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Direttore Responsabile (Editor in Chief)
Maurizio Vallino (AIFIRM General Manager, Italy)

Condirettore (Managing Editor)
Corrado Meglio (AIFIRM Vice President)

Graphic designer: Silvia Mandalà

Ownership, Newsroom and Secretariat:
AIFIRM Ricerca e Formazione Srl, Via Pelio 8, 16147 Genova

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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)

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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

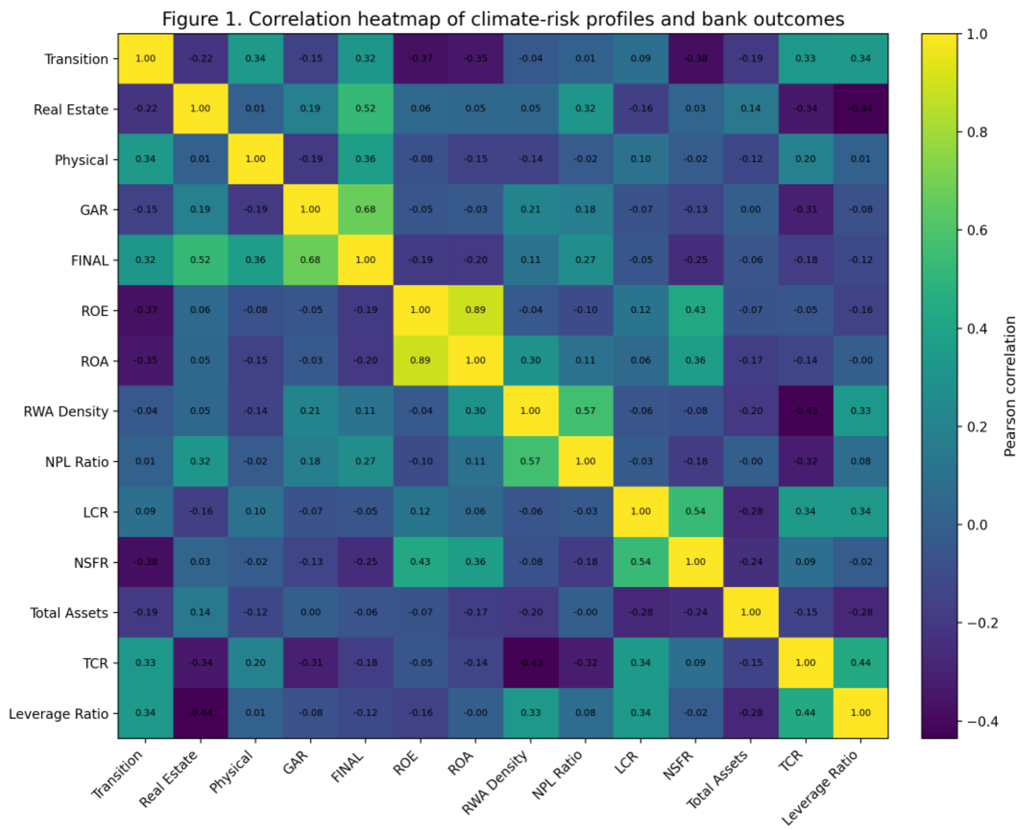
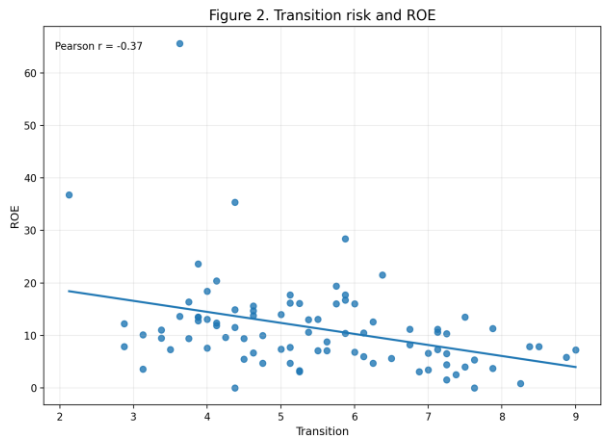


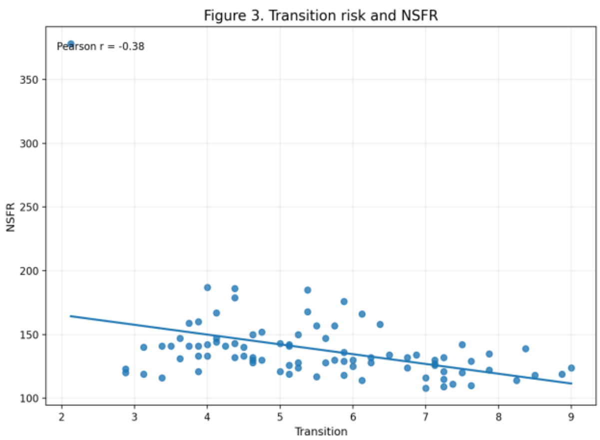
Figure 1: Heatmap of Pearson correlations among climate-risk profiles and bank performance/risk variables used in the empirical analysis (cross-sectional sample of 88 banks).

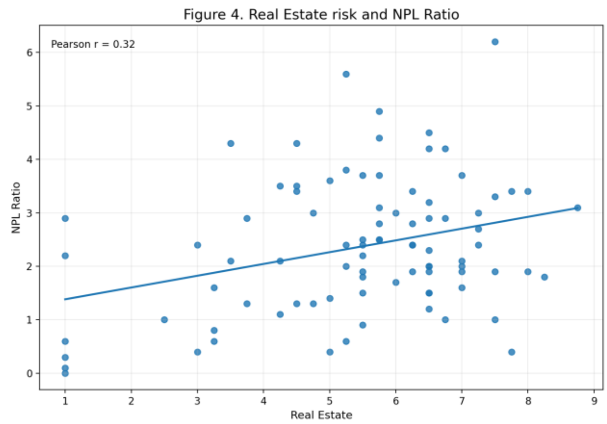
The correlation matrix[11], calculated using Pearson's coefficients, also demonstrates that there are frequently weak correlations between the variables, and p-values that exceed the conventional threshold of statistical significance. The

[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.







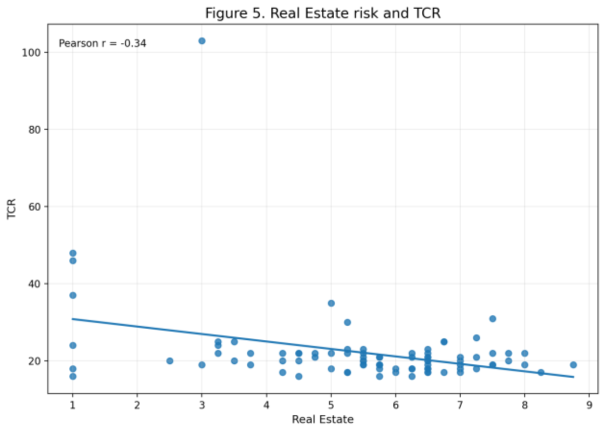


Figure 2. Transition risk and ROE Scatter plot of Transition score and ROE with fitted linear trend.

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	R²	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

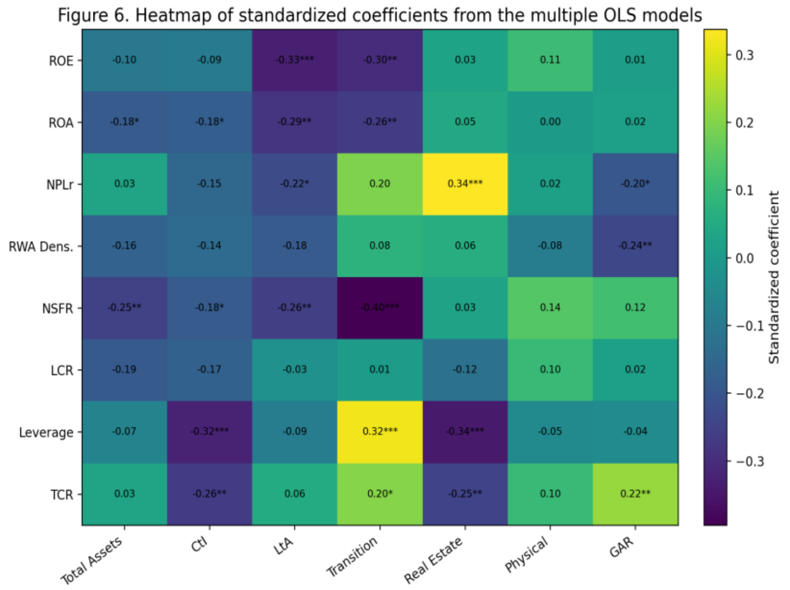


Figure 6. Heatmap of regression coefficients Heatmap of standardized coefficients from the multiple OLS models (dependent variables in rows; regressors in columns).

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.

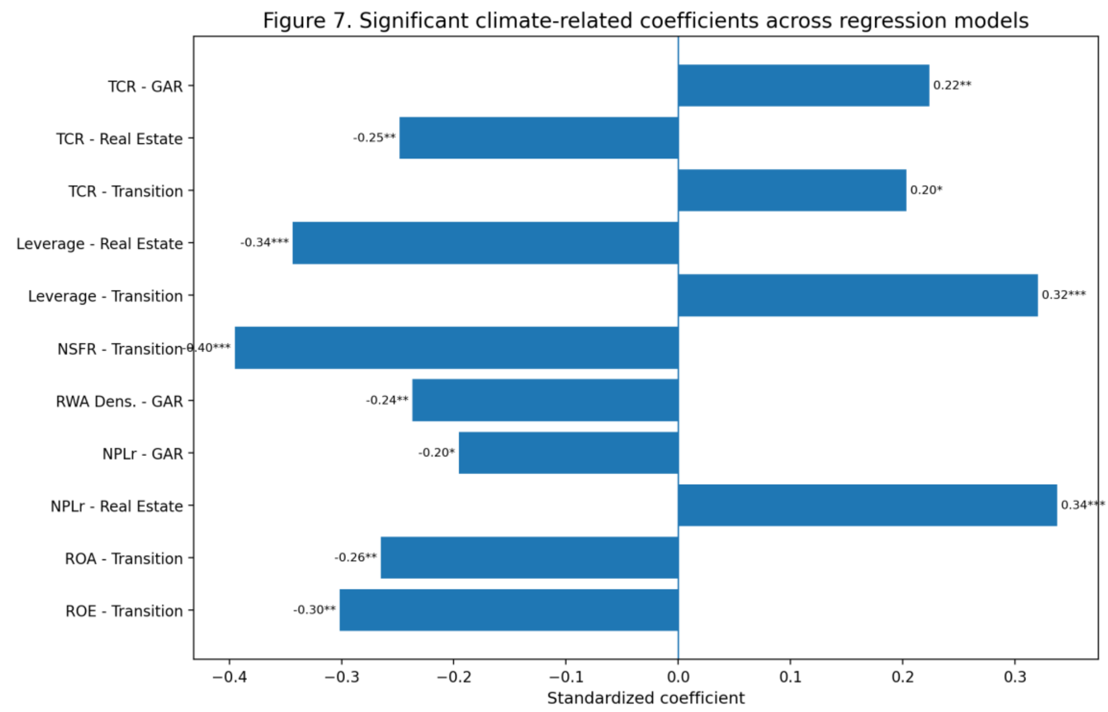


Figure 7. Significant climate-related coefficients Bar chart of statistically significant climate-related coefficients from the multiple OLS models.

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.

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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

Bridging RDARR and credit risk models: a data lineage-driven framework for sound data governance

Di Maria Alessandro (UniCredit), Frasca Vincenzo (UniCredit), Girardi Dario (UniCredit)[1]

Corresponding Author: Di Maria Alessandro (alessandro.dimaria@unicredit.eu)

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Abstract

The effective implementation of the Risk Data Aggregation and Risk Reporting (RDARR) principles introduced in 2013 by BCBS 239 continues to pose significant challenges for banking institutions, particularly in ensuring consistent interpretation and application across complex reporting domains. More than a decade later, the European Central Bank (ECB) has reinforced and broadened the scope of these principles through increasingly prescriptive supervisory expectations, following persistent implementation gaps. This paper aims to interpret the RDARR principles and, through a practical example, outline the changes and requirements necessary to achieve full compliance for credit risk models.

In doing so, this study first provides a mapping matrix to determine which credit risk models are RDARR-relevant, as this represents a necessary prerequisite for a consistent and risk-based application of the framework. Then, it focuses on Pillar I credit risk models, which are among the most advanced in terms of data quality and data architecture, owing to the regulatory frameworks established by the ECB and EBA. Building on this starting point, the paper analyses the main gaps in the application of RDARR principles and proposes a remediation framework for Pillar I models that attempts to mitigate the compliance burden often associated with RDARR. In particular, it leverages the introduction of an end-to-end data lineage concept as a key enabler to strengthen data governance and support the systematic integration of data quality controls aligned with ECB expectations. The proposed framework, developed for Pillar I models, serves as a benchmark for the broader set of credit risk models identified through the matrix, guiding their progressive alignment with RDARR principles.

Keywords: EU regulation, Data Governance, Data Quality, Credit Risk

JEL Classification: G18, G32, C45, C49

1. Introduction

The ability of financial institutions to manage and aggregate risk-related data in a consistent and reliable manner has become a fundamental prerequisite for sound decision-making and robust risk governance. Risk data aggregation and reporting (RDARR) not only underpins effective day-to-day management but also serves as the basis for strategic steering, regulatory compliance, and supervisory oversight. High-quality data enhance institutions' capacity to quantify exposures, monitor adherence to limits, and anticipate vulnerabilities under stress, while also enabling digitalisation, automation, and IT cost efficiency (European Central Bank, 2024).

Despite these clear benefits, recent supervisory assessments conducted by the European Central Bank (ECB) have demonstrated that structural weaknesses in RDARR remain widespread (European Central Bank, 2025). Since the 2008 financial crisis—when deficiencies in data accuracy, timeliness, and integrity amplified systemic vulnerabilities—regulators have prioritised the implementation of the Basel Committee's BCBS 239 principles (Basel Committee on Banking Supervision, 2013). Yet, more than a decade later, full adherence remains elusive. The ECB's thematic review on RDARR of 2016, subsequent on-site inspections, and the Supervisory Review and Evaluation Process (SREP) have consistently revealed shortcomings in governance, fragmented data architectures, extensive reliance on manual adjustments, and weak data quality controls (European Central Bank, 2018). In terms of timeliness of risk reporting, in many cases production times for monthly risk reports exceeded 40 working days, undermining institutions' ability to respond to evolving risks (European Central Bank, 2024). These findings highlight the slow progress of institutions in strengthening their RDARR compliance, with governance shortcomings and legacy IT infrastructures frequently cited as root causes. Many institutions continue to treat RDARR primarily as a compliance burden rather than as a strategic advantage, as highlighted in the latest ECB's newsletter on this topic (European Central Bank, 2025). The ECB's supervisory strategy for the coming years thus aims to enforce more substantial remediation

[1] The views and opinions expressed in this paper are solely those of the author(s) and do not necessarily represent the official stance of UniCredit.

efforts, stressing that adequate RDARR capabilities are not optional but a minimum expectation under European banking law and supervisory standards. Against this background, the publication of the ECB's *Guide on effective risk data aggregation and risk reporting* (European Central Bank, 2024) represents a fundamental step in clarifying regulatory expectations. The guide's purpose is "*to describe the practices which, in the ECB's view, are necessary from the perspective of RDARR to ensure effective processes are in place to identify, manage, monitor and report the risks supervised institutions are or might be exposed to*" (European Central Bank, 2024, p. 5). It identifies seven key supervisory principles that banks are expected to integrate in order to build a robust and resilient RDARR framework[2].

Several industry studies highlight the economic benefits of strong data governance and data quality frameworks. For example, banks with high-quality data can achieve a 5–6% increase in revenue and up to 20% higher profitability, while an effective data governance can reduce operational costs by 15–20% (McKinsey, 2025; Number Analytics, 2025). Similarly, banks with mature governance frameworks demonstrate significantly improved risk prediction accuracy and fewer unexpected losses, underscoring the direct link between robust RDARR practices and financial performance. Moreover, sound risk data management can lead to lower capital and liquidity buffers (due to data quality issues) and reduce costs related to data-related fines and data adjustment teams (Oliver Wyman, 2024). The SAS Institute (2024) emphasises that poor data quality remains the "Achilles' heel" of risk management, leading to costly reconciliation errors and undermining supervisory trust. In parallel, the digitalisation of finance, accelerated by artificial intelligence and advanced analytics, further raises the stakes: institutions with advanced data architectures gain significant advantages in risk monitoring, while those reliant on fragmented legacy systems face mounting vulnerabilities (Bank for International Settlements, 2024; Thite, 2025; Heß, 2025). Moreover, PwC (2025) highlights how the RDARR program can play a strategic role in enabling AI initiatives by improving data quality, governance, and infrastructure, and ensuring granular and reliable data that supports automation, emerging risk analysis, and model risk reduction. High-quality data allows to build robust AI models, minimising bias and inefficiencies, and delivering trustworthy outputs. Moreover, RDARR can strengthen governance and risk culture by integrating non-financial risks into decision frameworks and empowering competent oversight bodies. As a result, besides being a compliance effort, RDARR can act as a key enabler of innovation, better decision-making, and digital transformation.

The aim of this paper is to define a possible approach to achieving compliance with the RDARR principles for Internal Ratings-Based (IRB) Credit Risk Modelling framework. In this context, Internal Ratings-Based (IRB) credit risk models provide an ideal use case for operationalising RDARR principles. These models inherently generate, transform, and validate risk-relevant data through structured workflows, data pipelines, and embedded control mechanisms. This makes them a controlled environment in which RDARR expectations can be tested, assessed, and refined in practice. It is worth noting that Pillar I models have always been under the Supervisors' spotlight since the publication of BCBS 239, which laid the foundations for what later followed in the regulatory framework on data quality topics (European Banking Authority, 2016; European Commission, 2021). Over the years, supervised banks have aligned with these requirements, raising data quality standards within their organisations—standards that can be considered largely consistent with the data quality principles set out in the RDARR guidelines. Although achieving RDARR compliance across banking processes spans organisational, technological, and governance dimensions—and may significantly disrupt existing strategic and operational plans—the approach proposed in this paper is designed to minimise such disruption when the process under analysis is the IRB Credit Risk Modelling framework.

In pursuing compliance with RDARR principles within IRB Credit Risk Modelling framework, a key premise is that not all are intended to operate at the level of a specific process. For example, Principle 1 requires accountability of the management body for RDARR, Principle 6 requires sufficient timeliness of internal risk reporting, and Principle 7 demands the effective implementation of RDARR remediation programmes[3]. These principles are inherently cross-sectional and require institution-wide arrangements that extend beyond individual process pipelines and therefore cannot be meaningfully assessed on a single process level. Consequently, this paper identifies and isolates the principles that are most relevant at process level and, in particular, for credit risk models within the IRB framework. Specifically, among the RDARR principles, those most directly applicable to credit risk models are Principles 2, 3[4], 4, and 5, as they impose requirements that align closely with the scope, structure, data flows, and operational mechanics of the IRB modelling framework.

In response to contingent, compliance-driven needs arising from the practical application of RDARR principles, this paper proposes a methodology that positions data lineage—often the missing piece in IRB model frameworks—as the key enabler for fostering compliance with Principles 3, 4 and 5. The methodology is articulated as a sequence of replicable steps that can be applied, with proportionality, across different credit risk modelling environments.
In particular, it consists of: (i) a scoping step aimed at identifying RDARR-relevant credit risk models through a principle-based mapping matrix derived from Principle 2; (ii) a translation step whereby selected RDARR principles are operationalised via a

[2] A short description of the principles is provided in the Annex.

[3] See Annex for a more detailed description of these principles.

[4] For Principle 3, only subparagraph 1 will be covered as it can be considered process-specific. Subparagraphs 2, 3 and 4 relate to the roles of management body and central data governance function, internal validation and internal audit respectively. For the purpose of this paper – which adopts a process-driven perspective – central governance topics are out of scope.

structured mapping to DCAM capabilities, reducing interpretative discretion; (iii) an implementation step focused on the definition of layered data quality controls—technical, functional, model-specific and output-level—supported by a RACI-based governance framework; (iv) an architectural step centered on the design of end-to-end data lineage enriched with metadata, glossaries and taxonomies; and (v) a validation step addressing traceability and auditability through anomaly detection mechanisms and centralised registers. Together, these steps define a coherent methodological pathway that supports reproducibility, scalability and supervisory interpretability.

2. Sufficient scope of application for credit risk models

In line with the methodological approach outlined in the Introduction, the identification of RDARR-relevant credit risk models represents the first operational step of the proposed framework. This step is intentionally principle-based and proportional, translating the Principle 2 of the ECB Guide on RDARR (2024), "Sufficient scope of application" into a structured, yet flexible, scoping procedure. The output of this step is a mapping matrix that supports consistent prioritisation decisions, rather than prescribing exhaustive inclusion rules.

The objective of this section is therefore to outline the approach for identifying RDARR-relevant credit risk models and integrating them into the bank's RDARR plans and projects, ensuring full compliance with regulatory expectations.

According to this principle, institutions should establish a data governance framework that covers all material entities, risk types – including credit, market, liquidity, operational, and third-party risk – and the entire lifecycle of the data.

With respect to models, the scope of the data governance framework should include key internal risk management models, such as (but not limited to) Pillar I regulatory capital models (e.g. internal ratings-based (IRB) approaches for credit risk), Pillar II risk and capital models, and other key risk management models (such as IFRS9 collective provisioning models and value-at-risk models). This encompasses both input data for model development and resulting model outputs (e.g. exposure at default, probability of default, or loss-given-default estimates), which are essential for managing the institution's risks.

Furthermore, the scope should include relevant reports, including internal risk reports used for decision-making and strategic steering, financial reports externally published together with annual financial statements, and supervisory submissions such as FINREP and COREP templates, EBA and SSM stress test exercises, and Pillar 3 disclosures.

Based on the external regulatory expectations outlined above, we propose identifying the set of RDARR-relevant models through the following steps:

1. Identify the list of "RDARR-relevance criteria", against which assessing the relevance of credit risk models in terms of RDARR compliance. These criteria are derived from ECB Principle 2 and enriched to reflect the specific context of credit risk modelling.
2. Identify commonly used credit risk models within large commercial banks and classify them into "model families" based on their regulatory purpose or strategic importance – such as their role in provisioning, business support, credit origination, or credit monitoring.
3. Map each "model family" identified in step 2. to the set of "RDARR-relevance criteria" identified in step 1. If a "model family" meets any of these criteria, the entire family – and consequently all models within it – should be designated as RDARR-relevant.

The objective of step 1. is to define the list of "RDARR-relevance criteria" that will guide the identification of RDARR-relevant models. Starting from the ECB Principle 2 criteria, we expand and refine them for better alignment with credit risk modelling practices. Each criterion is further assigned a unique acronym for consistent reference throughout this section:

- <u>Internal risk reports for decision-making and steering processes</u> (which we label as "IRR"): this includes internal risk reports supporting executive and board-level decision-making and strategic steering, encompassing Risk Appetite Framework (RAF) indicators, key performance indicators (KPIs), and risk reports segmented by material risk types (e.g. credit, market, operational, and liquidity risks).
- <u>Externally published financial reports and financial statements</u>("FRFS"): this encompasses financial reports intended for external stakeholders, including audited annual financial statements, quarterly disclosures, and other regulatory filings that contain risk-relevant data. These reports are subject to public scrutiny and carry significant accountability implications.
- <u>Supervisory reports submitted to supervisory and regulatory authorities</u> ("SURE"): this encompasses periodic regulatory reports, such as FINREP, COREP, supervisory data collection (STE), EBA and SREP stress tests, and Pillar III disclosures.
- <u>Key internal risk management models</u> ("IRM"): this includes all internal models integral to the bank's risk management and regulatory capital framework. This spans models under Pillar I (e.g. IRB credit risk models), Pillar II (e.g. ICAAP frameworks), and other key models such as IFRS9 Expected Credit Loss Models for accounting and provisioning purposes

Having defined the "RDARR-relevance criteria" against which credit risk models will be mapped to assess their RDARR-relevance, we now proceed with step 2., identifying the model families which are expected to be commonly employed by large commercial banks. At a minimum, these include:

- *IRB models*: Pillar I models used for regulatory purposes, i.e. for the calculation of Risk Weighted Assets and regulatory capital ratios (e.g. rating systems used for IRB purposes).
- *IRB-Like models*: regulatory models that are either in the process of authorisation or developed to ensure the needed experience requirement for IRB Roll-Out.
- *Pillar II models*: models used for Pillar II regulatory purposes, such as the calculation of Economic Capital (e.g. credit risk satellite models, credit portfolio models, etc.)
- *IFRS9 models*: models used for accounting purposes to determine Expected Credit Loss (ECL) and Loan Loss Provisions (LLPs), including PD/LGD/EAD, Transfer Logic and behavioural IFRS9 models.
- *Managerial Models*: models covering non-IRB perimeters different from the ones covered by IRB-Like models. Their purpose is to support Economic Capital evaluation and credit business processes (e.g. perimeters under Permanent Partial Use and models decommissioned with the entry into force of Basel IV but still used for internal purposes). This family also includes models used only for business support, such as credit origination and monitoring, which do not contribute to other processes such as Economic Capital (e.g. Acceptance/ Transactional Scoring models, PSD2 models, Early Warning models).

The above-identified list of model families is designed to be as general as possible, ensuring applicability across commercial banks regardless of their specific characteristics. However, for some institutions, one or more model families may not be entirely relevant – for example, in the case of non-IRB banks, the first two families (IRB and IRB-Like) would not apply. This does not impair the validity of the proposed framework, as the absence of one model family does not affect the applicability of the others.

Having defined both the "RDARR-relevance criteria" and the list of model families, step 3. entails assessing each family for RDARR relevance. A model family should be flagged as RDARR-relevant if it meets at least one of the previously defined criteria. This assessment can be visualised using a matrix, where the rows represent the identified model families, and the columns represent the Data Criticality Criteria.

Model Family	IRR (Internal Risk Reporting)	FRFS (Financial Reports and Financial Statements)	SURE (Supervisory Reports)	IRM (Key Internal Risk Management Models)
IRB Models	✓		✓	✓
IRB-Like	✓			✓
Pillar II	✓		✓	✓
IFRS9 Models		✓	✓	
Managerial Models				✓

Table 1: mapping matrix for identifying RDARR-relevant credit risk models

As shown in the table above, all identified model families are considered potentially RDARR-relevant, as they meet at least one of the defined "RDARR-relevance criteria". It is important to note that the matrix presented is not intended to be universally prescriptive; rather, it reflects what is typically expected for large IRB-authorised commercial banks, where modelling frameworks are particularly complex and Pillar I and Pillar II models play a central role in supporting internal risk measurement and reporting. In other contexts – such as less significant institutions or organisations with less complex modelling frameworks – managerial models may instead assume a more prominent role. These models can support strategic activities and critical processes, including Internal Risk Reporting, which, in large and complex banks employing IRB models, is primarily supported by Pillar I and Pillar II models. However, this does not imply that RDARR principles are less relevant or that compliance is merely formalistic for non-IRB institutions. On the contrary, RDARR constitutes a structural requirement for all banks, irrespective of the regulatory approach adopted for credit risk. High-quality, traceable and reliable data are indeed fundamental prerequisites for sound risk management and effective internal risk reporting in any institution. Therefore, also non-IRB banks should be sufficiently equipped for complying with RDARR requirements, in a manner that is proportionate to their size, complexity and risk profile[5]. For these banks, the scalability of the framework proposed in this paper hinges first in the establishment of a robust data quality framework that achieves a degree of reliability comparable to that required for IRB models, and then in the development of the data lineage aspects described in the next section. Such a framework ensures that RDARR expectations

[5] Notice that the principle of proportionality in the application of ECB RDARR expectations is defined by the ECB Guide itself, which states that "*The Guide comprises the minimum supervisory expectations compiled by the ECB […]. The ECB intends to follow up on these expectations in its supervisory activities on a case-by-case basis, in line with the principle of proportionality*".

can be applied proportionately, yet meaningfully, thereby supporting improvements in the quality of management information and strengthening overall decision-making processes.

As we will show in the next section, we expect certain model categories – specifically Pillar I models – to be better aligned with RDARR principles, particularly regarding data quality requirements. This alignment is reinforced by requirements set out in the ECB Guide to Internal Models (2025), which already establishes detailed and rigorous expectations regarding data quality, thereby allowing for enhanced consistency with RDARR standards. Conversely, alignment with other, more innovative RDARR principles – such as data lineage – is expected to be currently less pronounced. These gaps can be progressively addressed by implementing the steps described in the next section.
For the other families of RDARR-relevant models, including those prevalent in non-IRB institutions, banks can expect to invest significant effort to align with the applicable RDARR expectations. This is because, unlike Pillar I models, the level of maturity and adherence to certain principles – such as data quality – is generally lower.
A separate mention deserves to be made regarding the Standardised Approach (SA) used for the calculation of regulatory capital requirements. Although this approach does not rely on internal models, its relevance has significantly increased following the introduction of Basel IV output floor requirements, which mandate that institutions' risk-weighted assets cannot fall below 72.5% of the corresponding Standardised Approach RWA. This regulatory constraint effectively requires banks – especially those applying the IRB Approach - to ensure that SA capital metrics are robust, traceable and comparable to their internally-modelled counterparts. This is particularly important because the Standardised Approach is entirely dependent on the accuracy, completeness and traceability of granular input data - such as counterparty classification, exposure type, collateral characteristics and external ratings - which directly determine the applicable risk weights. Any deficiency in these data elements can therefore materially affect the calculation of SA RWA and, consequently, the output floor benchmark.

Consequently, the data infrastructure supporting Standardised Approach calculations must also adhere to RDARR principles, despite not being formally classified as an internal model. Ensuring full RDARR compliance for SA processes is therefore essential to enable accurate benchmarking between IRB "advanced" calculations and their Standardised reference values and to support supervisory expectations regarding the consistency and reliability of output floor monitoring.

Before concluding this section, a brief consideration is warranted regarding climate risk, which represents one of the most challenging areas for data aggregation and reporting. Climate-related information is often affected by structural data quality issues, limited historical depth, and high variability driven by scenario-based projections. These challenges are particularly evident for Scope 3 emission data, where completeness and traceability remain limited due to heterogeneous data sources and supply-chain dependencies. Although a detailed treatment of climate risk is beyond the scope of this paper, the RDARR-oriented elements discussed—such as data lineage, metadata frameworks and structured data quality controls—offer a conceptual foundation that could support future developments in this area by enhancing transparency, semantic clarity and the evidencing of data provenance.

3. Data Lineage as element of Integrated Data Architecture

Building on the conclusions of section 2, this section analyses end-to-end data lineage as a practical cornerstone for operationalising the ECB's expectations on integrated data architecture (Principle 4) within IRB credit risk models. While IRB frameworks generally rely on comparatively mature, regulation-driven data quality controls (Principle 5), institutions often face structural challenges in demonstrating full, auditable traceability of risk data across their lifecycle - from source systems, through transformations and controls, to model outputs and downstream reporting. The ECB's 2024 RDARR Guide explicitly reinforces data lineage as a key evidencing mechanism for architecture, data quality, and governance outcomes, highlighting its role in bridging two domains that, although intrinsically linked, have frequently evolved separately in practice: data governance and data quality. Data governance has often been implemented through high-level, compliance-oriented policies that were insufficiently translated into binding, executable process requirements, management body awareness, and the involvement of internal control functions, weaknesses repeatedly noted by the ECB in relation to BCBS 239 implementation[6]. By contrast, data quality controls in the IRB context have a longer and more established history, rooted in Basel IRB requirements and subsequent supervisory guidance, including the European Commission Delegated Regulation (CDR) 2022/439 on IRB assessment methodology (European Commission, 2021). In particular, the CDR embeds binding supervisory expectations on core data quality dimensions—such as accuracy, integrity, completeness, consistency and timeliness—which substantially reflect the key principles introduced by BCBS 239 and later reiterated within the RDARR framework. However, these requirements have often developed as stand-alone arrangements within the modelling process, primarily focused on parameter estimation and validation needs[7].

[6] ECB Report on the Thematic Review on effective risk data aggregation and risk reporting (2018).
[7] Governance arrangements have also historically been present within the more mature IRB model landscape. However, these arrangements were often designed and implemented within the modelling process itself, without necessarily aligning with the broader data governance principles established at the bank level.

As a result, IRB models have evolved with localised data quality evidence that is not fully embedded within a broader RDARR governance framework run at bank level. The ECB's renewed expectations make clear that these existing IRB data quality frameworks must be integrated into the institution's overall data governance model, with data lineage providing the operational means to connect governance and quality by enabling transparent tracking of data origins, transformations (rules), applied controls, and qualitative and quantitative attributes across processes.

From an RDARR implementation perspective, this creates a pragmatic pathway for IRB models. In a typical enterprise rollout, the central data governance function oversees process owners as they identify in-scope processes, perform process mapping, and—supported by the data owner—implement data lineage. The resulting lineage is then used to define data perimeters and determine where data quality controls should be placed. For IRB models, however, several prerequisites are often already in place due to their long-standing regulatory and validation history: process knowledge is more structured, and a sound data quality control framework—fully or largely aligned with Principle 5—is typically already operating. Implementing lineage in this highly mature data quality context therefore delivers mutual benefits. First, it allows existing controls to be anchored to end-to-end traceability, strengthening evidencing and auditability in line with Principle 4. Second, it can enhance the traditional IRB set-up by making ownership boundaries explicit, formalising roles and responsibilities, and strengthening supporting governance tools such as metadata repositories, business glossaries/data dictionaries, and anomaly registers—ultimately improving standardisation, transparency, and the overall effectiveness of the data quality framework itself.

It is worth noting that this IRB-anchored design also enables the broader scalability of the proposed methodology. By construction, the methodological sequence outlined in this paper does not rely on IRB-specific artefacts, but on general architectural components—lineage, metadata, ownership allocation and layered data quality controls—that can be progressively extended to modelling domains with lower initial maturity. In practice, the same steps applied to IRB models can be replicated for IFRS 9, stress testing or managerial models, with the only differentiating factor being the degree of baseline data quality and process formalisation already in place. The methodology that will be described can also be used as a way to progressively raise maturity of models outside IRB domain: data lineage helps map fragmented processes, metadata gives a clear and consistent meaning to variables sourced from different systems, and the layering of controls provides a structured way to align these models with RDARR expectations.

In this sense, IRB models are not a special case, but simply the starting point: once the methodology is applied in a mature environment, it can be scaled to other model families identified under Principle 2 in a proportionate manner. This allows institutions to reduce the overall compliance burden while moving towards a more consistent RDARR framework across all modelling areas.

Consistently with the proposed methodology, this study adopts the Data Management Capability Assessment Model (DCAM)[8] - developed by the Enterprise Data Management Council (EDMC) - as a neutral translation layer to support the interpretation of RDARR principles. It is not employed as a compliance benchmark or maturity assessment tool, but as an industry-recognised taxonomy that enables the systematic mapping of supervisory expectations to data management capabilities, thereby reducing subjectivity and ensuring methodological transparency.

By mapping the relevant RDARR principles to the corresponding DCAM components enables the derivation of a set of verifiable criteria that a Pillar I credit risk model would be expected to meet to demonstrate alignment with RDARR model-level requirements. The analysis begins with a gap-assessment exercise in which selected RDARR sub-topics are systematically associated with the most pertinent DCAM components, providing a structured basis for deriving practical guidelines to support the interpretation of RDARR expectations in the context of Internal Ratings-Based (IRB) credit-risk models. Table 2 reports a summary of the gap analysis of selected RDARR principles declined for IRB credit risk models and evaluated via DCAM[9]. The strategy would be starting from *Not Compliant* on Principle 4 (Integrated Data Architecture, Data Lineage) to gain benefits on all the other not *Fully Compliant* topics to demonstrate how the design and implementation of data lineage may represent the foundation for full compliance with the selected principles in the context of credit risk models and which are the key questions that such activity would raise. Indeed, starting from the definition of data lineage given by the ECB[10] the full implementation of the data lineage ensures, at the same time, the coverage of the selected principles.

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[8] DCAM provides a structured reference model that articulates a set of capabilities commonly associated with mature data management practices. According to the EDMC technical documentation, the model defines the scope of organisational, architectural and operational requirements necessary to evaluate data accuracy, integrity, completeness and quality within a formalised control environment, and it is designed to support the examination of data management processes across complex organisational landscapes (EDMCouncil 2023).

[9] Note that the degree of compliance scores have been stated according to the assumptions described in this work and are illustrative. Compliance degree may vary from institution to institution.

[10] "*Data Lineage is the information about the movement and transformation of data from front (capture) to end and enables a bank to (i) understand if data quality controls are sufficient and well placed in the data flow, (ii) identify interconnections between data definitions and taxonomies, (iii) ensure that when data fields are loaded or transformed across or within systems they are still in line with the reporting requirements and definitions, (iv) support the identification of data points needed for specific ad hoc reporting needs, (v) in case of data quality incidents be able to track back the source of the issue in a timely manner and to (vi) allow traceability for (external) validation*" (ECB, 2024).

RDARR principle	Selected RDARR sub-topic	DCAM	Compliance degree (assumed)
Principle 3	Governance of DQ control framework	7.1.2 Accountable parties have been identified and roles and responsibilities have been assigned	Partially Compliant
Principle 4	Identification of CDE and data lineage design	4.5.2. Critical Data Elements (CDEs) have been identified and inventoried	Not Compliant
	Contribute to the definition of process relevant metadata (semantics, taxonomies and business terms)	5.2.1. Attribute level “business” definitions are defined, documented and approved by relevant stakeholders	Not Compliant
		5.2.2. Taxonomies and ontologies are created, documented, maintained and governed	
		5.2.3. Metadata is defined	
Principle 5	Controls definition on CDE	7.2.1. All relevant data have been identified and prioritized.	Partially compliant
		7.3.1. Data Quality ‘control points’ are in place along the full spectrum of the data supply chain.	
	Coverage of main DQ dimensions	7.2.2. Data is profiled, analysed and graded	Fully compliant
	Root cause analysis, escalation process and traceability	7.2.3. Data remediation has been planned, prioritized and actioned.	Partially compliant
		7.3.2. Data Quality Metrics are captured, reported and used to drive data remediation.	
		7.3.3. Root Cause analysis is performed	
		7.3.4. Data Quality processes are audited	

Table 2: Outcomes of the gap analysis between a hypothetical IRB model and RDARR principles, evaluated via DCAM matrix for

3.1 Addressing Principle 3 and strengthening Principle 5: why assigning roles and responsibilities is essential to data lineage implementation and strengthens the pre-existing data quality framework

While data lineage is often approached as a technical or documentation exercise, it can only fulfil its role under RDARR if it is embedded within a clearly defined governance framework. Without explicit ownership and accountability, lineage remains static and informational, rather than operational. From a methodological standpoint, data lineage implementation is conceived as a logical sequence rather than a technical prescription. The sequence starts from role assignment and ownership definition, proceeds through the identification of Critical Data Elements and the placement of data quality controls, and culminates in traceability and auditability mechanisms. This sequencing is intended to guide implementation choices while leaving room for institution-specific solutions.

This section therefore shows how the assignment of clear roles and responsibilities constitutes a prerequisite for effective data lineage, making its implementation a governance challenge and, at the same time, enabling compliance with Principle 3 at process level and strengthening the foundations of a comprehensive and effective Data Quality framework. To make the connection between data linage and assignment of roles and responsibilities even clearer, it might be useful starting from the definition reported by the ECB Guidelines on RDARR principles (ECB, 2024), where **data lineage** is defined as "*information about the movement and transformation of data from its initial capture to its final destination*."

A fundamental design question, especially when dealing with models, is therefore where lineage starts and where it ends. In practice, lineage should start at the authoritative capture/source - including the first controlled ingestion point - and end at the risk artefact that is actually consumed for decision-making and reporting (e.g. model outputs used in capital calculation and downstream risk reports).

From an operational perspective, governance mechanisms supporting data lineage must ensure:

- Clear accountability for the design, maintenance, and evidencing of lineage across the data lifecycle.
- Consistency between the process view (how risk data are produced and consumed), the data/functional view (CDEs, quality rules), and the technical view (systems, ETL, metadata).
- Ownership and placement of data quality controls at the right nodes of the lineage, with measurable thresholds and escalation.

In light of such multiple features, no single role can credibly own lineage end-to-end in isolation. From here, follows that, assuming that the analysis is conducted at a level where each process produces a single metric (e.g. the final PD parameter used for capital requirements calculation), the data flow can be segmented at least between the following stakeholders:

- **Process Owner** – accountable for the risk metrics outcome (process view)
- **Data Owner** – responsible for defining the functional data flow and the production of the risk metrics (functional/data view)
- **Application Owner** – responsible of the technological solution supporting the production of the risk metrics (data ingestion, ETL)

Ideally, roles and responsibilities should be formalised through a RACI matrix[11], which can be thought as follows:

Element	Process Owner	Data Owner	Application Owner
Risk metrics production	A	R	I
Process mapping	A	R	I
CDE identification	A	R	C
Data Lineage design and implementation	C	A/R	C
Technical controls	I	C	A/R
Functional controls	I	A/R	C
Model-specific controls	C	A/R	I
Output reconciliations	A	R	C/I

Table 3: RACI Matrix for E2E IRB modelling framework process under RDARR

[11] Reference on RACI matrix and players e.g. Responsible, Accountable, Consulted, Informed. See University of Oxford – RACI responsibility matrix for details.

As the Process Owner remains accountable for the **(a.)**, (**b.**) and **(c.)** with Data Owner acting as executor (responsible)[12], the main advantage of this configuration lies in leveraging the Data Owner's expertise to establish a centralized view, minimizing the number of data layers that constitute the data lineage (c.)[13]. A practical way forward could be to proceed by business data domain[14] thereby reducing the joint effort required. In addition to functional and risk considerations, the Application Owner may act as a third contributor, consultable for clearing the technical dimension (i.e. physical data and tables).

Once roles and responsibilities are clearly defined and assigned, the Data Owner can act as a pivotal figure by **(d.)** identifying all Critical Data Elements (CDEs)[15] already covered by pre-the existing data quality framework and tracing them back within the first data layer or legacy sources (e.g. balance sheet data, external credit bureau data, internal credit data), where technical controls designed by the Application Owner are typically applied. This approach should ensure an E2E coverage of the whole data flow feeding the model. Subsequently, the coverage of the first data layer—and its related CDEs—relies on two integrated sets of controls:

1. Technical controls **(e.)** - Application Owner may include – for instance – integrity of the data (check number of records from month to month, check missing values), uniqueness (no duplicate records), technical domains (values of fields must be included in predefined ranges).
2. Functional controls **(f.)** - Data Owner may leverage on risk logics: stability of distribution of raw input data needed for the calculation of the model's indicators, trend analysis, consistency of key values among different tables.

The key benefit of this approach is that the first data layer is common to most models, allowing this activity to be executed once for all models.

After designing this common layer, **(g.)** Model-specific controls can be developed by the Data Owner with support from the Process Owner. This involves identifying, for each model or rating calculation step, the relevant CDEs (e.g. risk scores associated with single modules that compose the model). These controls are expected to focus on risk considerations, such as detecting shifts in variable distributions or calibration segments over time (e.g. using empirical distribution analysis or PSI).

Finally, the last set of controls – **(h.)** Output reconciliations - targets the accuracy and consistency of metrics reported to Senior Management. Here, the focus shifts to the model outputs and their evolution over time. This stage, considered a monitoring phase, is shared by the Process Owner and Internal Validation, emphasising high-level business and risk perspectives rather than data errors (which were addressed earlier). Reconciliations with other risk reports using the same outputs may also be required.

In conclusion, the operating model described above—consistent with DCAM expectations—provides a structured way to link data lineage design, CDE identification, and layered control implementation to process-level governance of data quality. On this basis, the gap analysis results presented earlier can be updated to reflect the improved coverage of the relevant RDARR sub-topics. Such update is reported in the table below:

RDARR principle	Selected RDARR sub-topic	DCAM	Compliance degree (assumed)	Compliance degree (achieved)
Principle 3	Governance of DQ control framework	7.1.2 Accountable parties have been identified and roles and responsibilities have been assigned	Partially Compliant	Fully Compliant
Principle 4	Identification of CDE and data lineage design	4.5.2. Critical Data Elements (CDEs) have been	Not Compliant	Fully Compliant

[12] From ECB 2024 "*Data owners responsible for key risk indicators and critical data elements throughout the complete aggregation process (front to end)*".
[13] "Data layers" is here meant as a data domain feeding a particular step of risk metrics production. In this use case, one may think the first data layer as the collection of raw data (e.g. personal data, financial statements, external information from credit bureau etc.).
[14] For example: the Data Owner knows that different rating models are fed with financial indicators coming from the same data source. The calculation logics of such indicators (i.e. which data that need to be aggregated) is the same across all models. The Data Owner may then decide to propose a centralized view of this process step that optimizes the number of nodes which must be represented through the data lineage.
[15] As defined in ECB 2024, Critical Data Elements are "those data elements that are used to calculate the key risk indicators and have a direct or significant impact on the value of the indicator or technical routine of the calculation and the reporting".

		identified and inventoried		
	Contribute to the definition of process relevant metadata (semantics, taxonomies and business terms)	5.2.1. Attribute level “business” definitions are defined, documented and approved by relevant stakeholders	Not Compliant	
		5.2.2. Taxonomies and ontologies are created, documented, maintained and governed		
		5.2.3. Metadata is defined		
Principle 5	Controls definition on CDE	7.2.1. All relevant data have been identified and prioritized.	Partially compliant	Fully Compliant
		7.3.1. Data Quality ‘control points’ are in place along the full spectrum of the data supply chain.		Fully Compliant
	Coverage of main DQ dimensions	7.2.2. Data is profiled, analysed and graded	Fully compliant	Fully Compliant
	Root cause analysis, escalation process and traceability	7.2.3. Data remediation has been planned, prioritized and actioned.	Partially compliant	
		7.3.2. Data Quality Metrics are captured, reported and used to drive data remediation.		
		7.3.3. Root Cause analysis is performed		
		7.3.4. Data Quality processes are audited		

Table 4: Outcomes of the gap analysis between a hypothetical IRB model and RDARR principles, evaluated via DCAM - UPDATED

3.2 Complement the data lineage to fully comply with Principle 4: Introducing Metadata, Glossary and Taxonomies

Once roles and responsibilities for data lineage have been established, the next step is to ensure that the data lineage itself is enriched with a coherent semantic layer. End-to-end traceability alone describes how data move and transform across systems and processes, but does not fully explain what the data represent, how they should be interpreted, and under which business and regulatory assumptions they can be used. For this reason, achieving full compliance with Principle 4 requires complementing data lineage with a structured metadata framework encompassing data definitions, glossaries, and taxonomies.

This section therefore focuses on how Critical Data Elements (CDEs) identified through data lineage can be anchored to their underlying metadata, ensuring consistency between technical data, business meaning, and regulatory definitions[16]. It introduces the logical building blocks of this semantic framework—data elements, attributes, business terms, data dictionaries, and taxonomies—and explains how they interact to support both horizontal traceability across processes and vertical alignment from business concepts to technical implementations. By doing so, the section clarifies how metadata act as the missing link between lineage – built on CDE - and data quality – built on the technical fields (Technical Data Element, TDE), enabling effective governance of CDEs and reinforcing RDARR expectations on integrated data architecture and data quality standards.

Indeed, as reported in the ECB guidelines on RDARR program, the data lineage is expected to be designed "on data attribute level" which is something different to (critical) data element:

> *[…] a data element contains information as an independent field while a data attribute, in general, is a single value description (i.e. its metadata, such as a business description of the content, type, format, etc.) for a data element (or data point or data object). As an example, data attributes are often stored as a column in a table and are used in the technical mapping to calculate key risk indicators, whereas data elements impact the specific indicator values.*

The excerpt reported above highlights a clear breakdown between what should be considered a metadata and what should be considered a (critical) data element. According to this definition, we can interpret a metadata as the collection of attributes linked to a particular CDE. As an example, imagine a table storing information about credit exposures in a bank. One of the columns is called "Exposure Amount". The value in a specific row of the "Exposure Amount" column — for example, €1,000,000 — is a data element. It is an individual piece of information: a specific field containing data used in risk calculations.

On the other hand, the data attribute (metadata) describing that column — for instance:

- Name: Exposure Amount
- Type: Numeric
- ...
- Unit: Euro
- Format: Decimal with 2 digits
- Business Description: Total outstanding exposure of a counterparty at reporting date
  — these are data attributes. They describe what the data element is and how it should be interpreted, stored, or processed.

In the calculation of a hypothetical Key Risk Indicator (KRI) (e.g. Large Exposure Ratio), or in any weighting procedure which involves client exposures, the actual €1,000,000 is used in the formula — that is the data element affecting the outcome. Meanwhile, the data attributes help ensure the correct data is used — they guide the mapping and validation (e.g. ensuring the number is in euros, not dollars, and represents the correct concept).

Having established these definitions, as explicitly stated in Principle 4, banks are expected to have in place an internal Glossary which collects all the high-level descriptions - which can be easily understood by any stakeholder - of the Critical Data Element that constitute the data lineage: these descriptions are called Business Terms (BT). This capability is also remarked by DCAM which claims that "Attribute level "business" definitions are defined, documented and approved by relevant stakeholders".

On a different level, as required by DCAM, we have ontologies and taxonomies, which, respectively, represent how data entities are logically involved in the process (e.g. "EAD is calculated from Exposure Amount") and how they are related (e.g. EAD at counterparty level → EAD at facility level). In the context of credit risk models, according to the complexity of the organisation and processes in scope, taxonomies can make use of prefixes or suffixes to contextualize the Business Data Element (BDE)[17] within the process. This approach can be particularly relevant when defining the data lineage, as it ensures alignment between identified Critical Data Elements, their granularity, and the underlying business definitions. For example, consider the Exposure Amount defined earlier: this represents a Business Term included in the glossary and recognized by all stakeholders with its own definition. If we were mapping a credit risk model process, we would likely refer to the BDE "Exposure at Default (EAD)". However, in this context, using "Exposure Amount", even though it reflects the same broad business concept, could be misleading or less precise, as multiple types of exposures exist. This implies that BDEs, through the presence of taxonomies, can be nested to ensure accuracy of representation and effectiveness of the underlying semantics. In our example, BDEs might include "Regulatory Exposure Amount" and "Accounting (IFRS9) Exposure Amount".

[16] From ECB 2025 "*The management of data taxonomies should entail complete and up-to-date data lineages on data attribute level (starting from data capture and including extraction, transformation and loading) for the risk indicators, and their critical data elements, identified as being within the scope of application.*"

[17] The .the meaning and role of that specific data within the process.

Alongside with the semantics (Business Term) and business (Business Data Element) dimension, the CDE can be seen from another perspective: the technical dimension - Technical Data Element, TDE - which represents the actual physical asset used within the process which undergoes the actual data quality controls.

In conclusion, a (Critical) Data Element should be understood as a three-layer construct in which a Business Data Element becomes "critical" when it is relevant for the calculation of risk metrics or regulatory outputs, and is therefore coupled with its semantic attributes (BT, BDE, taxonomies) and its corresponding technical implementation (TDE).

The collection of BTs forms the Glossary, while BDEs and TDEs together constitute the Data Dictionary—an asset that associates technical data elements with business descriptions relevant to a specific process. The distinction between Glossary and Data Dictionary lies in their purpose: the Glossary is semantics-driven, enabling stakeholders to understand the meaning of a Business Term within the entity's context; the Data Dictionary is functionality-driven, featuring data elements used in specific processes and describing their functional dimensions (e.g. which calculation they feed).

Who compiles these definitions?

- TDE: Application Owner provides all technical attributes.
- BDE: Process Owner provides business definitions; Data Owner defines rules and active data quality controls, completing—along with Application Owner's input—the information required for the Data Dictionary.
- BT: All stakeholders, including those using the same TDE/BDE in other processes.

In summary, complementing data lineage with a structured metadata framework allows institutions to move from purely technical traceability to semantic traceability, ensuring that risk data are not only traceable, but also correctly interpreted and consistently used across processes, models, and reports. By anchoring Critical Data Elements to business terms, taxonomies, and technical implementations, banks can achieve vertical alignment between business meaning and physical data, and horizontal consistency across the end-to-end data lifecycle.
This semantic enrichment is a necessary condition for fully complying with Principle 4, as it enables integrated data architecture to be both transparent and intelligible, and provides the foundation for effective data quality governance under Principle 5. Moreover, it prepares the ground for traceability and auditability requirements by ensuring that each data point can be unambiguously reconstructed, understood, and validated in its regulatory and business context, as discussed in the following sectin.
The outcomes in terms of RDARR compliance achieved after implementing the steps described in this section are reported in the table below:

RDARR principle	Selected RDARR sub-topic	DCAM	Compliance degree (assumed)	Compliance degree (achieved)
Principle 3	Governance of DQ control framework	7.1.2 Accountable parties have been identified and roles and responsibilities have been assigned	Partially Compliant	Fully Compliant
Principle 4	Identification of CDE and data lineage design	4.5.2. Critical Data Elements (CDEs) have been identified and inventoried	Not Compliant	Fully Compliant
	Contribute to the definition of process relevant metadata (semantics, taxonomies and business terms)	5.2.1. Attribute level "business" definitions are defined, documented and approved by relevant stakeholders	Not Compliant	Fully Compliant
		5.2.2. Taxonomies and ontologies are created,		Fully Compliant

		documented, maintained and governed		
		5.2.3. Metadata is defined		Fully Compliant
Principle 5	Controls definition on CDE	7.2.1. All relevant data have been identified and prioritized.	Partially compliant	Fully Compliant
		7.3.1. Data Quality 'control points' are in place along the full spectrum of the data supply chain.		Fully Compliant
	Coverage of main DQ dimensions	7.2.2. Data is profiled, analyzed and graded	Fully compliant	Fully Compliant
	Root cause analysis, escalation process and traceability	7.2.3. Data remediation has been planned, prioritized and actioned.	Partially compliant	
		7.3.2. Data Quality Metrics are captured, reported and used to drive data remediation.		
		7.3.3. Root Cause analysis is performed		
		7.3.4. Data Quality processes are audited		

Table 5: Outcomes of the gap analysis between a hypothetical IRB model and RDARR principles, evaluated via DCAM - UPDATED

4. Traceability and Auditability

Having established the governance framework supporting data lineage and the semantic structures required to interpret Critical Data Elements consistently, the final step is to ensure that these arrangements translate into effective traceability and auditability, as explicitly required by Principle 5. From a supervisory perspective, data lineage, metadata and data quality controls deliver value only if they enable institutions to reconstruct end-to-end data flows in a timely, granular and reliable manner and to demonstrate the soundness of such flows to validators, internal audit and supervisory authorities. In this context, traceability refers to the institution's ability to identify – through the data lineage - the origin of the data quality issue, understand the root cause and activate – if needed - the related escalation process. Auditability extends this concept by requiring that such reconstruction is not merely theoretical, but supported by consistent documentation, control evidence and data governance tools that allow independent review and challenge. This section therefore focuses on how end-to-end data lineage, enriched with metadata and embedded within a data quality framework, enables institutions to meet ECB expectations on traceability and auditability, with particular attention to the implementation of a central anomalies register[18].

The ECB guidelines (ECB, 2024) claim that data lineage must allow institutions both to track back the source of data quality incidents in a timely manner and to provide sufficient transparency to external validators. This dual function translates into a real expectation for auditors and validators: not only should there be a documented flow of data from origination to reporting, but this documentation should be sufficiently granular to enable the analysis of any root-cause underpinning data quality

[18] "An up-to-date and complete overview ("register") of data quality issues and limitations, including (i) an assessment of the severity of these issues, (ii) a root cause analysis, (iii) a quantitative impact analysis of material/severe data errors on the risk and business areas affected, (iv) clearly defined processes and responsibilities for remediating and escalating data quality issues, depending on the materiality of the issues, (v) deadlines for remediation, and (vi) a date for effective remediation (including appropriate evidence)" (ECB, 2024).

problems. In practical terms, areas of data lineage that remain abstract or incomplete—e.g. documenting only systems but not transformation rules—compromise both remediation and assurance. Additionally, the ECB's approach requires institutions to maintain central anomalies register. This register serves as the inventory of all identified data quality issues, capturing information such as anomaly type, severity, business impact, root cause, responsible owner, and resolution timeline.

For validators and auditors, the register might represent a crucial control instrument, as it provides structured evidence that can be reconciled against both data lineage and data governance responsibilities. By systematically recording incidents, the register ensures that anomalies are not treated as isolated events but as part of a controlled feedback loop in the bank's data quality management framework. On top of that, auditors and validators can select samples of anomalies, verify whether they have been correctly classified, assess whether remediation has been carried out within agreed timelines, and test whether the incident can be traced back through the lineage to its origin. More importantly, the completeness of the register itself is an auditable element, since ensures compliance with ECB guidelines and a solid defence tool within the wider data governance framework.

To operationalise these tests, auditors and validators can define ad-hoc indicators that measure the effectiveness of the anomalies register and its integration with the data lineage. For instance, one could define the following metrics:

- **Data Lineage-to-anomaly traceability ratio**, defined as the proportion of anomalies in the register for which the root cause can be fully reconstructed using lineage documentation. For example, if 120 anomalies are registered over a quarter and only 96 can be traced back through to their source, the traceability ratio is 80%.
- **Ratio between the total number of Critical Data Element identified and the total number of data elements within a specific process.**
- **Average time used for fixing issues,** better if broken down by incident severity.
- A complementary measure, the **recurrence index,** can be used to detect whether the same anomaly reappears across multiple cycles, suggesting that root causes are treated symptomatically rather than structurally.

However, it is crucial to remember that these KPIs, while quantitative, cannot replace a qualitative assessment of the anomalies register. Validators and auditors must evaluate whether the register is comprehensive, whether responsibilities for logging and resolution are clearly assigned, and whether updates are embedded in change management processes. In addition, the register should be readily available for supervisory review, ensuring that external validators can trace anomalies seamlessly through the data lineage. A register that is technically complete but poorly governed will fail the ECB's standard of being both traceable and auditable. In sum, the ECB's 2024 emphasis on traceability and auditability elevates the anomalies register from a mere register of data issues to a core data governance tool that underpins data quality, strengthens supervisory dialogue, and positions internal audit as a central actor in the institution's data governance maturity. The table reported below presents the final outcomes achieved after having implemented all the methodological steps.

RDARR principle	Selected RDARR sub-topic	DCAM	Compliance degree (assumed)	Compliance degree (achieved)
Principle 3	Governance of DQ control framework	7.1.2 Accountable parties have been identified and roles and responsibilities have been assigned	Partially Compliant	Fully Compliant
Principle 4	Identification of CDE and data lineage design	4.5.2. Critical Data Elements (CDEs) have been identified and inventoried	Not Compliant	Fully Compliant
	Contribute to the definition of process relevant metadata (semantics, taxonomies and business terms)	5.2.1. Attribute level "business" definitions are defined, documented and approved by relevant stakeholders	Not Compliant	Fully Compliant

		5.2.2. Taxonomies and ontologies are created, documented, maintained and governed		Fully Compliant
		5.2.3. Metadata is defined		Fully Compliant
Principle 5	Controls definition on CDE	7.2.1. All relevant data have been identified and prioritized.	Partially compliant	Fully Compliant
		7.3.1. Data Quality 'control points' are in place along the full spectrum of the data supply chain.		Fully Compliant
	Coverage of main DQ dimensions	7.2.2. Data is profiled, analyzed and graded	Fully compliant	Fully Compliant
	Root cause analysis, escalation process and traceability	7.2.3. Data remediation has been planned, prioritized and actioned.	Partially compliant	Fully Compliant
		7.3.2. Data Quality Metrics are captured, reported and used to drive data remediation.		Fully Compliant
		7.3.3. Root Cause analysis is performed		Fully Compliant
		7.3.4. Data Quality processes are audited		Fully Compliant

Table 6: Outcomes of the gap analysis between a hypothetical IRB model and RDARR principles, evaluated via DCAM – UPDATED

4.1 Interaction with the Model Risk Management Framework

While the framework proposed in this paper does not aim to intervene directly in Model Risk Management (MRM) processes, the evidencing produced through RDARR operationalisation naturally interfaces with several elements of the MRM lifecycle. In particular, end-to-end data lineage enhances transparency on data sourcing and transformations, which are often among the most resource-intensive elements of independent validation. Likewise, layered data quality evidence may support assessments of model performance, stability and potential sources of model risk, without introducing RDARR-specific triggers or decision rules. Furthermore, anomaly tracking and ownership attribution strengthen documentation available for model change governance, again without redefining MRM practices, which remain governed by existing regulatory frameworks.

Importantly, the objective of this paper is not to integrate RDARR into the MRM framework nor to propose new validation methodologies. Instead, the intention is to highlight that the operational artefacts generated by RDARR implementation—data lineage, governance roles, metadata, and anomaly registers—can act as a complementary evidencing layer that supports existing validation and governance activities while remaining fully within current supervisory expectations.

A related regulatory development worth noting is the EBA's 2026 Final Report on the revised Regulatory Technical Standards for material model changes, issued on 30 March 2026 (EBA 2026), which streamlines supervisory approvals and strengthens documentation expectations for IRB model changes (e.g., clarity of data dependencies, consistency of supporting evidence, documentation of impacts). Although these RTS do not modify RDARR obligations, they underline the supervisory value of structured, transparent and traceable data processes—elements that RDARR implementation provides by design. The connection is therefore indirect but meaningful: RDARR artefacts can facilitate compliance with evolving documentation expectations for model changes, easing the activities needed to be carried out by modelers, validators and auditors when interfacing with the regulator.

5. Conclusions

This paper addressed the persistent gaps in banks' Risk Data Aggregation and Risk Reporting (RDARR) capabilities by translating the ECB's 2024 principles into a practical, process-level remediation strategy. After fulfilling Principle 2 through a risk-based scoping methodology to identify RDARR-relevant credit risk models, the study demonstrated how RDARR compliance for Pillar I models can be operationalised via DCAM in a scalable and evidence-based way for all the credit risk models.

A key finding is that the implementation of an end-to-end data lineage should be treated as the primary architectural lever to accelerate RDARR remediation in the credit risk modelling context as it needs pre-requisites that strengthen governance and data quality controls. Indeed, while IRB models often already include a structured set of data quality controls, the ability to demonstrate auditable traceability from source systems through transformations to model inputs, model outputs, and downstream reporting remains a frequent structural weakness. By designing lineage at the appropriate granularity and explicitly linking it to measurable data quality controls, banks can strengthen not only Principle 4 (Integrated Data Architecture) and Principle 5 (Group-wide Data Quality Management and Standards), but also provide the operational basis for Principle 3 (Effective Data Governance Framework) through clearer ownership boundaries, and enforceable accountability across the end-to-end chain.

Overall, the study contributes to designing a coherent implementation pathway that starts from a high-maturity domain (IRB), uses data lineage as the enabler for linking architecture, quality and governance – effectively reducing the compliance burden that banks often perceive as overwhelming under RDARR principles. Future work should empirically validate the proposed framework through implementation case studies, define standardised RDARR performance indicators for lineage coverage and control effectiveness, and assess its applicability in innovative modelling contexts increasingly shaped by AI-based approaches. These contexts may require enhancing traditional data-quality practices, as consolidated industry and regulatory frameworks may not fully capture new and yet unexplored data-quality dimensions introduced by AI-driven models.

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Annex

Here below a summary of RDARR principles stated in the Guide on effective risk data aggregation and risk reporting. European Central Bank 2024:

1. Responsibility of the management body: The ECB stresses that the ultimate accountability for RDARR lies with the management body (board of directors and senior executives). This includes not only approving the RDARR strategy but also ensuring sufficient resources, prioritisation, and integration into the overall risk management framework. Supervisory assessments have shown that insufficient steering and ownership at the top level have been a root cause of slow progress (European Central Bank, 2024). Effective implementation requires clear escalation processes and board-level reporting on RDARR performance indicators.

2. Sufficient scope of application: institutions should establish a data governance framework covering all material entities, risk types—including credit, market, liquidity, operational and third-party risk—and the entire lifecycle of the data. The scope should include internal risk reports used for decision-making and strategic steering, financial reports externally published together with annual financial statements, and supervisory submissions such as FINREP and COREP templates, EBA and SSM stress test exercises, and Pillar 3 disclosures. Furthermore, key risk indicators (KRIs), including risk appetite indicators as well as other key indicators referred to in the internal risk, financial and supervisory reports, should be included in the data governance framework. Lastly, in terms of models, the scope should cover key internal risk management models including, but not limited to, Pillar 1 regulatory capital models (such as internal ratings-based (IRB) approaches for credit risk), Pillar 2 risk and capital models and other key risk management models (such as IFRS9 collective provisions models and value-at-risk models). This includes input data for model development as well as resulting model outputs (e.g. exposure at default, probability of default or loss-given-default estimates) that are crucial for managing the risks faced by the institution.

3. Effective data governance framework: Robust governance is critical for ensuring that risk data are reliable and fit for purpose. According to the ECB Guide, institutions are expected to establish a comprehensive governance framework that operates both at group level and at the level of material legal entities. A key element is the designation of data owners responsible for key risk indicators and critical data elements across the full aggregation process. Their duties include defining and applying data quality controls, ensuring accuracy, integrity, completeness and timeliness, monitoring and reporting data quality, remediating deficiencies, and managing metadata such as data lineage and dictionaries. In addition, a central data governance function should issue policies, oversee implementation across the organisation, and participate in change processes with material impact on RDARR, including mergers, outsourcing, product launches or IT upgrades. The framework must also include a validation function in the second line of defence, independent from RDARR operations, which regularly assesses RDARR processes, IT infrastructure, and outsourced activities, while being adequately resourced and segregated to avoid conflicts of interest. Finally, an internal audit function as the third line of

defence should periodically review the effectiveness of the validation function, the overall governance framework, and the quality of data used for risk quantification, thereby providing independent assurance to management and supervisors.

4. Integrated data architecture: Data architecture and lineage must ensure transparency, traceability, and the minimisation of manual interventions. The ECB Guide (2024) requires institutions to implement and document an integrated data architecture at the group level, supported by harmonised taxonomies and metadata repositories. Supervisory reviews have shown that many banks still rely on fragmented legacy IT systems, resulting in complex reconciliation processes and excessively long production times for risk and financial reports. To address this, supervisory expectations now call for end-to-end documentation of data flows, the adoption of standardised architecture principles, and integrated IT solutions capable of producing consistent datasets across regulatory, supervisory, and internal reporting streams. Such integration also enables automation, reducing the frequency of errors and lowering operational risk. A key element of this framework is data lineage, which refers to the complete documentation of how data move and transform from their initial capture at source systems through intermediate processing (extraction, transformation, and loading) to their final use in risk models, key risk indicators, and reports. Effective lineage makes it possible to verify whether data quality controls are well placed in the flow, to trace back the source of errors or inconsistencies, to ensure that transformations preserve alignment with regulatory definitions, and to provide transparent audit trails for both internal validation and supervisory review. By embedding robust lineage practices, institutions can enhance the reliability, timeliness, and credibility of their risk data aggregation processes.

5. Group-wide data quality management and standards: The ECB requires institutions to establish harmonised data quality (DQ) frameworks across the entire group, embedded within the overall risk management or data governance framework. These frameworks must be supported by adequate data quality controls and measurable data quality metrics covering the key dimensions of accuracy, integrity, completeness, timeliness, and consistency, with systematic monitoring and clear tolerance levels. Institutions are expected not only to detect and report data quality breaches but also to maintain comprehensive registers of deficiencies, conduct root cause and quantitative impact analyses, and implement remediation processes with defined responsibilities, deadlines, and evidence of resolution. The framework must also integrate end-user applications and manual workarounds, ensuring that they are subject to adequate control mechanisms until migrated into IT-controlled environments. In addition, the ECB expects banks to properly consider data quality risks within their ICAAP and ILAAP processes, where unresolved data quality issues might lead to an underestimation of risks and should be reflected in the risk quantification through additional margins of conservatism.

6. Timeliness of internal risk reporting: Risk reports must be delivered frequently and quickly enough to support decision-making during normal and stressed conditions. Supervisory evidence collected by the ECB has shown that, in some institutions, monthly risk reports required over 40 working days to be produced, which is incompatible with effective risk management (European Central Bank, 2018). The ECB expects institutions to ensure that the combination of reporting frequency and production time is calibrated in such a manner as to allow for timely reactions to changes in its risk situation, thereby complying with its set of internal risk appetite indicators (metrics and limits) and ensuring that timeliness does not compromise accuracy or completeness. Moreover, in addition to sound reporting capabilities in normal situations, institutions should implement effective RDARR capabilities for stress or crisis situations to adequately manage unexpected stress events.

7. Effective implementation programmes: The ECB expects banks to manage RDARR remediation through structured, well-resourced programmes with clearly defined milestones, measurable deliverables, and independent oversight, with responsibility for the implementation attributed to the management body. Implementation programmes should include periodic reporting to senior management, external benchmarking, and alignment with broader digitalisation strategies. Good project management practices are essential to achieving tangible progress, as supervisory reviews have shown that many projects lacked sufficient prioritisation, suffered from frequent delays, and failed to integrate lessons from past inspections.

Multi-model credit rating system for SMEs: a deterministic methodology of arrangements with repetitions

Author: Claudio Cautiero (Credit Analyst) [1]

Abstract

The present document analyzes a proprietary methodological framework, developed in 2015, based on a deterministic approach for the temporal normalization of the scores on a two-year basis and for the determination of the final rating. The distinctive element of the system lies in the use of "*arrangements with repetitions*" to codify the expert decision rules for multi-model aggregation, in a rigorous logical structure. The system integrates five distinct scoring methodologies (SME Z-Score, Bank Score, EM Score, MCC Rating, Company Performance Index) reaching a final rating through an aggregation process that combines quantitative, qualitative and performance components.

Supplementary materials*: the technical appendices and spreadsheets supporting the analyses presented in the present work are available upon request from the author / or from the following repository:*
https://drive.google.com/drive/folders/1Xug079LzCeq1bBYpLaN1FhdQ6PoiHvvS

Keywords: credit rating, SME, arrangements with repetitions, time normalization, multi-model system, risk assessment.

1) Introduction

1.1) Context and purpose of the document

The multi-model rating system presented here represents a methodological approach developed about ten years ago for assessing the creditworthiness of Italian SMEs.
This document aims to analytically illustrate the implemented methodology, focusing on three fundamental elements:

- the engine for determining the scores of the individual models.
- the system of temporal normalization on a two-year basis through arrangements with repetitions.
- the final aggregation process.

The system should be contextualized in its development period (2014-2015), a historical phase characterized by:

- Pre-IFRS 9: the accounting standard IFRS 9 (International Accounting Standards Board, 2014), with full implementation in 2018, subsequently introduced requirements for probabilistic estimation of the Probability of Default (PD); this system was developed when current legislation favored rule-based approaches for unlisted SMEs.
- Data scarcity in the SME segment: the absence of deep historical series for small and medium-sized Italian companies made the application of Machine Learning models problematic, which would have suffered from "overfitting" on limited datasets; in this scenario, the deterministic approach based on expert rules therefore represented the most methodologically reliable solution that adhered to the operational context.
- Best practices pre-European banking crisis: the system reflects the risk management logics prevalent in the Italian banking system before the full implementation of Basel III (Basel Committee on Banking Supervision, 2010) and the EBA Guidelines (European Banking Authority, 2020).

The introduction on the historical context and the methodological paradigm that guided the development of the model is fundamental to understand that the contribution of the present work does not lie in the specific calibration of the parameters (which would require updating) but rather in the proposed methodological vision: i.e., adopting the logical architecture of the arrangements with repetitions as a multi-model aggregation tool with temporal memory.
This methodology is based on the principle that the combination of different models, each with its own strengths and specificities, as well as weighting on a two-year basis, can produce better results and reduce the average error compared to using any individual model. The multi-model approach would be inherently more robust as all models are unlikely to be simultaneously affected by the same anomalies. The combination of these models also provides a more complete and multidimensional assessment of credit risk.

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1 The opinions expressed in the present work are attributable exclusively to the author.
The methodological framework described is the result of independent research developed and formalized by the author in the period 2014–2015; it is not based on software, proprietary methodologies, confidential databases or confidential know-how belonging to third parties.

1.2) Structure of the document

The present document is organized to allow a complete understanding of the model through four main sections:

1. Score models: analytical description of the five models implemented.
2. Arrangements with repetitions: illustration of the "*original methodology*" for temporal normalization.
3. Final aggregation: description of the weighting system and determination of the final rating.
4. Operational considerations: analysis of the implementation and usage aspects.

Each section is analytically documented, reporting formulas, calculation logic and evaluation criteria exactly as implemented in the original system developed in a Microsoft Windows environment, using the Microsoft Excel software and the connected Visual Basic for Application (VBA).

2) Score models

2.1) SME Z-Score Model

The SME Z-Score represents the adaptation of the famous Altman model (1968) specifically calibrated for small and medium-sized enterprises. The model uses a linear formula that combines five standardized financial variables to produce a score that is then converted into a rating classification.

Formula: $Z = 1.981 \times X_1 + 9.841 \times X_2 + 1.951 \times X_3 + 3.206 \times X_4 + 4.037 \times X_5$

2.1.2) Specific variables and formulas

X_1 - Flexibility Assets Rate:

$$X_1 = \frac{\text{Net Working Capital}}{\text{Total Assets}}$$

X_2 - Return on Retained Earnings (RORE):

$$X_2 = \frac{\text{Retained Earnings}}{\text{Total Assets}}$$

X_3 - Return on Investment (ROI):

$$X_3 = \frac{\text{EBIT}}{\text{Total Assets}}$$

X_4 - Financial Autonomy Ratio:

$$X_4 = \frac{\text{Equity}}{\text{Total Liabilities}}$$

X_5 - Return on Sales Activity (ROSA):

$$X_5 = \frac{\text{Revenues}}{\text{Total Assets}}$$

2.1.3) Classification system

The Z-Score is converted into a rating through predefined thresholds:

$$\text{Classification}_Z = \begin{cases} \text{Low Probability of Default} & \text{if } Z > 8{,}105 \\ \text{Medium Probability of Default} & \text{if } 4{,}846 < Z \le 8{,}105 \\ \text{High Probability of Default} & \text{if } Z \le 4{,}846 \end{cases}$$

2.2) Bank Score

2.2.1) Discrete score structure

The Bank Score uses a discrete scoring system organized into four macro-assessment areas that cover all aspects relevant to credit assessment.

Each macro-area includes four specific indicators, for a total of twelve variables, each evaluated on a discrete scale that assigns scores from 0 to 3.

2.2.2) Macro-Area 1: Profitability and dynamics indicators

Operating profitability (1.1):

$$\text{Profitability} = \frac{\text{EBITDA}}{\text{Turnover}}$$

Score:

$$S_{\text{Profitability}} = \begin{cases} 3 & \text{if Profitability} \geq 15\% \\ 2 & \text{if } 10\% \leq \text{Profitability} < 15\% \\ 1 & \text{if } 5\% \leq \text{Profitability} < 10\% \\ 0 & \text{if Profitability} < 5\% \end{cases}$$

Self-financing capacity (1.2):

$$\text{Self} - \text{financing capacity} = \frac{\text{Cashflow}}{\text{Turnover}}$$

Score:

$$S_{\text{Self-financing}} = \begin{cases} 3 & \text{if Self-financing} \geq 15\% \\ 2 & \text{if } 8\% \leq \text{Self-financing} < 15\% \\ 1 & \text{if } 4\% \leq \text{Self-financing} < 8\% \\ 0 & \text{if Self-financing} < 4\% \end{cases}$$

Incidence of financial charges (1.3):

$$\text{Incidence of Financial charges} = \frac{\text{Financial Charges}}{\text{EBITDA}}$$

Score:

$$S_{\textbf{IncidenceFinancialCharges}} = \begin{cases} 0 & \text{if Incidence of Financial charges} < 0 \\ 3 & \text{if } 0 \leq \text{Incidence of Financial charges} \leq 20\% \\ 2 & \text{if } 20\% < \text{Incidence of Financial charges} \leq 40\% \\ 1 & \text{if } 40\% < \text{Incidence of Financial charges} \leq 60\% \\ 0 & \text{if Incidence of Financial charges} > 60\% \end{cases}$$

ROE (1.4):

$$\text{ROE} = \frac{\text{Net Income}}{\text{Shareholder's equity}}$$

Score:

$$\text{ROE Score} = \begin{cases} 3 & \text{if } ROE \geq 10\% \\ 2 & \text{if } 7{,}5\% \leq ROE < 10\% \\ 1 & \text{if } 3\% \leq ROE < 7{,}5\% \\ 0 & \text{if } ROE < 3\% \end{cases}$$

2.2.3) Macro-Area 2: Debt indicators

Financial debt ratio or Debt to sales ratio (2.1):

$$\text{Debt to Sales Ratio} = \frac{\text{Financial Debt}}{\text{Turnover}}$$

Score:

$$S_{\text{Debt to Sales Ratio}} = \begin{cases} 3 & \text{if Debt to Sales Ratio} \leq 50\% \\ 2 & \text{if } 50\% < \text{Debt to Sales Ratio} \leq 75\% \\ 1 & \text{if } 75\% < \text{Debt to Sales Ratio} \leq 100\% \\ 0 & \text{if Debt to Sales Ratio} > 100\% \end{cases}$$

Financial debt ratio (Current operations) (2.2):

$$\text{Current Debt Ratio} = \frac{\text{Net Financial Debt}}{\text{EBITDA}}$$

Score:

$$S_{\text{Current Debt Ratio}} = \begin{cases} 3 & \text{if Current Debt Ratio} \leq 4 \\ 2 & \text{if } 4 < \text{Current Debt Ratio} \leq 5{,}5 \\ 1 & \text{if } 5{,}5 < \text{Current Debt Ratio} \leq 7 \\ 0 & \text{if Current Debt Ratio} > 7 \end{cases}$$

Financial debt to equity Ratio (2.3):

$$\text{Net Debt to Equity} = \frac{\text{Net Financial Debt}}{\text{Shareholder's equity}}$$

Score:

$$S_{\text{Net Debt to Equity}} = \begin{cases} 3 & \text{if Net Debt to Equity} \leq 25\% \\ 2 & \text{if } 25\% < \text{Net Debt to Equity} \leq 32{,}5\% \\ 1 & \text{if } 32{,}5\% < \text{Net Debt to Equity} \leq 40\% \\ 0 & \text{if Net Debt to Equity} > 40\% \end{cases}$$

Working capital intensity Ratio (on turnover) (2.4):

$$\text{Working capital intensity Ratio} = \frac{\text{Current Assets}}{\text{Turnover}}$$

Score:

$$S_{\text{Working capital intensity}} = \begin{cases} 3 & \text{if Working capital intensity} > 1{,}2 \\ 2 & \text{if } 0{,}8 \leq \text{Working capital intensity} \leq 1{,}2 \\ 1 & \text{if } 0{,}6 \leq \text{Working capital intensity} < 0{,}8 \\ 0 & \text{if Working capital intensity} < 0{,}6 \end{cases}$$

2.2.4) Macro-Area 3: Capital structure and financial stability Ratios

Fixed asset coverage ratio QCI or Long-Term Solvency Ratio (3.1):

$$\text{QCI} = \frac{\text{Shareholder's equity} + \text{MLT Debt}}{\text{Fixed Assets}}$$

Score:

$$\text{QCI Score} = \begin{cases} 3 & \text{if } QCI > 1{,}5 \\ 2 & \text{if } 1 < QCI \leq 1{,}5 \\ 1 & \text{if } 0{,}5 < QCI \leq 1 \\ 0 & \text{if } QCI \leq 0{,}5 \end{cases}$$

Current Ratio CTR (3.2):

$$CTR = \frac{\text{Current Assets}}{\text{Current Liabilities}}$$

Score:

$$S_{\text{CTR}} = \begin{cases} 3 & \text{if CTR} \geq 2 \\ 2 & \text{if } 1{,}5 \leq \text{CTR} < 2 \\ 1 & \text{if } 1 \leq \text{CTR} < 1{,}5 \\ 0 & \text{if CTR} < 1 \end{cases}$$

Days Sales Outstanding (3.3):

$$\textbf{Days Sales Outstanding} = \frac{\text{Trade Receivables} \times 365}{\text{Turnover}}$$

Score:

$$S_{\text{Days Sales Outstanding}} = \begin{cases} 3 & \text{if Days Sales Outstanding} \leq 120 \\ 2 & \text{if } 120 < \text{Days Sales Outstanding} \leq 150 \\ 1 & \text{if } 150 < \text{Days Sales Outstanding} \leq 180 \\ 0 & \text{if Days Sales Outstanding} > 180 \end{cases}$$

Days Inventory Outstanding (3.4):

$$\text{Days Inventory Outstanding} = \frac{\text{Inventory} \times 365}{\text{Turnover}}$$

Score:

$$S_{\text{Days Inventory Outstanding}} = \begin{cases} 3 & \text{if Days Inventory Outstanding} \leq 120 \\ 2 & \text{if } 120 < \text{Days Inventory Outstanding} \leq 150 \\ 1 & \text{if } 150 < \text{Days Inventory Outstanding} \leq 180 \\ 0 & \text{if Days Inventory Outstanding} > 180 \end{cases}$$

2.2.5) Final score calculation

The determination of the score with the attribution of the relative alphabetical score follows the logic of the arrangements with repetitions which are referred to in the dedicated section (chapter 3).

2.3) EM Score Model

2.3.1) Alphabetical classification system

The EM Score model refers to the methodology developed by Altman *et al* (2010) for emerging markets, adapted to the context of Italian small and medium-sized enterprises. The model uses an approach that combines four fundamental indicators calculated on a time basis to identify development trends and predictive patterns.

2.3.2) Calculation formulas

The model builds a composite score that is subsequently converted into a 19-level alphabetical rating, from AAA to D, offering greater evaluation granularity compared to traditional models. Formula:

$$EM = 3{,}25 + 6{,}56 \times X_1 + 3{,}26 \times X_2 + 6{,}72 \times X_3 + 1{,}05 \times X_4$$

Specific variables and formulas:

The variables X_1, X_2, X_3, X_4, are variables identical to those of the SME Z-Score model, to which the reader should refer.

2.3.3) Classification system

The EM-Score is converted into alphabetical classification through predefined thresholds that identify 19 rating ranges:

$$Rating_{EM}^{(1)} = \begin{cases} D & \text{if } EM < 1{,}75 \\ CCC^{-} & \text{if } 1{,}75 \leq EM < 2{,}5 \\ CCC & \text{if } 2{,}5 \leq EM < 3{,}2 \\ CCC^{+} & \text{if } 3{,}2 \leq EM < 3{,}75 \end{cases}$$

$$Rating_{EM}^{(2)} = \begin{cases} B^- & \text{if } 3{,}75 \leq EM < 4{,}15 \\ B & \text{if } 4{,}15 \leq EM < 4{,}5 \\ B^+ & \text{if } 4{,}5 \leq EM < 4{,}75 \\ BB^- & \text{if } 4{,}75 \leq EM < 4{,}95 \\ BB & \text{if } 4{,}95 \leq EM < 5{,}25 \\ BB^+ & \text{if } 5{,}25 \leq EM < 5{,}65 \\ BBB^- & \text{if } 5{,}65 \leq EM < 5{,}85 \\ BBB & \text{if } 5{,}85 \leq EM < 6{,}25 \\ BBB^+ & \text{if } 6{,}25 \leq EM < 6{,}4 \end{cases}$$

$$Rating_{EM}^{(3)} = \begin{cases} A^- & \text{if } 6{,}4 \leq EM < 6{,}65 \\ A & \text{if } 6{,}65 \leq EM < 6{,}85 \\ A^+ & \text{if } 6{,}85 \leq EM < 7 \\ AA^- & \text{if } 7 \leq EM < 7{,}3 \\ AA & \text{if } 7{,}3 \leq EM < 7{,}6 \\ AA^+ & \text{if } 7{,}6 \leq EM < 8{,}15 \\ AAA & \text{if } EM \geq 8{,}15 \end{cases}$$

2.3.4) Categorization by risk class

The 19 alphabetical ratings are further aggregated into four macro-classes which summarize the level of credit reliability and the risk profile of the company.

Score Class:

$$Class = \begin{cases} \text{HIGH} & \text{if Rating} \in \{AAA, AA^+, AA, AA^-, A^+, A, A^-\} \\ \text{MEDIUM HIGH} & \text{if Rating} \in \{BBB^+, BBB, BBB^-\} \\ \text{MEDIUM LOW} & \text{if Rating} \in \{BB^+, BB, BB^-\} \\ \text{LOW} & \text{if Rating} \in \{B^+, B, B^-, CCC^+, CCC, CCC^-, D\} \end{cases}$$

Risk level:

$$Risk = \begin{cases} \text{MINIMUM} & \text{if Rating} = AAA \\ \text{MODEST} & \text{if Rating} \in \{AA^+, AA, AA^-\} \\ \text{LOW} & \text{if Rating} \in \{A^+, A, A^-\} \\ \text{ACCEPTABLE} & \text{if Rating} \in \{BBB^+, BBB, BBB^-\} \\ \text{ACCEPTABLE WITH CAUTION} & \text{if Rating} \in \{BB^+, BB, BB^-\} \\ \text{SPECIFIC CAUTION} & \text{if Rating} \in \{B^+, B, B^-, CCC^+\} \\ \text{UNDER STRICT ATTENTION} & \text{if Rating} \in \{CCC, CCC^-, D\} \end{cases}$$

2.4) MCC Rating

2.4.1) Sector based differentiation

The MCC Rating model corresponds to the evaluation methodology of the Guarantee Fund for Small and Medium-Sized Enterprises (Fondo di Garanzia per le Piccole e Medie Imprese, Law 662/1996), as documented in the Fund's Operational Provisions, Part VI "Economic-Financial Evaluation Criteria", operational version until the reform of March 2019 (Mediocredito Centrale, MCC, 2012)[2].

The model includes three sectoral configurations:

- A1: Manufacturing industry, construction, hotel owners, fishing.
- A2: Trade, services, tenant hotels.
- A3: Special sectors with annual production cycles.

Methodological note*: the use of the pre-reform version (2012) of the MCC Rating responds to the need for historical consistency since the original backtesting of the model was performed using the parameters and sectoral thresholds in force at that time. To maintain these parameters, under the circumstances here, ensures the integrity of the retrospective empirical validation, avoiding methodological anachronisms.*

2.4.2) Calculation system

The system used four main ratios, each adapted to sector specificities:

[2] Since 2017, the Guarantee Fund has used a completely reformed rating system compared to the one proposed.

1. Fixed assets coverage ratio (A1) / Current ratio (A2, A3).
2. Financial autonomy (differentiated by sector).
3. Liquidity (A1, A2) / Current assets turnover ratio (A3).
4. Incidence of operating activities on turnover.

The specific thresholds for each sector configuration are reported in the official Operational Provisions of the Guarantee Fund[3].

2.4.3) Final score

The final score is the sum of the 4 indicators (maximum 12 points):

- 10-12 points: Rating A (HIGH quality).
- 7-9 points: Rating B (MEDIUM quality).
- 0-6 points: Rating C (LOW quality).

The two-year normalization of the MCC rating takes place based on the range assigned by the model: the first range translates into the assignment of rating A, the second range translates into rating B and the third range into rating C.

2.5) Company performance index

2.5.1) Origin and transformation of the M-Index

The Company Performance Index represents the operational transformation of the theoretical intuition of the M-Index developed by Mella *et al* (2011), its conceptual framework having evolved into a quantitative system with precise thresholds and automatic scoring algorithms.

2.5.2) System structure: year score (static component)

The system evaluates company performance through five macro-areas, each with specific indicators.
The static component (year score) measures the exclusive performance of the year to which it refers (year n).
Methodological note*: a few indicators are evaluated solely through two-year variations (dynamic component) and therefore do not present a static score. The relevant formulas are described in Paragraph 2.5.3*

2.5.2.1) Macro-Area 1: Ratios on Balance in the capital structure

Fixed asset coverage ratio QCI (a):

$$\mathrm{QCI} = \frac{\text{Shareholder's equity} + \text{MLT Debt}}{\text{Fixed Assets}}$$

Score:

$$\text{QCI Score} = \begin{cases} 15 & \text{if } QCI > 1{,}5 \\ 10 & \text{if } 1 < QCI \leq 1{,}5 \\ 5 & \text{if } 0{,}5 < QCI \leq 1 \\ 0 & \text{if } QCI \leq 0{,}5 \text{ or } QCI = 0 \end{cases}$$

Quick Ratio QTR (b)*:*

$$QTR = \frac{\text{Current Assets} - \text{Inventory}}{\text{Current Liabilities}}$$

Score:

$$\text{QTR Score} = \begin{cases} 15 & \text{if } QTR > 1{,}5 \\ 10 & \text{if } 1 < QTR \leq 1{,}5 \\ 5 & \text{if } 0{,}5 < QTR \leq 1 \\ 0 & \text{if } QTR \leq 0{,}5 \end{cases}$$

[3] The 2012 operational provisions are available in the historical archive of the Guarantee Fund (www.fondidigaranzia.it).

Current Ratio CTR (c):

$$CTR = \frac{\text{Current Assets}}{\text{Current Liabilities}}$$

Score:

$$\text{CTR Score} = \begin{cases} 15 & \text{if } CTR > 2{,}2 \\ 10 & \text{if } 2 < CTR \leq 2{,}2 \\ 5 & \text{if } 1{,}5 \leq CTR \leq 2 \\ 0 & \text{if } CTR < 1{,}5 \end{cases}$$

2.5.2.2) Macro-Area 2: Profitability indicators and structure of the Income Statement

1.1 Financial Leverage Relationship (RFF)

The assessment simultaneously integrates five components:

- ROI
- RODF
- SPREAD: difference between ROI-RODF
- DER: Debt-to-Equity Ratio (Financial Debts/Equity)
- RO: Operating income

Score:

$$\text{RFF Score} = \begin{cases} 15 & \text{if } ROI > 0 \wedge \text{SPREAD} > 0 \wedge DER < 1 \\ 10 & \text{if } ROI > 0 \wedge \text{SPREAD} > 0 \wedge DER > 1 \\ 5 & \text{if } ROI > 0 \wedge \text{SPREAD} < 0 \wedge DER < 1 \\ 0 & \text{if } ROI > 0 \wedge \text{SPREAD} < 0 \wedge DER > 1 \\ -5 & \text{if } ROI < 0 \wedge RO < 0 \end{cases}$$

Methodological note: *the additional Ratios of Macro-Area 2 (Operating Income, Incidence of Financial Charges on the Value of Production, Financial Debts/Value of Production Ratio) are assessed in Section 2.5.3.*

2.5.2.3) Macro-Area 3: EBITDA

Methodological note: *assessed exclusively in Section 2.5.3 (dynamic component).*

2.5.2.4) Macro-Area 4: relationship between net income and PONT

Components of the relationship:

- 4.1) PONT (Net Non-Recurring Items)
- 4.2) Net Income (RN)
- 4.3) Profit before taxes (RAI)
- 4.4) Net Operating Profit (EBIT)

Score:

$$\text{RN-PONT Score} = \begin{cases} 10 & \text{if } RN > 0 \wedge PONT < 0 \wedge EBIT > 0 \\ 5 & \text{if } PONT > 0 \wedge RN > 0 \wedge PONT < RN \wedge EBIT > PONT \\ 0 & \text{if } RN > 0 \wedge PONT > 0 \wedge PONT < RN \wedge PONT < RAI \\ -5 & \text{if } RN > 0 \wedge PONT > 0 \wedge PONT > RAI \\ 0 & \text{if } RN < 0 \wedge PONT < 0 \\ -5 & \text{if } RN < 0 \wedge PONT > 0 \\ -5 & \text{if } RN < 0 \wedge EBIT < 0 \wedge PONT \geq 0 \\ 5 & \text{if } RN > 0 \wedge EBIT > 0 \wedge PONT \geq 0 \end{cases}$$

Legend:

- **RN** = Net Income
- **PONT** = Net Non-Recurring Items (Non-Recurring income and expenses, or tax related items)
- **EBIT** = Net Operating Profit (Earnings Before Interest and Taxes)
- **RAI** = Profit before taxes

The formula assesses the quality of company income through: Net Income, Net Non-Recurring Items and EBIT, with a hierarchical logic. It attributes:

- 10 points for pure operating profitability (positive net income and positive EBIT, negative extraordinary balance).
- 5 points when the positive extraordinary components are limited compared to net income and EBIT, or for residual cases with positive income and positive EBIT.
- 0 points for positive income with controlled extraordinary components but lower than the pre-tax result, or for losses with negative extraordinary balances.
- -5 points when the extraordinary components exceed the pre-tax result, or for losses despite positive extraordinary balances, or for operating losses.

The system generates scores from -5 to +10, evaluating the sustainability and origin of the profitability.

2.5.2.5) Macro-Area 5: Incidence of operating cash flow on the value of production

Methodological note*: evaluated exclusively in Section 2.5.3 (Dynamic Component).*

2.5.3) System structure: two-year score (delta from year n to n-1)

The dynamic component evaluates the changes in the indicators between year n and year n-1, capturing the development trend of company performance.

The dynamic score is based on:

- P_n: Current year base score (section 2.5.2).
- D_{n,n-1}: Change in the indicator between year n and year n-1.

2.5.3.1 Fixed Assets Coverage Ratio (QCI) -Dynamic-

Score:

$$\mathrm{QCI}_{\mathrm{dynamic}}\mathrm{Score} = \begin{cases} 15 & \text{if } P_n = 15 \wedge D_{n,n-1} > 0 \\ 15 & \text{if } P_n = 15 \wedge D_{n,n-1} < 0 \wedge D_{n,n-1} > -0{,}025 \\ 10 & \text{if } P_n = 10 \wedge D_{n,n-1} > 0 \\ 10 & \text{if } P_n = 10 \wedge D_{n,n-1} < 0 \wedge D_{n,n-1} > -0{,}025 \\ 5 & \text{if } P_n = 5 \wedge D_{n,n-1} > 0 \\ 5 & \text{if } P_n = 5 \wedge D_{n,n-1} < 0 \wedge D_{n,n-1} > -0{,}025 \\ 0 & \text{if } P_n = 0 \wedge D_{n,n-1} > 0 \\ -5 & \text{if } P_n \in \{15,10,5,0\} \wedge D_{n,n-1} \le -0{,}025 \end{cases}$$

Where:

$$P_n = \text{QCI Score year } n$$
$$D_{n,n-1} = \text{QCI Score change between year } n \text{ and } n-1$$

2.5.3.2 Quick Test Ratio (QTR) -Dynamic-

Score:

$$\text{QTR}_{\text{dynamic}}\ \text{Score} = \begin{cases} 0 & \text{if } P_n = 0 \wedge D_{n,n-1} = 0 \\ 15 & \text{if } P_n = 15 \wedge D_{n,n-1} > 0 \\ 15 & \text{if } P_n = 15 \wedge D_{n,n-1} < 0 \wedge D_{n,n-1} > -0{,}025 \\ 10 & \text{if } P_n = 10 \wedge D_{n,n-1} > 0 \\ 10 & \text{if } P_n = 10 \wedge D_{n,n-1} < 0 \wedge D_{n,n-1} > -0{,}025 \\ 5 & \text{if } P_n = 5 \wedge D_{n,n-1} > 0 \\ 5 & \text{if } P_n = 5 \wedge D_{n,n-1} < 0 \wedge D_{n,n-1} > -0{,}025 \\ 0 & \text{if } P_n = 0 \wedge D_{n,n-1} > 0 \\ -5 & \text{if } P_n \in \{15,10,5,0\} \wedge D_{n,n-1} \leq -0{,}025 \end{cases}$$

Where:

P_n = QTR Score year n
$D_{n,n-1}$ = QTR Score change between year n and $n-1$

2.5.3.3 SPREAD ROI-RODF -Dynamic-

Score:

$$\text{SPREAD}_{\text{dynamic}}\ \text{Score} = \begin{cases} 15 & \text{if } P_n = 15 \wedge D_{n,n-1} > 0 \\ 10 & \text{if } P_n = 10 \wedge D_{n,n-1} > 0 \\ 5 & \text{if } P_n = 5 \wedge D_{n,n-1} > 0 \\ 0 & \text{if } P_n = 0 \wedge D_{n,n-1} > 0 \end{cases}$$

Where:

P_n = Base Score year n assigned to the Financial Leverage Relationship
$D_{n,n-1}$ = Variation of the ROI-RODF spread from year n to $n-1$

2.5.3.4 RO (Operating Income) –Dynamic-

Score:

$$\text{RO Score} = \begin{cases} -5 & \text{if } RO_n < 0 \wedge RO_{n-1} < 0 \\ -2{,}5 & \text{if } RO_n < 0 \wedge RO_{n-1} > 0 \\ -2{,}5 & \text{if } RO_n > 0 \wedge RO_{n-1} < 0 \\ 0 & \text{if } RO_n > 0 \wedge RO_{n-1} > 0 \end{cases}$$

Where:

RO_n = Operating Income year n
RO_{n-1} = Operating Income year $n-1$

2.5.3.5 Incidence of financial charges on the value of production -Dynamic-

Score:

$$\text{IOF}_{\text{dynamic}}\ \text{Score} = \begin{cases} 15 & \text{if } P_n = 15 \wedge D_{n,n-1} < 0 \\ 15 & \text{if } P_n = 15 \wedge 0 < D_{n,n-1} < 0{,}025 \\ 10 & \text{if } P_n = 10 \wedge D_{n,n-1} < 0 \\ 10 & \text{if } P_n = 10 \wedge 0 < D_{n,n-1} < 0{,}025 \\ 5 & \text{if } P_n = 5 \wedge D_{n,n-1} < 0 \\ 5 & \text{if } P_n = 5 \wedge 0 < D_{n,n-1} < 0{,}025 \\ 0 & \text{if } P_n = 0 \wedge D_{n,n-1} < 0 \\ -5 & \text{if } D_{n,n-1} \geq 0{,}025 \text{ or } (P_n = 0 \wedge D_{n,n-1} \geq 0) \end{cases}$$

Where:

P_n = Score Incidence of financial charges year n
$D_{n,n-1}$ = Score Variation of Incidence of financial charges from year n to $n-1$

Ratio between financial debts and value of production -Dynamic-

Score:

$$
\text{RDFVP}_{\text{dynamic}}\ \text{Score} = \begin{cases} 15 & \text{if } P_n = 15 \wedge D_{n,n-1} < 0 \\ 15 & \text{if } P_n = 15 \wedge 0 < D_{n,n-1} < 0{,}025 \\ 10 & \text{if } P_n = 10 \wedge D_{n,n-1} < 0 \\ 10 & \text{if } P_n = 10 \wedge 0 < D_{n,n-1} < 0{,}025 \\ 5 & \text{if } P_n = 5 \wedge D_{n,n-1} < 0 \\ 5 & \text{if } P_n = 5 \wedge 0 < D_{n,n-1} < 0{,}025 \\ 0 & \text{if } P_n = 0 \wedge D_{n,n-1} < 0 \\ -5 & \text{if } (P_n = 15 \wedge D_{n,n-1} \geq 0{,}025) \text{ or} \\ & (P_n = 10 \wedge D_{n,n-1} \geq 0{,}025) \text{ or} \\ & (P_n = 5 \wedge D_{n,n-1} \geq 0{,}025) \text{ or} \\ & (P_n = 0 \wedge D_{n,n-1} \geq 0) \end{cases}
$$

Where:

P_n = Score Ratio between financial debts and value of production year n
$D_{n,n-1}$ = Variation of Ratio between financial debts and value of production from year n to $n-1$

2.5.3.6 Gross operating margin (EBITDA) –Dynamic-

Score:

$$
\text{EBITDA}_{\text{ dynamic}}\ \text{Score} = \begin{cases} 15 & \text{if } P_n = 15 \wedge D_{n,n-1} > 0 \\ 10 & \text{if } P_n = 10 \wedge D_{n,n-1} > 0 \\ 5 & \text{if } P_n = 5 \wedge D_{n,n-1} > 0 \\ 0 & \text{if } P_n = 0 \wedge D_{n,n-1} > 0 \\ 5 & \text{if } P_n = -5 \wedge D_{n,n-1} > 0 \\ -5 & \text{if } P_n \in \{15,10,5,0\} \wedge D_{n,n-1} < 0 \\ -5 & \text{if } P_n = -5 \wedge D_{n,n-1} < 0 \end{cases}
$$

Where:

P_n = EBITDA Score year n
$D_{n,n-1}$ = Variation of EBITDA Score from year n to $n-1$

2.5.3.7 Relationship between net income and PONT –Dynamic-

Score:

$$
\text{RN-PONT}_{\text{dynamic}}\text{Score} = \begin{cases} 10 & \text{if } P_n = 15 \wedge \Delta PONT < 0 \wedge \Delta RN > 0 \\ 5 & \text{if } P_n = 5 \wedge \Delta PONT > 0 \wedge \Delta RN > 0 \wedge PONT_n > PONT_{n-1} \wedge RAI_n > RAI_{n-1} \\ 0 & \text{if } P_n = 5 \wedge \Delta PONT > 0 \wedge PONT_n < RAI_n \wedge PONT_{n-1} < RAI_{n-1} \\ 0 & \text{if } P_n = 0 \wedge \Delta RN > 0 \wedge \Delta PONT > 0 \wedge PONT_n > RAI_n \wedge PONT_{n-1} > RAI_{n-1} \\ 0 & \text{if } \Delta RN < 0 \wedge \Delta RN < 0 \\ -5 & \text{if } \Delta RN < 0 \wedge \Delta PONT > 0 \end{cases}
$$

Where:

P_n = Score year n attributed to the Relationship between Net Income and PONT
$\Delta PONT$ = Variation of Net Non-Recurring Items from year n to $n-1$
ΔRN = Variation of Net Income from year n to $n-1$
RN_n = Net Income year n
RN_{n-1} = Net Income year $n-1$
$PONT_n$ = Net Non-Recurring Items year n
RAI_n = Profit before taxes year n
RAI_{n-1} = Profit before taxes year $n-1$

2.5.3.8 Incidence of operating cash flow on the value of production -Dynamic-

Score:

$$\mathrm{ICFOVP_{dynamic}\ Score} = \begin{cases} 10 & \text{if } P_{RN-PONT} = 10 \wedge \Delta ICFOVP > 0 \\ 10 & \text{if } P_{RN-PONT} = 10 \wedge \Delta ICFOVP < 0 \wedge \Delta ICFOVP > -0{,}025 \\ 5 & \text{if } P_{RN-PONT} = 5 \wedge \Delta ICFOVP > 0 \\ 5 & \text{if } P_{RN-PONT} = 5 \wedge \Delta ICFOVP < 0 \wedge \Delta ICFOVP > -0{,}025 \\ 0 & \text{if } P_{RN-PONT} = 0 \wedge \Delta ICFOVP > 0 \\ 0 & \text{if } P_{RN-PONT} = 10 \wedge \Delta ICFOVP \leq -0{,}025 \\ 0 & \text{if } P_{RN-PONT} = 5 \wedge \Delta ICFOVP \leq -0{,}025 \\ 0 & \text{if } P_{RN-PONT} = 0 \wedge \Delta ICFOVP < 0 \\ -5 & \text{if } P_{RN-PONT} = -5 \wedge \Delta ICFOVP < 0 \\ 5 & \text{if } P_{RN-PONT} = -5 \wedge \Delta ICFOVP > 0 \end{cases}$$

Where:

$P_{RN-PONT}$ = Score year n of the Relationship between Net Income and PONT
$\Delta ICFOVP$ = Variation of Incidence of operating cash flow on the value of production from year n to $n-1$

2.5.4) Classification system

The total score of the Company Performance Index is given by the sum of the scores on an annual basis and those on a two-year basis: $\mathrm{TOTAL\ SCORE} = \sum \mathrm{Base\ Score} + \sum \mathrm{Delta\ Score}$

The final assessment or Total Score is assigned based on the total score according to the following classification:

$$\mathrm{Total\ Score} = \begin{cases} \text{EXCEPTIONAL} & \text{if Score} \geq 140 \\ \text{VERY GOOD} & \text{if } 120 \leq \text{Score} < 140 \\ \text{GOOD} & \text{if } 90 \leq \text{Score} < 120 \\ \text{NORMAL} & \text{if } 50 \leq \text{Score} < 90 \\ \text{AT RISK} & \text{if } 30 \leq \text{Score} < 50 \\ \text{TO BE RESTRUCTURED} & \text{if } 0 \leq \text{Score} < 30 \\ \text{SEVERE DISTRESS} & \text{if Score} < 0 \end{cases}$$

The Score Class derives from the Total Score:

$$\mathrm{Class} = \begin{cases} A & \text{if Total Score} \in \{\text{EXCEPTIONAL, VERY GOOD}\} \\ B & \text{if Total Score} \in \{\text{GOOD, NORMAL}\} \\ C & \text{if Total Score} \in \{\text{AT RISK, TO BE RESTRUCTURED}\} \\ D & \text{if Total Score} = \text{SEVERE DISTRESS} \end{cases}$$

3) System of arrangements with repetitions

3.1) Mathematical foundations of the system of arrangements with repetitions

The system of arrangements with repetitions constitutes the innovative methodological core of the model[4], operating on three levels:

1. determination of the annual score for the Bank Score.
2. two-year normalization for each of the score models, SME Z-Score, Bank Score, EM Score.
3. concatenation and final aggregation of the five two-year scores SME Z-Score, Bank Score, EM Score, MCC Rating, Company Performance Index, normalized into a single quantitative score.

Arrangements with repetitions of n elements, taken k at a time, are defined mathematically as: D(n,k)= n^k
This formula represents the number of ways to choose k elements from a set of n elements.

---

4 The application of the combinatorial formula D(n,k)=n^k to credit rating represents an application innovation, not an abstract mathematical discovery (the formula is a foundation of combinatorics). The methodological originality lies in the operational use of this structure to:
(a) manage multi-model configurations with two-year temporal memory.
(b) overcome the intrinsic limitations of simple weighted averages, unable to capture distinct combinatorial patterns that can converge to the same numerical value.
(c) encode expert decision rules in deterministically replicable algorithmic form.

In the context of the scoring system, the parameters assume specific meanings:

For the two-year normalization:

- n = 4 (possible score states: A, B, C, D).
- k= 2 (periods considered: year n-1, year n).
- Total combinations: 4^2 = 16.

For the final quantitative score:

- n = 4 (possible score states: A, B, C, D).
- k = 5 (two-year scores of the five models: Z-Score, EM-Score, MCC Rating, Bank Score, Performance Index).
- Total combinations: 4^5 = 1024.

For the annual Bank Score:

- n = 4 (possible score states: A, B, C, D).
- k = 4 (classes of indicators per section).
- Total combinations per section: 4^4 = 256.

The system uses numerical coding (1=A, 2=B, 3=C, 4=D) to facilitate automatic calculations and subsequent conversion into alphabetical classifications.

3.2) Two-year normalization system

The practical implementation of the system of arrangements with repetitions for the two-year normalization is achieved through a matrix structure that systematically enumerates all 16 possible score combinations between two consecutive years.

Operating logic: the system compares the score of year n-1 with the score of year n, attributing a final score based on the frequency distribution of the score classes in the two-year period.

Through the described approach, both the current position and the trend pattern of the company are captured.

The matrix of arrangements for the two-year system is organized as follows:

Item	Year N-1	Year N	Combination	Calculation A	Calculation B	Calculation C	Calculation D	Final Score
1	A	A	AA	2	0	0	0	A
2	A	B	AB	1	1	0	0	B
3	A	C	AC	1	0	1	0	C
4	A	D	AD	1	0	0	1	D
5	B	A	BA	1	1	0	0	B
6	B	B	BB	0	2	0	0	B
7	B	C	BC	0	1	1	0	B
8	B	D	BD	0	1	0	1	B
9	C	A	CA	1	0	1	0	C
10	C	B	CB	0	1	1	0	B
11	C	C	CC	0	0	2	0	C
12	C	D	CD	0	0	1	1	C
13	D	A	DA	1	0	0	1	D
14	D	B	DB	0	1	0	1	B
15	D	C	DC	0	0	1	1	C
16	D	D	DD	0	0	0	2	D

Table 1 Matrix of arrangements with repetitions for a two-year system

Legend:

- Columns 1-3: they identify the combination of scores between the two years.
- Columns 4-7: they count the occurrences of each class (A, B, C, D) in the combination.
- Column 8: final score attributed according to the classification algorithm (described in Section 3.3.4)

The procedural methodology of the system of arrangements with repetitions is therefore based on a sequential process that guarantees the systematic management of all possible combinations.

3.3) Exemplification of the sequential process

The functioning of the system is illustrated through the application of the Bank Score model, adopting a sequence structured in nine analytical phases; this example allows us to clarify the operational logic of the framework and the process of aggregating the results[5].

3.4) Temporal normalization process on a two-year basis

Based on the illustrated and formalized sequential process, it is possible to proceed to the phase of aggregation of the results, aimed at determining the overall rating class and evaluating the consistency between the applied models.
The process described also applies for the normalization of the score obtained in the last two years (n, n-1) for each model.
Once the normalized scores on a two-year basis have been obtained for each model, we proceed to determine a single alphascore (quantitative score), deriving from the five normalized two-year scores, through the system of arrangements with repetitions, following the same logic as the sections described above.

4) Final aggregation system: Quantitative Score

To determine the final quantitative score, the process of arrangements with repetitions is applied to aggregate the 5 two-year scores into a single quantitative score, managing the 1024 possible combinations (4^5).

$$\text{Quantitative Score} = \text{Arrangements}(S_{MCC}, S_Z, S_{EM}, S_{PS}, S_{Bank})$$

Where: S represents the normalized two-year score of each model.

4.1) Final rating structure

To process the final rating, the three fundamental dimensions of the credit assessment are considered: quantitative analysis (deriving from the system of arrangements with repetitions), qualitative analysis and trend analysis.

4.2) Components of the aggregation system

4.2.1) Qualitative analysis section

Qualitative analysis evaluates non-quantifiable aspects through numerical models based on the analyst's discretionary assessment.

Components of Qualitative Analysis
In a non-exhaustive form:

Governance and corporate structure
Competitive positioning: position in the reference market
Corporate strategy: consistency and sustainability of the strategies
Historical track record

Qualitative Scoring System:

- A: Excellent (3 points)
- B: Good (2 points)
- C: Sufficient (1 point)
- D: Insufficient (-1 point)

4.2.2) Trend Analysis

The source of the data for the performance score is the Central Credit Risk Register of the Bank of Italy, an information system managed by the Bank of Italy according to the provisions of Circular no. 139 (Bank of Italy, 1991). Based on the performance variables contained therein, appropriately reclassified, a series of indices are processed, aimed at analyzing, not only in a static manner, the past of the borrower's credit relationships but also at reprocessing them in a dynamic way, deriving important qualitative information from them.
By analyzing each relationship in detail and attributing a weight to a series of performance indices, a performance score based on qualitative and quantitative indicators is determined.
In particular, the following aspects are analysed:

[5] For a complete consultation of the sequential process and the matrix tables used (Base Matrix, Alfascore, Frequency Matrix and Classification Vector), please refer to the supplementary material available in the online repository link: https://drive.google.com/drive/folders/1Xug079LzCeq1bBYpLaN1FhdQ6PoiHvvS , including the extraction of the original spreadsheet used in the application case.

- the borrower's behavior in using credit lines.
- the level of appropriateness of the composition of the credit portfolio (balance between different technical forms).
- the perception of the borrower from the banking system (positioning of the borrower with respect to the banking system).
- the risk level detected on both direct and indirect positions.

Methodological note: *the detailed analysis of the performance indicators is reported in Paragraph 5.5.*

4.3) Final weighting system

The system produces a final rating which represents the synthesis of all the analyses conducted through:

- integration of the three dimensions of assessment.
- calibration through the weighting system.
- stability resulting from the two-year normalization.

4.3.1) Assignment of weights

The system attributes specific weights to the three components of the analysis: qualitative, quantitative and trend analysis. Given the alphabetic numerical conversion system, the relevant scoring scale is as follows:

- 3 if Score A (Excellent)
- 2 if Score B (Good)
- 1 if Score C (Sufficient)
- -1 if Score D (Insufficient)

The system weighs the overall score according to a creditworthiness logic, assigning the following weights:

- 35% for quantitative analysis (P_Q).
- 55% for trend analysis (P_A).
- 10% for qualitative analysis (P_Qual).

$$\text{Overall Score} = 0{,}35 \times P_Q + 0{,}55 \times P_A + 0{,}10 \times P_{Qual}$$

From the sum of the scores thus obtained, the final rating is determined using the following weighting formula:

$$\text{Overall Rating} = \begin{cases} A & \text{if Overall Score} > 2{,}5 \\ B & \text{if } 1{,}5 \leq \text{Overall Score} \leq 2{,}5 \\ C & \text{if } 0{,}5 \leq \text{Overall Score} < 1{,}5 \\ D & \text{if Overall Score} < 0{,}5 \end{cases}$$

Rationale for the predominant trend weight (55%): the choice, defined in the development phase (2015), to assign a predominant weight to the performance component, reflects the operational practice of Loan Origination, according to which negative behavioral evidence (for example, persistent overdrafts detected in the Central Credit Register) represent highly relevant elements in the assessment of creditworthiness. The 55% weight operates mathematically to align the final rating with this operational condition, preventing positive quantitative scores from masking behavioral warning signals; this methodological approach, based on the negative adjustment of anomalies detected in the Central Credit Register, proves now consistent with subsequent supervisory regulatory developments, in particular the EBA Guidelines on Loan Origination and Monitoring (European Banking Authority, 2020), strengthening the theoretical solidity of the weighting originally implemented.

4.4) Performance Score

The performance score is calculated on N banks (maximum 10 in the developed model) based on the reclassification of data from the Bank of Italy’s Central Credit Risk Register.
Below is the example of a calculation relating to a single bank which can be extended to N banks which can potentially be analyzed and calculated with the relevant algorithm for determining the final performance score.

4.4.1) Performance Score: detailed analysis

The model developed determines the score on the following parameters organized into eight macro-sections.

4.4.2) Usage pattern

Definition: breakdown by reporting intermediary of the assessment of usage pattern resulting from the analysis of cash credit risk recorded in the Central Credit Register.

The indices contained in this section are taken from statements reclassified monthly, subsequently reported on an annual basis, summarizing the debt exposure and behavior of the subject registered towards the credit system as a whole. In particular, the performance information (Operational Credit Line and Used Credit Amount) is reported, broken down by intermediary, aggregated according to the risk census category of the cash credit section (Self-liquidating, with Maturity, Revocable).

Performance variables used:

- Operational Credit Line granted by reporting intermediary: amount of monthly/annual credit granted.
- Used by reporting intermediary: amount actually used in the month/year.
- Total operational credit granted: amount of global credit granted by the banking system in the month/year.
- Total credit used: size of the financial debt incurred by the registered entity (monthly/annual exposure amount to the system).
- Granted by a Bank/Total Granted: share of the global credit granted by a single banking intermediary.
- Single Bank Used/Total Used: share of total use per single bank.

From the ratio between Used/Granted, for each single bank and for all reporting subjects, the *Overdraft Bank Rate* and the *Overdraft System Rate* performance indicators are processed, respectively, used to analyze the situation of credit relationships; specifically, these indicators provide the percentage of monthly/annual use of the credit lines with respect to each reporting intermediary and with respect to the total of reports, highlighting any potential or occurred financial tensions and offering indications regarding the monthly/global requirement with reference to each credit line.
The analysis of this type of data represents one of the "early warning" tools traditionally used by the banking system to identify the deterioration of creditworthiness early during the process of monitoring the credit risk associated with the credit lines granted.

4.4.2.1) Usage pattern: indicators for self-liquidating credit lines

Indicators for self-liquidating credit lines

Assessment algorithm:

$$\text{Usage pattern: self-liquidating credit lines}(r) = \begin{cases} 0 & \text{if } r = \emptyset \text{ or } r = 0 \\ \alpha_1 & \text{if } r \in (0; 0{,}25] \text{ (Partially Positive)} \\ \alpha_2 & \text{if } r \in (0{,}25; 0{,}85] \text{ (Positive)} \\ \alpha_3 & \text{if } r \in (0{,}85; 0{,}9999] \text{ (Partially Negative)} \\ \alpha_4 & \text{if } r \in [1{,}00; 1{,}50] \text{ (Negative)} \\ \alpha_5 & \text{if } r > 1{,}50 \text{ (Extremely Negative)} \end{cases}$$

$$\text{where: } r = \frac{\text{credit used}}{\text{credit granted}}, \quad \alpha_i \in \mathbb{R}^+, \quad i = 1, \dots, 5$$

Indicators for revocable credit lines

Assessment algorithm:

$$\text{Usage pattern: revocable credit lines}(r) = \begin{cases} 0 & \text{if } r = \emptyset \text{ or } r = 0 \\ \alpha_1 & \text{if } r \in (0; 0{,}25] \text{ (Partially Positive)} \\ \alpha_2 & \text{if } r \in (0{,}25; 0{,}85] \text{ (Positive)} \\ \alpha_3 & \text{if } r \in (0{,}85; 0{,}9999] \text{ (Partially Negative)} \\ \alpha_4 & \text{if } r \in [1{,}00; 1{,}50] \text{ (Negative)} \\ \alpha_5 & \text{if } r > 1{,}50 \text{ (Extremely Negative)} \end{cases}$$

$$\text{where: } r = \frac{\text{credit used}}{\text{credit granted}}, \quad \alpha_i \in \mathbb{R}^+, \quad i = 1, \dots, 5$$

Indicators for short-term credit lines

Assessment algorithm:

$$\text{Usage pattern: short-term credit lines}(r) = \begin{cases} \text{Partially Positive} & \text{if } 0\% \le r < 100\% \\ \text{Positive} & \text{if } 100\% \le r < 100{,}99\% \\ \text{Negative} & \text{if } 100{,}99\% \le r < 150\% \\ \text{Extremely Negative} & \text{if } r \ge 150\% \end{cases}$$

$$\text{where: } r = \frac{\text{credit used}}{\text{Total operational credit granted}}$$

Indicators for medium-long term credit lines

Assessment algorithm:

$$\text{Usage pattern: medium-long-term lines MLT}(r) = \begin{cases} \text{Partially Positive} & \text{if } 0\% \leq r < 100\% \\ \text{Positive} & \text{if } 100\% \leq r < 100{,}99\% \\ \text{Negative} & \text{if } 100{,}99\% \leq r < 150\% \\ \text{Extremely Negative} & \text{if } r \geq 150\% \end{cases}$$

$$\text{where: } r = \frac{\text{credit used}}{\text{Total operational credit granted}}$$

4.4.3) Proper use

Trend indicators used:

- **overdraft by reporting intermediary**: i.e. the amount expressed in absolute values, resulting from the sum of the overdrafts/unpaid amounts reported by the intermediary; the data allows us to verify how much the registered entity has been negatively exposed compared to the credit granted to it, thus highlighting the extent of the overdraft/unpaid credit recorded.
- **total overdraft:** it shows the overall amount of the sum of overdrafts/unpaid payments in the system, in absolute terms.
- **total overdraft/total granted:** percentage of incidence of the total overdraft reported on the total granted by the banking system.

Indicators for self-liquidating credit lines

Assessment algorithm:

$$\text{self-liquidating overdrafts} = \begin{cases} \text{Partially Positive} & \text{if Months in overdraft } = 0 \\ \text{Partially Negative} & \text{if } 0 < \text{Months in overdraft} \leq 1 \text{ and Average UTR} \leq 101\% \\ \text{Negative} & \text{if } 0 < \text{Months in overdraft} \leq 3 \text{ and Average UTR} \leq 101\% \\ \text{Extremely Negative} & \text{if } 0 < \text{Months in overdraft} \leq 12 \text{ and Average UTR} > 101\% \end{cases}$$

where:
Average UTR = Average ratio credit Used/credit Granted
Months in overdraft = Number of months with overdrafts

Indicators for revocable credit lines

Assessment algorithm:

$$\text{overdrafts on revocable lines} = \begin{cases} \text{Partially Positive} & \text{if Months in overdraft } = 0 \\ \text{Partially Negative} & \text{if } 0 < \text{Months in overdraft} \leq 1 \text{ and Average UTR} \leq 101\% \\ \text{Negative} & \text{if } 0 < \text{Months in overdraft} \leq 3 \text{ and Average UTR} \leq 101\% \\ \text{Extremely Negative} & \text{if } 0 < \text{Months in overdraft} \leq 12 \text{ and Average UTR} > 101\% \end{cases}$$

Where:
Months in overdraft = Number of months with overdrafts
Average UTR = Average ratio credit Used/credit Granted

Indicators for short-term credit lines

Assessment algorithm:

$$\text{overdraft: short-term lines} = \begin{cases} \text{Partially Positive} & \text{if Months in overdraft } = 0 \\ \text{Negative} & \text{if Months in overdraft} > 0 \text{ and } 100\% < \text{Average UTR} \leq 101\% \\ \text{Extremely Negative} & \text{if Months in overdraft} > 0 \text{ and Average UTR} > 101\% \\ \text{Partially Negative} & \text{if Months in overdraft} > 0 \text{ and Average UTR} \leq 100\% \end{cases}$$

Where:

$$\text{Months in overdraft} = \text{Number of months with overdrafts}$$
$$\text{Average UTR} = \text{Average ratio credit Used/credit Granted}$$

Indicators for medium-long term credit lines

Assessment algorithm:

$$\text{overdraft: medium-long-term lines} = \begin{cases} \text{Partially Positive} & \text{if Months in overdraft} = 0 \\ \text{Negative} & \text{if Months in overdraft} > 0 \text{ and } 100\% < \text{Average UTR} \leq 101\% \\ \text{Extremely Negative} & \text{if Months in overdraft} > 0 \text{ and Average UTR} > 101\% \\ \text{Partially Negative} & \text{if Months in overdraft} > 0 \text{ and Average UTR} \leq 100\% \end{cases}$$

Where:

$$\text{Months in overdraft} = \text{Number of months with overdrafts}$$
$$\text{Average UTR} = \text{Average ratio credit Used/credit Granted}$$

4.4.4) Recurring overdrafts (last quarter)

The indicators used in this section correspond to the same performance variables used in the previous section but with a temporal logic limited to the last quarter rather than extended to a year.

Indicators for self-liquidating credit lines

Assessment algorithm:

$$\text{Self-liquidating Overdrafts: quarter} = \begin{cases} \text{Partially Positive} & \text{if Overdrafts} = 0 \\ \text{Negative} & \text{if } 0 < \text{Overdrafts} < 3 \\ \text{Extremely Negative} & \text{if Overdrafts} \geq 3 \end{cases}$$

Where:

$$\text{Overdrafts} = \text{Number of overdrafts in the past quarter}$$

Indicators for revocable credit lines

Assessment algorithm:

$$\text{Overdrafts Revocable credit lines: quarter} = \begin{cases} \text{Partially Positive} & \text{if Overdrafts} = 0 \\ \text{Negative} & \text{if } 0 < \text{Overdrafts} < 3 \\ \text{Extremely Negative} & \text{if Overdrafts} \geq 3 \end{cases}$$

Where:

$$\text{Overdrafts} = \text{Number of overdrafts in the past quarter}$$

Indicators for short-term credit lines

Assessment algorithm:

$$\text{Overdrafts: short-term lines} = \begin{cases} \text{Partially Positive} & \text{if Overdrafts} = 0 \\ \text{Negative} & \text{if Overdrafts} > 0 \text{ and } 100\% < \text{Average UTR} \leq 101\% \\ \text{Extremely Negative} & \text{if Overdrafts} > 0 \text{ and Average UTR} > 101\% \\ \text{Partially Negative} & \text{if Overdrafts} > 0 \text{ and Average UTR} \leq 100\% \end{cases}$$

Where:

$$\text{Overdrafts} = \text{Number of overdrafts in the past quarter}$$
$$\text{Average UTR} = \text{Average ratio credit Used/credit Granted}$$

Indicators for medium/long-term credit lines

Assessment algorithm:

$$\text{Overdrafts: MLT lines} = \begin{cases} \text{Partially Positive} & \text{if Overdrafts} = 0 \\ \text{Negative} & \text{if Overdrafts} > 0 \text{ e } 100\% < \text{Average UTR} \leq 101\% \\ \text{Extremely Negative} & \text{if Overdrafts} > 0 \text{ and Average UTR} > 101\% \\ \text{Partially Negative} & \text{if Overdrafts} > 0 \text{ and Average UTR} \leq 100\% \end{cases}$$

Where:

$$\text{Overdrafts} = \text{Number of overdrafts in the past quarter}$$

$$\text{Average UTR} = \text{Average ratio credit Used/credit Granted}$$

4.4.5) Unapproved credit use

An **extremely negative** assessment is typically assigned when, with respect to the reference period, the specific case of "absolute overdraft" occurs, referring to cases of use in the absence of a granted credit line.

$$\text{Used credit not granted} = \{\text{Extremely Negative} \quad \text{if used credit} > 0 \text{ and credit granted} = \emptyset$$

4.4.6) Indirect risk positions

Indirect risk positions are constituted by reports relating to the class of self-liquidating risks.
They refer to past due loans that expired during the month preceding the one being surveyed, distinguishing between paid and unpaid, attributing them to each reporting bank and reported with the relevant monthly/annual total.
Variables and performance indicators used:

- **paid overdue receivables**: valued when payment is received after the contractual deadline but within the month of observation. They report delays in collection by final debtors (customers of the registered entity) without representing definitive default.
- **unpaid overdue receivables (unpaid):** valued when payment is not received within the month of observation, representing a default by the final debtor.
- **Unpaid Overdue Rates**: an indicator that measures the ratio between unpaid overdue receivables and total overdue receivables, highlighting the share of unpaid debts compared to the overall maturities of the commercial portfolio.

Paid overdue receivables

Assessment algorithm:

$$\text{Paid overdue receivables} = \begin{cases} \text{no negative adjustment} & \text{if } 0\% < R \leq 10\% \\ \text{Partially Negative} & \text{if } 10\% < R \leq 35\% \\ \text{Negative} & \text{if } 35\% < R \leq 75\% \\ \text{Extremely Negative} & \text{if } R > 75\% \end{cases}$$

Where:

$$R = \frac{\text{Total Paid overdue receivables}}{\text{Total credit Used}}$$

Unpaid overdue receivables

Assessment algorithm:

$$\text{Unpaid overdue receivables} = \begin{cases} \text{no negative adjustment} & \text{if } 0\% < \text{Unpaid overdue receivables} \leq 5\% \\ \text{Partially Negative} & \text{if } 5\% < \text{Unpaid overdue receivables} \leq 10\% \\ \text{Negative} & \text{if } 10\% < \text{Unpaid overdue receivables} \leq 50\% \\ \text{Extremely Negative} & \text{if Unpaid overdue receivables} > 50\% \end{cases}$$

Where:

$$\text{Unpaid overdue receivables} = \text{Ratio Unpaid overdue receivables on Total credit used}$$

Unpaid overdue rates

Assessment algorithm:

$$\text{Unpaid Overdue Rates} = \begin{cases} \text{no negative adjustment} & \text{if } 0\% < \text{Unpaid Rate} \leq 10\% \\ \text{Partially Negative} & \text{if } 10\% < \text{Unpaid Rate} \leq 25\% \\ \text{Negative} & \text{if } 25\% < \text{Unpaid Rate} \leq 50\% \\ \text{Extremely Negative} & \text{if Unpaid Rate} > 50\% \end{cases}$$

Where:

$$\text{Unpaid Rate} = \frac{\text{Average Unpaid Overdue}}{\text{Total Overdue}}$$

4.4.7) Direct risk positions

The direct risk positions represent impaired loans of the registered entity, registered in the Central Credit Register according to the classification in force at the time of the model development[6].

Variables used:

- **Past due:** reporting from an objective evaluation (delays beyond the time threshold).
- **Bad loans:** reporting from the intermediary's subjective assessment (state of insolvency of the debtor).
- **Restructured loans:** exposures with modified contractual conditions.
- **Credits passed to loss:** exposures removed from the balance sheet.

Evaluation criterion:

Any evaluation in the categories indicated above automatically determines the attribution of the **"Extremely *Negative" rating.***

4.4.8) Risk positions of the past month

This section traces the same evaluation methods as in paragraph 4.4.2 (usage pattern), with a temporal focus referring exclusively to the last month, in relation to the following loan categories:

- Self-liquidating Credit lines
- Revocable Credit Lines
- Short-Term Credit Lines
- Medium-Long Term Credit Lines

4.4.9) Overall bank positions

The overall bank position represents the summary assessment of the relationship between the registered entity and each reporting intermediary.

The central indicator is the *Overdraft Bank Rate* which measures the percentage ratio between the amount actually used and the total operating amount granted, for each individual bank.

Assessment algorithm:

$$\text{OSR} = \begin{cases} \text{Extremely Positive} & \text{if no Overdraft and } 100\% \leq \text{Overdraft Rate} \leq 100{,}99\% \\ \text{Partially Positive} & \text{if } 0\% < \text{Overdraft Rate} \leq 25\% \\ \text{Positive} & \text{if } 25\% < \text{Overdraft Rate} \leq 85\% \\ \text{Partially Negative} & \text{if } 85\% < \text{Overdraft Rate} \leq 99{,}9999\% \\ \text{Negative} & \text{if } 99{,}9999\% < \text{Overdraft Rate} \leq 150\% \\ \text{Extremely Negative} & \text{if Overdraft Rate} > 150\% \end{cases}$$

Where:

$$\text{Overdraft Rate} = \frac{\text{Total credit Used Bank}}{\text{Total credit Granted Bank}}$$

4.4.10) Discretionary component

Section reserved for the analyst to attribute a discretionary evaluation aimed at integrating or modulating the assessment deriving from the algorithmic processing.

4.4.11) Single bank score

It refers to the final score determined based on the weighting of the sections of the model determined through the following equation:

$$\text{Score} = 3N_{A+} + 2N_A + N_{B+} - N_{B-} - 2N_C - 3N_D$$

Where:

$$N_{A+} = \text{Extremely Positive}, N_A = \text{Positive}, N_{B+} = \text{Partially Positive}, N_{B-} = \text{Partially Negative}, N_C = \text{Negative}, N_D = \text{Extremely Negative}$$

Hence the determination of the final assessment on the single bank based on the following algorithm:

6 The classification refers to the legislation in force at the time of the model development; the 2015 reform modified a few definitions without altering the conceptual categories.

$$
\text{Single Bank Score} = \begin{cases} \text{Extremely Negative} & \text{if Past Due} \neq 0 \text{ or Bad loans} \neq 0 \\ \text{Extremely Positive} & \text{if Score} > 12 \\ \text{Positive} & \text{if } 9 < \text{Score} \leq 12 \\ \text{Partially Positive} & \text{if } 6 < \text{Score} \leq 9 \\ \text{Partially Negative} & \text{if } 3 < \text{Score} \leq 6 \\ \text{Negative} & \text{if } 0 \leq \text{Score} \leq 3 \\ \text{Extremely Negative} & \text{if Score} < 0 \end{cases}
$$

4.4.12) Overall assessment of the banking system

The overall rating aggregates the scores of the banks with which the registered entity has relationships, using a dynamic threshold proportional to the number of banks:

$$
\text{Overall Score} = \begin{cases} \text{Extremely Positive} & \text{if Score Sum} \geq \text{Target Threshold} \\ \text{Positive} & \text{if Target Threshold} - 2 < \text{Score Sum} \leq \text{Target Threshold} \\ \text{Partially Positive} & \text{if Target Threshold} - 4 < \text{Score Sum} \leq \text{Target Threshold} - 2 \\ \text{Partially Negative} & \text{if Target Threshold} - 6 < \text{Score Sum} \leq \text{Target Threshold} - 4 \\ \text{Negative} & \text{if Target Threshold} - 9 \leq \text{Score Sum} \leq \text{Target Threshold} - 6 \\ \text{Extremely Negative} & \text{if Score Sum} < \text{Target Threshold} - 9 \end{cases}
$$

Where:

$$
\text{Target Threshold} = \frac{20}{N_{\text{banks}}}, \text{ Score Sum} = \sum_{i=1}^{N_{\text{banks}}} \text{Score}_i, N_{\text{banks}} = \text{Number of banks considered (max 10)}
$$

The model uses a proportional threshold (20/N_banks).

Connection Overall Score - Score Class:

$$
\text{Score Class} = \begin{cases} A+ & \text{if Overall Score} = \text{Extremely Positive} \\ A- & \text{if Overall Score} = \text{Positive} \\ B+ & \text{if Overall Score} = \text{Partially Positive} \\ B- & \text{if Overall Score} = \text{Partially Negative} \\ C & \text{if Overall Score} = \text{Negative} \\ D & \text{if Overall Score} = \text{Extremely Negative} \end{cases}
$$

Connection Score Class - Score Category:

$$
\text{Score Category} = \begin{cases} \text{HIGH} & \text{if Score} \in \{A+, A-\} \\ \text{MEDIUM HIGH} & \text{if Score} \in \{B+, B-\} \\ \text{MEDIUM LOW} & \text{if Score} = C \\ \text{LOW} & \text{if Score} = D \end{cases}
$$

Where:

$$
\text{Score} = \text{Score Class assigned}
$$

4.4.13) Complementary indicators

The model integrates three complementary indicators that provide additional perspectives on the position of the registered entity:

Financial Duration

It evaluates the appropriateness of the temporal composition of the credit structure:

$$
\text{Financial Structure} = \begin{cases} \text{Short term credit lines with no risk signals} & \text{if Short} = 0 \text{ and Others} > 0 \\ \text{Appropriate} & \text{if } 0\% < \text{Short Ratio} \leq 50\% \\ \text{Caution} & \text{if } 50\% < \text{Short Ratio} < 60\% \\ \text{Short term Unbalanced} & \text{if } 60\% \leq \text{Short Ratio} < 100\% \\ \text{Maturing credit lines with no risk signals} & \text{if Short Ratio} \geq 100\% \end{cases}
$$

Where:

$$\text{Short} = \text{Self liquidating} + \text{Revocable}; \text{Short Ratio} = \frac{\text{Self liquidating} + \text{Revocable}}{\text{Total Operational Credit}}$$

Overall Perception of the System

It evaluates the aggregate utilization pattern across the entire banking system:

$$\text{Perception of the System} = \begin{cases} \text{Regular utilization: Positive Perception} & \text{if } 25\% < \text{Total UTR} < 85\% \\ \text{Low utilization: Partially Positive Perception} & \text{if } 0\% < \text{Total UTR} < 25\% \\ \text{Tension: Partially Negative Perception} & \text{if } 85\% < \text{Total UTR} < 99{,}99\% \\ \text{Irregular utilization: Negative Perception} & \text{if } 100\% < \text{Total UTR} < 150\% \\ \text{Significant Overdraft: Extremely Negative Perception} & \text{if Total UTR} > 150\% \end{cases}$$

Where:

$$\text{Total UTR} = \frac{\sum \text{utilized Banks}}{\sum \text{granted Banks}}$$

5) Conclusions and future developments

5.1) Summary of methodological contributions

The present work documents a multi-model credit rating system for SMEs developed in 2014-2015, with two distinctive elements:

- two-year temporal normalization through arrangements with repetitions.
- aggregation based on configurational consistency rather than weighted average.

The supplementary material available in the online repository[7] fully documents a real case and five further cases in short, highlighting how the method was operationally applied and how the system aggregates five quantitative models (SME Z-Score, EM Score, MCC Rating, Bank Score, Performance Index) with performance analysis to produce a final rating consistent with the actual riskiness observed.

5.2) Nature of the model: a deterministic expert system and empirical robustness

The system presented is configured as a "*Deterministic Expert System*" (Rule-Based Expert System), a methodological category which is distinct from statistical Machine Learning models.

Focus: design choice

The determination of the weights (35%-55%-10%) and of the classification thresholds through expert judgment represents a mindful methodological choice, motivated by:

- privilege of logical stability: a rule-based system maintains decisional consistency over time, without being affected by the loss of validity of patterns learned from past data, which no longer represent current conditions.
- replicability of the human decision-making process (human in the loop): the system algorithmically codifies the rules that an expert credit analyst would apply, guaranteeing uniformity of evaluation between different operators.
- operation on individual SMEs without the need for Big Data: unlike ML models that require thousands of observations for training, the expert system effectively evaluates each company by applying a structured combination of consolidated indicators, rather than relying on emerging statistical patterns.

Focus: temporal contextual framing of the model

The deterministic approach constitutes the most solid solution from a methodological point of view and the most economically sustainable, considering the context in which it was developed, characterized by:

- absence of structured public datasets on Italian SMEs.
- limited computational power available for small financial structures.
- pre-IFRS 9 regulation which did not require statistical estimates of the Probability of Default (PD).

[7] The application cases are available as supplementary material in the online repository: https://drive.google.com/drive/folders/1Xug079LzCeq1bBYpLaN1FhdQ6PoiHvvS. The repository includes: (a) a fully documented real case with complete step-by-step application of the arrangements with repetitions methodology; (b) five additional cases presented in summary form; (c) the original Excel spreadsheet implementing the model, including the Base Matrix, Alfascore table, Frequency Matrix and Classification Vector used in the sequential process described in Section 3.3.

Focus: model limitations

With reference to the model presented, the following limitations should be specified:

- calibration not statistically optimized: the weights are not obtained by optimizing a loss function on historical data (for example by reducing false positives and false negatives in the training set), but they rather derive from an expert assessment of operational risks in the banking sector.
- empirical classification thresholds: the alphabetic score thresholds were mostly inherited from the original models without any recalibration (except for the Z-Score) on the Italian context.
- absence of large-scale backtesting: the documented empirical validation (see supplementary material at the online repository, footnote 7) is limited to 6 real cases, constituting an insufficient number for robust statistical inferences.

Focus: future developments of the model

The characteristics described above do not invalidate the system for its original purposes (internal rating for small portfolios), but they do make a methodological update necessary for contemporary applications, through:

- Bayesian optimization of weights on modern datasets.
- validation on larger panels.
- systematic comparison with external benchmarks.

5.3) Applicability and relevance of the framework in the context of Explainable AI (XAI)

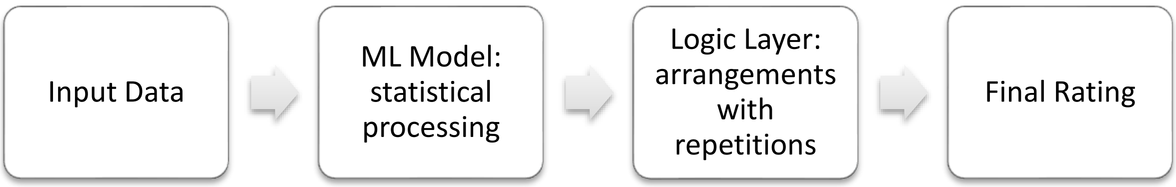
Today, the deterministic character of the system presents a renewed strategic value: the ability to operate at a logical verification level (Logic Layer) within complex Artificial Intelligence architectures.

5.3.1) The model as a guardrail mechanism for the Black Box

The documented framework qualifies as White Box architecture *par excellence*, while Machine Learning (Black Box) algorithms excel in the statistical processing of large volumes of data, although they often lack:

- decisional transparency: impossibility to analytically trace the path that leads from input to output, a critical problem in the credit sector considering the GDPR (EU Regulation 2016/679, art. 22), which recognizes the right of interested parties to the "*explanation*" of automated decisions.
- explicit regulatory controls: to ensure that predictions comply with hard-coded regulatory constraints.

This model is proposed as a potential complement to Hybrid AI architecture:



Guardrail Functioning:

The system intervenes downstream of the ML processing, applying deterministic logical constraints ('*hard stops*'), such as:

- if the ML predicts a "B" rating but the Central Credit Register detects bad loans, the Logic Layer automatically forces a downgrade to D.
- if the quantitative scores are volatile (A-D-B in the three-year period), the system of arrangements with repetitions applies codified smoothing rules, preventing potentially erroneous ratings.

The described architecture ensures:

- regulatory compliance: every decision is transparent and traceable through logging, aligned with the requirements of the EU Regulation on Artificial Intelligence (European Union, 2024, articles 12-13).
- robustness to bias: guardrails prevent statistical biases in the training set from propagating into the final rating.

5.3.2) Combinatorics as a methodological basis for Hybrid AI

The presented combinatorial architecture could form the structural basis for developing Neuro-Symbolic AI systems, in which:

- the neural component (neural networks, gradient boosting) dynamically optimizes weights and thresholds on contemporary data.
- the symbolic component (arrangements matrix) preserves the logical structure and the decision-making transparency.

Operational scenario:

1. An LSTM model predicts scores with confidence intervals.
2. The expert system codifies qualitative, quantitative and trend rules (for example if event *"X"* occurs: minimum penalty - 2 classes).

3 The combinatorial matrix (for example: 4^5) aggregates the results ensuring complete traceability.

This integration allows you to:

- exploit the predictive power of modern ML.
- maintain the transparency required by GDPR, EU AI Act, banking regulations.
- allow deterministic audits of credit decisions.

Conclusion: The lasting value of the system does not lie in the (historically situated) 2015 parameters, but in the architectural intuition of being able to use discrete combinatorial structures to formalize expert knowledge in algorithmically replicable and verifiable form, which today is central to the debate on responsible and trustworthy AI.

5.4) Cross-sector applicability of the Combinatorial Framework

The logical architecture of the system, based on combinatorial aggregation, suggests a potential methodological transferability to other decision-making domains.

Requirements for the extension and applicability of the model in further areas

The system of arrangements with repetitions appears technically adaptable to contexts that present:

- heterogeneity of the information sources: hence the need to synthesize quantitative, qualitative and trend indicators of a different nature.
- transparency requirements: regulated contexts where the decision must be auditable and justifiable (no "*black box*").
- presence of hard stops: situations in which specific negative conditions must prevail over positive signals (a non-linear logic that cannot be represented with weighted averages).
- temporal memory: relevance of development trends as well as the instantaneous state.

Areas of future investigation (illustrative examples):

1) ***ESG (Environmental, Social, Governance) assessment***

Scenario: an investment fund has to assign ESG ratings to companies by combining:

- Environmental score (CO_2 emissions, circular economy).
- Social score (job security, diversity).
- Governance score (transparency, anti-corruption).

Problem of weighted averages: a company with excellent environmental and governance scores could, with them, compensate for serious violations of human rights, producing an unacceptable "*averaged*" overall rating.
Combinatorial solution: the 4^3 matrix (3 ESG dimensions, 4 A-D classes) encodes hard stops:

- "A-A-D" configuration (D in governance for corruption) with a Final Rating D, regardless of E and S.
- "B-C-B" configuration with a Final Rating C (the algorithm makes social vulnerability prevail).

2) ***Supply Chain Risk Management***

Scenario: A multinational company has to classify critical suppliers by combining:

- Financial score (capital solidity).
- Operational score (on-time delivery, quality rate).
- Reputational score (legal disputes, sanctions).

Problem: a financially sound supplier but with pending legal disputes on product safety should not obtain a high rating.
Combinatorial solution: a 4^3 matrix that imposes an automatic downgrade for negative reputational score, even in the presence of excellent financial performance.
Methodological note: *these examples are purely illustrative of potential research directions.*

Effective applicability requires:

- complete redefinition of weights, thresholds and indicators for the specific sector.
- empirical validation on datasets which represent the new domain.
- adaptation of the combinatorial structure ($k \neq 5$, or $n \neq 4$ classes could be needed).

The methodological contribution does not lie in the mere transfer of parameters specific to credit evaluation in other contexts, but in demonstrating that the adoption of discrete combinatorial structures is feasible in certain domains and, probably more appropriate compared to the use of weighted averages, which tend to generate potentially misleading and, generally, semantically improper aggregations.

5.5) Purpose of the document

The present document pursues objectives of:

- methodological documentation: making an approach developed and operationally tested available to the professional and academic community.
- knowledge transfer: providing all the necessary elements to understand, replicate or adapt the system.

The complete documentation (algorithms, formulas, implementation process) has been made public to facilitate replicability and future developments.

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State-Issued Stablecoins and Financial Stability: Regulatory Fragmentation and Risks for the U.S. Banking System

Andrea Caresana

Abstract

Recent US stablecoin legislation has introduced a significant shift in American monetary federalism by permitting state-issued stablecoins under a federal exemption regime. This article examines whether state-level experimentation in digital currencies enhances financial innovation or risks reintroducing the monetary fragmentation that characterized the pre–Civil War banking system. Focusing on Wyoming's state stablecoin initiative and North Dakota's institutionally oriented Roughrider coin, the analysis highlights how divergent technological architectures, governance models, and regulatory frameworks reflect competing policy objectives within the same federal system. Drawing historical parallels with the Free Banking Era and the National Banking Acts of the nineteenth century, the paper argues that the absence of mandatory interoperability standards and uniform federal oversight may undermine the efficiency gains promised by digital payment technologies. From a law-and-economics perspective, the article evaluates the trade-offs between regulatory competition, market discipline, and systemic risk, emphasizing the potential for regulatory arbitrage and liquidity fragmentation. While state experimentation may function as a laboratory for innovation, the paper concludes that sustained coexistence of heterogeneous state stablecoins without coordination mechanisms is likely to generate inefficiencies and financial stability concerns, ultimately reviving pressures for federal harmonization of the US digital monetary system.

Keywords: Monetary Federalism, Stablecoins, State Banking Regulation, Financial Innovation

1 State Stablecoins and the Re-emergence of Monetary Federalism

The rapid growth of digital assets has reopened foundational questions about the allocation of monetary authority within federal systems. In the United States, this debate has recently intensified with the emergence of state-issued stablecoins operating under statutory exemptions from federal oversight. While stablecoins have largely been analyzed as privately issued instruments situated at the periphery of financial regulation, the entry of US states as issuers of dollar-denominated digital tokens represents a qualitatively different development. This development is closely linked to recent federal legislative initiatives, most notably the GENIUS Act, which preserves a regulatory space for state-level experimentation with digital payment instruments.

Proponents argue that such decentralization promotes innovation, regulatory competition, and financial inclusion. Critics, however, warn that allowing states to issue or sponsor stablecoins risks fragmenting the monetary system, undermining uniformity in payments, and generating new channels of systemic risk. These concerns raise a central research question: does state-level stablecoin issuance revive historical coordination failures associated with decentralized monetary regimes, or can digital technology reconcile state experimentation with national monetary stability?

This article addresses that question through a law and economics analysis of contemporary state stablecoin initiatives, focusing in particular on Wyoming's FRNT token and North Dakota's proposed Roughrider coin. These two projects exemplify sharply divergent institutional designs. Wyoming has embraced a retail-oriented stablecoin operating on public blockchains, emphasizing openness, transparency, and global accessibility. North Dakota, by contrast, has opted for a wholesale, institutionally focused token issued on a proprietary platform and designed primarily for interbank settlement. These contrasting models illustrate how states are not merely experimenting with technology, but are making fundamentally different choices about governance, risk allocation, and the role of public authority in digital money.

To assess the broader implications of these initiatives, the article situates contemporary state stablecoin experimentation within the historical context of US monetary federalism. Drawing parallels with the Free Banking Era of the nineteenth century, it highlights how decentralized issuance of money, despite fostering innovation, historically produced fragmentation, transaction costs, and recurrent financial instability. The National Banking Acts of the Civil War era ultimately imposed federal uniformity to resolve these coordination failures. This historical experience provides a useful analytical lens for evaluating whether today's digital stablecoins mitigate or amplify similar dynamics.

The analysis further emphasizes the critical, albeit indirect, role of federal institutions. Even where Congress has formally exempted state-issued stablecoins from certain federal requirements, agencies such as the Federal Reserve, the FDIC, and the Office of the Comptroller of the Currency retain substantial influence through their control over banking access, payment infrastructure, and systemic risk oversight. As a result, state stablecoins operate within a constrained institutional environment in which federal authorities function as de facto coordinators of last resort.

The emergence of state-issued stablecoins in the US therefore represents a qualitatively different development in the allocation of monetary authority. This shift is not just a domestic American concern, but it also has significant spillover effects that challenge the strategic autonomy of other supranational systems, such as the Eurozone. European policymakers regard the growth of US dollar-denominated stablecoins as a possible strengthening of the dollar's dominance in digital payments. Consequently, the digital euro project has transitioned, with acceleration in recent months, from theoretical exploration to a primary necessary monetary countermeasure intended to preserve the euro's role as a monetary anchor in the global landscape. This article situates contemporary state-level experimentation within this broader global competition, arguing that the US "laboratory of the states" and the EU's "monetary sovereignty" approach represent two ends of a spectrum in the quest for digital financial stability.

2 The Legal Architecture of State-Issued Stablecoins in the United States

The trajectory of US digital currency policy from 2021 to 2024 has been uneven and marked by sharp shifts. The confluence of rapid growth in digital asset markets (Then & Hill & Anderson, 2025), partisan disputes (Schonberger, 2023), and substantial fraud-related losses (ICBA, 2024) has given rise to heightened concerns regarding financial stability in traditional markets (Wells, 2024) and illicit activity within the crypto sector[1] (Wilmarth, 2025). In 2022, the US expressed support for both cryptocurrencies and the development of CBDCs (FED, 2022) concurrently (Tran & Matthews, 2025). However, by 2023, policy emphasis had shifted towards a regulation-by-enforcement strategy[2] (Cornerstone Research, 2023), led largely by the Securities and Exchange Commission (hereinafter, “SEC”) (Lom & Oropeza, 2024). This approach was met with controversy and was repeatedly invalidated by the courts[3] (Kemnitz et Al., 2025). In recent years, the Fed has increased its focus on stablecoins, reflecting their growing importance in US financial markets. Prior to the introduction of the GENIUS Act, Chair Jerome Powell indicated his support for the introduction of congressional action, thereby underscoring stablecoins as both a potential innovation and a risk to financial stability. In 2024, Congress assumed a more active role. Several bills were introduced that addressed digital assets and stablecoins (Cieplak et Al., 2024). Stablecoins are digital assets designed to maintain a stable value relative to a reference asset, typically a sovereign currency, such as the US dollar (FED, 2024). While the House of Representatives successfully passed legislation covering stablecoins, the measure encountered a standstill in the Senate, reflecting ongoing political gridlock over how best to regulate the sector.

The United States Generating Essential National Infrastructure Using Stablecoins Act of 2025 (hereinafter, “GENIUS Act”) signifies a pivotal moment in the evolution of US digital finance policy[4]. For the first time, a regulatory framework has been established that permits federally regulated banks[5] to issue fiat-backed stablecoins[6] under prudential supervision. Moreover, stablecoin issuers are required to maintain reserves at a minimum 1:1 ratio against all issued tokens and to comply with the Bank Secrecy Act[7] which mandates robust AML and CFT measures while strengthening consumer protection. Proponents of the Act posit that it will accelerate institutional adoption (Anus et Al., 2025), strengthen the international role of the US dollar[8], and firmly bring stablecoin activity within the perimeter of bank oversight.

Fed Governor Christopher Waller has been particularly vocal in his assertions, characterising payments as undergoing a technology-driven revolution. In speeches delivered throughout 2025, he emphasised stablecoins as a private-sector innovation that has now expanded beyond its original use in crypto trading. The attributes of these currencies, namely their 24/7 transferability, stability, and accessibility, have rendered them appealing as alternatives to the US dollar, particularly in countries with restricted banking access or high inflation[9] (Makridis, 2025; Goko, 2026). Waller’s position on the matter is that stablecoins have the potential to enhance the international role of the dollar, facilitate cross-border payments, and reduce remittance costs. While acknowledging the concerns that stablecoins might undermine trust in money, he contends that regulatory frameworks such as the GENIUS Act, which mandate one-to-one backing with safe and liquid assets, mitigate these risks. In his words, stablecoins represent a mere

[1] Empirical evidence demonstrates that stablecoins are not inherently stable. Over 20 stablecoins collapsed between 2016 and 2022, and even major ones repeatedly lost their peg to the USD or other reference values between 2019 and 2023.

[2] The SEC brought a record-high 46 cryptocurrency-related enforcement actions in 2023.

[3] A July 2023 ruling held that programmatic XRP sales on exchanges were not investment contract securities, curbing the SEC’s Howey theory for secondary markets, though institutional sales were securities; the impact was underscored in March 2025 when the SEC dismissed its Ripple case entirely.

[4] A bill introduced in the Senate on 4 February 2025 passed with bipartisan support, clearing the Senate on 17 June (68–30) and the House on 17 July (308–122).

[5] Stablecoin issuance is limited to insured depository institutions, including banks, credit unions, bank subsidiaries, and approved nonbank financial institutions able to comply with applicable law.

[6] Fiat-backed stablecoins such as USDT and USDC comprise the largest segment of the stablecoin market and are backed by reserves of short-term fiat assets, including Treasury bills, commercial paper, repos, and bank deposits.

[7] The Currency and Foreign Transactions Reporting Act of 1970 and related amendments, collectively known as the Bank Secrecy Act, authorize the US Treasury to impose reporting and recordkeeping requirements on financial institutions to combat money laundering and related crimes, including cash transaction reporting over $10,000 and suspicious activity filings.

[8] Projections suggest the GENIUS framework could achieve 50% stablecoin adoption in six years.

[9] Africa's biggest economies Nigeria and South Africa have seen the strongest growth in demand for stablecoins.

alternative for consumers and businesses, provided they remain secure and inexpensive (Waller, 2025). Critics have countered this by suggesting that S. 1582 (the Genius Act) may potentially compromise financial stability (Venkatesh, 2025) even though it restricts the issuance of stablecoins to regulated entities. As noted by several commentators (Warren, 2025), the bill would allow nonbank institutions[10] to offer uninsured stablecoins to the public without the protections of federal deposit insurance[11] or equivalent prudential safeguards (Wilmarth, 2025). This framework could undermine the traditional deposit base[12], heighten liquidity risks (Wilmarth, 2025), and increase the likelihood of digital bank runs (Basil, 2025), while also enabling big tech firms and commercial enterprises to enter the banking domain, thus eroding the long-standing US[13].

In his July 2025 semi-annual testimony before Congress, Powell observed a notable shift in attitude among banking institutions and financial entities, characterising this transformation as a significant development in the integration of cryptocurrency within the domain of mainstream finance. In July, Federal Open Market Committee participants underscored that the GENIUS Act could accelerate stablecoin adoption, enhance payment efficiency, and increase demand for Treasury securities, while cautioning that it may also pose risks to the banking system and the transmission of monetary policy. The Trump administration has reinforced this legislative shift with an executive order that charts a pro-blockchain, anti-CBDC path and delineates stablecoins as instruments that contribute to the dollar's preeminence[14] (Azzimonti & Quadrini, 2025). The formation of policy in relation to digital assets has been elevated to the level of the White House through the President's Working Group on Digital Asset Markets, while Congress and regulators have launched parallel initiatives[15]. The Senate Banking Committee has identified the enactment of legislation pertaining to stablecoin. Meanwhile, the House Financial Services Committee has committed to the establishment of a framework that aims to balance the promotion of innovation with the safeguarding of investor interests. At the regulatory level, the Commodity Futures Trading Commission (hereinafter, "CFTC") has expanded reliance on DLT for collateral management, while the SEC has established a crypto task force. The Federal Reserve's regional banks have also provided their perspective on the matter. Although the current issuance of stablecoins remains negligible, projections indicate the potential for rapid growth, which could result in a shift of funds from bank deposits to stablecoins. Such a redistribution would raise Treasury demand, as issuers are legally required to hold Treasuries and other safe assets, but could also constrain banks' lending capacity. Unlike deposits, partly backed by loans that support the real economy, stablecoin reserves are unavailable for direct lending. A significant shift in this balance could therefore pose broader questions for credit supply and financial intermediation in the US (Jacewitz, 2025).

The GENIUS Act signifies the inaugural significant US legislation concerning stablecoins, whereas Europe's MiCA establishes a more extensive regulatory framework for crypto assets. Despite the common objective of balancing innovation and stability, these two legislative approaches exhibit notable distinctions in their design. The GENIUS Act is a narrowly tailored legislation focused on payment stablecoins issued by federally approved entities and backed one-to-one by safe assets[16], treating them almost like bank deposits. In the context of the GENIUS Act other forms of stablecoins are not subject to the same regulatory framework as payment stablecoins, a digital asset issued on a public blockchain[17] with the purpose of facilitating payment and settlement. However, in the final part of the legislative text, the GENIUS Act expressly mandates a study on non payment stablecoins (including endogenously collateralized payment stablecoins) to be conducted within 365 days from its entry into force. Consequently, the legislation does not automatically extend to other categories of stablecoins, despite the legislator's acknowledgement of their existence. At present, such stablecoins are not prohibited, but they operate within a regulatory environment that has not yet been defined at the federal level under the GENIUS Act. MiCA, by contrast, provides a comprehensive regulatory framework for digital assets not previously addressed by financial legislation.

These differences are of strategic significance. The US model provides legal certainty for dollar-backed stablecoins, thereby reinforcing US monetary influence whilst concentrating benefits among large, well-capitalised institutions (Borg

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[10] A nonbank financial institution lacks a full banking licence and cannot accept public deposits but provides financial services such as investment management, brokerage, money transmission, and credit.

[11] A federally insured lender is a financial institution covered by federal deposit insurance, under which the US government protects customer deposits up to the insured limit in the event of failure.

[12] Banking associations have warned that, despite the GENIUS Act's ban on stablecoin issuers and banks paying interest, crypto exchanges may be able to indirectly offer yield on third-party stablecoins, creating a regulatory loophole. They argue this asymmetry could distort competition and accelerate deposit flight from banks; a US Treasury report (April 2025) estimated yield-bearing stablecoins could drain up to $6.6 trillion in bank deposits.

[13] Prominent policymakers and scholars have criticised the GENIUS and STABLE Acts, warning that they could enable Big Tech firms to issue stablecoins and expand their control over the payments system.

[14] Empirical evidence indicates that, over the long run, the reserve demand effect dominates the substitution effect, lowering US interest rates while increasing foreign borrowing.

[15] Congress has launched investigations and hearings into "Choke Point 2.0," alleged regulatory measures restricting crypto firms' access to banking and liquidity.

[16] The GENIUS Act requires US payment stablecoins to be fully backed by reserves held in safe assets, such as US dollars and Treasuries, to prevent risk-taking, reuse, or leverage.

[17] A public (permissionless) blockchain is a decentralized, open-access ledger not controlled by any single entity, where transactions are validated by consensus and recorded immutably, enabling transparency, P2P interaction, and censorship resistance.

& Scerri & Camilleri, 2025). While both frameworks enhance regulatory maturity in the sector[18], they embody distinct philosophies: the GENIUS Act favours a narrow, dollar-centric approach, while MiCA builds a wide transnational framework[19]. Ultimately, this divergence reflects deeper institutional differences between the two monetary systems. The US has a regulatory framework that allows for significant competition between federal and state authorities. In contrast, the euro area operates under a supranational monetary authority, which limits the scope for experimentation at the subnational level. Consequently, digital currencies are being integrated into these systems via governance logics that are fundamentally different.

3 The IPO Surge of Stablecoin-Related Firms Following Regulatory Reform

The recent regulatory shift in the US has created a new environment for stablecoin issuers to access public equity markets through initial public offerings (hereinafter, “IPOs”). This pro stablecoin development in Washington has resulted in a significant increase in listings, acquisitions, and new product launches. On 5 June 2025, Circle, the world’s second-largest stablecoin issuer, made an official public debut on the New York Stock Exchange[20]. Later that month, the company formally submitted a bank charter application to the Office of the Comptroller of the Currency to establish the First National Digital Currency Bank, seeking to capitalize on the resurgence of interest in digital currencies that has been precipitated by the administration’s pro-blockchain shift and the enactment of landmark stablecoin legislation.

Furthermore, Ripple has sought to consolidate its position by announcing a $200 million acquisition of Rail, a stablecoin infrastructure provider. In parallel, Ripple has raised approximately $500 million from investors valuing the company at around $40 billion. This fundraising round highlights the increasing interest of traditional financial institutions in stablecoin-focused enterprises, which are now widely perceived as an emerging pillar of the global payments ecosystem. Bullish, a global digital asset platform that offers institutional trading infrastructure and information services, has announced that it has secured $1.15 billion in stablecoin proceeds from its recent IPO. This development signifies a landmark occasion in the realm of stablecoin utilisation for funding purposes in a US IPO, thereby underscoring the growing integration of digital assets within mainstream capital markets. The stablecoin issuer, Figure Technologies, has also attracted the attention of investors, resulting in an increase in the size and price range of its impending IPO. This development follows a surge in demand from retail investors, which has led to a notable rise in crypto-related equities.

Further evidence of this trend can be found in the public market debut of Gemini Space Station, a global cryptocurrency platform, which was listed on the Nasdaq Global Select Market on 12 September. Gemini concluded its inaugural trading session with a 14% increase in share price, reaching $32 per share following its IPO price of $28 per share, above the proposed initial range of $22-26. The offering, conducted entirely through a capital increase, involved approximately 15.2 million ordinary shares, raising a total of $425 million and implying an initial market capitalisation of $3.3 billion, which increased to approximately $3.5 billion by the close of trading. A noteworthy development occurred in August of the year preceding the initial public offering. In this period, Gemini formally announced that it had successfully acquired authorisation from the Malta Financial Services Authority (MFSA), as stipulated under the MiCA Regulation of the European Union. This regulatory approval was pivotal in granting Gemini the authority to operate its activities within the jurisdiction of all 27 EU Member States. Within this evolving regulatory landscape, Tether, the operator of the world’s most traded cryptocurrency, announced plans to launch a fully regulated US dollar-backed stablecoin for the domestic market by the end of 2025. The company, which has already achieved significant profitability on an international level, is seeking to leverage the recently introduced US regulatory framework to facilitate its expansion into the world’s largest capital market.

The trend of public listings has persisted into 2026. On 13 January 2026, BitGo Holdings, a preeminent entity in the domain of cryptocurrency custody, formally initiated its IPO through a submission to the US SEC. As stated in the Form S-1, the offering consists of 11 million Class A ordinary shares issued by the company, in addition to 821.595 shares offered by existing shareholders. It is anticipated that the price per share will fall within the range of $15 to $17. This would result in an approximate total capital raise of $201 million, with the number of shares offered estimated at 11.8 million. In the initial phase of the company’s incorporation, BitGo filed confidentially in September 2025, thereby indicating its intention to list on the New York Stock Exchange under the ticker symbol ”BTGO”. The company, which has accumulated over $90 billion in assets under custody since its launch in 2013, is reportedly targeting a valuation of up to $1.96 billion through the offering.

In recent months, major financial institutions, including leading banks in both the US and Europe, have begun exploring the potential applications of stablecoins. A consortium of European banks has announced plans to introduce a euro-denominated stablecoin in the second half of 2026 (Leask, 2025). This suggests that the development of stablecoin

[18] Both laws reflect a maturing approach to crypto regulation, balancing innovation and investor protection: the GENIUS Act offers legal certainty for dollar-backed stablecoins and may reinforce the USD’s digital role but favors well-capitalized firms, while MiCA adopts a broader, conduct-based framework for all crypto-assets.

[19] The GENIUS Act bars unauthorized payment stablecoin issuance in the US, requiring foreign issuers to obtain a US license or partner with an approved entity, while MiCA similarly requires non-EU issuers to establish an EU presence and comply with EU rules.

[20] The US group raised $1.1 bn in a NYSE IPO priced at $31 after upsizing on strong demand; Circle became one of the year’s largest US listings, signaling an IPO market rebound after Trump’s April tariff shock, with shares jumping 168%.

innovations is no longer confined to the US and is increasingly influencing the strategic responses of European financial institutions. The emergence of privately issued euro-denominated stablecoins may also intensify policy discussions within the euro area regarding the role of public digital money, potentially accelerating institutional momentum behind the digital euro project.

4 Divergent State Models: Wyoming's FRNT and North Dakota's Roughrider Coin

On 29 August 2025, Wyoming made history as the first US state to issue its own stablecoin, the Frontier token (hereinafter, "FRNT"), thus marking a groundbreaking moment in the realm of state-level cryptocurrency adoption. This development stems from the Wyoming Stable Token Act, enacted on 17 March 2023, which authorised the creation of a commission to issue and manage a US dollar-redeemable virtual currency fully collateralised by US Treasury bills held in a dedicated trust account. The objective of the FRNT initiative is to establish a pioneering role for the state of Wyoming within the domain of public sector innovation in digital finance, thereby consolidating its established position as a leader in the field of blockchain regulation[21] (Apollo, 2024). FRNT exhibits the core economic attributes of a permissionless digital asset, namely that it may be transferred to any lawful person with an internet connection worldwide at negligible transaction costs on a continuous 24/7/365 basis, with near-instant settlement. Transactions are conducted on a peer-to-peer basis, eschewing the involvement of intermediaries. These transactions are meticulously recorded on an immutable ledger, a system that ensures immediate auditability and verifiability.

FRNT has been developed with the intention of differentiating itself from private stablecoins through the implementation of transparency and oversight mechanisms. The commission mandates quarterly audits by independent accounting firms and enforces a 102% reserve requirement[22] (Krause, 2025). The token is also intended to streamline payments in commodity markets and will be accepted for tax payments and licence fees within the state. The multi-chain architecture will initially support several blockchains, with the objective of achieving broad interoperability (Wright, 2025).

The GENIUS Act of 2025 establishes a regulatory framework that has the potential to implicitly support the rollout of FRNT (Krause, 2025). Specifically, the Act introduces a dual-track framework that allows smaller issuers (those with less than $10 billion in consolidated outstanding issuance) to operate under a certified state-level regulatory regime, provided that it is deemed substantially similar to the federal framework. This certification, overseen by the new Stablecoin Certification Review Committee effectively legitimizes state initiatives such as Wyoming's by enabling coordination with federal oversight rather than outright preemption (Daniel et Al., 2025).

Other states, such as Nebraska, which established LB64987 (the Financial Innovation Act) in 2021 to authorize Digital Asset Depository Institutions[23], are already positioning themselves to leverage this alignment to issue their own stablecoins (Schutz, 2025). However, it is important to note that the demographic and economic profile of certain states, such as Wyoming, does present certain limitations[24] (Krause, 2025). Absent any significant advantages in terms of cost, speed, or utility, there is a risk that FRNT may be perceived as a regulatory pilot project rather than a financial instrument that has gained widespread adoption. Of greater concern is the potential for the initiative to accelerate regulatory fragmentation. Should other states pursue analogous projects under differing regulations, businesses may encounter heightened compliance obligations, the possibility of federal preemption disputes, and a patchwork of non-uniform digital asset standards.

In October 2025, the Bank of North Dakota, announced a partnership with Fiserv to launch the "Roughrider Coin", North Dakota's first US dollar-backed stablecoin, scheduled for release in 2026[25]. The Roughrider Coin has been designed primarily as a wholesale instrument for bank-to-bank settlement. It will be available to community banks[26] and credit unions[27] within the state. The intention is that it will enhance payment efficiency, accelerate settlement times, and support broader merchant adoption of stablecoin-based transactions. In contradistinction to permissionless cryptoassets, the Roughrider Coin is to be operated on Fiserv's proprietary digital asset platform as opposed to on a

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[21] Several US states have pursued stablecoin initiatives: Wyoming has led in digital asset regulation; Texas has promoted a gold-backed model; New York issued guidance on dollar-backed stablecoins (July 2022); and California enacted the Digital Financial Assets Law, effective July 2025.

[22] Wyoming's initiative requires reserves of cash and short-term US Treasuries held at FDIC-insured institutions, exceeding typical private stablecoin standards, with reserve interest directed to the state's School Foundation Fund and projected to generate $10–20 million annually for education.

[23] The Nebraska Financial Innovation Act creates two paths for a Digital Asset Depository: a new Nebraska Digital Asset Depository Institution charter or authorization for an existing state-chartered institution to operate a Digital Asset Depository Department.

[24] Because of Wyoming's small population, even universal in-state adoption would represent only a marginal share of the stablecoin market, a constraint reinforced by the fact that only 17% of local businesses accept crypto payments.

[25] The Bank of North Dakota has announced its plan to launch the state's first stablecoin next September.

[26] Community banks are institutions with assets under $10 billion that follow a relationship-banking model, serving local businesses and consumers with loans funded by local deposits and income driven mainly by net interest. Typically locally owned and managed, they support small businesses, agriculture, and local development, and have historically provided relatively stable credit during economic stress.

[27] A federal credit union is a member-owned, not-for-profit cooperative chartered under the Federal Credit Union Act to provide affordable financial services to members linked by a common bond. Funded by member share deposits and governed on a one-member, one-vote basis with an elected volunteer board.

public blockchain. This positioning of North Dakota as a testing ground for tokenized deposits within a regulated, closed financial ecosystem is, once again, indicative of a significant move towards the integration of blockchain technology into the financial sector.

5 Historical Analogies: From the Free Banking Era to Digital State Currencies

The state exemption embedded in the GENIUS Act gives rise to fundamental questions regarding the future of American monetary federalism. It is a well-documented fact that legal and economic scholarships have long emphasised the historically significant efficiency costs imposed by monetary fragmentation. These costs have frequently necessitated federal intervention in order to restore uniformity.

Contemporary state-level experimentation with stablecoins evokes notable parallels with earlier periods of monetary issuance, particularly the Free Banking Era (1837–1864)[28], which followed the expiration of the Second Bank of the United States' federal charter. The War of 1812[29] exposed significant structural weaknesses in the US financial system. The disruption of trade engendered by British blockades resulted in a significant diminution of tariff revenues, consequently engendering considerable indebtedness on the part of the federal government[30] and the absence of a national bank consequent to the expiration of the charter of the First Bank in 1811[31]. In the absence of a central institution, state-chartered banks suspended specie payments and issued heterogeneous banknotes, contributing to monetary instability. In response to this crisis, Congress established the Second Bank of the United States in 1816 with the aim of restoring fiscal and monetary order. The Second Bank functioned in a dual capacity as both a fiscal agent for the federal government and a commercial bank. In this capacity, the Second Bank played a coordinating role by disciplining state bank note issuance through specie redemption and by facilitating nationwide payments through an extensive branch network. Despite its absence of contemporary monetary policy instruments, its magnitude enabled it to exert influence over credit conditions and to promote a more uniform currency. Nevertheless, the Bank's role in stabilising the financial system has been accompanied by significant political controversy. The concentration of financial power, coupled with the perception of insulation from democratic control, served as a catalyst for opposition, which was grounded in states' rights and anti-elite sentiment. This culminated in President Andrew Jackson's veto of its recharter and the subsequent removal of federal deposits. The closure of the Bank in 1836 signalled a return to monetary decentralisation, which was subsequently followed by recurrent financial crises that ultimately led to renewed federal intervention, as evidenced by the establishment of the Federal Reserve in 1913.

This episode demonstrates a recurring dynamic in American monetary federalism: decentralised financial arrangements persist until the economic costs of fragmentation outweigh resistance to centralisation. Furthermore, during the period known as the Free Banking Era, a significant number of states adopted regulatory frameworks that permitted the establishment of banks without the necessity of obtaining discretionary legislative approval, provided that the institutions in question met the stipulated capital and collateral requirements[32] (Sanches, 2016). State-chartered banks issued their own banknotes, which were backed by government bonds or mortgages deposited with state authorities. This resulted in thousands of distinct banknotes circulating simultaneously. Although redemption at par in specie was legally mandated, practical constraints including geographic distance, information asymmetries, and varying perceptions of issuer solvency, led banknotes to trade at discounts that differed by issuer and location. Market participants relied on newspapers and "note detectors" to assess relative values and identify counterfeits, while interstate commerce faced significant transaction costs. The absence of a standardised national currency gave rise to inefficiencies, which ultimately motivated the enactment of the National Banking Acts of 1863 and 1864[33]. These acts imposed federal uniformity through nationally chartered banks and a single currency framework.

The observed divergence between contemporary state-issued stablecoin initiatives reflects analogous dynamics in digital form. A comparison of the two cryptocurrencies reveals a marked contrast between the North Dakota Roughrider

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[28] The spread of free-banking statutes was closely linked to the Jacksonian Democratic movement's effort to diffuse financial power and limit the influence of large, centralized banks.

[29] Escalating Anglo-French trade restrictions between 1806 and 1807 sharply curtailed US commerce, prompting Congress to enact the costly and largely ineffective Embargo Act of 1807 and related Non-Intercourse Acts. Despite limited trade reopening in 1810, continued British blockades and impressment of American sailors combined with broader geopolitical ambitions to lead Congress to declare war in June 1812; the conflict ended with the 1814 Treaty of Ghent, restoring prewar boundaries while leaving underlying disputes unresolved.

[30] The War of 1812 was financed largely through public borrowing, expanding federal debt from $45.2 million in January 1812 to $119.2 million by September 1815.

[31] After independence, the United States faced severe fiscal and monetary instability, prompting Treasury Secretary Alexander Hamilton to propose a national bank to stabilize public finance and commerce. Chartered in 1791, the First Bank of the United States served as the government's fiscal agent, issued widely accepted notes, and exerted limited monetary control through lending and specie redemption, but constitutional and political opposition led Congress to let its charter expire in 1811.

[32] During the 1830s, states including Michigan, Georgia, and New York adopted free-banking regimes allowing banks to operate without special charters; by 1860, fifteen more states had followed, making free banking the dominant state-level system on the eve of the Civil War.

[33] The National Banking Acts of 1863 and 1864 marked a turning point in US banking, creating a system of federally chartered banks to finance Civil War expenditures and establish a uniform national currency. The Acts imposed federal supervision, capital and reserve requirements, authorized Treasury-backed banknotes, and effectively eliminated state banknotes through taxation, but failed to prevent recurring banking panics, contributing to the creation of the Federal Reserve in 1913.

coin and the Wyoming FRNT. The former is designed as a wholesale, institution-facing token operating on a proprietary platform, whereas the latter is structured as a retail-facing asset deployed on public blockchain networks. This divergence mirrors the heterogeneity of nineteenth-century state banknotes, albeit within a technologically advanced environment in which digital assets circulate instantaneously across jurisdictional boundaries. Absent federal interoperability mandates, state stablecoin programs risk recreating fragmentation through incompatible technical architectures and regulatory frameworks. A business seeking to transact across state lines may encounter frictions if stablecoins issued under different state regimes are unable to interoperate seamlessly. To illustrate this point, consider a Wyoming-based entity that is utilising FRNT on a public blockchain. Such an entity may encounter conversion or settlement barriers when engaging with a North Dakota counterparty that is operating within a closed, proprietary system.

Such frictions have the potential to compromise the efficiency gains that distributed ledger technology is otherwise capable of delivering. The issue is further complicated by regulatory divergence. Despite the adoption of dollar backing requirements in early state initiatives, the absence of uniform federal standards creates the possibility that future entrants may experiment with weaker reserve compositions, governance structures, or redemption mechanisms. The GENIUS Act's state exemption implicitly relies on market discipline and reputational constraints to deter excessive risk-taking. However, from a law and economics perspective, interjurisdictional competition may instead incentivise a regulatory "race to the bottom" as states seek to attract digital-asset firms and investment by offering more permissive regimes. These concerns are exacerbated by the fungibility and mobility of digital assets. In contrast to nineteenth-century banknotes, which were constrained by physical circulation and geographic limitations, digital stablecoins can move instantaneously across state lines and into federally regulated financial institutions. Consequently, risks originating within a single state's stablecoin ecosystem, such as a de-pegging event or reserve shortfall, may propagate rapidly through interconnected payment systems, potentially amplifying systemic effects rather than containing them. At the same time, state-level experimentation may generate valuable informational benefits. Regulatory competition can function as a laboratory for innovation, enabling states to test alternative approaches to stablecoin design, governance, and use cases. Wyoming's emphasis on transparency and full reserve backing, for example, may establish de facto standards that influence both federal policymakers and other states. Federal regulators retain indirect leverage through their authority over banks and payment systems that interact with state-issued stablecoins, as well as through systemic risk designation powers.

Ultimately, the success of the GENIUS Act's state exemption will depend on whether coordination mechanisms, whether market-driven, voluntary, or federally imposed, emerge to harmonize these parallel experiments. American monetary history suggests that periods of decentralization often persist only until the costs of fragmentation become sufficiently salient to justify uniform federal intervention. The central challenge, therefore, lies in capturing the innovative potential of state experimentation while avoiding the inefficiencies and systemic vulnerabilities that historically necessitated national monetary unification.

In his remarks from October 2025, former Vice Chair for Supervision Michael S. Barr further warned that, despite their potential benefits in areas such as remittances trade finance, and corporate liquidity management[34], stablecoins pose financial stability risks reminiscent of the 19th-century Free Banking Era[35] (Rockhoff, 1974; Hasan & Dwyer, 1994). He cautioned that unregulated issuers could face sudden redemption runs if reserves are not sufficiently safe and liquid, as stablecoins lack the protections provided to traditional banks, such as deposit insurance[36]. Barr also criticised the GENIUS Act for leaving gaps in oversight, notably allowing reserve assets that are not immune to stress, such as uninsured deposits or foreign assets authorised as means of payment. Moreover, he highlighted the danger of regulatory fragmentation, as four federal agencies and multiple state authorities can exert overlapping supervisory powers. In Barr's view, the US framework should introduce clearer capital requirements for issuing banks and stronger consumer protection tools[37]. As an alternative, he pointed to tokenised deposits, already integrated into existing prudential frameworks, as a safer model within the regulated banking perimeter. Wyoming's stablecoin therefore embodies a duality of innovation and uncertainty. Its emphasis on transparency and public benefit has the potential to provide a credible alternative to private issuers. Nevertheless, the question of whether a state-backed token can achieve meaningful scale in competition with established market leaders remains unresolved.

[34] Stablecoins can reduce remittance costs, especially where payment infrastructure is weak, while emerging acceptance networks improve speed and affordability. They may also enhance trade and trade finance through smart contracts and enable near real-time cross-border payments and liquidity management for firms, lowering costs and improving efficiency.

[35] During the Free Banking Era, privately issued banknotes circulated at varying values based on issuer creditworthiness and location, often trading below par and triggering frequent runs and panics despite asset backing. Although later reforms requiring full backing by US government securities improved stability, systemic fragility persisted, culminating in the Panic of 1907 and the subsequent creation of the Federal Reserve.

[36] Stablecoins' long-term stability depends on the quality, liquidity, and transparency of their reserves, as they lack deposit insurance and central bank liquidity access. Issuers' incentives to seek higher yields by increasing portfolio risk can boost profits in calm periods but heighten vulnerability to confidence shocks, making reliable par redemption critical even during market stress or issuer-specific distress.

[37] Stablecoin issuers are subject only to the Act's capital requirements, which may be insufficient as activities expand, making coordinated federal–state capital standards essential. The GENIUS Act supports this by allowing state requirements to be deemed substantially similar to federal ones.

In contrast to the US, the Euro area does not face the same internal fragmentation risks because monetary authority is centralized within the Eurosystem. However, the emergence of private global stablecoins introduces a different coordination challenge: preserving monetary sovereignty in a digital payments environment increasingly influenced by non-European issuers. Indeed, the fragmentation of the US free banking era, characterised by thousands of heterogeneous banknotes, provides a critical analytical lens for the ECB's current stance. The inefficiencies and "note detectors" of the nineteenth century are analogous to the technical and regulatory frictions that the ECB seeks to avoid by introducing a unified digital euro platform.

6 The European Response to US Stablecoin Regulation: The Digital Euro as a Monetary countermeasure

While recent US legislation has accelerated the integration of dollar-denominated stablecoins into domestic and global payment systems, it has also generated significant spillover effects beyond US borders. In particular, European policymakers have expressed growing concern that the expansion of regulated US stablecoins could reinforce the international dominance of the dollar in digital payments, prompting renewed institutional momentum behind the digital euro project. This development has led to a notable acceleration in the pace of discourse surrounding the concept of a digital euro which should therefore be understood not merely as a technological innovation, but as an institutional response to the changing structure of monetary authority in the digital age. The digital euro, actually, is perceived by many as a necessary measure to ensure the continued dominance of the euro within the single market (Gramegna, 2025). However, while the present political momentum has intensified only recently, the digital euro project has a more long-standing history and has followed a staged approach. In October 2020, the ECB published a report examining the potential issuance of a retail CBDC[38] (Brühl, 2025) in the form of a digital euro. One year later, in October 2021, the Eurosystem launched an investigation phase into its possible introduction. On 28 June 2023, the European Commission published three legislative proposals (COM/2023/369 final, COM/2023/368 final and COM/2023/364 final) that establish the legal framework for the digital euro. These proposals regulate its essential elements and grant the ECB the option, but not the obligation, to issue it[39]. On 18 October 2023, the ECB decided to advance to the preparation phase[40]. Subsequent to the culmination of the two-year preparatory phase, the ECB’s Governing Council has decided to move to the next phase of the digital euro project in October 2025[41]. The final issuance decision will be made only upon the conclusion of the EU legislative process, which is expected by officials to occur by mid-2026, with mid-2029 cited as a realistic target for potential implementation.

The legal basis for the digital euro is derived from the EU’s exclusive competence in the field of monetary policy for Member States whose currency is the euro, as outlined in Art. 3 of the Document 12012E/TXT (the Treaty on the Functioning of the European Union, hereinafter, “TFEU”). The definition and implementation of monetary policy are the responsibility of the European System of Central Banks. Based on Art. 133 TFEU, digital euro could be introduced as a new form of central bank money alongside cash, with its legal tender status representing a key consideration (Capdevila Penalva, 2024). The Court of Justice of the EU has defined legal tender as implying mandatory acceptance, acceptance at full face value, and the power to discharge payment obligations (Dietrich and Häring v Hessischer Rundfunk, 2021). The primary objectives of the digital euro can be distilled into four points. Firstly, it seeks to ensure that the euro remains a monetary anchor and to protect financial stability. Confidence in private money is founded on the capacity to convert it at par value into central bank money (Panetta, 2022). The decline in the utilisation of central bank money has the potential to erode public trust and compromise the efficacy of monetary policy transmission. The digital euro is therefore intended to offset the declining use of cash and to preserve the euro’s role as a monetary anchor in the future monetary system. Secondly, the digital euro is intended to promote innovation and competition in the field of payments. The introduction of universal access[42], price caps, and the capacity for users to switch providers is expected to generate competitive pressures on existing services. Digital euro will be a common platform compatible with private services, and it is intended to support the development of new services and allow smaller firms to offer advanced solutions at competitive prices[43].

Thirdly, the digital euro is presented as a tool to promote financial inclusion. Access to fundamental digital payment functionality will be universally available and free of charge. Users will have the capability to establish accounts with any payment service provider (hereinafter, “PSP”), and public entities may distribute the digital euro to those who are averse

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[38] A CBDC can be retail, serving as a digital alternative to cash for households and firms, or wholesale, representing central bank reserves used by financial institutions to settle payments and securities in real time.

[39] The proposed Digital Euro Regulation establishes an enabling framework that defines the digital euro’s core features without mandating issuance, leaving the decision to the ECB. It sets rules on legal tender status, privacy, AML safeguards, distribution, holding limits, cross-border use, and key technical functions, including online, offline, and conditional payments.

[40] Following its investigation phase, the ECB designed a digital euro distributed by supervised intermediaries, free for basic use, usable online and offline, and offering high privacy with instant settlement in central bank money, supporting P2P, retail, e-commerce, and government payments.

[41] The next phase will ensure the Eurosystem’s technical readiness for a potential digital euro issuance; if the Regulation is adopted in 2026, a pilot and initial transactions could begin by mid-2027, enabling readiness for a first issuance by 2029.

[42] The digital euro would be available to all euro-area citizens and businesses.

[43] The proposed structure would ease cross-border deployment for PSPs, allowing more efficient service provision and greater operational scale across Europe.

to onboarding with a PSP. The design is focused on meeting the needs of individuals with disabilities, older individuals, and those with limited digital skills. It is noteworthy that users will not be required to hold a non-digital euro payment account[44] (Lambert et Al., 2024), a factor that may appeal to those who wish to maintain unbanked status. Fourthly, the digital euro is intended to bolster the EU's strategic autonomy and monetary sovereignty. It could provide a payment infrastructure that is resilient to external disruptions and reduce dependence on foreign providers[45]. The digital euro could also serve as a backup during network outages, as its offline functionality would allow payment transactions to continue even when connectivity is disrupted. Issuing digital euro could also strengthen monetary sovereignty by enhancing the euro's international standing in competition with foreign CBDCs and privately issued stablecoins from non-EU actors.

A critical design feature relates to the holding limit. The concept of holding limits involves the establishment of maximum balances that users are permitted to maintain within digital euro wallets. It is vital to note that these factors serve to limit the capacity for deposits to be transferred from commercial banks to the central bank balance sheet. Despite the ECB's lack of a proposed limit, a minimum of eighteen months will be necessary to ascertain one following the issuance announcement[46]. The implementation of lower limits has the potential to mitigate financial stability risks; however, it may also result in the suppression of adoption, consequently weakening the monetary anchor function. The imposition of higher limits has been demonstrated to engender an escalation in competitive pressures, whilst concomitantly giving rise to the phenomenon of deposit flight and the necessity of reliance on wholesale funding. The actual rate of uptake remains uncertain and is contingent upon factors such as remuneration, convenience, prevailing financial conditions, and user preferences[47] (Demertzis & Mejino-Lopez, 2024).

However, the introduction of a digital euro is expected to cause an outflow of deposits from commercial banks, as households rebalance their assets. To mitigate these challenges, financial institutions may implement a range of strategies, including the utilisation of reserves, the reduction of assets, or the augmentation of wholesale funding. The utilisation of reserves has the potential to contravene regulatory stipulations pertaining to liquidity requirements. The reduction of assets will result in a tightening of credit availability and a weakening of banks' capacity to absorb shocks. An increase in wholesale funding may necessitate an elevated level of long-term debt issuance, which in turn could result in an augmentation of encumbrance ratios. In periods of financial stress, the liquidity needs of financial institutions may exceed the reserves available to them, particularly for smaller banks in countries with a high reliance on household deposits[48].

7 Innovation without Fragmentation?

The exploration of stablecoin development is not limited to the domains of stablecoin issuers and state governments; small businesses and consumers are also drawn to the potential of stablecoins. A notable example of this is Open Issuance, a new platform that enables any business to launch and manage its own stablecoin[49] (Mamujee, 2025). For small and medium-sized enterprises in the US, technology is especially attractive as a means to reduce one of their most significant expenses: payment processing fees[50] (Nunley, 2025). The impact of stablecoins is also being felt in the travel and tourism industry, where payment methods are evolving rapidly alongside the growth of the digital economy[51] (Manahov & Li, 2024). Beyond tourism, other sectors are adopting stablecoins to mitigate currency risk. In real estate, firms already use them for property transactions, easing international dealings[52], while in retail, clothing brands employ stablecoins to purchase gift cards and reduce revenue volatility from exchange rate fluctuations[53]. Collectively, these examples show how stablecoins have evolved beyond crypto-native institutions and are progressively integrating into the broader economy.

Meanwhile, the US Congress is advancing the Digital Asset Market Clarity Act, intended to establish a coordinated framework for digital and crypto assets. Although stablecoins fall outside their immediate scope, the legislation could still provide the legal certainty necessary to foster responsible innovation. The EU, through MiCA, has

[44] Some functions require linking a non-digital account to the digital euro wallet, notably "waterfall" mechanisms that route excess amounts to or from the linked account when payments exceed holding limits, allowing digital euro payments even without a prior wallet balance.
[45] To strengthen European payment sovereignty and reduce reliance on non-European providers, the EU has backed cross-border interoperability initiatives, including Wero, a pan-European account-to-account wallet developed by EPI using SEPA Instant rails.
[46] On 19 September 2025, EU finance ministers agreed on a governance process to set and adjust caps on individual digital euro holdings, involving ECB analysis, consultation with national central banks, a Eurogroup recommendation, and national implementation.
[47] The ECB has proposed digital euro holding limits of €3,000–€4,000, though some studies suggest €1,000 as a lower feasible level. Research indicates that holdings below €3,000 per household would not threaten financial stability, but limits between €1,000 and €3,000 could still affect banks' profitability and funding stability.
[48] A digital euro could pose financial stability risks, with estimated bank deposit outflows of up to €739 billion, particularly affecting banks in countries such as Slovenia, Latvia, and Greece where household deposits are a key funding source.
[49] Issuing proprietary tokens allows businesses to control the customer experience, mint and burn tokens without excessive fees or limits, and capture returns on reserves.
[50] With US merchant processing fees reaching $187.2 billion in 2024, small businesses such as Prevail Coffee are using stablecoin payment apps to cut costs and support local innovation.
[51] Firms including Travala.com and Destinia accept cryptocurrencies.
[52] Burnert Title, Lodgis, and Cypress Title accept stablecoins for transactions.
[53] Adidas, H&M and Allbirds use stablecoins.

already taken a lead in this field, offering valuable lessons on the importance of coherent implementation and proportional requirements[54]. Compared to the Fed's approach, characterised by openness to private-sector innovation under prudential guardrails, the ECB maintains a more sovereignty-oriented perspective. The ECB's primary concern lies in the potential erosion of monetary control and the risk that non-euro denominated stablecoins could weaken the transmission of monetary policy. While both central banks identify similar vulnerabilities, such as liquidity mismatches and redemption risks, their underlying priorities diverge: the Fed emphasises market functioning and financial stability, whereas the ECB focuses on protecting monetary autonomy and the integrity of the euro.

Finally, the comparison between the US and the Euro area shows that there are two possible ways to integrate digital currencies into advanced monetary systems. In the US, innovation is primarily driven by decentralised experimentation by states and private actors, with federal authorities playing a coordinating role when necessary. In contrast, the eurozone has seen a more centralised approach designed to preserve the role of central bank money in an increasingly digital payments landscape.

8 Conclusion

In conclusion, the Fed's approach has undergone a notable shift, progressing from a stance of circumspect observation to a more proactive engagement. Following the enactment of the GENIUS Act, the central bank is confronted with the dual challenge of monitoring risks while integrating stablecoins into the broader financial system. This represents a delicate balancing act with the potential to significantly impact both domestic credit markets and the dollar's global role. State-issued stablecoins represent one of the most consequential monetary innovations to emerge from the digital asset ecosystem.

By entering the stablecoin market, US states have moved beyond regulating private issuers and have assumed an active role in shaping the future of digital money. This article has argued that such experimentation, while innovative, revives enduring tensions at the heart of American monetary federalism. The comparative analysis of Wyoming's FRNT token and North Dakota's Roughrider coin demonstrates that state stablecoins are not a uniform phenomenon. Instead, they reflect distinct institutional objectives and governance models, ranging from open, retail-facing instruments on public blockchains to closed, wholesale settlement assets operating on proprietary platforms. These design choices carry significant economic and legal consequences, particularly with respect to interoperability, risk management, and market adoption. Historical experience offers a cautionary perspective. During the Free Banking Era, decentralized issuance of money fostered experimentation but also produced fragmentation, uneven acceptance, and recurrent instability. Federal intervention through the National Banking Acts ultimately restored uniformity, albeit at the cost of state autonomy. While digital technologies reduce some frictions associated with nineteenth-century banknotes, they do not eliminate the fundamental coordination problems inherent in a decentralized monetary system. On the contrary, the speed and fungibility of digital assets may amplify the transmission of localized failures across jurisdictions. The analysis further underscores that state-level autonomy is constrained by the institutional reality of federal oversight. Even in the presence of statutory exemptions, the Federal Reserve and other federal agencies retain decisive influence over payment rails, banking relationships, and systemic risk designation. As a result, state-issued stablecoins exist within an implicit federal backstop that both enables experimentation and limits its scope. This hybrid arrangement reflects a deliberate policy choice to balance innovation against stability, but it also creates uncertainty about the long-term viability of fragmented digital monetary regimes. From a law and economics perspective, the state exemption embodied in the GENIUS Act can be understood as a regulatory experiment rather than a settled equilibrium. Market discipline, reputational constraints, and voluntary coordination may mitigate some risks, but they are unlikely to fully resolve interoperability challenges or prevent regulatory arbitrage. Absent minimum federal standards or coordination mechanisms, competitive pressures among states could erode reserve quality or oversight rigor, undermining confidence in state-backed digital money.

Ultimately, the future of state-issued stablecoins will depend on whether decentralized innovation can be reconciled with the functional requirements of a national payments system. The United States has repeatedly oscillated between decentralization and uniformity in its monetary history, often in response to crises that exposed the costs of fragmentation. Digital stablecoins may follow a similar trajectory. Whether they evolve into a durable component of the monetary system or prompt renewed federal consolidation will shape the next chapter of American monetary federalism.

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[54] Given the EU's early lead in digital asset regulation, its experience offers valuable lessons for the US as it pursues a similar regulatory path.

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