RISK MANAGEMENT MAGAZINE

Vol. 21, Issue 1

January – April 2026

EXCERPT

Climate Risk and Performance of European Banks: Evidence from Pillar 3 Disclosures

Simone Alberto Valletta

https://www.aifirm.it/rivista/progetto-editoriale/

Climate Risk and Performance of European Banks: Evidence from Pillar 3 Disclosures

Simone Alberto Valletta (Sapienza University, Italy)
Corresponding author: Simone Alberto Valleta (simonealberto.valletta@uniroma1.it)

Article submitted to double-blind peer review, received on 27th Novembrer 2025 and accepted on 19th March 2026

Abstract
Climate-related risks have emerged as material factors in banking. This study explores the relationship between climate risk exposure and the financial and risk performance of European banks using a single-year cross-sectional sample of significant banking groups. A key contribution is the decomposition of environmental risk into distinct components allowing for an isolated analysis of each. In contrast to existing literature, novel indicators are constructed using banks' Pillar 3 disclosures, offering a direct and standardized measure of climate exposure. A multiple linear regression model is applied to evaluate their impact on profitability, risk metrics, and bank stability. Findings reveal that certain components are associated with weaker financial performance and increased capital risk. These results partially confirm the proposed hypotheses and enhance the climate-finance literature. The study provides insights for bank management and policy, reinforcing the need to integrate climate risk into regulation frameworks.

Keywords: Environmental risks; ESG; Performance in baking; Pillar 3 Disclosure; Transitional Risks; Physical Risks; GAR; Real Estate Guarantees; Regression Analysis; Regulation; Sustainability; ESG disclosure

JEL Codes: D63, G18, G21, G28, G30

1. Introduction

In the years following the global financial crisis, and especially in the aftermath of the COVD-19 pandemic, environmental, social, and governance (ESG) issues have become increasingly prominent in financial discourse, particularly in banking. Given the strategic role of banks in raising and allocating capital, they exert a substantial and immediate influence on society and investment decisions (Nurhalida et al., 2023). Accordingly, financial institutions are increasingly regarded as having a responsibility to promote environmental sustainability, both through their internal operations and their influence on clients and borrowers while simultaneously avoiding involvement in activities that poorly manage ESG risk exposures (Horobet et al., 2024). Among the ESG dimensions, environmental concerns have attracted increasing attention, particularly due to the heightened visibility of crises associated with environmental degradation (e.g. the PG&E case or the consequences of natural disasters) which has resulted in a focus on climate-related issues in both the public and academic spheres (Quiros et al., 2019). In addition, regulatory initiatives and voluntary commitments by private actors have advanced the development of methodologies for quantitatively assessing climate risk, enabling more objective analyses than those available for social or governance factors.

A seminal moment was the establishment of the Task Force on Climate-related Financial Disclosures (TCFD) in 2015 by the Financial Stability Board, which aims to define a shared framework for the identification and communication of climate risks. The research has identified two environmental risk categories, which have been demonstrated to exert a divergent effect on the stability of the financial system: physical risk, which stems from extreme weather events that damage physical and natural assets, thereby impairing production and increasing borrower default risk1, and transition risk, which refers to financial losses due to the shift toward a low-carbon economy. The first of these is influenced by the geographic location of the borrower or financed assets, while the latter is affected by regulatory changes, technological progress, and market sentiment, particularly affecting firms in emissions- intensive sectors, involving reputational damage, especially when institutions are perceived as unresponsive to environmental concerns.

While climate change is a global phenomenon, its financial consequences are highly context- dependent. The extent of losses and the devaluation of real assets – which are often used as collateral – is determined by variables such as geography, supply chain positioning, and sectoral exposure, that raises expected losses in the event of default. The erosion of collateral value, a conventional instrument of credit risk mitigation, consequently establishes an additional correlation between Environmental risk and banking performance. It is for this reason that the European Central Bank has issued guidance to credit institutions, urging them to assess collateral when evaluating environmental risks, focusing particularly on the location of property and its energy efficiency.

[1] Physical hazards can be acute, such as heat waves, droughts, floods, etc., or chronic, resulting from progressive climate changes such as sea level rise, rising average temperatures, and ocean acidification.

In this evolving regulatory context, sustainability has assumed a central role. European policy initiatives have progressively shaped sustainable finance, guiding banks through new disclosure obligations aimed at enhancing market transparency (Siani, 2023). A significant milestone was the EU Directive 2014/95, which introduced the requirement for certain firms to publish a non-financial statement (DNF) that must outline the company's ESG-related policies, risk management strategies, and performance using relevant non-financial indicators.

Subsequent advancements were witnessed in 2016 with the establishment of the High-Level Expert Group on Sustainable Finance, which promoted the implementation of a unified classification system for ESG activities and incentivised the integration of sustainability factors into financial decision- making processes2. In this regard, the disclosure obligations for banking intermediaries have been augmented, albeit only recently, within the scope "E". Banking institutions are currently obligated to adhere to quantitative disclosure requirements that are associated with the provisions for the calculation of the Green Asset Ratio (GAR), in addition to Implementing Regulation (EU) 2022/24533. The GAR was introduced by Delegated Regulation (EU) 2021/2178, a KPI measuring the proportion of bank assets aligned with the EU Taxonomy Regulation (Regulation 2020/852), which defines criteria for identifying environmentally sustainable activities, with the aim of promoting consistent language and reducing greenwashing risks4. The KPI is calculated by placing Taxonomy-aligned exposures in the numerator and eligible total assets in the denominator, with certain unquantifiable items excluded5. In furtherance of the aforementioned, Implementing Regulation (EU) 2022/2453, amending Implementing Regulation (EU) 2021/637 and in force since the end of 2022, requires banking institutions subject to non-financial disclosure obligations to provide detailed, quantitative environmental risk data using standardised templates. These templates disaggregate risks into physical and transition categories, with a particular focus on real estate collateral and GAR reporting, thereby enhancing comparability and data quality across institutions.

The mounting importance of this aspect has led to a surge of academic interest in investigating the relationships between sustainability performance and financial and risk indicators within the banking sector. Existing literature reveals that the majority of research has focused on the correlation with ROA, ROE, credit risk (through NPL ratio), and liquidity. Nevertheless, a considerable number of these studies depend substantially on ESG ratings produced by third-party providers, whose methodologies are frequently opaque and inconsistent (Fowler et al., 2007; Chatterji et al., 2009; Escrig-Olmedo et al., 2010; Stubbs et al., 2013; Dorfleitner et al. 2015, Avetisyan et al. 2017, Gibson et al. 2019, Kotsantonis et al. 2019, Capizzi et al. 2021, Berg et al. 2022, Billio et al. 2022, Kimbrough et al. 2022, Larcker et al. 2022, Liu 2022, Tang et al. 2022, Brock 2023). The present study has been designed in order to address the aforementioned limitations by reliance on data reported directly by banks under the European regulatory frameworks, and with the aim of assessing the relationship between climate risks and key financial indicators, with particular attention to the manner in which the different components of environmental risk affect the performance of banking institutions.

The remainder of the paper is structured as follows. Section 2 reviews the literature on climate risk in banking. Section 3 describes the sample, the construction of climate indicators based on Pillar 3 disclosures, the econometric methodology and formulates the research hypotheses. Section 4 presents the empirical results. Section 5 concludes and discusses the theoretical, managerial, and policy implications.

2. Literature Review

The relationship between ESG performance and financial outcomes or risk exposure has been extensively studied across various sectors, yet research focusing on the banking industry remains limited. This mismatch can be attributed to the unique regulatory frameworks and standardised accounting and disclosure practices that characterise this sector which limit its inclusion in broader multi-sector analyses (Finger et al., 2018; Miralles-Quirós et al., 2019). However, mounting regulatory pressures and the heightened sensitivity of institutional investors have catalysed a surge in scholarly interest in the ESG-finance nexus within the banking sector.

The initial research concentrated on the correlation between environmental performance and bank profitability, Soana (2011) utilised ethical ratings as a proxy for Corporate Social Performance and discovered no significant relationship with the ROA and ROE; this outcome was also reflected in the Polish context by Matuszak & Różyńska (2017). In contrast, more recent studies have demonstrated a positive correlation between environmental performance and financial outcomes in Italy and India (Menicucci et al., 2022; Debnath et al., 2024), while Loan et al. (2024) in Vietnam have identified effects that extend to

---

[2] Disclosure, along with assurance would be crucial elements in contributing to the reduction of information asymmetries between firms and lenders. Indeed, a positive correlation is found between increased debt and CSR disclosure (Hamrouni et Al., 2019), similarly, assurance on non-financial data would positively affect banks' lending decisions (Quick et Al. 2020).

[3] In addition to GAR, institutions have mandated BTAR (Book Taxonomy Alignment Ratio), which was introduced as a complementary GAR indicator because it also considers exposures to non-disclosure counterparties, however, its publication to date is on a voluntary basis.

[4] Specifically, an environmentally sustainable activity must contribute to one of the six defined environmental goals without harming one of the other goals while meeting minimum social safeguards.

[5] Are excluded those entities not required to report under the requirements of the Taxonomy, such as governments, central banks and small businesses not subject to CSRD.

net interest income. Shakil et al. (2019) further identify a positive relationship, albeit one that is moderated by institutional factors and the development of the financial system, as Cantero-Saiz et al. (2025) observe, there is a stronger ESG effect in developing economies. However, Buallay et al. (2020) find a negative relationship between ESG disclosure and accounting performance, regardless of development level of economy. El Khoury et al. (2022) proposed a nonlinear, concave relationship, suggesting that ESG benefits taper off beyond a threshold. Alghafes et al. (2024) and Wijaya et al. (2023) found evidence that ESG positively influences market perception, but not accounting indicators, aligning with the findings of La Torre et al. (2021), who argue that positive outcomes are driven only by voluntary ESG adoption. In contrast, Dragomir et al. (2022) and Lamanda et al. (2024) found no significant relationship at all. The findings of these studies underscore the dualistic character of ESG investments, indicating that while they may potentially enhance reputation, investor trust, and financing conditions (Agnese et al., 2023; Igbudu et al., 2018), the associated costs may either neutralize or outweigh these benefits (Di Giuli et al., 2014). The relationship could also be significantly influenced by contextual elements such as regulatory stringency, market maturity, and organisational culture (Ioannidis et al., 2025; Niedziółka et al., 2023; Zuraida et al., 2022).

In relation to the ESG's impact on risk resilience, Horobet et al. (2024) report a decline in NPL ratios in banks with stronger sustainability performance, despite a decline in ROE. Consistent findings have been reported by Liu et al. (2023), who attribute enhanced ESG to optimised borrower selection, and by Ananta et al. (2025), who document reduced default probabilities and NPLs, notably in nations with stringent regulation and environmental consciousness. Nonetheless, Korzeb et al. (2025) caution that inadequately administered ESG strategies have the potential to augment risk by amplifying adverse selection and moral hazard phenomena, which are among the principal factors contributing to banks' impaired loans (Gangi et al., 2018). Conversely, Di Tommaso et al. (2020) report a negligible risk reduction, concomitant with diminished firm value. Alternatively, other studies posit a bidirectional relationship, whereby higher ESG performance has been shown to raise market value, which in turn exerts an influence on risk levels (Mandas et al., 2024).

Researchers have also explored the connection between ESG and liquidity. The extant evidence points to a positive relationship, with enhanced ESG performance correlating with better liquidity management over the medium to long term (Liu et al., 2024; Yang, 2024), lower liquidity risk leading to higher ESG scores (Serino et al., 2024) and improved liquidity creation through ESG disclosures (Gupta et al., 2024), particularly in high geopolitical risk contexts (Lee et al., 2024). In fact, liquidity risk may also suffer second-round effects if poor ESG performance diminishes market confidence, reduces central bank funding access, or weakens collateral quality (Kalfaoglou, 2021).

In conclusion, the relationship between ESG factors and financial performance in the banking sector is significantly influenced by contextual variables. Furthermore, sustainability strategies are likely to be endogenous to bank performance and influenced by unobservable characteristics (Flammer, 2015). However, the presence of inconsistencies across studies may be attributed to definitional ambiguities, varying data sources and methodologies, and limited transparency in ESG rating assessments (Gillan et al., 2021; Widyawati, 2019). Consequently, this study adopts a binding European regulatory framework as its basis for quantitative analysis, with the aim of determining whether banks with stronger environmental performance exhibit superior financial outcomes, or whether ESG commitment yields neutral or context-dependent effects.

3. Methodology and Data Sample

The present study seeks to establish a potential association between environmental factors and financial and risk performance by utilising public data sources from the third pillar of bank reporting, which have been integrated following the endorsement of EU Regulation 2022/2453. The objective of the analysis is to ascertain whether superior performance in the domain of climate risk is associated with competitive advantages in terms of profitability, funding stability, reduced exposure to "traditional" risks or higher capitalisation. To test the hypothesised relationships, the empirical strategy relies on a multiple linear regression framework, estimated on a single-year cross-section of significant European banking groups. Specifically, for each dependent variable $Y_i(m)$, we estimate a separate specification of the form:

$$Y_i(m) = \alpha m + \beta m' X_i + \gamma m' C_i + \varepsilon_i(m)$$

Where:

- $Y_i(m)$ is the m-th dependent variable for bank i;
- X_i is the vector of main explanatory variables;
- C_i is the vector of control variables;
- βm and γm are the corresponding coefficient vectors;
- $\varepsilon_i(m)$ is the error term.

This specification allows us to estimate the net effect of each climate-risk dimension while holding constant the other climate variables and the bank-specific controls. The use of multiple regression is preferred to a bivariate (simple) specification because the climate indicators are conceptually related, and the correlation analysis shows that pairwise associations are often weak or non-significant; hence, a multivariate setting is required to avoid misleading inferences based on isolated relationships. In addition, all variables are standardised (z-scores) before estimation, so coefficients can be interpreted on a comparable scale across regressors and models.

As previously discussed, academic studies on the banking sector analyse the relationship between ESG performance and various possible areas of banking performance (Ahmed et al., 2019; Ngoc, 2018). In terms of profitability, the extant literature predominantly identifies a positive correlation between ESG performance and financial outcomes, primarily attributable to the satisfaction of stakeholders who are progressively attentive to environmental concerns. In accordance with this, ROA will be utilised as a metric of the intermediary's profitability, calculated as net income over total assets and ROE, to define the return on invested capital (Buallay, 2019; Buallay et al., 2020), assuming a directly proportional relationship with the ESG score (hypothesis 1). Improved financial performance has also been demonstrated to strengthen a bank's ability to withstand liquidity pressures, thus improving its stability profile. Therefore, in this analysis, we hypothesise an indirect relationship between liquidity and environmental risk-taking (hypothesis 2), where the former is measured using the two key indicators defined in banking regulations, the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR). These provide an overview of the intermediary's ability to withstand short-term shocks, as well as the structure of medium-term funding.

With regard to risk-taking, an enhancement in ESG ratings has been demonstrated to have the capacity to substantially mitigate commercial banks' risk appetite. Research has demonstrated that a high ESG rating can result in a reduction in operational risk, default risk and the risk inherent in the banking portfolio. Institutions with superior ESG ratings comprehensively consider sustainable development factors in their credit assessment, potentially mitigating adverse selection and moral hazard issues, thus reducing the risk associated with the loan portfolio (Liu, 2024). Given the established importance of ESG practices in credit assessment and management, as also determined by the GLOM EBA, this paper selects the NPL ratio as a risk measure and RWA density, defined as the ratio between RWA and assets, as a means to assess the intensity of the intermediary's risk (Kishore, 2018). Both would exhibit an inverse correlation with the intermediary's exposure to environmental risks (hypothesis 3).

Another feature that has been shown to correlate with ESG scores is the capitalisation of an intermediary (Crespi et al., 2020), considered both in relation to RWA and to balance sheet assets; indeed, the two indicators should be verified in tandem in order to obtain a complete picture of bank capitalisation (Masera et al., 2019). In the first case, the most expansive definition of capital was selected through the utilisation of the TCR (Platonova et al., 2018; Siueia et al., 2019), a pivotal metric of adherence to the capital requirements calculated as total own funds divided by RWA, and representing the bank's capacity to absorb losses through various components of capital. In the second case, the leverage ratio was estimated according to its regulatory measurement, given by the ratio between Tier 1 and total leverage ratio exposure[6]. The final hypothesis formulated is the positive correlation between TCR and performance linked to the reduction of climate risk exposure (hypothesis 4).

The empirical analysis is based on a single-year cross-section of 88 significant European banking groups, which differ in terms of characteristics but all fall within the scope of Implementing Regulation 2022/2453 that requires the publication of ESG disclosures on a consolidated basis by “significant institutions” with financial instruments listed on a regulated market in the EU. This act serves to supplement the prudential banking framework, with the objective of updating the Third Pillar disclosure requirements on ESG risks[7]. The climate-related variables are constructed from Pillar 3 ESG disclosures published in December 2023 (the first reporting date including GAR disclosure under the applicable framework), and the variables are matched to the same reporting period. Accordingly, the dataset used in the regressions is cross-sectional. The sample was constructed starting from the ECB’s official List of supervised entities, using the first list available after the reference period (cut-off date: 1 March 2024), which reports 112 significant supervised entities. The ECB list is compiled at the supervised-entity level and therefore includes credit institutions, financial holding companies, mixed financial holding companies and branches, whereas the empirical analysis in this paper is conducted at the consolidated banking-group reporting level. Accordingly, we applied a consolidation and eligibility filter to derive the final analytical sample. Specifically, we excluded: (i) entities outside the scope of the Pillar 3 ESG disclosure framework used in this study, i.e. entities for which the disclosure requirements under Article 449a CRR / Commission Implementing Regulation (EU) 2022/2453 were not applicable for the purposes of our sample construction; and (ii) entities belonging to a banking group already represented in the sample, in order to avoid double counting and retain a single consolidated reporting entity per group (Appendix 3 reports the sample selection flow and the list of ECB significant entities excluded from the final sample, with the corresponding exclusion reason).

For the purposes of this analysis, the data sources have been extrapolated from Template 1 and Template 5 to assess exposure to transition and physical risks: the structure of the two tables necessitate a detailed breakdown of exposures subject to the two risks, broken down respectively by ATECO code and geographical area of relevance, highlighting in each table the gross exposure, the accumulated impairment, the share of stage 2 and 3 according to the IFRS 9 and finally, the breakdown by maturity bucket with the average weighted maturity of the portfolio.

Another source utilised is Template 2, which concentrates on transition risks arising from loans secured by real estate; in this case, the columns of the template demonstrate the breakdown of exposures according to the energy efficiency level of the

---

[6] Given by the sum of: on-balance sheet exposures (excluding derivative and securities financing transaction exposures); derivative exposures; securities financing transaction exposures; and off-balance sheet items.

[7] It amends the previous Implementing Regulation (EU) 2021/637 to introduce uniform formats and instructions for ESG risk disclosure.

real estate collateral, expressed both as an energy consumption score (EP score in kWh/m²) and as an EPC label of collateral[8]. This approach facilitates an accurate representation of the environmental quality of the properties used as collateral, which are frequently also the subject of the loan, a crucial element in assessing exposure to regulatory and reputational transition risk. Ultimately, it has been used Template 8, dedicated to GAR exposed both as a portfolio stock and as a flow with respect to the assets financed in the last year.

Utilising the Third Pillar disclosures promulgated by intermediaries in December 2023 — the inaugural date on which the disclosure pertaining to the GAR was also rendered accessible — an environmental risk indicator was formulated, categorised into four primary profiles: transition risk, physical risk, risk emanating from collateral and GAR, each of which is constructed by aggregating a set of sub-profiles. The objective of defining these profiles was to capture the various manifestations of environmental risk to which banks are exposed, in line with the recommendations set out in regulatory literature and regulatory developments in Europe.

Transition risk and physical risk are divided into five sub-types: (i) gross exposure, calculated as the ratio between the total amount of exposures to the respective risk and total assets, reflecting the bank's overall environmental vulnerability (Battiston et al., 2017); ii) "exposure deterioration", obtained as measured as the ratio of Stage 2 and Stage 3 exposures to gross exposure within the same climate-risk perimeter (transition or physical), which captures the degree of credit-quality deterioration within the environmentally exposed portfolio; iii) the average maturity of exposures, a crucial indicator of climate risks, as a prolonged time horizon exposes the portfolio to the potential impact of uncertain regulatory and market scenarios in the medium to long term (Bolton et al., 2020), as well as to greater risks arising from the probability of extreme weather events or progressive environmental changes. This is accompanied by the share of exposures with maturities in excess of five years, which is instrumental in evaluating the degree of rigidity of the portfolio and the exposures that could be most affected by environmental risks; iv) the coverage ratio, understood as the ratio between provisions and the gross value of stage 2 and 3 exposures, measures the bank's ability to absorb any losses related to environmental shocks and v) The Herfindahl-Hirschman Index (HHI) a widely utilised metric within the literature for the analysis of concentration, it enables the capture of risk arising from exposures that are overly focused on certain sectors (Calabrese et al., 2014).

The assessment of real estate risk is conducted through the utilisation of three distinct sub-profiles. The first of these considers the ratio of collateral to total assets as a measure of the intermediary's dependence on the value of the properties used as collateral. The second analysis focuses on the percentage of collateral without an energy label, for which the bank is able to obtain less information and is potentially more vulnerable; in addition, such properties are frequently distinguished by diminished energy efficiency, consequently rendering them more vulnerable to risks and depreciation which, in the event of foreclosure, may result in a heightened Loss Given Default for the lender. The final indicator quantifies the requisite emission reduction for the intermediary's real estate portfolio to attain compliance with the standards stipulated in Regulation (EU) 2021/2139 that establishes energy consumption reduction targets of 20% for residential properties and 26% for non-residential properties. The existence of properties requiring energy efficiency improvements, which consequently incur costs for borrowers in achieving these targets, exposes financial institutions to a range of risks: primarily, there is a possibility of a decline in the value of the underlying collateral on the property market if the necessary improvements are not implemented, secondly, there is an increased likelihood of an escalation in credit risk if borrowers lack the financial capacity to cover the costs of the requisite modifications.

The GAR profile is calculated as the arithmetic mean of two components: the GAR stock, referring to assets aligned with the taxonomy present in the financial statements, and the GAR flow, relating to exposures generated in the last financial year. Both components are weighted according to the percentage of assets covered by the indicators out of total assets.

The value of the Final indicator is obtained as the arithmetic mean of the scores for each of the four profiles. In order to render the heterogeneous data relating to the sub-profiles comparable, the variables composing them have been converted to an ordinal scale. For each of these, the distribution of available observations has been divided into deciles, and each value has been assigned a score between 1 and 10 depending on the class to which it belongs. In constructing the score, the value 1 represents the most favourable performance, while the value 10 corresponds to the worst result recorded. To ensure full consistency of the ordinal scoring procedure with the convention adopted in this study (1 = most favourable outcome; 10 = least favourable outcome), each sub-metric is assigned a direction before decile classification. For sub-metrics that capture environmental risk intensity or vulnerability (e.g., exposure, deterioration, maturity, concentration, and real-estate vulnerability measures), the decile score is applied directly, so that higher values correspond to worse outcomes (higher score). By contrast, for sub-metrics that capture resilience or environmental alignment, the decile score is reverse-scored. In particular, the coverage ratio (in both transition and physical risk profiles), which measures loss-absorption capacity, is reverse-scored because higher coverage implies greater resilience and therefore a more favourable outcome. Likewise, GAR-based measures (GAR stock and GAR flow, weighted by the share of covered assets) are reverse-scored because higher

[8] Energy Performance Certificate, introduced by EU Directive 2010/31. Also provided for a separate classification for buildings without EPC certification.

taxonomy alignment is interpreted as more favourable. This sign convention is applied uniformly across all banks prior to the aggregation of sub-profile and profile scores. For transparency and replicability9.

This method thus allows the results obtained by the various intermediaries to be re- parameterised on the same scale, making them comparable and ensuring that the aggregate scores of the profiles and the summary indicator, in decimal terms, are in the range 1-10.

Despite the fact that this approach has not been extensively utilised within the extant literature, it does reflect the methodological practices adopted by the primary ESG rating agencies, which employ ordinal scale classification schemes to evaluate the sustainability performance of diverse corporate entities, including banking institutions. The adoption of a similar criterion therefore allows for consistency with the operating standards used by private operators and adopted in the literature for the construction of quantitative analyses.

The study uses eight dependent variables, grouped into four analytical dimensions of bank performance and resilience:

- Profitability variables are ROA (net income / total assets) and ROE (net income / shareholders' equity).
- Credit-risk and portfolio-risk variables are NPL Ratio (non-performing loans / total credit exposures) and RWA Density (risk-weighted assets / total assets).
- Liquidity variables are LCR (high-quality liquid assets / net cash outflows over 30 days) and NSFR (available stable funding / required stable funding).
- Capital adequacy variables are TCR (total regulatory capital / risk-weighted assets) and Leverage Ratio (Tier 1 capital / total leverage exposure).

These variables are used as alternative outcomes in separate multiple-regression specifications.

Finally, given the existence of numerous studies demonstrating that the size of an intermediary is correlated with performance in the areas identified as dependent variables (e.g. Parvin et al., 2019; Tharu et al., 2019; Varotto et al., 2018), a variable linked to the size of the intermediary and commensurate with total balance sheet assets has been introduced among the independent variables. In the empirical specification, alongside intermediary size (measured by total balance sheet assets), the cost-to-income ratio and the loan-to-asset ratio are included as control variables.

This choice is consistent with the recent literature showing that ESG- and climate-related factors may affect bank outcomes through both operating efficiency and lending composition channels. In particular, ESG practices and disclosure are found to be associated with bank efficiency, which supports the inclusion of the cost-to-income ratio as a standard proxy for operating efficiency (López-Penabad et al., 2023; Alam et al., 2022), while ESG orientation is also linked to changes in lending behaviour and portfolio composition, which supports the inclusion of the loan-to-asset ratio as a proxy for business model and asset mix (Mueller and Sfrappini, 2022; Sastry et al., 2024; Bressan, 2024). Table 1 reports the same variables, definitions, sources, and units in a compact format for reference.

Dependent variables		Sources
ROA	Net income / Total assets	Own's elaboration on Pillar 3 disclosure
ROE	Net income / Shareholders' equity	
Density of RWAs	Risk-Weighted Assets/ Total Assets.	
NPL Ratio	Non-performing loans / Total credit exposures	
LCR	High-quality liquid assets/Net cash flows expected in the next 30 days.	
NSFR	Available Stable Funding / Required Stable Funding	
TCR	Regulatory Capital/Risk-Weighted Assets.	
Leverage ratio	Tier 1/ Overall exposure to leverage risk	
Independent variables		
Transition	Arithmetic mean of scores obtained in the following subprofiles: i) Gross exposure to sectors contributing to climate change (net of sustainable exposures)/Total Assets; ii) Stage 2 and Stage 3 exposures/Gross exposure to sectors contributing to climate change; iii) Share of exposures with maturity greater than 5 years; iv) Average maturity of exposures; v) Coverage ratio exposures in St. 2 and 3; vi) Herfindal-Hirschman Index	

[9] Annex 2 reports the scoring direction (direct vs. reverse) for each sub-metric used in the construction of the environmental profiles

Real estate	Arithmetic mean of scores obtained in the following sub-profiles: i) Share of collateral in total assets; ii) Share of collateral without energy classification; iii) 20% reduction in average consumption for residential collateral; iv) 26% reduction in average consumption for non-residential collateral.	Own's elaboration on Pillar 3 disclosure
Physical	Arithmetic mean of the scores obtained in the following subprofiles: i) Gross exposure to physical risks/Total Assets; ii) Stage 2 and Stage 3 exposures/Gross exposure to physical risks; iii) Proportion of exposures with maturity greater than 5 years; iv) Average maturity of exposures; v) Coverage ratio exposures in st. 2 and 3; vi) Herfindal-Hirschman Index	
GAR	Arithmetic mean of the scores obtained in the following subprofiles: i) GAR Stock*%covered assets; ii) GAR flow*%covered assets	
Total Assets	Total consolidated balance sheet assets as of 12/31/23	Balance sheet
Cost to Income	Operating expenses / Operating income	Own's elaboration on FINREP (EBA Transparency Exercise 2024) or consolidated IFRS annual reports (where supervisory data were unavailable)[10]
Loan to Asset	Net loans to customers / Total consolidated assets	

Author's own elaboration

Table 1: List of variables

4. Findings

The descriptive analysis of the variables included shows a significant dispersion of data within the sample, even though the average values of the dependent variables are close to the average value of the scale. Anyway the extreme values signal a relevant margin of differentiation which is useful in discriminating banks that are more advanced in environmental terms from those that remain at reduced levels of preparedness for environmental impacts and can therefore be considered more exposed, furthermore the observations of the entire sample demonstrate a fragmented picture, with no relationships that can be generalised between climate performance and economic, financial and risk conditions (Cfr. Annex).

This evidence suggests that a more in-depth investigation is required into the relationships between dependent and independent variables, as they cannot be adequately captured through a mere descriptive analysis.

	Transition	Real estate	Physical	GAR	FINAL	Total Asset	TCR	Lev.	LCR	NSFR	ROE	RWA Dens.	NPLr	ROA	CtI	LtA
Avg.	5.486	5.469	5.5	5.313	5.442	301.485.47	0.222	0.071	2.188	1.386	0.114	0.361	0.024	0.008	0.52	0.542
St. Deviation	1.570	1.796	1.333	2.704	0.941	493.959.20	0.102	0.029	1.166	0.314	0.089	0.138	0.013	0.006	0.136	0.142
Min	2.125	1	2.125	1	3.281	4.809.32	0.16	0.04	1.35	1.08	0	0.03	0	0	0.218	0.003
Max	9	8.75	8.125	10	7.25	2.591.499.00	1.03	0.21	8.23	3.78	0.656	0.84	0.062	0.0373	1.06	0.86

Author's own elaboration

Table 2: Descriptive Analysis

[10] The Cost to Income and Loan to Asset ratios are computed on a consolidated basis using supervisory financial reporting data from the EBA Transparency Exercise 2024 (FINREP framework, reference date 31 December 2023). For institutions not covered in the supervisory dataset, the indicators are calculated using consolidated IFRS annual reports (FY2023). Operating income and operating expenses are derived from the consolidated income statement, while loans and total assets are extracted from the consolidated statement of financial position.

	Transition	Real Estate	Physical	GAR	FINAL	ROE	ROA	RWA Density	NPLr	LCR	NSFR	Tot. Asset	TCR	Lev. Ratio	Ctl	LtA
Transition	1.000															
Real Estate	-0.218**	1.000														
Physical	0.341***	0.006	1.000													
GAR	0.155	-0.189*	0.191*	1.000												
FINAL	0.515***	0.239**	0.601***	0.719***	1.000											
ROE	-0.372***	0.057	-0.076	0.053	-0.111	1.000										
ROA	-0.345***	0.051	-0.151	0.032	-0.142	0.891***	1.000									
RWA Density	-0.039	0.049	-0.142	-0.212**	-0.185*	-0.037	0.296***	1.000								
NPLr	0.008	0.316***	-0.023	-0.176	0.019	-0.102	0.108	0.566***	1.000							
LCR	0.090	-0.163	0.104	0.067	0.042	0.123	0.058	-0.058	-0.031	1.000						
NSFR	-0.384***	0.033	-0.021	0.133	-0.053	0.431***	0.364***	-0.076	-0.179*	0.538***	1.000					
Tot. Asset	-0.190*	0.140	-0.123	-0.000	-0.053	-0.066	-0.171	-0.198*	-0.001	-0.275***	-0.241**	1.000				
TCR	0.330***	-0.339***	0.197*	0.308***	0.252**	-0.049	-0.136	-0.430***	-0.320***	0.343***	0.088	-0.150	1.000			
Lev. Ratio	0.343***	-0.436***	0.007	0.082	-0.003	-0.158	-0.002	0.328***	0.078	0.344***	-0.019	-0.27***	0.441***	1.000		
Ctl	0.037	0.049	0.097	0.005	0.073	-0.102	-0.226**	-0.184*	-0.097	-0.226**	-0.251**	0.351***	-0.250**	-0.347***	1.000	
LtA	0.359***	0.054	0.258**	-0.221**	0.102	-0.398***	-0.356***	-0.100	-0.077	0.017	-0.355***	-0.062	0.110	0.037	-0.079	1.000

Asterisks indicate levels of statistical significance as follows: $p < 0.10$ (*), $p < 0.05$ (**), $p < 0.01$ (***).
Author's own elaboration

Table 3: Correlation Matrix

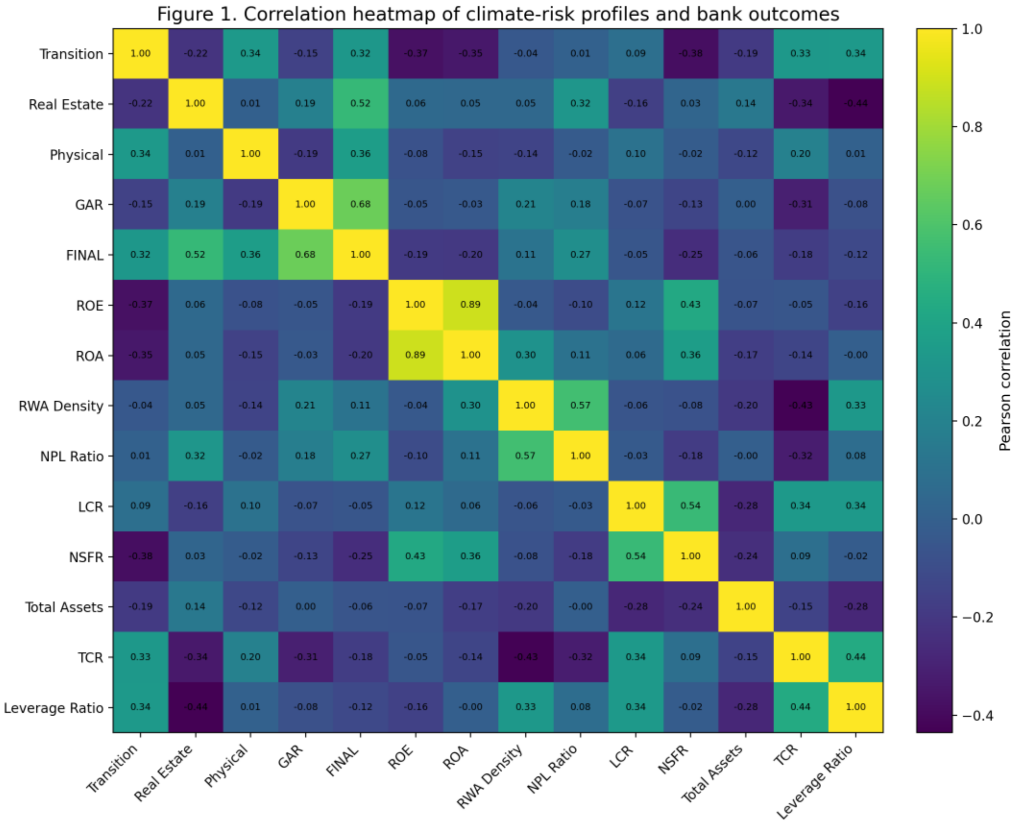
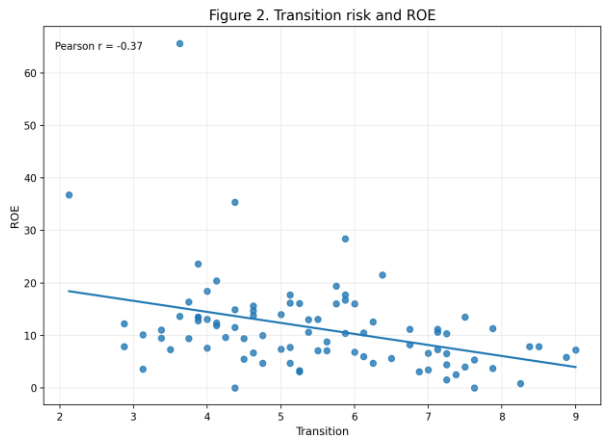


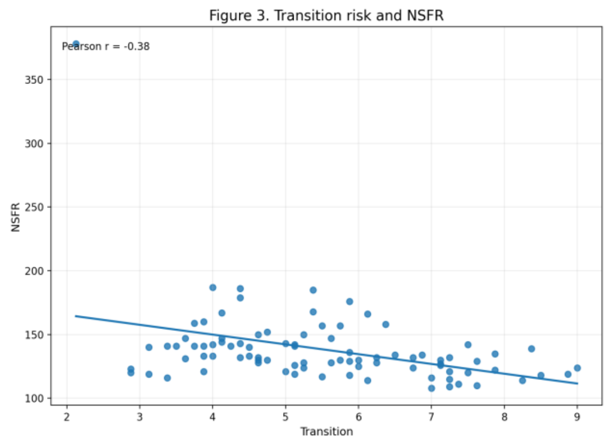
Figure 1: Heatmap of Pearson correlations among climate-risk profiles and bank performance/risk variables used in the empirical analysis (cross-sectional sample of 88 banks).

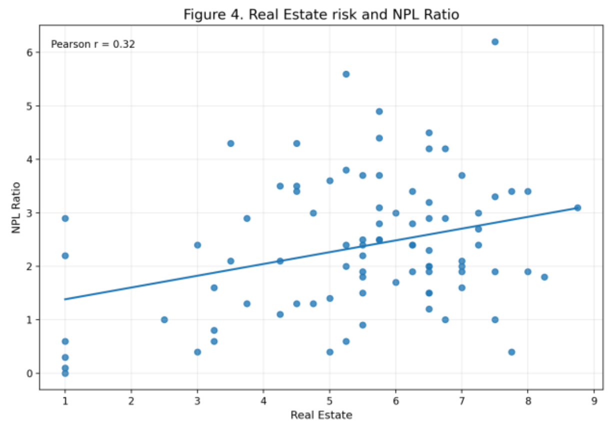
The correlation matrix[11], calculated using Pearson's coefficients, also demonstrates that there are frequently weak correlations between the variables, and p-values that exceed the conventional threshold of statistical significance. The

[11] Prior to the application of the empirical analyses, all variables were subjected to a standard normalization process (z-score). This approach was necessary in order to make the variables initially expressed on different scales comparable.

absence of strong bivariate links, with the exception of that between ROE and ROA and between GAR and Final, indicates the necessity to analyse these relationships in a multivariate context. Consequently, a multiple regression model was employed to estimate the net and isolated effect of each component on the various performance and banking risk indicators, enabling the statistical significance of the hypothesised relationships to be verified and the limitations observed in the exploratory phase to be overcome.







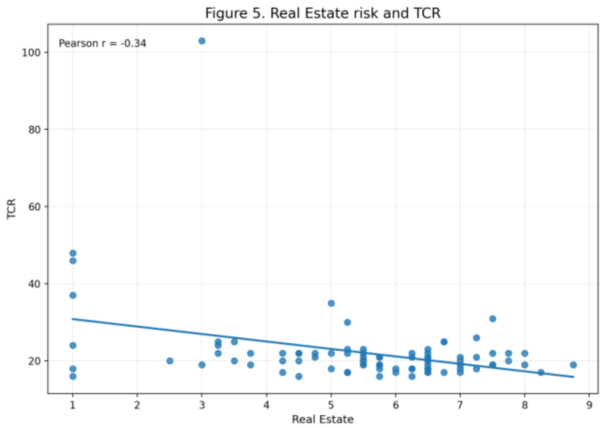


Figure 2. Transition risk and ROE Scatter plot of Transition score and ROE with fitted linear trend.

Figure 3. Transition risk and NSFR Scatter plot of Transition score and NSFR with fitted linear trend.

Figure 4. Real Estate risk and NPL Ratio Scatter plot of Real Estate score and NPL Ratio with fitted linear trend.

Figure 5. Real Estate risk and TCR Scatter plot of Real Estate score and TCR with fitted linear trend.

Dependent variable	Total Asset	CtI	LtA	Transition	Real Estate	Physical	GAR	R^2	F-stat
ROE	-0.1016	-0.0934	-0.329***	-0.3015**	0.0302	0.1063	0.0124	0.2539	3.89***
ROA	-0.1835*	-0.1769*	-0.2856**	-0.2649**	0.0468	0.0038	0.0192	0.2669	4.16***
NPLr	0.0313	-0.1513	-0.2246*	0.1965	0.3374***	0.0221	-0.1955*	0.1743	2.41**
RWA Dens.	-0.1647	-0.1378	-0.1838	0.0799	0.0620	-0.0842	-0.2369**	0.1386	1.84*
NSFR	-0.2538**	-0.1833*	-0.2565**	-0.395***	0.0267	0.1449	0.1163	0.3632	6.52***
LCR	-0.1876	-0.1666	-0.0252	0.0064	-0.1227	0.0991	0.0188	0.1211	1.57
Leverage	-0.0675	-0.3209***	-0.0863	0.3206***	-0.3435***	-0.0470	-0.0408	0.3831	7.10***
TCR	0.0322	-0.2637**	0.0551	0.2031*	-0.2481**	0.1018	0.224**	0.3075	5.08***

Asterisks indicate levels of statistical significance as follows: $p < 0.10$ (*), $p < 0.05$ (**), $p < 0.01$ (***).
Author's own elaboration

Table 4: Multiple Linear Regression

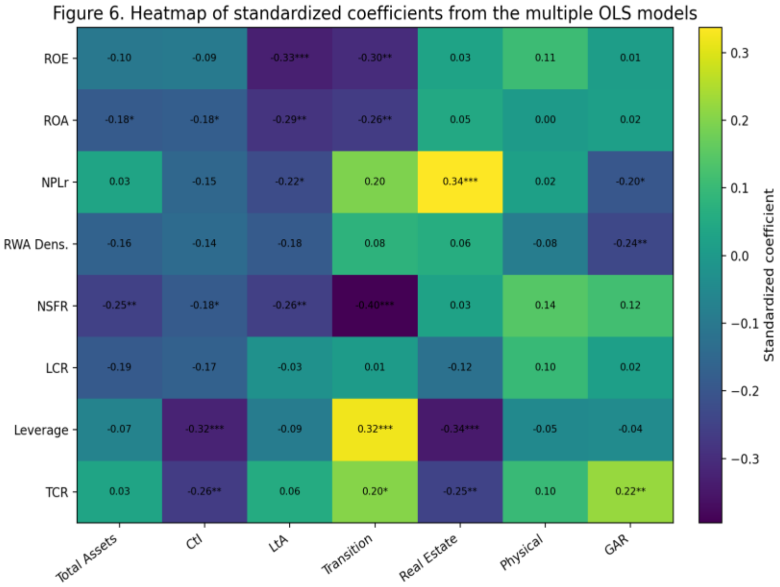


Figure 6. Heatmap of regression coefficients Heatmap of standardized coefficients from the multiple OLS models (dependent variables in rows; regressors in columns).

The empirical analysis has enabled the systematic investigation of the impact of environmental factors on various economic, financial and prudential indicators for European banks. The model incorporates four risk components — Transition, Real Estate, Physical and GAR — which are treated as distinct predictors of the dependent variables, in order to define the possible heterogeneous effects produced by the different types of environmental risk.

In terms of profitability regression model is statistically significant, with an R^2 coefficient of determination of25.39% for ROE and 26.69% for ROA. While the explanatory power is not particularly high, it is sufficient to highlight the presence of structural trends. The most significant result is the negative coefficient of transition risk, this means that banks most exposed to risks related to the ecological transition tend to be less profitable. Similar results are found for ROA, where transition risk has a considerable and negative weight in addition to total assets (linked by definition to ROA) and the other control variables (in line with the existing literature for the CtI[12]). Banks that are most exposed to regulatory shocks, environmental policy changes, or technological misalignments experience a reduction in operating profitability. Conversely, variables related to physical risk, the real estate guarantees, and the 'green' composition of the portfolio have no short-term effect on margins. The main impact of transition performance also suggests that failing to meet climate targets or being dependent on high-impact sectors incurs structural costs that negatively affect asset margins. This evidence contributes to a growing body of literature documenting the economic cost of climate non-compliance, particularly for financial institutions operating in highly regulated and market-preference environments (Krueger et al., 2020; La Torre, 2020). Furthermore, lower returns on equity indicate how markets and investors penalise environmental inefficiency in terms of equity returns too, in line with literature on the relationship between environmental performance and the cost of capital (Jang, 2020).

Interestingly, RWA density shows a statistically significant overall model, with GAR reaching individual statistical significance. This leads to the interpretation that a portfolio aligned with eco-sustainable activities causes higher risk-taking in the balance sheet. In this case, none of the control variables are significant predictor. The robust impacts of just one variable suggests that, despite the authorities' efforts to incorporate environmental considerations into risk assessment holistically, asset weighting remains anchored to prudential metrics that do not allow for differentiated weightings through the introduction of green and/or brown factors since the EBA is currently reluctant to implement these factors as it does not consider them to be an efficient solution for encouraging the efficient reallocation of capital and strengthening the resilience of the system.

The model is significant for NPLs, even if partially ($R^2 = 0.174$). The climate-relevant variable are real estate risk and GAR. The first has a positive effect: banks with greater exposure to vulnerable collateral tend to have higher levels of NPLs. This is consistent with studies showing that deterioration in credit quality is one of the main channels through which climate risk affects banking stability (Kalfaoglou, 2021), with real estate collateral remaining a key vulnerability (ECB, 2020; EeDaPP, 2020). Therefore, their systematic inclusion in credit risk models should be prioritised to strengthen the stability of the financial system in the long term. While the negative association with GAR suggests that banks with portfolios more aligned with environmental regulations tend to exhibit higher balance-sheet risk. Other variables are not significant, which may be due to the difficulty of translating systemic effects, such as green policies and regulatory changes, into observable effects on loan portfolio quality. The control variables are not significant predictors, with the exception of LtA. However, a stronger

[12] See Laporšek et al. (2024), Al Sharkas et Al. (2022).

lending-oriented business model (i.e., a higher loans-to-assets ratio) may expose banks to greater asset quality deterioration, as a higher share of loans in total assets has been associated with higher non-performing loan ratios in the literature.

The absence of compelling evidence from empirical analysis of the LCR regarding the impact of climate risk on banks' short-term liquidity coverage capacity (R^2 = 0.12) is unsurprising; in this context the only predictor that has been found to be statistically significant is total assets. This relationship is negative, indicating that larger banking institutions tend to exhibit lower levels of short-term coverage. This would therefore be perfectly consistent with the interpretation that sustainability risks, in baseline scenarios, act by definition in the medium to long term and would not have any effect on short-term indicators such as the LCR. When the focus shifts to a structural indicator, the model reports association of environmental factors on the NSFR making the model robust (R^2=0.36; $p < 0.001$), with transition risk playing a key role. This suggests that financial institutions with the greatest exposure to environmental change may also experience a lower level of stable funding, consequently, the uncertainty surrounding the ecological transition could potentially lead to an escalation in financial vulnerability, stemming from diminished access to medium-term funding sources. Conversely, the variable pertaining to physical risk, characterised by an unknowable probability of occurrence, exhibits no substantial effect, thereby suggesting that extreme weather events exert no direct influence on the funding structure. This absence may be attributed to a deficiency in the internalisation of these risks within funding models, as well as a regulatory framework that does not yet differentiate funding sources based on the climate profile of the underlying assets. Notwithstanding, the environmental quality of the portfolio and exposure to transition risks could already be considered discriminating factors in the financial structure of banks, despite the absence of ad hoc regulatory requirements. Finally, the control variables are significant with a negative sign, indicating that larger and less efficient banks tend to have a relatively lower NSFR.

From a capital perspective, the TCR ratio model shows a $R^{2=}$0.307, indicating that approximately one third of the change in regulatory capital can be explained by climate factors. The most significant variables recorded are Real estate and GAR, with opposite signs. Therefore, inefficiencies in the real estate assets used as collateral for balance sheet exposures and a portfolio with few eco-sustainable assets translate into lower capitalisation. It is asserted that financial institutions with exposure to real estate sectors deemed susceptible to climate change may experience diminished capitalisation levels, attributable to credit losses, asset write- downs or heightened prudential requirements. Conversely, the positive association with GAR suggests that a higher degree of environmental alignment in the portfolio is linked to lower capitalization levels, thereby confirming the greater risk exposure of these intermediaries. The behaviour of transition risk is also of interest, as it shows a positive and weakly significant coefficient, this could be indicative of more cautious capital policies on the part of banks exposed to industrial conversion risks. The role of transition remains consistent when considering its relationship with leverage, as it is positively and significantly associated with it: banks most exposed to this type of risk tend to make less intensive use of debt. In contrast, real estate risk demonstrates a negative correlation with leverage, so banking institutions with a high degree of exposure to energy-inefficient collateral may have adopted less conservative lending policies, resulting in an increase in assets.

Taken together, the results point to a differentiated pattern across climate dimensions, which can be interpreted by distinguishing between stronger associations, weaker or more heterogeneous relationships, and non-significant effects. The clearest pattern concerns Transition risk, which shows the most consistent negative association with profitability (ROE and ROA) and with NSFR, suggesting that banks with a worse transition-risk profile tend to be less profitable and to display weaker structural funding conditions. Real Estate risk also emerges as a relevant predictor, although in a more specific way, as it is associated with higher NPL ratios and lower capital indicators, particularly TCR and Leverage Ratio, thereby indicating that greater exposure to vulnerable or energy-inefficient collateral may translate into weaker asset quality and lower capital resilience. By contrast, GAR exhibits a more heterogeneous role across models: it does not appear to be informative for profitability or short-term liquidity, but it becomes relevant for selected prudential outcomes, such as RWA Density, NPL Ratio, and TCR. This result should be interpreted with caution, since the GAR profile is reverse-scored and captures only the share of the portfolio covered by taxonomy-based disclosure. Finally, Physical risk remains largely non-significant across the estimated specifications, while LCR does not show any meaningful relationship with the climate-related predictors. Rather than suggesting irrelevance, these non-significant effects may reflect the limits of a single-year cross-sectional setting, in which some climate-related channels—especially those linked to physical risk—are more likely to materialise over longer horizons than in contemporaneous balance-sheet indicators.

The evidence presented herein indicates that environmental risk, in its various forms, does not remain neutral with respect to capital resilience and should be integrated into ICAAP models, particularly portfolios linked to vulnerable real estate sectors with low energy efficiency, which are a systemic weakness, as also indicated in the ECB (2022) work on climate integration in the banking risk framework. However, the analysis of risk factors has yielded outcomes that do not fully align with existing literature on the subject, indeed Bakkar's (2023) findings indicate that European banks with heightened exposure to climate risk, conceptualised as a singular variable, demonstrate a propensity to sustain elevated levels of regulatory capital and expeditiously recalibrate their capital structure.

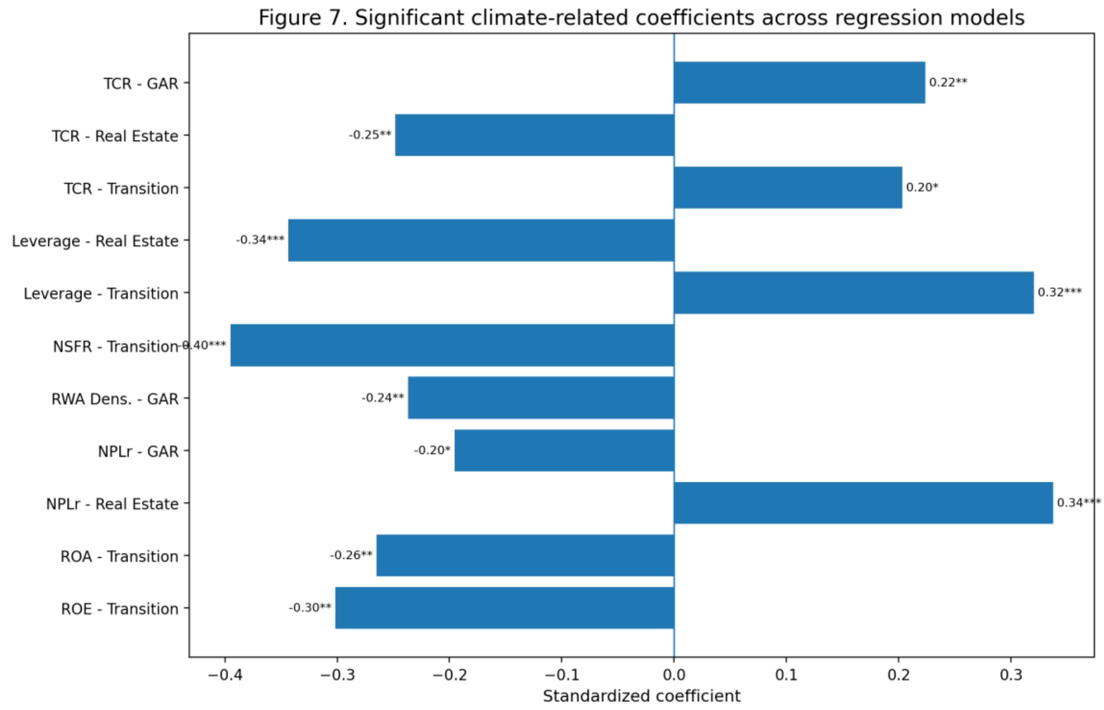


Figure 7. Significant climate-related coefficients Bar chart of statistically significant climate-related coefficients from the multiple OLS models.

Robustness checks. The sensitivity of the results to the construction of the environmental indicators is assessed through two alternative procedures, while preserving the same scoring architecture used in the baseline Excel framework (including the same nested averaging structure across sub-metrics and profiles). First, all sub-metrics are re-scored using a quintile-based discretization (1–5) instead of deciles, maintaining the baseline sign convention (direct scoring for risk/exposure and maturity variables; reverse scoring for the two coverage measures and the GAR stock and GAR flow variables). Second, continuous versions of the indicators are constructed by standardizing each raw sub-metric using z-scores, again applying sign reversals to coverage and GAR variables, and then averaging within each profile. In both cases, profile scores are computed as the arithmetic mean of the available sub-metrics, with missing values handled through available-case averaging within profile (missingness being limited to a small subset of real-estate sub-metrics). The results indicate a high degree of robustness, especially with respect to the ordinal scoring design: the final composite score remains almost unchanged under the quintile specification (Spearman correlation = 0.990 relative to the baseline), and remains strongly consistent also under the continuous z-score specification (Spearman correlation = 0.874). The regression evidence is likewise stable overall: compared with the baseline specification, 30 out of 32 climate-profile coefficients retain the same sign under quintile scoring and all 32 out of 32 retain the same significance status at the 10% level; under continuous z-scores, 24 out of 32 coefficients retain the same sign and 25 out of 32 retain the same significance status. Taken together, these robustness checks support the main empirical conclusions and suggest that the findings are not driven by the specific decile-based construction adopted in the baseline model, although some sensitivity remains for individual profile–outcome combinations under continuous standardization. (See Annex 4).

5. Discussion and Conclusions

The present study is based on an analysis of Pillar 3 Disclosures and the construction of climate risk indicators across four dimensions: physical risk, transition risk, exposure to real estate guarantees, and the GAR. The objective is to systematically investigate the relationship between these risks and the performance of European banks in order to the complement existing literature on the subject, as it identifies both areas of convergence and divergence. It is important to note that it offers an interpretation that is somewhat at odds with approaches that rely on external ESG ratings, which characteristically utilise a composite framework. Indeed, by disaggregating environmental risk into distinct components, it demonstrates that the dimensions of climate risks do not uniformly affect bank performance.

In accordance with previous contributions inspired by stakeholder theory, the findings confirm that superior management of environmental factors is associated with enhanced financial performance (Korzeb et al., 2024): within this theoretical framework, transition risk emerges as a particularly influential factor with regard to profitability indicators (ROE/ROA). The impact of such changes is twofold, affecting both traditional risk exposure and liquidity inefficiencies, that are typically mitigated when banking institutions reduce their exposure to sectors vulnerable to shifts in regulation or economic conditions.

Conversely, physical risk and exposure to real estate guarantees have been shown to have no statistically significant effect on profitability, contradicting in some way the expectations set out in extant literature, but the limited impact of physical risk may be indicative of delayed or indirect effects that were not captured in the current analysis. The findings of this study lend support to the notion that targeted climate risk indicators should be favoured over composite ESG indices, as they furnish stakeholders with more actionable insights for the management of exposure by sector, region and collateral selection.

Furthermore, no substantial correlation is evident between physical risk and key balance sheet or regulatory variables, while GAR demonstrates limited impact, significant associations are only observed with the TCR and the NSFR. This implies that a higher proportion of green assets does not necessarily lead to enhanced returns or a reduction in credit portfolio risk, and could be indicative of the potential for a sustainable portfolio to engender risk reduction in the long term; however, this interpretation is constrained by the limited information provided by the indicator, given its association with a reduced scope of exposures. Conversely, the judicious selection of collateral to support the credit portfolio may be associated with a lower credit risk, even in the short to medium term.

With regard to the initial hypotheses, the results offer partial validation. The first hypothesis is substantiated, demonstrating that enhanced environmental performance, notably better performance regarding transition risk, is associated with enhanced profitability. However, other environmental factors, namely physical risk and GAR, have been found not to have a significant impact on earnings. The second hypothesis is partially supported: stronger environmental profiles (lower transition risk and greener portfolios) tend to display higher NSFR values, indicating more stable funding structures. Despite this, no significant correlation has been identified between the Liquidity Coverage Ratio (LCR) and the variables under investigation. The third hypothesis is supported by empirical evidence: superior sustainability performance is generally associated with reduced credit risk, though there is no significant relationship with RWA density. The fourth hypothesis is partially accepted: banking institutions with reduced engagement in high-impact environmental activities – including those with limited exposure to inefficient real estate or elevated Greenhouse Gas emissions – demonstrate elevated TCR. This finding provides a rationale for the adoption of more robust capital buffers by environmentally conscious institutions. Nonetheless, the association is not consistent across all capital indicators, since no correlation is detected between environmental performance and leverage ratios.

From a managerial perspective, the evidence provides guidance for european banks tackling the climate challenge. Transition risk exerts a substantial negative influence on profitability, compelling intermediaries to incorporate climate considerations into their business strategies for portfolio composition and risk management processes, increased exposure to high-emission sectors renders them vulnerable to carbon pricing policies and shifts in investor preferences, resulting in diminished performance indicators; a proactive alignment with the green transition could mitigate future losses and enhance competitive and reputational standing. Moreover, although physical risk does not appear to have a significant impact, intermediaries should not underestimate its relevance since climate- related catastrophic events can cause severe losses so it would be advisable to integrate shock analysis into the portfolio to assess the resilience to physical events. On the opportunity side, it is incumbent upon banks to seize the benefits of financing sustainable activities although a high GAR score does not provide advantages in the short term, it can be a distinctive signal that could translate into lower capital costs or greater customer loyalty, intangible yet important advantages over the medium to long term.

In terms of regulation, these reforms represent a foundational step towards enhanced transparency and accountability, thereby facilitating deeper analysis. This should encourage supervisory authorities to continue to ensure the rigorous implementation of ESG regulations, attempting to outline as much as possible the content required to facilitate consistent reporting and enabling the development of best practices. Furthermore, the existence of a tangible impact of climate risk on bank performance provides an empirical basis for integrating environmental factors into the prudential supervision process. Consistent with the approach delineated by the ECB, supervisors could utilise impact evidence to refine their dialogue with intermediaries, thereby assessing banks' climate strategy as part of the SREP. However, regulatory limitations remain, including the absence of a single definition and the production of quantitative data for social and governance factors, which hinders a holistic ESG analysis. In addition, with respect to environmental risks, the GAR signifies a progression in the standardisation of the measurement of the sustainable alignment of bank portfolios but is encumbered by methodological limitations that diminish its informative value (Dispinzeri, 2023). The present study's findings, appear to corroborate this assessment, as the analysis reveals a counterintuitive correlation between a high GAR and performance which could be attributed to the limited representation of climate risk exposures in the GAR, in light of this, it would be prudent to complement the GAR with additional metrics, such as the BTAR, designed to expand its scope of application.

Despite its contributions the present study is not without limitations. Firstly, the data analysed are cross-sectional and founded on multiple linear regressions pertaining to a single financial year which means that the identified relationships signify contemporary associations rather than enduring causality. The use of new ESG disclosure data has resulted in limited observations over time, so it has not yet been possible to analyse the evolution of climate variables over several years. This limitation results in an inability to address endogeneity and unobserved time-invariant heterogeneity. Furthermore, the utilisation of a linear additive approach may not encapsulate complex or non-linear relationships between variables, for instance the effects of climate risks may only become apparent above certain thresholds or interact with other bank characteristics such as business model or geographical diversification. Other limitations concern the quality and coverage of data sources; despite the fact that the information are derived from standardised regulatory disclosures, the initial phase of implementation of these requirements may result in heterogeneity in reporting practices across intermediaries and discrepancies in internal calculation methodologies may compromise the comparability of data. Moreover, the scope of the analysis focused on the european banking groups subject to these disclosure requirements; this could limit the sharing of results with other types of intermediaries or other regulatory contexts where similar metrics are not available. A further limitation is that decile-based indicators are relative ordinal rankings within the sample, not absolute measures of climate risk, this improves comparability and reduces the impact of outliers, but it also compresses information on the magnitude of differences, in addition, the composite uses equal weights across sub-metrics and profiles, which is transparent but normative.

The aforementioned limitations give rise to numerous avenues for future research. One potential research direction could involve extending the analysis in temporal terms, thereby transforming the study into a longitudinal one as data on several years of ESG disclosure becomes available. A temporal extension would also facilitate the assessment of any impacts that may emerge over a longer time horizon and that cannot be captured by the present analysis. In addition, with regard to the sample analysed, future regulatory developments may lead to the inclusion of environmental risks on LSI banks, currently excluded from the analysis because they are not subject to binding regulations in this area.

References

Agnese, P. and Giacomini, E. (2023) 'Bank's funding costs: do ESG factors really matter?', *Finance Research Letters*, 51(c). doi:10.1016/j.frl.2022.103437.

Ahmed, S.P., Ahmed, S.U., Noor, M.F., Ahmed, Z. and Karmaker, U. (2020) 'The policy-led sustainability and financial performance linkage in the banking sector: Case of Bangladesh', *Banks and Bank Systems*, 14(4), pp. 89–103.

Alam, A. W.; Banna, H.; Hassan, M. K., 2022, 'ESG Activities and Bank Efficiency: Are Islamic Banks Better?'. *JIMF*, *8* (1), 65-88. https://doi.org/10.21098/jimf.v8i1.1428.

Alghafes, Y., et al. (2024) 'Influence of key ESG factors on Islamic banks' financial performance: Evidence from GCC countries', *International Review of Economics and Finance*. doi.org/10.1016/j.iref.2024.103629

Al-Sharkas, A. A., & Al-Sharkas, T. A. (2022). The impact on bank profitability: Testing for capital adequacy ratio, cost-income ratio and non-performing loans in emerging markets [Special issue]. *Journal of Governance & Regulation, 11*(1), 231–243. https://doi.org/10.22495/jgrv11i1siart4

Ananta, M.A. and Anwar, M. (2025) 'Does ESG affect credit risk?', *Jurnal Ilmiah Indonesia*, 10(1).

Avetisyan, E. and Hockerts, K. (2017) 'The consolidation of the ESG rating industry as an enactment of institutional retrogression', *Business Strategy and the Environment*, 26(3), pp. 316–330.

Bakkar, Y. (2023) 'Climate Risk and Bank Capital Structure'. doi.org/10.2139/ssrn.4523842.

European Central Bank (2020) *Guide on climate-related and environmental risks*. Frankfurt: ECB.

Basel Committee on Banking Supervision (2016) *Reducing variation in credit risk-weighted assets: constraints on the use of internal model approaches*. Basel: BIS.

Battiston, S., Mandel, A., Monasterolo, I., Schuetze, F. and Visentin, G. (2017) 'A climate stress- test of the financial system', *Nature Climate Change*, 7(4), pp. 283–288. doi:10.1038/nclimate3255.

Berg, F., Kölbel, J.F. and Rigobon, R. (2022) 'Aggregate confusion: the divergence of ESG ratings', *Review of Finance*, 26(6), pp. 1315–1344.

Billio, M., Costola, M., Hristova, I., Latino, C. and Pelizzon, L. (2020) 'Inside the ESG ratings: (Dis)agreement and performance', *SAFE Working Paper*, No. 284. doi:10.2139/ssrn.3659271.

Bolton, P., Després, M., Pereira da Silva, L., Samama, F. and Svartzman, R. (2020) 'The green swan: central banking and financial stability in the age of climate change'. *BIS Books, Bank for International Settlements*, number 31.

Bressan, S. (2024). 'Environmental, Social, and Governance Scores and Loan Composition Inside United States Banks', *Sustainability*, 16(18), 8075. https://doi.org/10.3390/su16188075

Brock, E.K. (2023) 'Rate the Raters 2023: ESG Ratings at a Crossroads'. London: SustainAbility Institute by ERM.

Buallay, A. (2019) 'Is sustainability reporting (ESG) associated with performance? Evidence from the European banking sector', *Management of Environmental Quality*, 30(1), pp. 98–115.

Buallay, A., Fadel, S.M., Alajmi, J. and Saudagaran, S. (2020) 'Sustainability reporting and bank performance after financial crisis', *Competitiveness Review: An International Business Journal*.

Calabrese, R. and Porro, F. (2014) 'Single-name concentration risk measurements in credit portfolios', in Balakrishna, R. et al. (eds.) *Mathematical and Statistical Methods for Actuarial Sciences and Finance*. Springer. doi:10.1007/978-3-319-02499-8_8.

Cantero-Saiz, M., Sanfilippo-Azofra, S., Torre-Olmo, B. and Bringas-Fernández, V. (2025) 'ESG and bank profitability: the moderating role of country sustainability', *Green Finance*, 7(2), pp. 288–331. doi:10.3934/GF.2025011.

Capizzi, V., et al. (2021) 'The divergence of ESG ratings: an analysis of Italian listed companies', *Journal of Financial Management, Markets and Institutions*, 9(2).

Chatterji, A.K., Levine, D.I. and Toffel, M.W. (2009) 'How well do social ratings actually measure CSR?', *Journal of Economics & Management Strategy*, 18(1), pp. 125–169.

Chatterji, A.K., Durand, R., Levine, D.I. and Touboul, S. (2016) 'Do ratings of firms converge?', *Strategic Management Journal*, 37(8), pp. 1597–1614. doi:10.1002/smj.2407.

Crespi, F. and Migliavacca, M. (2020) 'The determinants of ESG rating in the financial industry: the same old story or a different tale?', *Sustainability*, 12(16). doi:10.3390/su12166398.

Debnath, P., Bhuyan, A., Das, S., Saikia, B., Saha, A., Chakravarty, E., Debi, H. and Kanoo, R. (2024) 'Nexus between ESG reporting and financial performance in the banking sector', *Corporate Law and Governance Review*, 6(4), pp. 103–116. doi:10.22495/clgrv6i4p10.

Di Giuli, A. and Kostovetsky, L. (2014) 'Are red or blue companies more likely to go green? Politics and corporate social responsibility', *Journal of Financial Economics*, 111(1), pp. 158–180. doi:10.1016/j.jfineco.2013.10.002.

Di Tommaso, C. and Thornton, J. (2020) ‘Do ESG scores affect bank risk taking and value? Evidence from European banks’, *Corporate Social Responsibility and Environmental Management*, 27(5), pp. 2286–2298.
Dispienzieri, V.M. (2023) ‘Green Asset Ratio (GAR): ESG e trasparenza nel mondo bancario’, *Diritto Bancario*. Available at: https://www.dirittobancario.it/art/green-asset-ratio-gar-esg-e- trasparenza-nel-mondo-bancario/ (accesed on: 20.05.2025).
Dorfleitner, G., Halbritter, G. and Nguyen, M. (2015) ‘Measuring corporate responsibility risk: A comparison of ESG rating providers’, *Journal of Asset Management*, 16(7), pp. 450–466. doi:10.1057/jam.2015.31.
Dragomir, V., Radu, O., Ionescu, B.S. and Ionescu-Feleaga, L. (2022) ‘The influence of ESG factors on financial performance in the banking sector during the Covid-19 pandemic’, *Economic Computation and Economic Cybernetics Studies and Research*, 56(4), pp. 71–88. doi:10.24818/18423264/56.4.22.05.
EeDaPP (2020) ‘Final report on correlation analysis between energy efficiency and risk’.
El Khoury, R., Nasrallah, N. and Alareeni, B. (2022) ‘ESG and financial performance of MENAT region: concavity–convexity patterns’, *Journal of Sustainable Finance & Investment*, 12(2), pp. 568–587. doi:10.1080/20430795.2021.1929807.
Escrig-Olmedo, E., Fernández-Izquierdo, M.A., Ferrero-Ferrero, I., Rivera-Lirio, J. and Muñoz-Torres, M.J. (2019) ‘Rating the raters: Evaluating how ESG rating agencies integrate sustainability principles’, *Sustainability*, 11(3), Article 915. doi:10.3390/su11030915.
European Central Bank, European Systemic Risk Board (2022). ‘The macroprudential challenge of climate change’.
European Commission (2021) ‘Commission Delegated Regulation (EU) 2021/2178 supplementing Regulation (EU) 2020/852 with regard to the content and presentation of information to be disclosed *by* undertakings subject to Articles 19a or 29a of Directive 2013/34/EU’.
European Commission (2022a) ‘Commission Delegated Regulation (EU) 2022/1288 supplementing Regulation (EU) 2019/2088 with regard to regulatory technical standards’
European Commission (2022b) ‘Commission Implementing Regulation (EU) 2022/2453 laying down implementing technical standards for the application of Article 8 of Regulation (EU) 2020/852’.
European Parliament and Council (2020) ‘Regulation (EU) 2020/852 on the establishment of a framework to facilitate sustainable investment, and amending Regulation (EU) 2019/2088 (EU Taxonomy Regulation)’.
Finger, M., Gavious, I. and Manos, R. (2018) ‘Environmental risk management and financial performance in the banking industry: A cross-country comparison’, *Journal of International Financial Markets, Institutions and Money*, 52, pp. 240–261. doi:10.1016/j.intfin.2017.09.019.
Flammer, C. (2015) ‘Does corporate social responsibility lead to superior financial performance? A regression discontinuity approach’, *Management Science*, 61(11), pp. 2549–2568. doi:10.1287/mnsc.2014.2038.
Flammer, C. (2021) ‘Corporate green bonds’, *Journal of Financial Economics*, 142(2), pp. 499– 516.
Fowler, S.J. and Hope, C. (2007) ‘A critical review of sustainable business indices and their impact’, *Journal of Business Ethics*, 76(3), pp. 243–252. doi:10.1007/s10551-007-9590-2.
Gangi, F., Meles, A., D’Angelo, E. and Daniele, L.M. (2018) ‘Sustainable development and corporate governance in the financial system: Are environmentally friendly banks less risky?’, *Corporate Social Responsibility and Environmental Management*, 26(3), pp. 529–547. doi:10.1002/csr.1699.
Gibson, R., Krueger, P. and Schmidt, P. (2019) ‘ESG rating disagreement and stock returns’, *Swiss Finance Institute Research Paper*, 19(67). doi:10.2139/ssrn.3433728.
Gillan, S.L., Koch, A. and Starks, L.T. (2021) ‘Firms and social responsibility: A review of ESG and CSR research in corporate finance’, *Journal of Corporate Finance*, 66. doi:10.1016/j.jcorpfin.2021.101889.
Gupta, J. and Kashiramaka, S. (2024) ‘Examining the impact of liquidity creation on bank stability in the Asia Pacific region: Do ESG disclosures play a moderating role?’, *Journal of International Financial Markets, Institutions and Money*, 91, Article 106744. doi:10.1016/j.intfin.2024.101955.
Horobet, A., Rahat, B., Florea, A.M. and Belascu, L. (2024) ‘Green banks, golden returns?’, *Review of Accounting and Finance*. doi:10.1108/RAF-09-2024-0373.
Igbudu, N., Garanti, Z. and Popoola, T. (2018) ‘Enhancing bank loyalty through sustainable banking’, *Sustainability*, 10(11), Article 4049.
Ioannidis, F., Kosmidou, K. and Zopounidis, C. (2025) ‘The effect of national culture and social capital on banking ESG performance: Evidence from Europe’, *International Review of Financial Analysis*, 102(C). doi:10.1016/j.irfa.2025.104084.
Jang, G.Y., Kang, H.G., Lee, J.Y. and Bae, K. (2020) ‘ESG scores and the credit market’, *Sustainability*, 12(8), Article 3456. doi:10.3390/su12083456.
Kalfaoglou, F. (2021) ‘ESG risks: A new source of risks for the banking sector’, *Economic Bulletin*, Bank of Greece. doi:10.52903/econbull20215305.
Kimbrough, M.D., Wang, X., Wei, S. and Zhang, J. (2023) ‘Does voluntary ESG reporting resolve rating disagreements?’, *European Accounting Review*.
Kishore, K. (2018) ‘Risk-weighted assets density as a parameter of risk profile of bank assets: A study of Indian banks’, *The IUP Journal of Financial Risk Management*, 15(2), pp. 62–70.
Korzeb, Z., Niedziółka, P., Szpilko, D. and di Pietro, F. (2024) ‘ESG and climate-related risks versus traditional risks in commercial banking: A bibliometric and thematic review’, *Future Business Journal*, 10. doi:10.1186/s43093-024-00392-8.
Korzeb, Z., Karkowska, R., Matysek-Jędrych, A. and Niedziółka, P. (2025) ‘How do ESG challenges affect default risk? An empirical analysis from the global banking sector perspective’, *Studies in Economics and Finance*, 42(1), pp. 89–114. doi:10.1108/SEF-09-2023-0540.
Kotsantonis, S. and Serafeim, G. (2019) ‘Four things no one will tell you about ESG data’, *Journal of Applied Corporate Finance*, 31(2), pp. 50–58. doi:10.1111/jacf.12346.
Krueger, P., Sautner, Z. and Starks, L.T. (2020) ‘The importance of climate risks for institutional investors’, *The Review of Financial Studies*, 33(3), pp. 1067–1111. doi:10.1093/rfs/hhz137.
Lamanda, G. and Tamásné Vőneki, Z. (2024) ‘Is ESG disclosure associated with bank performance? Evidence from the Visegrad Four countries’, *Management of Environmental Quality*, 35(1), pp. 201–219. doi:10.1108/MEQ-02-2023-0064
La Torre, M., Leo, S. and Panetta, I.C. (2021) ‘Banks and environmental, social and governance drivers: Follow the market or the authorities?’, *Corporate Social Responsibility and Environmental Management*, 28(6), pp. 1416–1430. doi:10.1002/csr.2132.
Laporšek, S., Švagan, B., Stubelj, M., & Stubelj, I. (2025). Profitability Drivers in European Banks: Analyzing Internal and External Factors in the Post-2009 Financial Landscape. *Risks*, *13*(1), 2. https://doi.org/10.3390/risks13010002

Larcker, D.F., Watts, E.L. and Bacon, J.A. (2022) 'ESG ratings – A compass without direction?', *Stanford Closer Look Series*.
Lee, C., Lu, M., Wang, C. and Cheng, C. (2024) 'ESG engagement, country-level political risk and bank liquidity creation', *Pacific-Basin Finance Journal*, 83(C), Article 102260. doi:10.1016/j.pacfin.2024.102260.
Liu, S., Jin, J. and Nainar, K. (2023) 'Does ESG performance reduce banks' nonperforming loans?', *Finance Research Letters*, 55, Article 103859. doi:10.1016/j.frl.2023.103859.
Liu, J. and Xie, J. (2024) 'The effect of ESG performance on bank liquidity risk', *Sustainability*, 16(12), Article 4927. doi:10.3390/su16124927.
Loan, L.T.T., Binh, D.V. and Tuyen, N.P. (2024) 'ESG disclosure and financial performance: Vietnamese banks', *Banks and Bank Systems*, 19(1), pp. 208–220. doi:10.21511/bbs.19(1).2024.18.
López-Penabad, Iglesias-Casal, Silva Neto, Maside-Sanfiz (2023). 'Does corporate social performance improve bank efficiency? Evidence from European banks', *Review of Managerial Science*, Springer, vol. 17(4), pages 1399-1437, May.
Mandas, M., Lahmar, O., Piras, L. and De Lisa, R. (2024) 'ESG reputational risk and market valuation: Evidence from the European banking industry', *Research in International Business and Finance*, 69(C), Article 102286. doi:10.1016/j.ribaf.2024.102286.
Masera, R. (2020) 'Leverage and risk-weighted capital in banking regulation', *The IUP Journal of Bank Management*, 19(2).
Matuszak, Ł. and Różańska, E. (2017) 'An examination of the relationship between CSR disclosure and financial performance: The case of Polish banks', *Accounting and Management Information Systems*, 16(4), pp. 522–533.
Menicucci, E. and Paolucci, G. (2023) 'ESG dimensions and bank performance: An investigation in Italy', *Journal of Applied Accounting Research*.
Miralles-Quirós, M.M., Miralles-Quirós, J.L. and Redondo-Hernández, J. (2019) 'The impact of environmental, social, and governance performance on stock prices: Evidence from the banking industry', *Corporate Social Responsibility and Environmental Management*, 26(6), pp. 1465–1477. doi:10.1002/csr.1759.
Mueller, I., Verboven, D. (2022), 'Climate Change-Related Regulatory Risks and Bank Lending', ECB Working Paper No. 2670.
Ng, A. (2016) 'The tangibility of the intangibles: What drives banks' sustainability disclosure in the emerging economies?', *GEG Working Paper*, University of Oxford.
Ngoc, N.B. (2018) 'The effect of corporate social responsibility disclosure on financial performance: Evidence from credit institutions in Vietnam', *Asian Social Science*, 14(4), pp. 116– 128.
Niedziółka, P., Bernardelli, M. and Korzeb, Z. (2023) 'Factors of ESG ratings assigned to commercial banks – the cultural and credit risk dimensions', *Argumenta Oeconomica*, 2(51), pp. 33–63. doi:10.15611/aoe.2023.2.02.
Nizam, E., Ng, A., Dewandaru, G., Nagayev, R. and Nkoba, M. (2019) 'The impact of social and environmental sustainability on financial performance: A global analysis of the banking sector', *Journal of Multinational Financial Management*, 49, pp. 35–53. doi:10.1016/j.mulfin.2019.01.002.
Nurhalida, S. and Sofwan, M. (2023) 'Peran ESG terhadap profitabilitas di sektor perbankan Indonesia', *Contemporary Studies in Economic, Finance and Banking*, 2(1), pp. 13–25.
Parvin, S., Chowdhury, A.N.M.M.H., Siddiqua, A. and Ferdous, J. (2019) 'Effect of liquidity and bank size on the profitability of commercial banks in Bangladesh', *Asian Business Review*, 9(1), pp. 7–10.
Pérez Montes, C., Trucharte Artigas, C., Cristófoli, M.E. and Lavín San Segundo, N. (2018) 'The impact of the IRB approach on the risk weights of European banks', *Journal of Financial Stability*, 39(C), pp. 147–166.
Platonova, E., Asutay, M., Dixon, R. and Mohammad, S. (2018) 'The impact of corporate social responsibility disclosure on financial performance: Evidence from the GCC Islamic banking sector', *Journal of Business Ethics*, 151(2), pp. 451–471. doi:10.1007/s10551-016-3229-0.
Rahim, N., Yadav, P. and Hasan, M. (2024) 'Do ESG pillars matter for bank risk? Evidence from a developing economy', *Journal of Risk Finance*, 25(1), pp. 1–17.
Rizki, M., Fachrudin, K.A. and Fachrudin, H.T. (2024) 'Impact of ESG disclosure on financial performance of ASEAN banks', *Banks and Bank Systems*, 19(2), pp. 100–112.
Sastry, P., Verner, E., Marques-Ibanez, D. (2024), 'Business as usual: bank climate commitments, lending, and engagement', ECB Working Paper No. 2921
Serino, L., Spignese, A. and Campanella, F. (2024) 'Are ESG scores driven by financial information? Evidence from European banks', *Journal of Risk Management in Financial Institutions*, 17(4), pp. 409–425.
Shakil, M.H., Mahmood, N., Tasnia, M. and Munim, Z.H. (2019) 'ESG performance and financial outcomes of emerging banks', *Management of Environmental Quality*, 30(6), pp. 1331–1344. doi:10.1108/MEQ-08-2018-0155.
Siani, G. (2023) 'Il risparmio gestito: prime evidenze sulla gestione dei rischi climatici e ambientali', *Workshop "Il risparmio gestito e la lotta al cambiamento climatico: rischi e opportunità"*.
Siueia, T.T., Wang, J. and Deladem, T.G. (2019) 'Corporate social responsibility and financial performance: A comparative study in the Sub-Saharan Africa banking sector', *Journal of Cleaner Production*, 226, pp. 658–668.
Soana, M.G. (2011) 'CSR and financial performance in the banking sector', *Journal of Business Ethics*, 104(1), pp. 133–148. doi:10.1007/s10551-011-0894-x.
Stubbs, W. and Rogers, P. (2013) 'Lifting the veil on ESG rating methods', *Social Responsibility Journal*, 9(4), pp. 622–640.
Sykes, A.O. (1993) *An introduction to regression analysis*. University of Chicago, Coase-Sandor Institute for Law & Economics Working Paper No. 20.
Tang, D.Y., Yan, J. and Yao, Y. (2022) 'The determinants of ESG ratings: Rater ownership matters', in *Proceedings of Paris December 2021 Finance Meeting EUROFIDAI – ESSEC*. doi:10.2139/ssrn.3889395.
Tharu, N.K. and Shrestha, Y.M. (2019) 'The influence of bank size on profitability: An application of statistics', *International Journal of Financial, Accounting, and Management*, 1(2), pp. 81–89.
Varotto, S. and Zhao, L. (2018) 'Systemic risk and bank size', *Journal of International Money and Finance*, 82, pp. 45–70. doi:10.1016/j.jimonfin.2017.12.002.
Wijaya, A.T., Wibowo, A. and Tjahjadi, B. (2023) 'Exploring the effects of environmental, social and governance (ESG) on banking performance: A case study of Far East Asia', *Indonesian Journal of Economics and Management*, 15(3).
Widyawati, L. (2019) 'A systematic literature review of socially responsible investment and environmental social governance metrics',

Business Strategy and the Environment, 29(2), pp. 619– 637.
Yang, L. (2024) 'A study of the impact of ESG investments on the liquidity risk of commercial banks', *Proceedings of the 3rd International Conference on Business and Policy Studies*. doi:10.54254/2754-1169/71/20241467.
Yadav, P.K., Jain, R. and Pal, D. (2023) 'ESG disclosure, corporate performance, and investor perception', *Finance Research Letters*, 55, Article 104879.
Zuraida, Z. and Husin, A. (2022) 'Sustainability, Sharīʻah governance and financial performance: Evidence from companies listed on the Jakarta Islamic Index', *Wealth Management and Investment in Islamic Settings.* Springer, Singapore. https://doi.org/10.1007/978-981-19-3686-9_16

Annex 1

Bank/Indicator	Transition	Real estate	Physical	GAR	FINAL
ABANCA Corporación Bancaria, S.A.	3.875	5.25	3.75	1.5	3.59375
ABN AMRO Bank N.V.	3.125	5.5	7	7	5.65625
AIB Group plc	3.75	7.25	2.875	1.5	3.84375
Akcinė bendrovė Šiaulių bankas	5	3.75	2.875	4	3.90625
ALPHA SERVICES AND HOLDINGS S.A.	4.75	7.5	3.75	4	5
AS "Citadele banka"	4.125	4.25	6.25	9.5	6.03125
AS LHV Group	3.875	5.25	5.875	10	6.25
Atlantic Lux HoldCo S.à r.l.	7.25	6.5	7.5	9	7.5625
Banco de Sabadell, S.A.	4.5	5	6.875	1.5	4.46875
Barclays Bank Ireland plc	3.625	3.25	5.75	8	5.15625
BANCA MEDIOLANUM S.P.A.	5.875	5	6.125	4.5	5.375
BANCA MONTE DEI PASCHI DI SIENA S.P.A.	5.75	4.5	6.125	7.5	5.96875
Banca Popolare di Sondrio, Società per Azioni (S.p.A.)	7.125	7	5.375	3.5	5.75
Banco Bilbao Vizcaya Argentaria, S.A.	3.625	4.25	3.625	8	4.875
Banco BPM S.p.A.	5.875	5.75	4.5	3.5	4.90625
Banco Comercial Português, S.A.	4.125	4.5	6.5	6	5.28125
Banco de Crédito Social Cooperativo, S.A.	5.25	6.25	5.125	2.5	4.78125
Banco Santander, S.A.	2.875	4.5	6	2.5	3.96875
BANK OF CYPRUS HOLDINGS PUBLIC LIMITED COMPANY	6.375	8	6	10	7.59375
Bank of Ireland Group plc	5.75	8.75	5.5	2	5.5
Bank of Valletta plc	5.375	7.25	5.25	7.5	6.34375
Bankinter, S.A.	3.875	5.75	4.25	6.5	5.09375
Banque et Caisse d'Epargne de l'Etat, Luxembourg	5.125	6.25	4.25	7	5.65625
Banque Internationale à Luxembourg S.A.	6	6.5	7.875	10	7.59375
BAWAG Group AG	5.125	6.5	6.25	8	6.46875
Bayerische Landesbank	8.375	5.5	6.5	9.5	7.46875
Belfius Banque SA ; Belfius Bank NV ; Belfius Bank SA	5.625	8	4.75	6.5	6.21875
BNG Bank N.V.	8.875	1	6.625	9.5	6.5
BNP Paribas S.A.	3.375	6.75	2.25	9	5.34375
BPER BANCA S.P.A.	5.25	7.25	4.625	3.5	5.15625
Bpifrance	8.25	5.25	7	4.5	6.25
Caixa Geral de Depósitos, S.A.	4.375	5.5	7.75	6.5	6.03125
Caixabank, S.A.	4.125	6	4.5	3.5	4.53125
Cassa Centrale Banca - Credito Cooperativo Italiano S.p.A.	5.375	6.75	5.5	5	5.65625
Citibank Europe plc	4.375	3.25	4.625	8	5.0625
COMMERZBANK Aktiengesellschaft	4.625	3.75	4.5	5.5	4.59375
Confédération Nationale du Crédit Mutuel	6.125	6.25	5.375	2	4.9375
Coöperatieve Rabobank U.A.	6.75	7.5	6.625	4	6.21875
Credito Emiliano Holding S.p.A.	4.625	7	3.875	5	5.125
Crelan SA ; Crelan NV	4	7.5	7.125	10	7.15625
de Volksbank N.V.	6.125	6.75	5.25	2.5	5.15625
Deutsche Apotheker- und Ärztebank eG	5.25	6.5	7	8	6.6875
DekaBank Deutsche Girozentrale	7.25	3.25	5.625	6	5.53125

Deutsche Bank AG	5	7	6.75	6.5	6.3125
Deutsche Pfandbriefbank AG	7.375	5.5	6.875	7	6.6875
DZ BANK AG Deutsche Zentral-Genossenschaftsbank	7.125	4.25	6.75	9	6.78125
Erste Group Bank AG	7.5	6.5	7.125	6	6.78125
Erwerbsgesellschaft der S-Finanzgruppe mbH & Co. KG	7.625	4.75	5.375	6	5.9375
Eurobank Ergasias Services and Holdings S.A.	4.625	7.5	4.5	3.5	5.03125
FinecoBank S.p.A.	2.125	5	6.125	10	5.8125
GROUPE BPCE	7	6.25	7.875	5.5	6.65625
Groupe Crédit Agricole	5.5	7	5.875	7	6.34375
Hamburg Commercial Bank AG	7	3.5	3.125	8	5.40625
HASPA Finanzholding	6.875	6.5	4.5	6	5.96875
HSBC Continental Europe	3.5	6.5	5.75	9	6.1875
Ibercaja Banco, S.A.	4.25	6.5	5.75	3.5	5
ICCREA Banca S.p.A. - Istituto Centrale del Credito Cooperativo	5.5	5.25	5.375	5	5.28125
ING Groep N.V.	4.375	7	5.75	1.5	4.65625
INTESA SANPAOLO S.P.A.	3.875	5.5	5.25	2.5	4.28125
Investeringsmaatschappij Argenta NV	3.375	7.75	5.375	1	4.375
KBC Group NV	5.875	8.25	6.125	9	7.3125
Kuntarahoitus Oyj	9	3	7.625	10	7.40625
Kutxabank, S.A.	3.75	6	5.625	1	4.09375
La Banque Postale	6.25	4.5	4.875	5.5	5.28125
Landesbank Baden-Württemberg	7.625	2.5	5.25	6.5	5.46875
Landesbank Hessen-Thüringen Girozentrale	7.5	3	6	3.5	5
Luminor Holding AS	5.625	5.5	6.375	3.5	5.25
MDB Group Limited	5.125	5.5	8.125	1	4.9375
Mediobanca - Banca di Credito Finanziario S.p.A.	2.875	5.25	5.125	4.5	4.4375
Münchener Hypothekenbank eG	7.25	6.5	6.125	3.5	5.84375
National Bank of Greece S.A.	4.625	7.75	3.5	3.5	4.84375
Nederlandse Waterschapsbank N.V.	6.5	1	5.75	6	4.8125
Norddeutsche Landesbank -Girozentrale-	8.5	6.5	6.125	6	6.78125
Nordea Bank Abp	5.125	5.5	3.5	6.5	5.15625
NOVA LJUBLJANSKA BANKA D.D., LJUBLJANA	4	3.5	2.125	7.5	4.28125
Novo Banco, SA	5.875	5.75	6.375	8.5	6.625
OP Osuuskunta	7.125	6.5	4.625	1.5	4.9375
Piraeus Financial Holdings S.A.	4	6.25	3.875	3.5	4.40625
Raiffeisen Bank International AG	4.375	4.75	5.5	5	4.90625
Raiffeisenbankengruppe OÖ Verbund eGen	6.75	5.75	6.875	5	6.09375
RBS Holdings N.V.	4.5	1	4.5	6.5	4.125
RCI Banque SA	6.25	1	6.25	1	3.625
SFIL S.A.	7.875	1	4.125	9	5.5
Société Générale S.A.	3.125	6.5	3.75	8.5	5.46875
Unicaja Banco, S.A.	4.75	5.75	5.75	3	4.8125
UniCredit S.p.A.	6	5.75	3.75	3.5	4.75
Volkswagen Bank GmbH	7.25	1	5.75	7.5	5.375
Volksbanken Verbund	7.875	5.75	7.75	10	7.84375

Bank/indicator	TCR	Leverage	LCR	NSFR	ROE	RWA Dens.	NPLr	ROA	CtI	LtA
ABANCA Corporación Bancaria, S.A.	17.0%	7.0%	209.0%	133.0%	12.80%	43.50%	2.40%	0.95%	56.09%	59.85%
ABN AMRO Bank N.V.	19.0%	5.0%	144.0%	140.0%	10.10%	37.10%	1.80%	0.71%	59.38%	66.84%
AIB Group plc	21.0%	8.0%	186.0%	159.0%	16.40%	43.70%	2.70%	1.51%	43.25%	47.42%
Akcinė bendrovė Šiaulių bankas	22.0%	10.0%	236.0%	143.0%	14.00%	50.70%	2.90%	1.57%	38.18%	57.45%
ALPHA SERVICES AND HOLDINGS S.A.	19.0%	7.0%	176.0%	130.0%	10.00%	43.70%	6.20%	0.83%	40.27%	40.75%
AS "Citadele banka"	22.0%	9.0%	189.0%	147.0%	20.40%	47.60%	2.10%	2.13%	46.52%	54.67%
AS LHV Group	23.0%	7.0%	194.0%	160.0%	23.60%	36.40%	0.60%	1.97%	43.27%	45.82%
Atlantic Lux HoldCo S.à r.l.	23.0%	6.0%	204.0%	115.0%	1.50%	29.10%	4.20%	0.10%	36.30%	60.97%
Banco de Sabadell, S.A.	18.0%	5.0%	212.0%	140.0%	9.40%	33.30%	3.60%	0.57%	54.66%	61.68%
Barclays Bank Ireland plc	22.0%	5.0%	183.0%	147.0%	65.60%	25.90%	0.80%	3.73%	77.00%	6.59%
BANCA MEDIOLANUM S.P.A.	22.0%	7.0%	324.0%	176.0%	28.40%	16.90%	1.40%	1.06%	45.02%	42.41%
BANCA MONTE DEI PASCHI DI SIENA S.P.A.	22.0%	7.0%	186.0%	130.0%	19.40%	39.20%	4.30%	1.67%	57.61%	55.39%
Banca Popolare di Sondrio, Società per Azioni (S.p.A.)	18.0%	6.0%	174.0%	126.0%	11.20%	39.60%	3.70%	0.80%	43.44%	51.29%
Banco Bilbao Vizcaya Argentaria, S.A.	17.0%	7.0%	148.0%	131.0%	13.60%	46.90%	3.50%	1.09%	45.64%	47.89%
Banco BPM S.p.A.	19.0%	5.0%	186.0%	129.0%	10.40%	31.60%	3.70%	0.63%	54.66%	61.68%
Banco Comercial Português, S.A.	20.0%	6.0%	229.0%	167.0%	11.90%	42.10%	3.50%	1.00%	33.21%	49.04%
Banco de Crédito Social Cooperativo, S.A.	16.0%	6.0%	185.0%	150.0%	3.10%	42.30%	2.80%	0.21%	54.18%	56.91%
Banco Santander, S.A.	16.0%	5.0%	159.0%	123.0%	12.20%	34.70%	3.40%	0.68%	45.61%	56.53%
BANK OF CYPRUS HOLDINGS PUBLIC LIMITED COMPANY	22.0%	8.0%	330.0%	158.0%	21.50%	38.80%	3.40%	1.84%	33.82%	34.22%
Bank of Ireland Group plc	19.0%	6.0%	187.0%	157.0%	16.00%	33.80%	3.10%	1.03%	48.37%	50.63%
Bank of Valletta plc	26.0%	8.0%	437.0%	185.0%	13.00%	34.30%	3.00%	1.16%	47.82%	38.84%
Bankinter, S.A.	16.0%	5.0%	206.0%	141.0%	13.50%	34.50%	2.50%	0.75%	42.05%	68.10%
Banque et Caisse d'Epargne de l'Etat, Luxembourg	22.0%	8.0%	166.0%	142.0%	7.70%	39.40%	1.90%	0.67%	21.80%	48.00%
Banque Internationale à Luxembourg S.A.	19.0%	6.0%	158.0%	125.0%	6.80%	36.40%	4.50%	0.47%	67.15%	47.41%
BAWAG Group AG	20.0%	6.0%	215.0%	141.0%	17.70%	34.80%	2.00%	1.23%	34.05%	56.98%
Bayerische Landesbank	23.0%	5.0%	176.0%	139.0%	7.90%	23.60%	1.50%	0.43%	50.70%	61.82%
Belfius Banque SA ; Belfius Bank NV ; Belfius Bank SA	19.0%	7.0%	139.0%	128.0%	7.10%	38.80%	1.90%	0.52%	43.00%	63.92%
BNG Bank N.V.	46.0%	13.0%	167.0%	119.0%	5.80%	8.30%	0.60%	0.22%	34.88%	81.50%
BNP Paribas S.A.	17.0%	5.0%	136.0%	116.0%	9.50%	27.20%	2.90%	0.44%	69.58%	35.34%
BPER BANCA S.P.A.	18.0%	5.0%	187.0%	128.0%	16.10%	37.60%	2.40%	1.09%	60.92%	55.62%
Bpifrance	30.0%	21.0%	639.0%	114.0%	0.80%	84.00%	5.60%	0.19%	57.12%	42.53%
Caixa Geral de Depósitos, S.A.	21.0%	9.0%	303.0%	186.0%	14.90%	44.10%	2.40%	1.38%	31.42%	45.01%
Caixabank, S.A.	17.0%	6.0%	203.0%	144.0%	12.40%	37.60%	3.00%	0.79%	49.87%	60.68%
Cassa Centrale Banca - Credito Cooperativo Italiano S.p.A.	25.0%	9.0%	264.0%	168.0%	10.60%	36.80%	4.20%	0.97%	54.18%	56.91%
Citibank Europe plc	25.0%	11.0%	149.0%	179.0%	0.00%	47.90%	0.60%	0.00%	49.40%	24.91%
COMMERZBANK Aktiengesellschaft	19.0%	5.0%	136.0%	130.0%	6.70%	33.90%	1.30%	0.43%	59.86%	46.27%

Confédération Nationale du Crédit Mutuel	21.0%	7.0%	166.0%	114.0%	6.00%	31.50%	2.40%	0.40%	62.92%	68.63%
Coöperatieve Rabobank U.A.	22.0%	7.0%	161.0%	132.0%	8.20%	39.60%	1.90%	0.71%	56.91%	68.73%
Credito Emiliano Holding S.p.A.	17.0%	5.0%	200.0%	132.0%	15.60%	31.20%	1.90%	0.83%	56.94%	56.56%
Crelan SA ; Crelan NV	31.0%	4.0%	193.0%	142.0%	7.60%	15.60%	1.00%	0.37%	63.54%	82.75%
de Volksbank N.V.	25.0%	5.0%	350.0%	166.0%	10.50%	23.20%	1.00%	0.61%	56.25%	75.40%
Deutsche Apotheker- und Ärzteba nk eG	18.0%	5.0%	234.0%	124.0%	3.30%	31.30%	1.90%	0.19%	63.70%	69.61%
DekaBank Deutsche Girozentrale	24.0%	9.0%	154.0%	121.0%	10.30%	36.00%	1.60%	0.89%	51.55%	45.47%
Deutsche Bank AG	19.0%	5.0%	137.0%	121.0%	7.40%	26.70%	2.10%	0.37%	51.18%	64.63%
Deutsche Pfandbriefbank AG	20.0%	6.0%	255.0%	111.0%	2.50%	36.30%	3.70%	0.18%	51.18%	64.63%
DZ BANK AG Deutsche Zentral-Genossenschaftsbank	20.0%	6.0%	141.0%	127.0%	7.30%	23.60%	1.10%	0.35%	62.72%	52.91%
Erste Group Bank AG	20.0%	7.0%	136.0%	142.0%	13.50%	43.20%	2.00%	1.16%	51.33%	55.87%
Erwerbsgesellschaft der S-Finanzgruppe mbH & Co. KG	21.0%	7.0%	177.0%	129.0%	0.00%	41.90%	1.30%	0.00%	56.55%	59.31%
Eurobank Ergasias Services and Holdings S.A.	19.0%	8.0%	173.0%	128.0%	13.80%	54.40%	3.30%	1.43%	32.17%	48.28%
FinecoBank S.p.A.	35.0%	5.0%	823.0%	378.0%	36.80%	14.20%	0.40%	1.83%	35.94%	18.79%
GROUPE BPCE	18.0%	5.0%	145.0%	108.0%	3.40%	29.60%	2.40%	0.18%	77.92%	55.95%
Groupe Crédit Agricole	21.0%	5.0%	144.0%	117.0%	7.10%	27.90%	2.00%	0.41%	68.01%	55.06%
Hamburg Commercial Bank AG	25.0%	9.0%	160.0%	116.0%	6.60%	52.20%	4.30%	0.86%	43.21%	46.97%
HASPA Finanzholding	18.0%	8.0%	222.0%	134.0%	3.10%	46.60%	1.20%	0.26%	63.03%	61.58%
HSBC Continental Europe	21.0%	4.0%	158.0%	141.0%	7.30%	21.00%	2.00%	0.32%	62.44%	28.65%
Ibercaja Banco, S.A.	17.0%	6.0%	233.0%	141.0%	9.60%	34.10%	2.30%	0.56%	59.83%	60.80%
ICCREA Banca S.p.A. - Istituto Centrale del Credito Cooperativo	22.0%	8.0%	257.0%	157.0%	13.10%	36.90%	3.80%	1.06%	54.18%	56.91%
ING Groep N.V.	20.0%	5.0%	143.0%	132.0%	35.40%	32.70%	1.60%	2.31%	50.19%	61.30%
INTESA SANPAOLO S.P.A.	19.0%	6.0%	168.0%	121.0%	13.50%	31.40%	2.20%	0.80%	54.43%	51.43%
Investeringsmaatschappij Argenta NV	22.0%	5.0%	200.0%	141.0%	11.00%	21.20%	0.40%	0.51%	56.25%	66.35%
KBC Group NV	17.0%	5.0%	159.0%	136.0%	17.70%	32.60%	1.80%	0.98%	60.07%	55.63%
Kuntarahoitus Oyj	103.0%	12.0%	356.0%	124.0%	7.20%	3.00%	0.40%	0.22%	31.80%	67.44%
Kutxabank, S.A.	18.0%	8.0%	186.0%	141.0%	9.40%	47.30%	1.70%	0.80%	42.02%	70.89%
La Banque Postale	22.0%	7.0%	159.0%	132.0%	4.70%	13.00%	1.30%	0.13%	105.62%	55.45%
Landesbank Baden-Württemberg	20.0%	5.0%	135.0%	110.0%	5.30%	28.20%	1.00%	0.30%	60.31%	52.58%
Landesbank Hessen-Thüringen Girozentrale	19.0%	5.0%	189.0%	120.0%	4.00%	30.20%	2.40%	0.23%	56.52%	58.33%
Luminor Holding AS	20.0%	9.0%	177.0%	147.0%	8.80%	45.60%	1.90%	0.80%	51.02%	57.32%
MDB Group Limited	20.0%	4.0%	213.0%	126.0%	4.70%	25.20%	2.50%	0.24%	82.83%	57.86%
Mediobanca - Banca di Credito Fin anziario S.p.A.	17.0%	8.0%	166.0%	120.0%	7.90%	51.70%	2.00%	0.70%	51.71%	58.56%
Münchener Hypothekenbank eG	22.0%	4.0%	369.0%	109.0%	4.40%	19.70%	1.50%	0.19%	36.50%	85.95%
National Bank of Greece S.A.	20.0%	9.0%	267.0%	150.0%	14.70%	50.60%	3.40%	1.49%	34.46%	43.90%
Nederlandse Waterschapsbank N.V.	48.0%	21.0%	336.0%	134.0%	5.60%	6.10%	0.10%	0.17%	21.95%	70.95%
Norddeutsche Landesbank -Girozentrale-	17.0%	6.0%	143.0%	118.0%	7.90%	36.20%	1.50%	0.48%	77.44%	63.58%
Nordea Bank Abp	22.0%	5.0%	159.0%	119.0%	16.20%	23.70%	0.90%	0.84%	43.61%	50.41%

NOVA LJUBLJANSKA BANKA D.D., LJUBLJANA	20.0%	10.0%	238.0%	187.0%	18.40%	59.10%	2.10%	2.17%	47.40%	52.74%
Novo Banco, SA	21.0%	8.0%	169.0%	118.0%	16.70%	49.10%	4.40%	1.72%	55.41%	50.02%
OP Osuuskunta	21.0%	9.0%	199.0%	130.0%	10.60%	45.80%	3.20%	1.02%	43.66%	58.15%
Piraeus Financial Holdings S.A.	18.0%	6.0%	234.0%	133.0%	13.10%	43.70%	3.40%	1.03%	33.11%	44.07%
Raiffeisen Bank International AG	22.0%	8.0%	210.0%	143.0%	11.50%	47.60%	3.00%	1.20%	46.67%	46.75%
Raiffeisenbankengruppe OÖ Verbund eGen	18.0%	11.0%	179.0%	124.0%	11.20%	63.20%	4.90%	1.27%	55.62%	48.83%
RBS Holdings N.V.	24.0%	7.0%	0.0%	133.0%	5.50%	29.30%	0.00%	0.38%	62.96%	0.26%
RCI Banque SA	16.0%	8.0%	448.0%	128.0%	12.60%	61.00%	2.20%	1.23%	42.18%	76.82%
SFIL S.A.	37.0%	10.0%	673.0%	122.0%	3.70%	5.80%	0.30%	0.08%	66.48%	65.61%
Société Générale S.A.	18.0%	4.0%	159.0%	119.0%	3.60%	25.00%	2.90%	0.16%	76.70%	34.33%
Unicaja Banco, S.A.	19.0%	5.0%	289.0%	152.0%	4.70%	30.70%	3.10%	0.27%	55.41%	50.02%
UniCredit S.p.A.	21.0%	6.0%	154.0%	130.0%	16.00%	36.20%	2.50%	1.21%	57.06%	48.18%
Volkswagen Bank GmbH	18.0%	13.0%	256.0%	132.0%	6.50%	75.80%	2.90%	0.89%	46.30%	65.14%
Volksbanken Verbund	19.0%	8.0%	183.0%	135.0%	11.30%	49.90%	2.80%	1.07%	55.76%	65.43%

Annex 2

Profile	Sub-metric	Economic interpretation of a higher raw value	Scoring direction	Meaning of score = 1	Meaning of score = 10
Transition risk	Gross exposure / Total assets	Higher value = greater transition-risk exposure	Direct	Lower exposure	Higher exposure
Transition risk	Stage 2+3 exposure ("exposure deterioration") / Total assets	Higher value = worse asset quality under transition risk	Direct	Lower deterioration	Higher deterioration
Transition risk	Average weighted maturity	Higher value = longer duration (more climate uncertainty exposure)	Direct	Shorter duration	Longer duration
Transition risk	Share of exposures with maturity > 5 years	Higher value = more long-dated exposures	Direct	Lower long-term share	Higher long-term share
Transition risk	Coverage ratio (provisions / gross Stage 2+3)	Higher value = stronger loss-absorption capacity (better resilience)	Reverse	Higher coverage (more resilient)	Lower coverage (less resilient)
Transition risk	HHI concentration index	Higher value = greater concentration risk	Direct	Lower concentration	Higher concentration
Physical risk	Gross exposure / Total assets	Higher value = greater physical-risk exposure	Direct	Lower exposure	Higher exposure
Physical risk	Stage 2+3 exposure ("exposure deterioration") / Total assets	Higher value = worse asset quality under physical risk	Direct	Lower deterioration	Higher deterioration
Physical risk	Average weighted maturity	Higher value = longer duration (higher climate-event uncertainty horizon)	Direct	Shorter duration	Longer duration
Physical risk	Share of exposures with maturity > 5 years	Higher value = more long-dated exposures	Direct	Lower long-term share	Higher long-term share
Physical risk	Coverage ratio (provisions / gross Stage 2+3)	Higher value = stronger loss-absorption capacity (better resilience)	Reverse	Higher coverage (more resilient)	Lower coverage (less resilient)
Physical risk	HHI concentration index	Higher value = greater sector/geographic concentration risk	Direct	Lower concentration	Higher concentration
Real estate collateral risk	Collateral / Total assets	Higher value = greater dependence on real-estate collateral	Direct	Lower dependence	Higher dependence
Real estate collateral risk	Share of collateral without EPC label	Higher value = lower information quality / likely greater vulnerability	Direct	Lower share without EPC	Higher share without EPC
Real estate collateral risk	Required emission reduction to meet EU targets	Higher value = larger adjustment need / greater transition vulnerability	Direct	Lower required reduction	Higher required reduction
GAR profile	GAR stock × coverage weight	Higher value = greater taxonomy alignment (more favourable)	Reverse	Higher aligned stock (weighted)	Lower aligned stock (weighted)
GAR profile	GAR flow × coverage weight	Higher value = greater taxonomy alignment of new exposures (more favourable)	Reverse	Higher aligned flow (weighted)	Lower aligned flow (weighted)

Sub-metric	Profile	Pillar 3 template	Raw numerator	Raw denominator	Transformation	Scoring direction	Missing data treatment
Gross exposure / TA (transition)	Transition	Template 1	Gross carrying amount (climate-relevant sectors)	Total assets	Ratio scaled to % of TA	Direct	Listwise exclusion at bank level if required template unavailable
Deterioration (transition)	Transition	Template 1	Stage 2 + Stage 3 exposures (transition perimeter)	[gross transition exposure **or** TA, choose final]	Ratio scaled to %	Direct	Same as above
Average maturity (transition)	Transition	Template 1	Weighted maturity	—	No scaling (or years)	Direct	Same as above
>5y maturity share (transition)	Transition	Template 1	Exposures >5 years	Transition gross exposure	Ratio scaled to %	Direct	Same as above
Coverage ratio (transition)	Transition	Template 1	Provisions (Stage 2+3)	Stage 2+3 exposures	Ratio scaled to %	Reverse	Same as above
HHI concentration (transition)	Transition	Template 1	Sector shares	—	HHI computed from sector weights	Direct	Same as above
Gross exposure / TA (physical)	Physical	Template 5	Gross carrying amount (physical risk perimeter)	Total assets	Ratio scaled to % of TA	Direct	Same as above
Deterioration (physical)	Physical	Template 5	Stage 2 + Stage 3 exposures (physical perimeter)	[gross physical exposure **or** TA]	Ratio scaled to %	Direct	Same as above
Average maturity (physical)	Physical	Template 5	Weighted maturity	—	No scaling (or years)	Direct	Same as above
>5y maturity share (physical)	Physical	Template 5	Exposures >5 years	Physical gross exposure	Ratio scaled to %	Direct	Same as above

Sub-metric	Profile	Pillar 3 template	Raw numerator	Raw denominator	Transformation	Scoring direction	Missing data treatment
Coverage ratio (physical)	Physical	Template 5	Provisions (Stage 2+3)	Stage 2+3 exposures	Ratio scaled to %	Reverse	Same as above
HHI concentration (physical)	Physical	Template 5	Geographic/sector shares	—	HHI computed from shares	Direct	Same as above
Real estate collateral / TA	Real estate	Template 2	Real-estate collateral value	Total assets	Ratio scaled to %	Direct	Same as above
Share without EPC	Real estate	Template 2	RE collateral without EPC	Total RE collateral	Ratio scaled to %	Direct	Same as above
Emission reduction gap	Real estate	Template 2	Reported emissions gap metric	—	As disclosed / standardized if needed	Direct	Same as above
GAR stock × coverage	GAR	Template 8	GAR stock	Coverage share	Multiplicative index	Reverse	Same as above
GAR flow × coverage	GAR	Template 8	GAR flow	Coverage share	Multiplicative index	Reverse	Same as above

Annex 3

Sample selection flow

Step	Description	N
1	ECB List of supervised entities (Part A: significant entities directly supervised by the ECB), cut-off date 1 March 2024	112
2	Excluded: entities outside the Pillar 3 ESG disclosure perimeter used in this study (Art. 449a CRR / Implementing Regulation (EU) 2022/2453 not applicable for sample purposes)	23
3	Excluded: duplicate/non-consolidated entity already represented at group level (branch)	1
4	Final analytical sample (consolidated banking groups)	88

ECB significant entities not included in the final sample (N = 24)

The ECB supervised-entities list is not a list of consolidated banking groups; it includes credit institutions, holding companies and branches. The analytical sample is instead defined at the consolidated reporting level and restricted to entities within the mandatory Pillar 3 ESG disclosure perimeter used in this study. Therefore, ECB significant entities for which the disclosure framework was not applicable (for sample purposes) are not included in the final sample.

#	ECB supervised entity (Part A)	Exclusion reason
1	The Bank of New York Mellon SA/NV	Out of scope of Pillar 3 ESG disclosure perimeter used in the study (Art. 449a/Reg. 2022/2453 not applicable for sample purposes)
2	DSK Bank AD	Out of scope of Pillar 3 ESG disclosure perimeter used in the study (Art. 449a/Reg. 2022/2453 not applicable for sample purposes)
3	Citigroup Global Markets Europe AG	Out of scope of Pillar 3 ESG disclosure perimeter used in the study (Art. 449a/Reg. 2022/2453 not applicable for sample purposes)
4	Goldman Sachs Bank Europe SE	Out of scope of Pillar 3 ESG disclosure perimeter used in the study (Art. 449a/Reg. 2022/2453 not applicable for sample purposes)
5	J.P. Morgan SE	Out of scope of Pillar 3 ESG disclosure perimeter used in the study (Art. 449a/Reg. 2022/2453 not applicable for sample purposes)
6	LBS Landesbausparkasse Süd	Out of scope / timing of applicability for 2023 ESG reporting perimeter used in the study
7	Morgan Stanley Europe Holding SE	Out of scope of Pillar 3 ESG disclosure perimeter used in the study (holding entity not retained as reporting unit)
8	NatWest Bank Europe GmbH	Out of scope of Pillar 3 ESG disclosure perimeter used in the study (Art. 449a/Reg. 2022/2453 not applicable for sample purposes)
9	State Street Europe Holdings Germany S.à.r.l. & Co. KG	Out of scope of Pillar 3 ESG disclosure perimeter used in the study (holding entity not retained as reporting unit)
10	UBS Europe SE	Out of scope of Pillar 3 ESG disclosure perimeter used in the study (Art. 449a/Reg. 2022/2453 not applicable for sample purposes)
11	Wüstenrot Bausparkasse Aktiengesellschaft	Out of scope of Pillar 3 ESG disclosure perimeter used in the study (Art. 449a/Reg. 2022/2453 not applicable for sample purposes)
12	AS SEB Pank	Out of scope of Pillar 3 ESG disclosure perimeter used in the study (Art. 449a/Reg. 2022/2453 not applicable for sample purposes)
13	BANK OF AMERICA EUROPE DESIGNATED ACTIVITY COMPANY	Out of scope of Pillar 3 ESG disclosure perimeter used in the study (Art. 449a/Reg. 2022/2453 not applicable for sample purposes)
14	BofA Securities Europe SA	Out of scope of Pillar 3 ESG disclosure perimeter used in the study (Art. 449a/Reg. 2022/2453 not applicable for sample purposes)
15	Hellenic Bank Public Company Limited	Out of scope of Pillar 3 ESG disclosure perimeter used in the study (Art. 449a/Reg. 2022/2453 not applicable for sample purposes)
16	AS "SEB banka"	Out of scope of Pillar 3 ESG disclosure perimeter used in the study (Art. 449a/Reg. 2022/2453 not applicable for sample purposes)
17	Swedbank Baltics AS	Out of scope of Pillar 3 ESG disclosure perimeter used in the study (Art. 449a/Reg. 2022/2453 not applicable for sample purposes)
18	AB SEB bankas	Out of scope of Pillar 3 ESG disclosure perimeter used in the study (Art. 449a/Reg. 2022/2453 not applicable for sample purposes)
19	Revolut Holdings Europe UAB	Out of scope of Pillar 3 ESG disclosure perimeter used in the study (holding entity not retained as reporting unit)
20	Quintet Private Bank (Europe) S.A.	Out of scope of Pillar 3 ESG disclosure perimeter used in the study (Art. 449a/Reg. 2022/2453 not applicable for sample purposes)
21	Addiko Bank AG	Out of scope of Pillar 3 ESG disclosure perimeter used in the study (Art. 449a/Reg. 2022/2453 not applicable for sample purposes)
22	Agri Europe Cyprus Limited	Out of scope of Pillar 3 ESG disclosure perimeter used in the study (holding entity not retained as reporting unit)

#	ECB supervised entity (Part A)	Exclusion reason
23	OTP Luxembourg S.à.r.l.	Out of scope of Pillar 3 ESG disclosure perimeter used in the study (holding entity not retained as reporting unit)
24	Danske Bank A/S, Finland Branch	Branch / non-consolidated reporting entity (excluded to avoid double counting at group level)

Annex 4

Robustness checks on indicator construction

Table 1. Robustness designs and data treatment

Item	Baseline	Robustness A	Robustness B
Sub-metric transformation	Deciles (1-10)	Quintiles (1-5)	Continuous z-scores
Sign convention	Direct for risk/exposure/maturity; reverse for Coverage and GAR	Same as baseline	Same as baseline
Profile construction	Mean of sub-metrics	Mean of sub-metrics	Mean of sub-metrics
Composite construction	Mean of the four profiles	Mean of the four profiles	Mean of the four profiles
Missing data	Available-case averaging within profile	Same as baseline	Same as baseline
Winsorization	None	None	None

Note. Reverse-scored sub-metrics are: Transition coverage, Physical coverage, GAR stock, and GAR flow. All other sub-metrics are direct-scored (higher values correspond to worse outcomes).

Table 2. Missing data summary (used sub-metrics only)

Profile	No. of sub-metrics used in scoring	Total missing values (used sub-metrics)	Max missing in one used sub-metric
Transition	6	0	0
Real Estate	4	2	2
Physical	6	0	0
GAR	2	0	0

Table 3. Indicator-level robustness: correlation with baseline indicators

Indicator	Spearman (Baseline vs Quintiles)	Spearman (Baseline vs z-scores)	Pearson (Baseline vs Quintiles)	Pearson (Baseline vs z-scores)
Transition	0.977	0.927	0.980	0.834
Real Estate	0.983	0.952	0.988	0.961
Physical	0.980	0.865	0.986	0.808
GAR	0.991	0.927	0.992	0.661
Final composite	0.990	0.874	0.991	0.795

Table 4. Composite ranking overlap (baseline vs alternative scoring)

Comparison	Spearman correlation (FINAL)	Top-10 overlap	Bottom-10 overlap
Baseline deciles vs quintile-based composite	0.990	10/10	9/10
Baseline deciles vs z-score composite	0.874	5/10	6/10

Note. “Top 10” refers to the 10 banks with the most favourable composite scores (lowest-risk ranking).

Regression robustness (same outcomes and controls)

Table 5. Summary of coefficient stability (climate profiles only)

Robustness test	Same sign (out of 32 climate coefficients)	Same significance status @10% (out of 32)
Quintile scoring (sub-metric level)	30	32
Continuous z-scores (sub-metric level)	24	25

Note. The 32 coefficients correspond to 4 profiles x 8 dependent variables, estimated with the same controls used in the revised baseline regressions (size, cost-to-income, loan-to-asset).

Table 6. Coefficient stability by profile (climate block)

Profile	Same sign (Quintiles)	Same sig. @10% (Quintiles)	Same sign (z-scores)	Same sig. @10% (z-scores)
Transition	7/8	8/8	6/8	7/8
Real Estate	8/8	8/8	5/8	7/8
Physical	7/8	8/8	7/8	6/8
GAR	8/8	8/8	6/8	5/8

Table 7. Joint significance of the climate block and model fit

Dependent variable	p-value climate block (Baseline)	p-value climate block (Quintiles)	p-value climate block (z-scores)	R2 Baseline	R2 Quintiles	R2 z-scores
ROA	0.1561	0.3739	0.1294	0.2669	0.2448	0.2712
ROE	0.0990	0.2520	0.0505	0.2539	0.2311	0.2690
RWA density	0.1766	0.2309	0.9604	0.1386	0.1309	0.0758
NPL ratio	0.0071	0.0162	0.0115	0.1743	0.1548	0.1630
LCR	0.6686	0.5927	0.1206	0.1211	0.1257	0.1731
NSFR	0.0051	0.0119	0.0000	0.3632	0.3480	0.4735
TCR	0.0001	0.0004	0.0017	0.3075	0.2816	0.2527
Leverage ratio	0.0000	0.0001	0.0000	0.3831	0.3717	0.3920