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Do ESG Ratings Predict Credit Risk? Evidence From Croatian Firms and A Machine Learning Perspective*

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Abstract

This study investigates whether ESG ratings provide useful information for credit risk assessment in an emerging EU member-state context, where sustainability reporting is rapidly expanding but still institutionally developing. The motivation for the study arises from the increasing regulatory and financial relevance of ESG disclosure in the European Union and from the practical need to understand whether ESG indicators can support creditworthiness evaluation. Although prior research often links stronger ESG performance with lower credit risk, less is known about whether this relationship is observable in smaller and less mature markets, particularly during the early phase of adjustment to EU sustainability reporting requirements. To address this gap, the paper analyses firm-level data from the Croatian Chamber of Economy for 2024–2025. ESG is examined both as an aggregate score and through its Environmental, Social, and Governance components, while credit risk is measured using HGK creditworthiness indicators. The methodology combines descriptive and stratified analysis, pooled and within-firm econometric models, ordered-response and transition analyses, and random forest prediction to assess out-of-sample performance. The findings indicate a weak and unstable relationship between ESG measures and HGK credit ratings. Changes in ESG scores do not systematically translate into changes in credit ratings, and ESG variables add only modest predictive value. Overall, ESG ratings in this context appear to reflect firm size, sector, and reporting capacity more than a strong standalone signal of credit risk.

Keywords: credit risk, ESG ratings, machine learning, Croatia

Introduction – contextual framework

Environmental, social and governance (ESG) standards refer to a structured set of practices and disclosures through which firms measure, manage, and communicate (1) environmental externalities and resource use (emissions, energy, waste), (2) social impacts and human-capital outcomes (and safety, labor practices, community relations), and (3) governance quality (board oversight, ethics, internal controls). The growing importance of environmental, social, and governance (ESG) reporting has changed how companies communicate non-financial information to their stakeholders. Across the European Union, disclosing sustainability has gradually shifted from a voluntary practice toward a structured regulatory requirement. The EU regulatory framework requires firms to provide a comprehensive and balanced disclosure of their policies, outcomes, and risk exposures in the area of non-financial reporting (EUR-Lex, 2014). First, it started to be considered as a possible sign of resilience, excellent governance, and a long-term risk mitigation strategy. Then, this led to the formation of corporate sustainability reporting (CSR), a set of guidelines that firms must follow to find, analyse, and manage risks. This has a substantial impact on the environment, society, and long-term

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sustainability (Christensen et al., 2021). Today, it is considered crucially important to include ESG initiatives in policies and actions (Serafeim, 2020) in planning and decision-making, to ensure an environmentally and socially sustainable business. This transition has created new expectations for companies, not only in terms of transparency but also in how organisational processes are documented and standardised.

This is particularly relevant in smaller or developing EU economies, where the alignment of institutions with new reporting standards is still a work in progress, especially considering that financial markets seem to increasingly recognise climate and sustainability exposures as priced risks (Bolton and Kacperczyk, 2021). Namely, EU regulation requires financial institutions to explicitly integrate and disclose sustainability risks within their decision-making processes, reinforcing the role of ESG factors in financial risk assessment (EUR-Lex, 2019). The Croatian context provides a useful setting for examining these dynamics, using Croatian firm-level data for 2024–2025 from the Croatian Chamber of Economy (HGK). In Croatia, companies operate under rapidly evolving European sustainability regulations while simultaneously adjusting to domestic market structures and reporting practices. Flammer (2021) says that this answer is important for businesses, lenders, and politicians who want to know how quickly regulatory convergence could lead to better financial information. However, not all companies move at the same speed when new reporting rules appear, for different reasons. Some companies adjust quickly, while others need more time, resources, or experience. Following this, as well as the distinction between reduced-form and structural approaches (Blinder, 1973), this paper aims to explore ESG reporting as a structural and institutional phenomenon – an indication of credit risk prediction through ESG ratings.

From the literature point of view, the link between the CSR/ESG and the credit ratings usually indicates that ESG is a sign of lower downside risk, greater governance and internal controls, and fewer tail events, all of which rating systems try to measure. For example, corporate social responsibility is linked to better credit ratings after taking into account the company's features, which is in line with a risk-reduction and reputation channel (Attig et al., 2013). Evidence indicates that corporate social performance may influence credit ratings and loan prices, functioning through risk and information channels (Oikonomou et al., 2014). Research has also shown that increased CSR can lead to smaller loan spreads, although this is not always the case, and banks may use screening behaviour (Goss & Roberts, 2011). For example, a common way to get a loan is to say that CSR/ESG may lower information asymmetry and build trust among stakeholders, making it easier to get the loan (Cheng et al., 2014).

One reason for adopting ESG from a financial point of view is that ESG performance and disclosure can change how risky a company seems to be. ESG can lower the predicted losses from environmental liabilities, supply chain problems, not following the rules, labour disputes, corruption, or bad governance. It can also make a company more resilient by enhancing its internal controls, stakeholder management, and long-term strategic planning. In credit markets, these mechanisms should be important since lenders and rating systems set prices based on the risk of default and the loss that would happen if it did. Consequently, the empirical research frequently characterises ESG as a component in credit risk evaluation via mechanisms like risk management quality, vulnerability to transition and physical climate hazards, litigation and regulatory risk, and information asymmetry.

In empirical research, a significant practical concern is that “total ESG” indexes may obscure balancing linkages among their components. Prior research shows that the financial relevance of ESG depends on the materiality of sustainability issues, with stronger effects observed when firms perform well on financially material ESG dimensions (Khan et al., 2016). In the Croatian HGK dataset in this paper, first stratified diagnostics reveal that the overall ESG score lacks a significant correlation with the HGK numeric creditworthiness score across finely delineated strata categorised by year, business size, and ESG rating level. This makes a deconstructed analysis necessary, in which Environmental, Social, and Governance scores are modelled independently. This lets the data show if some dimensions include credit-relevant information even when the overall index does not.

Croatia's ESG relevance is even higher because it is a member of the EU, takes part in cross-border value chains, and faces challenges from exports and supply chains (for example, buyers' sustainability requirements, procurement standards, and documentation needs). Even companies that aren't required to report formally can nevertheless be affected by "trickle-down" ESG obligations from customers, banks, insurers, and bigger counterparties that have to follow CSRD/ESRS and EU Taxonomy-linked disclosures (EUR-Lex, 2022). The EU Taxonomy provides a standardized framework for identifying environmentally sustainable economic activities, thereby improving the consistency and comparability of ESG-related information (EUR-Lex, 2020). The regulatory framework further specifies how firms must measure and disclose taxonomy-aligned activities, thereby operationalising ESG reporting into quantifiable and comparable indicators (EUR-Lex, 2021).

The regulatory environment is also changing. The corporate sustainability due diligence framework (CSDDD) extends ESG requirements further by obliging firms to systematically identify, monitor, and manage environmental and human rights risks across their operations and value chains (EUR-Lex, 2024). In 2025, EU institutions talked about "Omnibus" simplification packages that would change the timelines and scope for some companies' sustainability reporting and due diligence. This would create uncertainty during the transition, but it wouldn't change the strategic direction toward standardised sustainability information (Council of the European Union, 2025).

In this context, an empirical study in Croatia examining the correlation between ESG ratings and credit risk ratings is significant for three reasons. First, it gives evidence from a specific country in the EU, where the size and structure of firms and the types of sectors are different from those in "old" member states. Second, credit institutions that are subject to supervisory standards must integrate ESG risks into their governance and risk management (European Banking Authority, 2021). The European Central Bank supervisory framework explicitly treats climate-related and environmental risks as underlying drivers of traditional financial risk categories, reinforcing their relevance for credit risk assessment (European Central Bank, 2020). Third, it helps people make decisions in the real world. For companies, it makes it clear whether ESG improvements affect creditworthiness. For politicians and chambers/sector groups, it shows where support and harmonisation could improve both sustainability readiness and access to financing.

There are other things important for a Croatia-focused HGK-based setup. First, there is more and more proof that ESG rating measurement is noisy and different between providers, which makes it harder to compare and understand. This means that scores that are specific to one country or one provider (or one framework) may be cleaner inside the country but less comparable outside of it (Berg et al., 2022; Billio et al., 2021). Second, the EU's goal of standardising regulations is to make it easier to compare sustainability information. However, transitional periods and reporting costs can affect the quality and coverage of the data, especially for smaller businesses and newer member states (EUR-Lex, 2022).

Methodology Framework

The research used HGK-based ESG and HGK-based creditworthiness measures. The final dataset consisted of 718 firm-year observations from Croatian firms for the period 2024–2025. The unbalanced sample included 399 firms in 2024 and 319 firms in 2025 after excluding observations with missing HGK credit ratings. A balanced panel subset was constructed for firms observed in both years and used for within-firm (first-difference) and transition analyses.

ESG is observed both as a total numeric score (ESG_index_HGK) and as an ordinal level (ESG_class_HGK: Low, Medium, High, Very High). The dataset also reports the three numeric component scores (Environmental, Social, and Governance) satisfying the identity ESG_index_HGK = Environmental (ENV_score_HGK) + Social (SOC_score_HGK) + Governance (GOV_score_HGK) for every observation. Creditworthiness is observed as a numeric score (credit_score_HGK) and an ordinal rating category (credit_class_HGK: D < C < CCC < B < BBB < … < AAA). The ordinal nature of credit_class_HGK motivates ordered-response models, while credit_score_HGK supports linear modeling and within-firm differencing. A general class of regression models specifically designed for ordinal data provides an appropriate framework for analysing ordered outcomes such as credit rating categories (McCullagh, 1980). However, the validity of such models depends on the proportional odds assumption, which must be explicitly tested (Brant, 1990).

The ESG components are on different ranges (Environmental $\in [0,105]$, Social $\in [0,53]$, Governance $\in [0,67]$, ESG_index_HGK $\in [0,213]$), so the coefficient magnitudes are not directly comparable across components in level form. For this reason, the component analyses report effects in (1) original units (for practical interpretability) and (2) standardised units (per one standard deviation) to enable meaningful comparison of Environmental vs Social vs Governance associations.

Observations with missing HGK missing credit score or rating classification were excluded from models in which credit_score_HGK or credit_class_HGK are outcomes, because the creditworthiness measure is structurally absent. This exclusion can induce selection bias if missingness is non-random (e.g., smaller firms, certain sectors). Therefore, the first step was a missingness audit: compare distributions of ESG and covariates between “HGK present” vs “HGK missing” groups via standardised mean differences and robust tests, and report whether excluded observations are systematically different. Finally, a panel required a firm-level key, so the identification number (OIB: firm_ID) was used. With only two years, the panel is inherently short (T=2), making first differences the natural within-firm estimator.

In terms of descriptive stratification and benchmarking, the research used structured description: ESG and HGK distributions by year, size group (G1–G3), sector, and region. The purpose of this was to establish whether the sample is dominated by certain sectors or locations, and whether year-to-year shifts reflect real changes or compositional changes.

Factors for industry/sector (sector_group) and county/region (region_unit) can be high-cardinality relative to sample size, so a two-track strategy was used: (1) granular categories for descriptive tables (counts, medians, interquartile ranges), and (2) aggregated groupings for modeling. A defensible aggregation can follow NACE-style logic where feasible: 6–8 macro sector groups and 4–6 macro regions. Sensitivity checks re-run key models with alternative aggregations.

Statistical comparisons used robust inference: heteroskedasticity-robust tests for mean differences, rank-based tests for medians where distributions are skewed, and effect sizes (standardised differences) rather than only p-values.

If higher ESG groups show consistently higher HGK scores across years and size groups, this supports a positive association. If the pattern appears only in pooled data but not within size/sector strata, this suggests compositional confounding. This paper follows a semiparametric perspective that allows the analysis of how structural and compositional factors shape the distribution of outcomes across firms, in line with the DiNardo approach (DiNardo et al., 1996). If 2025 shows a shift in ESG distribution but HGK does not shift (or vice versa), this motivates decomposition into composition vs within-firm change. If total ESG correlations are near zero within year×size×level strata, but one component exhibits non-trivial correlation in the same strata, this suggests that aggregation may be masking offsetting component effects. In that case, component-level regressions and within-firm Δ-component models become the primary empirical focus.

Finally, predictive modeling was used for the purpose of developing a risk prediction for ESG ratings based on machine learning. Predictive models are used as robustness/complement: do ESG variables improve out-of-sample prediction of creditworthiness beyond size/sector/region/year? A strict design was a year-based evaluation: train on 2024, test on 2025. A secondary design used cross-validation in pooled data. Classical ML references included random forests (Breiman, 2001) and gradient boosting (Friedman, 2001).

Before introducing machine-learning techniques, the analysis relied on a sequence of conventional statistical and econometric approaches applied to firm-level data for Croatian companies observed in 2024 and 2025. The dataset combined ESG ratings - both the overall ESG score and its three components (Environmental, Social, and Governance) with HGK creditworthiness indicators, measured as a numeric rating score and as an ordered rating category. Additional firm characteristics such as size group, industry sector, geographic location, and year were included as controls in the empirical models.

The analysis began with descriptive exploration of the data, examining how ESG scores and HGK credit ratings are distributed across years, firm sizes, and sectors. This step provided an initial overview of the structure of the dataset and highlighted important compositional patterns, particularly the strong relationship between ESG scores and firm size. The next stage examined whether ESG levels and HGK credit score categories are statistically related using contingency tables and chi-square tests, complemented by correspondence analysis to visualize how ESG categories and credit rating categories align in the data.

After the descriptive and association analyses, the study moved to multivariate models. Pooled regression models were estimated with the numeric HGK credit score as the dependent variable, allowing the relationship between ESG measures and creditworthiness to be assessed while controlling for firm size, sector, region, and year. To account for the possibility that cross-sectional differences between firms might drive the results, the analysis also considered within-firm dynamics using a balanced two-year panel. First-difference models were estimated to examine whether changes in ESG scores within the same firm correspond to changes in HGK credit ratings over time. Because credit ratings are inherently ordered categories, the analysis additionally employed ordered-response models for the categorical HGK credit score outcome. Finally, transition and mobility analyses were conducted to evaluate whether improvements in ESG are associated with rating upgrades, downgrades, or stability between 2024 and 2025, and reverse-direction models were estimated to explore whether creditworthiness might also influence ESG outcomes.

Once these econometric analyses were completed, machine-learning methods were introduced as a complementary step focused on prediction rather than inference. In particular, random forest models were used to test whether ESG variables improve the predictive performance of models for HGK credit ratings beyond standard firm characteristics such as size, sector, region, and year. This predictive exercise serves as an additional robustness check, helping to assess whether ESG indicators contain incremental information about credit risk that may not be fully captured by traditional regression approaches.

Ultimately, in terms of methodological issues and gaps, the following issues shape findings. Firstly, the endogeneity and reverse causality indicate that more creditworthy firms may invest more in ESG and disclosure capacity, while better ESG on the other hand, may improve credit outcomes. With limited covariates, association estimates are informative, but not causal.

Predictive modeling – A machine-learning approach to credit risk prediction based on ESG ratings

Reasoning and added value of a machine-learning complement

The regression and ordinal models were designed primarily for inference: they ask whether ESG (total or Environmental/Social/Governance components) has a statistically reliable association with HGK credit scores after controlling for firm size, sector, and geography. Predictive modelling asks a different, practically oriented question: even if coefficients are weak or insignificant in parametric models, do ESG variables contain incremental information that helps predict HGK numeric ratings out of sample? This matters because ESG may influence creditworthiness through nonlinearities (only beyond a threshold), interactions (stronger in certain industries), or complex combinations of covariates that linear models can miss.

The research estimates random forest (RF) models as a robustness-style complement: RF is an ensemble of decision trees built on bootstrap samples, where each split considers only a random subset of predictors. Aggregating many trees stabilises predictions and captures nonlinear and interaction structure without prespecifying functional forms. Importantly, RF does not yield causal interpretations of “effects” in the way regression coefficients do. Instead, it evaluates whether ESG features have predictive content for HGK credit scores in a forecasting sense.

What the reported metrics mean

The performance tables report three standard out-of-sample error metrics:

- RMSE (Root Mean Squared Error), a standard metric used to evaluate the accuracy of a machine-learning model's predictions (Hodson, 2022), measures the typical prediction error in the same units as the dependent variable (HGK numeric rating). Because errors are squared before averaging, RMSE penalises large mistakes more heavily; it is sensitive to occasional large misses.
- R^2 (coefficient of determination) summarises the share of variance in HGK credit scores explained by predictions out of sample (relative to a baseline mean-only prediction). In a predictive setting, an R^2 around 0.25 is usually interpreted as moderate, non-trivial structure is captured, but substantial firm-level idiosyncrasy remains.
- MAE (mean absolute error), a foundational statistical metric measuring the average magnitude of errors in credit risk predictions without considering their direction (positive or negative) (Willmott and Matsuura, 2005), is also in HGK credit score units, but averages absolute errors; it is more robust to outliers than RMSE and can be interpreted as the typical absolute deviation between predicted and actual HGK credit scores.

The column “metric_type = standard” indicates that these metrics were computed using the standard (unadjusted) definitions used in the modelling framework; it is not a separate model, but the default estimator for each metric. The “metric_value” column is the computed value for each metric.

Results: Random forest (RF) performance and what it implies about ESG's predictive power

The total-ESG random forest achieves RMSE = 29.40, MAE = 23.85, and $R^2 = 0.26$. Interpreted substantively, the typical absolute prediction error is about 24 HGK points, and the model explains roughly 26% of the out-of-sample variation in HGK numeric ratings.

This indicates that the feature set used in the RF (including ESG plus the controls such as size/sector/region) contains meaningful information about HGK credit scores, but the majority of variation remains unexplained, consistent with credit ratings reflecting additional financial, balance-sheet, and risk information not included in the ESG-focused dataset.

The components RF (using Environmental, Social, and Governance instead of total ESG) yields very similar performance: RMSE = 29.71, MAE = 23.92, and $R^2 = 0.25$. The near-equivalence across tables is informative: decomposing ESG into Environmental / Social / Governance does not improve predictive accuracy in this run, suggesting that (i) the components do not contain strong additional predictive signal beyond what is already captured by total ESG and the standard firm controls, and/or (ii) the sample size and signal-to-noise ratio are insufficient for the RF to exploit any incremental component-level patterns reliably.

Empirical discussion - result interpretation, multidimensional implications, and pathways to EU best practice

The empirical results show weak immediate ESG–HGK coupling, so the policy forms the question of what changes would make ESG performance more credit-relevant and more measurable in Croatia. The measures are framed as levers that (1) improve ESG quality and comparability, and (2) strengthen the channels through which ESG performance affects financing terms and risk classification: Legal and regulatory measures; Business and governance measures; Economic and industrial policy measures; Fiscal measures.

In terms of legal and regulatory measures, the priority is faithful and enforceable CSRD/ESRS implementation: clear national guidance, auditor readiness for sustainability assurance, proportionate enforcement, and practical reporting support for mid-sized firms. This is not merely compliance: it creates the data infrastructure that allows credit markets and rating systems to consistently price ESG-related risks and resilience (EUR-Lex, 2022; EUR-Lex, 2023).

From the perspective of business and governance measures, firms, especially SMEs, need managerial capacity to translate ESG into operational risk management. This includes board-level governance of sustainability risks, internal controls over ESG data, and integration of ESG into investment planning (energy efficiency, supply-chain resilience, workforce stability). International evidence suggests governance quality is often the most directly credit-relevant ESG component, because it affects default risk through managerial discipline and transparency, even if that channel is not yet strong in this short Croatian sample (Attig et al., 2013).

From the standpoint of economic and industrial policy measures, if Croatia aims to converge toward EU "best performers," industrial and energy policy should reduce transition risk by easing decarbonisation investments. This includes grid modernisation, renewable deployment, building retrofit programs, and targeted support for hard-to-abate sectors. These policies indirectly improve credit quality by stabilising cash flows against future carbon and regulatory shocks, precisely the type of channel supervisors increasingly emphasise (European Banking Authority, 2021).

In terms of fiscal measures, well-designed tax credits, accelerated depreciation for green capital investments, and predictable carbon-related fiscal frameworks can change firm incentives and make ESG investments financially attractive. The goal is to shift ESG from being primarily a reporting/output score to reflecting real risk-reducing capital formation.

Finally, financial-sector measures should point out that the Croatian banking system can accelerate convergence by embedding ESG into (i) borrower due diligence, (ii) covenant design, (iii) pricing add-ons/discounts linked to sustainability KPIs, and (iv) portfolio monitoring. Supervisory guidance already pushes EU banks in this direction (European Banking Authority, 2021). As these practices diffuse, HGK-like credit ratings are more likely to reflect ESG-relevant information.

Conclusion

Previous studies have documented the demand for sustainability data and the significant variability in its interpretation (Amel-Zadeh and Serafeim, 2018; Berg et al., 2022). However, this research interprets ESG reporting as a reflection of how institutions adapt to the changing European regulatory environment, in terms of credit risk prediction. Evidence from Croatian companies shows that ESG metrics are significantly influenced by structural factors such as company size and sector. This highlights the role of organizational capacity in shaping reporting results. This perspective aligns with the idea related to climate change and sustainability (Bolton and Kacperczyk, 2021; Giglio et al., 2021), taking into account risks that have already happened (Krueger et al., 2020).

Companies operating under the same EU rules can still produce very different ESG results. These differences are mainly connected to firm size, sector, and reporting experience. Therefore, ESG results should be read carefully, especially in periods when reporting standards are still new and companies are learning how to apply them. The Croatian evidence shows that companies follow different reporting paths even when they operate under the same EU framework. These differences are mainly linked to firm size, sector, and the timing of reporting adoption. This means that ESG scores should be interpreted as evolving outcomes that reflect different stages of adjustment to sustainability reporting standards rather than as fully stable indicators. At the same time, the findings should be interpreted within the limits of a short observation horizon and a specific national context, meaning that broader generalisations should be made with caution.

As companies gain more experience with reporting standards, the meaning and usefulness of ESG metrics will likely change over time. Future research may therefore benefit from focusing on longer adjustment horizons and institutional dynamics rather than short-term performance interpretation. The Croatian case therefore illustrates how ESG outcomes emerge through gradual institutional alignment, where diversity in reporting paths is a natural feature of early-stage standardisation rather than a deviation from expected performance patterns. The observed structural gradients and limited short-term dynamics indicate that Croatian firms are progressing through heterogeneous adaptation paths as sustainability reporting standards become embedded.

After accounting for firm size, sectoral affiliation, and geographic location, the empirical results indicate that neither the overall ESG score nor its individual Environmental, Social, and Governance components show a stable or statistically robust relationship with HGK credit risk ratings in pooled regression models. Although ESG rating categories and HGK rating classes are not independent from one another in a statistical sense, the association between them appears relatively weak and does not follow a clear monotonic pattern. Correspondence analysis suggests that the two rating systems share only partial structural similarity rather than forming a straightforward progression from low ESG performance to stronger credit quality.

Looking at changes within firms over time provides little additional support for a strong connection. Year-to-year movements in ESG scores do not consistently correspond with changes in HGK credit ratings, and the mobility analysis does not show reliable evidence that ESG improvements translate into rating upgrades or help firms avoid downgrades over the 2024–2025 period. Testing the relationship in the opposite direction yields similar conclusions. Models that treat ESG performance as the outcome variable provide limited evidence that stronger creditworthiness systematically leads to higher ESG scores within this framework.

From a predictive perspective, the models also show that HGK numeric ratings are only moderately predictable overall. Incorporating detailed Environmental, Social, and Governance components does not noticeably improve predictive performance relative to using the aggregate ESG measure in the random forest analysis. Conclusively, the share of observations with missing HGK credit scores is very small. Moreover, the pattern of missingness does not appear to be strongly linked to ESG levels in a way that would materially bias the main findings or alter the overall interpretation of the results.

Taken together, these results suggest that within the short time frame and sample considered here, ESG scores in Croatia primarily reflect broader firm characteristics. Most notable are factors related to firm size, reporting capacity, and disclosure practices, rather than acting as a decisive determinant of credit risk classification in the HGK rating system. In other words, ESG indicators seem to describe certain structural features of firms, but they do not yet appear to play a central role in explaining differences in creditworthiness within this dataset. This interpretation is broadly consistent with findings in the wider literature, where ESG has been shown to influence credit ratings and borrowing costs in some contexts, but the magnitude and consistency of these effects vary considerably depending on market structure, data quality, and the time horizon examined (Attig et al., 2013; Oikonomou et al., 2014; Friede et al., 2015).

From a policy perspective, however, the picture may evolve. Ongoing regulatory developments in the European Union, particularly the implementation of the Corporate Sustainability Reporting Directive (CSRD) and the European Sustainability Reporting Standards (ESRS), are expected to improve the comparability, coverage, and assurance of sustainability disclosures. At the same time, European banking supervision is increasingly incorporating ESG-related risks into prudential oversight. As these frameworks mature and reporting practices stabilize, the connection between ESG performance and credit risk assessment in Croatia may become more pronounced, both in actual financial decision-making and in the empirical relationships observable in future data (European Banking Authority, 2021). Future research could continue using machine-learning methods to better understand how ESG factors relate to credit risk in more complex ways.

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