Lisbon School of Economics & Management
Universidade de Lisboa

MASTER IN
FINANCE

MASTER FINAL WORK
DISSERTATION

BANK-LEVEL CLIMATE STRATEGIES AND CREDIT RISK: EVIDENCE FROM EUROPEAN LISTED BANKS

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Abstract

This study investigates whether bank-level climate strategies reduce credit risk. Using panel data from 87 European listed banks over the period from 2015 to 2024 we constructed a Bank-Level Climate Strategy Index (BCSI) following the methodology of D'Orazio and Thole (2022), which captures five specific climate transition strategies weighted by their bindingness level. To examine the relationship between bank-level climate strategies and credit risk, the analysis combines fixed-effects panel regressions with quantile regressions, allowing the relationship to vary across the credit risk distribution.

The baseline results show that the relationship between bank-level climate strategies and credit risk is not statistically significant in a linear way. However, the quantile regression estimates reveal a risk-reducing effect although concentrated among banks with moderate to higher credit risk. Additional tests examine the moderating role of three climate governance mechanisms, the CSR Strategy Score, the CSR Sustainability Committee and Environmental Management Team. The moderation analysis shows that bank-level climate strategies are more effective for banks with weaker governance structures. Bank size further conditions this relationship, showing that the risk-reducing benefit from bank-level climate strategies weakens as bank size increases. Overall, the findings suggest that the effectiveness of bank-level climate strategies in reducing credit risk depends on the bank's position in the credit risk distribution, its governance quality and its size.

Keywords: Transition Risk, Bank-Level Climate Strategies, Credit Risk, Non-Performing Loans, Loan Loss Provisions, Climate Governance, European Banks.

JEL Codes: G21, G28, Q54, M14

Resumo

Este estudo investiga se as estratégias climáticas ao nível bancário reduzem o risco de crédito. Utilizando dados em painel de 87 bancos europeus cotados em bolsa, no período de 2015 a 2024, foi construído um Índice de Estratégia Climática ao Nível Bancário (BCSI), seguindo a metodologia de D'Orazio e Thole (2022), que captura cinco estratégias específicas de transição climática ponderadas pelo seu nível de compromisso. Para examinar a relação entre as estratégias climáticas ao nível bancário e o risco de crédito, a análise combina regressões em painel com efeitos fixos e regressões em quantil, permitindo que a relação varie ao longo da distribuição do risco de crédito.

Os resultados base mostram que a relação entre as estratégias climáticas ao nível bancário e o risco de crédito não é estatisticamente significativa de forma linear. Contudo, as estimativas da regressão em quantil revelam um efeito de redução do risco, ainda que concentrado nos bancos com risco de crédito moderado a elevado. Adicionalmente, foi examinado o papel moderador de três mecanismos de governança climática: o CSR Strategy Score, o CSR Sustainability Committee e o Environmental Management Team. A análise de moderação mostra que as estratégias climáticas ao nível bancário são mais eficazes nos bancos com estruturas de governança mais fracas. A dimensão do banco condiciona ainda esta relação, evidenciando que o benefício de redução do risco associado às estratégias climáticas ao nível bancário diminui à medida que a dimensão do banco aumenta. No geral, os resultados sugerem que a eficácia das estratégias climáticas ao nível bancário na redução do risco de crédito depende da posição do banco na distribuição do risco de crédito, da qualidade da sua governança e da sua dimensão.

Palavras-chave: Risco de Transição, Estratégias Climáticas ao Nível do Banco, Risco de Crédito, Crédito Malparado, Imparidades, Governança Climática, Bancos Europeus.

Códigos JEL: G21, G28, Q54, M14

Acknowledgments

This dissertation marks the end of an important chapter in my academic journey. This achievement would not have been possible without the support, encouragement, and guidance of many people, to whom I would like to express my sincere gratitude.

First and foremost, I would like to thank my supervisor, Professor Victor Barros, for his guidance, patience, and constant encouragement throughout this process. Thank you for always making time to answer my questions, for challenging me to do better, and for making this journey much less overwhelming. I would also like to thank all the professors of the Master's program for sharing their knowledge and contributing to my academic and personal growth over the past two years.

To my family, especially my parents, thank you for believing in me, for always encouraging me to pursue my goals, and for reminding me not to give up even when I doubted myself. To my brothers, thank you for always being there, for cheering me on even during the most stressful moments.

To my partner, thank you for your patience and support during every step of this journey. Finally, to my friends, especially those with whom I shared this Master's journey with, thank you for all the memories and the support along the way. This experience would not have been the same without you.

Abbreviations

BCBS – Basel Committee on Banking Supervision

BCSI – Bank-Level Climate Strategies Index

CRFPI – Climate-Related Financial Policy Index

CSR – Corporate Social Responsibility

ECB – European Central Bank

EIS – Environmental Innovation Score

ESG – Environmental, Social and Governance

FE – Fixed Effects

GDP – Gross Domestic Product

ICAAP – Internal Capital Adequacy Assessment Process

LLP – Loan Loss Provisions

LSEG – London Stock Exchange Group

NGFS – Network for Greening the Financial System

NPL – Non-Performing Loans

OLS – Ordinary Least Squares

VIF – Variance Inflation Factor

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Disclaimer regarding the use of AI

This study was carried out in full compliance with the academic integrity policies and standards established by ISEG – Lisbon School of Economics and Management. Unless otherwise referenced, all content reflects my own independent research and analysis. To be clear and transparent, I acknowledge the limited and appropriate use of artificial intelligence tools during the process of this study.

Specifically, AI tools were used to support technical aspects of the work, including assistance with Stata code, the review and analysis of academic articles and, occasionally, to improve the clarity and structure of selected parts of the text. All final decisions regarding data collection, empirical analysis, interpretation of results and written content were made by me.

1. Introduction

Climate change has become one of the most significant risks facing the global economy. Its consequences can be transmitted into the financial system, primarily, through two main channels: physical risk and transition risk (BCBS, 2021b; Battiston et al., 2021). Physical risk derives from extreme weather events such as floods, wildfires and hurricanes, as well as long-term climate shifts like rising sea levels. Its impact on banks is felt through damaged collateral, higher default rates and rising non-performing loans (Chabot and Bertrand, 2023; Nguyen et al., 2022). Transition risk, on the other hand, arises from the shift to a low-carbon economy through policy changes, technological transformations and changes in market sentiment (BCBS, 2021b). These changes increase the costs and decrease the profitability of carbon-intensive firms, making their assets completely worthless before the end of their expected life, creating stranded assets (Battiston et al., 2021). As the value of firms deteriorates their ability to repay the loans weakens, leading to higher default rates and a higher proportion of non-performing loans. In response to threat posed by these risks, regulatory authorities have incorporated climate-related risks into prudential supervision, requiring banks to integrate climate considerations into their governance, lending decisions and risk management frameworks (BCBS, 2022; ECB, 2020; NGFS, 2019).

D'Orazio and Thole (2022) developed the Climate-Related Financial Policy Index (CRFPI), a composite measure of countries' engagement in climate-related financial policymaking. Using this index, D’Orazio (2025) found that stronger climate-related financial policies reduce non-performing loans and improve financial stability. Nguyen and Le (2025), also used this index, and their findings indicate that these policies reduce credit risk, particularly for banks with stronger environmental performance. These studies highlight the need to examine whether the individual strategies adopted by banks make a measurable difference to their credit risk.

Chiaramonte et al. (2024) found that environmentally engaged banks exhibit a lower probability of default. However, their measures capture general environmental practices rather than the specific climate transition actions banks adopt. To address this gap, this study constructs a Bank-Level Climate Strategies Index (BCSI) for a sample of 87 European listed banks over the period from 2015 to 2024, adapting the methodology of

D'Orazio and Thole (2022) to the bank-level, capturing five specific climate transition strategies weighted by their level of commitment. This research uses panel regressions to analyze the relationship between the BCSI, and credit risk proxied by Non-Performing Loans to Loans (NPL / Loans) and Loan Loss Provisions to Loans (LLP / Loans).

The main results show a statistically insignificant association between bank-level climate strategies and credit risk. This is in contrast with prior findings that found a negative relationship between environmental strategies and credit risk (Chiaramonte et al., 2024; An et al., 2023). However, other studies suggest that this relationship may not be uniform across banks. Song et al. (2025) found that green credit only reduces risk beyond a certain threshold, Zhou et al. (2022) documented different effects depending on bank size, and D'Orazio (2025) identified diminishing returns at higher levels of policy intensity. This evidence points to the need for a distributional analysis, therefore quantile regressions are applied at the 10th, 25th, 50th, 75th and 90th percentiles.

The quantile regression results show that bank-level climate strategies help decrease NPL / Loans at the 50th quantile. This indicates that the risk-reducing effect of bank-level climate strategies is concentrated among banks with moderate credit risk rather than being distributed uniformly across the sample.

This study further analyzes whether climate governance mechanisms, such as the CSR Strategy Score, the CSR Sustainability Committee and the Environmental Management Team moderate the relationship between bank-level climate strategies and credit risk. Contrary to the complementary relationship expected from the literature, the results with CSR Strategy Score and CSR Sustainability Committee as moderators show a positive relationship with both credit risk measures. When analyzing the marginal effects of this relationship the results demonstrate that bank-level climate strategies are only effective for banks with weaker governance structures. The Environmental Management Team shows no significant individual or moderating effect, suggesting that operational-level governance does not condition the relationship between climate strategies and credit risk in the way that higher-level governance mechanisms do.

Additionally, the study finds that bank size conditions the effectiveness of climate strategies. The interaction between the BCSI and bank size is positive and significant at upper quantiles, indicating that the risk-reducing effect of climate strategies weakens as bank size increases.

The remainder of this study is organized as follows. Section 2 reviews the literature and theoretical framework. Section 3 describes the data, variables and empirical methodology. Section 4 presents and discusses empirical results as well as robustness checks. Section 5 presents the conclusions and discussion. Section 6 concludes with limitations and direction for future research.

2. Literature Review

In recent decades, the global financial system has been increasingly vulnerable to the impact of climate change (NGFS, 2019; Battiston et al., 2021). Most regulatory authorities have claimed that climate change can generate systemic financial risks through its impact on economic activity (Battiston et al., 2021; NGFS, 2019). These bodies alongside academics have identified the main channels through which climate disruption affects the financial sector: physical risks and transition risks (BCBS, 2021b). Existing literature highlights the consequences of these risks and emphasizes the need for additional focus to climate-related risks in financial institutions worldwide (BCBS, 2021b; Chabot and Bertrand, 2023; Muzuva and Muzuva, 2024).

Physical risks refer to the economic costs that arise from drastic changes in weather or natural events (BCBS, 2021b). These risks can be categorized into acute risks, which result from extreme weather events such as hurricanes, wildfires or floods, and chronic risks, resulting from the impact of long-term climate change, such as rising sea levels or the gradual increase in temperature (IPCC, 2018; BCBS, 2021b). Physical risks may result in damaged properties, infrastructures and constrain the overall living conditions of citizens (IPCC, 2018). These disruptions have significant macroeconomic consequences (Battiston et al., 2021; Chabot and Bertrand, 2023; Roncoroni et al., 2021). A recent example is the 2024 Valencia floods, which generated significant economic disruption and recovery costs across Spain, highlighting the macroeconomic impact acute physical risks have on developed markets (Barrutiabengoa et al., 2025). From a financial perspective, these risks can significantly impact loan portfolios, particularly in the mortgage and housing markets. For example, homes located in areas prone to recurrent flooding often experience price discounts, slower price recovery and higher interest rates (Skouralis et al., 2024; Nguyen et al., 2022). As a result, banks are increasingly incorporating these risks into their lending decisions, reducing credit exposure to areas highly impacted by climate change (Brüggemann and Lueg, 2026; Chabot and Bertrand, 2023). This adjustment also extends to mortgage pricing, with banks charging higher interest rates in areas with elevated physical risk exposure (Nguyen et al., 2022). This limit of lending capacity increases default rates which may lead to higher levels of non-performing loans (NPLs) (Nkusu, 2011; Klein, 2013; Chiaramonte et al., 2024).

In contrast, transition risks arise from the process of adjusting to a lower-carbon economy. These risks result from regulatory changes, shifts in the market sentiment and technological advancements, for example, with the rise of renewables use (BCBS, 2021b). While some industries are heavily exposed to physical risks, there are several sectors that rely on the transition risk to mitigate exposure to climate related risks. Batten et al. (2016) and Chabot and Bertrand (2023) explain that the main transmission channel of this type of risk is through asset valuation adjustments, they underline that a smooth transition to a lower-carbon economy would require a shift in the investments from carbon-intensive sectors towards low or zero-carbon sectors. These stricter climate policies reduce the expected future profitability of carbon-intensive firms, making certain assets partially or completely worthless (Batten et al., 2016, Delis et al., 2018). This is important because banks, insurers, pension funds and asset managers may be exposed to these carbon-intensive firms through loans, bonds and equity holdings. As asset prices decline across multiples firms, this generates correlated losses for financial institutions. Consequently, banks may tighten lending conditions to preserve their capital buffers, reducing credit supply to the economy (Batten et al., 2016).

For instance, firms that do not manage the energy transition become more vulnerable over time. This is because carbon-intensive firms are more exposed to the volatility of non-renewable energy prices, which has been increasing in recent years due to sharp fluctuations in oil and gas followed from geopolitical events (Campos-Martins and Hendry, 2021; Delis et al., 2018). This price instability increases operating costs and reduces profitability for firms that rely heavily on fossil fuels (Delis et al., 2018).

Other studies also found that these risks are not isolated. Rather they can be amplified through financial contagion. The literature also identified the primary channels for this transmission. Battiston et al. (2021) used “Network Modelling” to prove that if one counterparty presented in a sector vulnerable to climate change fails it impacts a broader system of banks and financial institutions. However, Roncoroni et al. (2021) documented that this impact of climate policy shocks varies among scenarios. For instance, a transition to a less stringent policy scenario can lead to larger losses if the market conditions are weaker. It also refers to endogenous recovery rates, which explains that the amount banks recover from failing institutions depends on how many of them are already in financial distress. If many banks fail simultaneously, asset prices fall as well as liquidation values, reducing the money creditors can recover (Shleifer and Vishny, 1992; Acharya et al., 2009).

Transition risk is often prioritized in literature due to its potential for sudden and systemic asset revaluation. Also, this risk can be proxied through different variables such as carbon emissions, carbon intensity, and ESG scores which are increasing in available data (Fliegel, 2024; Brüggemann and Lueg, 2026). By contrast, physical risk, requires highly granular data that banks typically do not collect (Gambacorta et al. 2023; BCBS, 2021a).

Di Febo et al. (2026) found that transition risk has a significant positive impact on degrading credit quality, while physical risk has a minimal or statistically insignificant direct impact on credit risk in the European banking sector. Despite growing literature on climate related risks, the impact on financial stability remains less explored.

The Paris Agreement, established in 2015, represented a critical commitment for nations to limit global warming, encouraging regulatory bodies worldwide to begin addressing climate-related financial risks (UNFCCC, 2015). Subsequently, scientific evidence reinforced the urgency of addressing climate change by detailing the financial consequences of failing to limit climate warming to 1.5ºC (IPCC, 2018). These conclusions have since contributed to an acceleration of regulatory action. Regulatory institutions have been responding to the impact of transition risk by leveraging and extending existing frameworks. Basel III explains that Pillar 2 of the Basel framework is better suited to address climate-related risks such as physical and transition risks (BCBS, 2011). Pillar II goes beyond the quantitative capacities of Pillar I and enables banks and other financial institutions to assess their internal risk management and capital adequacy for risks that are harder to quantify or lie within the long-term spectrum, for example, operational risk, interest rate risk, and crucially, emerging risks (BCBS, 2011). Besides that, this pillar obligates banks to perform an Internal Capital Adequacy Assessment Process (ICAAP), which is an extensive evaluation of all material risks to ensure banks have enough capital to support these risks (BCBS, 2011; BCBS, 2022).

BCBS (2022) and ECB (2020) also emphasize that the development of strong climate strategies and governance mechanisms are a necessary response to these supervisory rules. In a similar way, Mueller and Sfrappini (2025), used the Paris Agreement as a critical shock, and concluded that a mandatory response to regulation is more effective than voluntary initiatives.

The difference in regulatory stringency is particularly stronger when comparing Europe and the United States. Under the ECB's more rigorous supervisory framework, European banks have been actively reallocating credit towards green initiatives and integrating climate risk into their governance structures (Mueller and Sfrappini, 2025; NGFS, 2019). In contrast, in the United States, where climate-related regulatory requirements remain less developed, many banks continue to increase their exposure to firms sensitive to climate regulatory changes (Mueller and Sfrappini, 2025). This divergence highlights how a green transition in the financial sector is driven more due to regulatory pressure rather than voluntary commitment with developed economies that rely on voluntary approaches showing slower progress than those with more binding regulatory frameworks (Mueller and Sfrappini, 2025; Ehlers et al., 2022; Park and Kim, 2020).

The evolution of these practices is further detailed by Feridun and Gungor (2020), which identified four major regulatory expectations: First, board-level attention to climate risks and integrating them into internal governance frameworks. It is now expected that banks' boards understand and know how to assess the financial risks emerging from climate change and how it affects the firm´s operations and balance sheet. Second, the integration of climate-related risks into overall strategies and risk management. Regulatory bodies already expect that, through their risk management frameworks and business strategies, banks identify, measure and manage their credit risk, market risk, and operational risk because of climate change. Third, the identification and disclosure of material exposures. Banks are obliged to identify any material exposures, explaining how this constitutes in the context of their business model and relating to the financial risks from climate change in their ICAAPs. Fourth, the use of scenario analysis to assess capital impact. Banks should monitor climate change risks frequently to identify and assess potential threats. For transition risk in specific, banks should stress test their lending portfolios to energy, transportation, and industrial sectors.

Climate stress tests have been a critical supervisory tool in this context. The European Central Bank (ECB) conducted its first worldwide climate stress test in 2021, testing the exposure of firms and consolidated banking groups to physical and transition risks under different scenarios (ECB, 2022). This kind of exercise revealed that banks that fail to incorporate climate risks into their risk management practices may face higher losses under adverse scenarios, reinforcing the importance of early integration of climate considerations into risk management (ECB, 2022; Battiston et al., 2021).

Furthermore, the existing literature has also highlighted that central banks and regulators are gradually shifting to a more active role, increasing and promoting green finance through policies that encourage banks to reduce lending to carbon-intensive sectors (NGFS, 2019; Park and Kim, 2020).

The impact of this lending decision is capture through "financed emissions", which refers to the greenhouse gas emissions (GHG) generated by the firms or economic activities that financial institutions, in this case banks, finance through loans, investments or underwriting (Ehlers et al., 2022, NGFS, 2019). These emissions are typically classified as Scope 3 emissions, since they arise from the activities associated with financial services rather than from the bank's own operations. Regarding this type of emissions, Chabot and Bertrand (2023) demonstrated that Scope 3 emissions are the ones that have the strongest negative impact on bank financial stability, as measured by the probability of default and the Z-score. This confirms the previous idea that banks are exposed to climate risk, especially transition risk, through the companies they finance, rather than their own emissions. As a result, managing financed emissions and reducing exposure to carbon-intensive sector is the key to protecting banks from transition risk.

To manage these exposures effectively, banks must adopt active internal strategies. The existing literature provides a robust foundation for this, primarily through the pioneering work of D'Orazio and Thole (2022). The authors developed a comprehensive methodology to create a climate-related financial policy index (CRFPI). The objective of this was to assess, quantify, and compare international commitment to climate-related financial policymaking. It tracks the commitment of central banks, financial supervisory authorities and governments and it's based on a taxonomy of five climate-related financial policy areas. Together, these policy areas reflect the growing integration of climate considerations into financial regulation.

The introduction of CRFPI enables future analysis to study the impact of climate-related financial policies on different angles. D'Orazio (2025) establishes that climate-related financial policies are essential to maintain financial stability because they mitigate credit and liquidity risks directly. By analyzing a global dataset, the author demonstrates that these policies improve key stability indicators such as the Z-score and reduce Non-Performing Loans (NPLs). However, D'Orazio (2025) notices that the benefits of climate-related financial policies have diminishing returns, meaning that these policies are effective at reducing credit risk and enhancing liquidity buffers, but at the same time, their impact weakens at higher levels of policy intensity.

Additionally, the effectiveness of this index in achieving broader environmental goals is confirmed by D'Orazio and Dirks (2022), which demonstrates that long-term climate-related financial policies in G20 countries between 2000 and 2017, using a quantile panel approach, lead to significant reductions in carbon emissions, particularly in high-emission countries. Conversely, short-term policies show a larger relative impact in low-emission countries. This shows that the cumulative impact of older policies is essential for decarbonization.

Furthermore, Nguyen and Le (2025) investigates the link between these policies and bank risk, across different measures of risk. It uses 2,534 bank-year observations from 33 countries between 2000 and 2021, and it concludes that stronger climate-related financial policies (CFPs) result in significantly lower credit risk, by reducing Loan Loss Provisions (LLP) and Non-Performing Loans (NPL). This research also revealed the existence of different policy effectiveness across different regions and other environmental measures. For banks with a higher Environmental Score, CFPs reduce risk significantly across all three measures used, LLP/Asset, LLP/Equity and LLP/Loans, in contrast, for banks with lower Environmental Scores, CFPs do not reduce risk significantly. This suggests that banks with broader environmental practices have stronger effects on reducing risk from CFPs. Additionally, Nguyen and Le (2025) proved that banks in countries with higher environmental stringency policies (EPS) have a smaller but still significant negative effect on risk compared to countries with lower EPS. This explains CFPs are more critical in reducing risk in countries with weaker environmental policies, while in countries with stronger environmental policies the effect is merely incremental.

Despite growing literature on climate-related financial policies at the country level, limited focus has been given into bank-level environmental strategies and their implications for financial stability (Nguyen and Le, 2025). Therefore, this study aims to address this gap by creating a similar index with bank-level environmental strategies.

Chiaramonte et al. (2024) further investigates the role of bank's environmental engagement in mitigating the effects of climate change on their financial stability. To measure environmental engagement the authors used the Environmental Innovation Score, which measures the engagement in environmental innovation financing practices by banks; Environmental Score, which measures the overall adoption of environmental practices; Environmental Product Responsibility, which measures if a bank finances and invests on environmental responsible products; and Resource Reduction Policy Financing, which indicates if a bank finances practices that aim to reduce resource consumption.

The research demonstrates that environmentally engaged banks exhibit a lower probability of default, this means that these banks have better conditions to mitigate credit losses resulting from either physical or transition risks. Although, the choice of variables to measure environmental engagement is coherent, they do not measure specific climate transition actions banks adopt, a limitation that motivates this study.

Nevertheless, banks should integrate environmental and climate-related risks into their risk management and prudential supervision to ensure financial resilience (BCBS, 2022; ECB, 2020). Climate governance provides the necessary structure for the effective execution of climate strategies. ACPR (2020) provides an extensive list of practices related to climate risk management within the French banking sector. It details that banks should incorporate climate risks within their governance frameworks, specifically integrating these considerations into strategies and assigning them to executive committee members. This is also emphasized by Orazalin et al. (2024), that analyzed a sample of global financial institutions and concluded that Corporate Social Responsibility (CSR) initiatives contribute to the financial sector's financial stability, CSR helps banks and insurers achieve higher credit ratings, which implies mitigation of exposure to credit risks. Moreover, Cucinelli et al. (2026) used a moderation analysis to examine whether governance tools strength the relationship between risk management and sustainability adoption. They concluded that these tools such as a CSR committee enhance the effect of risk management on environmental strategies, and this effect is stronger for smaller banks and banks operating in countries with established climate policies.

Wu and Chen (2024) found that strong ESG performance improves the operational efficiency of financial institutions, supporting the link between quality and overall stability.

Therefore, this study aims to answer the question “Do bank-level environmental strategies help reducing credit risk?”. To answer this question the following hypothesis is constructed:

Hypothesis I: Bank-level environmental strategies are negatively associated with credit risk.

To answer this question a similar index based on the work of D’Orazio (2025) will be constructed with bank-level environmental strategies. Unlike previous studies that focus primarily on country-level climate-related financial policies (D’Orazio, 2025; D’Orazio and Thole, 2022; Nguyen and Le, 2025; D’Orazio and Dirks, 2022), this index captures the specific environmental strategies adopted by individual banks.

While several studies highlight that green credit can reduce credit risk by improving asset quality and lowering default probabilities (An et al., 2023; Zhou et al., 2022), other findings suggest that green lending may increase risk under certain conditions, such as information asymmetries or policy implementation challenges (Zhou et al., 2024; Sutanto et al., 2025; Trinh, 2025).

Nguyen and Le (2025) showed that climate-related financial policies reduce credit risk significantly only for banks with higher environmental scores, while the effect is insignificant for banks with lower scores. This indicates that the relationship may be conditional on the bank’s broader environmental engagement. Similarly, D’Orazio (2025) found that results of climate-related financial policies exhibit diminishing returns, having a weaker impact at higher levels of policy intensity.

A nonlinear relationship was also found in the study of Song et al. (2025), who examine the relationship between green credit and risk-taking in Chinese commercial banks. To investigate this potential heterogeneity, quantile regressions will be applied.

Additionally, since governance has been proved to enhance risk management practices and contributes to financial resilience overall, this research also aims to understand if the adoption of climate governance mechanism enhances this effect. To test this the following hypothesis is constructed:

H2: Climate governance mechanisms moderate the relationship between bank-level environmental strategies and credit risk.

3. Data and Methodology

3.1. Sample

This study uses a sample of European banks between the period of 2015 to 2024. The starting point of 2015 is justified by previous literature, which highlights that the Paris Agreement, established in 2015, marked a significant shift into how banks address climate change increasing their consideration into their operations (Nguyen and Le, 2025; Mueller and Sfrappini, 2025; Cucinelli et al., 2026). This starting point is also driven by data availability.

The initial sample was constructed by selecting all listed European banks classified under the banking industry in LSEG Workspace, which covers a list of 320 banks. The sample is restricted to Europe for two main reasons. First, Europe has the most developed regulatory framework for climate-related financial risk when compared to other countries, having institutions such as the ECB and the European Banking Authority issued binding supervisory expectations on climate risk management since 2020 (ECB, 2020; EBA, 2021). Second, the European banking sector operates under a similar regulatory structure, making it easier to compare the sample internally.

Bank-level climate strategy and climate governance variables were retrieved from LSEG Workspace, as in several prior research (Chiaramonte et al., 2024; Cucinelli et al., 2026). Financial variables were retrieved from Bloomberg (Bui et al., 2023; Nguyen and Le, 2025). Macroeconomic variables were retrieved from World Bank, and these were included to ensure comparability of macroeconomic controls across the European countries represented in the sample (D'Orazio, 2025; Nguyen and Le, 2025). All variables' names and their respective sources are presented in Table 1.

[Insert Table 1 here]

The selection criteria resulted in a final sample of 660 bank-year observations across 87 unique banks. The reduction from the broader sample of 320 banks considered availability of data on climate strategy. This tilts towards larger banks as the smaller banks or with less international visibility are less likely to be covered (Drempetic et al., 2020; Dobrick et al., 2023).

3.2. Measuring Credit Risk

To assess financial stability, this research focuses on credit risk and uses two different indicators related to loan quality: the Non-Performing Loans (NPL) and the Loan Loss

Provision (LLP) (Klein, 2013; Nkusu, 2011; Bui et al., 2023; D'Orazio, 2025; Nguyen and Le, 2025).

More specifically, *Non-Performing Loans to Gross Loans* (NPL / Loans) is used to reflect current or realized credit losses. A higher NPL to Gross Loans ratio indicates a decrease in asset quality and higher credit risk, and a higher likelihood of default.

In contrast, *Loan Loss Provisions to Gross Loans* (LLP / Loans) represent expected or unrealized losses, they measure the amount banks set aside to cover potential losses. A higher LLP to Gross Loans means that banks are setting aside more provisions, this could indicate higher expected losses.

3.3. Measuring Climate Related Proxies

To test the first hypothesis, two different variables are used to measure bank-level environmental strategies. The first is *Environmental Innovation Score*, a variable used by Chiaramonte et al. (2024) which is a subcategory of the Environmental Pillar. This variable ranks banks from 0 to 100 and reflects the bank's capacity of reducing the environmental costs for its customers, creating new market opportunities using new environmental technologies and processes (LSEG, 2024). This score is relevant for understanding how banks reduce credit risk through the environmental strategies they apply to their lending portfolios. However, this score does not measure the financing decisions a bank does in response to climate transition risk.

To overcome that limitation, it is proposed the construction of a *Bank-Level Climate Strategies Index (BCSI)* based on the statistical methodology proposed by D'Orazio and Thole, 2022. This index incorporates the following variables to reflect better bank's commitment and exposure to climate related actions. The included variables are as follows:

- *Fossil-Fuel Divestment Policy*, which takes the value 1 if the bank has a public policy to divest from fossil-fuel use, and 0 otherwise. This captures the role of banks as primary financiers of fossil-fuel companies (Rickman et al., 2024).
- *Phase-Out Investments in Carbon-Intensive Sectors*, which takes the value of 1 if the bank has a strategy to reduce or eliminate financing for industries with high carbon emissions, and 0 otherwise. The variable emphasizes the need of banks to reduce financing to firms within high carbon emissions industries (Rickman et al., 2024).

- *Environmental Investment Initiatives*, which takes the value of 1 if the bank has a measure to make proactive environmental investments or expenditures to reduce future risks, and 0 otherwise. This can include investments made in new technologies as a treatment of emissions, as banks that invest more in environmental technologies reduce their exposure to future regulatory penalties and stranded asset risk (Sharma and Vredenburg, 1998; Mouti et al., 2026).
- *Environmental Project Financing*, which takes the value of 1 if the bank is involved in funding projects with positive environmental impacts, and 0 otherwise. Banks engaged in environmental project financing redirect capital away from polluting sectors towards borrowers with lower transition risk (Zhou et al., 2022; Mirza et al., 2024).
- *Climate Commitment*, which takes the value of 1 if the bank has public commitment to reduce GHG emissions or improve GHG emissions efficiency, and 0 otherwise. Public climate commitments show strategic intent to contribute to a lower-carbon economy. (Birindelli et al., 2022).

Based on D'Orazio and Thole, 2022 this index accounts for the level of bindingness of each strategy included in it. Therefore, indicators that represent mandatory policies are assigned a value of 3, as they imply a higher level of commitment. For indicators that represent voluntary measures that make banks move their capital a value 2 is given. Finally for indicators that represent only public statements or commitments to environmental goals without implying tangible actions or capital reallocation a value of 1 is attributed.

Regarding the bindingness level, the Fossil-Fuel Divestment Policy is assigned a value of 3, to Phase-Out Investments in Carbon Intensive Sectors, Environmental Project Financing and Environmental Investment Initiatives are assigned a value of 2, and the Climate Commitment is assigned a value of 1.

Once each indicator is assigned a value according to its bindingness, the next step is to aggregate them into a single score for each bank. The BCSI for a given bank is calculated as the simple arithmetic average of the weighted scores across all indicators as shown in equation 1.

$$\mathrm{BCSI} = \frac{1}{n}\sum_{i=1}^{n} X_i \qquad (1)$$

where X_i represents the score of indicator *i* and *n* the total number of indicators included in the index.

To address the second hypothesis, climate governance is examined as a moderating factor with two distinct approaches. First, with the *Corporate Social Responsibility (CSR) Strategy Score* as an initial measure, which measures the bank's overall commitment to corporate social responsibility, aggregating governance aspects related to sustainability. This score takes a value from 0 to 100, meaning that if a bank's score is closer to 100 it has a strong CSR strategy. Orazalin et al. (2024) found that stronger CSR engagement contributes to greater financial stability. Additionally, Neitzert and Petras (2022), found that the environmental component of CSR is the one that reduces bank risk the most, while social and governance activities show less consistent results.

Subsequently, more granular aspects of climate governance will be analyzed separately. First with the *CSR Sustainability Committee*, which takes the value of 1 if the bank has the presence and activity of a dedicated sustainability committee within the bank's governance structure, and 0 otherwise. Cucinelli et al. (2026) found that the presence of a CSR committee enhances the effect of risk management on environmental strategy adoption, with this effect being stronger for smaller banks and for banks operating in countries with more established climate policies.

Lastly, the Environmental Management Team is included, which takes the value of 1 if the bank has a team responsible for managing environmental risks and opportunities, and 0 otherwise. Gangi et al. (2019) found that banks with governance structures have higher environmental adoption, and this contributes to reduced bank risk.

3.4. Control Variables

For bank-specific controls, it is included a set of variables. The first one included is *Bank Size*, which is measured by the logarithm of Total Assets. Larger banks tend to benefit from economies of scale, which improves risk management and reduces the likelihood of default (Bourkhis and Nabi, 2013; Vithessonthi, 2016).

Leverage, which is measured by Total Assets divided by Total Equity. While higher leverage may increase financial risk, well-capitalized banks can manage their leverage effectively to mitigate risk (Zhang *et al.*, 2025).

Diversification, measured by Non-Interest Income divided by Total Income. Banks that diversify revenue through non-interest activities depend less on lending, thus reducing risk (DeYoung and Roland, 2001).

Revenue Growth, which is measured by the Annual Growth Rate of Revenue. Fast revenue growth may lead to riskier lending practices (Fahlenbrach et al, 2016).

Efficiency, which is measured by the Cost-To-Income Ratio. More efficient banks are generally better at controlling operations and reducing loan losses (Sun et al., 2017).

Regarding country-specific controls, the one chosen is *GDP Growth*, which is measured by the Annual Growth Rate of Gross Domestic Product, capturing overall economic health (Koju et al., 2018).

All continuous variables are winsorized at the 5% level per tail to mitigate the influence of outliers, following standard practice in the banking literature.

3.5. Empirical Strategy

To test the first hypothesis, the following baseline model is estimated:

$$\text{FinStability}_{it} = \alpha + \beta_1 \text{Environment}_{it-1} + \gamma \mathbf{X}_{it} + \mu_i + \lambda_t + \varepsilon_{it} \qquad (2)$$

FinStability_{it} represents the credit risk measure of bank *i* at time *t*, proxied by the indicators of NPL / Loans and LLP / Loans. $\text{Environment}_{it-1}$ represents the climate strategy variable lagged by one period. The $\text{Environment}_{it-1}$ variables were lagged by one period because the impact of climate decisions on financial risk may unfold overtime, since banks may not respond immediately to its shocks (Chiaramonte et al., 2024; Mouti, 2026; Nguyen and Le, 2025).

X_{it} is a vector of control variables, including bank-specific characteristics defined in section 3.4, along with the macroeconomic factors, such as GDP Growth. $\mu_i$and λ_t denote bank and time fixed effects, respectively, and ε_{it} is the error term.

To test the second hypothesis of whether climate governance moderates and strengthens the relationship between banks' climate strategies and financial risk an interaction term between both Environmental Innovation Score and BCSI is introduced. Climate $\text{Governance}_{\text{it-1}}$ is substituted first by CSR Strategy Score, then by CSR Sustainability Committee and finally by Environmental Management Team. All governance variables were also lagged by one period.

$$\begin{aligned}\text{FinStability}_{it} = {} & \alpha + \beta_1 \text{Environment}_{\text{it}-1} + \beta_2 \text{Climate Governance}_{it-1} \\ & + \beta_3 (\text{Environment}_{\text{it}-1} \times \text{Climate Governance}_{\text{it}-1}) + \gamma \mathbf{X}_{it} + \mu_i \\ & + \lambda_t + \varepsilon_{it}\end{aligned} \tag{3}$$

The first model includes climate governance interacting with Environmental Innovation Score and the second model includes climate governance interacting with BCSI.

4. Empirical Results

4.1. Descriptive Statistics

Table 2 presents the descriptive statistics for all variables used in this study, covering the period between 2015 and 2024. The total number of bank-year observations in the main estimation sample is 660.

Regarding the dependent variables, NPL / Loans have an average of 4.411%, with a standard deviation of 4.933%, suggesting substantial heterogeneity in credit risk across banks. It ranges from 0.283% to a maximum of 23.276% across the sample. This indicates the existence of banks with high levels of impaired loans. Additionally, LLP / Loans have a mean of 0.538%, which is acceptable within the banking industry with a maximum of 3.397%, reflecting considerable variation in provisioning practices.

When used Total Assets to scale for a robustness alternative, NPL / Assets and LLP / Assets show lower averages of 2.606% and 0.321% respectively, consistent with the fact that total assets exceed total loans in the bank balance sheet.

Regarding the main independent variables, the average BCSI value is 0.763. The Environmental Innovation Score averages 59.292 with a standard deviation of 32.603, this suggests that many banks in the sample engage with environmental innovation. But there is high variation in banks' capacity to develop environmental solutions.

Among the climate governance variables, 74.2% of the observations report the existence of a CSR Sustainability Committee, while 53.0% have an Environmental Management Team. The CSR Strategy Score presents a relatively high average value of 64.196 (out of 100), suggesting that, on average, banks in the sample integrate CSR principles within their governance and strategy frameworks. However, the standard deviation of 28.937 indicates meaningful differences across banks, this is consistent with the pace at what sustainability practices are adopted by the banking industry.

Regarding the control variables, Bank Size exhibits a mean of 4.985 (in logarithmic terms) with a maximum of 5.833 indicating that the sample is mostly constituted by large banks. Leverage is, on average, 13.663, indicating a highly leveraged banking structure. Efficiency averages 57.531% with a relatively high standard deviation of 14.272%, implying significant differences in operational performance across banks. Diversification averages 0.420, indicating that on average 42% of banks' total income derives from non-interest sources, with relatively limited variation across the sample. GDP Growth averages 2.163 %, with a minimum of -4.688% reflecting the crisis of 2020 during the COVID-19 pandemic. Revenue Growth shows variation, ranging from -15.214% to 62.932%, which is consistent with the heterogeneous performance of European banks across the 2015-2024 period.

[Insert Table 2 here]

The pairwise correlation matrix (Table 3) shows a positive correlation of 0.983 between NPL / Loans and NPL / Assets which is expected therefore NPL / Assets is used for a robustness alternative. The same result happens between LLP / Loans and LLP / Assets with a correlation of 0.963.

[Insert Table 3 here]

Both independent variables are negatively correlated with the dependent variables. BCSI has a correlation of -0.228 with NPL / Loans and -0.165 with LLP / Loans, which is expected and supports the analysis of the first hypothesis. Environmental Innovation Score has a correlation of -0.173 with NPL / Loans and -0.148 with LLP / Loans. Both these variables are positively correlated with one another which justifies the need to test them separately.

The governance variables, CSR Strategy Score, CSR Sustainability Committee, are also negatively associated with NPL and LLP ratios, consistent with the theoretical motivation for the second hypothesis. Environmental Management Team has a non-significant correlation with the dependent variables.

Regarding the control variables, Leverage is negatively correlated with the dependent variables, indicating that higher leveraged banks have less NPLs. The same result is found for Bank Size. Revenue Growth is negatively correlated with the dependent variables, which is consistent with the literature. Efficiency is negatively correlated with LLP ratios, although insignificant, and is positively correlated with NPL ratios. GDP growth is only significantly correlated with LLP ratios and has a negative correlation. Diversification has a non-significant correlation with the dependent variables.

4.2. Diagnostics Tests and Model Validation

The validity of the baseline Fixed Effects models is supported by a standard set of diagnostic tests. The Variance Inflation Factor (VIF) confirmed the absence of multicollinearity, with all variables below the accepted threshold of 10. The Fisher-type unit root test confirmed that all continuous variables are stationary. The Wooldridge test detected first-order autocorrelation in all baseline models, while the Modified Wald test confirmed the existence of heteroskedasticity in all baseline models. These results justify the use of robust standard errors throughout all specifications. Finally, the Hausman test rejected the null hypothesis in all models, confirming that Fixed Effects is preferred over Random Effects (NPL/Loans: $\chi^2 = 19.23$, $p = 0.008$ and $\chi^2 = 15.32$, $p = 0.032$; LLP/Loans: $\chi^2 = 19.39$, $p = 0.007$ and $\chi^2 = 22.54$, $p = 0.002$, for the Environmental Innovation Score and BCSI respectively).

4.3. Baseline Results

4.3.1. Bank-Level Climate Strategies and Credit Risk

Table 4 presents the baseline results for the first hypothesis, which examines the relationship between bank-level climate strategies and credit risk. The results indicate that neither the Environmental Innovation Score nor the BCSI is statistically significant across any specification. This contrasts with prior findings which reported negative association between environmental strategies and credit risk, as evidenced by lower non-performing loan ratios and default probabilities (Luo and Tian, 2025; An et al., 2023; Zhou et al., 2022; Chiaramonte et al., 2024). However, it is consistent with papers that found mixed results, suggesting that the relationship between environmental strategies and credit risk is not uniform across banks.

Regarding the control variables, Bank Size is negative and statistically significant across all models. This result is consistent with prior studies which emphasize that larger banks have better risk management which contributes to lower non-performing ratios and loan loss provisions (Berger and Bouwman, 2013). Revenue Growth is negatively associated with NPL / Loans and LLP / Loans, suggesting that banks with stronger revenue performance exhibit lower credit risk. GDP Growth is also negatively associated with both risk measures, this is consistent with the fact that better economic conditions improve borrowers' ability to pay their debt, reducing the likelihood of default and the need for banks to recognize credit losses through provisioning (Klein, 2013; Nkusu, 2011). Leverage is positively associated with LLP / Loans, indicating that highly leveraged banks face greater financial vulnerability and tend to provision more for expected losses (Cucinelli et al., 2026). The other control variables do not show a significant relationship with credit risk.

[Insert Table 4 here]

4.3.2. Quantile Regression

To further analyze the possibility of existence of a nonlinear relationship between bank-level climate strategies and credit risk, quantile regressions are estimated at the 10th, 25th, 50th, 75th and 90th quantiles for NPL / Loans and LLP / Loans distributions, with year fixed effects included.

The results for the Environmental Innovation Score (Table 5 and Table 7) show that the relationship between this score and both measures of credit risk is not uniform. Besides that, these results are not statistically significant, therefore precise conclusions cannot be drawn based on these results.

[Insert Table 5 and Table 7 here]

For the BCSI, the results reveal a more pronounced pattern of heterogeneity across the distribution (Table 6 and Table 8). The BCSI is positive and not statistically significant at lower quantiles for NPL / Loans, indicating no meaningful relationship between bank-level climate strategies and credit risk for banks with NPL / Loans below average. However, the coefficient becomes negative and statistically significant at the median quantile. The coefficient continues to decrease at the 75th quantile, although statistical significance is not maintained. This indicates that for banks with higher credit risk, climate strategies alone are not sufficient to reduce their risk.

[Insert Table 6 and Table 8 here]

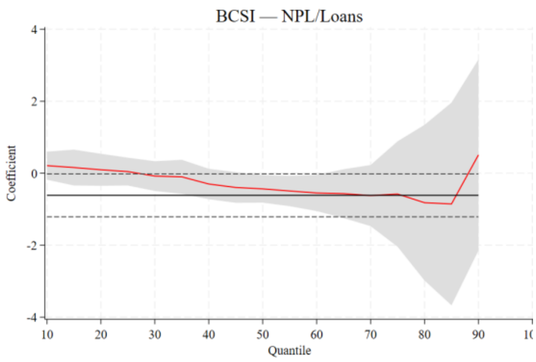
For LLP / Loans, the BCSI coefficient follows a consistent negative pattern across quantiles, beginning at quantile 25th. However, these results are not statistically significant.

Figure 1 presents the estimated BCSI coefficient for each quantile of the dependent variable, including a 95% confidence interval represented by the shaded area. The x-axis corresponds to the quantiles of NPL/Loans while the y-axis shows the corresponding coefficient. The horizontal lines represent the OLS benchmark estimate and its confidence interval. The graphs visually confirm the nonlinear pattern documented in the results. For both dependent variables, the coefficient is closer to zero and statistically insignificant at lower quantiles, but as the quantiles increase, the coefficients trend downward. This provides visual confirmation that the effect of bank-level climate strategies on credit risk is not uniform, rather it's concentrated among banks with credit risk above the average.

Among the control variables, Efficiency shows an interesting pattern compared to the baseline results. It has a positive and statistically significant effect across all quantiles for NPL / Loans increasing at higher quantile levels. This suggests that a higher cost-to-income ratio, meaning less operationally efficient banks exhibit higher NPL / Loans, and this effect intensifies with banks already facing elevated credit risk. This is consistent with the bad management hypothesis advanced by Berger and DeYoung (1997).

Contrarily to the baseline results, leverage is negatively associated with both credit risk measures at the 1% level, indicating that more leveraged banks have lower credit risk increasing the effect the higher the risk level. This is against prior studies that argue that more leveraged banks have higher credit risk (Klein, 2013; Louzis et al., 2012; Accornero et al., 2018).

Figure 1 - BCSI Coefficient across the Distribution of NPL / Loans.



4.3.3. Moderation Analysis

Given the nonlinear pattern detected in the baseline results, the moderation analysis for the second hypothesis is conducted using quantile regression rather than the base Fixed Effects estimator. Additionally, since the Environmental Innovation Score did not provide statistically significant results in the baseline results and in the quantile regression models, the moderation analysis takes only into consideration the BCSI.

The quantile regression results obtained for NPL / Loans using CSR Strategy Score as moderator (Table 9) reveal that the individual effect of BCSI is negative and statistically significant from the 50th quantile to the 90th quantile, confirming the results obtained in the quantile regression of the first hypothesis, and that bank-level climate strategies are associated with lower NPLs ratios among banks with credit risk above the average. The CSR Strategy Score coefficient is negative and significant across all quantiles at the 1% level, indicating that banks with stronger CSR governance strategies exhibit lower credit risk. This is consistent with prior literature that documented that stronger CSR governance contributes to financial stability through improved risk management and stakeholder engagement (Orazalin et al., 2024). For LLP / Loans (Table 10) a consistent pattern is obtained, where the relationship between the credit risk and BCSI is negative and significant from the 50th onwards.

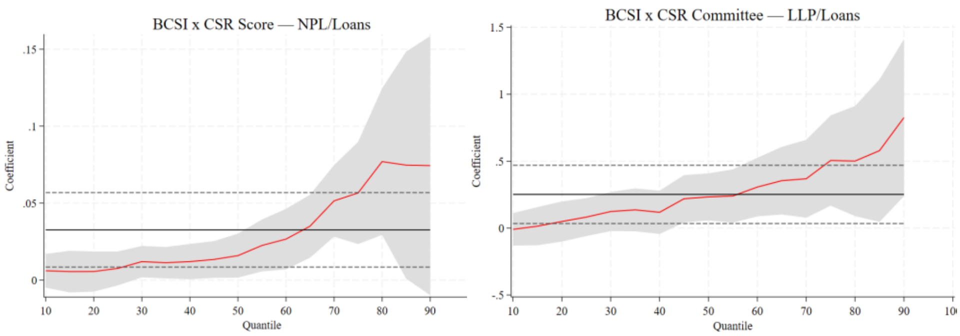
The interaction term between BCSI and CSR Strategy Score is not significant at the lower quantiles (10th and 25th), indicating that the moderating role is absent for banks that have credit risk below average. However, the interaction becomes positive and significant for the 50th, 75th and 90th quantile for both risk measures. This finding is in contrast with the finding of Gangi et al. (2019), who suggest that environmental strategy only reduces bank risk when supported by governance structures, and it is also against the finding of An et al. (2023), who document a positive moderating role of CSR between green credit and bank risk in Chinese banks suggesting complementarity between environmental strategies and governance.

The results indicate a heterogeneous and nonlinear interaction effect. The marginal effect of the BCSI is negative and statistically significant at the 25th percentile of the CSR Strategy Score indicating that bank-level climate strategies effectively reduce credit risk for banks with weaker governance structures. However, as governance strength increases, the marginal effect of BCSI attenuates and loses statistical significance at the median and 75th percentile of the CSR Score. These findings suggest that the effectiveness of bank-level climate strategies diminishes as governance strength increases, rather than providing clear evidence of a substitution.

[Insert Table 9 and Table 10 here]

Figure 2 follows the same structure as Figure 1, presenting the estimated interaction coefficients between BCSI and CSR Strategy Score across the quantiles of NPL / Loans, at the left, and LLP / Loans at the right. The shaded area represents the 95% confidence interval, and the horizontal lines indicate the OLS benchmark. For NPL / Loans the visual representation shows that for lower quantiles the interaction term remains close to zero, indicating that the moderating role of CSR Strategy Score is absent for banks with credit risk below average. From, approximately, the 70th quantile the coefficient rises sharply, suggesting that climate governance begins to condition the effectiveness of bank-level climate strategies only among banks with credit risk higher than average. For LLP / Loans, the interaction term follows a more gradual upward pattern, with coefficient rising slowly, consistent with the weaker statistical significance observed in the results.

Figure 2 – BCSI x CSR Strategy Score Coefficient across the Distribution of NPL / Loans and LLP / Loans.



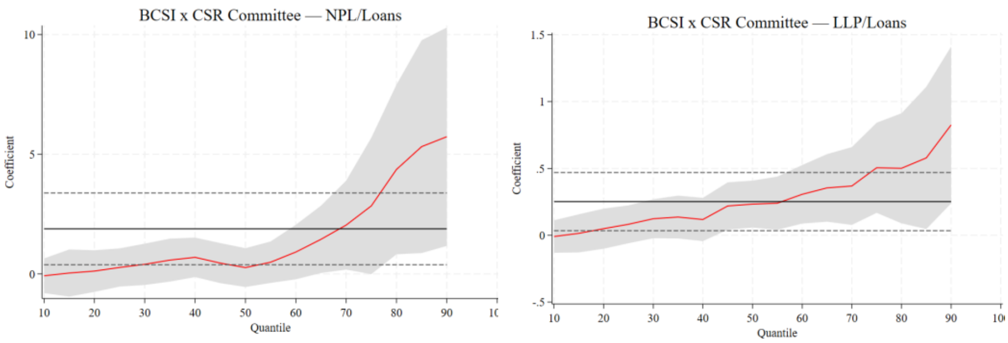
The results obtained with the CSR Sustainability Committee as a moderator provide similar results (Table 11 and Table 12). Regarding the individual coefficients, the CSR Sustainability Committee follows the same pattern as the CSR Strategy Score although with a weaker effect on credit risk, indicating that the presence of a CSR Sustainability Committee is associated with lower NPLs among banks with higher credit risk. This is in line with prior studies that document that board-level sustainability committees improve ESG oversight and integration into risk management, contributing to lower credit risk (Birindelli et al., 2018; Cucinelli et al., 2026).

The interaction term between BCSI and CSR Sustainability Committee is positive and significant at the 75th and 90th quantiles for NPL / Loans and at the 50th, 75th and 90th for LLP / Loans. Analyzing the marginal effects of BCSI across different levels of CSR Sustainability Committee reveals how the effectiveness of bank-level climate strategies changes with climate governance strength. For banks without a CSR Sustainability Committee, the BCSI has a negative and statistically significant effect on NPL / Loans at the 75th and 90th quantiles and on LLP / Loans at the 50th, 75th and 90th quantiles, indicating that bank-level climate strategies reduce credit risk for banks lacking climate governance structures. However, for banks with a CSR Sustainability Committee, the marginal effect of the BCSI attenuates and turns insignificant for both risk measures. These results follow the same pattern as the moderation role of the CSR Strategy Score, suggesting that banks with a CSR Sustainability Committee do not have additional credit risk reduction from the adoption of bank-level climate strategies.

[Insert Table 11 and Table 12 here]

Figure 3 follows the same structure as Figure 2, presenting the estimated interaction coefficients between BCSI and CSR Sustainability Committee across the quantiles of NPL / Loans, at the left, and LLP / Loans at the right. For NPL / Loans the coefficient of the interaction term is closer to zero at the lower quantiles, but it steadily increases, approximately, from the 60th quantile. For LLP / Loans, the interaction coefficient follows a similar upward trajectory but with some differences. The coefficient rises across quantiles, but the upward trend is less steep and less consistent than for NPL / Loans. However, from around the 80th quantile the coefficient rises steeply and sharply, suggesting that the effect between climate strategies and the CSR Sustainability Committee becomes economically meaningful only at the very upper tail of the provisioning distribution that is, among banks that are making the largest loan loss provisions.

Figure 3 - BCSI x CSR Sustainability Committee Coefficient across the Distribution of NPL / Loans and LLP / Loans.



Finally, the Environmental Management Team is tested as a moderator. In contrast to the CSR Strategy Score and CSR Sustainability Committee, the individual coefficient of the Environmental Management Team is not statistically significant across any quantile. The same nonsignificant result happens for the interaction term between BCSI and the Environmental Management Team. Since Environmental Management Team variable captures more operational-level environmental management capacity, the lack of significance suggests that operational environmental management does not affect the relationship between bank-level climate strategies and credit risk in the way that a higher level of governance mechanisms does such as the CSR Strategy Score and CSR Sustainability Committee.

4.4. Additional Analyses: Effect of Bank Size

Bank Size has been used in prior studies as a moderator of the relationship between environmental strategies and credit risk, even though findings are not uniform across them. Zhou et al. (2022) found that the relationship between green lending and credit risk depends on the size and structure of state ownership, particularly the study discovered that green lending reduces credit risk in larger Chinese banks while increasing it in smaller institutions. The performance discrepancy is due to information and expertise asymmetries; regional commercial banks have less access to information and expertise needed to evaluate the credit risk of green lending. Similarly, Luo and Tian (2025) documented that large state-owned commercial banks benefit more from green credit policies, linking this to stronger governance frameworks. However, both these findings are limited to the Chinese state-owned banking system.

Nevertheless, these studies identified bank size as a meaningful factor in the relationship between environmental strategies and credit risk. Additionally, the relationship between bank size and ESG risk management effectiveness is not straightforward. Bolibok (2024) found a nonlinear pattern in a cross-section of international banks, suggesting that while larger banks initially exhibit lower ESG risk, it can increase again at larger sizes. This motivates the introduction of an interaction term between BCSI and Bank Size into the quantile regression framework, to assess if the risk-reducing effect of bank-level climate strategies at upper quantiles is conditioned by bank size.

The results, reported in Table 13 and Table 14, reveal a consistent and statistically significant pattern across both credit risk measures. Regarding NPL / Loans the interaction term is positive and significant at the 75th and the 90th quantiles, while for LLP / Loans the interaction term is positive and significant at the 50th, the 75th and the 90th quantiles. The BCSI coefficient itself is negative and significant at upper quantiles which is consistent with the findings from the first hypothesis. However, due to the interaction term being positive, the risk-reducing effect of BCSI weakens as bank size increases. This implies that bank-level climate strategies reduce risk more effectively in smaller banks operating in the upper tail of the risk distribution, a finding that contrasts with Zhou et al.

(2022) and Luo and Tian (2025). This divergence could be due to the structural differences between Chinese and European banking systems. In China, larger banks benefit more because size is associated with state ownership and government support, which amplifies the effectiveness of environmental strategies through directed lending mandates (Zhou et al., 2022; Luo and Tian, 2025). In Europe, larger banks already have consolidated risk management practices, which limit the impact of climate strategies to reduce credit risk furthermore. By contrast, smaller banks lend to a narrower set of borrowers meaning that each individual lending decision has a greater impact on their overall portfolio quality. When these banks adopt climate strategies, the improvement in their credit portfolio is more pronounced than it would be for a larger, more diversified bank.

[Insert Table 13 and Table 14 here]

4.5. Robustness Checks

4.5.1. Redefining Risk Proxies

To assess the robustness of the main findings, the main quantile regression models are re-estimated using Total Assets as the denominator, that is using NPL / Assets and LLP / Assets as the dependent variables. This is consistent with prior studies that use asset-scaled credit risk measures as an alternative specification to confirm that results are not sensitive to differences in banks' lending activity levels (Nguyen and Le, 2025; 2024; Bruno et al., 2024).

When re-estimating the quantile regression for the first hypothesis using NPL / Assets as the dependent variable, the results are consistent with the results with NPL / Loans (Table 15). The BCSI is negative and statistically significant at the 50th. The lower quantiles do not provide a significant result; this confirms that even with this alternative the risk-reducing association between bank-level climate strategies and credit risk is concentrated among banks with higher levels of NPLs. For LLP / Assets the relationship is negative across all quantiles but isn’t statistically significant.

[Insert Table 15 here]

The positive relationship found between BCSI and CSR Strategy Score identified in the second hypothesis is also confirmed under NPL / Assets (Table 16). The BCSI coefficient is negative and significant from the 50^{th} quantile onwards, growing in magnitude at upper quantiles. For LLP / Assets (Table 17), the BCSI coefficient is negative and significant at the 50th, 75th and 90th quantile. The CSR Strategy Score itself is negative and significant from the 25th quantile onwards. The interaction term is positive and significant from the 50th quantile onwards, although with a weaker effect compared with NPL / Assets. These results are consistent when scaled under loans.

[Insert Table 16 and Table 17 here]

The results for the CSR Sustainability Committee are consistent with the main findings under both NPL / Assets and LLP / Assets (Table 18 and Table 19). The BCSI coefficient is negative and significant from the 50th onwards and the interaction term is positive and significant at upper quantiles. This confirms that the presence of a CSR Sustainability Committee attenuates the BCSI effect at upper quantiles under alternative scaling.

[Insert Table 18 and Table 19 here]

The additional analysis results are also confirmed under asset scaling (Table 20 and Table 21). The interaction term is positive and significant at quantile 75th and 90th for NPL / Assets and from the 50th quantile onwards for LLP / Assets. This confirms that the risk-reducing effect of climate strategies weakens as bank size increases regardless of whether credit risk is measured through non-performing loans or loan loss provisions, and irrespective of the scaling choice.

[Insert Table 20 and Table 21 here]

4.5.2. Unweighted BCSI

To assess the sensitivity of the results to the bindingness weighting method, the main models are re-estimated using an unweighted BCSI in which all five indicators receive an equal score. The baseline Fixed Effects results remain consistent with the main findings, with the unweighted BCSI being statistically insignificant for both risk measures. The re-estimated quantile regressions are also in line with the main findings. For NPL / Loans (Table 22), the unweighted BCSI is negative and statistically significant at the 50th quantile, while for LLP / Loans the results remain statistically insignificant across risk distribution. These findings confirm that the conclusions of this study are not driven by the choice of bindingness weights in the BCSI construction.

[Insert Table 22 here]

5. Conclusions and Discussion

Climate risk has become an increasingly important component of banking supervision, which leads researchers and regulators to examine whether banks' environmental, social and governance (ESG) strategies improve financial stability. Physical and transition risks are the primary channels through which climate change affects financial institutions. Among these, transition risk has become a central concern for regulators due to its potential for sudden and systemic revaluation of financial assets (BCBS, 2021b; Battiston et al., 2021). Country-level climate-related financial policies have been shown to improve bank stability (D'Orazio, 2025; Nguyen and Le, 2025), but there is still lack of evidence whether bank-level climate strategies impact bank stability, particularly credit risk. This study addresses that gap by constructing a Bank-Level Climate Strategies Index for a sample of European listed banks over the period from 2015 to 2024 and examining its relationship with credit risk as measured by NPL / Loans and LLP / Loans, along with the moderating role of climate governance, measured through CSR Strategy Score, CSR Sustainability Committee and Environmental Management Team.

The baseline results from the Fixed Effects model reveal no statistically significant relationship between bank-level climate strategies and credit risk, for either the Environmental Innovation Score or the BCSI. This result may indicate that the impact of bank-level climate strategies is not uniform across banks. Theoretical and empirical research suggests that the effectiveness of environmental initiatives depends on institutional characteristics, risk exposure, and the degree of sustainability integration (Song et al., 2025; D'Orazio, 2025; Zhou et al., 2022). To address the potential heterogeneity, a quantile regression was employed to all model specifications at the 10^{th}, 25^{th}, 50^{th}, 75^{th}, 90^{th} quantiles. This allows the relationship between climate strategies and credit risk to vary across different points of the risk distribution.

The quantile regression results reveal that the relationship between bank-level climate strategies and credit risk varies across the distribution. For the Environmental Innovation Score the results remain insignificant across all quantiles. However, the BCSI coefficient is negative and statistically significant at the 50^{th} quantile for NPL / Loans but loses significance for LLP / Loans. These findings suggest that bank-level climate strategies are more beneficial for banks that face moderate to relatively high levels of credit risk.

The moderation analysis between bank-level climate strategies and credit risk indicates that the relationship between them is contrary to the expected complementarity hypothesis. The interaction terms between BCSI and both the CSR Strategy Score and the CSR Sustainability Committee are positive and statistically significant at the upper quantiles of both NPL / Loans and LLP / Loans. While BCSI, CSR Strategy Score and CSR Sustainability Committee are individually associated with lower credit risk, their joint effect does not generate additional risk-reducing benefits for banks located in the upper tail of the credit risk distribution. These findings contrast with Gangi et al. (2019) and An et al. (2023), who documented that the effect between environmental strategies and governance mechanisms in global and Chinese banking samples is complementary.

The Environmental Management Team does not exhibit a statistically significant effect individually or as a moderator. This result suggests that operational-level environmental management does not influence the relationship between climate strategies and credit risk, at least within the European banking system. These findings emphasize the differences between governance mechanisms where strategic integration appears more relevant than operational implementation.

The additional analysis to assess the relationship between Bank Size and the BCSI shows that Bank Size conditions the effectiveness of climate strategies at upper quantiles. The interaction between BCSI and Bank Size is positive and statistically significant at upper quantiles for NPL / Loans, and at the median and upper quantiles for LLP / Loans. This indicates that the risk-reducing effect of climate strategies diminishes as bank size increases.

The robustness checks using Total Assets as denominator on the dependent variable confirm that the main results are not sensitive to the choice of denominator. The relationship between BCSI is still negative and significant at the 50^{th} quantile for NPL / Assets, and the climate governance moderation patterns are confirmed under asset scaling. Also, using an unweighted BCSI, the main findings remain consistent. This confirms that the results are not driven by the choice of the bindingness weighting scheme.

6. Policy and Practical Implications

This study also provides several policy and practical implications. While the findings should be interpreted as associations rather than evidence of a causal relationship, they suggest that bank-level climate strategies can contribute to lower credit risk, particularly among banks with moderate levels of credit risk.

From a policy perspective, the findings suggest that the effectiveness of bank-level climate strategies may vary across institutions rather than being universal. Since the association with lower credit risk is concentrated among banks with moderate levels of credit risk, supervisory authorities may benefit from adapting expectations regarding climate risk integrations to the characteristics of individual institutions, rather than adopting a similar approach across all institutions.

From a practical perspective, the finding that the additional effect of bank-level climate strategies becomes smaller as governance increases also suggests that banks with already well-established governance structures may obtain fewer additional benefits from adopting these strategies in isolation. Consequently, bank-level climate strategies should be implemented as part of an integrated risk management framework, taking into account each bank's existing governance structures.

7. Limitations and Future Research

These findings have direct implications for understanding the relationship between climate strategies and bank risk, highlighting that their effect is not uniform but depends on banks' position in the credit risk distribution and institutional characteristics.

This study is subject to several limitations that should be considered. First, the sample is restricted to European listed banks, which limits the external validity of the results. These findings may not be the same for non-listed institutions or to emerging market banking systems. Second, the panel is unbalanced due to missing observations across variables and years, this is primarily due to limited data availability in the databases used. Third, BCSI is constructed with binary variables that capture the adoption of climate-related strategies rather than their intensity or implementation quality. Consequently, the index does not distinguish between substantive integration of environmental considerations into lending decisions. Fourth, the BCSI and the Environmental Innovation Score have different scales which limit the direct comparability of their coefficients in magnitude. Finally, the relatively short time horizon, combined with structural shocks such as the COVID-19 crisis, may limit the ability to capture the full long-term effects of climate strategies on credit risk.

Future research should aim to further analyze the remaining regulatory expectations identified by Feridun and Gungor (2020). In particular, future research could test whether transparency amplifies the effectiveness of bank-level climate strategies and whether climate stress testing strengthens their impact on credit risk. Additionally, future research could include country-level environmental policy stringency as a moderating variable to examine whether the effects identified at the bank-level are stronger in countries with weaker regulatory frameworks.

7. Bibliography

Accornero, M., Cascarino, G., Felici, R., Parlapiano, F. and Sorrentino, A. M. (2018). Credit risk in banks' exposures to non-financial firms, *European Financial Management*, 24(5), 775–791. https://doi.org/10.1111/eufm.12138.

Acharya, V., Philippon, T., Richardson, M. and Roubini, N. (2009). The financial crisis of 2007–2009: causes and remedies, *Financial Markets, Institutions & Instruments*, 18(2), 89–137. https://doi.org/10.1111/j.1468-0416.2009.00147_2.x.

An, X., Ding, Y. and Wang, Y. (2023). Green credit and bank risk: does corporate social responsibility matter?, *Finance Research Letters*, 58, 104349. https://doi.org/10.1016/j.frl.2023.104349.

Barrutiabengoa, J. M., Garcia-Serrador, A. and Ulloa, C. (2025). *Quantifying the Economic Impact of Extreme Climate Events: Evidence from the Valencia Floods*. BBVA Research Working Paper.

Basel Committee on Banking Supervision. (2011). *Basel III: A Global Regulatory Framework for More Resilient Banks and Banking Systems*. Basel: Bank for International Settlements.

Basel Committee on Banking Supervision. (2021a). *Climate-Related Financial Risks: Measurement Methodologies*. Basel: Bank for International Settlements.

Basel Committee on Banking Supervision. (2021b). *Climate-Related Risk Drivers and Their Transmission Channels*. Basel: Bank for International Settlements.

Basel Committee on Banking Supervision. (2022). *Principles for the Effective Management and Supervision of Climate-Related Financial Risks*. Basel: Bank for International Settlements.

Batten, S., Sowerbutts, R. and Tanaka, M. (2016). Let's talk about the weather: the impact of climate change on central banks, *Bank of England Staff Working Paper*, No. 603. https://doi.org/10.2139/ssrn.2783753.

Battiston, S., Dafermos, Y. and Monasterolo, I. (2021). Climate risks and financial stability, *Journal of Financial Stability*, 54, 100867. https://doi.org/10.1016/j.jfs.2021.100867.

Berger, A. N. and Bouwman, C. H. S. (2013). How does capital affect bank performance during financial crises?, *Journal of Financial Economics*, 109(1), 146–176. https://doi.org/10.1016/j.jfineco.2013.02.008.

Berger, A. N. and DeYoung, R. (1997). Problem loans and cost efficiency in commercial banks, *Journal of Banking & Finance*, 21(6), 849–870. https://doi.org/10.1016/S0378-4266(97)00003-4.

Bergman, N. (2018). Impacts of the fossil fuel divestment movement: effects on finance, policy and public discourse, *Sustainability*, 10(7), 2529. https://doi.org/10.3390/su10072529.

Birindelli, G., Dell'Atti, S., Iannuzzi, A. P. and Savioli, M. (2018). Composition and activity of the board of directors: impact on ESG performance in the banking system, *Sustainability*, 10(12), 4699. https://doi.org/10.3390/su10124699.

Birindelli, G., Ferretti, P., Intonti, M. and Iannuzzi, A. P. (2022). Climate change commitment, credit risk and the country's environmental performance: empirical evidence from a sample of international banks, *Business Strategy and the Environment*, 31(4), 1641–1655. https://doi.org/10.1002/bse.2974.

Bolibok, P. M. (2024). Does firm size matter for ESG risk? Cross-sectional evidence from the banking industry, *Sustainability*, 16(2), 679. https://doi.org/10.3390/su16020679.

Bourkhis, K. and Nabi, M. S. (2013). Islamic and conventional banks soundness during the 2007-2008 financial crisis, *Review of Financial Economics*, 22(2), 68–77. https://doi.org/10.1016/j.rfe.2013.01.001.

Bressan, S. (2025). Does the environmental impact of banks affect their financial performance?, *Journal of Banking Regulation*, 26(2), 261–278. https://doi.org/10.1057/s41261-024-00257-8.

Bruggemann, T. and Lueg, R. (2026). Bank responses to physical and transition risks in lending: a diagnostic framework from a systematic literature review, *Business Strategy and the Environment*, 35(1), 195–212. https://doi.org/10.1002/bse.70176.

Bruno, E., Iacoviello, G. and Giannetti, C. (2024). Bank credit loss and ESG performance, *Finance Research Letters*, 59, 104719. https://doi.org/10.1016/j.frl.2023.104719.

Bui, D. G., Chen, Y., Chen, Y. S. and Lin, C. Y. (2023). Short-selling threats and bank risk-taking: evidence from the financial crisis, *Journal of Banking & Finance*, 150, 106834. https://doi.org/10.1016/j.jbankfin.2023.106834.

Campos-Martins, S. and Hendry, D. F. (2021). Geoclimate, geopolitics, and the geovolatility of carbon-intensive equity returns, *Department of Economics Discussion Paper Series*, No. 948. University of Oxford, Oxford.

Chabot, M. and Bertrand, J.-L. (2023). Climate risks and financial stability: evidence from the European financial system, *Journal of Financial Stability*, 69, 101190. https://doi.org/10.1016/j.jfs.2023.101190.

Chiaramonte, L., Dreassi, A., Goodell, J. W., Paltrinieri, A. and Pisera, S. (2024). Banks' environmental policies and banks' financial stability, *Journal of International Financial Markets, Institutions and Money*, 91, 101927. https://doi.org/10.1016/j.intfin.2023.101927.

Cucinelli, D., Nieri, L. and Pisera, S. (2026). Climate and environment risks and opportunities in the banking industry: the role of risk management, *International Journal of Finance & Economics*, 31(1), 1169–1185. https://doi.org/10.1002/ijfe.3083.

Delis, M. D., De Greiff, K. and Ongena, S. (2018). Being stranded on the carbon bubble? Climate policy risk and the pricing of bank loans. SSRN Working Paper. https://doi.org/10.2139/ssrn.3125017.

DeYoung, R. and Roland, K. P. (2001). Product mix and earnings volatility at commercial banks: evidence from a degree of total leverage model, *Journal of Financial Intermediation*, 10(1), 54–84. https://doi.org/10.1006/jfin.2000.0305.

Di Febo, E., Angelini, E. and Le, T. (2026). Climate-related risks and loan quality in Europe: do institutional quality, environmental commitment, and bank size matter?, *Research in International Business and Finance*, 81, 103206. https://doi.org/10.1016/j.ribaf.2025.103206.

Dobrick, J., Klein, C. and Zwergel, B. (2023). Size bias in Refinitiv ESG data, *Finance Research Letters*, 55, 104014. https://doi.org/10.1016/j.frl.2023.104014.

D'Orazio, P. (2025). Climate risks and financial stability: evidence on the effectiveness of climate-related financial policies, *International Review of Financial Analysis*, 105, 104304. https://doi.org/10.1016/j.irfa.2025.104304.

D'Orazio, P. and Dirks, M. W. (2022). Exploring the effects of climate-related financial policies on carbon emissions in G20 countries: a panel quantile regression approach, *Environmental Science and Pollution Research*, 29(5), 7678–7702. https://doi.org/10.1007/s11356-021-15655-y.

D'Orazio, P. and Thole, S. (2022). Climate-related financial policy index: a composite index to compare the engagement in green financial policymaking at the global level, *Ecological Indicators*, 141, 109065. https://doi.org/10.1016/j.ecolind.2022.109065.

Drempetic, S., Klein, C. and Zwergel, B. (2020). The influence of firm size on the ESG score: corporate sustainability ratings under review, *Journal of Business Ethics*, 167(2), 333–360. https://doi.org/10.1007/s10551-019-04164-1.

Ehlers, T., Packer, F. and De Greiff, K. (2022). The pricing of carbon risk in syndicated loans: which risks are priced and why?, *Journal of Banking & Finance*, 136, 106180. https://doi.org/10.1016/j.jbankfin.2021.106180.

European Banking Authority. (2021). *EBA Report on Management and Supervision of ESG Risks for Credit Institutions and Investment Firms*. Paris: EBA.

European Central Bank. (2020). *Guide on Climate-Related and Environmental Risks*. Frankfurt: ECB Banking Supervision.

European Central Bank. (2022). *2022 Climate Risk Stress Test*. Frankfurt: ECB Banking Supervision.

Fahlenbrach, R., Prilmeier, R. and Stulz, R. M. (2018). Why does fast loan growth predict poor performance for banks?, *Review of Financial Studies*, 31(3), 1014–1063. https://doi.org/10.1093/rfs/hhx109.

Feridun, M. and Gungor, H. (2020). Climate-related prudential risks in the banking sector: a review of the emerging regulatory and supervisory practices, *Sustainability*, 12(13), 5325. https://doi.org/10.3390/su12135325.

Fliegel, P. (2024). How you measure transition risk matters: comparing and evaluating climate transition risk metrics. SSRN Working Paper. https://doi.org/10.2139/ssrn.4742161.

Gambacorta, L., Pancotto, L., Reghezza, A. and Spaggiari, M. (2023). Do banks practice what they preach? Brown lending and environmental disclosure in the euro area, *BIS Working Papers*, No. 1101. Bank for International Settlements, Basel.

Gangi, F., Meles, A., D'Angelo, E. and Daniele, L. M. (2019). Sustainable development and corporate governance in the financial system: are environmentally friendly banks less risky?, *Corporate Social Responsibility and Environmental Management*, 26(3), 529–547. https://doi.org/10.1002/csr.1699.

Intergovernmental Panel on Climate Change. (2018). *Global Warming of 1.5 Degrees C: IPCC Special Report on Impacts of Global Warming of 1.5 Degrees C above Pre-Industrial Levels in Context of Strengthening Response to Climate Change, Sustainable Development, and Efforts to Eradicate Poverty*. Cambridge: Cambridge University Press. https://doi.org/10.1017/9781009157940.

Klein, N. (2013). Non-performing loans in CESEE: determinants and impact on macroeconomic performance. *IMF Working Paper* WP/13/72. International Monetary Fund, Washington D.C.

Koju, L., Koju, R. and Wang, S. (2018). Macroeconomic and bank-specific determinants of non-performing loans: evidence from the Nepalese banking system, *Journal of*

Central Banking Theory and Practice, 7(3), 111–138. https://doi.org/10.2478/jcbtp-2018-0026.

Lee, P.-L., Lye, C.-T. and Lee, C. (2022). Is bank risk appetite relevant to bank default in times of COVID-19?, *Central Bank Review*, 22(3), 109–117. https://doi.org/10.1016/j.cbrev.2022.08.003.

Louzis, D. P., Vouldis, A. T. and 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. https://doi.org/10.1016/j.jbankfin.2011.10.012.

LSEG. (2023). *Environmental, Social and Governance (ESG) Scores from LSEG*. London: LSEG Data & Analytics.

Luo, Y. and Tian, H. (2025). The impact of green credit on bank risk-taking: based on the moderating effect of FinTech, *Journal of Education, Humanities and Social Sciences*, 61, 455–464.

Mirza, N., Umar, M., Sbia, R. and Jasmina, M. (2024). The impact of blue and green lending on credit portfolios: a commercial banking perspective, *Review of Accounting and Finance*. https://doi.org/10.1108/raf-11-2023-0389.

Mouti, K., Kilincarslan, E. and Li, J. (2026). Environmental credit risk, climate change and bank performance: evidence from a global panel of banks, *Business Strategy and the Environment*, 35(2), 1646–1666. https://doi.org/10.1002/bse.70259.

Mueller, I. and Sfrappini, E. (2025). Climate change-related regulatory risks and bank lending, *Journal of International Economics*, 158, 104156. https://doi.org/10.1016/j.jinteco.2025.104156.

Muzuva, M. and Muzuva, D. (2024). The impact of climate change on banks' loan portfolios and strategies for effective climate risk management, *International Journal of Research in Business and Social Science*, 13(6), 148–157. https://doi.org/10.20525/ijrbs.v13i6.3510.

Neitzert, F. and Petras, M. (2022). Corporate social responsibility and bank risk, *Journal of Business Economics*, 92(3), 397–428. https://doi.org/10.1007/s11573-021-01069-2.

Network for Greening the Financial System. (2019). *A Call for Action: Climate Change as a Source of Financial Risk*. Paris: NGFS.

Nguyen, D. D., Ongena, S., Qi, S. and Sila, V. (2022). Climate change risk and the cost of mortgage credit, *Review of Finance*, 26(6), 1509–1549. https://doi.org/10.1093/rof/rfac013.

Nguyen Thi Truc, A. and Le Thanh, H. (2025). Climate-related financial policies and bank risks: do environmental sustainability factors matter?, *Asian Journal of Economics and Banking*, 9(3), 418–436. https://doi.org/10.1108/AJEB-04-2025-0037.

Nkusu, M. (2011). Nonperforming loans and macrofinancial vulnerabilities in advanced economies. *IMF Working Paper* No. 11/161. International Monetary Fund, Washington D.C.

Orazalin, N., Mahmood, M., Narbaev, T. and Tleubayev, A. (2024). Does CSR contribute to the financial sector's financial stability? The moderating role of a sustainability committee, *Journal of Applied Accounting Research*, 25(1), 105–125. https://doi.org/10.1108/JAAR-12-2022-0329.

Park, H. and Kim, J. D. (2020). Transition towards green banking: role of financial regulators and financial institutions, *Asian Journal of Sustainability and Social Responsibility*, 5(1), 5. https://doi.org/10.1186/s41180-020-00034-3.

Rickman, J., Semieniuk, G., Holden, P. B. and Edwards, N. R. (2024). The challenge of phasing-out fossil fuel finance in the banking sector, *Nature Communications*, 15(1), 7881. https://doi.org/10.1038/s41467-024-51662-6.

Roncoroni, A., Battiston, S., Escobar-Farfan, L. O. and Martinez-Jaramillo, S. (2021). Climate risk and financial stability in the network of banks and investment funds, *Journal of Financial Stability*, 54, 100870. https://doi.org/10.1016/j.jfs.2021.100870.

Sharma, S. and Vredenburg, H. (1998). Proactive corporate environmental strategy and the development of competitively valuable organizational capabilities, *Strategic Management Journal*, 19(8), 729–753. https://doi.org/10.1002/(SICI)1097-0266(199808)19:8<729::AID-SMJ967>3.0.CO;2-4.

Shleifer, A. and Vishny, R. W. (1992). Liquidation values and debt capacity: a market equilibrium approach, *The Journal of Finance*, 47(4), 1343–1366. https://doi.org/10.1111/j.1540-6261.1992.tb04661.x.

Skouralis, A., Lux, N. and Andrew, M. (2024). Does flood risk affect property prices? Evidence from a property-level flood score, *Journal of Housing Economics*, 66, 102027. https://doi.org/10.1016/j.jhe.2024.102027.

Song, J., Cao, W. and Shan, Y. G. (2025). Green credit and bank risk-taking: evidence from China, *International Journal of Managerial Finance*, 21(1), 157–184. https://doi.org/10.1108/IJMF-03-2024-0144.

Sun, P. H., Mohamad, S. and Ariff, M. (2017). Determinants driving bank performance: a comparison of two types of banks in the OIC, *Pacific-Basin Finance Journal*, 42, 193–203. https://doi.org/10.1016/j.pacfin.2016.02.007.

Sutanto, A., Ermawati, W. J. and Anggraeni, L. (2025). Assessing the impact of sustainable finance regulation on bank risk: evidence from Indonesia using a difference-in-differences approach, *Journal of Accounting and Strategic Finance*, 8(2), 209–234. https://doi.org/10.33005/jasf.v8i2.657.

United Nations Framework Convention on Climate Change. (2015). *Paris Agreement*. New York: UNFCCC.

Vithessonthi, C. (2016). Deflation, bank credit growth, and non-performing loans: evidence from Japan, *International Review of Financial Analysis*, 45, 295–305. https://doi.org/10.1016/j.irfa.2016.04.003.

Wu, Z. and Chen, S. (2024). Does environmental, social, and governance (ESG) performance improve financial institutions' efficiency? Evidence from China, *Mathematics*, 12(9), 1369. https://doi.org/10.3390/math12091369.

Zhang, X., Zhang, W. and Lee, C. (2025). Bank leverage and systemic risk: impact of bank risk-taking and inter-bank business, *International Journal of Finance & Economics*, 30(2), 1450–1474. https://doi.org/10.1002/ijfe.2973.

Zhou, X. Y., Caldecott, B., Hoepner, A. G. F. and Wang, Y. (2022). Bank green lending and credit risk: an empirical analysis of China's green credit policy, *Business Strategy and the Environment*, 31(4), 1623–1640. https://doi.org/10.1002/bse.2973.

Zhou, Z., Tong, J., Lu, H. and Luo, S. (2024). The impact of green finance and technology on the commercial banks' profit and risk, *Finance Research Letters*, 66, 105715. https://doi.org/10.1016/j.frl.2024.105715.

Table 1 - Variables Description and Source

Indicator	Variable Name	Source
Dependent Variables		
Non-performing Loans	NPL / Loans	Bloomberg
Loan Loss Provisions	LLP / Loans	Bloomberg
Independent Variables		
Bank-level Climate Strategies Index	BCSI	LSEG
Environmental Innovation Score	Environmental Innovation Score	LSEG
CSR Sustainability Committee	CSR Sustainability Committee	LSEG
CSR Strategy Score	CSR Strategy Score	LSEG
Environmental Management Team	Environmental Management Team	LSEG
Bank-Specific Controls		
Bank size	Bank Size	Bloomberg
Leverage	Leverage	Bloomberg
Efficiency	Efficiency	Bloomberg
Diversification	Diversification	Bloomberg
Revenue Growth	Revenue Growth	Bloomberg
Country-Specific Controls		
GDP Growth	GDP Growth	World Bank

Table 2 - Descriptive Statistics

	N	Mean	SD	Min	Max
NPL / Loans	660	4.411	4.933	0.283	23.276
LLP / Loans	660	0.538	0.689	-0.198	3.397
NPL / Assets	660	2.606	3.123	0.17	13.497
LLP / Assets	660	0.321	0.435	-0.107	1.931
BCSI	660	0.763	0.508	0	2.333
Environmental Innovation Score	660	59.292	32.603	0	98.723
CSR Sustainability Committee	660	0.742	0.438	0	1
CSR Strategy Score	660	64.196	28.937	0	99.81
Environmental Management Team	660	0.53	0.499	0	1
Bank Size	660	4.985	0.654	2.358	5.833
Leverage	660	13.663	4.382	5.797	21.056
Efficiency	660	57.531	14.272	36.161	92.696
Diversification	660	0.42	0.154	0.123	0.757
Revenue Growth	660	11.402	21.257	-15.214	62.932
GDP Growth	660	2.163	3.024	-4.688	7.392

Table 3 - Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) NPL / Loans	1.000														
(2) LLP / Loans	0.536***	1.000													
(3) NPL / Assets	0.980***	0.513***	1.000												
(4) LLP / Assets	0.576***	0.971***	0.576***	1.000											
(5) BCSI	-0.228***	-0.165***	-0.262***	-0.212***	1.000										
(6) Environmental Innovation Score	-0.173***	-0.148***	-0.212***	-0.193***	0.682***	1.000									
(7) CSR Sustainability Committee	-0.180***	-0.114***	-0.221***	-0.148***	0.202***	0.340***	1.000								
(8) CSR Strategy Score	-0.309***	-0.202***	-0.353***	-0.245***	0.378***	0.477***	0.589***	1.000							
(9) Environmental Team	0.015	-0.017	-0.040	-0.079**	0.223***	0.336***	0.385***	0.355***	1.000						
(10) Bank Size	-0.174***	-0.197***	-0.231***	-0.258***	0.448***	0.641***	0.437***	0.538***	0.400***	1.000					
(11) Leverage	-0.268***	-0.247***	-0.305***	-0.306***	0.212***	0.416***	0.280***	0.274***	0.177***	0.594***	1.000				
(12) Efficiency	0.164***	-0.047	0.144***	-0.076**	-0.018	0.073*	0.067*	0.021	0.115***	0.297***	0.374***	1.000			
(13) Diversification	-0.059	-0.103***	-0.102***	-0.151***	0.025	0.172***	0.091**	0.135***	0.099**	0.240***	0.352***	0.253***	1.000		
(14) Revenue Growth	-0.241***	-0.106***	-0.231***	-0.116***	0.071*	0.025	0.004	0.031	0.019	-0.094**	-0.021	-0.293***	-0.157***	1.000	
(15) GDP Growth	0.020	-0.110***	0.037	-0.088**	-0.066*	-0.075*	-0.094**	-0.067*	-0.059	-0.087**	-0.061	0.036	-0.035	0.021	1.000

*** p<0.01, ** p<0.05, * p<0.1

Table 4 - Baseline Results

VARIABLES	NPL/Loans	NPL/Loans	LLP/Loans	LLP/Loans
L.Environmental Innovation Score	-0.0207		-0.0007	
	(0.0169)		(0.0012)	
L.BCSI		-0.3441		-0.0564
		(0.5421)		(0.0562)
Revenue Growth	-0.0212***	-0.0216***	-0.0016*	-0.0015*
	(0.0075)	(0.0079)	(0.0009)	(0.0009)
Diversification	-0.1363	0.3918	0.0782	0.0679
	(1.8859)	(1.9597)	(0.1495)	(0.1472)
Efficiency	0.0525	0.0531	0.0063	0.0063
	(0.0344)	(0.0335)	(0.0041)	(0.0041)
Bank Size	-7.1534***	-8.0176***	-0.8020***	-0.7989***
	(1.5879)	(1.8547)	(0.2742)	(0.2696)
Leverage	-0.1151	-0.1185	0.0398**	0.0399**
	(0.1557)	(0.1552)	(0.0165)	(0.0165)
GDP Growth	-0.0862**	-0.0809*	-0.0400***	-0.0398***
	(0.0408)	(0.0421)	(0.0076)	(0.0076)
Constant	40.3327***	43.4603***	3.7426***	3.7322***
	(7.9234)	(9.6198)	(1.3506)	(1.3326)
Observations	660	660	660	660
R-squared	0.1627	0.1531	0.1419	0.1429
Number of id_bank	87	87	87	87
Estimator	FE	FE	FE	FE
Robust SE	Yes	Yes	Yes	Yes

Note: This table reports Fixed Effects (FE) panel regression estimates of the effect of bank-level climate strategies on credit risk. The dependent variables are NPL / Loans (columns 1 and 2) and LLP / Loans (columns 3 and 4). Columns 1–3 use the Environmental Innovation Score as the climate strategy variable; columns 2–4 use the BCSI. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5 - Quantile Regression for H1 (Environmental Innovation Score and NPL / Loans)

VARIABLES	q10	q25	q50	q75	q90
L.Environmental Innovation Score	0.0053	0.0030	-0.0007	0.0062	0.0249
	(0.0034)	(0.0034)	(0.0036)	(0.0133)	(0.0241)
Revenue Growth	-0.0048	-0.0010	-0.0019	-0.0140	-0.0312
	(0.0062)	(0.0061)	(0.0064)	(0.0238)	(0.0430)
Efficiency	0.0248***	0.0466***	0.0587***	0.0743***	0.0906*
	(0.0068)	(0.0067)	(0.0071)	(0.0263)	(0.0475)
Diversification	0.0027	-0.5296	-1.4777**	-0.3871	-1.9684
	(0.6431)	(0.6347)	(0.6698)	(2.4851)	(4.4886)
Bank Size	0.5999***	0.2191	0.2250	-0.8608	-3.6340***
	(0.1932)	(0.1907)	(0.2012)	(0.7467)	(1.3487)
Leverage	-0.1302***	-0.1786***	-0.2026***	-0.2505**	-0.3628**
	(0.0258)	(0.0255)	(0.0269)	(0.0999)	(0.1804)
GDP Growth	0.2639***	0.2232***	0.1542***	0.1394	0.0109
	(0.0513)	(0.0506)	(0.0534)	(0.1981)	(0.3578)
Constant	-2.4160***	0.5529	3.4023***	12.5408***	37.1750***
	(0.8689)	(0.8575)	(0.9049)	(3.3575)	(6.0643)
Observations	660	660	660	660	660
Quantile	10th	25th	50th	75th	90th
Year FE	Yes	Yes	Yes	Yes	Yes

Note: This table reports quantile regression estimates of the effect of the Environmental Innovation Score on NPL / Loans across the credit risk distribution. Columns correspond to the 10th, 25th, 50th, 75th, and 90th quantiles. All models include year fixed effects. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 6 - Quantile Regression for H1 (BCSI and NPL / Loans)

VARIABLES	q10	q25	q50	q75	q90
L.BCSI	0.2100	0.0450	-0.4351**	-0.5787	0.5094
	(0.1982)	(0.1964)	(0.1942)	(0.7457)	(1.3518)
Revenue Growth	-0.0083	-0.0030	0.0006	-0.0205	-0.0466
	(0.0063)	(0.0062)	(0.0062)	(0.0237)	(0.0430)
Efficiency	0.0217***	0.0454***	0.0622***	0.0684***	0.1024**
	(0.0069)	(0.0069)	(0.0068)	(0.0261)	(0.0473)
Diversification	-0.0580	-0.4483	-0.7793	-0.0098	-2.4434
	(0.6578)	(0.6519)	(0.6447)	(2.4751)	(4.4870)
Bank Size	0.6861***	0.3172*	0.3065*	-0.4304	-3.5523***
	(0.1842)	(0.1825)	(0.1805)	(0.6930)	(1.2563)
Leverage	-0.1256***	-0.1828***	-0.2063***	-0.2535**	-0.3977**
	(0.0265)	(0.0262)	(0.0259)	(0.0995)	(0.1804)
GDP Growth	0.2245***	0.2228***	0.1768***	0.1335	-0.0464
	(0.0525)	(0.0520)	(0.0514)	(0.1974)	(0.3579)
Constant	-2.5384***	0.2087	2.4780***	11.3405***	36.6918***

	(0.8529)	(0.8453)	(0.8359)	(3.2090)	(5.8176)
Observations	660	660	660	660	660
Quantile	10th	25th	50th	75th	90th
Year FE	Yes	Yes	Yes	Yes	Yes

Note: This table reports quantile regression estimates of the effect of the BCSI on NPL / Loans across the credit risk distribution. Columns correspond to the 10th, 25th, 50th, 75th, and 90th quantiles. All models include year fixed effects. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7 - Quantile Regression for H1 (Environmental Innovation Score and LLP / Loans)

VARIABLES	q10	q25	q50	q75	q90
L.Environmental Innovation Score	-0.0001	-0.0001	0.0002	0.0016	0.0024
	(0.0005)	(0.0007)	(0.0008)	(0.0016)	(0.0029)
Revenue Growth	0.0004	-0.0007	0.0015	0.0003	-0.0031
	(0.0010)	(0.0012)	(0.0014)	(0.0028)	(0.0053)
Efficiency	-0.0017	0.0009	0.0015	-0.0011	-0.0055
	(0.0011)	(0.0013)	(0.0016)	(0.0031)	(0.0058)
Diversification	0.1597	0.0514	-0.0090	-0.0735	0.5622
	(0.0995)	(0.1215)	(0.1502)	(0.2914)	(0.5493)
Bank Size	0.1007***	0.0644*	0.0115	-0.1064	-0.3372**
	(0.0299)	(0.0365)	(0.0451)	(0.0875)	(0.1650)
Leverage	-0.0062	-0.0167***	-0.0217***	-0.0369***	-0.0729***
	(0.0040)	(0.0049)	(0.0060)	(0.0117)	(0.0221)
GDP Growth	0.0033	0.0030	0.0156	0.0240	0.0352
	(0.0079)	(0.0097)	(0.0120)	(0.0232)	(0.0438)
Constant	-0.3356**	-0.0033	0.6238***	2.0891***	4.2192***
	(0.1344)	(0.1642)	(0.2029)	(0.3936)	(0.7421)
Observations	660	660	660	660	660
Quantile	10th	25th	50th	75th	90th
Year FE	Yes	Yes	Yes	Yes	Yes

Note: This table reports quantile regression estimates of the effect of the Environmental Innovation Score on LLP / Loans across the credit risk distribution. Columns correspond to the 10th, 25th, 50th, 75th, and 90th quantiles. All models include year fixed effects. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 8 - Quantile Regression for H1 (BCSI and LLP / Loans)

VARIABLES	q10	q25	q50	q75	q90
L.BCSI	0.0025	-0.0025	-0.0608	-0.0708	-0.0073
	(0.0311)	(0.0368)	(0.0442)	(0.0889)	(0.1743)
Revenue Growth	0.0004	-0.0006	0.0013	-0.0001	-0.0044
	(0.0010)	(0.0012)	(0.0014)	(0.0028)	(0.0055)
Efficiency	-0.0015	0.0010	0.0015	-0.0003	-0.0051
	(0.0011)	(0.0013)	(0.0015)	(0.0031)	(0.0061)
Diversification	0.1559	0.0571	0.0246	-0.1164	0.5235

	(0.1033)	(0.1222)	(0.1468)	(0.2952)	(0.5785)
Bank Size	0.0970***	0.0658*	0.0534	-0.0122	-0.2720*
	(0.0289)	(0.0342)	(0.0411)	(0.0826)	(0.1620)
Leverage	-0.0059	-0.0168***	-0.0261***	-0.0384***	-0.0674***
	(0.0042)	(0.0049)	(0.0059)	(0.0119)	(0.0233)
GDP Growth	0.0012	0.0030	0.0125	0.0244	0.0374
	(0.0082)	(0.0098)	(0.0117)	(0.0235)	(0.0461)
Constant	-0.3311**	-0.0179	0.4850**	1.7747***	3.8274***
	(0.1339)	(0.1585)	(0.1904)	(0.3827)	(0.7500)
Observations	660	660	660	660	660
Quantile	10th	25th	50th	75th	90th
Year FE	Yes	Yes	Yes	Yes	Yes

Note: This table reports quantile regression estimates of the effect of the BCSI on LLP / Loans across the credit risk distribution. Columns correspond to the 10th, 25th, 50th, 75th, and 90th quantiles. All models include year fixed effects. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 9 - Quantile Regression BCSI x CSR Strategy Score: NPL/Loans

VARIABLES	q10	q25	q50	q75	q90
L.BCSI	-0.3536	-0.4489	-1.2881**	-4.5718***	-6.2062*
	(0.4159)	(0.4181)	(0.5439)	(1.2629)	(3.2040)
L.CSR Strategy Score	-0.0268***	-0.0270***	-0.0308***	-0.0847***	-0.1281***
	(0.0050)	(0.0051)	(0.0066)	(0.0153)	(0.0387)
L.BCSI x CSR Strategy Score	0.0060	0.0075	0.0158**	0.0566***	0.0743*
	(0.0056)	(0.0056)	(0.0073)	(0.0169)	(0.0429)
Revenue Growth	-0.0071	-0.0032	-0.0015	-0.0233	-0.0315
	(0.0061)	(0.0061)	(0.0080)	(0.0185)	(0.0468)
Efficiency	0.0158**	0.0402***	0.0571***	0.0628***	0.0921*
	(0.0067)	(0.0068)	(0.0088)	(0.0204)	(0.0518)
Diversification	0.9828	-0.0656	-0.1194	-1.5306	-2.2120
	(0.6345)	(0.6379)	(0.8297)	(1.9266)	(4.8880)
Bank Size	1.3146***	0.9840***	0.7523***	0.5929	0.1263
	(0.2031)	(0.2042)	(0.2656)	(0.6166)	(1.5644)
Leverage	-0.1455***	-0.1926***	-0.2403***	-0.2581***	-0.4527**
	(0.0256)	(0.0257)	(0.0335)	(0.0777)	(0.1972)
GDP Growth	0.3041***	0.1747***	0.1801***	0.0868	-0.2487
	(0.0505)	(0.0508)	(0.0660)	(0.1533)	(0.3889)
Constant	-4.1504***	-1.2542	2.3361**	10.5134***	27.4777***
	(0.9038)	(0.9087)	(1.1819)	(2.7445)	(6.9629)
Observations	660	660	660	660	660
Quantile	10th	25th	50th	75th	90th
Year FE	Yes	Yes	Yes	Yes	Yes

Note: This table reports quantile regression estimates of the moderating effect of the CSR Strategy Score on the relationship between BCSI and NPL / Loans. L.BCSI x CSR Strategy Score is the interaction term. Columns correspond to the 10th, 25th, 50th, 75th, and 90th quantiles. All models include year fixed effects. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 10 - Quantile Regression BCSI x CSR Strategy Score: LLP/Loans

VARIABLES	q10	q25	q50	q75	q90
L.BCSI	0.0494	-0.0538	-0.2070**	-0.4819***	-0.8888**
	(0.0682)	(0.0798)	(0.1029)	(0.1819)	(0.3869)
L.CSR Strategy Score	-0.0011	-0.0029***	-0.0049***	-0.0074***	-0.0090*
	(0.0008)	(0.0010)	(0.0012)	(0.0022)	(0.0047)
L.BCSI x CSR Strategy Score	-0.0005	0.0006	0.0025*	0.0061**	0.0106**
	(0.0009)	(0.0011)	(0.0014)	(0.0024)	(0.0052)
Revenue Growth	0.0007	-0.0009	0.0012	-0.0007	-0.0047
	(0.0010)	(0.0012)	(0.0015)	(0.0027)	(0.0057)
Efficiency	-0.0025**	0.0003	0.0012	-0.0002	-0.0038
	(0.0011)	(0.0013)	(0.0017)	(0.0029)	(0.0062)
Diversification	0.2452**	0.0947	-0.0554	-0.1902	0.3283
	(0.1041)	(0.1218)	(0.1570)	(0.2776)	(0.5903)
Bank Size	0.1325***	0.1358***	0.1428***	0.0524	-0.2492
	(0.0333)	(0.0390)	(0.0503)	(0.0888)	(0.1889)
Leverage	-0.0077*	-0.0196***	-0.0263***	-0.0415***	-0.0661***
	(0.0042)	(0.0049)	(0.0063)	(0.0112)	(0.0238)
GDP Growth	0.0025	-0.0020	0.0263**	0.0355	0.0353
	(0.0083)	(0.0097)	(0.0125)	(0.0221)	(0.0470)
Constant	-0.4197***	-0.1212	0.2616	1.9184***	4.3853***
	(0.1483)	(0.1735)	(0.2237)	(0.3954)	(0.8409)
Observations	660	660	660	660	660
Quantile	10th	25th	50th	75th	90th
Year FE	Yes	Yes	Yes	Yes	Yes

Note: This table reports quantile regression estimates of the moderating effect of the CSR Strategy Score on the relationship between BCSI and LLP / Loans. L.BCSI x CSR Strategy Score is the interaction term. Columns correspond to the 10th, 25th, 50th, 75th, and 90th quantiles. All models include year fixed effects. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 11 - Quantile Regression BCSI x CSR Sustainability Committee: NPL/Loans

VARIABLES	q10	q25	q50	q75	q90
L.BCSI	0.2744	-0.1303	-0.6060*	-3.1564**	-4.9740**
	(0.3199)	(0.3529)	(0.3587)	(1.2621)	(2.0215)
L.CSR Sustainability Committee	0.0127	-0.1911	-0.3099	-3.8774***	-6.4118***
	(0.3177)	(0.3505)	(0.3563)	(1.2535)	(2.0078)
L.BCSI x CSR Sustainability Committee	-0.0774	0.2696	0.2643	2.8408*	5.7340**

	(0.3675)	(0.4055)	(0.4122)	(1.4502)	(2.3228)
Revenue Growth	-0.0078	-0.0037	0.0005	-0.0127	-0.0336
	(0.0060)	(0.0066)	(0.0067)	(0.0237)	(0.0380)
Efficiency	0.0218***	0.0428***	0.0613***	0.0746***	0.0856**
	(0.0066)	(0.0073)	(0.0074)	(0.0261)	(0.0418)
Diversification	0.1325	-0.4724	-0.8704	-1.7395	0.0318
	(0.6259)	(0.6905)	(0.7019)	(2.4695)	(3.9554)
Bank Size	0.7645***	0.3914*	0.3360	0.3253	-2.0749*
	(0.1918)	(0.2117)	(0.2152)	(0.7570)	(1.2125)
Leverage	-0.1377***	-0.1894***	-0.2010***	-0.2590**	-0.4760***
	(0.0254)	(0.0280)	(0.0285)	(0.1003)	(0.1606)
GDP Growth	0.2352***	0.2318***	0.1741***	0.1843	-0.2482
	(0.0498)	(0.0550)	(0.0559)	(0.1966)	(0.3149)
Constant	-2.8241***	0.1424	2.5724***	10.2671***	34.9076***
	(0.8602)	(0.9490)	(0.9647)	(3.3942)	(5.4364)
Observations	660	660	660	660	660
Quantile	10th	25th	50th	75th	90th
Year FE	Yes	Yes	Yes	Yes	Yes

Note: This table reports quantile regression estimates of the moderating effect of the CSR Sustainability Committee on the relationship between BCSI and NPL / Loans. L.BCSI x CSR Sustainability Committee is the interaction term. Columns correspond to the 10th, 25th, 50th, 75th, and 90th quantiles. All models include year fixed effects. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 12 - Quantile Regression BCSI x CSR Sustainability Committee: LLP/Loans

VARIABLES	q10	q25	q50	q75	q90
L.BCSI	0.0022	-0.0667	-0.2045***	-0.4504***	-0.7377***
	(0.0538)	(0.0626)	(0.0778)	(0.1492)	(0.2599)
L.CSR Sustainability Committee	0.0353	-0.0584	-0.1193	-0.3147**	-0.7386***
	(0.0534)	(0.0622)	(0.0773)	(0.1482)	(0.2582)
L.BCSI x CSR Sustainability Committee	-0.0098	0.0817	0.2328***	0.5047***	0.8250***
	(0.0618)	(0.0719)	(0.0894)	(0.1715)	(0.2987)
Revenue Growth	-0.0001	-0.0013	0.0006	0.0015	-0.0033
	(0.0010)	(0.0012)	(0.0015)	(0.0028)	(0.0049)
Efficiency	-0.0017	0.0005	0.0010	-0.0009	-0.0019
	(0.0011)	(0.0013)	(0.0016)	(0.0031)	(0.0054)
Diversification	0.1547	0.0619	0.0644	-0.1218	0.2417
	(0.1053)	(0.1224)	(0.1523)	(0.2920)	(0.5086)
Bank Size	0.0991***	0.0538	0.0233	-0.0295	-0.1882
	(0.0323)	(0.0375)	(0.0467)	(0.0895)	(0.1559)
Leverage	-0.0073*	-0.0179***	-0.0285***	-0.0417***	-0.0813***
	(0.0043)	(0.0050)	(0.0062)	(0.0119)	(0.0207)
GDP Growth	-0.0007	0.0011	0.0214*	0.0301	0.0195

	(0.0084)	(0.0097)	(0.0121)	(0.0232)	(0.0405)
Constant	-0.3377**	0.1366	0.7197***	2.1011***	4.1005***
	(0.1447)	(0.1683)	(0.2094)	(0.4013)	(0.6990)
Observations	660	660	660	660	660
Quantile	10th	25th	50th	75th	90th
Year FE	Yes	Yes	Yes	Yes	Yes

Note: This table reports quantile regression estimates of the moderating effect of the CSR Sustainability Committee on the relationship between BCSI and LLP / Loans. L.BCSI x CSR Sustainability Committee is the interaction term. Columns correspond to the 10th, 25th, 50th, 75th, and 90th quantiles. All models include year fixed effects. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 13 - Quantile Regression BCSI x Bank Size: NPL/Loans

VARIABLES	q10	q25	q50	q75	q90
L.BCSI	0.8050	-0.9401	-1.6469	-10.5143**	-18.2162**
	(1.2428)	(1.3588)	(1.4331)	(5.1162)	(8.2163)
Bank Size	0.8213***	0.1842	0.0678	-2.0280**	-4.5075***
	(0.2392)	(0.2615)	(0.2758)	(0.9845)	(1.5811)
BCSI x Bank Size	-0.1248	0.1944	0.2437	1.9065*	3.3343**
	(0.2432)	(0.2659)	(0.2804)	(1.0011)	(1.6077)
Revenue Growth	-0.0088	-0.0051	0.0009	-0.0259	-0.0310
	(0.0059)	(0.0064)	(0.0068)	(0.0242)	(0.0388)
Diversification	-0.0657	-0.5041	-1.0108	-1.0708	-2.2078
	(0.6121)	(0.6693)	(0.7058)	(2.5198)	(4.0467)
Efficiency	0.0215***	0.0436***	0.0614***	0.0765***	0.1052**
	(0.0065)	(0.0071)	(0.0075)	(0.0267)	(0.0429)
Leverage	-0.1304***	-0.1814***	-0.1944***	-0.2738***	-0.3990**
	(0.0247)	(0.0270)	(0.0285)	(0.1018)	(0.1635)
GDP Growth	0.2287***	0.2312***	0.1766***	0.1187	-0.1170
	(0.0489)	(0.0534)	(0.0563)	(0.2011)	(0.3230)
Constant	-3.1249***	0.9387	3.8674***	18.6250***	42.8280***
	(1.1829)	(1.2933)	(1.3640)	(4.8696)	(7.8204)
Observations	660	660	660	660	660
Quantile	10th	25th	50th	75th	90th
Year FE	Yes	Yes	Yes	Yes	Yes

Note: This table reports quantile regression estimates of the moderating effect of Bank Size on the relationship between BCSI and NPL / Loans. BCSI x Bank Size is the interaction term. Columns correspond to the 10th, 25th, 50th, 75th, and 90th quantiles. All models include year fixed effects. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 14 - Quantile Regression BCSI x Bank Size: LLP/Loans

VARIABLES	q10	q25	q50	q75	q90
L.BCSI	0.0566	-0.0801	-0.7703**	-1.9517***	-4.7106***
	(0.2162)	(0.2586)	(0.3085)	(0.6040)	(1.3141)
Bank Size	0.1053**	0.0558	-0.0887	-0.2917**	-0.8792***
	(0.0416)	(0.0498)	(0.0594)	(0.1162)	(0.2529)
BCSI x Bank Size	-0.0102	0.0148	0.1430**	0.3558***	0.8492***

	(0.0423)	(0.0506)	(0.0604)	(0.1182)	(0.2571)
Revenue Growth	0.0002	-0.0010	0.0010	0.0007	-0.0009
	(0.0010)	(0.0012)	(0.0015)	(0.0029)	(0.0062)
Diversification	0.1606	0.0560	0.0909	-0.0759	-0.1765
	(0.1065)	(0.1274)	(0.1520)	(0.2975)	(0.6472)
Efficiency	-0.0014	0.0007	0.0011	0.0006	-0.0003
	(0.0011)	(0.0013)	(0.0016)	(0.0032)	(0.0069)
Leverage	-0.0060	-0.0171***	-0.0275***	-0.0456***	-0.0604**
	(0.0043)	(0.0051)	(0.0061)	(0.0120)	(0.0261)
GDP Growth	0.0010	0.0021	0.0199	0.0255	0.0466
	(0.0085)	(0.0102)	(0.0121)	(0.0237)	(0.0517)
Constant	-0.3805*	0.0551	1.1950***	3.1684***	7.1029***
	(0.2058)	(0.2461)	(0.2937)	(0.5749)	(1.2508)
Observations	660	660	660	660	660
Quantile	10th	25th	50th	75th	90th
Year FE	Yes	Yes	Yes	Yes	Yes

Note: This table reports quantile regression estimates of the moderating effect of Bank Size on the relationship between BCSI and LLP / Loans. BCSI x Bank Size is the interaction term. Columns correspond to the 10th, 25th, 50th, 75th, and 90th quantiles. All models include year fixed effects. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 15 - Quantile Regression BCSI: NPL/Assets

VARIABLES	q10	q25	q50	q75	q90
L.BCSI	0.0250	-0.0956	-0.3129**	-0.5528	-0.0216
	(0.1108)	(0.1201)	(0.1311)	(0.4736)	(0.7596)
Revenue Growth	-0.0035	-0.0036	0.0001	-0.0113	-0.0164
	(0.0035)	(0.0038)	(0.0042)	(0.0151)	(0.0241)
Efficiency	0.0037	0.0192***	0.0314***	0.0421**	0.0613**
	(0.0039)	(0.0042)	(0.0046)	(0.0166)	(0.0266)
Diversification	-0.1221	-1.1342***	-1.3452***	-1.7042	-2.8945
	(0.3679)	(0.3986)	(0.4353)	(1.5719)	(2.5212)
Bank Size	0.3615***	0.1326	0.0426	-0.3376	-1.7275**
	(0.1030)	(0.1116)	(0.1219)	(0.4401)	(0.7059)
Leverage	-0.0773***	-0.0885***	-0.1346***	-0.1616**	-0.1824*
	(0.0148)	(0.0160)	(0.0175)	(0.0632)	(0.1014)
GDP Growth	0.1157***	0.1225***	0.1209***	0.1029	0.0285
	(0.0293)	(0.0318)	(0.0347)	(0.1254)	(0.2011)
Constant	-0.5921	0.8805*	3.2360***	9.4251***	20.5699***
	(0.4770)	(0.5169)	(0.5643)	(2.0380)	(3.2688)
Observations	660	660	660	660	660
Quantile	10th	25th	50th	75th	90th
Year FE	Yes	Yes	Yes	Yes	Yes

Note: This table reports quantile regression estimates of the effect of the BCSI on NPL / Assets across the credit risk distribution. Columns correspond to the 10th, 25th, 50th, 75th, and 90th quantiles. All models include year fixed effects. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 16 - Quantile Regression BCSI x CSR Score: NPL/Assets

VARIABLES	q10	q25	q50	q75	q90
L.BCSI	-0.0730	-0.4841*	-0.8153***	-3.1670***	-3.3781**
	(0.2409)	(0.2637)	(0.3142)	(0.7638)	(1.6055)
L.CSR Strategy Score	-0.0113***	-0.0147***	-0.0164***	-0.0596***	-0.0796***
	(0.0029)	(0.0032)	(0.0038)	(0.0092)	(0.0194)
L.BCSI x CSR Strategy Score	0.0014	0.0051	0.0086**	0.0362***	0.0392*
	(0.0032)	(0.0035)	(0.0042)	(0.0102)	(0.0215)
Revenue Growth	-0.0055	-0.0029	-0.0019	-0.0125	-0.0014
	(0.0035)	(0.0039)	(0.0046)	(0.0112)	(0.0235)
Efficiency	0.0041	0.0176***	0.0293***	0.0365***	0.0469*
	(0.0039)	(0.0043)	(0.0051)	(0.0123)	(0.0259)
Diversification	-0.0619	-0.6438	-1.4357***	-2.2391*	-2.5403
	(0.3675)	(0.4023)	(0.4793)	(1.1653)	(2.4493)
Bank Size	0.5976***	0.5124***	0.2766*	0.1204	-0.0493
	(0.1176)	(0.1288)	(0.1534)	(0.3730)	(0.7839)
Leverage	-0.0773***	-0.1187***	-0.1381***	-0.1422***	-0.2023**
	(0.0148)	(0.0162)	(0.0193)	(0.0470)	(0.0988)
GDP Growth	0.1017***	0.1148***	0.1459***	0.0397	-0.0668
	(0.0292)	(0.0320)	(0.0381)	(0.0927)	(0.1949)
Constant	-1.2181**	0.2593	3.0508***	9.3933***	16.1175***
	(0.5235)	(0.5731)	(0.6827)	(1.6600)	(3.4891)
Observations	660	660	660	660	660
Quantile	10th	25th	50th	75th	90th
Year FE	Yes	Yes	Yes	Yes	Yes

Note: This table reports quantile regression estimates of the moderating effect of the CSR Strategy Score on the relationship between BCSI and NPL / Assets. L.BCSI x CSR Strategy Score is the interaction term. Columns correspond to the 10th, 25th, 50th, 75th, and 90th quantiles. All models include year fixed effects. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 17 - Quantile Regression BCSI x CSR Score: LLP/Assets

VARIABLES	q10	q25	q50	q75	q90
L.BCSI	0.0128	-0.0405	-0.1074*	-0.2934***	-0.6960**
	(0.0389)	(0.0419)	(0.0613)	(0.1121)	(0.3363)
L.CSR Strategy Score	-0.0005	-0.0018***	-0.0023***	-0.0047***	-0.0086**
	(0.0005)	(0.0005)	(0.0007)	(0.0014)	(0.0041)
L.BCSI x CSR Strategy Score	-0.0002	0.0004	0.0013	0.0036**	0.0084*
	(0.0005)	(0.0006)	(0.0008)	(0.0015)	(0.0045)
Revenue Growth	0.0002	-0.0004	0.0007	-0.0007	-0.0003

	(0.0006)	(0.0006)	(0.0009)	(0.0016)	(0.0049)
Efficiency	-0.0014**	-0.0002	0.0010	-0.0003	-0.0005
	(0.0006)	(0.0007)	(0.0010)	(0.0018)	(0.0054)
Diversification	0.1365**	0.0144	-0.1445	-0.2951*	-0.2832
	(0.0593)	(0.0639)	(0.0935)	(0.1709)	(0.5130)
Bank Size	0.0804***	0.0832***	0.0388	0.0145	-0.1866
	(0.0190)	(0.0205)	(0.0299)	(0.0547)	(0.1642)
Leverage	-0.0068***	-0.0132***	-0.0176***	-0.0257***	-0.0413**
	(0.0024)	(0.0026)	(0.0038)	(0.0069)	(0.0207)
GDP Growth	0.0007	-0.0009	0.0162**	0.0200	0.0072
	(0.0047)	(0.0051)	(0.0074)	(0.0136)	(0.0408)
Constant	-0.2313***	-0.0168	0.4089***	1.3280***	3.3246***
	(0.0844)	(0.0911)	(0.1332)	(0.2435)	(0.7308)
Observations	660	660	660	660	660
Quantile	10th	25th	50th	75th	90th
Year FE	Yes	Yes	Yes	Yes	Yes

Note: This table reports quantile regression estimates of the moderating effect of the CSR Strategy Score on the relationship between BCSI and LLP / Assets. L.BCSI x CSR Strategy Score is the interaction term. Columns correspond to the 10th, 25th, 50th, 75th, and 90th quantiles. All models include year fixed effects. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 18 - Quantile Regression BCSI x CSR Committee: NPL/Assets

VARIABLES	q10	q25	q50	q75	q90
L.BCSI	0.1249	-0.1129	-0.6488***	-2.5222***	-3.6577***
	(0.2036)	(0.2012)	(0.2296)	(0.7560)	(1.2716)
L.CSR Sustainability Committee	0.0977	0.0502	-0.4405*	-2.9153***	-4.4764***
	(0.2023)	(0.1998)	(0.2280)	(0.7508)	(1.2630)
L.BCSI x CSR Sustainability Committee	-0.1052	0.0316	0.4399*	2.1883**	3.5282**
	(0.2340)	(0.2312)	(0.2638)	(0.8686)	(1.4612)
Revenue Growth	-0.0033	-0.0036	-0.0007	-0.0158	-0.0027
	(0.0038)	(0.0038)	(0.0043)	(0.0142)	(0.0239)
Efficiency	0.0041	0.0191***	0.0320***	0.0424***	0.0603**
	(0.0042)	(0.0042)	(0.0047)	(0.0156)	(0.0263)
Diversification	-0.1888	-1.1305***	-1.4357***	-1.7858	-3.2269
	(0.3984)	(0.3936)	(0.4492)	(1.4791)	(2.4881)
Bank Size	0.3473***	0.1193	0.0748	-0.1500	-1.1332
	(0.1221)	(0.1207)	(0.1377)	(0.4534)	(0.7627)
Leverage	-0.0761***	-0.0866***	-0.1296***	-0.1596***	-0.2197**
	(0.0162)	(0.0160)	(0.0182)	(0.0601)	(0.1011)
GDP Growth	0.1172***	0.1264***	0.1293***	0.0937	0.0131

	(0.0317)	(0.0313)	(0.0358)	(0.1177)	(0.1981)
Constant	-0.6279	0.8670	3.2137***	9.3332***	20.1687***
	(0.5476)	(0.5410)	(0.6174)	(2.0330)	(3.4198)
Observations	660	660	660	660	660
Quantile	10th	25th	50th	75th	90th
Year FE	Yes	Yes	Yes	Yes	Yes

Note: This table reports quantile regression estimates of the moderating effect of the CSR Sustainability Committee on the relationship between BCSI and NPL / Assets. L.BCSI x CSR Sustainability Committee is the interaction term. Columns correspond to the 10th, 25th, 50th, 75th, and 90th quantiles. All models include year fixed effects. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 19 - Quantile Regression BCSI x CSR Committee: LLP/Assets

VARIABLES	q10	q25	q50	q75	q90
L.BCSI	0.0051	-0.0545	-0.1221***	-0.2128*	-0.5499**
	(0.0256)	(0.0352)	(0.0443)	(0.1101)	(0.2390)
L.CSR Sustainability Committee	0.0138	-0.0389	-0.0498	-0.1775	-0.4353*
	(0.0255)	(0.0350)	(0.0440)	(0.1094)	(0.2374)
L.BCSI x CSR Sustainability Committee	-0.0063	0.0577	0.1077**	0.2126*	0.5734**
	(0.0294)	(0.0405)	(0.0509)	(0.1265)	(0.2747)
Revenue Growth	-0.0003	-0.0005	0.0006	-0.0012	0.0007
	(0.0005)	(0.0007)	(0.0008)	(0.0021)	(0.0045)
Efficiency	-0.0012**	-0.0003	0.0012	0.0008	0.0000
	(0.0005)	(0.0007)	(0.0009)	(0.0023)	(0.0049)
Diversification	0.0926*	-0.0220	-0.1235	-0.1655	-0.2067
	(0.0501)	(0.0689)	(0.0867)	(0.2155)	(0.4677)
Bank Size	0.0612***	0.0377*	-0.0007	-0.0641	-0.2055
	(0.0154)	(0.0211)	(0.0266)	(0.0660)	(0.1434)
Leverage	-0.0048**	-0.0106***	-0.0179***	-0.0286***	-0.0559***
	(0.0020)	(0.0028)	(0.0035)	(0.0088)	(0.0190)
GDP Growth	0.0014	0.0035	0.0173**	0.0243	0.0043
	(0.0040)	(0.0055)	(0.0069)	(0.0172)	(0.0372)
Constant	-0.1961***	0.1139	0.5154***	1.4789***	3.3047***
	(0.0689)	(0.0947)	(0.1191)	(0.2961)	(0.6428)
Observations	660	660	660	660	660
Quantile	10th	25th	50th	75th	90th
Year FE	Yes	Yes	Yes	Yes	Yes

Note: This table reports quantile regression estimates of the moderating effect of the CSR Sustainability Committee on the relationship between BCSI and LLP / Assets. L.BCSI x CSR Sustainability Committee is the interaction term. Columns correspond to the 10th, 25th, 50th, 75th, and 90th quantiles. All models include year fixed effects. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 20 - Quantile Regression BCSI x Bank Size: NPL/Assets

VARIABLES	q10	q25	q50	q75	q90
L.BCSI	0.2637	-0.4316	-1.5149*	-6.7368**	-10.3206*
	(0.7538)	(0.7866)	(0.9142)	(3.3463)	(5.4969)
Bank Size	0.3934***	0.0135	-0.1057	-1.4259**	-2.8599***
	(0.1451)	(0.1514)	(0.1759)	(0.6440)	(1.0578)
BCSI x Bank Size	-0.0437	0.0738	0.2317	1.1458*	1.8222*
	(0.1475)	(0.1539)	(0.1789)	(0.6548)	(1.0756)
Revenue Growth	-0.0041	-0.0035	-0.0003	-0.0150	-0.0101
	(0.0036)	(0.0037)	(0.0043)	(0.0158)	(0.0260)
Diversification	-0.1290	-1.0837***	-1.3075***	-1.6464	-3.5305
	(0.3713)	(0.3874)	(0.4503)	(1.6482)	(2.7074)
Efficiency	0.0041	0.0186***	0.0311***	0.0367**	0.0571**
	(0.0039)	(0.0041)	(0.0048)	(0.0175)	(0.0287)
Leverage	-0.0777***	-0.0848***	-0.1412***	-0.1577**	-0.1664
	(0.0150)	(0.0157)	(0.0182)	(0.0666)	(0.1094)
GDP Growth	0.1181***	0.1273***	0.1217***	0.0802	0.0126
	(0.0296)	(0.0309)	(0.0359)	(0.1315)	(0.2161)
Constant	-0.7927	1.4637*	4.0388***	14.2784***	27.0426***
	(0.7175)	(0.7487)	(0.8702)	(3.1851)	(5.2320)
Observations	660	660	660	660	660
Quantile	10th	25th	50th	75th	90th
Year FE	Yes	Yes	Yes	Yes	Yes

Note: This table reports quantile regression estimates of the moderating effect of Bank Size on the relationship between BCSI and NPL / Assets. BCSI x Bank Size is the interaction term. Columns correspond to the 10th, 25th, 50th, 75th, and 90th quantiles. All models include year fixed effects. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 21 - Quantile Regression BCSI x Bank Size: LLP/Assets

VARIABLES	q10	q25	q50	q75	q90
L.BCSI	0.0127	-0.0854	-0.5703***	-1.0513**	-3.0309***
	(0.1051)	(0.1429)	(0.1768)	(0.4349)	(0.9142)
Bank Size	0.0689***	0.0203	-0.0839**	-0.1955**	-0.6408***
	(0.0202)	(0.0275)	(0.0340)	(0.0837)	(0.1759)
BCSI x Bank Size	-0.0024	0.0148	0.1029***	0.1869**	0.5419***
	(0.0206)	(0.0280)	(0.0346)	(0.0851)	(0.1789)
Revenue Growth	-0.0003	-0.0005	0.0002	-0.0001	0.0005
	(0.0005)	(0.0007)	(0.0008)	(0.0021)	(0.0043)
Diversification	0.1103**	-0.0128	-0.1132	-0.1577	-0.4792
	(0.0517)	(0.0704)	(0.0871)	(0.2142)	(0.4503)
Efficiency	-0.0013**	-0.0001	0.0008	0.0006	0.0001
	(0.0005)	(0.0007)	(0.0009)	(0.0023)	(0.0048)
Leverage	-0.0053**	-0.0098***	-0.0167***	-0.0301***	-0.0386**
	(0.0021)	(0.0028)	(0.0035)	(0.0087)	(0.0182)
GDP Growth	0.0010	0.0027	0.0117*	0.0253	0.0117
	(0.0041)	(0.0056)	(0.0070)	(0.0171)	(0.0359)
Constant	-0.2175**	0.1465	0.9223***	2.0538***	5.2280***

	(0.1000)	(0.1360)	(0.1683)	(0.4139)	(0.8702)
Observations	660	660	660	660	660
Quantile	10th	25th	50th	75th	90th
Year FE	Yes	Yes	Yes	Yes	Yes

Note: This table reports quantile regression estimates of the moderating effect of Bank Size on the relationship between BCSI and LLP / Assets. BCSI x Bank Size is the interaction term. Columns correspond to the 10th, 25th, 50th, 75th, and 90th quantiles. All models include year fixed effects. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 22 - Quantile Regression BCSI Unweighted: NPL/Loans

VARIABLES	q10	q25	q50	q75	q90
L.BCSI Unweighted	0.5561	0.0334	-0.9857**	-1.6869	0.2006
	(0.4274)	(0.4347)	(0.4343)	(1.6300)	(3.0215)
Revenue Growth	-0.0068	-0.0032	0.0020	-0.0173	-0.0446
	(0.0061)	(0.0062)	(0.0062)	(0.0234)	(0.0433)
Efficiency	0.0221***	0.0450***	0.0606***	0.0641**	0.1064**
	(0.0067)	(0.0069)	(0.0068)	(0.0257)	(0.0476)
Diversification	-0.1022	-0.4117	-0.8855	-0.2596	-2.9034
	(0.6394)	(0.6503)	(0.6497)	(2.4386)	(4.5204)
Bank Size	0.6944***	0.3584*	0.3270*	-0.2157	-2.9412**
	(0.1809)	(0.1840)	(0.1838)	(0.6898)	(1.2788)
Leverage	-0.1281***	-0.1853***	-0.1996***	-0.2561***	-0.3630**
	(0.0258)	(0.0262)	(0.0262)	(0.0982)	(0.1820)
GDP Growth	0.2388***	0.2233***	0.1804***	0.1507	0.0006
	(0.0510)	(0.0519)	(0.0518)	(0.1945)	(0.3606)
Constant	-2.6055***	0.0640	2.6400***	10.9125***	33.5117***
	(0.8294)	(0.8435)	(0.8427)	(3.1630)	(5.8633)
Observations	660	660	660	660	660
Quantile	10th	25th	50th	75th	90th
Year FE	Yes	Yes	Yes	Yes	Yes

Note: This table reports quantile regression estimates using an unweighted BCSI across the NPL / Loans distribution. Columns correspond to the 10th, 25th, 50th, 75th, and 90th quantiles. All models include year fixed effects. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1