UNIVERSITY OF LJUBLJANA
SCHOOL OF ECONOMICS AND BUSINESS

MASTER’S THESIS

THE IMPACT OF ESG SCORES ON CREDIT RISK OF THE BANKS IN THE EU

Ljubljana, November 2024 IZA MATKO

AUTHORSHIP STATEMENT

The undersigned Iza Matko, a student at the University of Ljubljana, School of Economics and Business, (hereafter: SEB LU), author of this written final work of studies with the title The impact of ESG scores on credit risk of the banks in the EU, prepared under supervision of doc. dr. Riste Ichev.

D E C L A R E

1. this written final work of studies to be based on the results of my own research;
2. the printed form of this written final work of studies to be identical to its electronic form;
3. the text of this written final work of studies to be language-edited and technically in adherence with the SEB LU's Technical Guidelines for Written Works, which means that I cited and / or quoted works and opinions of other authors in this written final work of studies in accordance with the SEB LU's Technical Guidelines for Written Works;
4. to be aware of the fact that plagiarism (in written or graphical form) is a criminal offence and can be prosecuted in accordance with the Criminal Code of the Republic of Slovenia;
5. to be aware of the consequences a proven plagiarism charge based on the this written final work could have for my status at the SEB LU in accordance with the relevant SEB LU Rules;
6. to have obtained all the necessary permits to use the data and works of other authors which are (in written or graphical form) referred to in this written final work of studies and to have clearly marked them;
7. to have acted in accordance with ethical principles during the preparation of this written final work of studies and to have, where necessary, obtained permission of the Ethics Committee;
8. my consent to use the electronic form of this written final work of studies for the detection of content similarity with other written works, using similarity detection software that is connected with the SEB LU Study Information System;
9. to transfer to the University of Ljubljana free of charge, non-exclusively, geographically and time-wise unlimited the right of saving this written final work of studies in the electronic form, the right of its reproduction, as well as the right of making this written final work of studies available to the public on the World Wide Web via the Repository of the University of Ljubljana;
10. my consent to publication of my personal data that are included in this written final work of studies and in this declaration, when this written final work of studies is published.
11. that I have verified the authenticity of the information derived from the records using artificial intelligence tools.

Ljubljana, November 14th, 2024 Author's signature: Matko

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

LIST OF ABBREVIATIONS

sl. – Slovene

CSR – (sl. družbena odgovornost podjetij); Corporate Social Responsibility

CSRD – (sl. Direktiva poročanja podjetij o trajnostnosti); Corporate Sustainability Reporting Directive

EBA – (sl. evropski bančni organ); European Banking Authority

EBU – (sl. evropska bančna unija); European Banking Union

ECB – (sl. Evropska centralna banka); European Central Bank

EIB – (sl. Evropska investicijska banka); European Investment Bank

EMU – (sl. Ekonomska in monetarna unija); Economic and Monetary Union

ESG – (sl. okoljski, družbeni in upravljavski dejavniki); Environmental, Social and Governance

EU – (sl. Evropska unija); European Union

NFRD – (sl. Direktiva o poročanju o nefinančnih informacijah); Non-Financial Reporting Directive

NGO – (sl. nevladna organizacija); Non-Governmental Organization

SFRD – (sl. Uredba o razkritjih v zvezi s trajnostjo); Sustainable Finance Reporting Disclosure

UN – (sl. Združeni narodi); United Nations

1 INTRODUCTION

Managing credit risk is one of the primary concerns for banks and the banking system as a whole. As evidenced by the Global Financial Crisis of 2008, stringent policies regarding credit risk are necessary to improve the stability of the banking system and avert future crises (Jassaud & Vidon, 2017; Alnabulsi et al., 2022). To determine the appropriate regulatory measures required, and consequently, credit risk management techniques for banks, it is necessary to identify credit risk determinants and assess their impact.

With continuous introduction of new regulation regarding sustainability in the European Union (EU) aiming to enhance transparency in the disclosure of sustainability information, the topic of banks' engagement with Environmental, Social and Governance (ESG) issues is becoming increasingly relevant. In addition to increased pressure from regulators to comply with necessary regulations and improve ESG impact, banks with lower ESG scores may face higher credit risk by attracting undesirable clients, according to the stakeholder theory (Dathe et al., 2024). Furthermore, a bank's ESG score directly affects its credit risk, as banks are more likely to lend to clients with a similar ESG profile (Houston & Shan, 2022). Thus, the relationship between ESG scores and credit risk is becoming more important, highlighting the need for further research.

Although past research has been conducted in other sectors, such as private firms (Henisz & McGlinch, 2019; Chodnicka-Jaworska, 2021), the banking sector remains under-researched regarding ESG impact and credit risk. Existing research on ESG impact in banking primarily focuses on bank value, typically examining the impact of ESG scores on banks' market price and profitability (Azmi et al., 2021; Cornett et al, 2016; Di Tommaso & Thornton, 2020; Staroverova, 2022). Furthermore, there is a notable gap in the research concerning the credit risk and ESG-related topics for banks headquartered in the EU in contrast to banks headquartered in the Economic and Monetary Union (EMU), as well as differences between banks headquartered in developed and emerging countries within the EU.

To address the identified gap in existing literature, this master's thesis explores the relationship between a bank's ESG impact and its credit risk by posing the following three research questions: How do bank specific ESG scores vary across countries, years, and bank sizes? Is there a trade-off between bank specific ESG scores and their credit risk, and what are the primary financial determinants of credit risk? Are there statistically significant differences in the effects of ESG scores on the credit risk of banks headquartered in EU, EMU, non-EMU member countries, and in developed and emerging countries within the EU?

Based on a sample of 87 EU banks with data spanning from 2014 to 2023, the results indicate that higher bank-specific ESG scores are associated with lower credit risk. Furthermore, the analysis reveals differences in this relationship between banks headquartered in EMU and non-EMU countries, as well as between banks in developed and emerging EU markets. For banks based in EMU and developed markets, a statistically significant and negative relationship between ESG scores and credit risk is observed. However, no statistically significant relationship is found for banks based in non-EMU and in some cases, the reverse relationship is observed in emerging countries.

Understanding the relationship between banks' ESG scores and their credit risk is valuable to various stakeholders. First, credit risk management strategies stand to gain from exploring this connection, contributing to a more stable and resilient economy. Second, EU regulatory bodies could use insights from this relationship when constructing financial regulations, particularly as sustainability becomes an increasing focus. By examining how ESG scores influence credit risk and how this relationship varies between EMU and non-EMU countries, as well as between developed and emerging markets, policymakers could develop more effective regulations with a comprehensive view of their impact. Moreover, other stakeholders, such as lenders and borrowers, would benefit from understanding the ESG-credit risk dynamic, enabling them to better align their interests with those of banks.

The rest of this master's thesis is structured as follows: section 2 provides an extensive literature review focusing on the evolution and characteristics of ESG, along with a concise overview of credit risk and its key determinants. Sections 3 and 4 discuss the structure of the data used in the analysis and the methodology employed to address the proposed research questions respectively. Section 5 presents the results of the research and answers to the three research questions, followed by a discussion about how the findings relate to the existing literature. Lastly, section 6 offers concluding remarks, summarizes the main findings, discusses the limitations of the conducted research, and suggest areas for future research.

2 LITERATURE REVIEW

The literature review is divided into four sub-sections, providing an overview of existing research on the topic of ESG and credit risk. Additionally, since credit risk is a risk that banks must manage carefully, the review includes literature on its various financial determinants. Finally, studies examining the intersection of ESG impact and credit risk in the banking sector are discussed.

2.1 ESG impact

Managing ESG risk has become increasingly relevant in recent times, as many studies highlight the regulatory, reputational, and financial consequences involved. EU regulations are increasingly focused on enhancing transparency regarding sustainability disclosures by financial companies, which has resulted in heightened reputational risks for banks from various stakeholders. Additionally, research by Cornett et al. (2016) and Buallay (2019), among others, emphasizes the financial benefits of raising awareness about the ESG impact of banks, while a study by Staroverova (2022) indicates that avoiding negative publicity is also a financially responsible approach to ESG impact for banks.

In this section of the literature review, the ESG topic is first introduced within the broader context of sustainability and its relationship to Corporate Social Responsibility (CSR), as well as the beginnings of the term ESG. This is followed by a brief overview of EU regulations on sustainability. Next, the theoretical implications of how investing in ESG affects banks are discussed. Finally, the section reviews studies examining the impact of ESG on banks' profitability and value.

2.1.1 Differences and similarities between CSR and ESG

Sustainability efforts and their inclusion in business models of financial as well as non-financial companies have been relevant for some time, although under various names. One of the most common terms, besides ESG, that is still in use today is CSR.

CSR is closely associated with ESG scores and is sometimes even used interchangeably with the latter. However, there are key differences between the two concepts. The most commonly cited definition of CSR, as highlighted by Kaźmierczak (2022) in a comprehensive literature review, comes from the international standard ISO 26000, published in 2010. CSR is defined as "the responsibility of an organization for the impact of its decisions and activities on society and the environment, through transparent and ethical behaviour in key areas such as organizational governance, human rights, labour practices, the environment, fair operating practices, consumer issues, community involvement, and the development of the local community" (Kaźmierczak, 2022). CSR encompasses a broader concept, incorporating sustainable practices into corporate decision-making and emphasizing long-term business plans regarding sustainability (Kaźmierczak, 2022; Cini & Ricci, 2018).

On the other hand, ESG scores offer a concrete framework for assessing a company's sustainability efforts and serve as a key metric in sustainable investing (Cini & Ricci, 2018). By evaluating the positive or negative externalities generated by entities, ESG scores provide a clearer picture of the company's overall involvement in ESG issues (Li et al., 2021). While CSR mainly focuses on the environmental and social pillars, ESG scores also take governance into consideration.

CSR represents a broader and less defined concept of sustainability management, often employed by managers for addressing sustainability and reputational risks, as well as guiding company strategy. In contrast, ESG scores provide a more objective measure of externalities and are primarily utilized by external stakeholders, such as investors (Kaźmierczak, 2022). Despite these differences, both concepts share the fundamental goal of integrating sustainability into business decisions, which is why many researchers use the two terms interchangeably (Cornett et al., 2016; Neitzert & Petras, 2022; Cini & Ricci, 2018).

2.1.2 Origins of ESG

The ESG score, as a measure of sustainability, is a relatively novel concept. The term ESG, representing Environmental, Social, and Governance, was coined in 2004 in a report by the United Nations (UN) under the leadership of UN Secretary-General Kofi Annan. It was endorsed by 18 financial institutions from 9 countries, with cumulative assets under management of around 6 trillion USD. The research was funded by the Swiss government. The purpose of the report, titled *Who Cares Wins: Connecting Financial Markets to a Changing World* was not to prescribe regulatory measures but to foster discussion and raise awareness among all stakeholders, including investors, governments, regulators, analysts, non-governmental organizations (NGOs), consultants, accountants, educators, and companies. By encouraging critical thinking on ESG topics, the report aimed to create better investment markets with higher levels of integrated sustainability (United Nations Global Compact & UNEP Finance Initiative, 2004). The main recommendations are summarized in Table 1.

Table 1: Who cares wins, Connecting Financial Markets to a Changing World report recommendations

Stakeholder	Recommendation
Analysts and brokers	Incorporate ESG topics into research.
Investors	Reward ESG research and incorporate ESG topics into investment strategies.
Governments	Consider ESG topics in pension fund investments.
Regulators and stock exchanges	Implement reporting standards for ESG topics.
NGOs	Provide impartial assessments of companies' ESG standings.
Consultants	Integrate ESG topics with industry-level research and raise awareness.
Accountants and educators	Promote standardization and encourage critical thinking.
Companies	Incorporate ESG principles into the business model and improve reporting and disclosures.

Source: adapted from United Nations Global Compact & UNEP Finance Initiative (2004)

2.1.3 EU Regulation as a response to divergent ESG scores and promotion of corporate transparency

The call for greater involvement from regulatory bodies and, more importantly, a higher level of standardization regarding ESG scores from different providers can be discerned from the outset. This is evident from the UN report’s recommendation of promoting standardization and implementing reporting standards for regulators, accountants, and educators presented in Table 1.

In that respect, Dimson et al., (2020) aimed to explain the extent of divergence of ESG scores from different providers and its underlying reasons by comparing companies' ESG scores from three major providers: MSCI, FTSE Russell, and Sustainalytics. The correlation coefficient for the overall ESG score was highest between FTSE and Sustainalytics, at 0.59, and lowest between MSCI and FTSE, at 0.30. The correlation coefficients were even lower for individual pillars, with the highest being for the social pillar (0.43 between FTSE and Sustainalytics) and the lowest for the Governance pillar (-0.02 between MSCI and Sustainalytics). The Environmental pillar exhibited the most variation, with a correlation coefficient of 0.42 between FTSE and Sustainalytics and only 0.11 for MSCI and Sustainalytics.

Similarly, Sköld and Wassberg (2023) focused on companies in the Nordic region and used two different ESG score providers to test the same hypothesis of divergence. The results confirmed a divergence between ESG scores provided by S&P Global and Refinitiv. Reasons for this consistent divergence may include differing benchmarks, data imputation, information overload, data discrepancies, and varying weights assigned to specific topics (Dimson et al., 2020).

To address these concerns and enhance transparency in sustainability reporting, the EU has strengthened regulations on sustainability practices in recent years. EU regulators recognized the necessity for these regulations, as companies often integrate sustainability into their business models primarily for reputational benefits and to comply with regulatory pressures, rather than out of altruism (Kaźmierczak, 2022). The EU initially addressed these concerns with the 2010 - 2020 strategy plan *Europe 2020: A strategy for smart, sustainable and inclusive growth: Communication from the commission* (European Commission, 2010), reaffirming its commitment to sustainable economic development within the EU. This strategy was later reinforced by the Directive 2013/34/EU, also known as the Accounting Directive, which provides a framework for more transparent disclosure of financial information (Balcerzak et al., 2023) and updated with Directive 2014/95/EU, known also as the Non-Financial Reporting Directive (NFRD) which mandates CSR reporting for large public-interest entities with more than 500 employees (Chiaramonte et al., 2022).

Regulation (EU) 2019/2088 on sustainability-related disclosures in the financial service sector, commonly known as the Sustainable Finance Disclosure Regulation (SFDR), was adopted in November 2019 and came into effect in March 2021. The primary objective of the SFDR is to prevent greenwashing by requiring financial institutions to disclose their level of engagement with ESG issues, thereby increasing transparency (Cremasco & Boni, 2022). One of the key measures for achieving this transparency is the requirement for financial institutions to calculate and disclose the percentage of sustainable investments in their portfolios. This allows investors to better understand the environmental and social impacts of their investments (Cochran et al., 2024). However, some areas still require improvement. As Cochran et al. (2024) point out, a significant issue is the choice between adhering to the strict rules of alignment with the EU taxonomy and the vaguer principles outlined in the SFDR. Furthermore, support for the SFDR varies among EU institutions, which diminishes its overall effectiveness (Balcerzak et al., 2023).

To enhance existing regulations, primarily the NFRD and SFDR, and ensure the success of the European Green Deal, a new regulation came into force in January 2023. Directive (EU) 2022/2464, commonly known as the Corporate Sustainability Reporting Directive (CSRD), strengthens rules on company disclosures regarding risks, opportunities related to environmental and social issues, and the external impact of the company. It applies to all listed EU companies, except micro-companies, and even foreign companies with profits exceeding 150 million euros. According to Odobaša and Marošević (2023), the positive outcomes of the directive will include increased transparency, greater awareness, and reputational benefits for companies with strong ESG engagement.

The overview of current EU regulations on sustainability reveals a primary focus on regulating corporate disclosures. However, more attention should also be directed towards regulating ESG score providers. By establishing standardized benchmarks, data imputation methods, data inputs, and the weights assigned to specific topics (Dimson et al., 2020), the divergence in ESG scores from different providers could be reduced, resulting in a more consistent and reliable metric for evaluation.

2.1.4 Theoretical implications of ESG on market value and profitability

The impact of firms' negative externalities on the environment and society has grown over time, leading to the development of various theories on how to mitigate these negative effects. Among these theories, two main concepts stand out – the stakeholder theory and the trade-off theory.

The stakeholder theory argues that investing in ESG practices is not merely a cost but an opportunity and a strategic choice that can create a competitive advantage and increase market value for companies (Freeman, 2010). By understanding the motives and challenges of various stakeholders, companies can design ESG initiatives that benefit all parties involved. More specifically, higher stakeholder satisfaction can help companies avoid certain costs, such as those associated with union contracts and additional regulations, thereby enhancing their value and profitability (Azmi et al., 2021). Additionally, ESG initiatives should aim to integrate solutions for multiple stakeholders' issues, offering a cohesive rather than isolated approach to problem-solving (Freeman, 2010).

The trade-off theory offers an opposing perspective on the impact of ESG practices on market value and profitability. Unlike the stakeholder theory, which views ESG investments positively, the trade-off theory suggests that these investments represent inefficiently allocated resources that could be better utilized internally by the company. Additionally, Azmi et al. (2021) argue that companies that invest in ESG practices incur higher direct costs for the company, further reducing returns and profitability.

However, several less prominent theories have emerged alongside stakeholder and trade-off theory. These include stewardship theory, resource-based theory, agency theory, and others. Stewardship theory suggests that managers are merely stewards of a company and should act in the best interest of all stakeholders. By doing so, companies can create a competitive advantage by keeping stakeholders satisfied, thus generating additional value (Azmi et al., 2021). Similarly, resource-based theory views ESG practices as strategic investments that provide a competitive edge and help companies acquire skills that are difficult to replicate (Russo & Fouts, 1997). In contrast, agency theory suggests that managers may invest in ESG initiatives for personal gain, potentially at the expense of company efficiency and profitability (Azmi et al., 2021). Improperly incentivized managers are found to have increased ESG investments to enhance their own reputation and gain popularity (Jiraporn & Chintrakarn, 2013). As of today, there are still contradictions regarding the motives behind companies investing in ESG practices.

2.1.5 ESG and bank profitability

Many studies observed a positive relationship between sustainability efforts and bank profitability. Buallay (2019) studied 235 EU-based banks from 2007 to 2016, using ESG disclosure as the dependent variable and performance measured by ROE, ROA, and Tobin's Q. After controlling for bank-specific and macroeconomic factors, results revealed a statistically significant and positive relationship between the overall ESG score and all three performance metrics. Similarly, Danisman and Tarazi (2024) found that European banks with higher ESG involvement experienced smaller declines in profitability during times of crisis, as well as reduced credit and asset risk. This aligns with the findings of Chiaramonte et al. (2022), which suggest a positive effect of ESG strategies on the stability of the banking system.

Cornett et al. (2016) explored the relationship between ESG scores and financial performance, further focusing on this relationship before and after the Global Financial Crisis. The study analysed 235 U.S. banks from 2003 to 2013, excluding 2008 and 2009, the peak years of the Global Banking Crisis. ESG scores were used as a proxy for CSR, while profitability was primarily measured using ROE. Additionally, ROA, operating profit, and Tobin's Q were also used as metrics of financial performance. The analysis revealed a statistically significant and positive relationship between ESG scores and profitability.

Wu and Shen (2013) conducted empirical research based on data from 162 banks with CSR practices, examining the profitability, underlying motives, and the relationship between CSR and credit risk. While CSR and ESG have slight differences, they both fundamentally evaluate sustainability practices, as mentioned in subsection 2.1.1. They found that CSR practices positively associate with the profitability of banks. The positive relationship between CSR practices and profitability was also observed in Islamic banks by Platonova et al. (2018). Additionally, Wu and Shen (2013) identified three main motives for banks to focus on sustainability: strategic choices, altruism, and greenwashing. Each of these motives is associated with different theories on the financial viability of such practices in the banking sector. Based on their findings of a positive relationship between financial performance, measured by ROA, ROE, net interest income, and non-interest income, and sustainability efforts, they concluded that strategic choices are the primary drivers for investing in sustainability. Their findings align with the stakeholder theory, which also views sustainability investment as an opportunity and a strategic decision (Freeman, 2010).

However, a positive relationship between ESG scores and profitability does not necessarily indicate that higher ESG scores contribute to greater profitability in banks. Buallay (2019), using a Granger-causality test, concluded that the relationship is actually reversed. Their analysis found that Tobin's Q, a measure of profitability, Granger-causes higher ESG scores. Future research should focus on exploring the causality between ESG scores and profitability in more depth.

2.1.6 ESG and bank value

In addition to profitability, the relationship between a bank's value and the impact of ESG scores has been fairly well researched, however with contradicting findings. Staroverova (2022) demonstrated there exists a negative relationship between the ESG Controversies Score, which measures the impact of negative media coverage related to ESG incidents, and bank value, by employing a cross-country sample of 134 banks. This highlights the importance of adhering to sustainability regulations and establishing internal control mechanisms to prevent negative media attention.

Di Tommaso and Thornton (2020) analysed the effects of ESG investment on bank value and risk-taking. Similarly to the findings of Chiaramonte et al. (2022), their analysis revealed that higher ESG scores are associated with lower risk-taking, with board characteristics playing a significant role. However, when examining the relationship between ESG scores and bank value, they found a negative relationship, consistent with the trade-off theory.

Their results align partially with the research conducted by Buallay et al. (2020), which found a positive relationship between ESG scores and shareholder value, but a negative correlation between ESG scores and overall bank value. To further explore this relationship, Buallay et al. (2021) found that geographical location plays a role. In developed countries, the relationship between ESG scores and bank value tends to be positive, while in developing countries, it remains negative. This finding aligns with both stakeholder theory, where developed countries are more sensitive to stakeholder pressures as basic needs are met, and the trade-off theory, suggesting that investments may be better allocated internally for other priorities.

2.2 Bank credit risk and its metrics

Credit risk is a central topic in discussions of bank management and is widely recognized as one of the primary risks that has contributed to numerous financial crises, including the Great Depression of the 1920s and 1930s, the Dot-Com bubble of the 1990s, and more recently, the Global Financial Crisis of 2008 (Jorion, 2009). The importance of effective credit risk management has been further emphasized by the continuous evolution of financial regulations, advancements in risk management strategies, and the growth of the secondary market for credit risk (Altman, 2002).

In statistical analysis, the non-performing loans (NPL) ratio is commonly used as a proxy for credit risk, as determined by an extensive literature review conducted by Naili and Lahrichi (2022). Common ratios include NPL to gross loans (Naili & Lahrichi, 2022; Thiagarajan et al., 2011; Ahmad & Ariff, 2008; Vithessonthi, 2016), NPL to total assets (Vithessonthi, 2016; Iyer et al., 2014) and NPL to total equity (Munangi & Sibindi, 2020; Lee & Hsieh, 2014). Each of these ratios represent credit risk observed from a different perspective. Additionally, other variables, such as CDS spreads (Di Tommaso & Thornton, 2020; Li & Zinna, 2018) and credit ratings (Samaniego-Medina & Giráldez-Puig, 2022), are used to measure credit risk.

The NPL ratio was used as a measure of credit risk when the European Central Bank (ECB) assessed the state of the EU banking system in 2014, in preparation for its role as a regulatory body (Steffen, 2014). This was a transitional period aimed at creating a unified European Banking Union (EBU). NPLs posed a significant challenge to the completion of the EBU. Currently, depositors are guaranteed up to 100,000 EUR by their governments if a bank fails to meet its financial obligations. Upon completing the third pillar of the EBU, this guarantee would be funded by a joint fund rather than by individual member states, thereby enhancing stability.

However, as Busch (2022) highlighted, some countries, particularly the Netherlands and Germany, argue that the burden of depositor guarantees would predominantly fall on the more financially stable nations. Consequently, southern members with higher NPL ratios like Italy, Spain, and Greece are expected to reduce their NPL levels to more manageable amounts before the transition to a fully realized EBU. Although NPL levels did decrease before 2020 (Busch, 2022), the COVID-19 pandemic caused many borrowers to face difficulties repaying their loans, leading to an increase in NPLs (Kasinger et al., 2021). As discussed in a report made by Kasinger et al. (2021) at the request of the Committee on Economic and Monetary Affairs of the European Parliament, one strategy for addressing high NPL levels and progressing toward a full EBU is the ongoing development of the secondary market for NPLs within the EU, which could help reduce banks' NPL levels and free up assets for new loans. However, even with an increased focus on reducing the NPL levels and consequently managing credit risk, it remains one of the main concerns for banks, necessitating a deeper understanding of its determinants and drivers.

2.3 ESG and credit risk

The relationship between ESG engagement and credit risk is not as extensively researched as the connection between ESG scores and profitability, but it is gaining attention. Samaniego-Medina and Giráldez-Puig (2022) conducted a study examining the effects of the ESG Controversies score on credit risk. Their analysis utilized various tools, including the ordered logit model, marginal effects, and matching analysis. Using data from 65 European banks over the period from 2011 to 2022, they found that a higher ESG Controversies score negatively impacts the likelihood of achieving a higher credit rating in the future.

Research by Neitzert and Petras (2022) also underscored the influence of ESG scores on risk, using a multi-country sample of 582 banks with data spanning from 2002 to 2018. Their study revealed that higher ESG scores, which reflect banks' CSR, positively affect credit risk, measured by the z-score, and portfolio risk, assessed by risk density. Furthermore, when examining the individual pillars of ESG, they found that the Environmental pillar had a mitigating effect on risk, while the Social and Governmental pillars yielded inconclusive results. This finding highlights the significance of investing in environmental initiatives.

Similarly, Di Tommaso and Thornton (2020) observed a negative relationship between ESG scores and risk-taking. Chiaramonte et al. (2022), using distance to default as a risk measure, found that higher ESG scores reduce risk, with the effect being more pronounced for banks with longer ESG coverage.

A negative relationship between ESG scores and credit risk is also evident in other industries. Research on Chinese companies revealed that firms with higher ESG engagement, measured by scored sourced from the Kinder, Lydenberg, and Domini database, achieve higher credit ratings (Jiraporn et al., 2014). Their findings show that credit ratings can improve by up to 4.5% for companies that increase their ESG engagement by one standard deviation. Similarly, in a study by Li et al. (2022), a favourable relationship between ESG scores and default rates was observed. One of their key conclusions is that investors can enhance credit risk management by considering ESG scores, as a higher ESG score indicates a lower likelihood of default, particularly for manufacturing firms.

2.4 Financial determinants of credit risk

2.4.1 Bank size

The statistically significant determinants of credit risk vary across studies, with one of the most frequently cited factors being the size of the entity, often measured by the logarithm of total assets (Naili & Lahrichi, 2022). This factor was found to be statistically significant in banking systems worldwide. For example, Zhang et al. (2016) focused on the Chinese banking system and found a relationship between bank size and credit risk, while Albaity et al. (2019) found similar results in the Middle East and North Africa region. Additionally, Alzoubi and Obeidat (2020) confirmed the relationship in the Islamic banking system. The significance of bank size has also been highlighted in studies of the European banking system (Izcan & Bektas, 2022).

The relevance of size stems from the "too big to fail" concept, where banks may assume that regulators will intervene during financial difficulties, leading to less stringent risk policies and, consequently, higher credit risk (Zhang et al., 2016), however some researcher argue size should be negatively correlated with credit risk as diversification becomes easier for larger banks which reduces the overall risk (Salas & Saurina, 2002).

2.4.2 Bank profitability

Another frequently used determinant in the study of bank credit risk is profitability, typically measured by variables such as Return on Assets (ROA), Return on Equity (ROE), or net interest margin. To avoid bias related to the timing of data collection, similar indicators like Return on Average Assets (ROAA) and Return on Average Equity (ROAE) are also employed in studies of profitability (Petria et al., 2015). Most research indicates a positive impact of profitability on credit risk (Makri et al., 2014; Petria et al., 2015; Chaibi & Ftiti, 2015), suggesting that management may be incentivized, either through financial rewards or reputational benefits, to enhance risk management, thereby improving profitability and reducing credit risk (Zhang et al., 2016; Chaibi & Ftiti, 2015).

2.4.3 Cost efficiency

Closely related to profitability is cost efficiency, which Berger and DeYoung (1997) found to be statistically significant in relation to credit risk. They identified a negative relationship between cost efficiency, measured as a percentage of the maximum cost-efficiency frontier of best-practice banks, and credit risk, measured by the ratio of NPL to total loans. Additionally, they conducted a Granger-causality test, which revealed that issues with cost efficiency led to future credit risk problems.

This negative relationship between efficiency and credit risk was later confirmed by Ozili (2019), who used the ratio of cost to income as a proxy for bank efficiency. Supporting these findings, Chaibi and Ftiti (2015) identified a relationship between inefficiency, measured as operating expenses divided by operating income, and credit risk, measured as impaired loans to gross loans, in French banks operating in a market-based economy. This contrasts with the results for banks in Germany, which function in a bank-based economy.

2.4.4 Capitalization

Capitalization was examined by Kattel (2014) in relation to credit risk in Nepalese banks. Adequate capital reserves were found to be a key determinant of future bank stability. The equity-to-assets ratio, representing a bank's ability to avoid over-reliance on external funding, was highlighted as a critical measure to ensure stability. In addition to a bank's self-regulation in managing capitalization, regulators also play an important role. As Ahmad and Ariff (2008) demonstrated in their study, the regulatory capital is linked to the management of credit risk in banks. The positive relationship was also confirmed by Makri et al. (2014).

2.4.5 Liquidity management and year-on-year loan growth

Similar to profitability and capitalization, the liquidity ratio is a crucial metric that must be closely monitored. Poor liquidity management contributes to financial difficulties in banks, which in turn leads to higher credit risk (Samaniego-Medina & Giráldez-Puig, 2022). Additionally, loan growth is another indicator of future credit risk in banks, as demonstrated by Skrabic Peric and Konjusak (2017). They found that, alongside bank-specific and macroeconomic variables, past loan growth has a negative impact on credit risk.

2.4.6 Bank leverage

The relationship between bank leverage and credit risk has produced inconsistent results. Di Tommaso and Thornton (2020) found a statistically significant link between leverage and credit risk, whereas Ahmad and Ariff (2008) found no such relationship. This discrepancy may be due to differences in the focus of their studies, with Di Tommaso and Thornton (2020) concentrating on European banks and Ahmad and Ariff (2008) conducting a multi-country analysis that included countries like Australia, France, Japan, the US, India, Korea, Malaysia, Mexico, and Thailand. Similarly, Chaibi and Ftiti (2015) found leverage to be statistically significant in Germany, a bank-based economy, but not in France, a market-based economy.

2.4.7 Macroeconomic determinants

Additionally, macroeconomic factors such as Gross Domestic Product (GDP) growth, the housing price index, the unemployment rate, interest rates, and credit growth influence the credit risk of banks (Castro, 2013). GDP growth, interest rates, the unemployment rate, and the exchange rate were also found to be statistically significant in the research conducted by Chaibi and Ftiti (2015). Furthermore, Makri et al. (2014) identified public debt as having a statistically significant relationship with credit risk, along with the previously mentioned factors.

3 DATA

To address the proposed research questions, both financial and ESG-related bank-specific annual data were collected from the London Stock Exchange Group (LSEG) Workspace. As a provider of financial data, LSEG Workspace (formerly known as Refinitiv) offers a comprehensive coverage of financial and ESG information for both publicly traded and private entities.

Financial data are sourced from annual reports and other financial statements, while the ESG scores are calculated using LSEG's proprietary methodology using information from diverse publicly available sources. (LSEG Data and Analytics, 2023). The panel dataset used in this master's thesis consists of 87 EU banks, spanning the period from 2014 to 2023.

The criteria for selecting the 87 banks included in the dataset centred on the availability of ESG scores for the most recent year, 2023. In addition to the ESG scores, the data incorporates the ESG Combined (ESGC) scores, which represent regular scores adjusted to account for negative media coverage of significant controversies impacting the ESG profile of banks (which are measured by the ESG controversies score).

It is worth noting, that the combined scores represent a downward only adjustment of regular scores, calculated as the simple average of both controversies and regular scores – if the controversies score is lower than the regular one. In other words, ESGC is either lower (if there was negative media coverage of ESG controversies present) or the same as the regular scores (LSEG Data and Analytics, 2023).

The methodology employed in computing both types of scores is grounded in empirical data and encompasses three foundational ESG pillars. These are further delineated into ten distinct categories: emissions, innovation, resource use, community engagement, human rights, product responsibility, workforce practices, CSR strategy, management structure, and shareholder relations. To further improve the understanding of the drivers behind the overall ESG score, which is calculated from these ten categories, the data for each individual pillar was also collected in this master's thesis.

In addition to ESG metrics, the financial determinants for the analysis were selected based on a review of existing literature regarding factors influencing credit risk. These financial metrics include profitability (ROAA, ROAE, net interest margin), capitalization (equity-to-total-assets ratio), liquidity (cash-to-liabilities ratio, liquidity coverage ratio), leverage (debt-to-assets ratio, liabilities-to-assets ratio), bank size (log of assets, log of gross loans), cost efficiency (operating costs to operating income), and year-on-year gross loan growth. Complete variable definitions along with formulae are shown in Table 2.

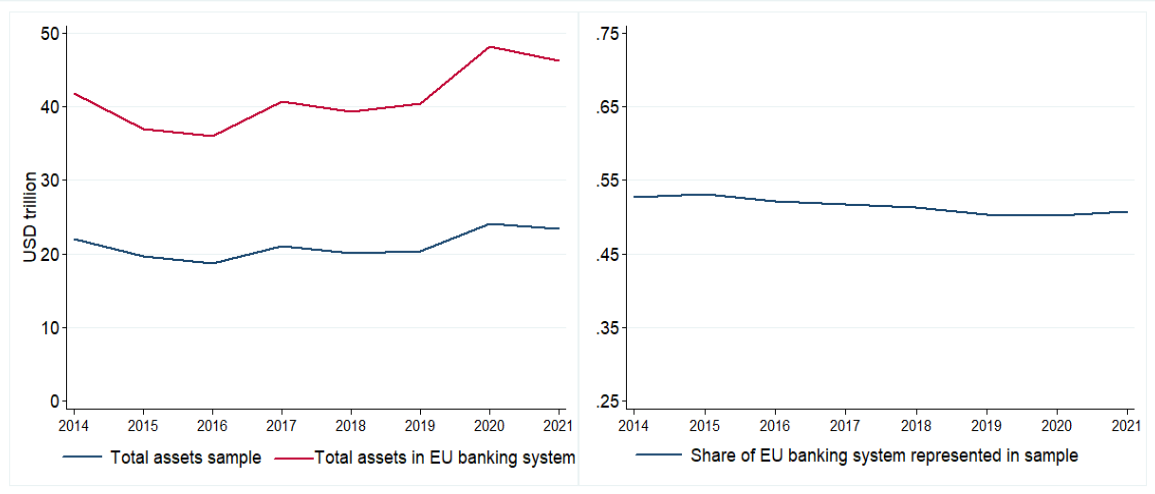
Table 2: Variable definitions and equations

NPL to gross loans ratio (decimal)	$NPLToLoans_{it} = \frac{non\ performing\ loans_{it}}{gross\ loans_{it}}$
NPL to total assets ratio (decimal)	$NPLToAssets_{it} = \frac{non\ performing\ loans_{it}}{total\ assets_{it}}$
NPL to equity ratio (decimal)	$NPLToEquity_{it} = \frac{non\ performing\ loans_{it}}{equity_{it}}$
Return on Average Assets (decimal)	$ROAA_{it} = \frac{net\ income_{it}}{average\ total\ assets_{it}}$
Return on Average Equity (decimal)	$ROAE_{it} = \frac{net\ income_{it}}{average\ total\ equity_{it}}$
Net interest margin (decimal)	$NetInterestMargin_{it} = \frac{net\ interest\ income_{it}}{average\ earning\ assets_{it}}$
Equity to assets ratio (decimal)	$EquityToAssets_{it} = \frac{equity_{it}}{total\ assets_{it}}$
Cash to liabilities ratio (decimal)	$CashToLiabilities_{it} = \frac{cash_{it}}{total\ liabilities_{it}}$
Liquidity coverage ratio (decimal)	$LiquidityCoverageRatio_{it} = \frac{high\ quality\ liquid\ assets_{it}}{total\ net\ cash\ outflows\ over\ a\ 30-day\ stress\ perios_{it}}$
Debt to total assets ratio (decimal)	$DebtToAssets_{it} = \frac{debt_{it}}{total\ assets_{it}}$
Liabilities to total assets ratio (decimal)	$LiabilitiesToAssets_{it} = \frac{total\ liabilities_{it}}{total\ assets_{it}}$
Log of total assets	$lnAssets_{it} = \ln{(total\ assets)}_{it}$
Log of gross loans	$lnAssets_{it} = \ln{(gross\ loans)}_{it}$
Operating expenses to operating income ratio (decimal)	$OpexToOperatingProfit_{it} = \frac{operating\ expenses_{it}}{operating\ income_{it}}$
Growth of loans (decimal)	$GrowthOfLoan_{it} = \frac{total\ loans_{it} - total\ loans_{it-1}}{total\ loans_{it-1}}$

Source: Own work.

To assess the sample coverage, the total assets of the EU banking sector were compared to the total assets of the sample. The total assets of the EU banking system amounted to 46.24 trillion USD in 2021 (Saravia, 2023). Comparing the sample size to the EU banking system, the right panel in Figure 1 illustrates that, on average, the sample's share of total assets relative to the EU banking system's total assets stood at approximately 50% between 2014 and 2021. This percentage fluctuated slightly, reaching its highest point at 53.1% in 2015 and its lowest at 50.2% in 2020. The left panel of Figure 1 presents the comparison of total assets in our sample to the total assets in the EU banking system from 2014 to 2023 in absolute terms. It should be noted that the measurement of the EU banking system's size excludes UK banks, in consideration of Brexit implications. Additionally, the currency has been converted to USD using the corresponding exchange rates provided by the European Central Bank.

Figure 1: Sample coverage in terms of total assets



Note: Data for total assets in the EU banking system was sourced from European Banking Federation Report Banking in Europe: Facts & Figures 2022 (Saravia, 2023) and converted to USD at the end of year conversion rate.

Source: Own work.

As credit risk is the primary focus in this master's thesis, Figure 2 illustrates the trend in the simple average share of NPLs relative to total gross loans, total assets, and equity, respectively (from left to right) in the sample. The first metric measures credit risk from the perspective of general loan portfolio, the second measures it from the perspective of management and the last from the perspective of shareholders. The NPL ratios begin at a relatively high level in 2014, decrease in 2015, and then rebound in 2016 and 2017. As the ECB prepared to assume regulatory oversight in 2014, it conducted its first Asset Quality Review (AQR) and a stress test analysis to assess the stability of the EU banking sector, focusing on NPL ratios and explaining the variability of NPL ratios in the following years. Although the AQR faced criticism for potentially misaligning incentives for member states to disclose information on problem assets and for excluding systemic risk from the analysis (Steffen, 2014), it compelled many banks to reclassify loans that had not previously been recognized as non-performing, thereby increasing transparency and consequently raising the reported NPL ratios (De Groen, 2014).

A noticeable drop in NPL ratios is observed in 2018, potentially due to new strict regulations. The European Banking Authority (EBA) published revised guidelines aimed at reducing NPL levels across banks at consolidated, sub-consolidated, and solo levels. In 2017, the ECB launched an initiative to address the rising NPL ratios, introducing comprehensive standards for management strategies, recognition rules, and forbearance. The following year, the ECB issued an Addendum to the NPL Guidance, emphasizing the importance of timely provisioning for loans that become non-performing (Budnik et al., 2022). In addition, a slight decrease in NPL ratios is observed after 2020, coinciding with the European Council's publication of the NPL Action Plan, which aimed to finalize the creation of a unified EBU (Busch, 2022).

Figure 2: Average NPLs ratios from 2014 to 2023

Source: Own work.

Descriptive statistics for the variables employed in the analysis are presented in Table 3. These statistics comprise the number of observations (N), the mean, minimum (min), and maximum (max) values of each variable, the standard deviation (St. dev), as well as the values at the 5th (p5) and 95th (p95) percentiles. Upon critical evaluation of the employed dataset, some data limitations become evident. Those expectedly arise from the availability of key metrics, such as NPL ratios and ESG scores. In Table 3, the number of observations for each metric is listed in the second column. As shown, data availability for NPL ratios is lower than for most metrics, with 435 observations, while ESG and ESGC scores each have 687 observations. Individual E, S and G pillars each have 695 observations. The discrepancy between 687 and 695 observations is due to some banks having scores for each individual pillar, but not for the weighted ESG score. Nevertheless, this discrepancy is minimal.

Table 3: Sample summary statistics

	N	mean	min	max	St. dev	p5	p95
NPLToLoans	435	0.073	0.000	0.788	0.108	0.005	0.320
NPLToAssets	435	0.048	0.000	0.560	0.078	0.003	0.230
NPLToEquity	435	0.593	0.000	7.541	0.920	0.052	2.540
ESG	687	57.819	1.397	95.722	21.691	15.777	86.265

To be continued

Table 3: Sample summary statistics (cont.)

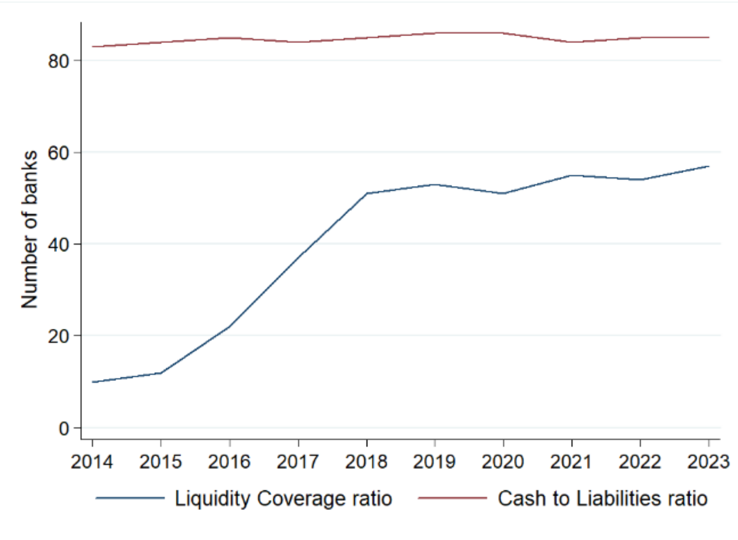
	N	mean	min	max	St. dev	p5	p95
E	695	70.21	15.25	98.34	24.42	19.83	95.52
S	695	60.82	0.37	97.65	23.15	12.68	91.20
G	695	56.32	2.21	95.13	23.60	17.45	89.82
ESGC	687	54.072	1.397	90.205	19.771	15.777	81.312
ROAA	836	0.006	-0.207	0.042	0.013	-0.009	0.021
ROAE	836	0.087	-0.816	0.392	0.122	-0.118	0.254
NetInterestMargin	385	0.045	0.005	2.452	0.186	0.010	0.055
EquityToAssets	860	0.082	-0.021	0.475	0.037	0.038	0.141
CashToLiabilities	847	0.081	0.000	0.412	0.066	0.008	0.210
LiquidityCoverageRatio	402	1.982	0.490	30.000	1.591	1.210	3.380
DebtToAssets	835	0.133	0.000	0.835	0.134	0.009	0.387
LiabilitiesToAssets	859	0.919	0.525	1.044	0.038	0.859	0.963
lnAssets	859	24.878	18.870	28.743	1.746	22.177	28.038
lnGrossLoans	845	24.356	15.443	27.800	1.739	21.513	27.050
OpexToOperatingProfit	861	1.205	-868.064	693.450	46.097	-7.010	13.285
GrowthOfLoans	757	0.206	-0.993	52.018	2.802	-0.170	0.297

Note: Variable definitions are presented in Table 2.

Source: Own work.

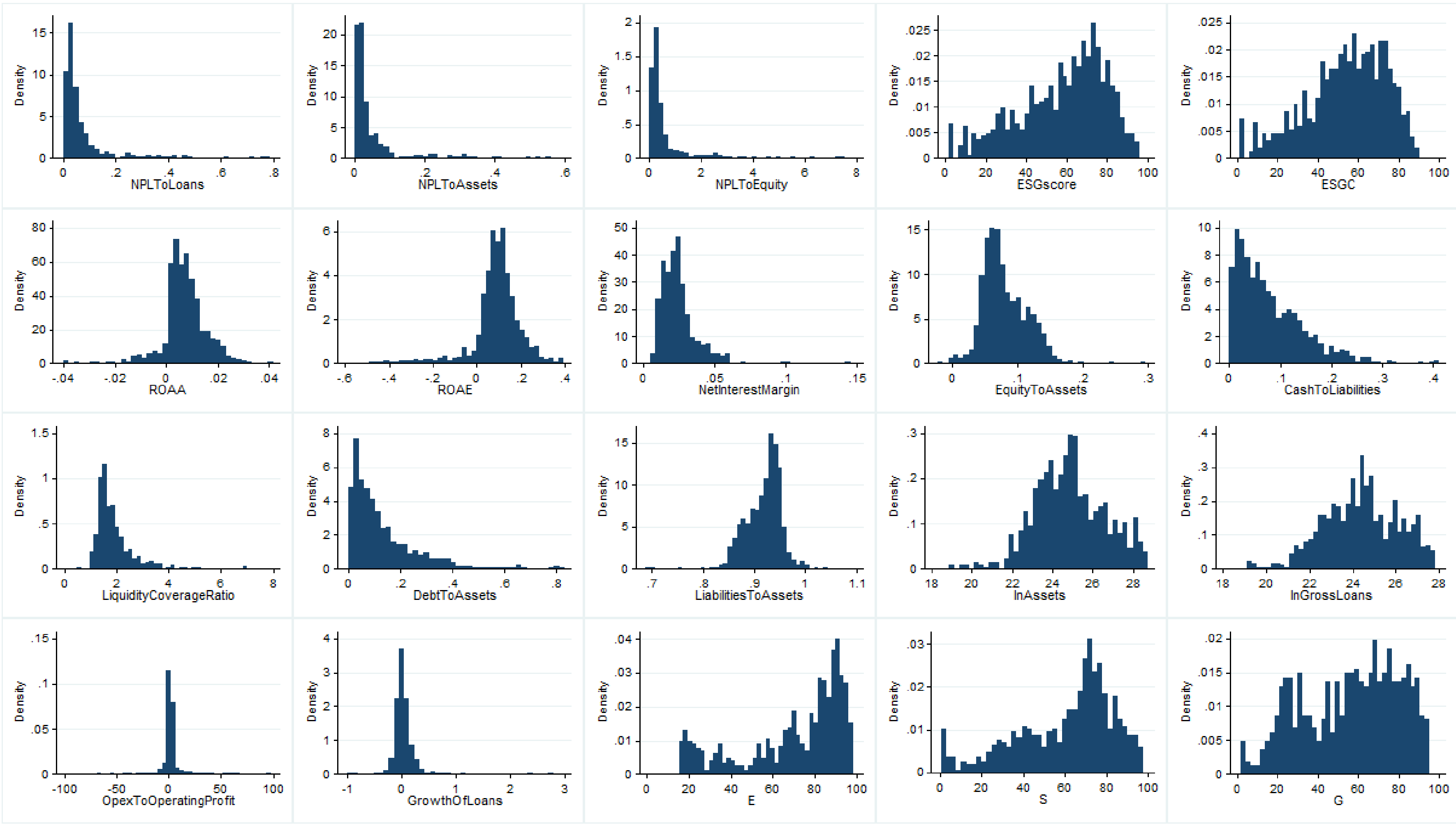
Additionally, the net interest margin has even fewer available data points, and the availability for the liquidity coverage ratio is quite limited. As a result, data on the simpler cash-to-liabilities ratio was also employed as the liquidity metric. The disparity in data coverage for liquidity metrics is illustrated in Figure 3. To further illustrate the characteristics of the dataset used in our analysis, Figure 4 presents the distribution of data points for all variables utilized in this master's thesis.

Figure 3: Data availability for Liquidity Coverage ratio and Cash to Liabilities ratio



Source: Own work.

Figure 4: Variable distribution



Source: Own work.

4 METHODOLOGY

To address the variation in bank specific ESG scores across countries, years and bank sizes a comprehensive analysis of the trends and characteristics of the ESG and ESGC scores was conducted for the period from 2014 to 2023, as well as the scores for individual pillars of ESG. This analysis explored the scores from the LSEG Workspace platform, variations in the data availability across countries, and how these differences correlate with the average ESG scores in those countries. Furthermore, the simple and weighted average ESG and ESGC scores for the sample during the study period were compared, along with the relationship between bank size and their respective scores. Since the third research question focused on differences between banks headquartered in EU, EMU, and non-EMU countries, as well as between developed and emerging EU nations, the analysis for the first research question considered disparities in data availability and ESG and ESGC scores based on these groups. Methodologically, simple statistical techniques and weighted averages based on total assets, were employed.

To address the potential relationship between ESG scores and credit risk and the complex connection of bank-specific factors influencing bank's credit risk, a panel data regression modelling technique was used. A sequential process was followed – firstly, to distinguish between using a pooled Ordinary Least Squares (OLS) or a random/fixed effects model, the Breusch-Pagan Lagrange Multiplier test was employed. This test tests against the null hypothesis that no random effects are present in the model. If the hypothesis is rejected, random effects are likely present and therefore, either random or fixed effects estimator is more appropriate to pooled OLS. To further distinguish between random and fixed effects estimator, Hausman test was employed. The logic of the Hausman test is the following: if random effects are present in the model, both random and fixed effects estimators will give unbiased and consistent coefficient estimates, however, a random effects model would be more efficient and thus preferred. If, however, the effects are fixed, only fixed effects estimator will give consistent results. If the null hypothesis is rejected, a fixed effects model is preferred.

It should be noted that operationally, one cannot go wrong with always using a fixed effects model as it is always unbiased and consistent (if it is correctly specified) as the only penalty comes in terms of estimator efficiency. This is why a fixed effects estimator was used for all primary models and in cases where the Hausman test favoured a random effects model, these estimation results are also reported to ensure efficiency and robustness of the analysis.

By utilizing a fixed effects estimator, the model accounts for both additional variation in bank-specific and broader macroeconomic environment impacting each bank, consolidating these effects into a single variable α_i (Di Tommaso & Thornton, 2020; Petria et al., 2015) which is why it is frequently a preferred choice in the literature even without the Hausman test.

A review of the literature on credit risk determinants identified several potential regression models, including GMM (Berger & DeYoung, 1997; Louzis et al., 2012; Danisman & Tarazi, 2024), random effects (Munangi & Sibindi, 2020), and fixed effects models (Ozili, 2019; Neitzert & Petras 2022), as the most commonly used. Due to difficulties with selecting valid instruments to employ in a GMM model for ESG related topics we opted for a simpler, yet no less illustrative static form of the model. The primary regression equation used for empirical analysis to address the second research question in its basic and extended forms are represented by equations (1) and (2) respectively.

$$\begin{aligned} Credit\ risk_{it} = {} & \beta_1 ESG_{it} + \beta_2 Profitability_{it} + \beta_3\ Capitalization_{it} + \beta_4 Liquidity_{it} \\ & + \beta_5 Leverage_{it} + \beta_6 Size_{it} + \alpha_i + \varepsilon_{it} \end{aligned} \tag{1}$$

$$\begin{aligned} Credit\ risk_{it} = {} & \beta_1 ESG_{it} + \beta_2 Profitability_{it} + \beta_3\ Capitalization_{it} + \beta_4 Liquidity_{it} \\ & + \beta_5 Leverage_{it} + \beta_6 Size_{it} + \beta_7 Efficiency_{it} + \beta_8 Growth\ of\ loans_{it} \\ & + \alpha_i + \varepsilon_{it} \end{aligned} \tag{2}$$

The dependent variable ($Credit\ risk_{it}$), is commonly assessed using one of three ratios, each offering a distinct perspective on credit risk. Firstly, the non-performing loans ratio which is calculated as non-performing loans relative to total gross loans, measures default rates relative to the total gross loans extended by the bank. This ratio is frequently employed in analysing a bank's credit risk (Naili & Lahrichi, 2022; Thiagarajan et al., 2011; Ahmad & Ariff, 2008; Munangi & Sibindi, 2020). Secondly, non-performing loans to total assets ratio, evaluates default rates relative to the size of the bank as employed by Vithessonthi (2016) and Iyer et al. (2014). Lastly, the non-performing loans to equity ratio portrays the default rate of loans from the shareholders' standpoint. This ratio offers a perspective on credit risk pertinent to shareholders and their equity stakes in the bank (Munangi & Sibindi, 2020; Lee & Hsieh, 2014). Each ratio measures credit risk from a perspective, tailored to the interests of the relevant stakeholders. Regressions were estimated separately for each of the three mentioned variables used as dependent. This approach ensures that credit risk is measured from multiple perspectives.

The variable ESG_{it} was evaluated through two distinct metrics: the ESG and the ESGC scores. These metrics are sourced from the LSEG workspace and are regarded as objective and transparent assessments derived from their internally developed methodology. In this setting, a negative and statistically significant β_1 coefficient estimate suggests that higher ESG or ESGC scores on average, ceteris paribus, associate with lower NPL ratios and thus lower credit risk. All other coefficient estimates follow a similar logic. To gain further insight into which pillar associates with credit risk, regression containing individual E, S and G scores were also estimated.

The variable $Profitability_{it}$ was assessed using ROAA as employed in Platonova et al. (2018) and Petria et al. (2015). It was chosen due to its upsides in dealing with seasonality and fluctuations inherent in the observed period, thereby offering a more accurate depiction of profitability over a specified timeframe compared to ROA, which relies on year-end results. Furthermore, concerns have been raised regarding the adequacy of metrics based solely on total assets for measuring profitability due to the significant contribution of off-balance sheet assets to a bank's profitability. To address this, Petria et al. (2015) advocates for the use of ROAE as an additional metric. For this purpose, ROAE was utilized as a profitability metric in robustness checks, in addition to the net interest margin, to ensure a varied representation of profitability standpoints.

Total equity as a percentage of total assets was utilized as a metric representing capitalization ($Capitalization_{it}$), drawing inspiration from Berger and DeYoung (1997). This indicator assesses the entity's capacity to fulfil bank's financial obligations and quantifies the size of the buffer available to the bank in terms of its solvency, demonstrated by Kattel (2014) as an important factor of bank's financial stability. A higher capitalization ratio signifies a greater proportion of assets financed through equity, indicating a reduced risk of defaulting on repayments. Given its role in ensuring the stability of banks, this metric holds significant importance within discussions concerning the banking system and credit risk in general.

To control for bank liquidity ($Liquidity_{it}$), two ratios were used: the cash-to-liabilities ratio and the liquidity coverage ratio. Both reflect a bank's ability to meet its obligations and its exposure to potential liquidity risks (Samaniego-Medina & Giraldez-Puig, 2022). The straightforward cash-to-liabilities ratio was employed in the primary regression models to assess overall bank liquidity. Despite its simplicity, this ratio remains significant as it provides valuable insights into a bank's liquidity position. The liquidity coverage ratio, as defined by Basel III, has limited data coverage (refer to Figure 3), however, it still serves as a useful metric for evaluating liquidity and was applied as a robustness check in this thesis.

As demonstrated by Di Tommaso and Thornton (2020), leverage is a statistically significant and theoretically important metric in evaluating a bank's overall risk, which consequently impacts the NPL ratio. Higher leverage levels are typically linked to higher risk-taking behaviour exhibited by the bank increasing the value of non-performing loans. To control for the effect of leverage on credit risk, the total liabilities to total assets ratio that was employed in the analysis (denoted as $Leverage_{it}$).

Literature suggests that the size of a bank is a crucial metric in credit risk analysis, consistently showing statistical significance in numerous studies (Zhang et al., 2016; Albaity et al., 2019). To control for the effect of bank size on credit risk, the variable $Size_{it}$ was included measured by the logarithm of total assets, as supported by an extensive literature review by Naili and Lahrichi (2022). Furthermore, some researchers argue that bank size should be measured through total loans, also using a logarithmic transformation, as it may better capture the bank's risk factors (Izcan & Bektas, 2022). Consequently, the logarithm of total loans was used as a robustness check.

The extended regression model, represented by equation (2), incorporates two additional financial metrics to enhance the analysis. Firstly, operating efficiency ($Efficiency_{it}$) is included as a metric that determines the profitability of a bank from an operational perspective. As suggested by the literature, operating efficiency is calculated by dividing operating expenses by operating profit (Naili & Lahrichi, 2022). Empirical research conducted by Ozili (2019) indicates that operating efficiency is negatively correlated with the NPL ratio, underscoring its relevance for inclusion in the analysis. Secondly, variable $Growth\ of\ loans_{it}$ is considered a significant parameter that could explain variations in the NPL ratio. This metric is calculated as the year-over-year growth in total loans, expressed as a percentage (Skrabic Peric and Konjusak, 2017). Including loan growth in the extended version of the primary regression equation (2) adds an important dimension to the analysis of the NPL ratio.

To address the differences in the relationship between ESG scores and credit risk across different economic areas within the EU, the same primary regression equations were applied to different country sub-groups. Firstly, the sample was divided to EU-headquartered banks, EMU-headquartered banks and EU-but-non-EMU headquartered banks and secondly, to banks headquartered in countries with developed and emerging markets within EU, based on classification developed by FTSE Russell (2023).

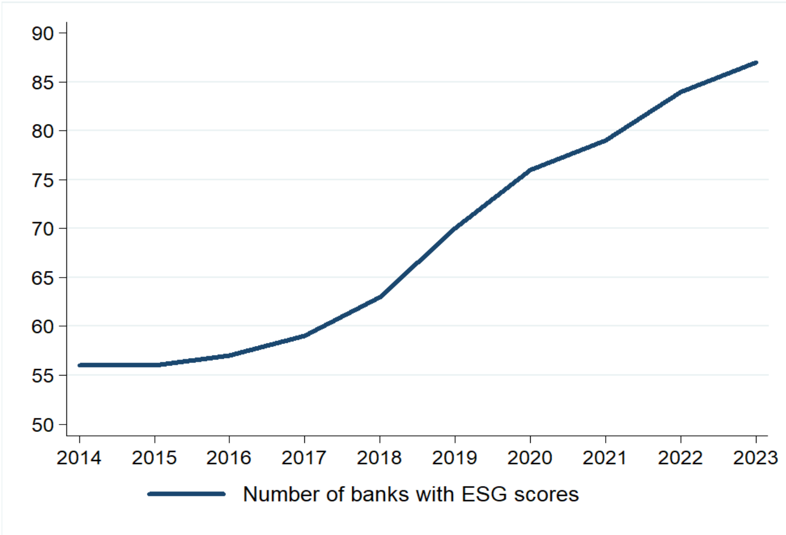
5 RESULTS AND DISCUSSION

5.1 Research question 1: How do bank specific ESG scores vary across countries, years, and bank sizes?

To address the first research question and gain a deeper understanding of the movement of ESG scores among EU banks across various parameters, a statistical analysis was conducted using a sample of 87 EU banks. These findings were further supported by reviewing existing research in the field.

The data indicates an upward trend in the number of banks with accessible ESG scores sourced from the LSEG workspace, as shown in Figure 5. In 2014, ESG score data was available for 56 banks, rising to 87 by 2023. Despite this increase, the number remains relatively low, considering that there were 5,441 banks in the EU in 2020 (Eurostat, n.d.). This means our sample, which included 76 banks in 2020, represents only 1.4% of all EU banks. This suggests that ESG evaluation is still a relatively novel concept. However, despite this initial limitation, comparison of total assets of banks included in our sample to the total assets of the banking sector shows the sample provides a good representation of the EU banking sector. The cumulative total assets of the banks in our sample accounted for over half of the total assets within the EU banking system throughout the period of analysis (refer to Figure 1). Therefore, our sample provides a good representation of larger banks, with limited representation of smaller banks which provides an interesting topic for further research. The data coverage for ESGC scores as well as the individual pillars E, S and G scores mirrors that of ESG scores, as it is internally computed by LSEG Workspace.

Figure 5: Number of banks with ESG score



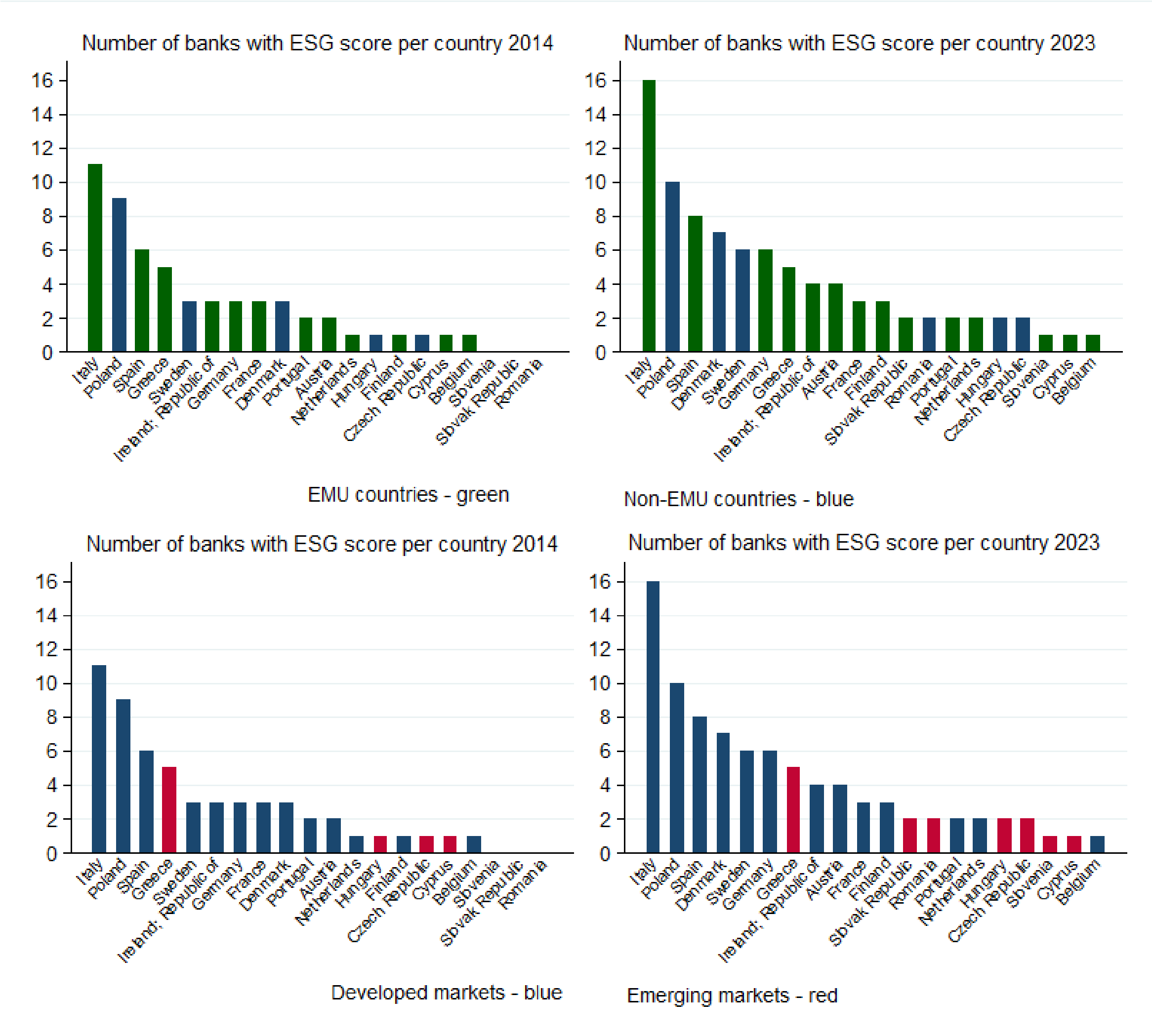
Source: Own work.

The dataset includes banks from 20 EU countries. Figure 6 presents the number of banks with ESG scores per country for the years 2014 and 2023. Italy, Poland, and Spain had the highest number of banks with available ESG scores at both the beginning and the end of the analysed period. With a total of 299 observations throughout the time frame, these three countries collectively represent 34% of all 870 observations.

In 2014, our sample included no banks with ESG scores headquartered in Slovenia, Slovakia or Romania. By 2023, our sample included two banks for both Slovakia and Romania, while Slovenia has one bank represented. Cyprus and Belgium also had one bank each with an ESG score in 2023. The largest increase in the number of banks with ESG scores occurred in Italy, rising from 11 in 2014 to 16 in 2023, followed closely by Denmark, which saw an increase from 3 banks in 2014 to 7 in 2023. In contrast, the number of represented banks with ESG scores remained constant in Greece, France, Portugal, Cyprus, and Belgium. Notably, no country experienced a decrease in the number of banks with ESG scores between 2014 and 2023.

In addition to showing the number of banks with available ESG scores per country, the upper graphs in Figure 6 illustrate the distribution of countries based on their classification as EMU members or EU countries outside the EMU. While the number of EMU countries is greater, with 14 compared to 6 non-EMU countries, no clear trend in ESG score availability is evident. The lower two graphs in Figure 6 depict the division of countries between developed and emerging markets within the EU. As anticipated, banks based in countries with emerging markets tend to have lower ESG data availability.

Figure 6: Number of banks with ESG scores per country 2014 and 2023



Source: Own work.

The increasing availability of ESG scores for banks in the whole sample may be attributed to stricter regulations on sustainability disclosures in the EU for bigger banks, such as the NFRD, SFRD and CSRD. Additionally, this trend may also reflect growing pressure from stakeholders who are holding banks more accountable for their actions. The rising number of banks with ESG data, even in smaller countries like Slovenia and Cyprus, suggests that sustainability issues are gaining significant traction.

The assumption of banks having higher ESG scores in countries where the frequency of banks with ESG scores available is higher presents. This is grounded in notion that these countries are more exposed to sustainability pressures and thus the different stakeholders encourage banks to improve their ESG impact (Freeman, 2010). However, the frequency of banks with ESG scores in a particular country does not consistently correlate with a higher weighted average ESG score for that country in our sample. This discrepancy could be due to varying motivations behind investing in sustainability, other ESG incentives, or the general political attitude towards ESG issues. In countries where sustainability is viewed as an opportunity for banks to contribute to environmental preservation and societal betterment, banks might be more inclined to follow the stakeholder theory and aim for higher ESG scores. Conversely, in countries where ESG reporting is perceived primarily as an administrative or regulatory obligation rather than a chance to drive meaningful change, banks may lack the incentive to improve their ESG scores beyond a basic compliance level. This view aligns more closely with the trade-off theory.

Table 4 presents the weighted average ESG scores and the weighted average E, S and G scores by country for 2023 in a descending order. To account for the suggested tendency of larger banks having higher ESG scores (Cornett et al., 2016), the weighted averages were calculated using total assets of a bank as weights. For example, in the Netherlands, the cumulative total assets for ABN Amro Bank and ING Group (originally ING Groep) in 2023 amounted to 1,493,708,000,000.00 EUR, with ABN Amro Bank having total assets of 417,058,000,000.00 EUR and ING Group having total assets of 1,076,650,000,000.00 EUR. The weight for ABN Amro Bank was calculated by dividing 417 million EUR by 1,494 million EUR, resulting in a weight of 0.28. Similarly, the weight for ING Group was calculated as 1,076 million EUR divided by 1,494 million EUR, resulting in a weight of 0.72. The weighted average ESG score for the Netherlands was then calculated as the sum of the products of these weights and the bank-specific ESG scores as follows: $0.28 * 67.79 + 0.72 * 76.06 = 73.75$. A simple average would suggest that the country's average ESG score is 71.92. However, a weighted average, which gives more weight to the larger bank, provides a more accurate depiction of the average, asset weighted ESG score. The weighted average E, S and G scores were calculated using the same logic.

Table 4: Weighted average ESG data for 2023 per country

Country	ESG	E	S	G	Country	ESG	E	S	G
Spain	86.66	94.35	91.93	79.05	Sweden	67.53	89.64	68.33	54.17
Italy	81.79	89.04	82.00	80.59	Poland	67.31	82.57	70.02	63.47
France	80.74	96.44	81.99	76.46	Portugal	65.38	78.08	75.64	59.19
Germany	78.94	92.50	48.51	69.18	Denmark	63.39	84.06	57.10	67.09
Romania	77.83	82.41	76.98	79.05	Czech Republic	59.32	73.20	59.37	58.86
Finland	74.88	83.82	68.03	90.22	Belgium	59.01	94.14	72.83	23.88
Slovenia	74.71	90.96	65.70	83.33	Ireland	58.22	73.80	67.28	49.47
Netherlands	73.75	92.05	66.86	78.31	Cyprus	55.64	73.90	60.35	43.96
Austria	71.16	82.10	79.90	58.90	Greece	46.83	59.24	48.51	47.29
Hungary	69.49	85.72	85.18	48.49	Slovak Republic	37.85	60.28	29.03	46.70

Source: Own work.

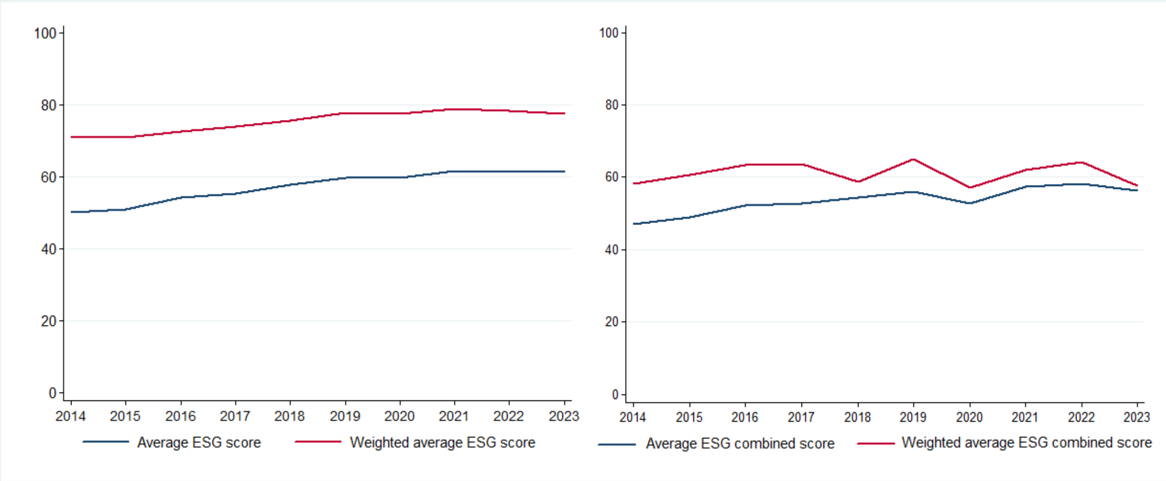
Examining the top three countries with the highest number of ESG scores available, it becomes evident that a higher frequency of scores does not consistently correspond to a higher weighted average ESG score for banks. While Spain and Italy, representing first and third place in ESG score availability for both year 2014 and 2023, rank among the top three, with weighted average ESG scores of 86.66 and 81.79, respectively, Poland, which represents the second country in terms of ESG score availability in 2014 and 2023, ranks 12th with a modest weighted average ESG score of 67.31. On the other side of the ESG score availability list is Slovenia, which has only one bank (Nova Ljubljanska banka d.d.) with an ESG score available in 2023, yet it has a relatively high ESG score of 74.71, further proving frequency of ESG score available in a certain country does not necessarily translate to a higher score.

Looking at Poland as an example, its lower ESG rating can be attributed to several factors, particularly political ones, as Poland is considered a politically conservative country where sustainability is not a top priority (Gottenhuber & Mulholland, 2020). Despite this, multinational banks operating in Poland are compelled, either legally or by market forces, to obtain an ESG score. According to the trade-off theory, these banks may prioritize achieving an acceptable ESG rating without over-investing resources that could be allocated elsewhere (Azmi et al., 2021). Additionally, due to the political climate, trust in institutions is lower in Poland, which may explain why Gen Z in Poland is less sensitive to environmental degradation issues compared to their counterparts in Germany (Andruszkiewicz et al., 2023) and more focused on more basic needs such as stability of the system. This could further reduce the incentives for banks to pursue higher ESG scores as sustainability is not among the top issues in Poland.

While the trend of banks in Western EU countries having higher ESG scores is evident, there are exceptions. For example, Romania and Slovenia have high scores, while Sweden, Belgium, and Ireland have relatively poor ESG scores. Future research should track the evolution of banks' ESG scores while considering factors such as each country's progressiveness on ESG issues, political orientation, and geographical location.

To analyse the trend of the average ESG score and the average ESGC score for the entire sample over time, both the simple and weighted averages were calculated for each parameter. These time series are presented in Figure 7. The weighted averages were determined by using each bank’s total assets for a specific year as a proportion of the aggregated total assets within the sample in the same year as weighting factors. Similar to the analysis of country-specific weighted average ESG scores, total assets were used as weights to account for and further explore the phenomenon of larger banks having higher ESG scores (Cornett et al., 2016; Bătae et al., 2020). A slight improvement is noticeable from 2014 to 2023, with the simple average ESG score rising from 50 at the beginning of the period to 61.5 in 2023 (left panel of Figure 6). A similar trend is observed for the simple average of the ESGC score, which increased from 47.04 to 56.26 (right panel of Figure 6).

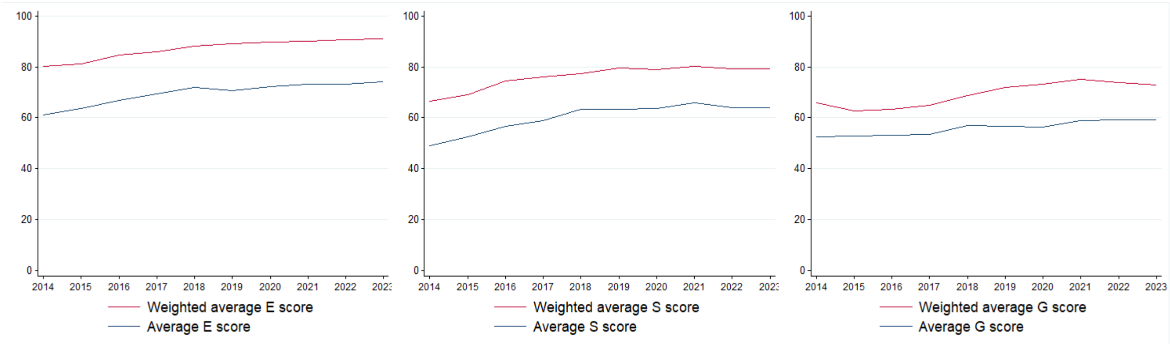
Figure 7: Simple and weighted average ESG and ESGC scores from 2014 to 2023



Source: Own work.

A notable trend emerges where the weighted average consistently shows a higher value compared to the simple average, as illustrated in Figure 6. This pattern is observed for both ESG scores and ESGC scores consistently throughout the whole observed period. In addition, Figure 8 illustrates the simple and weighted averages for individual E, S and G scores, which exhibit a similar behaviour to the overall ESG score. It's also worth noting that the highest scores are consistently observed for the environmental pillar, while the governance pillar exhibits the lowest scores through the observed period in our sample.

Figure 8: Simple and weighted average E, S, G scores from 2014 to 2023



Source: Own work.

The findings support the assumption that larger banks tend to have higher ESG scores. Weighted average thus offers a more comprehensive asset-based depiction of the ESG averages over the selected period. Such results align with the research of Cornett et al., (2016), who also found that larger banks consistently achieve higher scores. In addition, our results are partially consistent with the work of Bătae et al. (2020), which analysed ESGC scores from LSEG Workspace. While their statistical analysis found no statistically significant relationship between bank size and ESGC scores, a relationship was identified between individual ESG pillars and bank size. This suggests a connection between bank size and ESG scores, though not with ESGC scores. Their research, based on a cross-section data from 2018, may explain the non-significant results for the ESGC score, as the difference observed in our sample for 2018 is also minimal. As expected, the weighted average ESG score exceeds the weighted average ESGC score, as the ESGC score is calculated using only downward adjustments from the ESG score (Figure 7).

While the simple and weighted averages for the ESG score move in parallel over the years (left panel of Figure 6), the two averages for the ESGC score do not follow the same pattern (right panel of Figure 6). The weighted average ESGC score exhibits a more pronounced decline in 2018, 2020, and 2023 compared to the simple average, suggesting that media coverage of controversies poses a greater challenge for larger banks.

Tables 5 and 6 further illustrate that media coverage of controversies tends to have a greater impact on larger banks. Among the 56 banks with available ESG scores for the year 2014, 9 banks had differing ESG scores and ESGC scores, as shown in Table 5, which represents 16% of available banks. Of these, 6 were among the 10 largest banks based on total assets, and 8 had total assets greater than the mean value. In addition, the magnitude of the difference between the ESG score and the ESGC score shows a positive relationship with bank size, meaning that larger banks face a more pronounced impact from negative media coverage than smaller banks.

Table 5: Difference in ESG and ESGC scores in 2014 with corresponding bank size rank

Bank size rank	Bank name	ESG	ESGC	Difference
1	BNP Paribas SA	82.32	50.73	31.59
2	Deutsche Bank AG	83.86	45.32	38.53
4	Societe Generale SA	85.09	56.74	28.34
5	Banco Santander SA	83.57	76.04	7.53
6	ING Groep NV	67.34	47.87	19.47
8	Nordea Bank Abp	69.66	41.31	28.35
21	Banca Monte dei Paschi di Siena SpA	54.06	52.65	1.41
26	Raiffeisen Bank International AG	41.14	32.91	8.22
37	Alpha Services and Holdings SA	55.67	53.45	2.22

Source: Own work.

A similar trend is observed in Table 6 for the year 2023, with even more banks experiencing a downward adjustment from ESG to ESGC scores, rising to 23 banks in 2023. With the total number of banks in the sample at 87, this represents an increase to 26% of all available banks. This signifies the increased media attention of sustainability issues for the banking sector in comparison to the year 2014 and evolving pressures to manage ESG impact of banks. Of the 23 banks with a difference between their ESG score and ESGC score, 9 are among the 10 largest banks in the sample, accounting for 39%. Additionally, 20 of these banks fall within the top half based on size. The magnitude of the difference between the

ESG score and ESGC score again shows a positive correlation with bank size, where smaller banks experience smaller differences.

Table 6: Difference in ESG and ESGC scores in 2023 with corresponding bank size rank

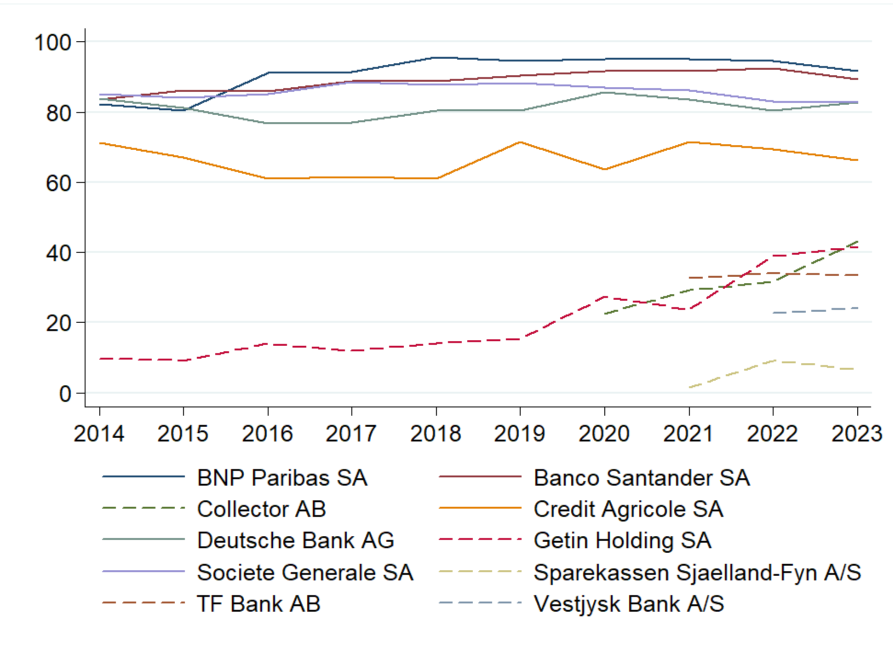
Bank size rank	Bank name	ESG	ESGC	Difference
1	BNP Paribas SA	91.77	52.78	38.98
2	Credit Agricole SA	66.20	46.22	19.98
3	Banco Santander SA	89.37	53.12	36.25
4	Societe Generale SA	82.85	55.23	27.62
5	Deutsche Bank AG	82.66	42.71	39.95
7	Intesa Sanpaolo SpA	92.02	69.01	23.00
8	UniCredit SpA	84.47	56.04	28.43
9	Banco Bilbao Vizcaya Argentaria SA	88.33	82.51	5.82
10	CaixaBank SA	85.22	80.95	4.27
11	Nordea Bank Abp	75.49	55.07	20.41
12	Commerzbank AG	76.01	49.66	26.35
13	Danske Bank A/S	70.30	45.73	24.57
19	Swedbank AB	72.98	48.14	24.83
20	Bankia SA	86.16	61.26	24.90
21	Banco de Sabadell SA	89.27	61.96	27.30
23	Raiffeisen Bank International AG	73.29	53.97	19.31
26	Unione di Banche Italiane SpA	80.12	54.56	25.56
30	Jyske Bank A/S	46.76	46.38	0.37
33	OTP Bank Nyrt	68.71	57.36	11.35
43	Santander Bank Polska SA	77.50	77.09	0.41
49	mBank SA	78.72	77.70	1.01
53	Banca Transilvania SA	80.46	78.57	1.89
71	BRD Groupe Societe Generale SA	72.52	49.38	23.14

Source: Own work.

At both the beginning and end of our sample period, Deutsche Bank experienced the largest decrease in the ESG score when adjusted to the ESGC score, with a difference of 38.5 in 2014 and 39.9 in 2023 (Tables 5 and 6). The trend of Deutsche bank having significantly lower ESGC scores compared to their ESG score is present throughout our sample with possible scandals that could be included into recalculation of their scores including the Greenwashing scandal, in which Deutsche bank and its subsidiary DWS were accused of misleading the public regarding the actual sustainability impact of their portfolios (Arons et al., 2022) and the money laundering scandal that involved the Deutsche bank and the Estonian branch of Danske bank (Bowers, 2020). In addition, the strong difference between Deutsche bank's ESG and ESGC scores may be attributed to Germany's strong emphasis on sustainability, which is a higher priority for consumers (Andruszkiewicz et al., 2023). Consequently, negative media coverage related to ESG issues could have a greater impact on public perception of the bank's efforts to address these concerns. This is also consistent with the research by Bătae et al. (2020), which found that western banks and banks from developed European countries experience significantly larger adjustments to their ESG scores due to negative media coverage, compared to northern banks and those in emerging markets. Furthermore, since Deutsche Bank ranks among the five largest banks in our sample, these findings align with the theory that larger banks are more heavily impacted by negative news.

To further highlight the differences between larger and smaller banks in our sample, Figure 9 presents the movement of ESG scores for the five largest and five smallest banks. Bank size was determined by the simple mean of each bank's total assets over the 10-year period analysed. The 5 biggest banks are BNP Paribas, Deutsche Bank, Société Generale, Banco Santander and Credit Agricole. The movement of their ESG scores is noted with a solid line. The 5 smallest banks in our sample are Collector, TF Bank, Getin Holding, Sparkassen Sjaelland-Fyn and Vestjysk Bank. The movement of ESG scores for these banks is noted with a dashed line. As observed, a clear trend of bigger banks having higher ESG scores appears. Additionally, some of the smallest banks lack ESG data for the entire sample period, suggesting that larger banks may have greater incentives to obtain and maintain high ESG scores.

Figure 9: ESG scores for 5 biggest and smallest banks based on total assets



Source: Own work.

5.2 Research Question 2: Is there a trade-off between bank specific ESG scores and credit risk, and what are the primary financial determinants of credit risk?

Research question 2 explores the relationship between ESG scores of banks in the EU and their credit risk, as well as the primary determinants of credit risk. The selection of specific financial determinants of credit risk, used alongside ESG metrics, was based on literature review, which identified the most commonly studied and statistically significant factors. The estimation results for regression equations (1) and (2) are presented in Tables 7 and 8 and structured as follows: credit risk is assessed using three metrics: the NPL-to-loans ratio, the NPL-to-assets ratio, and the NPL-to-equity ratio, each offering a different perspective on credit risk. The three metrics are used as the dependent variables and each of them is estimated in three model forms, denoted by (1), (2) and (3). In columns denoted as (1), the estimation results include only financial determinants. Columns denoted as (2) present the results incorporating financial determinants along with the ESG score as an individual metric of ESG performance. Lastly, columns denoted as (3) display the results with financial determinants and the combined ESG score used as the metric for ESG performance.

In addition, estimation results for regression equations (1) and (2) including the individual E, S and G scores as metrics of ESG impact of banks, are shown in Table 9. A similar structure is followed with columns denoted by (1) representing estimation results for regression equation (1) and columns denoted by (2) representing estimation results for regression equation (2).

5.2.1 Model selection, estimation technique and model fit

Tables 7, 8 and 9 also present the Breusch and Pagan Lagrange Multiplier test for the presence of random effects and Hausman test results, including the χ^2 statistic and p-value to help identify and differentiate if a fixed or a random effects model is more appropriate. In all regression subvariants, the Breusch and Pagan Lagrange Multiplier test points to a likely presence of random effects in the models, ruling out pooled OLS technique. Table 7, which contains the estimation results for regression equation (1), indicates that the fixed effects model is appropriate for all variations, with Hausman test p-values ranging from 0.000 to 0.016, which is well below the 0.05 significance threshold. Similarly, Hausman test p-values in Table 9 range from 0.000 to 0.047, also indicting the fixed effects model is appropriate. The Hausman test results for regression equation (2), shown in Table 8, are slightly less consistent. For models using the NPL-to-loans and NPL-to-assets ratios as dependent credit risk metrics and including only financial variables (columns (1)), the test yielded p-values of 0.060 and 0.069, respectively. Additionally, a p-value of 0.053 was observed for the model using the NPL-to-assets ratio as the credit risk metric, when including the combined ESG score (columns (3)). Since these p-values exceed the 0.05 threshold, we fail to reject the null hypothesis, indicating no strong evidence against the assumption that the random effects model may be more efficient in these cases.

However, since the p-values still indicate the Hausman test recommends a fixed effects model at a more liberal 10% statistical significance level, and for purpose of consistency and comparability across all variations of regression equations (1) and (2), the fixed effects model was estimated for all model forms. Nevertheless, the more efficient random effects model was estimated as a robustness check, for all regressions where it was so indicated by the Hausman test. The estimation results for these robustness checks are provided in Table A1 in the Appendix. The coefficient estimates remain consistent in terms of statistical significance, magnitude, and direction.

Since the fixed effects model was used, the overall, within, and between R^2 values were calculated. However, the result tables present only the within R^2 values, as this metric is most relevant for fixed effects models. The within R^2 shows how much of the variation in the dependent variable within entities, in our model the specific measures of credit risk within individual banks, is explained by the model over time.

Estimation results for both regression equations (1) and (2) in Tables 7 and 8 reveal that models in columns (2) and (3), which include ESG score and ESGC score, have higher within R^2 values compared to models in column (1), which include only financial determinants. However, this is expected and should not be used as an indicator of model fit as R^2 either increases or remains the same even if statistically non-significant variables are added to the model. Therefore, we do not compare models in columns (1) and (2) or (1) and (3) based on R^2 since the number of explanatory variables differs. In contrast, models in columns (2) and (3), where the only distinction is between the use of ESG and ESGC scores, have the same number of variables and observations, making R^2 an appropriate metric for comparing model fit. In all cases, the differences in model fit between columns (2) and (3) are negligible.

Nevertheless, a general discussion of model fit is possible – when NPL to gross loans ratio is used as a dependent variable, the models explain between 28% to 32% of its variance within banks. When NPL to assets ratio is used as a dependent variable, estimated models fit even better with R^2 ranging from 37 % to 40%. A similar fit of 31% to 41% is observed in models using NPL to equity ratio as dependent variable. Overall, this signals that the model fit is reasonably strong and while the within R^2 is not a perfect measure of model accuracy, it provides a useful indication of how well the model explains the variation in the data

Table 7: Regression equation (1) – estimation results

	(1) NPLToLoans	(2) NPLToLoans	(3) NPLToLoans	(1) NPLToAssets	(2) NPLToAssets	(3) NPLToAssets	(1) NPLToEquity	(2) NPLToEquity	(3) NPLToEquity
ROAA	**-5.029*** **	**-4.271*** **	**-4.641*** **	**-3.997*** **	**-3.564*** **	**-3.775*** **	**-47.108*** **	**-39.745*** **	**-43.397*** **
	(0.655)	**(0.681)**	**(0.653)**	**(0.677)**	**(0.709)**	**(0.698)**	**(6.344)**	**(5.278)**	**(5.689)**
EquityToAssets	0.808	0.593	0.563	**0.971***	0.836	0.818	-3.857	-6.727	-6.968
	(0.509)	(0.577)	(0.588)	**(0.437)**	(0.501)	(0.506)	(4.275)	(4.471)	(4.506)
CashToLiabilities	**-0.348*** **	**-0.310** **	**-0.356** **	**-0.251** **	**-0.230** **	**-0.257** **	**-3.160*** **	**-2.759** **	**-3.177*** **
	(0.100)	**(0.107)**	**(0.104)**	**(0.075)**	**(0.078)**	**(0.077)**	**(0.865)**	**(0.816)**	**(0.858)**
DebtToAssets	0.281	**0.301***	**0.358***	0.193	0.210	**0.244***	3.957	4.605	5.145
	(0.145)	**(0.143)**	**(0.160)**	(0.107)	(0.112)	**(0.121)**	(2.477)	(2.722)	(2.890)
lnAssets	0.023	**0.073***	0.041	0.023	**0.051***	0.033	0.167	0.611	0.307
	(0.027)	**(0.036)**	(0.031)	(0.020)	**(0.023)**	(0.021)	(0.302)	(0.377)	(0.326)
ESG		**-0.002***			**-0.001***			**-0.018** **	
		(0.001)			**(0.000)**			**(0.006)**	
ESGC			**-0.001***			**-0.001***			**-0.009***
			(0.000)			**(0.000)**			**(0.003)**
Constant	-0.572	-1.729	-0.970	-0.593	**-1.258***	-0.819	-3.445	-13.717	-6.499
	(0.713)	(0.923)	(0.818)	(0.524)	**(0.615)**	(0.579)	(7.940)	(9.679)	(8.595)
Breusch -Pagan LM test									
χ^2	140.42	140.51	136.38	176.83	172.63	168.93	185.74	189.86	183.56
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hausman test									
χ^2	15.30	22.34	19.36	13.98	20.52	17.86	32.60	42.73	39.30
p value	0.009	0.001	0.004	0.016	0.002	0.007	0.000	0.000	0.000
R-squared	0.28	0.32	0.31	0.37	0.40	0.39	0.34	0.41	0.39
Observations	435	410	410	435	410	410	435	410	410
Number of Banks	63	60	60	63	60	60	63	60	60

*Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. All of the models include bank specific fixed effects.*

Source: Own work.

Table 8: Regression equation (2) – estimation results

	(1) NPLToLoans	(2) NPLToLoans	(3) NPLToLoans	(1) NPLToAssets	(2) NPLToAssets	(3) NPLToAssets	(1) NPLToEquity	(2) NPLToEquity	(3) NPLToEquity
ROAA	**-4.222*** **	**-3.876*** **	**-4.078*** **	**-3.449** **	**-3.218** **	**-3.346** **	**-39.573** **	**-35.658***	**-37.815** **
	(0.979)	**(0.974)**	**(0.978)**	**(1.085)**	**(1.123)**	**(1.113)**	**(14.378)**	**(13.517)**	**(13.844)**
EquityToAssets	**1.578***	**1.475***	**1.464***	**1.469***	**1.405***	**1.397***	1.287	0.038	-0.067
	(0.690)	**(0.704)**	**(0.707)**	**(0.604)**	**(0.622)**	**(0.624)**	(5.442)	(5.776)	(5.770)
CashLiabilities	**-0.319** **	**-0.310***	**-0.330** **	**-0.234***	**-0.229***	**-0.243***	**-2.701** **	**-2.531** **	**-2.750** **
	(0.119)	**(0.121)**	**(0.122)**	**(0.090)**	**(0.092)**	**(0.093)**	**(0.856)**	**(0.859)**	**(0.877)**
DebtToAssets	0.141	0.165	0.191	0.119	0.138	0.155	2.845	3.636	3.910
	(0.126)	(0.146)	(0.154)	(0.107)	(0.128)	(0.134)	(2.399)	(2.869)	(2.969)
lnAssets	0.026	0.055	0.036	0.025	0.044	0.031	0.014	0.342	0.135
	(0.033)	(0.035)	(0.034)	(0.023)	(0.024)	(0.023)	(0.263)	(0.311)	(0.283)
OpexToOperatingProfit	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
GrowthOfLoans	-0.051	-0.056	-0.051	-0.033	**-0.037***	-0.034	-0.178	-0.232	-0.174
	(0.031)	(0.031)	(0.033)	(0.018)	**(0.018)**	(0.019)	(0.246)	(0.239)	(0.260)
ESG		**-0.001***			-0.001			**-0.011***	
		(0.001)			(0.000)			**(0.005)**	
ESGC			-0.000			-0.000			-0.005
			(0.000)			(0.000)			(0.003)
Constant	-0.677	-1.381	-0.918	-0.684	-1.137	-0.838	0.167	-7.657	-2.747
	(0.881)	(0.926)	(0.922)	(0.625)	(0.650)	(0.637)	(6.964)	(8.071)	(7.520)
Breusch -Pagan LM test									
χ^2	187.89	183.01	180.84	152.75	146.71	144.98	141.77	139.10	136.62
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hausman test									
χ^2	12.08	17.39	15.39	11.70	15.40	13.90	23.13	29.70	27.83
p value	0.060	0.015	0.031	0.069	0.031	0.053	0.001	0.000	0.000
R-squared	0.38	0.40	0.39	0.41	0.42	0.42	0.33	0.37	0.36
Observations	388	368	368	388	368	368	388	368	368
Number of Banks	63	60	60	63	60	60	63	60	60

*Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. All of the models include bank specific fixed effects.*

Source: Own work.

5.2.2 Relationship between ESG scores and credit risk

Results in Table 7 show the primary coefficient estimate of interest, those of ESG and ESGC scores. They are negative and statistically significant in all 6 regression variants that incorporate ESG metrics. Although the coefficients are modest in size, the results indicate a negative association between ESG impact and credit risk. This signals that higher ESG or ESGC score on average, ceteris paribus associate with lower credit risk.

In Table 8, the coefficient estimates for ESG and ESGC score variables become less statistically significant after the inclusion of two additional financial metrics. Only the coefficient estimates for ESG score in columns (2), where credit risk is measured with NPL-to-loans and NPL-to-equity as dependent variables, remain statistically significant, with values of -0.001 and -0.011, respectively. Although the coefficients are relatively small, the combined results from both Table 7 and 8 in general indicate a negative and statistically significant association between ESG impact and credit risk in 8 out of 12 regressions that include a form of ESG metric as explanatory variable. In other words, no evident trade-off between ESG impact and credit risk is observed in the data, showcasing that there is no evident credit risk penalty if banks improve their ESG scores. In fact, the data points to a reverse conclusion – better ESG impact might be a credit risk mitigating strategy.

This aligns with the findings of Wu and Shen (2013), who also identified a negative association between CSR and credit risk. Their analysis, conducted a decade ago when sustainability efforts were gaining momentum, addressed the emerging questions of whether, when, and why to invest in sustainability. Although the concept of CSR differs somewhat from ESG scores, as previously discussed, the results are still comparable, as both concepts share the underlying concept of banks investing in sustainability.

As discussed in research question 1, the analysis of the average ESG and ESGC score reveals an upward trend (Figure 6), indicating that banks are increasingly improving their ESG performance. In addition, Figure 4 shows a trend of increasing number of banks with the ESG scores available. From this, we can infer that the relationship between ESG scores and credit risk will be an important topic for banks to understand in the coming years and could provide a potential credit risk mitigating strategy for the overall banking system.

A similar conclusion was reached by Danisman and Tarazi (2024), who examined the relationship between ESG engagement and credit and asset risk in banks during the 2008 Global Financial Crisis. They found that banks with higher ESG scores, particularly in the environmental pillar, experienced less contraction in lending during the crisis thus exhibiting a less pronounced pro-cyclical behaviour. The increased stability of banks with higher ESG scores during financial crises was also established by Chiaramonte et al. (2022), who additionally emphasized the long-term benefits of sustained ESG engagement for bank stability.

However, the assumption that banks' engagement with ESG initiatives directly leads to reduced credit risk and greater system stability may not necessarily hold true. The regression results only suggest that banks with higher ESG scores exhibit a negative relationship with credit risk, but they do not establish causality. A possibility is also a reverse causality, where larger and more stable banks with better credit risk management have higher ESG scores. As Buallay (2019) highlighted in their findings, the profitability indicator Tobin's Q Granger-causes higher ESG scores, indicating a statistically significant and positive relationship between profitability and ESG scores, but in the opposite direction to what was previously assumed. The same reasoning could apply to the relationship between credit risk and ESG scores. While our research finds a statistically significant and negative relationship in many regressions, the causality between these two variables remains an interesting topic for further research.

5.2.3 Relationship between individual pillars of ESG score and credit risk

Table 9 presents the estimation results for regression equations (1) and (2), incorporating the individual pillars of E, S, and G as metrics for the ESG impact of banks. Contrary to expectations, the environmental pillar scores do not exhibit statistically significant coefficient estimates in any of the regression models. However, the social pillar scores show a statistically significant and negative coefficient estimate in half of the models. Additionally, the governance pillar scores demonstrate statistically significant and negative coefficient estimates in 4 out of 6 models. These findings suggest that the primary drivers behind the significant relationship between overall ESG scores and credit risk, as observed in Table 7, are the social and governance pillars.

Table 9: Regression equation (1) and (2) estimation results – individual pillars of ESG

	(1) NPLToLoans	(2) NPLToLoans	(1) NPLToAssets	(2) NPLToAssets	(1) NPLToEquity	(2) NPLToEquity
ROAA	**-4.244***** **(0.686)**	**-3.885***** **(1.003)**	**-3.552***** **(0.715)**	**-3.222**** **(1.139)**	**-40.467***** **(5.410)**	**-36.331*** **(13.947)**
EquityToAssets	0.532 (0.609)	**1.432*** **(0.708)**	0.811 (0.509)	**1.370*** **(0.621)**	-6.953 (4.539)	-0.136 (5.665)
CashToLiabilities	**-0.286**** **(0.098)**	**-0.280*** **(0.118)**	**-0.205**** **(0.073)**	**-0.205*** **(0.090)**	**-2.367**** **(0.719)**	**-2.221*** **(0.840)**
DebtToAssets	**0.271*** **(0.130)**	0.163 (0.133)	0.200 (0.106)	0.144 (0.120)	4.430 (2.636)	3.564 (2.710)
lnAssets	0.066 (0.037)	0.043 (0.031)	0.045 (0.022)	0.035 (0.021)	0.453 (0.301)	0.170 (0.219)
OpexToOperatingProfit		-0.000 (0.000)		-0.000 (0.000)		-0.000 (0.001)
GrowthOfLoans		-0.044 (0.027)		-0.029 (0.015)		-0.115 (0.209)
Environmental	0.000 (0.001)	0.000 (0.001)	0.000 (0.000)	0.000 (0.000)	0.004 (0.004)	0.003 (0.004)
Social	**-0.001*** **(0.001)**	-0.001 (0.000)	**-0.001*** **(0.000)**	-0.001 (0.000)	**-0.011*** **(0.004)**	-0.005 (0.003)

To be continued

Table 9: Regression equation (1) and (2) estimation results – individual pillars of ESG (cont.)

	(1) NPLTo Loans	(2) NPLTo Loans	(1) NPLTo Assets	(2) NPLTo Assets	(1) NPLTo Equity	(2) NPLTo Equity
Governance	**-0.001****	**-0.001***	**-0.001***	-0.000	**-0.011***	-0.009
	(0.000)	**(0.000)**	**(0.000)**	(0.000)	**(0.004)**	(0.004)
Constant	-1.525	-1.060	-1.088	-0.912	-9.623	-3.267
	(0.918)	(0.824)	(0.584)	(0.579)	(7.756)	(5.811)
Breusch -Pagan LM test						
χ^2	139.38	188.01	176.37	150.28	195.01	143.19
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Hausman test						
χ^2	22.36	20.25	19.85	18.51	40.55	31.54
p-value	0.004	0.027	0.011	0.047	0.000	0.001
R-squared	0.34	0.41	0.41	0.43	0.42	0.39
Observations	412	370	412	370	412	370
Number of Banks	60	60	60	60	60	60

*Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. All of the models include bank specific fixed effects.*

Source: Own work

5.2.4 Financial determinants of credit risk

When assessing the financial determinants of credit risk based on the estimation results for our sample and regression models, two variables consistently remain statistically significant across all variations of regression equations (1) and (2): ROAA and the cash-to-liabilities ratio. Additionally, the equity-to-assets ratio, debt-to-assets ratio, logarithm of total assets, and loan growth show statistically significant relationships with credit risk in certain regression variations of our models. In contrast, the variable OPEX-to-operating profit does not show a statistically significant relationship with credit risk in our sample.

The estimation results presented in Tables 7 and 8 demonstrate a strong, statistically significant and negative relationship between ROAA, a measure of profitability, and the three NPL ratios, which measure credit risk, consistently across various model specifications. The coefficients range from approximately -3 to -4 for models that include NPL-to-loans and NPL-to-assets, and around -40 for models that use NPL-to-equity as a measure of credit risk. This difference in coefficients arises from the calculation of the credit risk metrics, as equity represents a smaller portion of a bank's overall value compared to loans and assets and is present for all variables.

A robustness check for profitability was conducted for regression equation (1) using ROAE and net interest margin as variables, as presented in Tables A2 and A3 in the Appendix, respectively. The statistical significance of the coefficients in the estimation results using ROAE as the profitability metric remains unchanged. Coefficient estimates continue to be statistically significant and negative across all variations of regression equation (1), although with a lower magnitude compared to coefficients for ROAA.

In contrast, the estimation results for the relationship between net interest margin and credit risk reveal a slightly different picture. The coefficients are not consistently statistically significant, and while the magnitude of the relationship is close to 0, it is positive. This difference may be attributed to data limitations, as the number of observations decreases by more than 130 when using net interest margin. Another explanation may stem from the fundamental differences among these three profitability indicators. Since net interest income reflects the profitability of interest-earning assets only, it exhibits a more specific relationship with credit risk. The reasoning follows that a higher net interest margin indicates a different customer base, which, in this case, is associated with higher credit risk indicated by the positive relationship.

Nevertheless, as the estimation results for ROAA and ROAE remain consistently statistically significant and negative, the notion of the negative relationship between these two commonly used indicators of profitability and credit risk is supported, as found by other researchers (Makri et al., 2014; Chaibi & Ftiti, 2015).

The second variable that consistently shows statistically significant coefficient estimates is the cash-to-liabilities ratio, representing banks' liquidity. The relationship is negative, with coefficients ranging from -0.36 to -0.23 for models measuring credit risk using the NPL-to-loans and NPL-to-assets ratios, and from -3.18 to -2.53 for models assessing credit risk with the NPL-to-equity ratio. This suggests that managing a bank's liquidity risk is a statistically significant factor that associates with managing credit risk. A similar conclusion is drawn by Samaniego-Medina and Giráldez-Puig (2022), who examined the credit ratings of 65 European banks between 2011 and 2022 and found a positive impact of liquidity ratio on credit ratings.

As mentioned in the Section 4 (Methodology), due to data limitations concerning the liquidity coverage ratio as defined in Basel III, a simple cash-to-liabilities ratio was used in the primary regression equations. For robustness, the liquidity coverage ratio reported by banks was also incorporated as a liquidity ratio parameter. However, as shown in Table A4 in the Appendix, the estimation results for regression equation (1) reveal no statistically significant coefficients for the liquidity ratio using this parameter. This inconsistency is likely due to data limitations (refer to Figure 3), as the availability of liquidity coverage ratio data is quite limited before the introduction of Basel III in 2018. Nevertheless, the simple cash-to-liabilities ratio offers better data availability over the sample period, making it a more reliable indicator of the relationship between liquidity and credit risk, thus signifying the statistically significant relationship between liquidity and credit risk.

Capitalization, measured by the equity-to-assets ratio, has a statistically significant coefficient estimates in only one variation of regression equation (1). In the variations of regression equation (2), capitalization demonstrates greater statistical significance, although not in all models. In both Table 7 and 8, the equity-to-assets ratio has a statistically significant coefficient estimate in 7 out of 18 regressions that include capitalization as an explanatory variable. With coefficients ranging from 0.97 to 1.58, a potential positive relationship between capitalization and credit risk is inferred. This contrasts with the findings of Makri et al. (2014), who identified a negative relationship between capitalization and credit risk, and Sinkey Jr and Greenawalt (1991), who showed that adequately capitalized banks tend to experience lower NPLs in the future. The importance of sufficient regulatory capital was also highlighted in research conducted by Ahmad and Ariff (2008).

Additionally, the findings on the impact of leverage on credit risk by Ahmad and Ariff (2008) partially align with our results. Similar to their study, our estimation results for regression equation (2) indicate no statistically significant relationship between leverage and credit risk. On the other hand, in some variations of regression equation (1), statistically significant and positive coefficient estimates for leverage, measured by the debt-to-assets ratio, are observed. These results align with those of Di Tommaso and Thornton (2020), who found a statistically significant relationship between NPLs and leverage. In addition, a regression equation (1) using the liabilities-to-assets ratio as an explanatory variable of leverage was estimated as a robustness check. In Table A6 in the Appendix, the coefficient estimates are observed to have a statistically significant and negative relationship in models including the ESG metric.

Contrary to expectations, the coefficient estimates for bank size, measured by the logarithm of total assets, show statistical significance in only two variations of regression equation (1) and none in the estimation results of regression equation (2). Bank size is commonly associated with credit risk, as highlighted by an extensive literature review by Naili and Lahrichi (2022). Research by Zhang et al. (2016) demonstrated a statistically significant relationship between bank size and credit risk in the Chinese banking system, while Albaity et al. (2019) found similar results in the MENA region. The importance of bank size was also emphasized in studies of the European banking system (Izcan & Bektas, 2022). A robustness check was conducted using the logarithm of gross loans for regression equation (1). As shown in Table A5 in the Appendix, the coefficients are not consistently statistically significant even when using a different size metric; however, the relationship remains positive for those coefficients that do exhibit statistical significance.

In addition to bank size, the estimation results for loan growth contrast with our expectations. As shown in Table 8, loan growth coefficient estimates are statistically significant in only one variation of regression equation (2). This finding is only partially consistent with the research by Skrabic Peric and Konjusak (2017), which found statistical evidence that loan growth contributes to higher credit risk.

Operating efficiency, represented by the OPEX-to-operating profit ratio in our analysis (Naili & Lahrichi, 2022), was not found to be a statistically significant determinant of credit risk, as shown in Table 8. Operating efficiency was included as one of two financial determinants in regression equation (2) to control for an additional aspect of credit risk. This contrasts with the findings of Ozili (2019) and Berger and DeYoung (1997), both of whom identified operating efficiency as a key determinant of credit risk. The discrepancy in findings could be due to differences in data employed as Ozili (2019) studied a global sample of banks, and Berger and DeYoung (1997) focused on U.S. banks, in contrast to our sample that encompasses EU banks.

Additionally, Berger and DeYoung (1997) explored the causality between operating efficiency and credit risk using the Granger causality test, concluding that inefficiencies in operations could lead to future credit risk issues. Their research employed the GMM model for dynamic data, which may explain the difference in the statistical significance of the results. Management quality, in relation to credit risk, was also studied by Louzis et al. (2012), who found that both performance and efficiency play a role in credit risk. Their study, like Berger and DeYoung's (1997), used the dynamic GMM model.

Financial determinants that show statistically significant coefficient estimates in Table 9 remain similar with the estimation of regression equations (1) and (2) using the individual E, S and G scores. As in Tables 7 and 8, profitability, measures by ROAA, and liquidity, measured by the cash to total liabilities ratio, show statistically significant and negative relationship with credit risk across all three NPL ratios. Additionally, capitalization shows a statistically significant and positive relationship with credit risk in two models of regression equation (1), while other financial determinants do not show a relationship with credit risk.

5.3 Research Question 3: Are there statistically significant differences in the effects of ESG scores on the credit risk of banks headquartered in EU, EMU, non-EMU member countries, and in developed and emerging countries within the EU?

To analyse the differences in the relationship between ESG scores and credit risk for banks categorized by two parameters: economic regions, which include EU, EMU, and non-EMU, and market classification, which includes developed and emerging markets, a fixed effects regression model was employed using regression equation (1). For robustness, the same fixed effects model was applied to regression equation (2), as shown in Tables A9, A10, A11 and A12 in the Appendix. In addition, the Hausman test shows p-values exceeding the threshold of 5% for models that include banks headquartered in non-EMU countries and countries with emerging markets. Tables A7 and A8 in the Appendix show the estimation results for regression equation (1) using the random effects model as a more efficient estimator as well as a robustness check.

Tables 10 and 12 present the estimation results for regression equation (1), which includes the ESG score as measures of ESG impact, while Tables 11 and 13 display the results for models incorporating the ESGC scores. All tables follow a consistent structure, with credit risk measured through the ratios of NPL to total loans, NPL to total assets, and NPL to equity, as in the tables for research question 2. Additionally, columns denoted by (1) provide the estimation results for models based on a sample of all EU banks, columns denoted by (2) present the results for banks headquartered in non-EMU countries (Tables 10 and 11) and those in developed markets (Tables 12 and 13), and columns denoted by (3) show the estimation results for banks headquartered in EU but non-EMU countries (Tables 10 and 11) and those in emerging markets (Tables 12 and 13).

The results point to a distinction between EU, EMU and non-EMU countries (Tables 10 and 11), a significant trend emerges where the estimation results for the economic areas of the EU and EMU display statistically significant coefficients for several financial parameters, as well as ten out of twelve ESG impact coefficients, which aligns with the results from research question 2.

In contrast, the estimation results for banks headquartered outside the EMU show no statistically significant relationship for either financial parameters or ESG impact with credit risk. In addition, the same results are observed in Table A7 in the Appendix, using the random effects regression model to estimate regression equation (1) for banks headquartered in non-EMU countries. This discrepancy may be attributed to data limitations, as non-EMU headquartered banks account for a significantly smaller percentage of overall observations (31%) compared to EMU-headquartered banks.

Despite this limitation, two key conclusions can be drawn. First, banks headquartered in EMU countries show a higher level of involvement in ESG activities, as evidenced by a statistically significant and negative relationship between ESG involvement and credit risk. Second, banks headquartered outside the EMU do not exhibit a similar relationship between ESG impact and credit risk. Instead, their credit risk seems to rely more on other financial determinants, such as macroeconomic factors, which were not captured by our regression models and represent an interesting area for future research.

Additionally, as shown in Tables A9 and A10 in the Appendix, operating efficiency is statistically significant for non-EMU banks, with coefficient estimates ranging from 0.000 to 0.001. Although these coefficients are almost negligible, the statistical significance indicates a relationship, whereas no such relationship is observed for EMU banks. This further suggests that different determinants of credit risk apply to banks headquartered in EMU versus non-EMU regions.

Table 10: Regression equation (1) including ESG score – estimation results for banks headquartered in EU, EMU and non-EMU countries

	(1) NPLToLoans	(2) NPLToLoans	(3) NPLToLoans	(1) NPLToAssets	(2) NPLToAssets	(3) NPLToAssets	(1) NPLToEquity	(2) NPLToEquity	(3) NPLToEquity
ROAA	**-4.271*** **	**-5.092*** **	-1.076	**-3.564*** **	**-4.363*** **	-0.607	**-39.745*** **	**-45.312*** **	-8.549
	(0.681)	**(0.627)**	(1.472)	**(0.709)**	**(0.743)**	(0.814)	**(5.278)**	**(5.423)**	(10.080)
EquityToAssets	0.593	1.411	-0.119	0.836	**1.666** **	0.027	-6.727	-4.407	-4.615
	(0.577)	(0.726)	(0.506)	(0.501)	**(0.612)**	(0.276)	(4.471)	(6.418)	(3.601)
CashToLiabilities	**-0.310** **	-0.173	-0.224	**-0.230** **	-0.097	-0.145	**-2.759** **	-2.368	-1.423
	(0.107)	(0.132)	(0.171)	**(0.078)**	(0.095)	(0.107)	**(0.816)**	(1.361)	(1.041)
DebtToAssets	**0.301***	**0.431***	0.002	0.210	**0.324***	-0.014	4.605	5.965	0.150
	(0.143)	**(0.162)**	(0.258)	(0.112)	**(0.127)**	(0.142)	(2.722)	(3.084)	(1.799)
lnAssets	**0.073***	0.063	0.020	**0.051***	0.041	0.004	0.611	0.592	0.140
	(0.036)	(0.045)	(0.066)	**(0.023)**	(0.031)	(0.035)	(0.377)	(0.553)	(0.448)
ESG	**-0.002***	**-0.002***	-0.001	**-0.001***	**-0.002***	-0.001	**-0.018** **	**-0.021** **	-0.011
	(0.001)	**(0.001)**	(0.001)	**(0.000)**	**(0.001)**	(0.001)	**(0.006)**	**(0.007)**	(0.009)
Constant	-1.729	-1.533	-0.319	**-1.258***	-1.049	-0.006	-13.717	-13.439	-1.984
	(0.923)	(1.176)	(1.567)	**(0.615)**	(0.809)	(0.844)	(9.679)	(14.333)	(10.665)
Breusch-Pagan LM test									
χ^2	140.51	75.26	0.51	172.63	76.11	0.08	189.86	119.46	0.11
p-value	0.000	0.000	0.238	0.000	0.000	0.387	0.000	0.000	0.368
Hausman test									
χ^2	22.34	22.99	2.87	20.52	22.17	2.59	42.73	28.96	2.09
p-value	0.001	0.001	0.825	0.002	0.001	0.858	0.000	0.000	0.911
R-squared	0.32	0.44	0.06	0.40	0.52	0.08	0.41	0.51	0.06
Observations	410	281	129	410	281	129	410	281	129
Number of banks	60	39	21	60	39	21	60	39	21
Headquarters	EU	EMU	non-EMU	EU	EMU	non-EMU	EU	EMU	non-EMU

*Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. All of the models include bank specific fixed effects.*

Source: Own work

Table 11: Regression equation (1) including ESGC score – estimation results for banks headquartered in EU, EMU and non-EMU countries

	(1) NPLToLoans	(2) NPLToLoans	(3) NPLToLoans	(1) NPLToAssets	(2) NPLToAssets	(3) NPLToAssets	(1) NPLToEquity	(2) NPLToEquity	(3) NPLToEquity
ROAA	**-4.641*** **	**-5.617*** **	-0.837	**-3.775*** **	**-4.685*** **	-0.467	**-43.397*** **	**-50.279*** **	-6.789
	(0.653)	**(0.536)**	(1.368)	**(0.698)**	**(0.726)**	(0.761)	**(5.689)**	**(5.744)**	(9.267)
EquityToAssets	0.563	1.275	-0.116	0.818	**1.581***	0.027	-6.968	-5.639	-4.598
	(0.588)	(0.776)	(0.492)	(0.506)	**(0.638)**	(0.270)	(4.506)	(6.747)	(3.464)
CashToLiabilities	**-0.356** **	-0.260	-0.265	**-0.257** **	-0.151	-0.169	**-3.177*** **	**-3.158***	-1.728
	(0.104)	(0.133)	(0.165)	**(0.077)**	(0.098)	(0.104)	**(0.858)**	**(1.535)**	(1.008)
DebtToAssets	**0.358***	**0.484** **	0.091	**0.244***	**0.357***	0.035	5.145	6.436	0.796
	(0.160)	**(0.177)**	(0.329)	**(0.121)**	**(0.134)**	(0.178)	(2.890)	(3.231)	(2.291)
lnAssets	0.041	0.025	0.005	0.033	0.017	-0.004	0.307	0.242	0.031
	(0.031)	(0.041)	(0.050)	(0.021)	(0.029)	(0.027)	(0.326)	(0.519)	(0.343)
ESGC	**-0.001***	-0.001	-0.001	**-0.001***	-0.001	-0.001	**-0.009***	**-0.008***	-0.009
	(0.000)	(0.001)	(0.001)	**(0.000)**	(0.000)	(0.000)	**(0.003)**	**(0.004)**	(0.006)
Constant	-0.970	-0.614	0.021	-0.819	-0.472	0.179	-6.499	-5.090	0.493
	(0.818)	(1.100)	(1.235)	(0.579)	(0.789)	(0.673)	(8.595)	(13.706)	(8.334)
Breusch-Pagan LM test									
χ^2	136.38	73.60	0.50	168.93	74.95	0.02	183.56	113.81	0.13
p-value	0.000	0.000	0.240	0.000	0.000	0.439	0.000	0.000	0.358
Hausman test									
χ^2	19.36	19.05	3.82	17.86	18.96	3.38	39.30	26.59	2.61
p-value	0.004	0.004	0.701	0.007	0.004	0.760	0.000	0.000	0.857
R-squared	0.31	0.42	0.06	0.39	0.50	0.08	0.39	0.49	0.06
Observations	410	281	129	410	281	129	410	281	129
Number of Banks	60	39	21	60	39	21	60	39	21
Headquarters	EU	EMU	non-EMU	EU	EMU	non-EMU	EU	EMU	non-EMU

*Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. All of the models include bank specific fixed effects.*

Source: Own work.

Table 12: Regression equation (1) including ESG score – estimation results for banks in EU, EU-developed and EU-emerging countries

	(1) NPLToLoans	(2) NPLToLoans	(3) NPLToLoans	(1) NPLToAssets	(2) NPLToAssets	(3) NPLToAssets	(1) NPLToEquity	(2) NPLToEquity	(3) NPLToEquity
ROAA	**-4.271*** **	**-3.159***	**-5.608*** **	**-3.564*** **	**-2.603***	**-4.571** **	**-39.745*** **	**-40.945***	**-45.742*** **
	(0.681)	**(1.380)**	**(0.825)**	**(0.709)**	**(1.140)**	**(1.137)**	**(5.278)**	**(17.474)**	**(5.759)**
EquityToAssets	0.593	-0.715	**2.715***	0.836	-0.376	**2.933** **	-6.727	**-16.579*** **	9.463
	(0.577)	(0.403)	**(1.012)**	(0.501)	(0.217)	**(0.611)**	(4.471)	**(4.421)**	(6.111)
CashToLiabilities	**-0.310** **	**-0.152***	-0.551	**-0.230** **	**-0.096***	-0.377	**-2.759** **	**-1.901***	-3.991
	(0.107)	**(0.068)**	(0.335)	**(0.078)**	**(0.042)**	(0.218)	**(0.816)**	**(0.804)**	(2.220)
DebtToAssets	**0.301***	**0.326***	0.400	0.210	**0.235***	0.320	4.605	4.379	7.339
	(0.143)	**(0.150)**	(0.406)	(0.112)	**(0.114)**	(0.391)	(2.722)	(2.663)	(4.055)
lnAssets	**0.073***	0.057	-0.002	**0.051***	0.031	0.014	0.611	0.610	-0.077
	(0.036)	(0.041)	(0.063)	**(0.023)**	(0.026)	(0.040)	(0.377)	(0.522)	(0.374)
ESG	**-0.002***	**-0.003** **	0.002	**-0.001***	**-0.002*** **	0.001	**-0.018** **	**-0.023*** **	0.006
	(0.001)	**(0.001)**	(0.002)	**(0.000)**	**(0.000)**	(0.002)	**(0.006)**	**(0.006)**	(0.012)
Constant	-1.729	-1.230	-0.078	**-1.258***	-0.657	-0.558	-13.717	-13.003	2.115
	(0.923)	(1.048)	(1.678)	**(0.615)**	(0.681)	(1.045)	(9.679)	(13.372)	(9.867)
Breusch-Pagan LM test									
χ^2	140.51	46.85	0.01	172.63	108.06	0.01	189.86	162.02	0.01
p-value	0.000	0.000	0.999	0.000	0.000	0.999	0.000	0.000	0.999
Hausman test									
χ^2	22.34	27.82	10.95	20.52	30.09	9.05	42.73	46.82	9.12
p-value	0.001	0.000	0.090	0.002	0.000	0.171	0.000	0.000	0.167
R-squared	0.32	0.28	0.54	0.40	0.37	0.61	0.41	0.41	0.55
Observations	410	354	56	410	354	56	410	354	56
Number of Banks	60	52	8	60	52	8	60	52	8
Classification	EU	EU-developed	EU-emerging	EU	EU-developed	EU-emerging	EU	EU-developed	EU-emerging

*Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. All of the models include bank specific fixed effects.*

Source: Own work.

Table 13: Regression equation (1) including ESGC score – estimation results for banks in EU, EU-developed and EU-emerging countries

	(1) NPLToLoans	(2) NPLToLoans	(3) NPLToLoans	(1) NPLToAssets	(2) NPLToAssets	(3) NPLToAssets	(1) NPLToEquity	(2) NPLToEquity	(3) NPLToEquity
ROAA	**-4.641*** **	**-3.734** **	**-5.369*** **	**-3.775*** **	**-2.947* **	**-4.401** **	**-43.397*** **	**-46.390* **	**-44.007*** **
	(0.653)	**(1.336)**	**(0.857)**	**(0.698)**	**(1.112)**	**(1.197)**	**(5.689)**	**(17.796)**	**(6.703)**
EquityToAssets	0.563	-0.764	**2.615* **	0.818	-0.406	**2.855** **	-6.968	**-16.972*** **	8.904
	(0.588)	(0.440)	**(0.981)**	(0.506)	(0.240)	**(0.592)**	(4.506)	**(4.424)**	(6.132)
CashToLiabilities	**-0.356** **	**-0.212** **	-0.558	**-0.257** **	**-0.133** **	-0.382	**-3.177*** **	**-2.417** **	-4.042
	(0.104)	**(0.069)**	(0.357)	**(0.077)**	**(0.044)**	(0.233)	**(0.858)**	**(0.902)**	(2.361)
DebtToAssets	**0.358* **	**0.409* **	0.412	**0.244* **	**0.285* **	0.322	5.145	5.119	7.563
	(0.160)	**(0.173)**	(0.454)	**(0.121)**	**(0.126)**	(0.418)	(2.890)	(2.888)	(4.504)
lnAssets	0.041	0.009	0.002	0.033	0.002	0.017	0.307	0.173	-0.037
	(0.031)	(0.035)	(0.070)	(0.021)	(0.025)	(0.045)	(0.326)	(0.460)	(0.427)
ESGC	**-0.001* **	**-0.001* **	0.001	**-0.001* **	**-0.001** **	0.001	**-0.009* **	**-0.010** **	0.002
	(0.000)	**(0.000)**	(0.002)	**(0.000)**	**(0.000)**	(0.002)	**(0.003)**	**(0.003)**	(0.015)
Constant	-0.970	-0.071	-0.142	-0.819	0.049	-0.594	-6.499	-2.537	1.441
	(0.818)	(0.925)	(1.843)	(0.579)	(0.648)	(1.159)	(8.595)	(12.019)	(11.021)
Breusch-Pagan LM test									
χ^2	136.38	42.94	0.82	168.93	102.00	0.01	183.56	153.50	0.20
p-value	0.000	0.000	0.182	0.000	0.000	0.999	0.000	0.000	0.328
Hausman test									
χ^2	19.36	26.46	8.33	17.86	28.40	9.43	39.30	43.21	7.61
p-value	0.004	0.000	0.215	0.007	0.000	0.151	0.000	0.000	0.268
R-squared	0.31	0.24	0.54	0.39	0.33	0.60	0.39	0.37	0.55
Observations	410	354	56	410	354	56	410	354	56
Number of Banks	60	52	8	60	52	8	60	52	8
Classification	EU	EU-developed	EU-emerging	EU	EU-developed	EU-emerging	EU	EU-developed	EU-emerging

*Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. All of the models include bank specific fixed effects.*

Source: Own work.

Tables 12 and 13 present the estimation results for regression equation (1), this time focusing on banks divided into developed and emerging markets within the EU. Data availability remains a concern, as the number of observations for banks in emerging markets is substantially smaller. This aligns with the findings of Bătae et al. (2020), who also included a significantly smaller number of banks from emerging markets compared to those from developed markets in their research. Despite this limitation, several conclusions can be drawn from the estimation results. A statistically significant and negative relationship between ESG impact and credit risk is observed in banks headquartered in developed markets, while no such relationship exists for banks in emerging markets when using the fixed effects estimator. A possible explanation for the discrepancy could be because developed countries generally have stronger regulatory frameworks that promote ESG integration in the corporate practices of both banks and their clients. As a result, offering financing to clients with better ESG impacts, which also enhances a bank's ESG impact, may be easier in developed countries. With more clients demonstrating strong ESG performance and banks having more advanced loan screening processes, including better risk assessment due to stricter regulations, banks in developed countries can afford to be more selective in their lending decisions and choose within a subset of clients with good ESG impact the least risky ones. This selectivity can potentially act as a risk-mitigation strategy which could explain the statistically significant relationship between ESG impact and credit risk in developed markets.

In contrast, when using a more efficient random effects estimator, supported by the Hausman test, the reverse dynamic may be present in emerging markets as estimation results for regression equation (1) in Table A8 in the Appendix shows statistically significant and positive coefficient estimates in three out of six models. In other words, as investing in ESG is not among the top priorities in countries with emerging markets, banks may face a trade-off relationship between ESG impact and credit risk.

Additionally, the financial determinants of credit risk in developed markets that show a statistically significant relationship with credit risk are liquidity and leverage, whereas capitalization exhibits statistically significant coefficient estimates in four out of six models that include banks based in countries with an emerging market. Profitability is statistically significant across all models for banks headquartered in both countries with developed and emerging markets. Similar results are also observed in the estimation results for regression equation (2) in Tables A11 and A12 in the Appendix.

6 CONCLUSION

Credit risk management is an important area for financial institutions, particularly banks, where credit risk remains one of the most significant challenges. To gain a deeper understanding, researchers have analysed credit risk using various statistical models to identify its key drivers, including dynamic and statis panel data models among others. In recent years, another factor has gained prominence in the lending decisions of individual banks due to the pressure from regulators and stakeholders: the ESG impact. This has introduced a new dimension to credit risk discussions. While sustainability initiatives, such as CSR, have been part of bank risk management for some time, ESG provides a more objective and measurable assessment of banks' impacts. The management of both credit risk and risk arising from banks' ESG impact, and the relationship between the two, is an important issue for banks and serves as the primary focus of this master's thesis.

Although research has been conducted in other sectors, such as private firms, there is a distinct literature gap for the relationship between ESG impact and credit risk in banks. Furthermore, there is a notable gap in the research concerning the credit risk and ESG-related topics for banks headquartered in the EU in contrast to banks headquartered in the EMU, as well as differences between banks headquartered in developed and emerging countries within the EU. By addressing these gaps, this master's thesis provides valuable insights and practical implications for various stakeholders. Banks can adjust their credit risk management strategies to incorporate sustainability factors, thereby improving their credit standing. Regulatory bodies introducing new legislation focused on financial disclosures and sustainability can gain a clearer understanding of the impact and how it should be tailored to different regions. Additionally, stakeholders such as borrowers and lenders can better understand the relationship between ESG scores and credit risk, and align their interests with the banks'.

This master's thesis explores the relationship between a bank's ESG impact and its credit risk by posing the following three research questions: How do bank specific ESG scores vary across countries, years, and bank sizes? Is there a trade-off between bank specific ESG scores and their credit risk, and what are the primary financial determinants of credit risk? Are there statistically significant differences in the effects of ESG scores on the credit risk of banks headquartered in EU, EMU, non-EMU member countries, and in developed and emerging countries within the EU? To address these questions, a comprehensive data on 87 EU headquartered banks was collected for the period spanning from 2014 to 2023. Data includes covers various ESG oriented metrics along with bank financials gathered from LSEG Workspace platform

6.1 Main findings

This subsection provides the main findings from addressing the three research questions. They are the following:

Research question 1: How do bank-specific ESG scores vary across countries, years, and bank sizes?

The main findings in response to the first research question regarding ESG score characteristics align with expectations. Data availability for bank-specific ESG scores improved from 2014, when 56 banks had ESG scores available on the LSEG Workspace platform, to 2023, where 87 banks had them. When analysing ESG scores based on the countries where banks are headquartered, Italy, Poland, and Spain stand out as having the most banks with ESG scores in both 2014 and 2023. In contrast, Slovenia, Slovakia, and Romania had no banks reporting ESG scores in 2014, and in 2023, Slovenia, Cyprus, and Belgium each had only one bank reporting ESG scores.

However, higher availability of ESG scores in a particular country does not always correspond to higher ESG scores. For instance, while Poland ranks second in ESG score availability in 2023, it is 12th in terms of the weighted average ESG score. Conversely, Slovenia, with the fewest banks reporting ESG scores, ranks 7th in terms of weighted average ESG score. When examining the overall movement of ESG and ESG combined scores, which are adjusted for negative media coverage of significant controversies, for the entire sample, additional patterns emerge. Both scores show improvement in terms of simple averages and weighted averages. Notably, the weighted average is consistently higher than the simple average, supporting the assumption that larger banks tend to have higher ESG scores (Cornett et al., 2016; Bătae et al., 2020). However, larger banks also experience greater discrepancies between regular and combined scores, indicating that media coverage of ESG scandals has a more significant and damaging impact on them. These findings highlight the growing importance of sustainability issues in the EU banking sector, particularly for larger banks.

Research question 2: Is there a trade-off between bank-specific ESG scores and credit risk, and what are the primary financial determinants of credit risk?

The second research question was by employing various static panel data models, in order to analyse the relationship between credit risk and ESG impact, as well as the financial determinants of credit risk for EU banks. The most important finding, with practical implications for banks, is the statistically significant and negative relationship between both types of ESG scores and all three credit risk metrics: NPL to loans, NPL to assets, and NPL to equity. In other words, no evident trade-off between ESG impact and credit risk is observed in the data, showcasing that there is no evident credit risk penalty if banks improve their ESG scores. In fact, our findings point to a reverse conclusion – better ESG impact might be a credit risk mitigating strategy. Looking at the individual scores of E, S and G, a statistically significant and negative relationship is evident with social and governance pillars and credit risk, while no such relationship is observed for the environmental pillar.

In terms of financial determinants of credit risk, profitability and liquidity consistently show statistically significant coefficients. The results suggest that higher ROAA, as a measure of profitability, and a higher cash-to-liabilities ratio, as a measure of liquidity, are both associated, on average, ceteris paribus, with lower credit risk. In contrast, cost efficiency does not exhibit a statistically significant relationship with credit risk in any model. Other financial determinants, capitalization, leverage, size, and loan growth, show mixed results in the estimations.

Research question 3: Are there significant differences in the effects of ESG scores on the credit risk of banks headquartered in EU, EMU, non-EMU member states, and in developed versus emerging EU countries?

The third research question addressed the relationship between credit risk, ESG impact, and financial determinants, with a focus on how these relationships vary across different economic and market regions. Firstly, exploring differences based on EMU, regression models were estimated for banks headquartered in the EU, the EMU, and banks headquartered in the EU but non-EMU. The results on the relationship between ESG impact and credit risk align with our original estimations from research question 2 for banks in the combined EU group and EMU subgroup, while no significant relationship was found for banks in non-EMU countries. Moreover, banks headquartered in EMU countries display similar results for financial determinants as those in the EU, while for banks based in non-EMU countries, cost efficiency is the only financial determinant with a statistically significant coefficient.

Secondly, the same analysis was conducted for banks in countries with developed and emerging markets within the EU, with the entire EU sample included for reference. Banks based in developed markets exhibit a statistically significant and negative relationship between ESG scores and the three NPL ratios representing credit risk, which aligns with the findings in research question 2, whereas a reversed relationship is found in some instances for banks based in emerging markets, showcasing a possible trade-off effect in emerging markets and a risk mitigating strategy in more developed markets. In terms of financial determinants of credit risk, profitability is a significant determinant for banks in both developed and emerging markets, liquidity and leverage are significant determinants only in developed countries, while capitalization shows statistically significant coefficient estimates only in emerging countries. The overall results imply that there are significant differences in credit risk determinants between countries with developed and emerging markets withing the EU.

6.2 Data limitations

The first data limitation encountered when constructing the database was the availability of ESG scores for EU banks. However, given that the ESG metric is a relatively new concept, this limitation was expected. Additionally, the robustness of the ESG metric provided by the LSEG Workspace comes into question, as several researchers have noted the divergence in ESG scores from different providers. Nevertheless, in the absence of regulatory standardization for ESG score computation, the LSEG Workspace scores are a suitable metric for analysis, while acknowledging their limitations and the potential implications.

Furthermore, the availability of ESG scores becomes even more restricted when dividing the EU into subgroups. The number of banks with ESG scores in non-EMU countries and those in emerging markets is considerably smaller compared to banks in EMU countries and developed markets. While this offers insight into the distribution of ESG data availability, as discussed in the first research question, it also limits the robustness of the estimation results derived from these models. Therefore, the same analysis should be conducted again once ESG score availability improves to ensure the validity of the results. Additionally, certain financial indicators, such as the net interest margin and liquidity coverage ratio, were constrained by data availability, highlighting the need for future research to focus on improving data access for these variables.

6.3 Areas of future research

First area for future research could focus on a deeper analysis of the reasons behind the discrepancies in the number of banks with available ESG scores across different EU countries and the actual values of those scores, since countries with a higher number of banks with the ESG scores available do not necessarily exhibit higher overall ESG scores. Investigating country-specific factors and other bank-specific determinants that contribute to this phenomenon could provide valuable insights into the characteristics of ESG scores, which may, in turn, enhance banks' decision-making processes.

The second area of future research could examine the relationship between credit risk and other financial determinants not included in this master's thesis, such as macroeconomic factors. These determinants, as suggested by existing literature, play an important role and should be explored further to understand how they fit within the context of credit risk and the ESG impact of banks.

The third area for future research could focus on the causality of the relationship between credit risk and ESG scores, an important yet under-researched issue. Understanding the extent to which these two factors influence each other is important for banks, as it can help them better adjust their risk management strategies and respond to regulatory pressures. Additionally, future research could explore the causal relationships between credit risk and the individual E, S and G pillar, to gain deeper insights into the specific drivers behind these relationships.

REFERENCE LIST

1. Ahmad, N. H., & Ariff, M. (2008). Multi-country study of bank credit risk determinants. *International Journal of banking and Finance, 5*(1), 135-152.

2. Albaity, M., Mallek, R. S., & Noman, A. H. M. (2019). Competition and bank stability in the MENA region: The moderating effect of Islamic versus conventional banks. *Emerging Markets Review*, *38*, 310-325.

3. Alnabulsi, K., Kozarević, E., & Hakimi, A. (2022). Assessing the determinants of non-performing loans under financial crisis and health crisis: Evidence from the MENA banks. *Cogent Economics & Finance*, *10*(1), 2124665.

4. Altman, E. I. (2002). Managing credit risk: A challenge for the new millennium. *Economic Notes*, *31*(2), 201-214.

5. Alzoubi, T., & Obeidat, M. (2020). How size influences the credit risk in Islamic banks. *Cogent business & management*, *7*(1), 1811596.

6. Andruszkiewicz, K., Grzybowska-Brzezińska, M., Grzywińska-Rąpca, M., & Wiśniewski, P. D. (2023). Attitudes and Pro-Environmental Behavior of Representatives of Generation Z from the Example of Poland and Germany. *Sustainability*, *15*(20), 15068.

7. Arons S., Matussek K., & Comfort N. (2022, May 31). Deutsche Bank's DWS unit raided amid allegations of greenwashing. *Bloomberg.* https://www.bloomberg.com/news/articles/2022-05-31/deutsche-bank-s-dws-unit-raided-amid-allegations-of-greenwashing

8. Azmi, W., Hassan, M. K., Houston, R., & Karim, M. S. (2021). ESG activities and banking performance: International evidence from emerging economies. *Journal of International Financial Markets, Institutions and Money*, *70*, 101277.

9. Balcerzak, A. P., MacGregor, R. K., Pelikánová, R. M., Rogalska, E., & Szostek, D. (2023). The EU regulation of sustainable investment: The end of sustainability trade-offs?. *Entrepreneurial Business and Economics Review*, *11*(1), 199-212.

10. Bătae, O. M., Dragomir, V. D., & Feleagă, L. (2020). Environmental, social, governance (ESG), and financial performance of European banks. *Accounting and Management Information Systems*, *19*(3), 480-501.

11. Berger, A. N., & DeYoung, R. (1997). Problem loans and cost efficiency in commercial banks. *Journal of banking & finance*, *21*(6), 849-870.

12. Bowers, S. (2020, October 16). German prosecutors drop probe into Deutsche Bank ties to Estonian dirty money scandal. *International Consortium of Investigative Journalists.* https://www.icij.org/investigations/fincen-files/german-prosecutors-drop-probe-into-deutsche-bank-ties-to-estonian-dirty-money-scandal/

13. Buallay, A. (2019). Is sustainability reporting (ESG) associated with performance? Evidence from the European banking sector. *Management of Environmental Quality: An International Journal*, *30*(1), 98-115.

14. Buallay, A., Fadel, S. M., Al-Ajmi, J. Y., & Saudagaran, S. (2020). Sustainability reporting and performance of MENA banks: is there a trade-off?. *Measuring Business Excellence*, *24*(2), 197-221.

15. Buallay, A., Fadel, S. M., Alajmi, J., & Saudagaran, S. (2021). Sustainability reporting and bank performance after financial crisis: evidence from developed and developing countries. *Competitiveness Review: An International Business Journal*, *31*(4), 747-770.

16. Budnik, K., Dimitrov, I., Groß, J., Kusmierczyk, P., Lampe, M., Vagliano, G., & Volk, M. (2022). *The economic impact of the NPL coverage expectations in the euro area* (No. 297). ECB Occasional Paper.

17. Busch, D. (2022). The future of EU financial law. *Capital markets law journal*, *17*(1), 52-94.

18. Castro, V. (2013). Macroeconomic determinants of the credit risk in the banking system: The case of the GIPSI. *Economic Modelling*, *31*, 672-683.

19. Chaibi, H., & Ftiti, Z. (2015). Credit risk determinants: Evidence from a cross-country study. *Research in international business and finance*, *33*, 1-16.

20. Chiaramonte, L., Dreassi, A., Girardone, C., & Piserà, S. (2022). Do ESG strategies enhance bank stability during financial turmoil? Evidence from Europe. *The European Journal of Finance*, *28*(12), 1173-1211.

21. Chodnicka-Jaworska, P. (2021). ESG as a Measure of Credit Ratings. *Risks*, *9*(12), 226

22. Cini, A. C., & Ricci, C. (2018). CSR as a Driver where ESG Performance will Ultimately Matter. *Symphonya. Emerging Issues in Management*, *1*(1), 68-75.

23. Cochran, I., Mackenzie, C., & Brander, M. (2024). EU's sustainable finance disclosure regulation: does the hybrid reporting regime undermine the goal to reorient capital to climate action? *Climate Policy*, 1–13. https://doi.org/10.1080/14693062.2024.2353115

24. Cornett, M. M., Erhemjamts, O., & Tehranian, H. (2016). Greed or good deeds: An examination of the relation between corporate social responsibility and the financial performance of US commercial banks around the financial crisis. *Journal of Banking & Finance*, *70*(1), 137-159.

25. Cremasco, C., & Boni, L. (2022). Is the European Union (EU) Sustainable Finance Disclosure Regulation (SFDR) effective in shaping sustainability objectives? An

analysis of investment funds' behaviour. *Journal of Sustainable Finance & Investment*, *14*(4), 1018–1036.

26. Danisman, G. O., & Tarazi, A. (2024). ESG activity and bank lending during financial crises. *Journal of Financial Stability*, *70*, 101206.

27. Dathe, T., Helmold, M., Dathe, R., & Dathe, I. (2024). ESG Stakeholders. In *Implementing Environmental, Social and Governance (ESG) Principles for Sustainable Businesses: A Practical Guide in Sustainability Management* (pp. 113-131). Cham: Springer International Publishing.

28. De Groen, W. (2014). Was the ECB's Comprehensive Assessment up to Standard?. *CEPS Policy Briefs*, (325).

29. Di Tommaso, C., & Thornton, J. (2020). Do ESG scores effect bank risk taking and value? Evidence from European banks. *Corporate Social Responsibility and Environmental Management*, *27*(5), 2286-2298.

30. Dimson, E., Marsh, P., & Staunton, M. (2020). Divergent ESG ratings. *The Journal of Portfolio Management*, *47*(1), pp. 75-86

31. European Commission. (2010). *Europe 2020: A strategy for smart, sustainable and inclusive growth: Communication from the commission.* Publications Office of the European Union. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52010DC2020

32. Eurostat. (n.d.). *Non-performing loans. European Economy* [Fact sheet]. European Commission. https://ec.europa.eu/eurostat/cache/digpub/european_economy/bloc-3d.html?lang=en

33. Freeman, R. E. (2010). *Strategic management: A stakeholder approach*. Cambridge university press.

34. FTSE Russell. (2023). *FTSE country classification update*. London Stock Exchange Group. https://www.lseg.com/content/dam/ftse-russell/en_us/documents/country-classification/ftse-country-classification-update-latest.pdf

35. Gottenhuber, S., & Mulholland, E. (2020). Implementing the sustainable development goals in times of rising right-wing populism in Europe. *Sustainability*, *12*(20), 8465.

36. Henisz, W. J., & McGlinch, J. (2019). ESG, material credit events, and credit risk. *Journal of Applied Corporate Finance*, *31*(2), 105-117

37. Houston, J. F., & Shan, H. (2022). Corporate ESG profiles and banking relationships. *The Review of Financial Studies*, *35*(7), 3373-3417.

38. Iyer, R., Peydró, J. L., da-Rocha-Lopes, S., & Schoar, A. (2014). Interbank liquidity crunch and the firm credit crunch: Evidence from the 2007–2009 crisis. *The Review of Financial Studies*, *27*(1), 347-372.

39. Izcan, D., & Bektas, E. (2022). The relationship between ESG scores and firm-specific risk of Eurozone banks. *Sustainability*, *14*(14), 8619.

40. Jassaud, N., & Vidon, E. (2017). European NPLs through the crisis: a policy review. *Journal of Financial Regulation and Compliance*, *25*(4), 413-421.

41. Jiraporn, P., & Chintrakarn, P. (2013). How do powerful CEOs view corporate social responsibility (CSR)? An empirical note. *Economics Letters*, *119*(3), 344-347.

42. Jiraporn, P., Jiraporn, N., Boeprasert, A., & Chang, K. (2014). Does corporate social responsibility (CSR) improve credit ratings? Evidence from geographic identification. *Financial management*, *43*(3), 505-531.

43. Jorion, P. (2009). Risk management lessons from the credit crisis. *European Financial Management*, *15*(5), 923-933.

44. Kasinger, J., Krahnen, J. P., Ongena, S., Pelizzon, L., Schmeling, M., & Wahrenburg, M. (2021). *Non-performing loans-new risks and policies? NPL resolution after COVID-19: Main differences to previous crises* [White paper, No. 84]. Leibniz Institute for Financial Research SAFE, Frankfurt a. M.

45. Kattel, I. K. (2014). Evaluating the financial solvency of selected commercial banks of Nepal: An application of bankometer. *Journal of Advanced Academic Research*, *1*(1), 88-95.

46. Kaźmierczak, M. (2022). A literature review on the difference between CSR and ESG. *Scientific Papers of Silesian University of Technology.* Organ. Manag. Ser. 162, 291–314.

47. Lee, C. C., & Hsieh, M. F. (2014). Bank reforms, foreign ownership, and financial stability. *Journal of International Money and Finance*, *40*, 204-224.

48. Li, H., Zhang, X., & Zhao, Y. (2022). ESG and firm's default risk. *Finance Research Letters*, *47*, 102713.

49. Li, J., & Zinna, G. (2018). How much of bank credit risk is sovereign risk? Evidence from Europe. *Journal of Money, Credit and Banking*, *50*(6), 1225-1269.

50. Li, T. T., Wang, K., Sueyoshi, T., & Wang, D. D. (2021). ESG: Research progress and future prospects. *Sustainability, 13*(21), 11663.

51. Louzis, D. P., Vouldis, A. T., & Metaxas, V. L. (2012). Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios. *Journal of banking & finance, 36*(4), 1012-1027.

52. LSEG Data and Analytics (2023) *Environmental, social and governance scores from LSEG.* https://www.lseg.com/content/dam/data-analytics/en_us/documents/methodology/lseg-esg-scores-methodology.pdf

53. Makri, V., Tsagkanos, A., & Bellas, A. (2014). Determinants of non-performing loans: The case of Eurozone. *Panoeconomicus*, *61*(2), 193-206.

54. Munangi, E., & Sibindi, A. B. (2020). An empirical analysis of the impact of credit risk on the financial performance of South African banks. *Academy of Accounting and Financial Studies Journal*, *24*(3), 1-15.

55. Naili, M., & Lahrichi, Y. (2022). The determinants of banks' credit risk: Review of the literature and future research agenda. *International Journal of Finance & Economics*, *27*(1), 334-360.

56. Neitzert, F., & Petras, M. (2022). Corporate social responsibility and bank risk. *Journal of Business Economics*, *92*(3), 397-428.

57. Odobaša, R., & Marošević, K. (2023). Expected contributions of the European corporate sustainability reporting directive (CSRD) to the sustainable development of the European union. *EU and comparative law issues and challenges series, 7*, 593-612.

58. Ozili, P. K. (2019). Non-performing loans and financial development: new evidence. *The Journal of Risk Finance*, *20*(1), 59-81.

59. Petria, N., Capraru, B., & Ihnatov, I. (2015). Determinants of banks’ profitability: evidence from EU 27 banking systems. *Procedia economics and finance*, *20*, 518-524.

60. Platonova, E., Asutay, M., Dixon, R., & Mohammad, S. (2018). The impact of corporate social responsibility disclosure on financial performance: Evidence from the GCC Islamic banking sector. *Journal of business ethics*, *151*, 451-471.

61. Russo, M. V., & Fouts, P. A. (1997). A resource-based perspective on corporate environmental performance and profitability. *Academy of management Journal*, *40*(3), 534-559.

62. Salas, V., & Saurina, J. (2002). Credit risk in two institutional regimes: Spanish commercial and savings banks. *Journal of financial services research*, *22*(3), 203-224.

63. Samaniego-Medina, R., & Giráldez-Puig, P. (2022). Do sustainability risks affect credit ratings? Evidence from European banks. *Amfiteatru Economic*, *24*(61), 720-738.

64. Saravia, F. (2023). *Banking in Europe: EBF Facts & Figures 2022* [Fact sheet]. European Banking Federation. https://www.ebf.eu/wp-content/uploads/2023/05/Banking-in-Europe-EBF-Facts-and-Figures-2022.-Updated-2023.pdf

65. Sinkey Jr, J. F., & Greenawalt, M. B. (1991). Loan-loss experience and risk-taking behavior at large commercial banks. *Journal of Financial services research, 5*(1), 43-59.

66. Sköld, S., & Wassberg, M. (2023). *ESG Rating Divergence & Portfolio Consequences of Relying on a Single Rating Provider - A study conducted on companies in the Nordic region* (Dissertation). https://urn.kb.se/resolve?urn=urn:nbn:se:hj:diva-60561

67. Skrabic Peric, B., & Konjusak, N. (2017). How did rapid credit growth cause non-performing loans in the CEE countries?. *South East European Journal of Economics and Business*, *12*(2), 73-84.

68. Staroverova, M. (2022). The Impact of ESG Controversies on Bank Value and Risk-Taking. *Корпоративные финансы*, *16*(3), 5-29.

69. Steffen, S. (2014). *Robustness, validity, and significance of the ECB's asset quality review and stress test exercise* (SAFE White Paper No. 23). Goethe University Frankfurt, SAFE - Sustainable Architecture for Finance in Europe.

70. Thiagarajan, S., Ayyappan, S., & Ramachandran, A. (2011). Credit risk determinants of public and private sector banks in India. *European Journal of Economics, Finance and Administrative Sciences*, *34*(34), 147-153.

71. United Nations Global Compact & UNEP Finance Initiative. (2004). *Who Cares Wins: Connecting Financial Markets to a Changing World.* https://www.unepfi.org/fileadmin/events/2004/stocks/who_cares_wins_global_compact_2004.pdf

72. Vithessonthi, C. (2016). Deflation, bank credit growth, and non-performing loans: Evidence from Japan. *International review of financial analysis*, *45*, 295-305.

73. Wu, M. W., & Shen, C. H. (2013). Corporate social responsibility in the banking industry: Motives and financial performance. *Journal of Banking & Finance, 37*(9), 3529-3547.

74. Zhang, D., Cai, J., Dickinson, D. G., & Kutan, A. M. (2016). Non-performing loans, moral hazard and regulation of the Chinese commercial banking system. *Journal of Banking & finance*, *63*, 48-60.

APPENDICES

Appendix 1: Povzetek (Summary in Slovene language)

Obvladovanje kreditnega tveganja je ena od primarnih nalog bank in bančnega sistema kot celote. Finančna kriza iz leta 2008 dokazuje, da so strožji standardi glede kreditnega tveganja potrebni za izboljšanje stabilnosti bančnega sistema in preprečevanje prihodnjih kriz (Jassaud in Vidon, 2017; Alnabulsi in drugi, 2022). Za določitev ustreznih regulatornih ukrepov in posledično tehnik upravljanja kreditnega tveganja za banke je potrebno identificirati dejavnike kreditnega tveganja in oceniti njihov vpliv.

Poleg kreditnega tveganja postajajo vprašanja vezana na okolje, družbo in upravljanje (ESG) vse bolj aktualna. Z nenehnim uvajanjem novih predpisov glede trajnosti v Evropski uniji (EU) se povečuje preglednost pri razkritju informacij povezanih s trajnostjo v finančnem sektorju. Poleg povečanega pritiska s strani regulatorjev, se lahko banke z nižjimi ESG ocenami soočijo tudi z večjim kreditnim tveganjem, ker v skladu s teorijo deležnikov pritegnejo nezaželene stranke (Dathe in drugi, 2024). ESG ocene bank tudi neposredno vplivajo na njihova kreditna tveganja, saj obstaja visoka verjetnost, da bodo banke posojale strankam s podobnim ESG profilom (Houston in Shan, 2022). Tako postaja povezava med ESG ocenami bank in njihovim kreditnim tveganjem vse pomembnejša, kar poudarja potrebo po nadaljnjih raziskavah.

Čeprav so bile raziskave izvedene v drugih sektorjih, na primer med zasebnimi podjetji (Henisz in McGlinch, 2019; Chodnicka-Jaworska, 2021), ostaja bančni sektor premalo raziskan glede povezave med ESG ocenami in kreditnim tveganjem. Obstoječe raziskave o vplivu ESG ocen v bančništvu se osredotočajo predvsem na bilančno vrednost banke, pri čemer običajno preučujejo vpliv ESG ocen na tržno ceno delnic in dobičkonosnost bank (Azmi in drugi, 2021; Cornett in drugi, 2016; Di Tommaso in Thornton, 2020; Staroverova, 2022). V raziskavah je mogoče opaziti izrazito pomanjkanje preučevanja kreditnega tveganja in vprašanj povezanih s trajnostjo, med bankami s sedežem v EU, tistimi s sedežem v Ekonomski in monetarni uniji (EMU) in tistimi v EU ne pa EMU. Podobno pomanjkanje raziskav obstaja tudi med bankami, ki imajo sedež v razvitih državah ter tistimi iz razvijajočih trgov znotraj EU.

Za naslovitev tem, ki so manj raziskane v obstoječi literaturi, to magistrsko delo raziskuje povezavo med ESG vplivom bank in njihovim kreditnim tveganjem z zastavljanjem naslednjih treh raziskovalnih vprašanj: Kako se ESG ocene posameznih bank razlikujejo glede na države, leta in velikosti bank? Ali obstaja kompromis med ESG ocenami bank in njihovim kreditnim tveganjem ter katere so glavne finančne determinante kreditnega tveganja? Ali obstajajo pomembne razlike v razmerju med ESG ocenami in kreditnim tveganjem bank s sedežem v EU, EMU, državah nečlanicah EMU ter v razvitih državah in državah v vzponu znotraj EU?

Za odgovore na ta vprašanja so bili zbrani podatki o 87 bankah s sedežem v EU za obdobje od 2014 do 2023, pridobljeni iz LSEG Workspace platforme. Kot ponudnik finančnih podatkov LSEG Workspace ponuja tudi obsežno pokritost ESG ocen tako za javne kot zasebne entitete (LSEG Data and Analytics, 2023). Merilo za izbiro 87 bank, vključenih v nabor podatkov, je razpoložljivost ESG ocen za zadnje leto, torej za leto 2023. Poleg ESG ocen je analiza vključevala tudi kombinirane ocene ESG (ESGC). Slednje upoštevajo medijsko pomembne škandale, ki vplivajo na ESG profil bank. Omeniti velja, da ESGC ocene predstavljajo prilagoditev rezultatov ESG samo navzdol, kar pomeni, da ESG škandali negativno vplivajo na standardne ocene.

Pri prvem raziskovalnem vprašanju je bila izvedena analiza trendov ESG in ESGC ocen za obdobje od 2014 do 2023 kot tudi analiza ocen za posamezne trajnostne stebre E, S in G. Metodološko so bile uporabljene preproste statistične tehnike in tehtana povprečja na podlagi velikosti bank. Za analizo kompleksne povezave med ESG ocenami, finančnimi determinantami ter kreditnim tveganjem bank je bil ocenjen regresijski model s fiksnimi učinki. Za odgovor na tretje raziskovalno vprašanje je bil ocenjen enak regresijski model ločen na dveh podskupinah bank glede na distinkcijo vključenosti držav v EMU in razvitostjo trga v državah, v katerih so bazirane banke. Veljavnost uporabe regresijskega modela s fiksnimi učinki namesto regresijskega modela z naključnimi učinki je bila podkrepljena s Hausmanovim testom. Glavne ugotovitve:

Raziskovalno vprašanje 1: Kako se ESG ocene posameznih bank razlikujejo glede na države, leta in velikosti bank?

Ugotovitve so v skladu s pričakovanji. Razpoložljivost podatkov ESG ocen za posamezne banke se je izboljšala od leta 2014, ko je bilo na platformi LSEG Workspace na voljo 56 bank z ESG ocenami, do leta 2023, ko jih je bilo na voljo 87. Pri analizi rezultatov ESG glede na države v katerih imajo banke sedeže, izstopajo Italija, Poljska in Španija, ki imajo največ bank z ESG ocenami v letih 2014 in 2023. V nasprotju Slovenija, Slovaška in Romunija leta 2014 niso imele bank, ki bi poročale o ESG ocenah, v letu 2023 pa so imele Slovenija, Ciper in Belgija le po eno banko, ki je poročala o ESG ocenah.

Zanimivo je, da višja razpoložljivost ESG ocen v določeni državi ne pomeni nujno višjo povprečno ESG oceno. Na primer, medtem ko je Poljska leta 2023 na drugem mestu po razpoložljivosti ocen, je dvanajstem mestu glede na tehtano povprečje ocen. Na drugi strani pa je Slovenija z najmanj bankami, ki imajo ESG oceno, na sedmem mestu glede na tehtano povprečje ESG ocen. Pri preučevanju splošnega gibanja ESG in ESGC ocen za celoten vzorec se pokažejo dodatni vzorci. Rezultati kažejo na izboljšanje preprostih in tehtanih povprečij ocen. Predvsem je tehtano povprečje dosledno višje od preprostega povprečja, kar podpira domnevo, da imajo večje banke običajno višje ESG ocene (Cornett in drugi, 2016; Bătae in drugi, 2020). Te ugotovitve poudarjajo vse večji pomen vprašanj trajnosti v bančnem sektorju EU, zlasti za večje banke.

Raziskovalno vprašanje 2: Ali obstaja kompromis med ESG ocenami bank in njihovim kreditnim tveganjem ter katere so glavne finančne determinante kreditnega tveganja?

Drugo raziskovalno vprašanje je bilo naslovljeno z uporabo različnih ekonometričnih panelnih podatkovnih modelov. Najpomembnejša ugotovitev je statistično značilno in negativno razmerje med obema vrstama ESG ocen in vsemi tremi metrikami kreditnega tveganja: deležem slabih posojil (NPL) v bruto posojilih, deležem NPL v celotnih sredstvih in deležem NPL v celotnem lastniškem kapitalu. Z drugimi besedami, v podatkih ni opaziti nobenega očitnega kompromisa med kreditnim tveganjem in višjimi ESG ocenami. Pravzaprav ugotovitve kažejo na obraten zaključek – boljši vpliv ESG je lahko strategija za zmanjševanje kreditnega tveganja. Če pogledamo posamezne E, S in G ocene, je razvidna statistično značilna in negativna povezava s socialnim (S) in upravljavskim (G) stebrom ter kreditnim tveganjem, medtem ko pri okoljskem (E) stebru takšne povezave ni.

Kar zadeva finančne determinante kreditnega tveganja, donosnost in likvidnost dosledno izkazujeta statistično značilne koeficiente. Rezultati kažejo, da sta višja donosnost na povprečna sredstva (ROAA) kot merilo donosnosti in višje razmerje deleža denarja napram obveznostim kot merilo likvidnosti v povprečju, ceteris paribus, povezana z nižjim kreditnim tveganjem. Nasprotno pa stroškovna učinkovitost v nobenem modelu ne kaže statistično značilne povezave s kreditnim tveganjem. Druge finančne determinante, kapitalizacija, zadolženost, velikost banke in rast posojil kažejo mešane rezultate.

Raziskovalno vprašanje 3: Ali obstajajo pomembne razlike v razmerju med ESG ocenami in kreditnim tveganjem bank s sedežem v EU, EMU, državah nečlanicah EMU ter v razvitih državah in državah v vzponu znotraj EU?

Tretje raziskovalno vprašanje je obravnavalo razmerje med kreditnim tveganjem, vplivom ESG in finančnimi dejavniki s poudarkom na tem, kako se ta razmerja razlikujejo v različnih gospodarskih in tržnih regijah. Najprej so bili za namen raziskovanje razlik na podlagi vključenosti v EMU ocenjeni regresijski modeli za banke s sedežem v EU, EMU in banke s sedežem v EU, ne v EMU. Rezultati o povezavi med vplivom ESG in kreditnim tveganjem se ujemajo s prvotnimi ugotovitvami iz drugega raziskovalnega vprašanja za banke v združeni skupini EU in podskupini EMU, medtem ko za banke v državah, ki niso članice EMU, ni bilo ugotovljenega statistično značilnega razmerja med ESG ocenami in kreditnim tveganjem. Poleg tega kažejo banke s sedežem v državah EMU podobne rezultate glede finančnih determinant kot tiste v EU, medtem ko je za banke s sedežem v državah zunaj EMU stroškovna učinkovitost edina finančna determinanta s statistično značilnim koeficientom.

Enaka analiza je bila izvedena za banke v državah z razvitimi in nastajajočimi trgi znotraj EU, pri čemer je bil za referenco vključen celoten vzorec bank v EU. Banke s sedežem v državah z razvitimi trgih kažejo statistično značilno in negativno razmerje med rezultati ESG in tremi deleži NPL, ki predstavljajo kreditno tveganje, kar je v skladu z ugotovitvami drugega raziskovalnega vprašanja, medtem ko je obratno razmerje v nekaterih primerih ugotovljeno za banke s sedežem v državah s trgi v razvoju. Ti dve ugotovitvi nakazujeta na obstoj kompromisa pri bankah, ki nastopajo na trgih v razvoju in pa potencialne strategije za zmanjševanje tveganja pri bankah na razvitih trgih. Kar zadeva finančne determinante kreditnega tveganja, je donosnost pomembna determinanta za banke tako na razvitih trgih kot na trgih v razvoju, likvidnost in zadolženost pa sta pomembni determinanti le v razvitih državah, medtem ko kapitalizacija kaže statistično značilne ocene koeficientov le v državah v vzponu. Skupni rezultati kažejo, da obstajajo znatne razlike v determinantah kreditnega tveganja med državami z razvitimi trgi in trgi v vzponu znotraj EU.

Analiza podatkov tekom celotnega magistrskega dela ima seveda par pomembnih omejitev, ki jih je potrebno upoštevati. Prva podatkovna omejitev pri ustvarjanju baze podatkov je bila razpoložljivost ESG ocen za banke v EU, kar je popolnoma pričakovano, saj je metrika ESG razmeroma nova. Vprašljiva je tudi robustnost te metrike, ki jo ponuja LSEG Workspace, saj raziskovalci opažajo razlike v rezultatih med različnimi ponudniki. ESG ocene LSEG so kljub odsotnosti regulativne standardizacije ob zavedanju njihovih omejitev še vedno ustrezna metrika za analizo. Razpoložljivost ESG ocen postane še bolj omejena, ko EU razdelimo na podskupine, saj je število bank z ESG ocenami v državah zunaj EMU in na trgih v razvoju precej manjše kot v EMU in razvitih trgih. To omejuje robustnost rezultatov iz teh modelov, kar nakazuje na potrebo po ponovnem pregledu analize ob izboljšani razpoložljivosti rezultatov ESG, za kar bo verjetno potrebno še par let.

Tekom nastajanja magistrskega dela se je pojavilo tudi nekaj tem, ki bi jih bilo dobro nasloviti v prihodnjem raziskovalnem delu. Tako bi se lahko prihodnje raziskave lahko osredotočile na več ključnih področij. Prvo področje bi lahko preučilo razloge za razlike v številu bank z razpoložljivimi ESG ocenami v različnih državah EU in njihove dejanske vrednosti, saj države z več bankami ne dosegajo nujno višje skupne ocene. Drugo področje bi lahko obravnavalo razmerje med kreditnim tveganjem in drugimi finančnimi dejavniki, kot so makroekonomski dejavniki, ki niso vključeni v to magistrsko delo. Razumevanje teh determinant bi bilo ključno za kontekst kreditnega tveganja in vpliva ESG. Tretje področje bi se lahko osredotočilo na vzročnost razmerja med kreditnim tveganjem in rezultati ESG, saj bi razumevanje njihove medsebojne povezanosti bankam omogočilo boljše prilagajanje strategij upravljanja tveganj in odzivanje na regulatorne pritiske. Poleg tega bi raziskave lahko raziskale vzročne povezave med kreditnim tveganjem in posameznimi stebri E, S in G, kar bi prineslo globlji vpogled v specifične dejavnike teh povezav.

Appendix 2: Robustness checks

Table A1: Estimation results for regression equations (2) and (3) - random effects

	(1) NPLToLoans	(2) NPLToAssets	(3) NPLToAssets
ROAA	**-4.470*** **	**-3.770*** **	**-3.802*** **
	(0.906)	**(0.930)**	**(0.958)**
EquityToAssets	**1.521*** **	**1.268** **	**1.232** **
	(0.443)	**(0.392)**	**(0.433)**
CashToLiabilities	**-0.274** **	**-0.202** **	**-0.211** **
	(0.091)	**(0.069)**	**(0.068)**
DebtToAssets	-0.008	0.009	0.019
	(0.055)	(0.041)	(0.049)
lnAssets	0.002	0.001	0.001
	(0.005)	(0.005)	(0.005)
OpexToOperatingProfit	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
growth	-0.057	-0.033	-0.034
	(0.029)	(0.018)	(0.018)
ESGC			-0.000
			(0.000)
Constant	-0.046	-0.030	-0.033
	(0.160)	(0.139)	(0.147)
Hausman test			
χ^2	12.08	11.70	13.90
p value	0.060	0.069	0.053
Observations	388	388	368
Number of Banks	63	63	60

*Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. All models include random effects.*

Source: Own work.

Table A2: Estimation results for regression equation (1) using ROAE as profitability variable

	(1) NPLToLoans	(2) NPLToLoans	(3) NPLToLoans	(1) NPLToAssets	(2) NPLToAssets	(3) NPLToAssets	(1) NPLToEquity	(2) NPLToEquity	(3) NPLToEquity
ROAE	**-0.420*****	**-0.351*****	**-0.382*****	**-0.326*****	**-0.286*****	**-0.304*****	**-4.006*****	**-3.357*****	**-3.659*****
	(0.064)	**(0.064)**	**(0.064)**	**(0.064)**	**(0.065)**	**(0.065)**	**(0.644)**	**(0.554)**	**(0.586)**
EquityToAssets	0.739	0.523	0.487	0.925*	0.786	0.764	-4.580	-7.473	-7.773
	(0.517)	(0.576)	(0.588)	(0.444)	(0.502)	(0.508)	(4.515)	(4.608)	(4.640)
CashToLiabilities	**-0.356****	**-0.319****	**-0.366****	**-0.260****	**-0.239****	**-0.268****	**-3.205*****	**-2.815****	**-3.247*****
	(0.103)	**(0.110)**	**(0.107)**	**(0.078)**	**(0.081)**	**(0.080)**	**(0.870)**	**(0.828)**	**(0.870)**
DebtToAssets	0.255	**0.270***	**0.327***	0.174	0.186	0.220	3.698	4.307	4.830
	(0.135)	**(0.135)**	**(0.151)**	(0.099)	(0.105)	(0.113)	(2.323)	(2.573)	(2.727)
lnAssets	0.027	**0.075***	0.043	0.026	**0.054***	0.034	0.204	0.625	0.318
	(0.027)	**(0.036)**	(0.031)	(0.020)	**(0.024)**	(0.022)	(0.302)	(0.367)	(0.320)
ESG		**-0.002***			**-0.001***			**-0.018****	
		(0.001)			**(0.000)**			**(0.006)**	
ESGC			**-0.001***			**-0.001***			**-0.009***
			(0.000)			**(0.000)**			**(0.003)**
Constant	-0.658	-1.769	-0.992	-0.662	**-1.306***	-0.844	-4.238	-13.921	-6.619
	(0.730)	(0.925)	(0.825)	(0.542)	**(0.623)**	(0.591)	(7.932)	(9.388)	(8.396)
R-squared	0.28	0.32	0.31	0.36	0.39	0.38	0.34	0.41	0.39
Observations	435	410	410	435	410	410	435	410	410
Number of Banks	63	60	60	63	60	60	63	60	60

*Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. All models include fixed effects.*

Source: Own work.

Table A3: Estimation results for regression equation (1) using net interest margin as profitability variable

	(1) NPLToLoans	(2) NPLToLoans	(3) NPLToLoans	(1) NPLToAssets	(2) NPLToAssets	(3) NPLToAssets	(1) NPLToEquity	(2) NPLToEquity	(3) NPLToEquity
InterestMargin	**0.000*** **	**0.000*** **	**0.000*** **	0.000	0.000	0.000	0.001	**0.001***	**0.001***
	(0.000)	**(0.000)**	**(0.000)**	(0.000)	(0.000)	(0.000)	(0.001)	**(0.001)**	**(0.001)**
EquityToAssets	0.897	0.751	0.749	0.802	0.695	0.694	0.168	-1.236	-1.266
	(0.540)	(0.518)	(0.532)	(0.413)	(0.401)	(0.413)	(4.267)	(4.150)	(4.310)
CashToLiabilities	**-0.361****	**-0.338***	**-0.357****	**-0.271****	**-0.253****	**-0.268****	**-2.927****	**-2.656****	**-2.850****
	(0.125)	**(0.126)**	**(0.126)**	**(0.086)**	**(0.087)**	**(0.087)**	**(0.848)**	**(0.854)**	**(0.850)**
DebtToAssets	0.075	0.062	0.113	0.095	0.080	0.120	1.475	1.313	1.824
	(0.122)	(0.117)	(0.117)	(0.104)	(0.101)	(0.102)	(1.285)	(1.252)	(1.283)
lnAssets	-0.011	0.016	0.004	-0.007	0.014	0.005	-0.196	0.066	-0.051
	(0.028)	(0.030)	(0.028)	(0.020)	(0.021)	(0.020)	(0.192)	(0.185)	(0.186)
ESG		**-0.001***			**-0.001***			**-0.010***	
		(0.000)			**(0.000)**			**(0.004)**	
ESGC			**-0.001***			**-0.001***			**-0.007***
			(0.000)			**(0.000)**			**(0.003)**
Constant	0.298	-0.319	-0.048	0.175	-0.302	-0.087	5.646	-0.329	2.394
	(0.737)	(0.782)	(0.751)	(0.539)	(0.551)	(0.537)	(5.150)	(4.840)	(4.956)
R-squared	0.17	0.19	0.19	0.19	0.22	0.21	0.17	0.21	0.20
Observations	288	276	276	288	276	276	288	276	276
Number of Banks	55	52	52	55	52	52	55	52	52

*Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. All models include fixed effects.*

Source: Own work.

Table A4: Estimation results for regression equation (1) using Liquidity Coverage ratio as a measure of liquidity

	(1) NPLToLoans	(2) NPLToLoans	(3) NPLToLoans	(1) NPLToAssets	(2) NPLToAssets	(3) NPLToAssets	(1) NPLToEquity	(2) NPLToEquity	(3) NPLToEquity
ROAA	**-5.862****	**-4.891***	**-5.285****	**-4.250****	**-3.576***	**-3.845****	**-53.980****	**-44.505***	**-48.366****
	(1.935)	**(1.988)**	**(1.939)**	**(1.336)**	**(1.371)**	**(1.343)**	**(17.685)**	**(18.036)**	**(17.644)**
EquityToAssets	0.169	0.153	0.176	0.181	0.170	0.187	-4.622	-4.745	-4.502
	(0.699)	(0.646)	(0.699)	(0.506)	(0.470)	(0.506)	(6.668)	(6.070)	(6.577)
LiquidityCoverage Ratio	-0.008	-0.008	-0.009	-0.006	-0.005	-0.006	-0.067	-0.057	-0.070
	(0.007)	(0.014)	(0.013)	(0.005)	(0.009)	(0.008)	(0.057)	(0.111)	(0.102)
DebtToAssets	**0.385***	**0.351***	**0.408***	**0.277***	**0.253***	**0.293***	**3.472***	**3.083***	**3.661***
	(0.177)	**(0.157)**	**(0.163)**	**(0.126)**	**(0.109)**	**(0.115)**	**(1.656)**	**(1.397)**	**(1.489)**
lnAssets	-0.059	-0.015	-0.049	-0.041	-0.011	-0.034	-0.670	-0.237	-0.577
	(0.043)	(0.036)	(0.037)	(0.031)	(0.026)	(0.026)	(0.432)	(0.345)	(0.369)
ESG		**-0.002***			**-0.001***			**-0.018***	
		(0.001)			**(0.001)**			**(0.008)**	
ESGC			**-0.001***			**-0.001***			**-0.008***
			(0.000)			**(0.000)**			**(0.004)**
Constant	1.565	0.542	1.355	1.083	0.371	0.941	18.153	8.033	16.199
	(1.169)	(0.989)	(1.021)	(0.838)	(0.702)	(0.729)	(11.767)	(9.467)	(10.238)
R-squared	0.37	0.43	0.40	0.39	0.46	0.43	0.37	0.44	0.41
Observations	250	241	241	250	241	241	250	241	241
Number of Banks	50	49	49	50	49	49	50	49	49

*Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. All models include fixed effects.*

Source: Own work.

Table A5: Estimation results for regression equation (1) using lnGrossLoans as a measure of size

	(1) NPLToLoans	(2) NPLToLoans	(3) NPLToLoans	(1) NPLToAssets	(2) NPLToAssets	(3) NPLToAssets	(1) NPLToEquity	(2) NPLToEquity	(3) NPLToEquity
ROAA	**-4.933*** **	**-4.119*** **	**-4.504*** **	**-3.860*** **	**-3.300*** **	**-3.564*** **	**-45.632*** **	**-36.628*** **	**-41.065*** **
	(0.612)	**(0.570)**	**(0.586)**	**(0.643)**	**(0.651)**	**(0.658)**	**(5.690)**	**(4.534)**	**(5.092)**
EquityToAssets	0.725	0.324	0.421	**0.918***	0.693	0.759	-3.963	-8.440	-7.323
	(0.467)	(0.585)	(0.581)	**(0.382)**	(0.458)	(0.459)	(4.385)	(4.893)	(4.704)
CashToLiabilities	**-0.336*** **	**-0.267***	**-0.329** **	**-0.242*** **	**-0.193** **	**-0.235** **	**-3.118*** **	**-2.322** **	**-2.971*** **
	(0.094)	**(0.102)**	**(0.097)**	**(0.069)**	**(0.072)**	**(0.070)**	**(0.779)**	**(0.746)**	**(0.768)**
DebtToAssets	**0.283***	**0.296***	**0.355***	0.200	0.208	**0.248***	4.061	4.579	5.214
	(0.141)	**(0.142)**	**(0.154)**	(0.104)	(0.109)	**(0.117)**	(2.436)	(2.642)	(2.814)
lnGrossLoans	0.032	0.067	0.044	0.043	**0.070***	**0.054***	0.452	**0.826***	0.574
	(0.032)	(0.036)	(0.037)	(0.023)	**(0.027)**	**(0.027)**	(0.322)	**(0.378)**	(0.354)
ESG		**-0.002** **			**-0.001** **			**-0.019*** **	
		(0.001)			**(0.000)**			**(0.005)**	
ESGC			**-0.001***			**-0.001***			**-0.010** **
			(0.000)			**(0.000)**			**(0.003)**
Constant	-0.766	-1.516	-1.007	-1.100	**-1.687***	-1.340	-10.580	-18.708	-13.103
	(0.834)	(0.947)	(0.981)	(0.591)	**(0.699)**	(0.708)	(8.190)	(9.522)	(9.093)
R-squared	0.29	0.32	0.31	0.38	0.42	0.40	0.35	0.42	0.40
Observations	435	410	410	435	410	410	435	410	410
Number of Banks	63	60	60	63	60	60	63	60	60

*Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. All models include fixed effects.*

Source: Own work.

Table A6: Estimation results for regression equation (1) using liabilities to assets ratio as a measure of leverage

	(1) NPLToLoans	(2) NPLToLoans	(3) NPLToLoans	(1) NPLToAssets	(2) NPLToAssets	(3) NPLToAssets	(1) NPLToEquity	(2) NPLToEquity	(3) NPLToEquity
ROAA	**-5.192*** **	**-4.328*** **	**-4.805*** **	**-4.110*** **	**-3.606*** **	**-3.888*** **	**-49.412*** **	**-40.705*** **	**-45.834*** **
	(0.658)	**(0.640)**	**(0.616)**	**(0.649)**	**(0.652)**	**(0.641)**	**(7.974)**	**(5.804)**	**(7.129)**
EquityToAssets	0.486	0.062	0.012	0.764	0.503	0.472	-8.173	-13.240	-13.522
	(0.534)	(0.625)	(0.648)	(0.449)	(0.521)	(0.530)	(6.429)	(7.102)	(7.228)
CashToLiabilities	**-0.408*** **	**-0.368** **	**-0.431*** **	**-0.292*** **	**-0.269** **	**-0.308*** **	**-4.005** **	**-3.622** **	**-4.242** **
	(0.110)	**(0.110)**	**(0.115)**	**(0.083)**	**(0.082)**	**(0.085)**	**(1.308)**	**(1.153)**	**(1.355)**
LiabilitiesToAssets	-0.189	**-0.407** **	**-0.401***	-0.116	**-0.247***	**-0.244***	-2.450	**-4.634***	**-4.414***
	(0.102)	**(0.147)**	**(0.159)**	(0.074)	**(0.095)**	**(0.102)**	(1.597)	**(2.085)**	**(2.041)**
lnAssets	0.017	0.073	0.034	0.018	**0.051***	0.028	0.080	0.599	0.200
	(0.028)	(0.037)	(0.031)	(0.020)	**(0.024)**	(0.022)	(0.295)	(0.404)	(0.310)
ESG		**-0.002***			**-0.001***			**-0.022** **	
		(0.001)			**(0.001)**			**(0.008)**	
ESGC			-0.001			**-0.001***			**-0.010***
			(0.001)			**(0.000)**			**(0.004)**
Constant	-0.167	-1.240	-0.312	-0.327	-0.950	-0.397	2.063	-7.642	1.743
	(0.664)	(0.826)	(0.724)	(0.490)	(0.561)	(0.527)	(6.293)	(7.939)	(6.316)
R-squared	0.27	0.31	0.29	0.35	0.39	0.37	0.30	0.36	0.33
Observations	435	410	410	435	410	410	435	410	410
Number of Banks	63	60	60	63	60	60	63	60	60

*Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. All models include fixed effects.*

Source: Own work.

Table A7: Regression equation (1) including ESG and ESGC score – estimation results for non-EMU banks using random effects

	(1) NPLToLoans	(2) NPLToAssets	(3) NPLToEquity	(1) NPLToLoans	(2) NPLToAssets	(3) NPLToEquity
ROAA	0.105	-0.219	-1.821	0.127	-0.220	-1.687
	(0.480)	(0.277)	(3.121)	(0.487)	(0.288)	(3.176)
EquityToAssets	-0.093	-0.038	-4.708	0.010	0.023	-4.019
	(0.392)	(0.212)	(2.901)	(0.349)	(0.199)	(2.601)
CashToLiabilities	-0.209	-0.117	-1.628	-0.264	-0.149	-2.010
	(0.149)	(0.082)	(0.975)	(0.174)	(0.093)	(1.152)
DebtToAssets	-0.092	-0.054	-0.657	-0.049	-0.029	-0.362
	(0.053)	(0.027)	(0.362)	(0.040)	(0.021)	(0.251)
lnAssets	0.007	0.002	0.006	-0.003	-0.003	-0.058
	(0.009)	(0.005)	(0.062)	(0.006)	(0.004)	(0.045)
ESG	-0.002	-0.001	-0.014			
	(0.001)	(0.001)	(0.008)			
ESGC				-0.002	-0.001	-0.011
				(0.001)	(0.000)	(0.007)
Constant	0.037	0.060	1.645	0.230	0.173	**2.966***
	(0.152)	(0.085)	(1.074)	(0.170)	(0.096)	**(1.231)**
Hausman test						
χ^2	2.87	2.59	2.09	3.82	3.38	2.61
p-value	0.825	0.858	0.911	0.701	0.760	0.857
Observations	129	129	129	129	129	129
Number of Banks	21	21	21	21	21	21

*Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. All models include random effects.*

Source: Own work.

Table A8: Regression equation (1) including ESG and ESGC score – estimation results for banks in emerging countries using random effects

	(1) NPLToLoans	(2) NPLToAssets	(3) NPLToEquity	(1) NPLToLoans	(2) NPLToAssets	(3) NPLToEquity
ROAA	**-6.169*** **	**-5.076*** **	**-47.259*** **	**-6.098*** **	**-5.052*** **	**-47.091*** **
	(0.708)	**(0.753)**	**(5.235)**	**(0.613)**	**(0.802)**	**(5.103)**
EquityToAssets	**2.254** **	**2.402*** **	7.515	**2.455** **	**2.300*** **	8.016
	(0.875)	**(0.585)**	(5.515)	**(0.804)**	**(0.602)**	(5.158)
CashToLiabilities	-0.526	-0.403	-3.578	-0.484	-0.394	-3.425
	(0.325)	(0.211)	(2.254)	(0.269)	(0.206)	(2.010)
DebtToAssets	0.700	0.487	**9.248* **	0.609	0.489	**9.062* **
	(0.460)	(0.400)	**(4.381)**	(0.420)	(0.382)	**(4.288)**
lnAssets	0.033	0.015	**0.315* **	0.043	0.021	**0.374* **
	(0.021)	(0.014)	**(0.151)**	(0.026)	(0.016)	**(0.180)**
ESG	**0.004** **	**0.003*** **	0.021			
	(0.002)	**(0.001)**	(0.011)			
ESGC				0.003	**0.003** **	0.015
				(0.002)	**(0.001)**	(0.012)
Constant	**-1.110* **	**-0.666* **	**-8.514** **	**-1.298* **	**-0.779* **	**-9.653* **
	(0.466)	**(0.330)**	**(3.269)**	**(0.569)**	**(0.390)**	**(3.875)**
Hausman test						
χ^2	10.95	9.05	9.12	8.33	9.43	7.61
p-value	0.090	0.171	0.167	0.215	0.151	0.268
Observations	56	56	56	56	56	56
Number of Banks	8	8	8	8	8	8

*Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. All of the models include bank specific random effects.*

Source: Own work.

Table A9: Regression equation (2) including ESG score – estimation results for banks headquartered in EU, EMU and non-EMU countries

	(1) NPLToLoans	(2) NPLToLoans	(3) NPLToLoans	(1) NPLToAssets	(2) NPLToAssets	(3) NPLToAssets	(1) NPLToEquity	(2) NPLToEquity	(3) NPLToEquity
ROAA	**-3.876*** **	**-4.809*** **	0.648	**-3.218** **	**-4.071** **	0.400	**-35.658***	**-43.568***	4.053
	(0.974)	**(1.175)**	(0.962)	**(1.123)**	**(1.362)**	(0.610)	**(13.517)**	**(16.194)**	(6.081)
EquityToAssets	**1.475***	**2.357***	0.301	**1.405***	**2.271** **	0.241	0.038	2.945	-1.720
	(0.704)	**(0.882)**	(0.181)	**(0.622)**	**(0.772)**	(0.125)	(5.776)	(7.785)	(1.481)
CashToLiabilities	**-0.310***	-0.176	-0.230	**-0.229***	-0.092	-0.151	**-2.531** **	-1.909	-1.559
	(0.121)	(0.158)	(0.190)	**(0.092)**	(0.116)	(0.119)	**(0.859)**	(1.278)	(1.213)
DebtToAssets	0.165	0.318	-0.243	0.138	0.266	-0.149	3.636	5.262	-1.571
	(0.146)	(0.161)	(0.140)	(0.128)	(0.141)	(0.089)	(2.869)	(3.313)	(0.959)
lnAssets	0.055	0.042	-0.048	0.044	0.024	-0.032	0.342	0.173	**-0.345***
	(0.035)	(0.051)	(0.027)	(0.024)	(0.035)	(0.016)	(0.311)	(0.438)	**(0.154)**
OpexToOperating Profit	0.000	-0.000	**0.000*** **	0.000	-0.000	**0.000*** **	0.000	-0.001	**0.001*** **
	(0.000)	(0.000)	**(0.000)**	(0.000)	(0.000)	**(0.000)**	(0.001)	(0.001)	**(0.000)**
growth	-0.056	-0.037	0.006	**-0.037***	-0.016	0.005	-0.232	0.100	0.014
	(0.031)	(0.046)	(0.011)	**(0.018)**	(0.025)	(0.008)	(0.239)	(0.367)	(0.099)
ESG	**-0.001***	-0.001	-0.000	-0.001	-0.001	-0.000	**-0.011***	**-0.013***	-0.003
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	**(0.005)**	**(0.006)**	(0.002)
Constant	-1.381	-1.105	1.289	-1.137	-0.683	**0.864***	-7.657	-3.489	**9.620***
	(0.926)	(1.357)	(0.694)	(0.650)	(0.945)	**(0.411)**	(8.071)	(11.484)	**(3.941)**
R-squared	0.40	0.51	0.16	0.42	0.54	0.21	0.37	0.46	0.15
Observations	368	254	114	368	254	114	368	254	114
Number of Banks	60	39	21	60	39	21	60	39	21
Headquarters	EU	EMU	non-EMU	EU	EMU	non-EMU	EU	EMU	non-EMU

*Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. All of the models include bank specific fixed effects.*

Source: Own work.

Table A10: Regression equation (2) including ESGC score – estimation results for banks headquartered in EU, EMU and non-EMU countries

	(1) NPLToLoans	(2) NPLToLoans	(3) NPLToLoans	(1) NPLToAssets	(2) NPLToAssets	(3) NPLToAssets	(1) NPLToEquity	(2) NPLToEquity	(3) NPLToEquity
ROAA	**-4.078*** **	**-5.198*** **	0.788	**-3.346** **	**-4.321** **	0.506	**-37.815** **	**-47.613** **	5.293
	(0.978)	**(1.172)**	(0.957)	**(1.113)**	**(1.330)**	(0.613)	**(13.844)**	**(16.583)**	(6.078)
EquityToAssets	**1.464***	**2.310***	0.285	**1.397***	**2.240** **	0.232	-0.067	2.490	-1.838
	(0.707)	**(0.887)**	(0.177)	**(0.624)**	**(0.775)**	(0.121)	(5.770)	(7.796)	(1.421)
CashToLiabilities	**-0.330** **	-0.209	-0.248	**-0.243***	-0.114	-0.164	**-2.750** **	-2.245	-1.718
	(0.122)	(0.162)	(0.190)	**(0.093)**	(0.120)	(0.119)	**(0.877)**	(1.337)	(1.219)
DebtToAssets	0.191	0.341	-0.212	0.155	0.281	-0.123	3.910	5.493	-1.279
	(0.154)	(0.170)	(0.150)	(0.134)	(0.147)	(0.097)	(2.969)	(3.411)	(1.007)
lnAssets	0.036	0.015	-0.050	0.031	0.006	**-0.035***	0.135	-0.103	**-0.365***
	(0.034)	(0.052)	(0.024)	(0.023)	(0.034)	**(0.014)**	(0.283)	(0.423)	**(0.136)**
OpexToOperating Profit	0.000	-0.000	**0.000*** **	0.000	-0.000	**0.000*** **	0.000	-0.001	**0.001*** **
	(0.000)	(0.000)	**(0.000)**	(0.000)	(0.000)	**(0.000)**	(0.001)	(0.001)	**(0.000)**
growth	-0.051	-0.029	0.006	-0.034	-0.011	0.005	-0.174	0.177	0.009
	(0.033)	(0.048)	(0.010)	(0.019)	(0.027)	(0.007)	(0.260)	(0.402)	(0.088)
ESGC	-0.000	-0.000	**-0.000***	-0.000	-0.000	**-0.000***	-0.005	-0.004	**-0.004***
	(0.000)	(0.000)	**(0.000)**	(0.000)	(0.000)	**(0.000)**	(0.003)	(0.003)	**(0.001)**
Constant	-0.918	-0.460	**1.327***	-0.838	-0.265	**0.916***	-2.747	3.149	**10.093***
	(0.922)	(1.394)	**(0.620)**	(0.637)	(0.930)	**(0.364)**	(7.520)	(11.264)	**(3.556)**
R-squared	0.39	0.50	0.16	0.42	0.53	0.22	0.36	0.45	0.16
Observations	368	254	114	368	254	114	368	254	114
Number of Banks	60	39	21	60	39	21	60	39	21
Headquarters	EU	EMU	non-EMU	EU	EMU	non-EMU	EU	EMU	non-EMU

*Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. All of the models include bank specific fixed effects.*

Source: Own work.

Table A11: Regression equation (2) including ESG score – estimation results for banks headquartered in developed and emerging markets

	(1) NPLToLoans	(2) NPLToLoans	(3) NPLToLoans	(1) NPLToAssets	(2) NPLToAssets	(3) NPLToAssets	(1) NPLToEquity	(2) NPLToEquity	(3) NPLToEquity
ROAA	**-3.876***	**-3.865***	**-3.494***	**-3.218****	**-3.026***	**-2.969**	**-35.658***	**-50.958***	**-24.617***
	(0.974)	**(1.556)**	**(1.132)**	**(1.123)**	**(1.227)**	**(1.538)**	**(13.517)**	**(23.278)**	**(9.772)**
EquityToAssets	**1.475***	-0.091	**4.525***	**1.405***	-0.042	**4.289****	0.038	**-11.857*****	**25.675***
	(0.704)	(0.319)	**(1.567)**	**(0.622)**	(0.178)	**(1.213)**	(5.776)	**(3.357)**	**(9.068)**
CashToLiabilities	**-0.310***	-0.134*	-0.548	**-0.229***	-0.085	-0.378	**-2.531****	**-1.334***	-4.041
	(0.121)	(0.063)	(0.328)	**(0.092)**	(0.043)	(0.219)	**(0.859)**	(0.633)	(2.166)
DebtToAssets	0.165	0.218	-0.534	0.138	0.182	-0.488	3.636	3.547	-2.874
	(0.146)	(0.130)	(0.570)	(0.128)	(0.113)	(0.556)	(2.869)	(2.511)	(4.370)
lnAssets	0.055	0.022	0.026	0.044	0.018	0.024	0.342	0.252	-0.051
	(0.035)	(0.045)	(0.073)	(0.024)	(0.033)	(0.057)	(0.311)	(0.482)	(0.461)
OpexToOperating Profit	0.000	0.000	-0.000	0.000	0.000	-0.000	0.000	0.001	-0.003
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.005)
growth	-0.056	-0.034	-0.166	**-0.037***	-0.027	-0.094	-0.232	-0.203	-1.105
	(0.031)	(0.026)	(0.117)	**(0.018)**	(0.017)	(0.067)	(0.239)	(0.188)	(0.811)
ESG	**-0.001***	**-0.001****	0.003	-0.001	**-0.001****	0.003	**-0.011***	**-0.014****	0.024
	(0.001)	**(0.000)**	(0.003)	(0.000)	**(0.000)**	(0.003)	**(0.005)**	**(0.005)**	(0.021)
Constant	-1.381	-0.408	-1.063	-1.137	-0.361	-1.044	-7.657	-4.427	-1.197
	(0.926)	(1.156)	(1.936)	(0.650)	(0.842)	(1.415)	(8.071)	(12.363)	(11.647)
R-squared	0.40	0.44	0.56	0.42	0.47	0.63	0.37	0.44	0.53
Observations	368	318	50	368	318	50	368	318	50
Number of Banks	60	52	8	60	52	8	60	52	8
Classification	EU	EU-developed	EU-emerging	EU	EU-developed	EU-emerging	EU	EU-developed	EU-emerging

*Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. All of the models include bank specific fixed effects.*

Source: Own work.

Table A12: Regression equation (2) including ESGC score – estimation results for banks headquartered in developed and emerging markets

	(1) NPLToLoans	(2) NPLToLoans	(3) NPLToLoans	(1) NPLToAssets	(2) NPLToAssets	(3) NPLToAssets	(1) NPLToEquity	(2) NPLToEquity	(3) NPLToEquity
ROAA	**-4.078*** **	**-4.149***	**-3.210***	**-3.346****	**-3.227***	-2.767	**-37.815****	**-53.931***	-22.509
	(0.978)	**(1.610)**	**(1.341)**	**(1.113)**	**(1.269)**	(1.658)	**(13.844)**	**(24.085)**	(11.356)
EquityToAssets	**1.464***	-0.105	**4.283***	**1.397***	-0.056	**4.086****	-0.067	**-11.982*****	**23.849***
	(0.707)	(0.341)	**(1.407)**	**(0.624)**	(0.197)	**(1.114)**	(5.770)	**(3.359)**	**(8.015)**
CashToLiabilities	**-0.330****	**-0.152***	-0.539	**-0.243***	**-0.100***	-0.375	**-2.750****	**-1.516***	-3.976
	(0.122)	**(0.066)**	(0.362)	**(0.093)**	**(0.045)**	(0.240)	**(0.877)**	**(0.666)**	(2.412)
DebtToAssets	0.191	0.263	-0.412	0.155	0.216	-0.434	3.910	4.005	-1.994
	(0.154)	(0.143)	(0.590)	(0.134)	(0.124)	(0.566)	(2.969)	(2.662)	(4.483)
lnAssets	0.036	-0.012	0.038	0.031	-0.007	0.030	0.135	-0.088	0.032
	(0.034)	(0.040)	(0.085)	(0.023)	(0.029)	(0.062)	(0.283)	(0.412)	(0.537)
OpexToOperating Profit	0.000	0.000	-0.000	0.000	0.000	-0.000	0.000	0.001	-0.004
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.004)
growth	-0.051	-0.022	-0.148	-0.034	-0.017	-0.078	-0.174	-0.073	-0.972
	(0.033)	(0.026)	(0.116)	(0.019)	(0.016)	(0.069)	(0.260)	(0.197)	(0.784)
ESGC	-0.000	-0.001	0.002	-0.000	**-0.000***	0.002	-0.005	-0.005	0.015
	(0.000)	(0.000)	(0.003)	(0.000)	**(0.000)**	(0.002)	(0.003)	(0.003)	(0.021)
Constant	-0.918	0.395	-1.249	-0.838	0.231	-1.117	-2.747	3.785	-2.535
	(0.922)	(1.061)	(2.178)	(0.637)	(0.758)	(1.565)	(7.520)	(10.808)	(13.518)
R-squared	0.39	0.41	0.55	0.42	0.44	0.62	0.36	0.41	0.52
Observations	368	318	50	368	318	50	368	318	50
Number of Banks	60	52	8	60	52	8	60	52	8
Classification	EU	EU-developed	EU-emerging	EU	EU-developed	EU-emerging	EU	EU-developed	EU-emerging

*Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. All of the models include bank specific fixed effects.*

Source: Own work.