.0000
SDG_SCORE	-0.298550	0.091899	-3.248691	0.0012
SZE	-0.009807	0.003059	-3.205872	0.0014
C	5.641358	0.378633	14.89928	0.0000

R-squared	0.277580	Mean dependent var	4.278584
Adjusted R-squared	0.264972	S.D. dependent var	0.121245
S.E. of regression	0.103948	Akaike info criterion	-1.671197
Sum squared resid	6.191368	Schwarz criterion	-1.588887
Log likelihood	498.9894	Hannan-Quinn criter.	-1.639116
F-statistic	22.01675	Durbin-Watson stat	1.246197
Prob(F-statistic)	0.000000		

Dependent Variable: CREDIT_RATING_SCORE
Method: Panel Least Squares
Date: 11/18/25 Time: 15:38
Sample: 2017 2024
Periods included: 8
Cross-sections included: 73
Total panel (balanced) observations: 584
Cross-section SUR (PCSE) standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
E_SCORE	-0.022137	0.012494	-1.771805	0.0770
S_SCORE	0.050775	0.019125	2.654863	0.0082
G_SCORE	0.008983	0.014200	0.632622	0.5273
PRE_VS_POST	0.185843	0.200747	0.925759	0.3550
E_SCORE_P	-0.029024	0.025162	-1.153488	0.2493
S_SCORE_P	0.030059	0.034121	0.880950	0.3788
G_SCORE_P	-0.040905	0.020874	-1.959599	0.0506
LEVERAGE__D_E_	-0.032268	0.029438	-1.096151	0.2735
SDG_SCORE	0.646583	0.473478	1.365601	0.1727
SZE	-0.046130	0.026240	-1.757977	0.0794
C	1.833379	1.956706	0.936972	0.3492

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.615072	Mean dependent var	4.278584
Adjusted R-squared	0.552070	S.D. dependent var	0.121245
S.E. of regression	0.081146	Akaike info criterion	-2.054172
Sum squared resid	3.298955	Schwarz criterion	-1.433107
Log likelihood	682.8181	Hannan-Quinn criter.	-1.812112
F-statistic	9.762712	Durbin-Watson stat	2.111788
Prob(F-statistic)	0.000000		

Dependent Variable: CREDIT_RATING_SCORE
Method: Panel Least Squares
Date: 11/18/25 Time: 15:40
Sample: 2017 2024
Periods included: 8
Cross-sections included: 73
Total panel (balanced) observations: 584
Cross-section SUR (PCSE) standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMISSIONS	-0.006582	0.014435	-0.455981	0.6486
INNOVATION	0.017361	0.005168	3.359429	0.0008
RESOURCE_USE	-0.041712	0.015196	-2.744966	0.0062
COMMUNITY	0.025039	0.015352	1.630972	0.1035
HUMAN_RIGHTS	-0.012131	0.010821	-1.121015	0.2628
PRODUCT_RESPONSIBILITY	0.009303	0.008971	1.037050	0.3002
WORKFORCE	0.091591	0.025016	3.661347	0.0003
CSR_STRATEGY	-0.002455	0.013791	-0.177982	0.8588
MANAGEMENT	-0.007648	0.009122	-0.838396	0.4022
SHAREHOLDERS	-0.004773	0.003440	-1.387357	0.1659
D01	0.302248	0.141650	2.133762	0.0333
EMISSIONS_D	0.027621	0.025745	1.072870	0.2838
INNOVATION_D	-0.017985	0.006736	-2.670153	0.0078
RESOURCE_USE_D	-0.029801	0.019771	-1.507319	0.1323
COMMUNITY_D	-0.037101	0.017295	-2.145189	0.0324
HUMAN_RIGHTS_D	0.047490	0.015444	3.074954	0.0022
PRODUCT_RESPONSIBILITY_D	-0.014544	0.009272	-1.568636	0.1173
WORKFORCE_D	-0.063708	0.033202	-1.918806	0.0555
CSR_STRATEGY_D	0.002933	0.018529	0.158276	0.8743
MANAGEMENT_D	0.027197	0.016165	1.682443	0.0930
SHAREHOLDERS_D	-0.002512	0.006301	-0.398649	0.6903
LEVERAGE__D_E_	-0.105915	0.010844	-9.767371	0.0000
SDG_SCORE	-0.383600	0.100101	-3.832133	0.0001
SZE	-0.007784	0.003448	-2.257409	0.0244
C	5.757108	0.419917	13.71012	0.0000

R-squared	0.349634	Mean dependent var	4.278584
Adjusted R-squared	0.321712	S.D. dependent var	0.121245
S.E. of regression	0.099855	Akaike info criterion	-1.728323
Sum squared resid	5.573841	Schwarz criterion	-1.541255
Log likelihood	529.6703	Hannan-Quinn criter.	-1.655413
F-statistic	12.52151	Durbin-Watson stat	1.297300
Prob(F-statistic)	0.000000		

Dependent Variable: CREDIT_RATING_SCORE
Method: Panel Least Squares
Date: 11/18/25 Time: 15:43
Sample: 2017 2024
Periods included: 8
Cross-sections included: 73
Total panel (balanced) observations: 584
Cross-section SUR (PCSE) standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMISSIONS	-0.040909	0.012697	-3.221849	0.0014
INNOVATION	0.014038	0.007092	1.979319	0.0483
RESOURCE_USE	-0.032406	0.011641	-2.783879	0.0056
COMMUNITY	-0.024729	0.007984	-3.097257	0.0021
HUMAN_RIGHTS	0.007436	0.008519	0.872926	0.3831
PRODUCT_RESPONSIBILITY	0.015318	0.008891	1.722826	0.0856
WORKFORCE	0.133495	0.032280	4.135473	0.0000
CSR_STRATEGY	0.015129	0.008648	1.749441	0.0808
MANAGEMENT	0.008540	0.009048	0.943817	0.3457
SHAREHOLDERS	-0.014110	0.005187	-2.720428	0.0068
PRE_VS_POST	0.452922	0.158668	2.854529	0.0045
EMISSIONS_P	-0.012261	0.030783	-0.398300	0.6906
INNOVATION_P	-0.003488	0.004424	-0.788498	0.4308
RESOURCE_USE_P	-0.017073	0.032415	-0.526701	0.5986
COMMUNITY_P	0.043218	0.019432	2.224110	0.0266
HUMAN_RIGHTS_P	0.013018	0.015326	0.849414	0.3961
PRODUCT_RESPONSIBILITY_P	0.000501	0.010170	0.049275	0.9607
WORKFORCE_P	-0.108191	0.029579	-3.657723	0.0003
CSR_STRATEGY_P	0.006173	0.013739	0.449324	0.6534
MANAGEMENT_P	-0.022629	0.008837	-2.560674	0.0107
SHAREHOLDERS_P	0.003055	0.004689	0.651482	0.5150
LEVERAGE__D_E_	-0.029559	0.025572	-1.155914	0.2483
SDG_SCORE	0.387119	0.406195	0.953037	0.3410
SZE	-0.041781	0.023815	-1.754421	0.0800
C	2.713305	1.703273	1.592995	0.1118

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.661527	Mean dependent var	4.278584
Adjusted R-squared	0.594805	S.D. dependent var	0.121245
S.E. of regression	0.077178	Akaike info criterion	-2.134837
Sum squared resid	2.900825	Schwarz criterion	-1.409014
Log likelihood	720.3724	Hannan-Quinn criter.	-1.851948
F-statistic	9.914720	Durbin-Watson stat	2.154300
Prob(F-statistic)	0.000000		