Sustainability for Lower Risk?

Examining ESG Scores as Indicators of Credit Risk in African Firms

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Building capacity to mobilize & align finance for development

Declaration

I, **VIMBAI MELISSA MALANDU**, hereby declare that the work on which this thesis is based is my original work (except where acknowledgements indicate otherwise) and that neither the whole work nor any part of it has been, is being, or is to be submitted for another degree in this or any other university. I authorise the University to reproduce for the purpose of research either the whole or any portion of the contents in any manner whatsoever.

Signature: Signed by candidate

Date: 31 January 2025

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Abstract

In light of the growing consideration of Environmental, Social, and Governance (ESG) metrics in credit appraisal, this study investigates the relationship between ESG performance and credit risk for African firms from 2012 to 2022. Using Refinitiv ESG scores and Altman's Z"-score as the primary credit risk measure, this analysis employs OLS, fixed effects, random effects, instrumental variables, and GMM estimations.

While the combined ESG score shows no significant relationship with credit risk, the study makes original contributions as one of the first African emerging market studies to examine ESG as a non-financial credit risk determinant. It uniquely applies a multi-model econometric approach and combines multiple credit risk proxies, including the National University of Singapore Credit Research Initiative's Probability of Default. This triangulation enhances analytical robustness and contributes to the empirical foundation for ESG-credit risk research in emerging markets.

Accounting for endogeneity through GMM, the Governance pillar shows a short-term, significant negative impact on credit risk, indicating governance's time-sensitive role in creditworthiness. The Environmental and Social pillars show no significant impact, with mixed results in static models, highlighting sensitivity to model selection.

Industry-specific analysis reveals no significant relationship between aggregated ESG scores and default risk. However, the Environmental pillar positively impacts credit risk in Industrials, while Governance negatively impacts credit risk in Basic Materials. No significant ESG effects are found in Consumer Staples, Consumer Discretionary, or Real Estate sectors.

The study is limited by constrained ESG data coverage for African firms, reflecting broader challenges in ESG reporting across the continent. These findings emphasise the need for mandatory, standardised ESG disclosures to enable nuanced credit risk assessments, critical for African markets where development capital and effective risk management frameworks are in high demand.

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List of Abbreviations and Acronyms

BVE	Book Value of Equity
BPLM	Breusch and Pagan Lagrangian Multiplier test for random effects
CDS	Credit Default Swaps
CRA	Credit Rating Agencies
CSR	Corporate Social Responsibility
DTD	Distance-to-Default
Env or (E)	Environmental Pillar
EBIT	Earnings Before Interest and Tax
ESG	Environmental, Social and Governance
FEM	Fixed Effects Model or Fixed Effects Panel Estimation
Gov or (G)	Governance Pillar
GMM	Generalised Method of Moments
ICB	Industry Classification Benchmark
IV	Instrumental Variable
JSE	Johannesburg Stock Exchange
Log(PD)	The natural logarithm of the Probability of Default
-Log(Z"-score)	The negative natural logarithm of the Z"-score
NUS- CRI	National University of Singapore Credit Research Initiative
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
PD	Probability of Default based on the NUS-CRI model
REM	Random Effects Model or Random Effects Panel Estimation
Soc or (S)	Social Pillar
UNPRI	United Nations Principles for Responsible Investment
US$	United States Dollar
US/USA	United States of America
VIF	Variance Inflation Factor
Z"-score	Altman (1995) Z-score Model specific to Emerging Markets
Z'-score	Altman (1993) Z-score Model specific to Private Companies
Z-score	Altman (1968) Z-score Model

Chapter 1
Introduction

1.1 Background

In the last decade, Environmental, Social, and Governance (ESG) factors have advanced, becoming integral to investment strategy which signals a rising consideration of their relevance on financial performance and risk. Recognising this trend, the United Nations Principles for Responsible Investment (UNPRI) (2023) in 2016 launched the "ESG in Credit Risk and Ratings Initiative" to increase disclosure and standardise the assimilation of ESG factors into credit ratings. Aligning with this, the European Banking Authority (EBA) released a guideline requiring banking firms to evaluate ESG risks when examining borrowers' credit risk (European Banking Authority (EBA), 2021). The emergence of new accounting standards incorporating ESG reporting further underscores its importance in financial decision-making (Deloitte, 2022). Driven by pressures from investors and regulators for more sustainable investments, ESG considerations in credit risk mitigate not only investment risk but also direct capital towards companies that actively engage with critical issues like social equity and climate change. Over time, firms with consistent ESG practices have reduced risk as sustainability becomes central to their operational ethos (EBA, 2021). For instance, Fitch Ratings asserts that ESG factors can help identify quality credit opportunities with reduced risk, thus fostering sustainable business prospects (Lock, n.d.).

Despite substantial research on the influence of ESG practices on equity investments, a scarcity of research addressing its implications for bond markets and credit risk remains (Orsagh et al., 2019). While equity research has primarily focused on potential upside gains, fixed-income investors recognise ESG factors as relevant downside risk mitigants because they communicate non-financial information about an issuer's ability to fulfil financial commitments (Mendiratta et al., 2021). Moreover, ESG metrics reveal how a company manages ESG risks, therefore complementing traditional financial assessments (EBA, 2021). Financial risks stemming from ESG concerns typically manifest over time through various transmission channels, detailed in Chapter 2 (Brogi et al., 2022). Given the long-term nature and lower liquidity of fixed-income securities compared to equities, prioritising integrating ESG factors into credit risk assessments is vital. Adverse ESG incidents can make selling challenging, significantly impacting prices and heightening default risk (Orsagh et al., 2019). Consequently, mismanaged ESG risks can reduce borrower cashflows and increase their risk of default on financial obligations. Understanding ESG risks when conducting credit assessments equips financial institutions to manage risks in their debt portfolios and facilitates an accurate prediction of the issuer's long-term risks and maintains the overall stability of financial markets (EBA, 2021).

As regulations around ESG issues evolve, Credit Rating Agencies (CRAs) must also reassess their default prediction models (Chodnicka-Jaworska, 2021). Major agencies, including Fitch, S&P, and Moody's, currently integrate ESG ratings into their credit evaluations, indicating the degree to which ESG metrics impact credit ratings. The UNPRI (2023) emphasises that ESG factors only affect credit ratings through an issuer's default probability, with the impact varying by sector and the sector's capacity to absorb ESG risk costs. Furthermore, research indicates that ESG metrics influence different industries and regions in unique ways (Apergis et al., 2022; Bannier et al., 2022; Brogi et al., 2022; Chodnicka-Jaworska, 2021; Jang et al., 2020).

Although ESG elements have long been considered in credit analysis, their consideration is limited due to insufficient data, unstandardised ESG disclosures, and underdeveloped expertise (UNPRI, 2018). This research explores the significance of ESG metrics in credit evaluation processes by employing Altman's Z"-score to represent credit risk for African listed companies. While ESG investing has become prevalent in developed countries, especially Europe, there is sparse research on its impact on credit risk in Africa, where unlocking additional finance is crucial for advancing sustainable development goals (World Economic Forum, 2023). This dissertation studies the connection between ESG metrics and credit risk across African firms, with its sample size biased towards South Africa, reflecting the country's more advanced ESG practices than the rest of the continent. Furthermore, this research contributes to understanding non-financial factors as determinants of default probability, as suggested by Altman and Hotchkiss (2006).

This study distinguishes itself from prior ESG–credit risk research in emerging markets by employing a rigorous multi-model econometric approach—comprising OLS, fixed and random effects models, instrumental variable regression, and the Generalized Method of Moments (GMM). Additionally, it utilizes two distinct measures of credit risk: the traditional Altman Z-score and the forward-looking NUS-CRI probability of default (PD). This dual-metric strategy provides complementary insights and strengthens the study's robustness. To the researcher's knowledge, no existing study has combined this level of methodological depth in the context of African markets, where ESG-credit dynamics remain underexplored. As such, this rigorous design strengthens the empirical foundation for future ESG–credit risk research in Africa and similar underexplored markets.

The research adopts a pooled ordinary least squares (OLS) regression to estimate the ESG ratings and credit risk relationship, where credit risk is represented by Altman's Z"-score (Altman, 2005), drawing from the methodology outlined by Brogi et al., (2022). To enhance robustness and address endogeneity and also align with the multi-model approach being widely applied to ESG-credit risk studies, the study develops four specifications for both the overall and individual ESG scores: (i) Pooled OLS without fixed effects, (ii) Pooled OLS incorporating year and industry fixed effects, (iii) a random effects model (REM), and (iv) a fixed effects model (FEM) with year and industry fixed effects. Each specification applies clustered standard errors to address heteroskedasticity. The FEM incorporates industry and time fixed effects to manage endogeneity in the ESG-credit risk relationship, which may stem from unobserved, time-invariant factors, such as industry-specific characteristics not captured in the analysis (Aslan et al., 2021; Kim & Li, 2021). To distinguish the appropriate model for the analysis, the Breusch and Pagan Lagrangian Multiplier (BPLM) test followed by the Hausman test will be utilised (Brogi et al., 2022).

Using individual pillar scores will help identify the ESG components most relevant to credit risk within the African context, while pooled OLS regressions by industry will explore the ESG-credit risk relationship at the industry level. Robustness checks will be incorporated, including alternative quantifiers of credit risk such as the National University of Singapore Credit Research Initiative's (NUS-CRI) Probability of Default (PD). Additionally, Instrumental Variables (IV) based on macroeconomic indicators and a Two-Step System Generalised Method of Moments (GMM) estimation is employed to improve the reliability of the findings.

1.2 Research Problem

The growing prominence of climate change and business controversies, and the legacy of the 2008 global crisis highlight the significant impact of poor oversight, lack of transparency, and weak governance on financial markets. These issues have affected the pricing, volatility, and stability of fixed-income markets globally (EBA, 2021). In African economies, where institutional frameworks are often weaker than those in more developed markets, the impact of these risks can be even more pronounced due to less stringent regulatory environments and underdeveloped financial structure (African Development Bank (AfDB) et al., 2021; Yimer, 2024). The COVID-19 crisis emphasised the materiality of social factors in credit risk, which are traditionally difficult to measure. It also revealed how ESG factors are interconnected, exacerbating systemic shocks. For instance, during the pandemic, public health and safety became significant concerns, and companies with weak governance and inadequate risk management policies faced severe financial and operational disruptions due to lockdowns, leading to substantial revenue losses (EBA, 2021).

ESG risks can increase credit risk by elevating default risk, as they negatively impact cash flows and create financial uncertainty when they materialise, posing a challenge particularly relevant for African firms with less robust financial buffers (EBA, 2021). Governance failures, such as corporate scandals, have led to significant financial losses globally, with African firms not being immune. The Steinhoff scandal, a significant case of corporate fraud in South Africa, resulted in over US$3.4 billion in claims due to stock value losses following the accounting fraud. Similarly, global examples of governance failures, such as the Volkswagen diesel emissions scandal, costing US$34.69 billion in fines and settlements (Taylor, 2020), and the failure of Enron, one of the most significant bankruptcies in history due to corporate fraud (Li, 2010) underscore the potential financial damage from weak governance structures. Even smaller firms, often overlooked in global scrutiny, face greater risk because of their weaker financial resilience (Hoos & Tavares, 2023). The Bank of America Global Research estimated that ESG controversies caused S&P 500-listed companies to lose over $600 billion in market capitalisation between 2014 and 2020, highlighting that investors and lenders may view companies that overlook ESG considerations as higher risk (Reprisk, 2020).

The UNPR launched the “ESG in Credit Rating Initiative” under its “Principles for Responsible Investment” in 2016 to include ESG factors in credit ratings through stakeholder engagement with credit analysts and asset managers among others. This initiative stemmed from research highlighting the systemic risks climate change poses to financial markets. The EBA (2021) emphasises that, unlike traditional risks, ESG risks involve multiple dimensions, are non-linear, and are forward-looking. This dynamic nature triggers complex ripple effects and makes ESG risks difficult to predict. For instance, the impact of global warming tends to escalate over time, usually resulting in more significant consequences than the initial event itself.

Banks that finance businesses with poor ESG practices, such as having high levels of pollution or labour exploitation, amplify these risks. Lending to energy-intensive firms that are vulnerable to evolving ESG regulations can result in higher compliance costs, which may constrain their capacity to fulfil financial commitments, thereby impacting the profitability and stability of lenders (EBA, 2021). Given the increasing global emphasis on ESG, banks face heightened financial losses if they continue lending to non-compliant companies. The EBA (2021) further underscores that ESG risks, transmitted through various channels, emerge as financial risks (credit risk included), and can lead to systemic consequences if financial institutions neglect to address them.

Conventional risk management methods are largely based on historical data and often fall short regarding ESG risks. Altman and Hotchkiss (2006) note that the fraudulent activities of Enron and WorldCom, which resulted in two of the largest bankruptcies in history, maintained investment-grade ratings before their collapses, underscoring the necessity for integrating qualitative analyses into credit assessments to address the hard-to-quantify costs of bankruptcy. ESG risks are forward-looking and often materialise over extended periods, sometimes decades, making them difficult to predict and irreversible when realised. For example, industrial pollution may result in serious health issues, such as cancer, long after exposure (EBA, 2021). The lack of data on ESG risks further complicates their integration into risk management practices, particularly in African markets. This research aims to advocate for improved ESG disclosure and encourage better data availability, especially in Africa and other emerging markets. African firms, often reliant on extractive industries which include energy and mining, face heightened exposure to ESG risks due to prevalent social challenges and weaker governance frameworks (African Development Bank (AfDB) et al., 2021).

While ESG integration is more prominent in equity markets, the global fixed-income market is three times larger than the equity market (CFA Institute, 2024). In Orsagh et al., (2019), a practitioner in South Africa highlighted that the liquidity of the fixed-income market compared to equities, a major ESG event, would significantly impact the price of the fixed-income security to the extent of default. Moreover, fixed-income markets are essential for economic growth, providing long-term and cost-effective financing for development projects (Mustapha et al., 2021). Incorporating ESG metrics into credit assessments offers more profound insights into the risks issuers face, enabling the allocation of capital toward businesses that may have previously been overlooked. Furthermore, integrating ESG considerations into credit ratings can address imperfect information regarding an entity's operations (Bonacorsi et al., 2024; Do & Vo, 2023). By factoring in ESG risks, CRAs can more accurately reflect the financial health of firms, leading to downgrades for vulnerable entities and upgrades for those with resilient ESG practices.

Although ESG considerations are not new to credit analysts, their application is limited by inadequate ESG disclosure and a lack of expertise among analysts (UNPRI, 2023). Some risks are still nascent, while others have yet to fully manifest or be fully understood, underscoring the need for increased focus on ESG issues and their impact on credit risk (EBA,2021). Building capacity through enhanced ESG disclosure and providing training for analysts is essential to increasing data access and effective ESG integration in credit appraisal.

A deficit in scholarly work exists on the complementation of ESG elements into credit risk analysis, with much of the focus on equity markets and studies biased toward the U.S. and Europe. Africa has limited research available on this topic area. Accordingly, this study will be a pioneering study in the convergence of ESG and credit risk for African firms, expanding the current focus beyond developed markets.

This study responds to an unexplored area by examining African firms and offers practical insights for policymakers and lenders to improve credit risk models. By integrating ESG considerations beyond traditional credit ratings, this research seeks to contribute to developing more resilient financial markets in Africa.

1.3 Research Questions and Aims

In line with this problem, the subsequent research question will be explored:

Does the ESG performance of listed African companies affect their credit risk?

The study explores whether a relationship can be identified between ESG performance and credit risk for African companies.

1.4 Research Hypothesis

$\boldsymbol{H_0}$*: ESG Scores have no statistically significant relationship with corporate credit risk.*
$\boldsymbol{H_1}$*: ESG Scores have a significant relationship with corporate credit risk.*

1.5 Research Justification

The appeal of ESG elements in risk reduction is unique to different markets (Bannier et al., 2022). Despite growing global interest, limited literature examines the ESG and credit risk connection in emerging economies, particularly Africa. Many African countries lack comprehensive ESG data, making it challenging for stakeholders to examine risks and rewards linked to ESG factors (Duru, 2021; Stewart, 2022). While the global community has observed the detrimental effects of ESG risks on credit standing in developed markets, the African context is still largely unexplored (Stewart, 2022). If African firms and financial institutions do not enhance their understanding and integration of ESG considerations into their risk assessments, they may become vulnerable as these risks manifest (African Development Bank (AfDB et al., 2021).

This study enhances the expertise of ESG assimilation in debt markets in the African context, providing valuable insights for various stakeholders.

1.5.1 Impact on Risk Mitigation

Integrating ESG considerations in credit markets could enable riskier companies to leverage improved transparency and disclosure to reduce information asymmetry, thus accessing credit at lower costs (Mendiratta et al., 2021). Additionally, ESG integration can help identify undervalued or unexplored issues that impact credit drivers, contributing to a more comprehensive assessment of credit risk (Fitch Ratings, 2020). A report by Bank of America indicated that between 2008 and 2015, investors who held S&P 500 companies with superior ESG performance would have avoided 90% of company failures, highlighting the potential financial benefits of ESG investing (Fitch Ratings, 2020).

1.5.2 Relevance to Stakeholders

This research is relevant to various stakeholders. ESG integration in credit risk ratings is still new and complex, requiring collaborative efforts across the credit investment cycle.

1.5.2.1 Contribution to Sustainability Literature

i. **Filling Research Gaps**: As a pioneering study on the convergence of ESG and credit risk in emerging economies, this research provides critical insights into ESG investing in Africa, particularly regarding its potential to mitigate downside risk.

ii. **Exploring Non-Financial Variables as Predictors of Credit Risk**: This study will contribute to examining alternative or non-financial variables in determining credit risk, as suggested by Altman and Hotchkiss (2006).

1.5.2.2 Implications for Policy Makers, Regulators and Supervisory Bodies

i. **Guiding ESG Adoption**: Given that regulation drives ESG adoption in South Africa (Johnson et al., 2019), this study will assist regulatory bodies in assessing the influence of ESG aspects across sectors, aiding in the reconstruction of investor portfolios. Additionally, African policymakers may utilise ESG scores to prioritise support during crises, like the COVID-19 pandemic by favouring entities with lower ESG risks as indicators of long-term viability. This study's findings may also inform the development of legislation and frameworks around ESG policy.

ii. **Mandating ESG Integration**: The findings may persuade regulatory bodies to mandate the incorporation of ESG metrics in credit risk appraisals, thereby enhancing the resilience of financial systems.

iii. **Standardising ESG Data**: Giese et al. (2019) noted that the implications of ESG on financial metrics remain undetermined due to non-standardised ESG data reporting. This study can encourage regulatory bodies to develop frameworks that standardise ESG ratings, making them comparable across data providers and ultimately allowing financial institutions to incorporate these factors into credit models.

1.5.2.3 Benefits to Corporate Management

Effective use of ESG metrics in credit ratings hinges on adequate data availability (McAdam, 2012). This study encourages greater corporate disclosure and implementation of pertinent ESG practices, enabling firms to harness benefits from sustainability and secure capital under favourable conditions. Improved data transparency will also assist lenders and credit rating agencies in unlocking the financing required.

1.5.2.4 Support for Financial Institutions and Credit Rating Agencies (CRAs)

Financial institutions can enhance model accuracy by incorporating ESG measures into credit risk models in light of evolving regulations (Chodnicka-Jaworska, 2021). This research builds capacity and expertise in the significance of ESG factors across various scenarios.

Similarly, numerous studies have indicated that credit rating agencies (CRAs) have yet to fully integrate ESG factors into their credit ratings (UNPRI, 2018). This study provides a blueprint for CRAs to incorporate ESG considerations into existing ratings or develop separate reports for borrowers. This can improve understanding of ESG dynamics in credit risk assessments and facilitate the classification of ESG factors by their nature, importance, and urgency.

1.5.2.5 Boarder Societal Impact

Beyond the financial sector, this study emphasises the broader societal benefits of ESG compliant practices. Strong ESG performance contributes to increased environmental protection, improved social equity, and better institutional accountability. This reinforces inclusive and sustainable growth in communities.

1.6 Organisation of the Study

This study is segmented into five (5) chapters. The first chapter introduces the study, presents the research problem, outlines the corresponding research hypothesis, and describes the study's relevance to literature and credit market stakeholders. Chapter 2 will review the theory of credit risk, ESG and the point of convergence between ESG and credit risk. Chapter 2 will also assess prior work on the ESG and credit risk relationship and create a conceptual framework. The third Chapter will expand on the research method employed to ascertain if ESG performance impacts credit risk and whether the effect depends on the pillar or industry. Chapter 4 will present the data and unpack the research insights. Finally, Chapter 5 will analyse the findings established in Chapter 4 by referring to the prior research on the ESG-credit relationship. The chapter will also include policy recommendations for regulators, financial institutions and CRAs and end with suggested avenues for subsequent research on the intersection of ESG and default risk in Africa.

Chapter 2
Review of Literature

2.1 Introduction

This chapter delves into existing research work and theories that explore the nexus between ESG factors and credit risk. The primary outcome of the literature review is to refine the research problem and address the current study's limitations, serving as a foundational framework for interpreting the research findings.

The chapter begins by tracing the history and defining the concept of ESG, including exploring its pillars. It then contextualises the role of ESG in Africa, focusing on South Africa, as this region provides the bulk of available data for the study. Following this, the chapter will define credit risk and present an overview of various credit risk models. Subsequently, the Chapter will discuss theoretical frameworks that connect ESG factors to credit risk, primarily focusing on legitimacy, signalling, and stakeholder theories. Additionally, the chapter will introduce modern theories that illustrate the nexus between ESG and credit risk through various transmission channels, as highlighted in recent studies (Giese et al., 2019; Mendiratta et al., 2021). Finally, the chapter will synthesise the empirical literature identified and present the conceptual framework guiding this study.

2.2 Definitions in ESG and Credit Risk

2.2.1 Defining ESG

ESG is a principle whose framework encompasses three critical dimensions: environmental, social, and governance outlined in Table 1. According to the EBA (2021), the dimensions are factors that influence the financial stability, solvency, or performance of an organisation, government, or individual.

The ESG concept originates from "responsible investment" practices, which consider ESG aspects when making investment decisions (Li et al., 2021). Investment approaches that integrate ESG issues are often referred to as "sustainable investing", "ethical investing", or "impact investing" and are used interchangeably. "Responsible investment" on the other hand encompasses strategies to achieve financial returns while promoting positive social outcomes (UNPRI, 2024).

Corporate Social Responsibility (CSR) is synonymous with ESG in scholarly work (Gillan et al., 2021). The term ESG was established in 2004 after Kofi Annan who was the United Nations Secretary-General, advocated for action on ESG matters. ESG is the integration of ESG factors in an entity's operating activities. At the same time, CSR pertains to a company's initiatives that align with being a socially conscious corporate citizen (Gillan et al., 2021). One key distinction between the two is that governance is included explicitly as a factor in ESG. In contrast, CSR traditionally emphasises social and environmental issues with little attention to governance. Consequently, ESG is considered a broader term compared to CSR. This dissertation will, therefore, primarily reference ESG, although the foundational literature on CSR is pertinent to the research (Gillan et al., 2021).

Table 1: Description of ESG

Environmental (E) ***Conserving the natural resources***	**Social (S)** ***Consideration of human beings and their relationships***	**Governance (G)** ***Standards for business operations***
Climate Change Carbon Emissions Management of Waste Air and Water Pollution Water scarcity Energy Efficiency Biodiversity Deforestation Depletion of Resources	Human Rights Child labour Employment conditions Community Relations Data protection and privacy Customer Satisfaction Gender and Diversity Modern slavery	Corruption and Bribery Board independence Board composition Executive compensation Political contributions Transparency Tax Strategies Whistle-blower schemes
This factor reflects the influence of externalities, including climate change, natural resource utilisation, and various environmental policies.	This factor reflects an organisation’s engagement with both internal and external stakeholders, encompassing employees, clients, supply chain stakeholders the society.	This factor reflects the organisation's policy on management’s responsibility to shareholders, employees and the community.

Note. Adapted from “*What is ESG investing?”* by CFA Institute, 2024, https://www.cfainstitute.org/insights/articles/what-is-esg-investing

Various achievements have contributed to the advancement of ESG, such as ESG evaluation systems, standards for disclosure, and index systems (Li et al., 2021). An increasing number of ESG rating agencies has also played a significant role, as these agencies scrutinise companies and evaluate their corporate sustainability performance by employing diverse research methods. Consequently, ESG ratings can vary considerably across providers (UNPRI, 2023). ESG rating agencies have become critical benchmarks for stakeholders when assessing sustainability performance, including corporations, financial institutions, and academia (Escrig-Olmedo et al., 2019). Several ESG ratings depend purely on financial data, while some integrate financial and non-financial information from publicly available sources and company questionnaires.

However, the complexity of ESG leads to several shortcomings in ESG ratings, necessitating careful interpretation. Key issues include a lack of transparency, differing methodologies among rating agencies, limited comparability, insufficient data, the aggregated nature of diverse ESG factors, and opaque weighting methodologies (Senadheera et al., 2021). This dissertation expands scholarly work by emphasising the significance of ESG in credit risk appraisal and encouraging policy reforms to address these challenges.

2.2.2 African Continent Context of ESG

The relevance of ESG considerations in Africa is on the rise, especially among policymakers, investors, and international development partners in the wake of COVID-19. PwC's 26th Annual Global CEO Survey (2023) highlights that sub-Saharan African companies are increasingly concerned about climate risks and social inequality, especially in Southern Africa, among the world's most unequal regions. This growing awareness underscores the prevalence of ESG risks in Africa.

Africa, one of the most resource-rich continents globally, is uniquely positioned to benefit from sustainable investments in mining, agriculture, and energy sectors, all of which heavily depend on natural resources (AfDB et al., 2021; Duru, 2021). However, this reliance also exposes Sub-Saharan Africa to significant climate-change related transition risks, emphasising the necessity for adopting sustainable management practices (AfDB et al., 2021).

Numerous African Union member states have adopted sustainability policies and strategies, yet the implementation of these measures varies significantly. A baseline survey conducted by the African Development Bank (AfDB) in 2021 revealed a willingness among many African countries to introduce regulations promoting sustainability within their financial sectors. However, a few nations, including Kenya, South Africa, Nigeria, Ghana, Morocco, Egypt, Mauritius, and Zimbabwe, have successfully implemented such regulations (AfDB et al., 2021).

For instance, in Nigeria, the Central Bank has mandated sustainability disclosures for banks, and the Nigerian Stock Exchange has established Sustainability Disclosure Guidelines supported by the Securities and Exchange Commission's Sustainable Financial Principles. Ghana's Bank of Ghana introduced ESG principles in 2015. Kenya's constitution incorporates sustainability into public policy. It has led to the culmination of a Green Economy Strategy and Implementation Plan (GESIP) for 2016-2030, emphasising the financial sector's role in promoting sustainability. Morocco and Egypt have also established ESG disclosure guidelines to foster integrated reporting (Yimer, 2024).

Despite these advancements, the comprehensive implementation of ESG initiatives is underexplored. The PwC 26th Annual Global CEO Survey (2023) highlights that while 52% of companies anticipate climate risks will significantly impact their cost structures in the coming year, only half have developed enterprise-level strategies to mitigate these risks, compared to 65% globally. This discrepancy indicates a considerable gap in strategic ESG integration across the region, primarily due to governments' insufficient capacity to fund sustainable practices and private firms' weak corporate governance structures that undermine transparency and accountability. Additionally, PWC South Africa (2023) notes ongoing challenges such as the absence of sustainability champions, diverse regulatory requirements, and the perception of risk mitigation as a cost rather than an investment.

Another critical barrier to ESG adoption is the inconsistent collection of ESG data, which stifles motivation for adopting sustainable practices. The lack of awareness regarding the importance of ESG disclosure, coupled with underdeveloped infrastructure for data collection and weak institutional frameworks for integrating ESG information, hampers sustainable investment efforts. Furthermore, the absence of standardised disclosure practices creates significant hurdles, especially given Africa's estimated development financing needs of US$ 574 billion annually through 2030 (Duru, 2021). Prioritising ESG disclosure is crucial, as it can reduce information asymmetry and enhance Africa's capacity for managing ESG risks.

The insufficient integration and reporting of ESG factors adversely affects both capital-seeking entities and those providing funds, creating a reinforcing cycle that slows adoption and limits access to ESG-aligned financing. A World Bank and the African Pension Supervisors Network study found that while African pension funds disclose financial performance and strategies, only half report their sustainability approaches. This limited ESG disclosure reflects the broader corporate governance initiatives of their investee companies (Stewart, 2022). A UNPRI examination of disclosure practices across nine Sub-Saharan markets revealed considerable variation in the quality of ESG data disclosed, with South Africa leading at 75% data availability, followed by Nigeria and Ghana at around 50% (Stewart, 2022). This lack of standardised ESG information is most likely due to underdeveloped capital markets and a scarcity of expertise in ESG implementation.

Duru (2021) recognises that addressing these gaps in ESG integration and disclosure is crucial for nurturing sustainable development in Africa. Through improved transparency and accountability, sovereign and non-sovereign entities can attract more investment and better allocate resources to meet their development needs.

2.2.3 ESG Country Context

Since the data in this study is primarily obtained from South African countries, the following section will explore sustainability and ESG in South Africa in greater detail, noting that South Africa has the most developed capital markets and ESG frameworks on the continent.

2.2.3.1 ESG in the South African Context

Although ESG issues are becoming increasingly mainstream in South Africa, research on the topic remains relatively limited. Current studies tend to focus primarily on corporate governance, neglecting the importance of all three components of ESG in the context of sustainability. According to Johnson et al., (2019), the most commonly reported metrics by listed companies are governance factors, attributed to the presence of a robust framework in the country. In contrast, environmental factors are reported the least frequently, yet they are significant in South Africa, primarily due to the economy's heavy industry and mining activities. The same study also notes a growing focus on social aspects driven by policies related to Broad-Based Black Economic Empowerment (BBBEE), poverty reduction initiatives, and efforts to combat HIV/AIDS. Nevertheless, social scores continue to be low reflecting ongoing challenges of high unemployment and social inequity derived from the country's post-colonial legacy. These issues have undermined public trust, driving the exodus of financial and human capital, riot outbreaks, escalating violence, and worsening environmental decay (Pfaff, 2021).

Orsagh et al., (2019) revealed the following insights regarding South Africa:

a) Governance factors, despite their contextual importance, were the most integrated into equity and bond investment frameworks, surpassing environmental and social considerations.
b) While the inclusion of social factors in the investment process remains limited, South Africa incorporates them at a higher rate compared to many other countries.
c) Regulatory frameworks play a more prominent role in driving ESG advancements in South Africa than in other markets.

The study highlights that governance factors receive greater emphasis in ESG due to their measurable, comprehensible, and objective nature, in contrast to the complexity of environmental and social factors. Despite the limited understanding of environmental considerations within the country, they are generally easier to quantify compared to social factors, which are often shaped by regulatory influences. Moreover, assessing sector-specific risks plays a more significant role when evaluating social and environmental factors than it does for governance (Orsagh et al., 2019).

2.2.3.2 The Johannesburg Stock Exchange (JSE) and Sustainability

The JSE being Africa's largest exchange, ranks among the top 20 globally, making it a leading player in sustainability within emerging markets (JSE, 2024a). The exchange is a signatory to the UNPRI and has pioneered several initiatives to enhance ESG reporting and disclosure (Orsagh et al., 2019). Significantly, it was among the earliest exchanges to implement compulsory ESG disclosure, incorporating integrated reporting under a "comply or explain" framework. This initiative reflects the country's commitment to integrated reporting, making it the first country to mandate financial and non-financial performance disclosure for publicly listed entities (JSE, 2024b).

In alignment with this, the “King IV Report on Corporate Governance” requires all companies to produce integrated sustainability reports with third-party assurance. Integrated reports comprehensively describe financial, social, and environmental elements shaping companies holistically. The King IV code emphasises results in performance, robust oversight, ethical culture and legitimacy (Institute of Directors in Southern Africa, 2016).

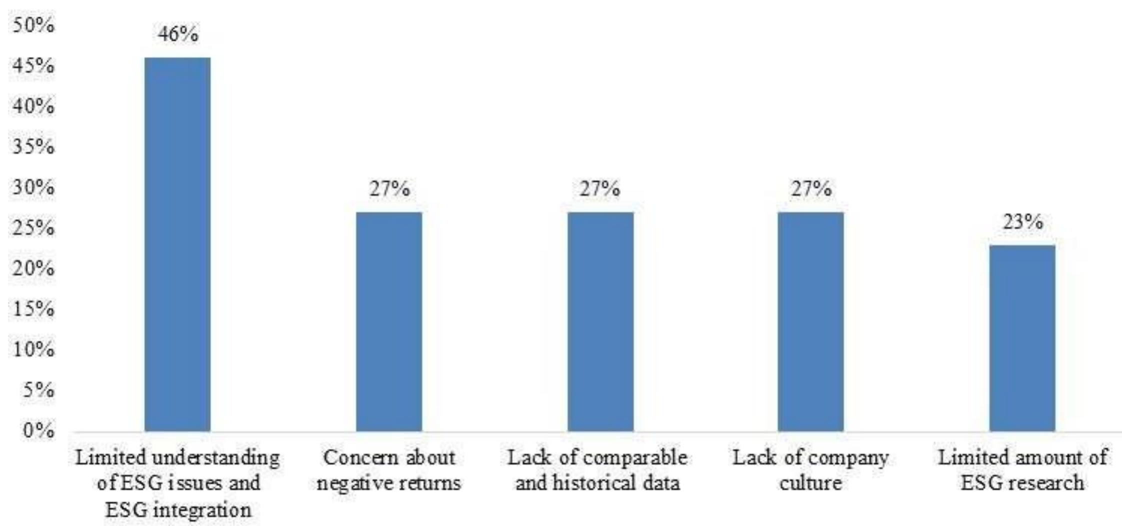
Moreover, in 2004, the JSE was a pioneering exchange globally, establishing a sustainability index, that screens listed firms based on ESG-related metrics. This index was split into the “FTSE/JSE Responsible Investment Index” and the “FTSE/JSE Responsible Investment Top 30 Index” (JSE, 2024c). The JSE enhanced its commitment to transparency by releasing the “Sustainability and Climate Disclosure Guidance” in June 2022. The guidance was designed to advocate for good governance and clarify ESG disclosure criteria for listed entities (JSE, 2024b). Other significant ESG-related initiatives in South Africa are the “Regulation 28 of the South African Pension Fund Act” adjustments and the “Code for Responsible Investing in South Africa (CRISA)” launch. CRISA directs institutional investors, promoting sound governance in investment analysis and practices (Orsagh et al., 2019).

The country also boasts a relatively mature credit market that actively expands its sustainability-focused fixed-income securities segment. It is Africa’s largest debt market, known for its substantial liquidity and market capitalisation, with around ZAR 25 billion (South African rand) traded each day. Since the debut of corporate bond issuance in 1992, more than 1,500 corporate bonds have been listed on the exchange. (JSE, 2023d). However, a lack of comprehensive information regarding ESG integration in the credit market, aside from the issuance of sustainability bonds, persists. Research indicates that while considering ESG metrics in credit ratings is still in its infancy, the long-term aspect of fixed-income investing prompts the account of ESG criteria into bond pricing, particularly following major ESG incidents (Orsagh et al., 2019).

Despite these advancements, South Africa faces significant challenges, including insufficient resources and expertise to integrate ESG factors into investing decisions. Furthermore, the absence of standardised disclosure practices for ESG factors hampers the development of effective frameworks and comparability (Orsagh et al., 2019).

Denhere (2022) highlights that although mandatory integrated reporting has led to improvements in ESG reporting among South African firms, the quality and depth of this information remains inadequate. Many reports are considered greenwashing—portraying a positive image without reflecting genuine efforts— due to the unclear frameworks governing integrated reporting. Unlike the well-established guidelines governing financial reporting, the lack of uniform standards raises concerns about the reliability and credibility of the ESG data disclosed (Denhere, 2022).

Figure 1: Obstacles to the inclusion of ESG elements in South Africa's Fixed Income Securities



Note. Adapted from "*ESG Integration in Europe, the Middle East and Africa: Markets, Practices and Data* (p.192)," by Orsagh, M., et al., 2019, CFA Institute & United Nations Principles for Responsible Investment (https://www.unpri.org/download?ac=6036)

2.3 Credit Risk

Credit risk, synonymous to default risk is the expectation of a borrower's inability to honour financial commitments to a lender according to agreed terms. This risk becomes significant when the borrower's credit quality declines, increasing the possibility of financial loss (Devalle et al., 2017). The most severe deterioration in credit quality is a default event, which occurs when a firm fails to honour its debt servicing obligations, potentially leading to bankruptcy and substantial financial losses for lenders or security holders (Altman & Hotchkiss, 2006).

The 2007/8 global financial crisis tested financial institutions' ability to assess, quantify, and manage credit risk. The situation was exacerbated by the failure of banks to fulfil this role effectively, contributing to the collapse of global credit markets. A key factor in this failure was the inadequate assessment and management of credit risk (Saunders & Allen, 2010). Thus, the measurement and management of default risk is essential to minimising the impact of unpredictable losses (Jumbe & Gor, 2022).

Various credit scoring frameworks exist, including structural and reduced-form models.. Structural credit models define default as when a firm's liabilities exceed its assets over a specific time horizon. Examples include Merton's PD and Distance-to-Default (DTD), as well as the Kealhofer, McQuown, and Vasicek (KMV) Model, a modified version of Merton's models. However, a notable drawback of structural models is their reliance on distributional assumptions, such as normality, which may not accurately reflect bond spreads. Despite this, structural models benefit from incorporating stock price data into an options-theoretic framework, thus providing a dynamic way to assess a firm's financial standing (Saunders & Allen, 2010).

In contrast, reduced-form models treat default events as random processes and assume they are exogenous and observable in debt prices and yields through the default risk premium (Grasselli & Hurd, 2010; Saunders & Allen, 2010). These models rely on bond spreads, equity prices, credit default swaps (CDS) spread, and accounting data, making them computationally simpler than structural models (Saunders & Allen, 2010). Various methodologies for reduced-form models include linear probability, probit, logit, and discriminant analysis models, all used for multivariate credit scoring (Saunders & Allen, 2010). Among the earliest and most enduring models is Altman's Z-score (1968), which measures an entity's financial health and indicates default risk using accounting data. Despite its linearity, an aspect that fails to capture the non- linear path to bankruptcy—the Z-score remains relevant and has been adapted for emerging market contexts (Altman, 2005).

Altman and Hotchkiss (2006) emphasise that while quantitative risk measures, such as financial ratios and market data, are critical, qualitative factors are also relevant in credit risk appraisal. Credit ratings provided by CRAs like Moody's, S&P, and Fitch represent a measure of risk that incorporates both quantitative and qualitative aspects. Credit ratings are particularly valuable as they filter out short-term fluctuations in the business cycle, offering a more stable measure of creditworthiness (Altman & Rijken, 2004; Bannier et al., 2022; Löffler, 2004).

More recently, the rise of artificial neural networks has introduced machine learning techniques into credit risk modelling, enhancing the ability to predict defaults by incorporating subjective and non-quantifiable data and allowing for quantitative data integration (Saunders & Allen, 2010).

2.4 Theoretical Review: A Classic Perspective of ESG and Credit Risk

The understanding of the theoretical foundations that explain the relationship between ESG performance and credit risk is essential to contextualise the study's empirical investigation. Given the multidimensional nature of ESG and its diverse implications across firms and sectors, researchers have adopted a multi-theory approach to articulate this nexus (Izcan & Bektas, 2022). Among the most commonly adopted theories in ESG literature are stakeholder theory, legitimacy theory, and signalling theory, each offering a different but complementary lens for interpreting how ESG practices may influence credit risk (Santamaria et al., 2021).

Legitimacy theory is prevalently recognised in social and environmental accounting (Saini et al., 2023). It links institutions with society, asserting that a company’s activities and strategies must align with societal beliefs, norms, and expectations to avoid crises such as financial scandals or environmental accidents (Suchman, 1995). Li et al., (2021) further argue that ESG practices, under the lens of legitimacy theory, serve as a competitive tool to mitigate risks. Non- financial disclosures, such as ESG reports, provide a platform for demonstrating legitimacy (Saini et al., 2023). In this context, CSR acts as an instrument for legitimising a company’s activities and profits (Farache & Perks, 2010). Good ESG practices also enhance a firm’s relationship with society and help build social capital**,** which strengthens a company's reputation, trust, and credibility (Adler & Kwon, 2002; Doh et al., 2010; Li et al., 2021). In this study, legitimacy theory supports the hypothesis that firms engaging in ESG activities are perceived as more stable and trustworthy, leading to lower credit risk.

Social capital can be classified by moral and exchange capital. Moral capital, gained through ethical behaviour, can act as an insurance mechanism, reducing the severity of consequences when companies face crises (El Ghoul & Karoui, 2017). Furthermore, Godfrey et al., (2009) argue that when stakeholders perceive corporate missteps as unintentional or non-malicious, the company is less likely to face harsh punitive measures. In this sense, ESG creates moral capital by building a strong, positive reputation that mitigates credit risk.

Stakeholder theory**,** alternatively, expands the scope of a firm's obligations beyond just shareholders and incorporates a wider stakeholder base particularly creditors, employees, clients, and society (Donaldson & Preston, 1995). By addressing the interests of these diverse groups, firms can generate long-term value (Santamaria et al., 2021). Firms that actively address the ESG needs of stakeholders tend to outperform those that neglect these concerns (Li et al., 2021). From this perspective, companies should consider using non-financial reporting to foster transparency and improve stakeholder relations (Bakri et al., 2023). The alignment of stakeholder interests also enhances corporate legitimacy, as a firm that serves multiple stakeholder needs is considered more socially responsible (Izcan & Bektas, 2022). This study uses stakeholder theory to interpret how ESG activities, by addressing diverse stakeholder needs, may reduce operational and reputational risks that influence a firm's credit standing.

Signalling theory**,** introduced by Spence (1973), focuses on information asymmetry reduction between companies and capital providers. The theory implies that firms that disclose their ESG performance convey positive indications to the market regarding their financial standing, thereby increasing investor confidence and lowering the firm's perceived risk (Antunes et al., 2023). ESG disclosure is a key risk-mitigating tool because even when ESG scores are imperfect, the very act of disclosure improves transparency and potentially reduces the entity's borrowing costs (Antunes et al., 2023; Sharfman & Fernando, 2008). In this study, signalling theory underpins the notion that ESG disclosures reduce information asymmetry in financial markets, which could result in lower risk premiums and better credit outcomes.

While many scholars advocate for the benefits of ESG practices in enhancing firm stability, Freeman and Dmytriyev (2020) group CSR critiques into three key standpoints: *"violating the obligation to shareholders," "covering wrongdoing,"* and *"creating false dichotomies."* These critiques are particularly relevant in the credit risk context, where ESG disclosures may be used as window dressing or suffer from greenwashing, thus weakening their value as reliable predictors of creditworthiness.

The *criticism of "Violating the obligation to shareholders" is* articulated by Friedman (1970), stating that a firm's core responsibility is maximizing profits rather than pursuing social goals. He argues that CSR engagement can misallocate resources, thus detracting from the firm's primary economic role. This perspective invites ongoing debate about the economic value of CSR and ESG efforts.

The second argument, *"covering wrongdoing,"* identifies three CSR manifestations that arise from unethical practices (Freeman & Dmytriyev, 2020).

1. The first aspect is that CSR can create a distorted view of business by leading companies to prioritise their image over genuine ethical behaviour. Companies may feel guilty about prioritising profits and, in response, engage in CSR initiatives merely to enhance their public image.
2. The second aspect involves moral licensing, wherein firms believe that doing good in one area allows them to offset adverse impacts in another. This behaviour can lead to complacency, where a firm feels justified in neglecting responsibilities to specific stakeholders due to its positive actions elsewhere.
3. The third aspect relates to "window dressing," where firms adopt CSR initiatives primarily to pre-empt stricter regulations rather than from a commitment to genuine social responsibility. Such practices can lead to the perception that CSR is merely a façade to cover ethical lapses rather than a sincere effort to improve stakeholder relations.

The critique of *"creating false dichotomies"* highlights how CSR can unnecessarily segregate economic interests from social and ethical considerations. This perspective argues that CSR often frames profits and societal good as opposing forces, which can mislead business education and practice (Freeman & Dmytriyev, 2020).

Another significant criticism of CSR is the risk of greenwashing, which stems from reliance on self-reported data. Firms may misrepresent their sustainability practices to project a false image of responsibility, often because companies are unwilling to disclose negative information, leading to an overstatement of positive actions. Additionally, sustainability information typically suffers from information asymmetry**,** limiting audiences' ability to access or verify data and thus undermining its reliability (Delmas & Burbano, 2011; Reilly, 2020). These arguments demonstrate why ESG factors should be handled with caution when using them as predictors of credit risk.

2.4.1 How ESG Impacts Credit Risk – A Modern Perspective by Giese et al., (2019)

While Section 2.4 provided the theoretical rationale for how ESG may influence credit risk, it is equally important to explore the mechanisms through which these effects materialise in empirical contexts. This section examines the empirical model developed by Giese et al., (2019), which links ESG metrics to company valuation and performance. Mendiratta et al., (2021) validated this model in the context of credit risk, highlighting three key transmission pathways: the cashflow, idiosyncratic risk (firm-specific risks), and the valuation channels (systematic risks like regulatory changes and technological advancements).

The Cashflow Channel

The Cashflow Channel explains that ESG characteristics enable companies to establish a competitive advantage through resource efficiency, human capital development, and innovation management (Giese et al., 2019). This advantage translates to improved financial metrics, such as profitability ratios and coverage ratios. Collectively, these metrics increase the distance to default, thereby reducing credit risk (Mendiratta et al., 2021). Additionally, profitability measures in the Z-score (Altman, 1968; Altman, 1995; Altman, 2005) models are essential for predicting default, reinforcing the implications of ESG-driven corporate performance and default risk.

The Idiosyncratic Risk Channel

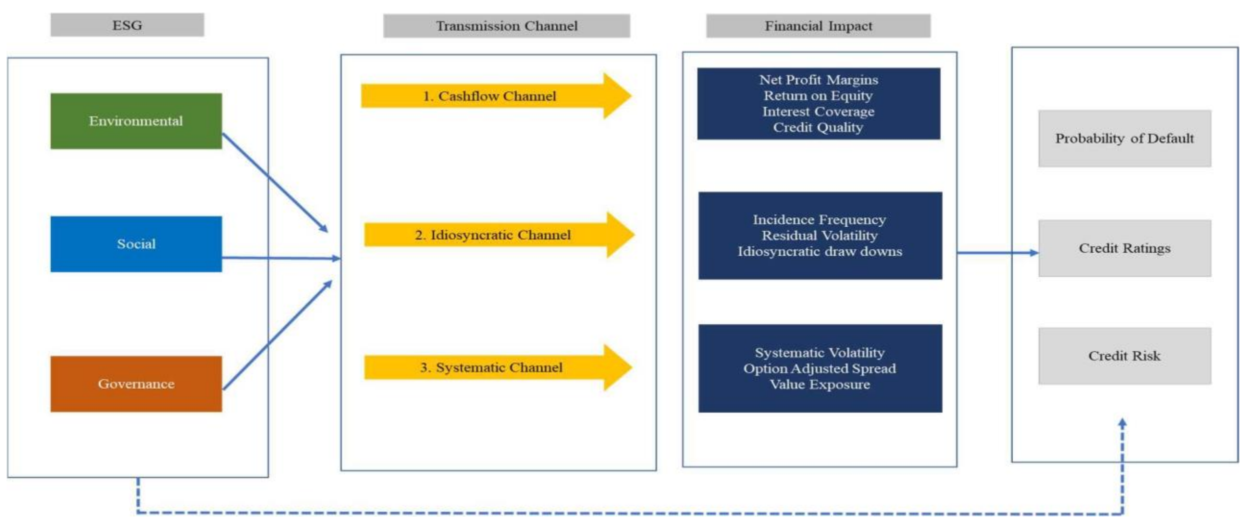
The idiosyncratic risk channel demonstrates how top ESG-performing companies manage risks related to business and operations beyond those reflected in credit ratings (Mendiratta et al., 2021). High ESG performance demonstrates robust compliance and risk control in a firm and relationships with stakeholders. Companies with effective risk management practices are more resilient to fraud, corruption, and lawsuits, factors that negatively impact company value (Mendiratta et al., 2021). In support of the above, research by He et al., (2022) shows that CSR initiatives can significantly reduce idiosyncratic risk.

The Valuation or Systematic Risk Channel

The Valuation Channel illustrates that entities with leading ESG ratings are defensive to market volatility and have reduced systematic risk than those with poor ESG ratings (Giese et al., 2019). For example, energy-efficient companies are less affected by fluctuations in energy prices, resulting in reduced systematic risk. Mendiratta et al., (2021) argue that the reduction in systematic risk, due to a more robust ESG profile, leads to a decreased cost of capital, which in turn contributes to higher valuations. This supports the well-established "Term Structure of Interest Rates" theory, indicating an inverse relationship between bond rates and pricing (Malkiel, 1962).

Figure 2 on the next page summarises how ESG affects Credit Risk through Economic Transmission Channels.

Figure 2: How ESG Affects Credit Risk



Note. Adapted from "How ESG Affected Corporate Credit Risk and Performance," by R. Mendiratta, H. D. Varsani, & G. Giese, 2021, *The Journal of Impact and ESG Investing – Special Issue on Climate: Part 2*, *2*(2), p.4 (https://www.msci.com)

2.5 Empirical Studies

2.5.1 Overall ESG Scores and Credit Risk

A number of studies emphasise the value of integrating ESG considerations into equity investments (Friede et al., 2015; Gehricke et al., 2024; Henisz & McGlinch, 2019), with Jang et al., (2020) emphasising greater importance of ESG integration in bond markets due to frequent refinancing pressures that necessitate low debt costs. The topic of ESG integration in credit markets is nascent, but a number of studies have emerged over the years with varying results, calling for on-going research into the nuances of the ESG-credit risk relationship.

Regulatory changes are propelling the incorporation of ESG metrics in credit rating models to enhance predictive accuracy and lower capital costs (Chodnicka-Jaworska, 2021). While traditional credit ratings provide valuable insights, ESG metrics offer additional risk indicators and act as “insurance” against defaults (Bannier et al., 2022; Jang et al., 2020). Transparency and mandatory ESG disclosures have also reduced default risk by minimising information asymmetry (Bonacorsi et al., 2024; Do & Vo, 2023). For example, a study of 17 emerging countries, including South Africa, found that mandatory ESG disclosures lowered default risk (Do & Vo, 2023).

The connection between ESG and credit ratings is further supported by Jiraporn et al., (2014), who found that a single unit increase in standard deviation in CSR led to a 4.5% credit rating improvement and reduced default risk. Similarly, Attig et al., (2013) found that greater CSR engagement led to better credit ratings. Goss and Roberts (2011) noted US firms demonstrating poor CSR faced higher credit spreads and shorter loan maturities.

Research using Altman's Z-score also reveals a connection between ESG and creditworthiness. Brogi et al., (2022) observed that high ESG scores exhibit a positive relationship with creditworthiness in US and United Kingdom (UK) firms. Aslan et al., (2021) reported that leading ESG scores were associated with decreased default risk, particularly for energy firms. Lin and Dong (2018) demonstrated that firms with leading CSR records have a reduced chance of bankruptcy and recover more quickly from financial distress. Singh (2024) observed that ESG-sensitive companies in India faced less financial distress, enhancing their stakeholder reputation.

While many studies show that higher ESG performance reduces credit risk, some suggest it may increase risk, indicating that ESG investments may actually increase risk under certain conditions. For example, Badayi et al., (2021) found that firms in Africa and the Middle East overinvested in CSR, reducing the firm value and raising default risk. Similarly, Aslan et al., (2021) noted that ESG costs can outweigh benefits for firms in sectors more susceptible to external shocks. These mixed findings highlight a lack of consensus in the literature, with regards to the ESG–credit risk relationship, and suggest that emerging markets may yield distinct dynamics. Most existing studies are concentrated in developed markets, leaving limited empirical evidence from Africa — a gap this study aims to fill. Some studies suggest the absence of an ESG and credit risk relationship. One study by McAdam (2012) did not identify any evidence of how ESG elements impacted credit ratings at the time, attributing this to the absence of ESG regulatory frameworks. However, McAdam acknowledged the potential for ESG to enhance credit risk assessments as regulatory landscapes evolve. Supporting this view, Gehricke et al., (2024) observed that while responsible investment does not immediately affect bond portfolios, the ESG-return relationship strengthens as investor awareness of ESG risks and opportunities grows. Kanno (2023) further notes that ESG's impact on credit risk is more pronounced over the long term, particularly in contexts where ESG compliance incurs high costs.. This highlights the need for ongoing research, particularly in markets where ESG awareness is still developing, as findings are likely to become more robust and reliable over time as the body of evidence grows.

The ESG-credit risk relationship also varies depending on specific conditions. Apergis et al., (2022) identified that ESG metrics were relevant to credit risk in primary bond markets but not in secondary markets, highlighting the importance of context specific research for studies on listed companies. Similarly, Bannier et al., (2022) noted that ESG offers downside protection when evaluated through market-based risk metrics like CDS spreads and Merton’s DTD. Still, this effect may not be reflected in traditional credit ratings, which tend to filter out short-term risk fluctuations.

2.5.2 Decomposed ESG Pillars and Credit Risk

The influence of ESG components on default risk varies by industry, country, regulatory context, and data quality. For instance, Kim and Li (2021) found that while overall ESG performance improves credit ratings, the social pillar boosts ratings, whereas the environmental factor has a negative impact. Likewise, Shi et al., (2023) observed that in Asia Pacific airlines, the environmental pillar increases financial risk, while the social and governance pillars reduce it, possibly due to a substitution effect where firms with higher credit ratings prioritise other factors over environmental issues.

Bakri et al., (2023) determined that in Malaysia, superior environmental performance mitigates bankruptcy risk. Saidane and Abdallah (2021) study of African firms showed that CSR improves creditworthiness, governance lowers risk, and environmental performance can harm stability due to costs, suggesting a priority on governance. In Spain and Italy, Devalle et al., (2017) found that social and governance factors impact credit ratings, while Fu et al., (2024) highlighted similar effects in China's mining sector, with no impact from the environmental pillar.

Governance scores often have the weakest effect on credit risk, as the market understands them and factors them into traditional assessments, unlike social and environmental factors (Mendiratta et al., 2021; Yang et al., 2021). Bhattacharya and Sharma (2019) found governance's impact in India insignificant due to mandatory disclosures, while Zanin (2022) reported mixed results. However, Lisin et al., (2022) and Kiesel and Lücke (2019) found governance the most influential pillar of credit ratings.

Regarding social factors, Bhattacharya and Sharma (2019) and Kim and Li (2021) ranked the most important in Asia, especially for family-controlled firms, with Maquieira et al., (2024) confirming a positive relationship with Altman’s Z-score. Fabozzi et al., (2021) found no significance in Japan, and Zanin (2022) also found inconclusive results. However, Kim and Li (2021) highlighted the strong impact of the social pillar on larger firms' credit ratings.

Drawing from the literature reviewed, the findings on which decomposed ESG factors impact credit risk are contradictory and appear dependent on various contexts. The research, therefore, poses the additional hypothesis below to establish the relationship between decomposed ESG factors and credit risk.

H_0*: Environmental Scores have no statistically significant relationship with corporate credit risk.*
H_1*: Environmental Scores are significantly correlated with corporate credit risk.*

H_0*: Social Scores have no statistically significant relationship with corporate credit risk.*
H_1*: Social Scores are significantly correlated with corporate credit risk.*

H_0*: Governance Scores have no statistically significant relationship with corporate credit risk.*
H_1*: Governance Scores are significantly correlated with corporate credit risk.*

2.5.3 ESG Metrics and Credit Risk within Industries

ESG factors and default risk demonstrate a nuanced and industry-specific relationship, as different sectors face varying degrees of ESG-related risks (Apergis et al., 2022). Given this variability, a bespoke technique should be applied to ESG assessment, with Mendiratta et al., (2021) advocating for an industry-weighted ESG score to capture the nuances of how these factors impact credit ratings across different sectors. Such an approach reinforces the importance of decomposing ESG elements to understand their specific implications for credit risk.

Sectors like energy, industrial materials, mining, transport, and utilities are susceptible to ESG risks, especially regarding environmental factors. These industries often operate under stringent regulatory oversight, and certain ESG factors are critical for demonstrating resilience (Chodnicka-Jaworska, 2021; Jang et al., 2020; Aslan et al.; Fu et al.; Kiesel and Lücke, 2019). In the mining sector, for instance, strong environmental management signals long-term viability, which CRAs reward with favourable assessments (Zanin, 2022).

Conversely, the dynamics between ESG ratings and credit risk vary significantly within sectors. For instance, Palmieri et al., (2023) found that improved environmental scores in the industrial and healthcare industries might increase firm risk, suggesting that the compliance costs could surpass the economic benefits. This observation contradicts Jang et al., (2020), who reported that the environmental pillar has little impact on credit risk in the healthcare and cyclical consumer sectors.

Interestingly, a study by Johnson (2020) in South Africa highlighted the dual nature of ESG's effects. It revealed that while ESG disclosure reduced the weighted average cost of capital and thus company risk within the consumer goods and services sectors, it had the opposite effect in the industrial sector, indicating the complexity of ESG impacts across industries.

The financial and Technology sectors are also not immune to ESG risks. In the Technology sector, a strong focus on the social pillar can decrease the probability of default, aligning with policy expectations for sustainable practices (Palmieri et al., 2023). The diverse findings in industry studies underscore the necessity of contextualising ESG evaluations within specific industries, as the implications for credit risk can vary widely based on sector-specific dynamics.

Drawing from the literature reviewed, the research poses the additional hypotheses below:

$\boldsymbol{H_0}$*: The relationship between ESG and credit risk is consistent across industries.*
$\boldsymbol{H_1}$*: The relationship between ESG and credit risk varies across industries.*

2.5.4 Size Dynamics in the ESG-Credit Risk Relationship

The interaction between ESG performance and credit risk varies by firm size. Larger firms are more favourable beneficiaries of ESG adoption, with Fu et al., (2024) highlighting a stronger connection between ESG and default risk for larger companies. Fabozzi et al., (2021) and Kim and Li (2021) found similar results, suggesting that larger firms face more pressure to adopt ESG policies, enhancing their credit ratings.

However, Jang et al., (2020) argue that ESG's effect on credit risk is more pronounced for smaller entities, as they rely on non-financial metrics like ESG performance to compensate for limited resources and reduce information asymmetry. Bhattacharya and Sharma (2019) suggest that larger firms, already benefiting from higher credit ratings, observe little returns from ESG adoption. Vivel-Búa et al., (2023) align with this, noting that ESG may increase risk for larger firms, as its implementation could add costs without providing significant benefits, reinforcing the idea that ESG adoption may be redundant for larger firms.

While it would be useful to examine the impact of size on the ESG-credit risk relationship, this study excludes it in the empirical analysis in order to maintain a focused scope.

2.5.5 Economic Cycle Influence on the ESG and Credit Risk Relationship

Vivel-Búa et al., (2023) confirmed that the effect of ESG on credit risk varies with the economic cycle, and Apergis et al., (2022) emphasised that the influence of ESG metrics fluctuates over time, underscoring the need for economic context-specific evaluations. During economic distress, like the COVID-19 pandemic, ESG factors became crucial for predicting credit risk, highlighting that creditworthiness extends beyond traditional financial measures (Chodnicka- Jaworska, 2021).

Habermann and Fischer (2023) showed that strong CSR performance reduces financial default risk during crises but may increase economic upswings. Aslan et al., (2021) noted the significant impact of ESG on credit risk during the global financial crisis (2008), suggesting that ESG relevance rises during regulatory shocks as CRAs integrate these factors to assess long-term resilience. Michalski and Low (2024) highlighted the widespread relevance of ESG factors for investment- and speculative-grade entities after the 2007–2008 global financial crisis.

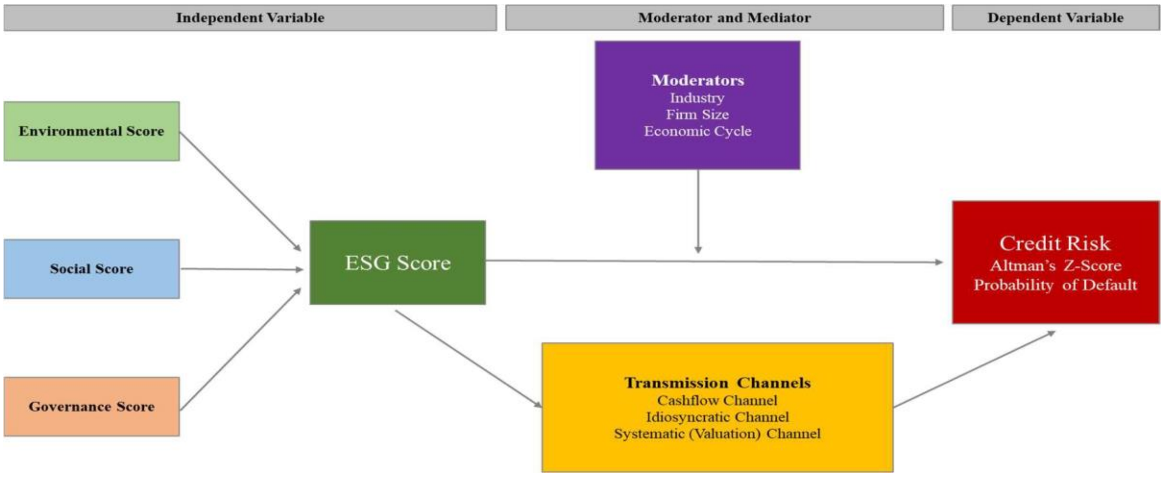
While it would be useful to examine the impact of the economic cycle on the ESG-credit risk relationship, this study excludes it in the empirical analysis in order to maintain a focused scope.

2.6 Conceptual Framework

The theoretical and empirical findings above, form the basis of a conceptual framework that illustrates the relationship between ESG scores and credit risk, proxied by metrics such as the Z-score and the PD. The framework posits that the ESG pillars individually and collectively influence credit risk. The relationship is explained through economic transmission channels, namely the cashflow, idiosyncratic, and systematic (valuation) channels, with moderators such as industry, firm size, and economic cycle affecting the magnitude and orientation of the relationship.

This dissertation uses a pooled dataset to ascertain the relationship under study and explores the impact of a company’s industry classification on the ESG-credit risk relationship by conducting a regression analysis by industry as seen in Brogi et al., (2022). Although the conceptual framework acknowledges the importance of transmission mechanisms and other moderating factors, such as firm size and economic cycles, these aspects are not within the scope of this study and are proposed for subsequent investigation. Figure 3 below illustrates this relationship.

Figure 3: Conceptual Framework explaining ESG's relationship to Credit Risk



Note. Created by the author.

2.7 Conclusion

This literature review uncovers the intricate relationship between ESG performance and credit risk. While ESG increases its relevance in fixed income investing, its impact varies by region, industry, firm size, and economic cycle. Evidence shows that ESG generally minimizes credit risk in Europe, the US, and Asia, but data from Africa is limited, indicating a need for further research.

Industries such as energy and mining face heightened ESG-related credit risks, particularly from environmental factors, while governance factors generally may not have a great impact because they are well understood and already factored into credit risk assessment. Larger firms gain more from high ESG scores, whereas small firms can leverage strong ESG performance to stand out despite resource limitations. ESG's effect on credit risk is reliant on the economic cycle, becoming more significant during crises, especially for well-governed firms.

In summary, incorporating ESG factors into credit risk assessments offers a comprehensive view of firm risk, benefiting creditors and companies in navigating economic challenges. However, more research, particularly in regions like Africa, is essential for understanding the global implications of ESG on credit risk.

Chapter 3
Research Methodology

3.1 Introduction

This chapter details the research method adopted in this dissertation. An overview of the research approach, and design and a detailed description of the sample are provided. The independent and dependent variables and their respective measurement techniques for this study are defined. Finally, the model specifications addressing the research questions are presented, followed by an outline of the robustness estimations.

3.2 Philosophical Foundations and Approach

This research applies a quantitative method due to the positivist nature of the research question, which posits that there is a singular and observable reality. The focus is on measurable and factual data, with the researcher maintaining objectivity to uncover relationships (Saunders et al., 2019). This study specifically seeks to uncover the correlational link between ESG performance and credit risk, utilising a dataset that covers over 11 years, comprising of more than 1,000 observations. The time horizon selected is reasonable for examining the ESG and credit risk relationship, which is usually observed in the long-term (EBA,2021). This quantitative methodology is appropriate as it is independent of the researcher's biases or beliefs. Accordingly, the researcher can draw generalisable conclusions regarding the impact of ESG performance on credit risk (Saunders et al., 2019).

3.3 Research Framework

This study utilises secondary panel data from ninety-one (91) publicly listed African companies, including eighty-four (84) from South Africa and seven (7) from Egypt, Morocco, and Zimbabwe. Private companies were excluded from the study due to data scarcity which would have made the collection time-consuming. Listed companies, however, serve as a robust proxy for African firms because their data is readily accessible. Each company in the dataset is identified by its unique Reuters Identification Code (RIC) and is classified into industries according to the Industry Classification Benchmark (ICB), covering sectors such as industrials, basic materials, real estate, and consumer staples (a more detailed breakdown is presented in Section 4.2.1).

Key variables in the study include Altman's Z”-score, which measures credit risk using financial ratios, and ESG Scores, which serve as the independent variable representing ESG performance. The selected companies are listed on their respective stock exchanges, with firm- level data sourced from the Eikon Database. Each ESG and financial variable data point was collected based on the companies' financial year-end reports. Macroeconomic variables, used for instrumental variables, were sourced from the World Bank. At the same time, an alternative measure of credit risk, PD was acquired from NUS-CRI.

Secondary data is appropriate for this study because it was readily accessible from credible sources with transparent methodologies. This approach saved time and financial resources, allowing for a comprehensive analysis without needing primary data collection.

The study selected a time frame of 2012 to 2022 because it provided the most consistent dataset, avoiding earlier years when ESG data for African companies was sparse and ensuring the 2023 and 2024 data, being incomplete during the study, was excluded. This period results in a balanced dataset encompassing 11 years of data, resulting in over 1,000 observations.

Although over 1,000 publicly listed companies are in Africa, consistent ESG rating data from 2012 to 2022 was only available for a balanced panel of 108 firms. The data limitations highlight the insufficient level of ESG disclosure across the continent, with South Africa leading the way, mainly due to the promotion of sustainable reporting by the Johannesburg Stock Exchange's (JSE). After excluding certain banks and financial institutions, the study reduced the sample to 91 companies. The research excludes the firms due to their complex capital structures making it challenging to derive the Z”-score, because of working capital data constraints.

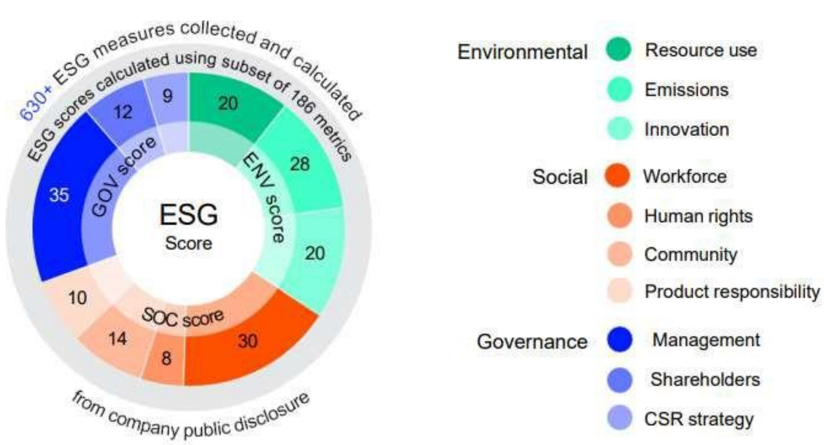
3.4 ESG Ratings

This study draws from Brogi et al., (2022) to comprehend the influence of ESG performance on credit risk, with ESG ratings being the primary independent variable. ESG ratings, developed initially to meet the needs of shareholders, have evolved into key non-financial products widely utilised by various investors. They provide a synthetic measure of a firm's ESG risk exposure, offering valuable perspectives for assessing corporate sustainability practices (UNPRI, 2023).

Several agencies provide ESG ratings, including Refinitiv, Bloomberg, MSCI Analytics, S&P, and Moody's (UNPRI, 2023). This research uses Refinitiv ESG ratings from the Eikon Database to represent overall ESG scores and individual pillar scores. Refinitiv ESG scores are prevalently recognised in the literature (Badayi et al., 2021; Bakri et al., 2023; Habermann & Fischer, 2023; Lisin et al., 2022; Saidane & Abdallah, 2021) and offer comprehensive global coverage of over 15,500 public and private companies. This vast dataset includes more than 630 company-level ESG metrics, with significant coverage globally (LSEG, 2023).

Refinitiv ESG scores offer an objective review of an entity's ESG adoption, commitment, and efficiency relative to its counterparts. The ratings are derived from over 630 company-level data points, spanning 10 major themes, including emissions, innovation, shareholder engagement, and human rights. The data is sourced from various public documents, including stock exchange filings, news reports, CSR documents, annual reports, Non-Governmental Organisations (NGOs) and company websites. Both algorithmic processes and human oversight are employed to ensure data accuracy and quality, with the data standardised to ensure comparability across industries and regions (LSEG, 2023).

Figure 4: ESG Scores Structure



Note. From "*Environmental, Social and Governance Scores from LSEG*" (2023, December), by London Stock Exchange Group, (https://www.lseg.com/en/data-analytics/sustainable-finance/esg-scores#methodology)

The methodology for Refinitiv ESG ratings emphasises the metrics relevant to the industry in question while mitigating biases related to company size and ESG disclosure. This granularity enables the system to differentiate between limited reporting and a genuine lack of transparency. This dissertation employs the overall ESG score, measuring from 0 to 100 (reflecting a percentile), and the decomposed E, S and G pillars, rated on the same scale. A higher score indicates stronger ESG performance. This study will transform the ESG Scores into decimal percentiles (i.e., dividing the original scores by 100). This transformation ensures consistency with the percentile scale and aligns the ESG scores with the scale of other variables used in the analysis, improving interpretability and comparability across models (LSEG, 2023).

Each pillar is assigned specific weights, with the final ESG scores calculated from the weighted sum of pillar ratings. Industry-specific weights are adopted for the E and S pillars, while the G pillar is weighted according to the country. This method facilitates the accurate reflection of the unique materiality of ESG factors across various industries and geographical regions (LSEG, 2023).

Figure 5: ESG Percentile Classification

Score range	Grade	Description	
0.0 <= score <= 0.083333	D -	'D' score indicates poor relative ESG performance and insufficient degree of transparency in reporting material ESG data publicly.	ESG laggards
0.083333 < score <= 0.166666	D		
0.166666 < score <= 0.250000	D +		
0.250000 < score <= 0.333333	C -	'C' score indicates satisfactory relative ESG performance and moderate degree of transparency in reporting material ESG data publicly.	
0.333333 < score <= 0.416666	C		
0.416666 < score <= 0.500000	C +		
0.500000 < score <= 0.583333	B -	'B' score indicates good relative ESG performance and above- average degree of transparency in reporting material ESG data publicly.	
0.583333 < score <= 0.666666	B		
0.666666 < score <= 0.750000	B +		
0.750000 < score <= 0.833333	A -	'A' score indicates excellent relative ESG performance and high degree of transparency in reporting material ESG data publicly.	
0.833333 < score <= 0.916666	A		ESG leaders
0.916666 < score <= 1	A +		

Note. From "*Environmental, Social and Governance Scores from LSEG*" (2023, December), by London Stock Exchange Group, (https://www.lseg.com/en/data-analytics/sustainable- finance/esg-scores#methodology)

Refinitiv ESG scores in this research provide objectivity, comprehensiveness, and reliability in evaluating the relationship. However, it is essential to account that Refinitiv ESG scores are less consistently available outside of major regions like the U.S., Europe, and Asia, leading to a smaller dataset for African companies (LSEG, 2023). Despite this limitation, Refinitiv was the most suitable and consistent source of ESG ratings for this study.

3.5 Credit Risk

This dissertation employs the Altman Z-score as the credit risk proxy, which serves as the dependent variable. The Z-score is selected because it is easy to calculate and relies on publicly available financial data. Compared to other credit risk measures, such as credit ratings or CDS spreads, which may not be as accessible or consistent—especially in emerging markets—the Z-score provides a straightforward and transparent method. This approach follows Brogi et al., (2022) and other studies that have utilised the Z-score to explore ESG and default risk (Badayi et al., 2021; Bakri et al., 2023; Bonacorsi et al., 2024; Fu et al., 2024; Habermann & Fischer, 2023; Maquieira et al., 2024; Oyegunle et al., 2023; Suganda & Kim, 2023). CRAs, regulators, and financial institutions have widely recognised and applied the Altman Z-score. Over its 50 years of use, it has become a prominent indicator of financial distress (Altman, 2018).

The original version of the Z-Score (Altman, 1968) is denoted below:

$$\text{Z-score} = 1.2\ Q_1 + 1.4\ Q_2 + 3.3\ Q_3 + 0.6\ Q_4 + 1.0\ Q_5$$

Such that:

$$Q_1 = \left(\frac{Working\ Capital}{Total\ Assets}\right)$$

$$Q_2 = \left(\frac{Retained\ Earnings}{Total\ Assets}\right)$$

$$Q_3 = \left(\frac{EBIT}{Total\ Assets}\right)$$

$$Q_4 = \left(\frac{Market\ Value\ of\ Equity}{Total\ Debt}\right)$$

$$Q_5 = \left(\frac{Sales}{Total\ Assets}\right)$$

Over time, the Z-score has evolved to fit different contexts, leading to variations such as the Z'-score specific to privately held companies and the Z"-score specific to emerging markets (Altman, 2005; Altman & Hotchkiss, 2006). These models incorporate the book equity value in place of market value (as in variable Q_4), ensuring applicability to privately held and publicly traded companies. The Z"-score model excludes the asset turnover variable (Q_5), which is sensitive to industry-specific characteristics, and includes a constant (3.25) to standardise the score, aligning it with bond ratings by assigning a zero score to D-rated bonds (Altman & Hotchkiss, 2006)

Brogi et al., (2022) evaluate various Z-score models and select the original Altman Z-score (Altman, 1968) to study large publicly listed US and European firms. This study follows a similar evaluation approach and determines that the emerging markets Z"-score (Altman, 1995) is better suited to the dataset of African firms, thus adopting this model for its analysis. Although Altman and Hotchkiss (2006) argue that the original Z-score could be applied globally, given that the fundamentals of corporate insolvency are universally relevant, the study also emphasises that unique regional characteristics should be considered. The Z"- Score model accounts for these specific credit risk factors in emerging markets, making it the most appropriate choice for studies focused on these economies (Altman, 2005).

Moreover, the emerging markets Z"-score is not restricted to manufacturing firms, addressing a limitation of the original model. Given that the sample in this study includes firms from various non-manufacturing sectors, the Z"-score model's broader applicability is essential. Its effectiveness has been tested across multiple emerging markets, including Brazil, Argentina, and several South Asian countries, demonstrating robustness in diverse contexts (Altman & Hotchkiss, 2006).

This study does not adjust the model for specific country or industry factors; instead, it uses the generic emerging markets Z"-score. While tailored adjustments could enhance the model's precision, this research aims to identify broader trends in ESG and credit risk in Africa, providing a foundation for future studies in the region.

The Emerging Markets Z"- Score (Altman, 2005) is denoted as:

$$Z''\text{-score} = 6.56\, Q_1 + 3.26\, Q_2 + 6.72\, Q_3 + 1.05\, Q_4 + 3.25$$

Such that:

$$Q_1 = \left(\frac{Working\ Capital}{Total\ Assets}\right)$$

$$Q_2 = \left(\frac{Retained\ Earnings}{Total\ Assets}\right).$$

$$Q_3 = \left(\frac{EBIT}{Total\ Assets}\right)$$

$$Q_4 = \left(\frac{Market\ Value\ of\ Equity}{Total\ Debt}\right)$$

The interpretation of the Z”- Score is shown below:

Figure 6: Z”-score and Bond Rating Equivalent

	Z"-Score		Rating	Z"-Score		Rating	
	8.15	>8.15	AAA	5.65	5.85	BBB–	
	7.60	8.15	AA+	5.25	5.65	BB+	
	7.30	7.60	AA	4.95	5.25	BB	Gray Zone
	7.00	7.30	AA–	4.75	4.95	BB–	
Safe Zone	6.85	7.00	A+	4.50	4.75	B+	
	6.65	6.85	A	4.15	4.50	B	
	6.40	6.65	A–	3.75	4.15	B–	
	6.25	6.40	BBB+	3.20	3.75	CCC+	Distress Zone
	5.85	6.25	BBB	2.50	3.20	CCC	
				1.75	2.50	CCC–	
				<1.75	1.75	D	

Note. From “An emerging markets scoring system,” by E.I. Altman & E. Hotchkiss, in *Corporate financial distress and bankruptcy* (3rd ed., pp. 233–297), 2006, John Wiley & Sons, Inc.

Using Discriminant analysis, Altman (1968) finds that the following financial ratios are most relevant in predicting corporate failure:

Table 2: Explanation of the Z"-score formula

Ratio	Explanation
$\frac{Retained\ Earnings}{Total\ Assets}$ (RE/TA)	The ratio measures the accumulated profitability over time by factoring in its age. Younger firms typically have lower retained earnings, resulting in lower RE/TA ratios and a higher risk of bankruptcy. In contrast, older firms usually ratios and a reduced risk of financial distress (Altman, 1968). This ratio also reflects the firm's leverage: a higher RE/TA ratio indicates that the company has funded its assets primarily through retained earnings, suggesting lower dependence on debt. Conversely, firms with low RE/TA ratios are likely more leveraged, relying on debt to finance their assets (Altman & Hotchkiss, 2006).
$\frac{Working\ Capital}{Total\ Assets}$ WC/TA	This ratio captures the interaction between size and liquidity. It quantifies an entity's net current assets relative to its total assets. A decline in this ratio suggests that a company is experiencing operational losses as its current assets shrink in proportion to its total assets. This indicator is useful for assessing firms' short-term financial health and liquidity (Altman, 1968)
$\frac{EBIT}{Total\ Assets}$ EBIT/TA	The ratio represents asset productivity in the absence of tax and leverage. It reflects the entity's capacity to earn returns from its assets, which is crucial for continued operations. Insolvency or bankruptcy is triggered when liabilities surpass the market value of the company's assets. This ratio is considered as efficient as a cashflow ratio in detecting default risk, underscoring its importance in assessing financial stability (Altman, 1968).
$\frac{Book\ Value\ of\ Equity}{Total\ Debt}$ BE/TD	This measure evaluates the extent to which an entity's value declines before insolvency which occurs when total debt is above the market value of equity (Altman, 1968). This concept also aligns with Merton's (1974) default model, which integrates this relationship into an option-theoretic structural model. However, the Z"-score is modified to substitute market value for the book value of equity, making the approach applicable to both private and public firms (Altman & Hotchkiss, 2006). This adjustment ensures broader applicability in diverse contexts, including emerging markets.

Note: *Altman (1968) also recognises Sales/Total Assets but is excluded in the Z"-score (Altman, 2005) calculation.*

3.5.1 Altman's Z"-score Transformation

The natural log transformation (log) was applied to address the skewness and non-linearity of the Z"-score variable (Brogi et al., 2022). This transformation improves data normality and optimises the statistical properties of the models, ensuring more reliable results (Brogi et al., 2022). Additionally, the **negative** log(Z"-score) is used in the analysis to facilitate interpretation. This adjustment ensures that more negative Z"-scores correspond to higher credit risk, aligning with the intuitive understanding of credit risk (Suganda & Kim, 2023). The regression models will use this adjusted Z"-score (-log(Z"-score)) to assess its relationship with ESG performance across various specifications.

Note: The Z"-score referred to in the context of this study's results is in its transformed form.

3.6 Model Specification

This study draws on the work of Brogi et al., (2022), which employs four econometric models for robustness and to address endogeneity. It employs four econometric models— pooled OLS with constant intercepts and slopes (Equation 1), pooled OLS with fixed effects (Equation 2), FEM (Equation 3), and REM (Equation 4)—to analyse the relationship between a firm's -log(Z"-score) and corresponding ESG scores. While existing literature predominantly suggests that overall ESG scores mitigate credit risk, the findings related to the decomposed pillars vary. Therefore, decomposing the ESG score into its constituent elements provides deeper insights into the relative importance of each pillar, as evidenced by previous studies (Brogi et al., 2022; Devalle et al., 2017; Kim & Li, 2021). Disaggregation into single pillars is crucial, as the significance of different ESG components may vary by context (Apergis et al., 2022). Individual pillars are mutually exclusive constituents of the combined score, making their separate evaluation necessary (Bannier et al., 2022).

The analysis will proceed with the following regression models for each approach:

i. Regression of the -log(Z"-score) on the overall ESG score using four specifications: (i) Pooled OLS without fixed effects, (ii) Pooled OLS with fixed effects, (iii) FEM with industry and year fixed effects, and (iii) REM. Industry-clustered standard errors will be applied to account for heteroskedasticity and within-group correlation (MacKinnon et al., 2023).

ii. Regression of the -log(Z”-score) on the single pillar scores (E, S and G) in four specifications: (i) Pooled OLS without fixed effects, (ii) Pooled OLS with fixed effects, (iii) FEM with industry and year fixed effects, and (iii) REM. Industry-clustered standard errors will be applied to account for heteroskedasticity and within-group correlation (MacKinnon et al., 2023).

Note: Country-fixed effects are excluded from the model due to insufficient variation across countries in the dataset.

The fixed effects are incorporated to address the potential reverse causality between ESG activities and credit risk. It is possible that more creditworthy companies, with fewer financial problems and lower borrowing costs, have the financial power to invest in ESG improvements (Brogi et al., 2022). This reverse causality implies that superior financial performance could lead to improved ESG scores rather than ESG practices directly reducing credit risk (Bonacorsi et al., 2024). The FEM minimises the impact of unobserved, time-independent elements, such as industry-specific characteristics, which are not explicitly included in the analysis but could bias the results if omitted (Aslan et al., 2021; Kim & Li, 2021). The FEM allows a more accurate estimation ESG and credit risk relationship.

In contrast, the REM assumes that company-specific factors are distributed randomly and do not have an existing correlation with the independent variables (Brogi et al., 2022). This model is generally more efficient than fixed effects when this assumption holds, as it allows for both within and between-firm variation in the analysis. However, the model may produce biased estimates if the random effects correlate with the independent variables (Bell et al., 2019).

As a measurement of credit risk, the Altman Z”-score accounts for multiple dimensions of corporate performance. As a result, this study will not include additional control variables, avoiding potential multicollinearity issues. Macroeconomic variables will also be excluded at this stage, as they will be incorporated as instrumental variables for robustness (Brogi et al., 2022).

The proposed specifications are summarised as follows:

$$-\log(Z'' - score_{it}) = \alpha + \beta_i X_{it} + \varepsilon_{it} \quad \text{(Equation 1)}$$
$$-\log(Z'' - score_{it}) = \alpha + \beta_i X_{it} + \pi + \varepsilon_{it} \quad \text{(Equation 2)}$$
$$-\log(Z'' - score_{it}) = \alpha_i + \beta_i X_{it} + \pi + \varepsilon_{it} \quad \text{(Equation 3)}$$
$$-\log(Z'' - score_{it}) = \alpha + \beta_i X_{it} + \omega_{it} + \varepsilon_{it} \quad \text{(Equation 4)}$$

Where:

$-\log(Z'' - score_{it})$ is the negative natural logarithm of the Z"-score for each company (i) in year (t)

α denotes the intercept.

X_{it} denotes the dependent variables E, S, G or ESG

β_i is the coefficient term Π is the fixed effects

ω_{it} is the random effect

ε_{it} denoted the error term

The study incorporates a robust approach by employing clustered standard errors to mitigate potential distortions in the analysis caused by heteroskedasticity. This method enhances the reliability of results by adjusting for any inconsistencies in the variance of error terms (MacKinnon et al., 2023). A multicollinearity test is performed to further ensure the validity of the models by detecting potential collinearity issues in the decomposed ESG models (Hair et al., 2021).

In the analysis, the sample is segmented by industry based on the Industry Classification Benchmark (ICB), an internationally recognised standard for categorising companies by industry and sector (LSEG, n.d). The JSE and other African exchanges widely utilise the ICB framework for consistent industry and sector classification (as shown in Table 3). This segmentation enables the study to explore the divergent effects of the relationship across industries, aligning with recommendations from Chodnicka-Jaworska (2021). The study will therefore conduct analysis by industry to determine the ESG-relationship in specific industries.

Table 3: Industry Classification Benchmark

ICB Industry Description			
1	Technology	7	Consumer Staples
2	Telecommunications	8	Industrials
3	Health Care	9	Basic Materials
4	Financials	10	Energy
5	Real Estate	11	Utilities
6	Consumer Discretionary		

Note. Data was obtained from the LSEG website.

3.7 Robustness

3.7.1 Probability of Default

This dissertation introduces an additional experiment as a robustness check by employing a substitute, market-based measure of credit risk: the one- year PD from NUS-CRI. The data is collected at the financial year-end for each company. PD and credit risk are directly related, suggesting that a higher probability of default signifies elevated credit risk.

The PD is a primary product of the NUS-CRI, derived from the forward intensity model proposed by Duan et al. (2012). This technique uses independent stochastic Poisson processes based on a period in the future rather than the present. It leverages macroeconomic, market- based, and firm-specific data to generate forward-looking PD term structures. The approach integrates a reduced-form model derived from the forward intensity framework with a structural model that employs the DTD based on Merton (1974) as a critical input. This comprehensive model accounts for both default risk and other risks, such as corporate exits. The NUS-CRI publishes daily PDs for over 45,000 publicly listed firms across 134 countries (NUS-CRI, 2022).

Below are the input covariates for the NUS-CRI PD model:

Table 4: NUS-CRI Probability of Default Methodology

	Model Inputs	**Description**
	Equity Index Return	The trailing one-year yield of the primary stock exchange, which was winsorized and also accounted for currency exchange.
	Short Maturity Treasury Bill	The yield on three-month government bonds.
Macro-Financial Factors	Financial Firm's Country-level DTD	Financial entity's and non-financial entity's median DTD in each country, including foreign entities listed in that country.
	DTD for non-financial firms	
	DTD (level)	The volatility-adjusted leverage derived from Merton (1974) with adjustments.
	DTD (trend)	
	Cash-to-Total Assets (level)	The measure of financial firms' liquidity– The logarithmic transformation of an entity's cash and cash equivalents total assets
	Cash-to-Total Assets (trend)	
	Current Assets-to-Current Liabilities(level)	The measure of non-financial firms' liquidity – The logarithmic transformation of a company's current assets divided by its current liabilities.
	Current Assets-to-Current Liabilities(trend)	
Firm-Specific Attributes	Net Profit-to-Total Assets (level)	A profitability measure, calculated as the ratio of each company's net profit to total assets.
	Net Profit-to-Total Assets (trend)	
	Normalised Size (level)	The logarithmic transformation of an entity's market capitalization to the country's median market capitalization in the last year.
	Normalised Size (trend)	
	Normalised Market-to Book Ratio	Each company's stock mispricing opportunity in comparison to the economy's median market-to-book ratio.
	Idiosyncratic Volatility	Each company's one-year idiosyncratic volatility, calculated by the standard deviation of errors in the market model.

Note. Adapted from *Probability of Default White Paper* (p.4) by National University of Singapore Credit Research Initiative (CRI), 2022 (https://d.nuscri.org/static/pdf/Probability%20of%20Default%20White%20Paper.pdf)

The NUS-CRI Probability of Default (PD) model is a valuable variable in this study as it combines both market-based and financial aspects of credit risk. Unlike Merton's PD, which primarily focuses on market-based risk factors, the NUS-CRI model integrates market signals (such as credit spreads and investor sentiment) and financial fundamentals (such as liquidity, profitability, and leverage). This comprehensive approach makes the NUS-CRI PD a more holistic measure of default risk, providing enhanced insights into how ESG interacts with credit risk (NUS-CRI, 2022).

This study prioritises using PD obtained from the NUS-CRI over Merton's (1974) model, as delineated by Brogi et al., (2022). The NUS-CRI's readily calculated PD data facilitates a more efficient analysis. At the same time, Merton's model is inherently complex, requiring an iterative process and prior knowledge of the firm’s historical asset volatility to precisely derive PD. Additionally, the NUS-CRI model serves as a more granular gauge of credit risk, employing a Nelson-Siegel term structure function as well as Monte Carlo optimisations to estimate the model. Given the researcher's emphasis on data reliability, selecting NUS-CRI data is essential to ensure robustness and accuracy in the study's findings. Notably, the model achieves high accuracy ratio scores across all regions within its coverage, indicating its reliability (NUS-CRI, 2022).

Furthermore, since the PD incorporates numerous inputs correlating with credit risk, the decision to omit control variables remains justified. Additionally, the PD variable will be log- transformed to address skewness and improve the statistical properties of the data.

3.7.2 Instrumental Variable (IV)

This study incorporates an additional robustness model by employing an IV regression following (Brogi et al., 2022) derived from the Gross Domestic Product (GDP) growth rate, Rule of Law and Primary Education Enrolment Ratio, captured from the World Bank database. The Gini Index utilised in Brogi et al., (2022) is excluded due to a lack of data. Other studies, such as Goss and Roberts (2011), also implement an IV regression to account for endogeneity.

The GDP growth captures a country’s economic performance, the standard of living and productivity. At the same time, the Rule of Law assesses confidence in societal rules and institutions, and the Primary Education Enrolment Ratio reflects access to primary school education, which is the fundamental right of every child (World Bank, 2024). The Principal Component Analysis (PCA) is employed to combine the variables into a single factor that captures the majority of their variance. This resulting factor acts as the IV, and its relationship with the overall ESG score is subsequently examined. An IV regression is employed alongside the PD and Z”-score models to enhance the reliability of the study. By accounting for potential endogeneity, this methodology strengthens the reliability of the research and offers a more robust assessment of the relationships among the variables involved (Li et al., 2022).

3.7.3 GMM Estimation

The Two-Step System GMM estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998) is employed to address endogeneity and ensure robust estimation when examining the relationship between ESG scores and credit risk. This method handles potential endogeneity in dynamic panel data arising from simultaneity or unobserved firm-level effects. Endogeneity is addressed by using lagged values of ESG scores as instruments, which enhances efficiency and reduces bias. The Two-Step System GMM also adjusts for heteroskedasticity, further improving the precision of the estimates.

This approach is particularly effective for datasets with moderate periods and many observations, making it suitable for analysing credit risk proxies like the Altman Z”-score and PD. Model validity will be assessed using the Arellano-Bond test for autocorrelation and the Hansen J-test for instrument exogeneity and to enhance robustness.

3.8 Conclusion

This study adopts a comprehensive quantitative research approach, leveraging secondary panel data from 91 publicly listed African companies spanning 2012 to 2022, primarily from South Africa, with additional data from Morocco, Egypt, and Zimbabwe. The analysis uses the transformed Z”-score as the predicted variable to measure credit risk and Refinitiv ESG scores, along with E, S, and G scores as the independent variables to investigate the ESG-credit risk relationship.

The methodology begins with pooled (OLS) regressions, followed by fixed and random effects panel estimations to ensure robust results. The BPLM test will be applied to select between the OLS and REMs. In contrast, the Hausman test will determine the preference between REM and FEM. Clustered standard errors will be used to address heteroskedasticity concerns, and the VIF will be applied to identify multicollinearity among variables.

Industry-specific regressions will explore variations in the ESG-credit risk relationship, allowing for a deeper understanding of how these dynamics might differ across sectors. This segmentation follows the ICB, enabling a detailed examination of industry-specific moderating effects.

To reinforce the robustness of findings, the study incorporates additional models using an alternative risk metric, the transformed PD sourced from NUS-CRI. IV regressions involving macroeconomic variables and a Two-Step System GMM is conducted to account for possible reverse causality.

Chapter 4
Results Discussion

4.1 Introduction

This chapter delivers and discusses the findings associated with the research, drawing on the methodology detailed in Chapter 3. A summary of the descriptive statistics and pairwise correlations, highlighting the relationships between the variables is provided. Furthermore, the outcome of the inferential statistical analyses is presented and discussed in comparison to existing literature.

4.2 Preliminary Evaluation

This section describes the variables adopted in the research and provides an overview of their correlations and distributions.

4.2.1 Descriptive Statistics

This section displays the descriptive statistics corresponding to the variables adopted in the analysis drawing from Brogi et al., (2022). This step is essential for understanding the fundamental properties of the data. The descriptive analysis also provides a foundation for interpreting the empirical findings and is crucial for validating the assumptions and reliability of the econometric models in the dissertation.

Table 5: Variable Descriptive Statistics

Variable Name	**Data Origin**	**Variable Explanation**	**Number**	**Mean**	**St. Dev**	**Min**	**Max**
Z"-score	Eikon Database	Credit Risk	1001	8.37	21.86	-1.65	512.73
Probability of Default	NUS-CRI	Credit Risk	955	0.00	0.01	0.00	0.33
ESG Score	Eikon Database	ESG Score	1001	0.47	0.19	0.01	0.89
E-Score	Eikon Database	Environmental Score	1001	0.40	0.24	0.00	0.95
S-Score	Eikon Database	Social Score	1001	0.49	0.22	0.01	0.95
G-Score	Eikon Database	Governance Score	1001	0.53	0.22	0.03	0.97
Industry	**N**	**Percentage (%)**	**Z"-score**	**ESG - Score**	**E-Score**	**S-Score**	**G-Score**
Basic Materials	187	18.68	7.09	0.59	0.55	0.61	0.61
Consumer Discretionary	143	14.29	8.42	0.50	0.40	0.53	0.52
Consumer Staples	121	12.09	7.09	0.48	0.44	0.47	0.54
Energy	11	1.10	7.90	0.64	0.81	0.78	0.30
Financials	55	5.49	22.26	0.30	0.22	0.31	0.38
Health Care	44	4.40	6.60	0.61	0.46	0.66	0.65
Industrials	220	21.98	9.60	0.43	0.34	0.43	0.53
Real Estate	110	10.99	5.69	0.35	0.29	0.33	0.44
Technology	44	4.40	5.87	0.49	0.31	0.49	0.54
Telecommunications	66	6.59	5.90	0.45	0.33	0.48	0.49

Note: The table illustrates the description of variables utilised in the study. It begins with the Z"-score calculated as shown in 3.4 and the NUS-CRI probability of default, both proxies of credit risk. The aggregated ESG-Score and decomposed E-, S-, and G-Scores and their respective Mean, Standard Deviation (St. Dev), Minimum (Min) and Maximum (Max) values are also displayed.

4.2.1.1 Credit Risk Measures

The dataset comprises 1001 observations across all the variables except Probability of Default (PD), where the dataset drops to 955 observations due to data availability. The dataset is a balanced panel. The **Z"-score**, sourced from Eikon, reports a mean of 8.37 and a standard deviation of 21.86, conveying that the sample has variable credit risk profiles. The minimum and maximum Z"-scores are -1.65 and 512.73, respectively, suggesting significant variation in creditworthiness. The Z"-score distribution is further detailed in Table 6 below.

Table 6: Z”-Score Categorised distribution of sample observations and corresponding S&P rating.

Rating	**Z”-score**	**Number**	**Frequency**	**Cumulative**
AAA	≥ 8.15	256	25.57	25.57
AA+	< 8.15	65	6.49	32.06
AA	< 7.60	38	3.80	35.86
AA−	< 7.30	43	4.30	40.16
A+	< 7.00	23	2.30	42.46
A	< 6.85	35	3.50	45.96
A−	< 6.65	41	4.10	50.06
BBB+	< 6.40	30	3.00	53.06
BBB	< 6.25	86	8.59	61.65
BBB−	< 5.85	45	4.50	66.15
BB+	< 5.65	79	7.89	74.04
BB	< 5.25	52	5.19	79.23
BB−	< 4.95	35	3.50	82.73
B+	< 4.75	30	3.00	85.73
B	< 4.50	36	3.60	89.33
B−	< 4.15	36	3.60	92.93
CCC+	< 3.75	23	2.30	95.23
CCC	< 3.20	27	2.70	97.93
CCC−	< 2.50	5	0.50	98.43
D	< 1.75	16	1.60	100.00

Table 6 shows that the distribution is notably right skewed, with company observations for each year not evenly distributed across the credit risk categories and a concentration of observations in the higher credit rating groups. This right-skewness confirms the high standard deviation of the Z”-score shown in Table 5. Such skewness in the data justifies the log transformation of the Z”-score variable to normalise the variables’ distribution (Brogi et al., 2022). Additionally, the log transformation of the Z”-score is applied with a negative sign (-log(Z”-score)) to facilitate a more intuitive interpretation of credit risk, thereby establishing a direct relationship between the Z”-score and credit risk (Suganda & Kim, 2023).

The **PD**, obtained from NUS-CRI, exhibits a mean of 0.00 with a standard deviation of 0.01, signalling a relatively low average default risk. The respective minimum and maximum values are0.00 and 0.33, , suggesting that most firms in the sample possess a low likelihood of default, aligning with the Z"-score distribution. The distribution of the PD data further justifies its log transformation, similar to the Z"-score.

4.2.1.2 ESG Scores

The key characteristics of the ESG Scores in the sample are as follows:

- **Overall ESG Score:** The mean score is 0.47, with a standard deviation of 0.19, suggesting moderate ESG performance across the sample. This indicates that, on average, the firms demonstrate a balanced approach to issues, consistent with the expected improved reporting practices of South African firms (Denhere, 2022). The minimum score of 0.01 and the maximum score of 0.89 highlights variation in ESG performance across firms, indicating room for improvement in ESG practices across the sample.
- **E-Score:** The mean score is 0.40, with a standard deviation of 0.24, demonstrating moderate environmental performance among the sample firms. This indicates that, on average, these firms have taken steps to address environmental issues, such as reducing carbon emissions or improving energy efficiency. However, there is significant variation in environmental performance across firms, as evidenced by the standard deviation.
- **S-Score:** The mean score is 0.49, with a standard deviation of 0.22, signalling moderate social performance. This means that the firms in the sample have made efforts to address social issues, such as human rights and community engagement with room for improvement.
- **G-Score:** The mean score is 0.53, with a standard deviation of 0.22, conveying moderate governance performance. This implies sample companies have implemented reasonable corporate governance practices, such as robust ethics policies, shareholder rights and board independence. The higher mean for the G-Score also speaks to earlier findings on governance, the most reported pillar for South African firms (Johnson et al., 2019).

While the distribution of the ESG Scores shows variability, outliers are not considered problematic in the regression analysis because they are not significant.

4.2.1.3 Industry Level Analysis

Table 5 provides an industry-level breakdown of the variables, showing that the most significant proportion of firms in the dataset are in the Industrials (21.98%) and Basic Materials (18.68%) sectors. In contrast, fewer firms are represented in the Technology (4.40%), Healthcare (4.40%), Financials (5.49%), and Telecommunications (6.59%) sectors. The Financials sector demonstrates a notably higher mean Z”-score compared to other industries, indicating lower credit risk. This is consistent with expectations, as financial institutions are often subject to strict regulatory frameworks and minimum capital adequacy requirements (EBA, 2021). The mean Z”-scores for other industries are close to the overall mean and remain within the "safe" zone, except for the Real Estate sector (comprising 11% of the sample), which falls within the "grey" zone. Notably, no industry falls into the "distress" zone.

Regarding ESG Scores, the Energy and Healthcare sectors show the highest average scores at

0.64 and 0.61, respectively, while the Financials and Real Estate sectors exhibit the lowest scores at 0.30 and 0.35. The Energy sector's strong ESG performance is primarily driven by its high average Environmental Score (0.81), likely reflecting adherence to stringent environmental regulations (Chodnicka-Jaworska, 2021; Jang et al., 2020; Aslan et al.; Fu et al.; Kiesel & Lücke, 2019). Conversely, this sector demonstrates the lowest average Governance Score. The Basic Materials sector also records a relatively high Environmental Score (0.55), with its Social and Governance scores averaging 0.61. Notable Social Scores are observed in the Consumer Discretionary (0.53), Energy (0.78), and Healthcare (0.66) sectors, with Healthcare achieving the highest average Social Score at 0.65. Consumer discretionary, consumer staples, and technology sectors have moderate social scores.

This industry-level analysis delivers critical insights into the variability of credit risk and ESG performance across sectors, despite limitations in sample size for some sectors.

4.2.2 Pairwise Correlations

This section explores the pairwise correlations of the variables providing preliminary information on the strength and direction of the ESG and credit risk relationship. This step also assists in identifying potential multicollinearity that can compromise the analysis' robustness.

Table 7: Pairwise Correlation Matrix

Variables	**- Log (Z"-score)**	**Log (PD)**	**ESG-Score**	**E-Score**	**S-Score**	**G-Score**
- Log (Z"-score)	1.000					
Log (PD)	0.461	1.000				
ESG-Score	0.053	-0.006	1.000			
E-Score	0.091	0.021	0.835	1.000		
S-Score	0.032	-0.022	0.910	0.725	1.000	
G-Score	0.023	-0.011	0.698	0.351	0.466	1.000

Table 7 displays the pairwise correlations between the transformed dependent variables namely the negative natural logarithm of the Z"-score (-log(Z"-score)), the natural logarithm of the Probability of Default (log(PD))—and ESG scores. As expected, -log(Z" -score) and log(PD) exhibit a moderate positive correlation of 0.46, reflecting their shared focus on credit risk. Although the correlation is strong the two credit risk measures capture different dimensions of risk, offering complementary insights into the ESG and default risk relationship.

The –log(Z"-score) and the ESG scores demonstrate a weak and positive correlation, contrasting expectations from the literature that suggest a negative relationship between ESG performance and credit risk (Bannier et al., 2022; Brogi et al., 2022; Jiraporn et al., 2014). This observation may indicate what the regression analysis could reveal. When the log(PD) as the credit risk proxy is used, a similarly weak relationship with ESG Scores is observed, which becomes negative in this instance, except for the Environmental Score, which remains positively correlated. This shift in the direction of the relationship also suggests the relationship's sensitivity to the measure of risk employed.

The combined ESG score and its pillar scores display a relatively strong correlation, ranging from 0.7 to 0.9, with the social score showing the strongest relationship. This suggests that the social pillar may be more significant in determining credit risk within African firms.

Additionally, while the correlations between the individual ESG pillars are high, the highest interaction is observed between the environmental and social scores (0.725). However, multicollinearity appears negligible in the decomposed models, as indicated by the mean VIF of 1.91, with individual VIFs ranging from 1.28 to 2.35 all considerably less than 5 (Hair et al., 2021). These values suggest that multicollinearity is not problematic to the study, allowing the analysis to proceed as planned.

4.3 Results of the Analysis

This segment displays the results of exploring the role of ESG scores on credit risk. The analysis includes regressions of ESG scores (both overall and disaggregated) on credit risk measured by the *Z*”-score, applied across four specifications: pooled OLS without fixed effects, pooled OLS with fixed effects, FEM with industry and year fixed effects, and REM. The analysis applies a systematic diagnostic approach to distinguish the suitable mode4.3.1 Results of the ESG Score on Credit Risk (Z”-Score)

Table 8:Pooled OLS Regression Results of ESG on Z”-score

Variables	**OLS (1)**	**OLS (2)**	**OLS (3)**	**OLS (4)**
ESG-Score	0.142		0.178	
	(0.198)		(0.246)	
E-Score		0.298		0.362*
		(0.197)		(0.211)
S-Score		-0.169		-0.167
		(0.202)		(0.247)
G-Score		0.020		-0.015
		(0.149)		(0.143)
Constant	-1.946***	-1.926***	-2.070***	-2.055***
	(0.106)	(0.109)	(0.183)	(0.188)
Observations	996	996	996	996
R-squared	0.003	0.011	0.074	0.085
Year FE	EX	EX	IN	IN
Industry FE	EX	EX	IN	IN

Note I: Robust Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
Note II: Models 1 to 4 report the OLS regression models whose dependent variable is the negative log(Z”-score). Model 1 includes the combined ESG Score without fixed effects. Model 2 includes the decomposed E-Score, S-Score, and G-Score without fixed effects. Model 3 is the specification, which includes the combined ESG Score and controls for fixed effects. Model 4 specifies the decomposed E-Score, S-Score and G-Score and controls for fixed effects.
Note III: EX, Excluded; IN, Included; OLS, ordinary least squares

Table 9: Fixed Effects and Random Effects Panel Estimations for the Z”-Score

Variables	REM (5)	REM (6)	FEM (7)	FEM (8)
ESG-Score	0.354		0.376	
	(0.236)		(0.385)	
E-Score		0.276*		0.278
		(0.166)		(0.226)
S-Score		0.078		0.093
		(0.143)		(0.242)
G-Score		0.054		0.117
		(0.131)		(0.153)
Constant	-2.044***	-2.052***	-2.138***	-2.173***
	(0.124)	(0.135)	(0.159)	(0.177)
Observations	996	996	996	996
R-squared			0.034	0.039
Year FE	EX	EX	IN	IN
Industry FE	EX	EX	EX	EX

Note I: Robust Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
Note II: Models 5 and 6 account for the REM. Models 7 and 8 report a FEM with year-fixed effects with the negative log(Z”-score) as the dependent variable. Industry fixed effects cannot be applied to the models due to insufficient variability within industries, which would limit the reliability and interpretability of results due to overfitting or multicollinearity. Model 5 includes the combined ESG Score without fixed effects. Model 6 specifies the decomposed E-Score, S-Score and G-without fixed effects. Model 7 includes the combined ESG Score and controls for fixed effects. Model 8 specifies the decomposed E-Score, S-Score and G-Score and controls for fixed effects.
Note III: EX, Excluded; IN, Included; REM, Random Effects Model; FEM, Fixed Effects Model.

Tables 8 and 9 present the outcome of the analysis using -log(Z”-score). In Models 1, 3, 5, and 7, where the combined ESG-Score is the exogenous variable, the results consistently highlight that ESG is not a relevant predictor of credit risk for African firms. While ESG scores exhibit a positive coefficient, suggesting a potentially positive relationship with credit risk, the relationship is not statistically robust.

These findings diverge from prior studies that utilised Altman’s Z-score to proxy risk. For instance, Brogi et al., (2022), Do and Vo (2023), and Lin and Dong (2018) reported an indirect relationship between ESG scores and credit risk. In contrast, Badayi et al., (2021) observed a positive relationship for African firms. Notably, the results align with McAdam (2012), who found no evidence of ESG considerations influencing credit ratings during the study period. McAdam attributed this to the absence of ESG regulatory frameworks at the time.

Similarly, the nascent stage of ESG frameworks and reporting in Africa, characterised by underdeveloped markets and limited ESG implementation, may explain this study's lack of statistical significance. This underdevelopment could suggest that ESG factors have yet to become a substantial determinant of credit risk within the African context, calling for continued research on the topic.

When analysing the decomposed ESG pillars, the governance and social dimensions are not significant predictors of credit risk. Conversely, the E-Score has a positively significant relationship with credit risk at the 10% level in two models: the OLS model with year-fixed effects and the REM. This result implies that stronger environmental performance may be associated with increased credit risk. Similar conclusions have been presented by Kim and Li (2021), Saidane and Abdallah (2021), and Shi et al., (2023), who attribute this relationship to the high costs associated with environmental initiatives.

The conflicting results across different models highlight the complexity of the environmental pillar's influence and underscore the need for further investigation to provide deeper insights into its implications for credit risk, particularly in the context of African firms.

4.3.1.1 Model Selection and Diagnostic Tests

To assess the suitability of the REM, the BPLM test for random effects was conducted. The analysis reported p-values close to zero, providing strong evidence against the null hypothesis and supporting the use of the REM over pooled OLS for univariate and multivariate specifications. The Hausman test further refined model selection and compared the FEM and REM. The test produced a p-value of 0.0721 for the univariate model, while the multivariate model yielded a p-value of 0.1127. At the 5% significance level, the null hypothesis could not be rejected, indicating support for the REM.

4.3.1.2 Conclusion of Negative Log (Altman Z"-score) Regressions

The findings indicate that combined ESG scores are not significant predictors of credit risk, represented by the -log(Z"-score), for African firms. However, when the ESG score is disaggregated, the environmental pillar reveals a weak but positively significant relationship with credit risk in the chosen REM model. In contrast, the governance and social pillars do not significantly influence credit risk. These results underscore the intricacy of the ESG-credit risk relationship, suggesting that the environmental pillar merits additional attention in understanding how sustainability factors affect financial outcomes in Africa.

4.3.2 Regression Analysis by Industry

Table 10: OLS Regression by Industry Segments (Part A)

Variables	Basic Materials	Basic Materials	Consumer Discretionary	Consumer Discretionary	Consumer Staples	Consumer Staples
ESG-Score	-0.758		0.326		-0.007	
	(0.469)		(0.434)		(0.524)	
E-Score		-0.400		0.779		0.839
		(0.570)		(0.489)		(0.503)
S-Score		0.088		-0.636		-0.771
		(0.603)		(0.493)		(0.534)
G-Score		-0.466*		-0.024		-0.173
		(0.259)		(0.457)		(0.343)
Constant	-1.515***	-1.479***	-2.382***	-2.218***	-2.020***	-1.940***
	(0.293)	(0.292)	(0.167)	(0.196)	(0.207)	(0.202)
Observations	185	185	143	143	121	121
R-squared	0.142	0.153	0.101	0.215	0.023	0.144
Year FE	IN	IN	IN	IN	IN	IN
Industry FE	EX	EX	EX	EX	EX	EX

Table 11: OLS Regression by Industry Segments (Part B)

Variables	Financials	Financials	Healthcare	Healthcare	Industrials	Industrials
ESG-Score	1.715		1.676***		0.663	
	(1.203)		(0.184)		(0.606)	
E-Score		0.978		0.859**		0.861*
		(1.892)		(0.240)		(0.425)
S-Score		0.378		0.453**		0.144
		(0.992)		(0.121)		(0.547)
G-Score		1.045		0.492		-0.275
		(0.676)		(0.306)		(0.261)
Constant	-2.996***	-3.240***	-2.658***	-2.663***	-2.141***	-2.039***
	(0.294)	(0.346)	(0.190)	(0.124)	(0.220)	(0.193)
Observations	55	55	44	44	220	220
R-squared	0.228	0.250	0.530	0.636	0.038	0.089
Year FE	IN	IN	IN	IN	IN	IN
Industry FE	EX	EX	EX	EX	EX	EX

Table 12:OLS Regression by Industry Segments (Part C)

Variables	Real Estate	Real Estate	Technology	Technology	Telecoms	Telecoms
ESG-Score	0.491		0.805		0.088	
	(0.285)		(0.392)		(0.327)	
E-Score		0.092		0.497		0.460
		(0.281)		(0.567)		(0.492)
S-Score		0.172		-0.220		-1.099*
		(0.258)		(0.112)		(0.427)
G-Score		0.239		0.562***		1.274**
		(0.176)		(0.093)		(0.438)
Constant	-1.703***	-1.724***	-2.319***	-2.325***	-2.068***	-2.334***
	(0.135)	(0.147)	(0.107)	(0.224)	(0.209)	(0.266)
Observations	110	110	41	41	66	66
R-squared	0.280	0.282	0.183	0.235	0.284	0.607
Year FE	IN	IN	IN	IN	IN	IN
Industry FE	EX	EX	EX	EX	EX	EX

Note I: Robust Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
Note II: The table displays the industry analysis of the previous OLS regressions in Table 8, Models 3 and 4 controlled for year fixed effects. The industry fixed effects are omitted due to insufficient variability within industries, which would limit the reliability and interpretability of results due to overfitting or multicollinearity. **Note III:** EX, Excluded; IN, Included; OLS, ordinary least squares

The results presented in Tables 10 to 12 align with Apergis et al., (2022), asserting that the relationship in question varies across industries due to differing ESG-related risk exposures. However, the analysis in this study is constrained by limited variability within industries, which complicates definitive conclusions.

4.3.2.1 Combined ESG Scores

The combined ESG rating for industries with sufficient sample sizes (n > 10; 110 observations), which include Consumer Discretionary, Basic Materials, Consumer Staples, Real Estate and Industrials, is not significantly related to credit risk. These results convey that, at the aggregate level, ESG performance does not impact credit risk across these sectors.

4.3.2.2 Decomposed ESG Pillars

When ESG scores are disaggregated into their pillars, more nuanced relationships emerge. In the **Industrials Sector**, a positively significant relationship is noted between the E-Score and credit risk at the 10% level, with a strong coefficient of 0.861. This suggests that improvements in environmental performance, such as reduced carbon footprint and sustainable resource management may increase credit risk for industrial firms in Africa. This counterintuitive finding is supported by Saidane and Abdallah (2021) and Johnson (2020), who argue that environmental compliance costs, particularly in African firms, may harm financial stability. Similarly, Palmieri et al., (2023) find the same for European firms. The results contradict Chodnicka-Jaworska (2021), Jang et al., (2020) and Kiesel and Lücke (2019) who find that the improved environmental performance reduces credit risk for industrial firms.

In the **Basic Materials Sector**, the G-Score exhibits a significant negative relationship with credit risk, indicating that improved governance practices mitigate credit risk in this sector. These results may be influenced by the stringent regulations governing the Basic Materials industry, where strong governance practices enhance operational and financial stability. This finding is consistent with Saidane and Abdallah (2021), who demonstrate that prioritising governance performance reduces credit risk in African firms.

In the **Healthcare Sector**, the aggregated ESG score, and E-Score show a positive relationship with credit risk, consistent with Palmieri et al., (2023), which suggests that compliance costs may outweigh the economic benefits in ESG-sensitive sectors. However, the findings must be interpreted cautiously because of the limited sample size (n = 4). In the **Technology Sector**, the G-Score reports a positively significant relationship with default risk, while social scores demonstrate a relationship in the opposite direction. These results, too, should be interpreted cautiously on account of the limited sample sizes (n < 110 observations), which limit the reliability and generalisability of the findings.

4.3.2.3 Industry Analysis Conclusions

The results above emphasise that the relationship studied is non-consistent across industries, prompting the need for industry-specific considerations in ESG risk management and credit risk assessment. For sectors such as Industrials and Basic Materials, which are particularly sensitive to ESG risks, targeted strategies addressing environmental and governance dimensions may be necessary. Future research should aim to address sample size limitations to provide more robust and generalisable insights.

4.4 Robustness

This section of the chapter reports the regression results of the robust models employed, such as using the NUS-CRI PD as a substitute credit risk measure and is applied to OLS regressions, REMs and FEMs. The analysis applies a systematic diagnostic approach to distinguish the suitable model. Further robustness models include the IV regression and the Two-Step GMM estimation to support the reliability of the results.

4.4.1 Regression Results for ESG Scores on Credit Risk (PD)

Table 13: Pooled OLS Regression Outcomes for ESG on PD

Variables	**OLS (1)**	**OLS (2)**	**OLS (3)**	**OLS (4)**
ESG-Score	-0.060		-0.958	
	(0.768)		(0.709)	
E-Score		0.601		0.615
		(0.795)		(0.701)
S-Score		-0.653		-1.689*
		(0.961)		(0.871)
G-Score		-0.016		0.036
		(0.731)		(0.681)
Constant	-6.904***	-6.844***	-6.797***	-6.747***
	(0.423)	(0.461)	(0.500)	(0.503)
Observations	955	955	955	955
R-squared	0.000	0.003	0.299	0.310
Year FE	EX	EX	IN	IN
Industry FE	EX	EX	IN	IN

Note I: Robust Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
Note II: Models 1 to 4 report the OLS regression models whose endogenous variable is the log(PD). Model 1 specifies the combined ESG Score without fixed effects. Model 2 is the specification, which includes the decomposed E-Score, S-Score, and G-Score, without fixed effects. Model 3 is the specification, which includes the combined ESG Score and controls for fixed effects. Model 4 is the specification that consists of the decomposed E-Score, S-Score, and G-Score controls for fixed effects.
Note III: EX, Excluded; IN, Included; OLS, ordinary least squares

Table 14: Panel Estimation Results for ESG on PD

Variables	REM (5)	REM (6)	FEM (7)	FEM (8)
ESG-Score	1.954***		0.776	
	(0.747)		(0.945)	
E-Score		0.766		0.441
		(0.688)		(0.605)
S-Score		1.553**		-0.158
		(0.741)		(0.768)
G-Score		-0.372		0.559
		(0.518)		(0.506)
Constant	-7.879***	-7.821***	-8.490***	-8.544***
	(0.424)	(0.452)	(0.417)	(0.440)
Observations	955	955	955	955
R-squared			0.269	0.271
Year FE	EX	EX	IN	IN
Industry FE	EX	EX	EX	EX

Note I: Robust Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
Note II: Models 5 and 6 report the random effects panel regression models. Models 7 and 8 report fixed effects panel estimations with year fixed effects with the log(PD) as the dependent variable. Industry fixed effects cannot be applied to the models due to insufficient variability within industries. Model 5 specifies the combined ESG Score without fixed effects. Model 6 is the specification, that includes the decomposed E-Score, S-Score, and G-Score, in the absence of fixed effects. Model 7 specifies the combined ESG Score and controls for fixed effects. Model 8 specifies the decomposed E-Score, S-Score and G-Score with fixed effects.
Note III: EX, Excluded; IN, Included; REM, Random Effects Model; FEM, Fixed Effects Model.

When using log(PD) as a default risk measure, the analysis reveals varying relationships between ESG scores and credit risk for all regression models. In the OLS regressions, combined and individual ESG scores are not statistically significant determinants of credit risk, with mixed signs. Similarly, the FEM reveals a positive but not significant relationship. In contrast, the REM identifies a positively significant relationship concerning combined ESG-scores and default risk.

For decomposed pillars, the social pillar presents ambiguous results. In the REM the social pillar exhibits a significant positive relationship with credit risk, while it demonstrates a significant negative relationship in the OLS model incorporating fixed effects. In the OLS model without fixed effects and the FEM, the social pillar is not statistically significant. Meanwhile, the environmental and governance pillars are consistently insignificant across all models. These findings differ substantially from those derived using the Z''-score (Tables 8 and 9), demonstrating the sensitivity of the relationship to the measure of risk and model specification employed.

4.4.1.1 Model Selection and Diagnostic Tests

To provide further clarity on the appropriate model, the BPLM test was conducted, yielding a p-value of zero which supports the use of the REM. However, the subsequent Hausman test to compare the REM and FEM produced a very small p-value, proposing that the FEM is appropriate for the analysis.

4.4.1.2 Conclusions of the Log (PD) Regressions

According to the FEM, neither aggregated ESG scores nor individual E-, S-, or G-Scores show a statistically significant relationship with credit risk as measured by log(PD). The combined ESG score results align with those obtained using Altman's Z"-score, suggesting a consistent lack of significance for ESG factors in explaining credit risk in African firms. These findings contrast with prior studies, namely Bannier et al., (2022), Brogi et al., (2022), Do and Vo (2023), and Suganda and Kim (2023), which report that improved ESG performance can mitigate market-based risk measures, including the DTD and the PD.

The disaggregated pillar score results on the other hand, have a discrepancy in the environmental pillar result, where the Z"-Score selected model demonstrates that an improvement in the E-Score increases credit risk. The variation in the pillar results warrants further investigation.

4.4.1.3 Conclusions and Implications of Log (PD) Regressions

Despite the fact that the selected models in the PD and Z"-Score models are aligned, the overall discrepancies between the general model outcomes underscore the sensitivity of ESG-credit risk relationships to the chosen risk metric. Furthermore, the conflicting findings between the FEM and the REM in the log(PD) analysis alone highlight the influence of model specification on results. These inconsistencies suggest further investigation, employing advanced estimators such as IV regression and GMM to better understand the dynamics of the ESG-credit risk relationship.

4.4.2 Instrumental Variable Regression

A first-stage regression was conducted and revealed that GDP growth, Rule of Law, and Education Enrolment Ratio are all significant predictors of ESG scores. However, after performing PCA, only the factor combining GDP growth and the Rule of Law remains significant, leading to the exclusion of the Education Enrolment Ratio from further analysis. The first stage results are shown in Table 15.

Rule of Law is positively correlated with ESG scores, consistent with the expectation that stronger institutions enhance ESG performance. Surprisingly, GDP growth negatively correlates with ESG scores in African countries, indicating possible trade-offs between economic growth and sustainability activities. The PCA factor combining GDP growth and the Rule of Law confirms the instrumental variable regression's reliability in Table 16, highlighting the importance of macroeconomic conditions in shaping ESG outcomes.

Table 15: First Stage Regression Results between ESG Score and IV Factor

Variables	**IV Model 1- (OLS)** **ESG Score**	**IV Model 2 – (OLS)** **ESG Score**
GDP Growth	-1.128*** (0.233)	
Rule of Law	0.177*** (0.023)	
IV Factor		0.033*** (0.005)
Constant	0.498*** (0.007)	0.473*** (0.006)
Observations	1,001	1,001
R-squared	0.053	0.030

Note I: Robust Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
Note II: IV Model 1 and IV Model 2 show the Instrumental Variable's composition, which synthesises the combined ESG Score with the Rule of Law estimate and the GDP growth rate. The dataset is sourced from the World Bank and captures different macroeconomic aspects believed to correlate with ESG Scores and not the error term. The IV factor is created through PCA.
Note III: EX, Excluded; IN, Included; IV, Instrumental Variable

Table 16:Second Stage IV Regression Results

Variables	IV-OLS (1)	IV-OLS (2)	IV -FEM (3)	IV-REM (4)
ESG-Score	-0.859	0.247	33.606	0.247
	(1.290)	(0.718)	(525.008)	(0.729)
Constant	-1.473**	-2.108***	-16.554	-2.108***
	(0.614)	(0.437)	(227.807)	(0.444)
Observations	996	996	996	996
R-squared		0.074		
Year FE	EX	IN	IN	IN
Industry FE	EX	IN	EX	EX

Note I: Robust Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
Note II: IV Model 1 to 4 shows the regressions of ESG on negative log(Z"-score) using the IV Factor as an instrument. The models are OLS without fixed effects, OLS with year and industry fixed effects, Fixed Effects panel regressions with year fixed effects and Random Effects Models, respectively. High coefficients influence the coefficient for IV Model 3 in the year fixed effects in some years.
Note III: EX, Excluded; IN, Included; FEM, Fixed Effects Model; IV, Instrumental Variable Regression; OLS, Ordinary Least Squares; REM, Random Effects Model

Table 16 shows results from the IV regression models (Models 1 to 4), indicating that ESG scores are not significant predictors of credit risk. These findings align with the conclusions from earlier models, including the fixed effects PD and Altman Z"-score regressions, reinforcing the robustness of the results. The subsequent section applies a GMM estimator to validate these findings further and address potential endogeneity concerns, ensuring no relationships have been obscured. The additional step aims to provider further clarity into the dynamics between ESG and credit risk comprehensively.

4.4.3 Results of the GMM

Table 17: Results of the GMM Estimation using -log(Z"-score)

Variables	(GMM 1/2)	(GMM 1/2)	(GMM 2/3)	(GMM 2/3)
ESG-Score	0.349		-0.147	
	(0.458)		(0.340)	
E-Score		0.049		0.082
		(0.317)		(0.355)
S-Score		0.183		0.042
		(0.375)		(0.397)
G-Score		-0.320*		-0.194
		(0.164)		(0.350)
Constant	-2.020***	-1.816***	-1.805***	-1.829***
	(0.222)	(0.152)	(0.165)	(0.245)
Observations	996	996	996	996

Note I: Robust Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
Note II: GMM 1/2 reports the results of the first and second lag, while GMM 2/3 reports the second and third lag results for robustness.
Note III: GMM, Generalised Method of Moments

The validity of the chosen instruments in the GMM was evaluated by diagnostic tests. The Arellano-Bond test for autocorrelation indicates no significant first- or second-order serial correlation (p-values > 0.10), supporting the appropriateness of the selected lag structure across all models. However, the Difference-in-Hansen test raises concerns regarding the validity of additional instruments applied to the combined ESG Score model, with p-values of 0.044 for first-order lags and 0.033 for GMM 2/3. These findings suggest the need for additional robustness checks, such as modifying the instrument set or exploring alternative methods to address endogeneity.

4.4.3.1 An analysis of Combined ESG Scores

The GMM results (GMM 1/2 and GMM 2/3) demonstrate insufficient evidence of a relationship concerning the combined ESG Scores and credit risk, despite some inconsistencies in the relationship's direction. However, the failed Hansen tests suggest that combined ESG scores may be highly endogenous, preventing reliable conclusions from being drawn. This underscores the challenges in isolating the implications of combined ESG scores on credit risk, suggesting a cautious approach when interpreting these results.

4.4.3.2 An analysis of Decomposed ESG Scores

In contrast to the combined ESG score results, the Hansen test results for the decomposed pillar models (p-values of 0.339 and 0.421) validate the instrument sets, enabling reliance on these findings. The discrepancy in instrument validity between combined ESG scores and individual pillars suggests that overall ESG scores may encapsulate greater endogeneity compared to their components.

The GMM analysis reveals that the social and environmental pillars are not related to credit risk, while the results for the governance pillar reveal that governance scores significantly and negatively influence credit risk at shorter lag intervals (lags 1 and 2), with significant results at the 10% level. However, the GMM with longer lag intervals shows that the governance factor is not significant, demonstrating that the influence of governance practices diminishes over time. This means that governance improvements have a time-sensitive or short-lived impact on credit risk and emphasises the importance of focusing on recent governance practices when assessing their influence on financial stability.

Comparing individual pillar results across OLS, REM, FEM, and GMM reveals mixed findings. These inconsistencies may be attributed to endogeneity, which, when addressed through GMM, provides more reliable results. These findings reiterate the complexity of the relationship in question and underline the importance of dynamic models like GMM in capturing lagged effects and mitigating endogeneity biases.

4.5 Chapter Conclusion

This reported on the analysis of the interaction between ESG and credit risk for African firms, utilising the pooled OLS, FEM, REM, IV regression and two-step system GMM models. The outcome of the analysis demonstrates that the combined ESG score was not a significant estimator of credit risk across all selected model specifications. In contrast, the disaggregated ESG pillars displayed varying degrees of significance in relation to credit risk, particularly in specific industries. This highlights the complexity of the relationship in question and suggests a granular approach to understanding the full dynamics.

The implications of these observations will be further explored in Chapter 5, where potential drivers behind the insignificance of the combined ESG score will be investigated. Chapter 5 will also provide a more detailed analysis of the conflicting results across the individual ESG pillars. Additionally, the practical implications of these findings will be discussed along with policy recommendations aimed at improving ESG-related risk management in the African context.

While this study focuses on the relationship between ESG and credit risk, a counterfactual consideration, namely, what the credit risk profile of firms might look like in the absence of ESG engagement, offers a useful conceptual benchmark. In contexts where ESG integration is minimal, firms may face high operational, reputational, or regulatory risks, potentially leading to a higher probability of default. This further reinforces the importance of ESG as a non-financial determinant of creditworthiness in emerging markets.

Finally, it is important to reflect on data limitations. While Refinitiv is a widely used ESG data provider, its coverage of African firms is relatively limited, which constrained the sample size, limited country variation and potentially excluded firms with weaker disclosure practices. This may affect the representativeness of the findings. Future research would benefit from including region-specific ESG datasets or alternative ESG data sources to enhance the contextual depth and critical insight into ESG-credit dynamics in Africa.

Chapter 5
Conclusions

5.1 Introduction

This last chapter brings the study to a close by drawing attention to the study's key insights and the subsequent implications. It discusses the limitations of the research and delivers policy recommendations tailored to various stakeholders. Furthermore, the chapter suggests avenues for future research, highlighting opportunities to expand on the findings.

5.2 Overview of Key Insights

This dissertation studies the ESG performance and credit risk relationship for African firms, using Altman's Z"-score (2005) as the primary quantifier of credit risk. An alternative measure, the Probability of Default from NUS-CRI, was employed for robustness testing. The dataset comprises 91 listed firms from South Africa, Morocco, Egypt, and Zimbabwe from 2012–2022, with ESG and financial data sourced from Refinitiv Eikon.

The analysis employed various specifications, including OLS regressions, fixed effects and random effects estimations, Instrumental Variable Regression, and Two-Step System GMM, to uncover the intricate dynamics in the ESG-default risk relationship. The study's conceptual framework hypothesised that ESG scores influence credit risk through transmission channels moderated by industry, firm size, and economic cycle. However, the transmission mechanisms as well as firm size and economic moderators are beyond the scope of this study.

Key findings include:

1. **Altman's Z"-score as credit risk (OLS, FEM, REM)**: The aggregated ESG score did not display a statistically significant relationship with credit risk across multiple models. The environmental pillar exhibited a modest, yet positively significant relationship with credit risk, whereas the social and governance pillars remained largely insignificant in the REM, which was identified as the most suitable model based on the Hausman test.

2. **Industry Analysis**: Industry-level findings revealed variations in the ESG-credit risk

relationship. For instance, the environmental pillar had a positive relationship with credit risk in the Industrials sector, suggesting overinvestment in environmental initiatives may outweigh their benefits. Conversely, governance was significant in the Basic Materials sector, demonstrating its role in mitigating risk.

3. **PD as credit risk (OLS, REM, FEM):** The combined ESG score was not significant in the FEM which the Hausman test deemed as the most appropriate model. Additionally, the single pillars also did not exhibit a significant relationship in the chosen specification.

4. **GMM and IV Results**: The IV regression supported the selected Z"-score and PD models that the aggregated ESG Score is not a significant determinant of credit risk. The GMM approach highlighted potential endogeneity in the combined ESG score, complicating definitive conclusions about its insignificance. Nonetheless, it revealed a negative short-term relationship between governance and credit risk, although this effect diminished over time.

5.3 Conclusion

The regression results imply a complex relationship between ESG performance and credit risk, particularly for African firms, challenging the commonly presumed straightforward link. While ESG performance had no observable influence on credit risk quantified by the Z"-score and the PD, this contrasts global studies (e.g., Brogi et al., 2022; Do & Vo, 2023; Lin & Dong, 2018) and African research (e.g., Saidane & Abdallah, 2021) that generally indicate a negative relationship. Conversely, studies focused on African and Middle Eastern firms such as Badayi et al., (2021) suggest that higher ESG performance may increase a firm's default probability highlighting regional variations. By excluding Middle Eastern firms, differences in sample composition may partly explain these discrepancies, as incorporating these regions could provide a more robust sample size.

Interestingly, this study's findings align with McAdam (2012), who observed no evidence of ESG considerations in credit ratings at that time, attributing this to the lack of ESG regulatory frameworks. McAdam (2012) emphasised the potential for ESG to influence credit assessments as regulatory landscapes evolve. However, in African contexts, ESG frameworks and reporting remain underdeveloped (Denhere, 2022; Duru, 2021; Inderst & Stewart, 2018). Limited standardisation and data availability further constrain empirical analyses, contributing to this study's absence of significant findings.

Subsequently, methodological differences may also account for the divergent results. For example, Saidane and Abdallah (2021) used a different Z-score measure and a PVAR autoregressive GMM approach, which better addresses time dynamics and endogeneity issues.

Their study found that governance scores negatively correlated with credit risk, suggesting that robust governance reduces risk, while the social pillar showed no effect. In contrast, this analysis failed to establish a robust relationship between credit risk and environmental and social scores. However, the GMM revealed that the improvement in governance ratings lowered credit risk in the short run, with its effect decaying with time. The diminishing long-term impact of governance may be attributed to the well-established governance practices in South Africa, which are likely already priced into market assessments, reducing the incremental effect of further improvements in governance (Johnson, 2020).

Industry-specific analysis revealed further nuances. Governance scores negatively impacted credit risk in the Basic Materials sector, indicating industry-specific dynamics. This suggests that robust governance mitigates risks in highly regulated industries, echoing Saidane and Abdallah's (2021) findings. Conversely, in the Industrials sector, environmental performance showed a positive relationship with credit risk. This aligns with insights from Badayi et al., (2021), suggesting that excessive investments in environmental initiatives within this sector may lead to diminishing returns, where costs outweigh benefits.

In conclusion, the results underscore the complexity of the ESG-credit risk relationship in African contexts. Differences in methodologies, measures of credit risk, regulatory environments, and sectoral dynamics have a critical role in the results, emphasising the need for tailored approaches in analysing ESG impacts on credit risk.

5.4 Research Limitations

The research is subject to several limitations. Firstly, the sample size and industry concentration, particularly the dominance of South African firms and the Basic Materials sector, may limit the generalisability of the results. Secondly, the sample exclusively included firms in the "safe" zone, with no observations in the default zone, potentially obstructing the relationship analysis between ESG and credit risk under extreme financial distress. These limitation may have risen from the constrained ESG data coverage available for African firms on the Refinitiv platform. Many listed companies across the continent either do not report ESG metrics or are not covered by major data providers, resulting in a sample that may not fully reflect the diversity of ESG practices across regions and sectors in Africa. This underscores the need for improved and regionally tailored ESG reporting frameworks and data collection efforts to support more representative and nuanced analyses in future research.

Endogeneity posed another significant issue. Although IV regression and GMM models were employed to curb potential biases, some endogeneity concerns remain unresolved, particularly for the combined ESG Score, suggesting the need for advanced methods such as dynamic panel models or alternative proxies for ESG performance. Furthermore, the time-dependent effects highlighted in the GMM models suggest a short-term influence of governance on credit risk requires deeper exploration to understand its temporal dynamics fully.

The study also encountered methodological constraints, as the reliance on linear models may overlook potential non-linear relationships between sustainable practices and credit risk. Moreover, while useful, the Z”-score may not entirely reflect the complexities of credit risk. The absence of control variables namely leverage, firm size and profitability, due to concerns about multicollinearity with the Z”-score may also introduce omitted variable bias, potentially affecting the estimated relationship between ESG and credit risk.

5.5 Pathways for Future Studies

Studies in future should explore the expansion of the dataset to include more African countries and a broader range of industries, which would enhance the representativeness and variability of the panel, thereby providing deeper insights into ESG-credit risk dynamics. Investigating non-linear models and alternative risk measures could also help to capture the nuanced relationship between ESG performance and credit risk more effectively. Moreover, conducting industry-focused research would provide deeper insights into sectoral variations in ESG impacts, offering tailored recommendations for different economic sectors.

Future studies should incorporate control variables to address omitted variable bias and examine potential multicollinearity within the Z-score calculation to improve the robustness of findings. It is also essential to explore the ESG-credit risk relationship over a longer period, to account for institutional and regulatory developments in Africa, which are likely to evolve significantly over time. Lastly, researchers should investigate the role of emerging ESG frameworks and their implications for credit risk assessments, as these frameworks will increasingly influence how firms are evaluated in African financial markets.

5.6 Policy Recommendations

5.6.1 Theoretical Implications

This dissertation underscores the complexity of the relationship under study, highlighting the importance of conducting context-specific analyses, particularly in emerging economies like those in Africa, where ESG frameworks and adoption are in their infancy. The findings also reveal significant sectoral variations in ESG performance, where Environmental scores increased credit risk in the Industrials sector, while Governance had a mitigating effect on credit risk in Basic Materials. This calls for further research into industry- specific dynamics to provide more nuanced insights and strategies. Additionally, the study challenges the assumption that aggregated ESG scores uniformly predict credit risk, emphasising the need to disaggregate ESG components in future research. Scholars can better understand the distinct roles of ESG components in shaping credit risk outcomes by examining the individual contributions of ESG factors, rather than treating ESG as a uniform construct.

5.6.2 Practical Implications0

The sectorial variations in the relationship between ESG and Credit risk, for example, this study found that Environmental scores increased credit risk in the Industrials sector, while Governance had a mitigating effect on credit risk in Basic Materials. In response, credit risk managers should adopt sector-specific strategies when incorporating ESG factors into risk assessments. For example, firms in the Industrials sector should critically assess the cost-benefit balance of environmental investments. In contrast, companies in the Basic Materials sector could gain from reinforcing governance practices to mitigate risk.

The study also found that E, S and G factors do not uniformly predict credit risk. As a result, financial institutions are advised to exercise caution when relying on aggregated ESG scores as standalone indicators of risk. Instead, they should emphasise disaggregated ESG scores and develop tailored models that capture the unique dynamics of each ESG component. Investing in ESG expertise will enhance their ability to assess and interpret the nuanced impacts of ESG metrics on credit risk, enabling more sophisticated and context-sensitive approaches to integrate ESG considerations into their risk assessment structures.

This study's findings align with McAdam (2012), who observed no evidence of ESG considerations in credit ratings at the time of study, attributing this to the lack of ESG regulatory frameworks. Additionally, Denhere (2022) and Inderst and Stewart (2018) also highlight the role of the underdevelopment of ESG frameworks and reporting in constraining empirical analyses. In response to this, policymakers are crucial in advancing ESG considerations in credit markets and are encouraged to prioritise mandatory ESG disclosures and establish standardised reporting frameworks. These measures can enhance data quality and availability, enabling effective assimilation of ESG factors into investment practises.

5.7 Conclusions

This dissertation adds to the expanding body of knowledge on ESG and credit risk through insights tailored to the African context. Although aggregated ESG scores are not significant predictors of credit risk, the governance pillar shows a notable short-term impact, especially within the Basic Materials sector. These results emphasise the critical role of context, industry dynamics, and methodological precision in understanding ESG-credit risk relationships. Future research should develop these findings further by tackling the identified limitations and broadening the analysis to reflect the evolving significance of ESG in financial decision-making across diverse African markets.

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