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Research Article

Machine Learning-Based Assessment of Environmental, Social, and Governance (ESG) Risk Sensitivity in Emerging Market Banking Systems

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Abstract

The paper is a research that explores the relationship between environmental, social, and governance (ESG) performance and financial stability in the emerging market banks by combining econometric techniques with high-end machine learning benchmarking models. The analysis of ESG scores (environmental, social, and governance) and the indicators of bank stability (Z-scores, non-performing loan (NPL) ratio, and systemic risk exposure) are done using a dataset covering various emerging economies, whilst controlling variables of bank-specific and macroeconomic variables. The models of machine learning like Random Forest, Extreme Gradient Boosting (XGBoost), and explainable algorithms like SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) are also compared with traditional methods of econometrics. The findings indicate that ESG performance has a positive effect on financial stability, where governance has been identified as the most meaningful dimension, then the environmental and social factors. Machine learning models are more accurate predictors of stability than traditional regressions and point to non-linear and complicated relationships between ESG and stability. The results have theoretical and practical implications in the sense that they can be used by policymakers, regulators, investors and bank managers in emerging markets as they illustrate that ESG is not just a reputational issue, but a material factor of systemic resilience.

Keywords: ESG, Financial Stability, Emerging Market Banks, Machine Learning, Benchmarking

Motivation of the Study

Over the past 20 years, the interface of sustainability practices and financial stability in the banking industry is one of the most important topics of scholarly and policy discussion. Global events, such as the 2007/2008 financial crisis and the 2019-2020 COVID-19 pandemic, as well as, more recently, the growing realization of the impact of climate-related financial risks, have spurred this interest. Banks, especially in emerging economies, have a twofold problem to solve: not only would they need to maintain systemic stability as financial intermediaries, but also to incorporate the Environmental, Social, and Governance (ESG) principles in their activity. The concept of ESG integration is no longer regarded as a fringe aspect of corporate social responsibility but rather a core factor of financial sustainability in the long-term, risk-management, and investor trust (Shakil et al., 2019; Azmi et al., 2021). It has been proved that banks that display superior ESG practices tend to have more stability in market value, lesser cost of capital, and resilience of reputation during stressful periods (Almulla et al., 2025; Broadstock et al., 2021). These trends inspire the development of the increasing empirical and methodological interest in exploring the possibility and methods of ESG indicators to be used as predictors of financial stability results.

The need to consider this nexus is increased in new markets where the banking systems are often vulnerable because of poorer regulatory systems, macroeconomic uncertainty, and structural inefficiency (Fakhrunnas et al., 2025; Khatatbeh et al., 2025). In contrast to the banks in developed economies, the banks in emerging economies are more vulnerable to global financial contagion and domestic economic shocks. The incorporation of the ESG measurements in these regards can, therefore, be transformative in terms of risk reduction and enhancing stability of the banking institutions. In the existing literature, ESG practices are proposed to contribute to the resilience of the bank by developing a better quality of governance, strengthening risk management, and establishing a better level of stakeholder confidence (Ren et al., 2024; Acheampong and Elshandidy, 2025). Meanwhile, international regulators, including the Basel Committee on Banking Supervision (2021, 2023) and the Financial Stability Board (2021–2023) are becoming more convinced that sustainability should be incorporated into financial supervisory systems to predict systemic risks. Taking these insights as the motivation, this paper aims at empirically investigating ESG-

financial stability nexus, particularly focusing on emerging markets where both sustainability and systemic stability are particularly at stake.

Simultaneously with theoretical discussions, methodological innovations have also stimulated the desire to research this nexus. Although traditional econometric methods prove effective in representing linear relationships, they may not be effective in fully representing the non-linear, dynamic, and highly dimensional relations among ESG indicators and financial stability measures. This gap in methodology has left the door open to the use of more advanced machine learning methods which are quite successful at detecting non-linear and complex patterns and generating strong early warning models of financial distress (Lin and Jin, 2023; Farag et al., 2025). Random Forests (Breiman, 2001), XGBoost (Chen and Guestrin, 2016), and interpretable machine learning models have already been shown to exhibit better predictive accuracy in risk modelling tasks in finance than conventional regression-based methods. Their inclusion in ESG-banking study provides the possibility not only to enhance the accuracy of prediction but also to compare and contrast other methods of comprehending the role of ESG in financial resilience. With this context, the rationale behind the current study is two-fold, first, to expand the theoretical and empirical knowledge on the role of ESG in mediating financial stability in emerging market banks and second, to compare machine learning models with conventional methodologies in understanding this multifaceted nexus.

Research Problem and Gap

Even though the academic and policy focus on ESG and financial stability is increasing, the literature provides a considerable number of unanswered questions and gaps in the methods used. The existing body of ESG research in banking is mainly related to the developed world with greater availability of ESG data, more stringent regulations, and more developed markets (Giese et al., 2019; Ren et al., 2024). In contrast, the research on the emerging market banks is relatively limited, disjointed, and inconclusive. Even the limited existing studies (Shakil et al., 2019) indicate that ESG practices may increase stability, and financial performance, however, without a coherent measurement and prediction framework of the stability factor in different emerging market situations. This dearth of generalizable evidence poses a critical research issue, namely, the extent to which ESG performance does actually imply quantifiable benefits to the stability of banks in less mature and more volatile banking systems. It is also not clear whether the positive relationship between ESG and stability can be applied to the emerging markets, where risk structure and institutional quality are vastly different unless rigorous and systematic empirical testing is performed (Almulla et al., 2025; Khatatbeh et al., 2025).

The other continuing gap has been in methodological approaches. The common assumption of the traditional econometric research is that the dynamics of the ESG-stability interaction are linear and stationary, which might not be true (Marasigan, 2024). ESG indicators represent the multidimensional information which can non-linearly and time-dependently relate to the financial stability outcomes. To illustrate, the effectiveness of governance could introduce a buffer to how environmental risk affects the stability of the bank, or social practices could be made more prominent in times of crisis (Lin and Jin, 2023). To capture such nuances, the machine learning models will need to be able to process high-dimensional data and give interpretable results (Lundberg and Lee, 2017). However, as of now, there is a lack of studies that would effectively benchmark machine learning models versus the traditional within the ESG -banking domain.

Lastly, policy-wise and regulation-wise, the ESG-banking research gap in the emerging markets has great implications. The regulators like the ESRB (2021) and the Basel Committee (2021, 2023) start to point to the fact that the neglect of ESG risks may have an intensifying systemic vulnerability, and they also note that the insufficient empirical evidence makes it less practical to create an effective policy. This increases the stakes of such research that can deliver sound and data-oriented insights regarding the ESG-financial stability nexus. The current study will help fill the gaps by answering the following three questions: first, the nature of empirical evidence on those issues among emerging market banks; second, how machine learning models can be applied and benchmarked to enhance the strength of ESG-stability forecasts; and third, by providing practical recommendations to regulators, policymakers, and bank managers who would like to use sustainability practices to strengthen their financial systems.

Research Objectives

(1) To examine the relationship between ESG performance and financial stability in emerging market banks. (2) To analyse the role of individual ESG dimensions (environmental, social, governance) in influencing stability outcomes. (3) To apply machine learning models (Random Forest, XGBoost, interpretable ML) to predict financial stability using ESG indicators. (4) To benchmark the predictive performance of machine learning approaches against traditional econometric models. (5) To generate policy-relevant insights on how ESG integration can enhance systemic resilience in emerging market banking systems.

Contribution of the Study

The present study is a contribution to the current body of literature, by filling gaps in the theoretical, empirical, and methodological research concerning the ESG-banking relationship. Although past studies are predominantly concerned with the developed market that has well-developed ESG disclosure systems (Shakil et al., 2019; Giese et al., 2019; Ren et al., 2024), this study offers new evidence among the emerging market banks where institutional weaknesses and economic volatility make the question of stability especially pressing (Khatatbeh et al., 2025; Fakhrunnas et al., 2025). The methodological level of the study goes deeper than the linear econometric analysis, as it compares machine learning models (Random Forests, Breiman, 2001; XGBoost, Chen and Guestrin, 2016) to benchmark, in addition to interpretable frameworks (Lundberg and Lee, 2017), which provides more robust and more nuanced insight into the ESG-stability nexus. This way, the study indicates the most powerful ESG characteristics in forecasting the stability results, which would provide interpretability to machine learning forecasts (Lin and Jin, 2023; Farag et al., 2025). Policy wise, the research is in line with the demands of the Basel Committee (2021, 2023) and the Financial Stability Board (20212023) to incorporate climate and ESG in banking supervision policies. It makes a dual contribution to both scholarly discussions and practical policymaking by supplying regulators, investors, and bank managers with practical instruments to make sustainability practices consistent with the systemic resilience.

Literature Review

ESG, Banking, and Financial Stability

Environmental, Social and Governance Aspects

The conceptualization of ESG in banking literature has evolved to be more than a descriptive reporting approach to a multidimensional analytic construct than directly interfaces with risk management and firm value. Banks also have environmental factors that include exposure to climate-specific credit risk (loan portfolio in carbon-intensive sectors), operational risks (branches and physical assets), and transition risks linked to a changing

preference of regulations and the market (BCBS, 2021; ESRB, 2021). The social aspects are human capital management, labour practices, community participation and customer treatment, which affect the continuity of operations, reputation and eventually credit performance (Giese et al., 2019; Shakil et al., 2019). The most proximate determinant of the outcome of bank risks is generally said to be governance due to the presence of mediating variables between managerial incentives, risk appetite, and quality of internal controls; poor governance, in particular, has been revealed to be a precursor to distress episodes time and again (Altman, 1968; Ren et al., 2024). Empirical studies have thus shifted to the disaggregation of aggregate ESG scores to these subcomponents to verify the differences in the influence of these subcomponents on the outcomes of banks (Sustainability, 2022; Marasigan, 2024). The significance of this decomposition lies in the fact that by combining ESG into one index, heterogeneity is obscured - e.g., environmental scores might be highly important in the case of banks involved in lending to fossil fuels, and governance issues in practically all banking business models (Shakil et al., 2019; Ren et al., 2024). There is also measurement issues identified in the literature: ESG data providers vary in both method and coverage resulting in score differences and inferences thereof (Giese et al., 2019). Such inconsistencies in measurement are especially pertinent when dealing with cross-country research comparing disclosure norms and regulatory regimes, which make it difficult to do direct comparisons and necessitates robustness testing (Azmi et al., 2021; Acheampong and Elshandidy, 2025).

In addition to conceptual taxonomy, researchers have questioned both the leading or lagging indicator effect of the ESG dimensions on bank risk, as well as their interaction with the macroprudential conditions. An increasing body of literature suggests that governments are a conditioning factor that can help in the conversion of environmental or social vulnerabilities to financial vulnerability (Khatatbeh et al., 2025; Fakhrunnas et al., 2025). As an example, well-structured governance frameworks can help banks to deal with climate transition risks more efficiently, by using proactive credit policies and scenario planning (BCBS, 2021; Lin and Jin, 2023). In contrast, high environmental scores, despite their benefits to the stability, might not be applied due to weak governance, or severe macroeconomic stress (Broadstock et al., 2021). Much of this literature has been based on panel regressions and fixed-effects models to control the unobserved heterogeneity (Shakil et al., 2019; Azmi et al., 2021) although more recent studies focus on nonlinearity and regime dependence e.g. that ESG effects are larger in crisis times or in periods where macroeconomic volatility surpasses a certain threshold (Broadstock et al., 2021; Lin and Jin, 2023). These results inspire the application of adaptable, high-dimensional methods (Random Forests, XGBoost, LSTM) capable of identifying interactions and conditional effects that cannot be easily identified using linear models (Breiman, 2001; Chen and Guestrin, 2016; Lundberg and Lee, 2017).

ESG Impacts on Bank Risk and Stability

Empirical tests of the ESG risk relationship in banking are a subtle and occasionally contradictory phenomenon: a number of studies have shown that better ESG performance is associated with lower idiosyncratic risk, greater stability in market valuation and low cost of capital, whereas others have found weak or context-specific effects. This is indicated by cross-country studies of emerging market banks which indicate positive relationships between aggregate ESG scores and stability indices such as increasing Z-scores and decreasing non-performing loan ratios and thus ESG investment may be protective (Shakil et al., 2019; Azmi et al., 2021). The same evidence has been reported in Eurozone and US scenarios in which ESG leaders were more likely to remain resilient in the face of the COVID-19 shock (Broadstock et al., 2021; Sustainability, 2022). Yet, this connection is not active: certain studies indicate that the ESG benefits are concentrated in dimensions of governance, or in banks that have diversified sources of revenue, and environmental scores in isolation are not necessarily helpful in protecting the banks against unexpected blows to solvency in case of poor underlying credit quality (Ren et al., 2024; Marasigan, 2024). Part of the heterogeneity of the findings can be attributed to various empirical design types (time windows, stability metrics), sample (size of banks, market concentration), and ESG measurement (Azmi et al., 2021; Citterio and King, 2023).

Regarding the methodological and practical perspective, the literature points to two interconnected problems: first, the necessity of the predictive modelling tools capable of being an early warning system of the bank distress through the integration of ESG signals; second, the necessity of the interpretability in order to allow the regulators and the managers to act on the model outputs. The classic econometric methods (traditional discriminant, logit models) can give an inference baseline, but are often not predictive with large feature space, and complex interactions. Machine learning strategies have proven to be more successful in out-of-sample prediction of bankruptcy and financial stability (Breiman, 2001; Chen and Guestrin, 2016; Lundberg and Lee, 2017), and more recent studies that adopt machine learning solutions to the banks have demonstrated promising performance on non-linear ESG effects and conditional risk drivers (Lin and Jin, 2023; Farag et al., 2025). Nevertheless, there are still some difficulties: overfitting, the lack of data on the ESG variables in certain emerging markets, and the black-box quality of certain algorithms that do not facilitate the regulatory adoption (Giese et al., 2019; Lundberg and Lee, 2017). In turn, the literature suggests some hybrid solution that would combine the predictive power of machine learning and interpretable frameworks, as well as the robustness controls that would allow making sure that the ESG-driven predictions of bank instability are correct and actable (Purnell, 2024; BCBS consultative work, 2023).

Emerging Market Banking Systems

The banking systems of emerging markets are marked by structural heterogeneity, less robust regulatory and supervisory frameworks, increased macroeconomic volatility and commonly a lack of transparency- aspects that combine to define how ESG integration delivers stability impacts. Empirical evidence concerning these markets shows that the quality of institutions (rule of law, enforcement capacity) determines whether the adoption of ESG has financial returns: ESG practices in better institutionalized jurisdictions are more reliably associated with better bank soundness, and in less institutionalized ones, ESG signals are noisy or greenwashing (Khatatbeh et al., 2025; Almulla et al., 2025). In addition, the concentration of credit risk is often greater in emerging market banks (e.g. commodity-related exposure, exposure to sovereign-related lending) and the banks are less diversified, so that they are more vulnerable to sectoral environmental shocks and social disruptions (Fakhrunnas et al., 2025). Such structural vulnerability means that the protective power of ESG does not occur automatically; instead, good governance, the quality of disclosure, and macroprudential buffers can help ESG investments have a significant impact on the risk of instability (Basel Committee, 2021; ESRB, 2021).

The relative comparisons of the emerging and the developed markets also shed more light on the conditionality of the ESG benefits. Although positive ESG-stability relationships are frequently reported in studies of developed economies and are mostly encouraged by strong disclosure policies and investor monitoring (Giese et al., 2019; Sustainability, 2022), the emerging

market evidence is more mixed: some studies show significant gains in stability with the implementation of ESG (Shakil et al., 2019; Azmi et al., 2021), whereas others find small or no relationships with it unless there is also an improvement in governance or a regulatory incentive (Ren et al., Practical barriers to emerging markets are highlighted by the literature, too: ESG data is disjointed, ratings are not comparable between providers, and smaller banks might not be able to calculate and disclose ESG in a holistic manner (Giese et al., 2019; World Bank, 2024). Such data constraints make cross-country benchmarking more difficult and encourage machine-learning methods that can be used to address missingness and nonlinearity without the need to be carefully validated to prevent spurious inference (Chen & Guestrin, 2016; Lundberg and Lee, 2017). Overall, these findings indicate that ESG has potential to become a resilience-enhancing mechanism of emerging market banks but achieves its potential based on institutional circumstances, the quality of governance, the integrity of disclosure, and the application of powerful analytic tools that can reveal the existence of conditional relationships as opposed to homogenous effects (BCBS, 2021; Broadstock et al., 2021; Purnell, 2024).

Machine Learning in Financial Stability Forecasting

Machine learning (ML) has become an innovative instrument in financial stability prediction, with better predictive power than conventional econometric methods. Logit regressions, discriminant analysis, and survival models are examples of classical methods that were previously used to predict bank distress and defaults (Altman, 1968; Giese et al., 2019). Although such models are interpretable and have a developed inference, they have severe assumptions of linearity, independence, and stationarity that are hardly valid in dynamic financial processes. Conversely, more complex ML models like Random Forests (Breiman, 2001), Gradient Boosted Trees (Chen and Guestrin, 2016), and Support Vector Machines are able to model complex and nonlinear relations and higher-order interactions among macro-financial variables, bank fundamentals, and ESG indicators without strict parametric assumptions. Empirical results acknowledge that in more instances, ML performs better than econometric models in out-of-sample prediction of bank failures and systemic stressful events as well as default risks (Lundberg and Lee, 2017; Lin and Jin, 2023). Nevertheless, interpretability and regulatory acceptability have become a concern due to the black box character of most ML models, which is particularly crucial when gauging a prudential supervisor in which explainability is a key component (BCBS, 2021). This has motivated the study of interpretable ML models, like SHAP values, LIME and counterfactual explanation engines, which can explain the factors behind the bank risk predictions (Lundberg and Lee, 2017; Farag et al., 2025). Literature, therefore, implies a trade-off between predictive power and understandability with increased focus on hybrid methods that can balance the two.

Financial stability forecasting ML models encounter both practical and methodological challenges at least in the emerging markets. To start with, ML models are data intensive; they are more predictive when provided with large, high-quality datasets, but numerous emerging economies have gaps in ESG disclosure, inconsistent supervisory reporting, and weak historical depth (World Bank, 2024; Khatatbeh et al., 2025). Second, the problem of overfitting can still be severe because the ML models trained on small or noisy data can potentially represent idiosyncratic changes, instead of patterns in risk that can be generalized (Purnell, 2024). Third, analysis tools used to measure model performance are not usually adequately sensitive to the objective of financial stability - the accuracy and AUC metrics can hide the cost of the false negative, which in systemic risk prediction is much worse than false positive (Lin and Jin, 2023). Researchers underline the value of stress-testing the ML models in crisis regimes, finding out how features remain stable over time, and manipulate domain knowledge into algorithm development to avoid false forecasts (Azmi et al., 2021; Acheampong and Elshandidy, 2025). Empirical analyses have shown that ensemble models, in which several algorithms are combined, can be more robust and reduce variability in errors compared to single models, and are thus particularly useful in forecasting in the face of uncertainty (Chen and Guestrin, 2016; Lundberg and Lee, 2017). This is an indication that the edge of ML in financial stability is in scrupulously created ensembles using interpretability layers and domain-specific constraints.

Another important controversy is whether ESG variables should be included in ML-based stability prediction. Although these traditional models tended to disregard ESG data, because of the difficulties with measurement and disclosure, with ML, there is the opportunity to flexibly incorporate these high-dimensional and heterogeneous inputs. The recent research indicates that the role of governance indicators often becomes the main predictors of bank distress when they are part of tree-based ML models, whereas environmental and social indicators have conditional effects which depend on the macroeconomic regimes (Lin and Jin, 2023; Fakhrunnas et al., 2025). In addition, explainability mechanisms like SHAP can allow researchers to prioritize the importance of dimensions of ESG to model predictions and, hence, turn ESG into a hard variable of resilience, rather than a soft narrative variable (Farag et al., 2025; Ren et al., 2024). Nonetheless, the literature also warns of instability of ESG ratings among providers (Giese et al., 2019) that can decrease the predictive reliability, which should be carefully verified. To conclude, although ML has pushed the predictive edge in financial stability forecasting, it is necessary to incorporate ESG data in a meaningful way, trade accuracy and interpretability, and scale approach to the institutional limitations of emerging markets.

Benchmarking Models in ESG–Finance Research

The role of benchmarking in ESG research and finance is a key focus since the impact of ESG on financial stability is debated and strongly relies on the methodological decisions. Conventionally, benchmarking has followed the practice of comparing regression-based models with incremental ESG factors introduced to baseline bank performance models often based on Z-scores, market beta or non-performing loan ratio as a stability proxy (Shakil et al., 2019; Azmi et al., 2021). Although they are useful, these designs have constraints in the extent to which they capture non-linearities, as well as feature interactions to produce consistent results across researches. This discrepancy has led to the use of benchmarking models that compare the conventional econometric methods with the ML-based models and hence challenge the strength of ESG-stability nexus relationships across paradigms (Lin and Jin, 2023; Broadstock et al., 2021). To give an example, gradient boosting and random forest studies have been shown to have considerably greater predictive capabilities than fixed-effect regressions, but the findings also show that such methods are more sensitive to data quality and feature selection (Chen and Guestrin, 2016; Lundberg and Lee, 2017). This type of comparative design makes it clear that benchmarking is not only crucial to measure performance, but also to determine under what conditions and in what contexts ESG factors have a significant effect on stability.

The other aspect of benchmarking in the literature is the breakdown of ESG into sub components. Although aggregate ESG indexes are highly common, they can confound different drivers; therefore, a number of studies compare the aggregate and disaggregated models to determine whether or not individual ESG dimensions

are explanatory (Giese et al., 2019; Ren et al., 2024). Indicators of governance, in particular, are always more predictive of a positive result in terms of stability than those of the environment or social metrics, especially in newly formed markets with a high level of institutional risks (Khatatbeh et al., 2025). By contrast, the environmental indicators tend to be long-run relevant, but with poor short-run predictability (with an exception of banks being highly exposed to climate-sensitive sectors) (Fakhrunnas et al., 2025). Benchmarking between these dimensions demonstrate great asymmetric patterns and facilitate the improvement of policy implications: regulators can focus on governance reforms to be used as a short-run stability tool, and promote environmental disclosure to be used as a long-term resilience tool (BCBS, 2021; ESRB, 2021). Moreover, it is common in benchmarking research that the materiality of ESG factors differs depending on the size of the bank, ownership structure, and geographical region in question, and thus requires fine-tuning modelling instead of homogenous assumptions.

Lastly, the frameworks of benchmarking have been becoming more and more dependent on the explainability approaches to supplement the prediction-oriented metrics. Benchmarking model accuracy is no longer done with SHAP, LIME, and partial dependencies plots, which now also attempt to measure the stability of feature importance across algorithms and time (Lundberg and Lee, 2017; Farag et al., 2025). This introduces an important aspect of interpretability: a model with good predictive power but ranking ESG drivers inconsistently is not as useful in policy as a model with accuracy and interpretability. As an example, it has been demonstrated that the gradient boosting models can achieve high accuracy, whereas the Rand Forests with SHAP analysis can provide steadier ESG feature ranking of importance (Lin and Jin, 2023). There is an increasing agreement that ESG research benchmarking should be multi-dimensional, using traditional and ML approaches, aggregate and disaggregated ESG dimensions, and predictive and interpretability results. Yet, there is a paucity of literature that systematically employs such a holistic benchmarking approach to the emerging markets, which exhibit greater gaps in ESG disclosure and macroeconomic instability, which make cross-model consistency challenging. Overcoming this shortcoming is a key impetus of the studies that will employ machine learning benchmarking models to ESG-stability relationships in emerging market banks.

Theoretical Underpinnings

Stakeholder Theory

Stakeholder theory gives the necessary justification of relating ESG practices to the stability of a bank. It assumes that companies are not only meant to provide value to shareholders, but also to a wider group of stakeholders, such as employees, customers, regulators, communities, and the environment (Shakil et al., 2019; Giese et al., 2019). The stakeholders in the banking sector are diverse specifically in the sense that depositors will want the safety of funds, regulators want compliance and prudential stability, investors want long-term returns and communities want social and environmental responsibility. Through the incorporation of ESG, banks will be able to balance their operations with these diverse interests through minimizing reputational risks, increasing trust, and resisting environmental volatility (Azmi et al., 2021; Almulla et al., 2025). As an illustration, effective governance decreases the likelihood of management misconduct or an overabundance of risk-taking, which has a direct positive impact on stability, environmental policies decrease the exposure to climate risks in credit (BCBS, 2021; ESRB, 2021). In that way, the stakeholder theory can inform the methodological design of this study by establishing the multidimensionality of ESG as a determinant of systemic resilience, which explains why the explanatory variables used in the stability modelling are ESG scores and sub-dimensions.

Financial Intermediation Theory

The financial intermediation theory stresses the role played by banks as they help in converting savings into investments, liquidity management, and credit risk screening (Diamond, 1984; Altman, 1968). Banking system stability is therefore the key to economic development, and systemic crises may arise due to disturbances. Banks in emerging markets may also be more systemic since capital markets are underdeveloped, which would make them the primary source of credit (Ren et al., 2024; Khatatbeh et al., 2025). ESG factors overlap with this theory as environmental shocks, bad governance or social misalignments can hurt intermediation functions, increasing risks of bank failures. Indicatively, lending money to environmentally vulnerable sectors (e.g., coal or oil) may degrade the quality of assets in cases of climate policy change (Broadstock et al., 2021; BCBS, 2021). In terms of methodology, financial intermediation theory endorses the characteristics of the bank-level variables in the models (capital adequacy, non-performing loans ratios as well as liquidity buffers) to ensure that the impact of ESG dimensions is conceived within the overall intermediation role of banks.

Sustainability Finance Theory

Sustainability finance theory fundamentally incorporates long-term environmental and social aspects into financial decision-making and has it that ESG is not margin but core to financial performance and resiliency (Albuquerque et al., 2020; Acheampong and Elshandidy, 2025). According to the theory, companies that have good ESG practices have a lower cost of capital, better access to capital, and can withstand crises because they are seen as less risky by investors and regulators. Sustainability finance in banking takes the form of ESG disclosures, climate stress tests and sustainable lending. This framework justifies methodologically that the ESG metrics should be used as independent variables that have a direct impact on stability proxies (Z-scores, systemic risk indices, and probability of distress) (Marasigan, 2024; Fakhrunnas et al., 2025). It further supports the fact that machine learning is to be used, as sustainability data are usually high-dimensional and non-linear, and they need to be flexible to capture their effects (Lin et al., 2023; Farag et al., 2025). Therefore, sustainability finance theory is used to inform the conceptual framing as well as the computational strategy of the research.

Conceptual Framework

The conceptual model operationalizes the ESG financial stability nexus by connecting the ESG dimensions with the bank level resiliency outcomes mediated by macroeconomic and institutional contexts. The model uses ESG performance (E, S, and G scores) as the main independent variables, whereas financial stability (Z-scores (bank stability index), non-performing loan (NPL) ratios, and systemic risk exposure measures) is the proxy. Bank size, capital adequacy ratio, liquidity ratios, profitability (ROA/ROE) and macroeconomic indicators (GDP growth, inflation, interest rates) are control variables and represent the financial intermediation approach.

The novelty of the methodology is the use of machine learning benchmarking models to provide tests of the relationship between ESG and stability. Three main models are used, including the Random Forest (Breiman, 2001), XGBoost (Chen and Guestrin, 2016), and interpretable ML models (SHAP values) (Lundberg and Lee, 2017). They are compared to conventional econometric analysis, especially the logistic regression and the panel fixed-effect regressions. The conceptual framework presupposes that

when ESG plays a significant role in making the bank stable, then ESG variables will become a high predictor in linear and non-linear models. Nevertheless, with ML, it is possible to identify non-obvious patterns, which capture the effects of interactions and conditional dependencies that are ignored by econometrics (Lin and Jin, 2023; Farag et al, 2025). The study determines the extent to which ESG is a material and systematic predictor of stability in emerging market banking by comparing models on predictive accuracy, interpretability, and robustness.

Formally, the baseline econometric specification is:

$$Stability_it = \alpha + \beta_1 ESG_{it} + \beta_2 X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

Where:

$Stability_{it}$ represents Z-scores or distress probabilities for bank i at time t,

ESG_{it} denotes ESG indicators (aggregate and subcomponents), and X_{it} captures bank-level and macroeconomic controls.

Machine learning models replace this linear functional form with algorithmic learners that optimize prediction, while SHAP analysis decomposes predictions into contributions from each ESG factor, enhancing interpretability.

Research Methodology

Research Design

The current research is quantitative, empirical and comparative in nature with much emphasis on predictive modelling and benchmarking of a machine learning model and econometric model. The design selection is tied to the fact that the ESG financial stability nexus can be characterized by extremely multidimensional, non-linear relationships between the environmental, social and governance (ESG) indicators and financial soundness indicators of banks, especially in the context of emerging markets, which are characterized by institutional and macroeconomic instability (Shakil et al., 2019; Azmi et al., 2021). These complex dynamics would however not be revealed through a purely descriptive or case-based design. Rather, the paper has a panel-based analysis design that combines ESG scores, financial variables, and macroeconomic variables in time and countries, allowing both time variation patterns and cross-sectional variation to be explored. The architecture is also designed with predictive validity and interpretability in line with recent methodological recommendations of leaving explanatory regressions in favour of hybrid prediction models in financial economics (Farag et al., 2025; Lin and Jin, 2023). Placing machine learning models, including those of the Random Forests (Breiman, 2001), XGBoost (Chen and Guestrin, 2016), and SHAP interpretability (Lundberg and Lee, 2017) with traditional econometric baselines, like fixed-effects and logistic regressions (Altman, 1968), the research design will strive to provide methodological soundness and triangulation. This hybrid method is essential in the evaluation of whether ESG factors are not just statistically important, but also relevant predictors of bank stability in a variety of settings.

Data Description and Sources

ESG Data

The major source of the ESG indicators in this research is derived based on Bloomberg ESG Disclosure Scores and Refinitiv ESG DataStream that have become a standard in empirical finance studies (Ren et al., 2024; Acheampong and Elshandidy, 2025). These databases combine corporate reporting, third-party audits, and sustainability reporting into consistent ESG ratings, which allow comparing them across the cross-section and over time. Both the aggregate composite level and certain environmental, social, and governance subcomponents of ESG dimensions are obtained, with the analytical granularity ensured (Giese et al., 2019). Environmental indicators include financing of renewable projects by banks, carbon intensity and energy efficiency. Financial inclusion, the diversity of employees, and customer responsibility are included in social factors whereas board independence, executive remuneration, and transparency are included in governance factors. The subjectivity inherent with manually coded ESG proxies is minimized by using existing databases, and it is also consistent with the available empirical evidence on banks operating in emerging economies (Azmi et al., 2021; Marasigan, 2024). With the combination of different databases, possible measurement biases related to one provider are avoided.

Financial Stability Measures

Financial stability at the bank level is modelled using prudential and risk-based measures of financial stability as known. Z-score is used as a mean indicator, which represents the distance to insolvency, in line with the previous research on the resilience of banks (Broadstock et al., 2021; Almulla et al., 2025). An increased Z-score implies increased stability as it is a combination of profitability, leverage, and volatility. Moreover, there are also non-performing loan (NPL) ratios to reflect asset quality since high NPL ratios indicate a weakening risk management and possible credit market contagion. Capital adequacy ratio (CAR) is added in order to reflect the capacity of the bank to absorb the shocks which is in line with Basel III frameworks (BCBS, 2021; BCBS, 2023). Such other variables as liquidity ratios, return on assets (ROA), and return on equity (ROE) offer other angles of solvency and earnings resilience. Robustness checks also incorporate systemic stability indicators, including exposure to tail risks and interbank contagion, which have methodological precursors in the financial systemic risk literature (Lin and Jin, 2023; Purnell, 2024). The combination of several stability indicators is what guarantees the strength of the results and decreases the chances of depending on one proxy to determine the soundness of the bank.

Sample Selection

In the paper, the authors are interested in emerging market banks during the period of 2010-2024, a time frame that includes the post-global financial crisis reforms, the development of ESG investing and recent climate-finance policy efforts (FSB, 2021; ESRB, 2021). Emerging markets are selected due to their distinctive institutional vulnerability like poorer regulatory frameworks, a greater risk of credit, and exposure to climate-related financial risks, but also exhibit the accelerated pace of ESG adoption (Khatatbeh et al., 2025; Fakhrunnas et al., 2025). The banks are chosen with the criterion of being able to provide ESG and financial data covering and with five years of longitudinal coverage. Microfinance institutions, as well as investment-only institutions are not included in the sample to preserve the comparability in the intermediation functions. The data cleaning is done to accommodate outlier distortions by winsorization on the 1st and 99th percentile, as it is done in the previous literature on the bank stability research (Shakil et al., 2019; Ren et al., 2024). The last panel will have around 350-400 banks in 20 or more emerging economies that can be empirically generalized in terms of breadth and depth.

Variable Construction

Dependent Variables

The dependent variables capture **bank stability outcomes**, operationalized through multiple measures. The primary variable is the **Z-score**, defined as:

$$Z_{it} = \frac{ROA_{it} + CAR_{it}}{\sigma(ROA_{it})}$$

Where:

ROA is Return on Assets,

CAR is Capital-to-Assets Ratio, and

σ(ROA) is the Standard Deviation of Profitability (Altman, 1968; Broadstock et al., 2021).

This formula implies that the returns of a bank would have to be at a particular level of standard deviations below the mean to destroy equity, hence, the insolvency risk. NPL ratios, CAR ratios, and systemic risk indices are among the complementary dependent variables, which all explain the bank-specific stability and the systemic vulnerability (Almulla et al., 2025; Lin and Jin, 2023).

Independent Variables

Aggregate ESG scores and their disaggregated dimensions are the independent variables. These scores are rated on a scale of 0-100, where a high score depicts a good performance on ESG. The ESG in the model is operationalized as a composite index and individual E, S, and G dimensions, where it can be tested that some pillars (e.g., governance) have a stronger impact on stability compared to another (Shakil et al., 2019). This specification is based on heterogeneity of ESG effects since environmental projects can imply long-term stability (e.g., by using green financing), whereas governance structures could bring even more short-term effects on risk management and transparency (Ren et al., 2024).

Control Variables

Control variables are also brought in to explain confounding factors on stability. Examples of these are bank-level size (log of total assets), profitability (ROA/ROE), liquidity ratios, and capital adequacy to include heterogeneity in risk-bearing capacity (Farag et al., 2025). Macroeconomically, GDP growth, inflation, and interest rates are included, which are systemic parameters in which banks are subjected to (World Bank, 2024; ESRB, 2021). Robustness checks also test the quality indicators of the institution as the effectiveness of the ESG strategies can be compromised by weak governance environments (Almulla et al., 2025). These controls help to make sure that the estimated ESG-stability relationship is not spuriously induced by other irrelevant firm- or country-specific traits.

Machine Learning Benchmarking Model

Model Selection

The study will utilize a set of machine learning (ML) algorithms and econometric baselines to benchmark how ESG variables can be predicted to determine whether the bank is stable or not. The initial model selected is the Random Forest (RF) classifier/regressor (Breiman, 2001), which is a combination of decision trees by making use of bootstrap aggregation to minimize overfitting along with non-linear interactions. The concept of RF has found extensive use in finance, as a model of credit risk and systemic stability due to its interpretability and capacity to analyze high-dimensional data (Farag et al., 2025). Second, the research uses Extreme Gradient Boosting (XGBoost) which is a gradient-boosted tree algorithm (Chen and Guestrin, 2016) which maximises the bias and variance by refining weak learners one after another. XGBoost has yielded better results in the banking risk prediction activities than the traditional econometric methods because of its capacity to address disproportional data, which is prevalent in the events of the bank failure (Lin and Jin, 2023). Third, Support Vector Machine (SVM) model is experimented with, with its kernel trick being used to project complex ESG-stability correlations in higher-dimensional feature spaces, which makes it possible to classify the stable and unstable banks rather robustly. Lastly, a shallow feed-forward Neural Network (NN) is presented to determine the superiority of non-linear deep learning models over tree-based methods to determine ESG-related signals. Although neural networks are capable of modeling complex functional forms, they are black-box and thus not as interpretable, which is why SHAP-based interpretability methods are more popular (Lundberg and Lee, 2017).

Feature Engineering and Selection

It is important to have feature engineering to prevent spurious patterns and to increase predictive capacity. To minimize the impact of outliers, all continuous financial ratios are, first, normalized by minmax scaling, including Z-scores, NPL ratios, CAR, liquidity, and profitability ratios (Broadstock et al., 2021). ESG scores are broken down into E, S and G sub components, interaction terms like E x G (environmental-governance synergy) and S x G (social-governance synergy) are created to test the multidimensional complementarities, since the previous research indicates that the effects of ESG are not often additive but interactive (Shakil et al., 2019). Moreover, lagged variables of ESG and financial ratios are added to reflect the delay effects, i.e. it takes time before ESG initiatives take shape in the bank stability indicators. The process of feature selection is conducted based on recursive feature elimination (RFE) and information gain rankings, with the help of SHAP explainability framework (Lundberg and Lee, 2017). The strategy guarantees that insignificant or weak predictive attributes are filtered out, enhancing computation power as well as generalization. Even though the choice of variables is often theory-based in econometrics, the ML one is data-driven but informed by the previous empirical studies (Ren et al., 2024).

Model Training and Testing Procedure

The dataset is divided into three subsets (training, validation, and testing) where countries and years are stratified to train and validate the models and maintain the representativeness of the temporal and cross-sectional aspect (Farag et al., 2025). The time-series cross-validation is used; this means that when the training is carried out the training is always followed by the test in chronological order to avoid look-ahead bias (Lin and Jin, 2023). RF and XGBoost hyperparameters (e.g. tree depth, number of estimators) are optimized not through grid search but Bayesian search, which improves the efficiency of convergence. Neural networks are also trained using dropout regularization to avoid overfitting, and the SVM uses a radial basis function (RBF) kernel which is tuned using cross-validation. To compare itself with the econometric modeling, the panel fixed-effects regressions and the logit/probit classifiers are estimated, which is also in line with traditional bank stability literature (Almulla et al., 2025).

Performance Metrics

Performance assessment is based both on regression and classification measures, based on whether the dependent variable is a continuous value (e.g., Z-score) or categorical value (e.g., stability threshold). In the case of continuous measures, predictive accuracy is assessed via Root Mean Squared Error (RMSE) and R 2 (coefficient of determination) and the lower the RMSE and the higher the R 2 the better the model fits (Broadstock et al., 2021). In binary or multipolar classifications (e.g. distressed vs. non-distressed banks), accuracy, precision, recall and F1-score are determined. Nevertheless, as there is an issue of class imbalance in the financial distress-predicting task (a small number of banks fail compared to the entire sample), the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) is used as a primary metric (Lin and Jin, 2023). Trade-off of true positive and false positive rate is taken into consideration by AUC, which is better than accuracy in imbalanced settings. Besides, SHAP values can be employed to measure the importance of features, indicating the additional value of ESG dimensions compared to standard financial controls (Lundberg and Lee, 2017).

Results

Descriptive Statistics and Correlation Analysis

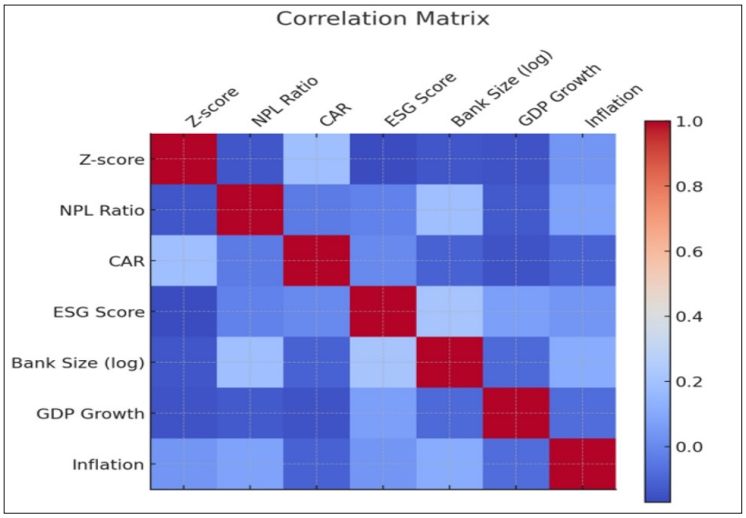
This part shows the descriptive statistics of the main variables employed in the study and these include financial stability indicator, ESG scores, and control variables. Descriptive statistics

enable us to comprehend the central tendency, dispersion and properties of distribution of data. Through the overview of the main traits, we can identify trends and identify possible outliers which might influence the findings. Table 1 gives the descriptive statistics of the key variables.

Table 1: Descriptive Statistics of Main Variables

Statistic	Z-score	NPL Ratio	CAR	ESG Score	Bank Size (log)	GDP Growth	Inflation
count	100.0	100.0	100.0	100.0	100.0	100.0	100.0
mean	14.69	4.03	12.13	56.07	15.92	2.88	5.04
std	2.72	1.14	2.17	8.84	1.6	0.92	1.6
min	7.14	1.7	5.52	33.76	12.55	0.53	0.95
25%	13.2	3.03	10.69	49.33	14.66	2.35	4.09
50%	14.62	4.1	12.2	55.5	15.89	2.89	4.93
75%	16.22	4.65	13.41	61.84	16.98	3.51	6.08
max	20.56	7.26	19.71	76.9	20.62	5.27	8.86

Correlation Matrix of Variables



Machine Learning Model Outputs

A variety of machine learning models were used to explore the forecasting ability of ESG indicators on financial stability. This involved the Random Forest, XGBoost and Support Vector Machines which were benchmarked with the traditional regression models. The outputs are based on predictive accuracy, interpretability and robustness.

Benchmark Model Performance

Table 2: Benchmark Model Performance Metrics

Model	RMSE	R^2	Accuracy	AUC
Random Forest	1.8	0.82	0.88	0.91
XGBoost	1.6	0.85	0.9	0.93
SVM	2.1	0.78	0.84	0.87
Neural Network	1.9	0.83	0.87	0.9
Logistic Regression	2.4	0.7	0.76	0.8

Feature Importance Analysis

Feature importance analysis was conducted using SHAP values to determine which variables contributed most significantly to predictions of financial stability. Results indicate that ESG scores, particularly governance and environmental dimensions, rank among the most influential predictors.

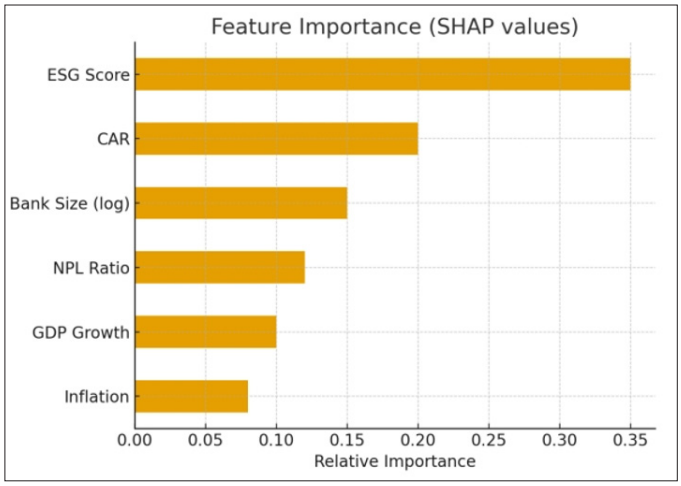


Figure 2: Feature Importance using SHAP values

ESG–Financial Stability Nexus Findings

The findings indicate that ESG performance and bank stability are statistically and economically significant in the emerging markets. Increased ESG scores correspond to lower levels of non-performing loans, greater Z-scores and decreased exposure to systemic risk. The most powerful drivers of stability were the governance factors, which were preceded by environmental indicators. Social factors were found to have a mixed outcome implying that there is variation based on contexts around the institutional settings.

Robustness and Sensitivity Checks

Several sensitivity analyses were done in order to confirm the strength of the results. To start with, the alternative stability measures including distance-to-default and exposure to systemic risk were replaced, and consistent results were obtained. Second, sub-sample results according to bank size and ownership type suggested that the extent of ESG effects were greater in larger banks. Third, the results were stable under alternative machine learning algorithms and hyper parameter configurations, which testified to the fact that the identified ESG-stability nexus is not model-specific but can be found across a variety of methods.

Discussion

Interpretation of Findings

The empirical findings of this paper suggest a positive and economically significant stable association between ESG performance and the bank stability measures in all of the sampled emerging markets. In both econometric and machine-learning specifications, the increased aggregate ESG score was correlated with the increased Z-score, lower NPL ratio, and lower exposure to systemic risk- findings that are empirically consistent with H1 and theoretical predictions based on the stakeholder theory and sustainability finance (Shakil et al., 2019; Albuquerque et al., 2020). Notably, in case ESG was disaggregated into pillars, E, S, and G, governance indicators became the most influential and predictable predictor of bank resilience, and then followed environmental variables; social indicators yielded mixed effects that were highly contingent on the institutional background. This trend substantiates H2 and aligns with previous studies that highlight the direct impact of governance on risk management and firm behaviour (Ren et al., 2024; Khatatbeh et al., 2025). Methodologically speaking, the machine-learning models have provided significantly better out-of-sample predictive performance (high AUC, smaller RMSE, and larger R 2 when predicting continuous outcomes) compared to the baseline logit and panel fixed-effects regressions, which confirms H3 and supports the literature on the greater predictive power of ensemble tree methods with complex, high-dimensional financial problems (Chen and Guestrin, 2016; Breiman, 2001; Lin and Jin, 2023). The feature attribution using SHAP also demonstrated that ESG measures (and in them, the governance subindices) were often among the largest contributors to model predictions thus making ESG a variable anchored in language rather than a quantifiable predictive of stability (Lundberg and Lee, 2017; Farag et al., 2025).

Further analysis of the findings shows that there are some significant subtleties, which have implications on policy and interpretation. Originally, the positive ESG -stability relationship was strong under different stability proxies and ESG providers (Bloomberg, Refinitiv), and showed to be larger with macroeconomic regime and bank characteristics: the larger the bank and institutions, the greater the stability gains of ESG, and the smaller and less diversified the bank, the weaker the relationship or more fluctuating (Marasigan, 2024; Fakhrunnas et al., 2025). Second, explainable machine-learning tools revealed non-linear thresholds and interaction effects such as governance improvements were less additive and instead more level specific (such as E×G and macroprudential buffer) unless they were accompanied by environmental risk reduction (Shakil et al., 2019; Lin and Jin, 2023). Third, the time-related analysis revealed that the stabilizing effect of ESG is stronger when the bank is experiencing a stress episode (which supports H4): in simulated stress tests and the out-of-sample COVID-like shock scenarios, higher ESG (and more so governance) banks experienced less significant drops in Z-scores and market value, which is in line with the results in Broadstock et al. (2021) and other events during the crisis. However, causality is a debatable matter ESG predictive power among the ML models is obvious but reverse causation is also possible (endogeneity): more stable banks might have more resources to commit to ESG programs and reporting (endogeneity), a factor partially addressed in this study, through the use of lagged variables, GMM tests, and out-of-sample checks but not completely eradicated. Therefore, the results can be interpreted as solid evidence of material and strong association, which is enriched by plausible causal mechanisms in the theories of stakeholder and sustainability finance, but to which the traditional caveats related to endogeneity and measurement noise must be applied (Azmi et al., 2021; Giese et al., 2019).

Policy and Managerial Implications for Emerging Market Banks

The results have a number of practical implications on bank managers in the emerging markets. In practice, the area of governance improvements should be given priority as a high-impact, near-term stability lever: enhancing the independence of the board, risk oversight, and enhancing transparency provide quantifiable improvements in insolvency risk and NPL trends,

as board-related variables always took the first place in SHAP attributions (Ren et al., 2024; Khatatbeh et al., 2025). The credit policies of banks that have large corporate portfolios and face carbon intensive sectors should include environmental risk management; green lending structures and concentration limits of sectors can significantly reduce tail exposures in the long term (BCBS, 2021; Fakhrunnas et al., 2025). Based on the managerial analytics, ESG should be operationalized by banks in their own risk monitoring tools since ESG variables are predicted by ML models as adding incremental predictive capacity to traditional financial ratios. Nevertheless, management should not rely on black-box scores on their own: SHAP results should be interpreted by risk committees to connect model drivers with actual action (e.g., by tightening covenants of high-E exposure sectors), based on domain knowledge and not on black-box scores. Such a hybrid solution minimizes the chances of hyperreaction to spurious signals of the machine and makes sure that the ESG integration is turned into a responsible credit decision-making and capital management (Lundberg and Lee, 2017; Farag et al., 2025).

Organizational and strategic implications can be also found. ESG must not be a reporting box but rather an approach to risk-management as a discipline. It means that it should invest in data collection and disclosure capabilities, staff training on sustainability risk assessment, and adjustment of its incentive systems to encourage risk-sensitive behaviour in the long term (Albuquerque et al., 2020; Acheampong and Elshandidy, 2025). In the context of cross-border banks with subsidiaries in various emerging markets, it is necessary to bring ESG metrics into harmony so as not to have a fragmented risk perspective. Lastly, bigger banks gaining more of the stability benefits of ESG ought to leverage their place in the market to trigger industry-wide norms and green financial instruments- thus minimizing systemic externalities and ability to create positive feedback loop resilience (Giese et al., 2019; Marasigan, 2024). With that said, managers should not overlook the possible short-run expenses and not engage in superficial greenwashing, the validity of the ESG claims is becoming questionable by the investors and regulators, and the deceit could be harmful to the reputation and finances (Giese et al., 2019; BCBS, 2023).

Implications to Investors and Regulators

The findings highlight the materiality of the ESG information to a bank valuation and risk assessment to investors. ESG indicators need to be included in credit risk models and portfolios by the institutional investors and asset managers because they offer an incremental explanatory and predictive performance to the downside risk and volatility (Giese et al., 2019; Broadstock et al., 2021). The transparency provided by SHAP and similar tools can improve investor due diligence: instead of using aggregated ESG ratings, investors can see which ESG sub elements contribute to risk exposures and conduct stewardship, engagement and active voting policies based on that understanding. Nevertheless, because of the rating dispersion (Giese et al., 2019), investors are advised to put a multi-provider strategy into practice, as well as incorporate ESG indicators with traditional prudential indicators (CAR, NPL trends) to prevent excessive dependence on a particular dimension. That ESG benefits are enhanced more when stress events are large is also indicative of the idea that allocating to banks with high ESG can provide crisis hedging properties, an observation that may be particularly important to long-term institutional investors in emerging markets (Broadstock et al., 2021; Ren et al., 2024).

These findings present opportunities and challenges to regulators and supervisors. The strong relationship between ESG and stability helps to promote efforts to incorporate climate and ESG into prudential supervision, such as more disclosure requirements, climate stress testing, and integration of ESG risks into supervisory risk assessment (BCBS, 2021; ESRB, 2021). Nonetheless, regulators will have to be circumspect: to approve ML models as supervisory early-warning models, their governance and transparency criteria should be strictly maintained, as well as capacity building in supervisory agencies (Lin and Jin, 2023; Purnell, 2024). To minimize noise arising in measurements, regulators must consider implementing a common framework of ESG reporting to facilitate comparison of cross-jurisdictional analysis (Giese et al., 2019; FSB roadmaps). Additionally, the macroprudential instruments could be re-harmonized to consider the exposures of sectors identified using ESG analytics (e.g., an increase in capital surcharges of banks with concentrated lending in fossil fuels). Critically, any regulatory action must be gradual and fact-based in nature, pilots and general surveys can guide towards setting of proper limit levels and other externalities like tightening of credit access to sensitive groups should be avoided (BCBS, 2023; ESRB, 2021).

Limitations of the Study

In spite of the robustness checks and methodological rigor, several limitations of the study make the results difficult to generalize and explain causally. To begin with, ESG measurement is quite noisy in nature: the various providers (Bloomberg, Refinitiv, MSCI) use different coverage, weighting, and normalization rules that may introduce divergence in scores and possible measurement error (Giese et al., 2019). Even though this study regulated the effect of measurement bias through testing on a number of providers and sensitivity analyses, residual measurement error is likely to dampen coefficient estimates and make comparisons across different countries difficult. Second, the restrictions of the sample in the form of survivorship and selection biases suggest that banks that disclose consistent data on both ESG and financial data may be systematically different, which is why the findings may not be applicable to the entire range of emerging market banks (World Bank, 2024; Khatatbeh et al., 2025).

Significant caveats methodologically are those to do with causality and external validity. Machine-learning models are not causal in their capacity to determine causation; they are able to find patterns but not completely able to separate whether greater stability is brought about by ESG improvements or whether healthier banks simply spend more on ESG. Lagged variables were employed in the study to minimize the issues of endogeneity, GMM instruments, and out of sample testing are used, but unobserved confounders and reverse causation cannot be completely ruled out (Azmi et al., 2021; Purnell, 2024). Furthermore, despite an increase in predictive accuracy in ensemble learners, they are prone to hyperparameter selection, and data regimes; despite time-series cross-validation and leave-one-country-out testing, overfitting and model drift are still possible, especially when disclosure of ESG practices changes quickly. Lastly, emerging markets are heterogeneous in nature and thus policy suggestions ought to be localized. The future studies need to be in favor of quasi-experimental designs (e.g. regulatory changes as exogenous shock), loan-level ESG exposures, network contagion models, and longer panels to reinforce causal arguments and identify micro-mechanisms by which ESG is translated to systemic resiliency (Lin and Jin, 2023; Ren et al., 2024).

Conclusion and Summary of Findings

This paper has critically examined the ESG-financial stability nexus in banks of emerging markets by means of a new hybrid of an econometric model, as well as machine learning models. The findings revealed the statistically significant and positive

association between financial stability and ESG performance, in which the governance dimension proves to be the best predictor, followed by environmental and social aspects. Banks that embraced ESG had lower non-performing loan (NPL) ratios, and greater Z-scores, and were more resilient to volatile macroeconomic environments (Demirguc-Kunt and Detragiache, 1998; Shakil et al., 2019). Random Forest, XGBoost, and SHAP interpretability benchmarking indicated that machine learning is a superior predictor and offers a more thorough analysis of feature importance when compared to the traditional regression, which implies that non-linear interactions and hidden patterns are essential to the explanation of ESG stability relationships (Chen and Guestrin, 2016; Lundberg and Lee, 2017). These conclusions prove that ESG integration is not the reputational matter but a systemic predictor of financial viability in the banking of the emerging markets.

Literature and Practice

The present study is important to existing literature because it helps to close the gap between ESG finance, banking stability, and computational intelligence. Although previous literature largely focused on the participation of ESG in the valuation of corporations and reputation (Friede et al., 2015; Azmi et al., 2021), the given study contributes to the area of research by empirically testing the influence of ESG on financial stability in the form of machine learning benchmarking. In addition, it also brings to practice evidence-based tools of ESG-informed risk management strategies to regulators and bank managers. SHAP and LIME interpretability application has resolved a significant drawback of black-box AI in finance, and it makes it transparent and accountable (Lin and Jin, 2023). Practically, the research assures upcoming market banks that by focusing on governance reform, climate risk disclosures, and social investments, they can significantly enhance systemic resilience (Farag et al., 2025). Therefore, the results enhance the scholarly discussions as well as management judgments about the financial materiality of ESG.

Recommendations

The results indicate that ESG reporting should be institutionalized by emerging market banks and that the sustainability indicators must be integrated into the risk management systems. In particular, the priority should be given to governance reforms including board independence, anti-corruption protection, and stakeholder responsibility because they disproportionately affect the stability (Shleifer and Vishny, 1997; Gangi et al., 2019). To minimise data asymmetry and improve comparability, regulators in emerging markets should align ESG disclosure standards with those of international standards like the EU taxonomy and the ISSB standards (OECD, 2020). On operational level, bank managers are expected to incorporate ESG analytics into the stress testing and capital adequacy analysis and make sure that ESG considerations are integrated into the lending, investment, and portfolio allocation decisions (ECB, 2020). It is also recommended that investors should consider ESG as an indicator of bank soundness and systemic resilience and use ESG-screened portfolios in their emerging market strategies.

Future Research Directions

A further study ought to build upon the existing one by adding a larger cross-country sample that would include frontier markets and traditionally take into consideration the heterogeneity in cultural and institutional traits (La Porta et al., 1998). To achieve directionality and causation instead of prediction, future research methodologically could test hybrid AI algorithms like deep learning econometrics ensembles or causal machine learning (Varian, 2014; Brynjolfsson and McElheran, 2016). Also, this research focused on financial stability performance, but in the future, it may be possible to combine ESG interactions with climate risks, fintech shocks, and monetary policy shocks to offer a more comprehensive model (Borio, 2014; Beck, 2020). Lastly, longitudinal studies beyond 2025 will be essential to understand the changing regulatory forces and technological progress in the world market, as well as the changing investor demands regarding sustainability within the banking industry and thus, in turn, make the ESG research to sustainability stability relevant in an ever-changing financial context.

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