MULTIDISCIPLINARY SCIENTIFIC RESEARCH
BJMSR VOL 10 NO 1 (2025) P-ISSN 2687-850X E-ISSN 2687-8518
Available online at https://www.cribfb.com
Journal homepage: https://www.cribfb.com/journal/index.php/BJMSR
Published by CRIBFB, USA

IMPACT OF GREEN FINANCE ON ENVIRONMENTAL AND SOCIAL RISK MANAGEMENT INFLUENCING PERFORMANCES OF BANKS: EVIDENCE FROM BANGLADESH

Md. Jahangir Alam Siddikee [(a)1] *AHM Ziaul Haq* [(b)] *Shahnaz Parvin* [(c)] *Humaira Begum* [(d)] *Mst. Rinu Fatema* [(e)]

[(a)] *PhD Fellow, Institute of Bangladesh Studies (IBS), University of Rajshahi, Rajshahi and Associate Professor, Hajee Mohammad Danesh Science and Technology University, Dinajpur, Bangladesh; E-mail: msiddikee@yahoo.com*
[(b)] *Professor, University of Rajshahi, Rajshahi, Bangladesh, E-mail: zia_haq2001@yahoo.com*
[(c)] *Professor, Hajee Mohammad Danesh Science and Technology University, Dinajpur, Bangladesh; E-mail: shahnazhstu09@gmail.com*
[(d)] *MPill Fellow, Institute of Bangladesh Studies (IBS), University of Rajshahi, Rajshahi and Associate Professor, Hajee Mohammad Danesh Science and Technology University, Dinajpur, Bangladesh; E-mail: humaira.begum@hstu.ac.bd*
[(e)] *Assistant Professor, Noakhali Science and Technology University, Noakhali, Bangladesh; E-mail: fatemarenu.thm@nstu.edu.bd*

ARTICLE INFO

Article History:

Received: 26th September 2024
Reviewed & Revised: 26th September 2024 to 29th January 2025
Accepted: 1st February 2025
Published: 5th February 2025

Keywords:

Green Finance, Environment, Impact, Relationship and Performance

JEL Classification Codes:

C58, G21, Q53

Peer-Review Model:

External peer review was done through double-blind method.

ABSTRACT

The growing emphasis on green finance (GF) presents significant attention for banks as they navigate environmental and social risk management (ESRM) while striving for financial performance. Emerging the global phenomenon with respect to environmental issues focuses on highlighting the study of GF with ESRM, which leads to the profitability and non-performing loans of banks. This study investigates the impacts of GF on ESRM and, in turn, impacts the performance-profitability and non-performing loans of banks, providing empirical evidence from Bangladesh. This study employs the numerical data collected from annual reports of the central bank- Bangladesh Bank, from 2015 to 2023. The study has focused on variables such as GF sectors, environmental and social risk management, profitability, and non-performing loans. Regression models (Panel ordinary least square, quarantine regression, fixed effect model, random effect model, and panel generalized method of the moment) are employed to examine the effects of GF on ESRM and the impact of ESRM on performance - profitability and non-performing loans. The result shows that GF significantly influences ESRM because the p-value is $0.00 \lesssim$ p-value $\lesssim 0.10$, rejecting the null hypothesis. ESRM has a significant impact on the performance of banks as a mediating factor with a p-value of $0.00 \lesssim$ p-value $\lesssim 0.10$. The findings of this study suggest that GF practices significantly enhance ESRM, which impacts the performance of banks and provides valuable insights for policymakers, regulators, and banking stakeholders in mitigating environmental and social risks and improving the performance of banks.

INTRODUCTION

Green finance plays a crucial role in environmental and social risks by promoting sustainable banking practices, ensuring long-term financial stability, and enhancing the performance of banks. Bangladesh has made significant studies in recent decades. However, its financial sector faces its own set of challenges, including concerns related to non-performing loans, financial stability, and corporate governance. As a result, there is growing recognition of the importance of GF in addressing environmental and social risk management as well as performance. Moreover, this study is significant as it provides empirical evidence from a developing country like Bangladesh, where financial organizations increasingly integrate green finance to address climate risks, regulatory compliance, and ESRM, ultimately influencing profitability and non-performing loans, fostering a responsible and profitable banking sector (Siddikee et al., 2024).

The study of (Fan et al., 2024) states that investments in clean and affordable energy can promote sustainable development. It may reduce the risk of loan defaults by aligning financial support with environmentally friendly practices. By incorporating GF practices into their strategic plans, financial institutions can contribute to environmental well-being and achieve sustainability goals over short and long periods (Abuatwan, 2023). GF serves as an intermediary between green

[1]Corresponding author: *ORCID ID: 0009-0003-1138-2390*

https://doi.org/10.46281/bjmsr.v10i1.2285

To cite this article: Siddikee, M. J. A., Haq, A. Z., Parvin, S., Begum, H., & Fatema, M. R. (2025). IMPACT OF GREEN FINANCE ON ENVIRONMENTAL AND SOCIAL RISK MANAGEMENT INFLUENCING PERFORMANCES OF BANKS: EVIDENCE FROM BANGLADESH. *Bangladesh Journal of Multidisciplinary Scientific Research*, *10*(1), 34-45. https://doi.org/10.46281/bjmsr.v10i1.2285

banking and environmental performance, with green banking activities exerting a noteworthy influence on environmental performance (Zhang et al., 2022). GF positively influences environmental performance by safeguarding and restoring ecosystems (Xi et al., 2021). The worldwide financial landscape is witnessing a paradigm change towards green finance. The study of sustainable finance has become a recognized discipline in the literature on finance (Poyser & Daugaard, 2022). They emphasize that a mental reset is necessary to map the published information on indigenous sustainable finance (Hasan et al., 2025).

This study employs the panel ordinary least square (POLS) to justify GF's impact on ESRM on profitability and non-performing loans on mean distribution. Quarantine regression is employed to determine the conditional impact. Next, this study conducts fixed effect models (FEM) and random effect models, and panel generalized method of moment (PGMM) in identifying the fixed, random and dynamic impact of GF on ESRM that on performance. Overall, this study aims to investigate the effect of GF on ESRM and the impact of ESRM on profitability and bank non-performing loans.

This article is structured as follows: It begins with a literature review, then materials and methods, followed by results, discussion, and conclusion.

LITERATURE REVIEW

Green finance refers to financial investments that maintain environmentally sustainable development. It encompasses various financial instruments, policies, and practices to promote ecological balance and mitigate climate issues. The concept aligns with the broader goals of green development, integrating environmental, social, and governance considerations into financial decision-making. GF plays a considerable role in driving the green enterprise transition by facilitating market-oriented governance, green oversight, and green governance, and its promotional impact is more pronounced in regions with strong state environmental governance, in firms with less public environmental oversight, and in firms that actively disclose green information (Chi & Yang, 2023). On a global scale, GF refers to incorporating environmental protection within financial organizations' economic strategies, prioritizing investments in environmental protection initiatives to endorse the transition to a green economy (Zheng et al., 2021). Green banking is also social or responsible (Park & Kim, 2020). GF highlights the social responsibilities of banks in promoting environmental sustainability. This underscores the frequent intersection between social and environmental concerns.

Economic growth is significantly influenced by the financial performance of financial institutions, especially within the banking sector, attracting attention from regulators and scholars. Investments in green sectors, the extension of green credit, energy accounting practices, and fostering creativity have been positively connected to the financial performance of banks in developing nations (Banani & Sunarko, 2022). Guan et al. (2017) highlight green loans elevating credit risk. Qian and Yu (2024) focus on connecting GF and ESG performance. While GF policies can alleviate financing constraints on green innovation in general, privately owned enterprises are less likely to have access to green credits (Yu et al., 2021). Various factors, such as fossil fuel imports, chemical usage, green funding, and nuclear energy demand, can impact regional environmental quality. Because climate risks directly affect central banks' core activities, financial institutions must integrate climate-related physical and transition risks into their policy frameworks to safeguard macro-financial stability (Dikau & Volz, 2021). Additionally, a study shows that government investments in human capital and renewable energy contribute to a profitable green economy through advancements in labor and technology, albeit with varying impacts across nations (Feng et al., 2022)—financial performance bridges between economic development and green finance. Green investment contributes to enhancing financial performance through the advancement of green energy.

The banks ' green finance and financial performance call for emerging research issues. The relationship between green banking and banks' environmental performance is mediated by green financing (Zhang et al., 2022). However, this study neglects the linkage between Environmental and Social Risk Management (ESRM) and bank performance. There is a positive relationship between green banking practices and the financial performance of banks (Hossain et al., 2020). Investing in green sectors that mitigate the adverse effects of business activities on air quality, natural resources, and biodiversity enhances corporate reputation and supports sustainable financial performance (Banani & Sunarko, 2022). Green investment significantly impacts banks' environmental performance (Ngwenya & Simatele, 2020). Despite the opposite correlation between social stability and financial performance, the limited sample size of banks across 21 countries and the lack of consideration for banking operations' typical stability restricts the generalizability of these findings (Liu et al., 2021). Banks' green performance is connected to environmental performance (Taneja & Özen, 2023). Firm performance is assessed using financial and productivity metrics, yet these indicators are insufficient for sustainable performance (Tangen, 2004). A rapid and transformative change toward sustainability requires a financial system that serves as the primary funding source for this transition (Esposito et al., 2022). Standardized credit risk assessment is particularly vital for banking sectors in developed economies, especially for banks with portfolios heavily dependent on externally rated exposures. On the other hand, smaller and transitioning economies have historically encountered externally rated exposures later than their developed counterparts (Milojević & Redžepagić, 2020). Financial performance helps to maintain the sustainability of the development and developing economy. Effective management of environmental and social exposures contributes to enhancing financial performance.

Risk management challenges in the banking sectors impact bank performance and influence national economic growth and business development. Green banking practices have improved environmental performance by reducing negative environmental impacts from routine operations, such as minimizing paper usage and reducing energy consumption, fuel usage, and emissions (Shaumya & Arulrajah, 2017). Yang et al. (2020) highlight the relationship between environmental outcomes and the financial system. Green regulations moderate and strengthen the connection between green financing and investments in renewable energy (Li et al., 2022). GF is a crucial intermediary linking corporate social responsibility with environmental performance, demonstrating a notable linkage between GF and environmental performance (Dai et al., 2022). Additionally, a meaningful relationship exists between bank performance and risk management practices (Adeusi et al., 2014). Strengthening capital and risk management practices further incentivizes banks to ensure financial steadiness (Milojević & Redžepagić, 2020). Banks engage in risk management to mitigate potential adverse effects on their performance.

Encouraging green finance within the banking sector incentivizes businesses to opt for eco-friendly loans. Yan and Gong (2024) find that while green lending and investments enhance credit risk profiles, associated risks can influence their profitability. Xi et al. (2021) argue that GF positively influences green performance by protecting and restoring ecosystems. Consistent with prior studies, a notable negative correlation exists between risk and profitability (measured by ROA and ROE), aligning with findings from (Kwan & Eisenbeis, 1997). Shaumya and Arulrajah (2017) find that green banking practices alleviate adverse environmental effects, which, in turn, influence financial performance. Stock prices also reflect these financial risks (Husna & Satria, 2019). A proposed dividend increase is anticipated to positively affect stock prices, significantly influencing the firm's overall value (Crane et al., 2016). Although beneficial to multiple stakeholders, environmentally friendly finance raises concerns regarding the long-term sustainability of banking operations due to not handling green credit effectively, as it affects both credit risk and profitability. Purposely, this study investigates the impact of GF on ESRM and the impact of ESRM on profitability and non-performing loans. Therefore, this study considers the following hypotheses.

H_1: GF influences significantly ESRM
H_2: ESRM has a significant impact on return on asset (ROA)
H_3: ESRM has a significant impact on return on equity (ROE)
H_4: ESRM has a significant impact on the expenditure-income ratio (EIR)
H_5: ESRM influences significantly on non-performing loans (NPL)

The conceptual framework of this study is presented in Figure 1 below.

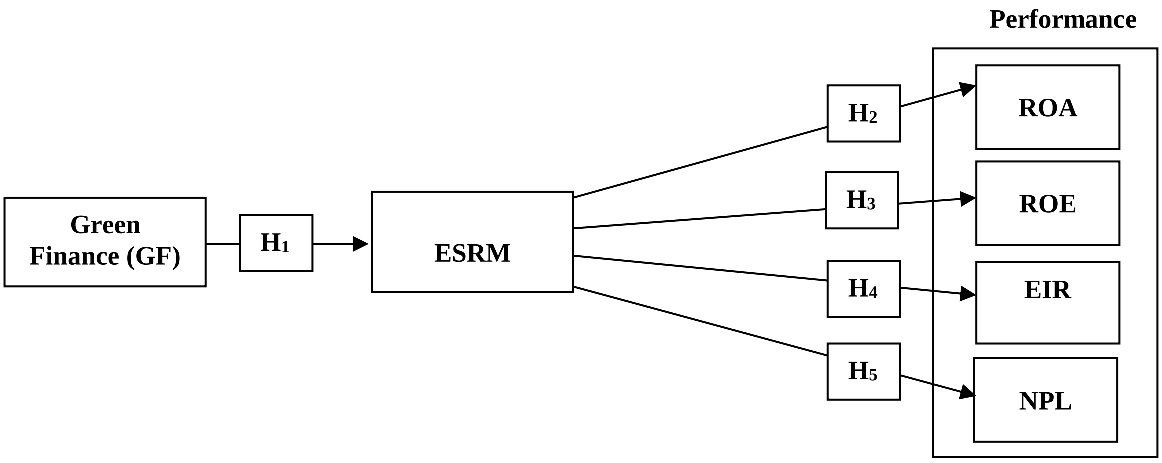

Figure 1. Conceptual Framework and Hypotheses

MATERIALS AND METHODS

The selection of samples for this research was based on data obtained from the annual report of Bangladesh Bank. The dataset covers various categories of banks, including state-owned commercial banks (SCBs), specialized banks (SBs), private commercial banks (PCBs), and foreign commercial banks (FCBs). The study employs balanced panel data, covering four different categories of banks: six SCBs, three SBs, forty-three PCBs, and nine FCBs. The research spans nine (9) years, from 2015 to 2023. The study categorizes its variables into exogenous (independent) and endogenous (dependent) variables. The independent variables are comprised of alternative energy (AE), efficient energy (EE), renewable energy (RE), wastage management (WM), recycling and manufacturing of recyclable goods (RMRG), green industry and establishment (GIE), environmentally friendly brick production (EFBP), and green other factor investment (GOFI). On the other hand, the dependent variables consist of ROA, ROE, EIR, and NPL. Moreover, ESRM is a dependent variable when GF is the independent variable, and ESRM is an independent variable when the performance variables are dependent. These classifications aim to examine the impact of green banking initiatives on ESRM as well as to investigate the impact of ESRM on performance. A detailed overview of such variables is presented in Table 1.

Table 1. Variable Clarification

Var.	Sectors of green investment	Explanation
	RE	Renewable energy harnesses solar, wind, and hydropower to engender sustainable electricity. As crucial contributors to economic development, these energy sources significantly mitigate environmental issues and promote sustainability (Shinwari et al., 2022).
	EE	Efficient energy enhances energy efficiency to lessen waste, support sustainability, and boost output. Energy efficiency involves achieving an identical output level while consuming less energy (Dunlop, 2022).
	AE	In contemporary society, energy improvement increasingly emphasizes alternative sources, strongly focusing on solar and wind energy (Baitanayeva et al., 2020).

GF	WM	Waste management involves the systematic processes of gathering, moving, and removing waste materials to reduce waste through proper handling and disposal to ensure environmental safety and cleanliness (Panchal et al., 2021).
	RMRG	Recycling involves collecting packaging waste and converting it into new items by reprocessing the materials, which helps reduce the need for raw resources and minimizes waste by reusing materials to create different products (Filyaw, 2022).
	GIE	The green industry encompasses more than just environmentally friendly industrial growth; it includes adopting comprehensive, sustainable, and optimized industrial systems that uphold efficiency and effectiveness in the long term (Aryani Siregar et al., 2020).
	EFBP	Eco-bricks provide supplementary advantages, including enhanced thermal and sound insulation, increased durability, and excellent recyclability, making them an environmentally friendly option with long-lasting benefits. (Jha & Kewate, 2024)
	GOFI	This sector encompasses manufacturing, factory safety, and other environmentally friendly investments. Ensuring safety in production also requires implementing both technological and managerial approaches (Pačaiová et al., 2024).
Profitability	ROA	Return on Assets (ROA) is often used to measure the rate of return on total assets. Return on Assets (ROA) measures a company's efficiency in generating profit from the assets it utilizes or invests in over a given period (Indriani et al., 2022).
	ROE	ROE can provide a general idea of a company's financial performance (Fauzi & Nurasik, 2023).
	EIR	EIR is the proportion of expenditure and income. Expenditure and income budget include revenue and expenditure.
Non performing loan	NPL	A loan is considered non-performing when payments are overdue by 90 days or more, indicating a higher risk of default within the following years. NPLs are a critical indicator of loan risk, highlighting the chance of repayment failure (Alnabulsi et al., 2023).

Model Selection and Methods

A unit root test validated the econometric analysis to ensure the data were stationary or non-stationary. This study employed several statistical methods to analyze the relationship between GF, ESRM, and performance. Panel Ordinary Least Squares (POLS) were chosen to estimate the overall impact of independent variables across entities and time periods without accounting for specific individual or time-based characteristics. The decision to select POLS was based on the results of collinearity tests, including tolerance levels (TOL) and the variance inflation factor (VIF). Panel Vector Autoregression (PVAR) was used to explore the internal effects of variables on performance dynamics. PLS also serves as a foundational method for more advanced techniques, such as Fixed Effects Models (FEM) or Random Effects Models (REM). The Hausman test and the Redundant Fixed Effect Likelihood LM ratio test results determined the choice of FEM in this study. Quantile regression was utilized to understand how GF influences ESRM and the performance across various data percentiles. Correlation analysis helped assess the relationship between GF, ESRM, and performance. Finally, the study used the Panel Generalized Method of Moments (PGMM) to analyze GF's dynamic and multi-dimensional impact on ESRM performance.

Unit Root Test

The unit root test shows strong evidence against unit roots for all examined indicators. Henry Ntarmah et al. (2019) applied the unit root test to evaluate the stationarity of their variables at both the level and first difference. Their findings suggest that the data for all indicators are not likely to exhibit non-stationary behavior, implying they behave in a stationary way. The equations of the unit root test are as follows-

$$\mathrm{P} = -2\sum_{i=1}^{N} \ln(P_{\ i}) \quad (1) \qquad \mathrm{Z} = \frac{1}{\sqrt{\mathrm{N}}}\sum_{i=1}^{N} (\pi_{\ i}) \quad (2)$$

Where

P_i is the p-value of the unit root test with respect to the i^{th} cross-section.

N is the number of cross-sections in the panel.

$\pi_{\ i}$ is the individual Phillips-Perron test statistic concerning the i^{th} cross-section.

Panel Ordinary Least Squares (POLS)

POLS method for regression is used in our panel data. The independent variables are GF and ESRM, and the dependent variables are performance. Accordingly, the equation for the Panel Ordinary Least Squares regression is-

$$\mathrm{ESRM_t} = \beta_0 + \beta_i \sum \mathrm{GF_{it}} + \varepsilon_{it} \quad (3)$$

$$\mathrm{PI_{it}} = \beta_0 + \beta_1 \mathrm{ESRM}_{\ t} + \varepsilon_{it} \quad (4)$$

Where:

PI: Performance

$\mathrm{PI_{it}}$ and $\mathrm{ESRM_t}$ are the values of the endogenous variables for the i^{th} observation at time t.

GF_{it} is the value of the explanatory variable (GF) for the i^{th} observation at time t.

β_0 is the intercept.

β_i is the coefficient of explanatory variables.

ε_i is the error term.

Quantile Regression

This allows us to observe how GF influences not just the central tendency but also the extremes or other specific quantiles of ESRM that affect performance, thus offering a deeper insight into the variability and distributional aspects of GF on ESRM as well as the ESRM influences on performance. The equations for quantile regression are:

$$\mathrm{Q\tau(ESRM/GF)} = GF'\beta\tau \tag{5}$$
$$\mathrm{Q\tau(PI/ESRM)} = ESRM'\beta\tau \tag{6}$$

Where

$\mathrm{Q\tau(ESRM/GF)}$ defines τ th conditional quantile of the response variable ESRM given the predictors GF.
$\mathrm{Q\tau(ESRM/GF)}$ defines τ th conditional quantile of the response variable ESRM given the predictors PI.
GF' and ESRM' represent the transpose of the predictor vector, respectively.
$\beta\tau$ is the vector of coefficients for the τ^{th} quantile.

Hausman Test

The Hausman (1978) test for panel data is a general specification test, where rejecting the null hypothesis indicates model misspecification rather than endorsing the fixed effects estimator. On the other hand, not rejecting the null suggests that the random effects estimator is efficient (Baltagi, 2024). A spatial Hausman test is recommended to compare fixed and random effects models (Mutl & Pfaffermayr, 2011). This helps determine whether a time-varying covariate is exogenous in the random effects model for panel data (Mainzer, 2018). The test compares estimators from both the random effects (RE) and fixed effects (FE) models. The Hausman test statistic (H) equation is as follows:

$$\mathrm{H} = (\hat{\beta}_{FE} - \hat{\beta}_{RE})' \,[\mathrm{Var}(\hat{\beta}_{FE}) - \mathrm{Var}(\hat{\beta}_{FE})]^{-1}(\hat{\beta}_{FE} - \hat{\beta}_{RE}) \tag{7}$$

Where:

$(\hat{\beta}_{FE})$ is the estimated coefficient for the fixed effects model,
$(\hat{\beta}_{RE})$ is the estimated coefficient for the random effects model,
$\mathrm{Var}(\hat{\beta}_{FE})$ and $\mathrm{Var}(\hat{\beta}_{RE})$ are the variances of the coefficients for the respective models.

Redundant Fixed Effect Likelihood LM Ratio Test

Likelihood ratio tests for fixed model terms are recommended for analyzing linear mixed models with residual maximum likelihood estimation, incorporating Bartlett-type adjustments to the test statistics based on an approximate data decomposition (Welham & Thompson, 1997). Additionally, a redundant fixed effect likelihood test (RFELRT) was performed to confirm the model specification further. The equation of the redundant fixed effect likelihood LM ratio test (REFLRT) is:-

$$\mathrm{RFELRT} = -2(\mathrm{Log}\, L_{restricted}) - \mathrm{Log}\, L_{unrestricted}) \tag{8}$$

Where:

log $L_{\text{restricted}}$ is the log-likelihood from the restricted model (without fixed effects).
log $L_{\text{unrestricted}}$ is the log-likelihood from the unrestricted model (with fixed effects).
RFELRT follows a Chi-square ($\chi 2$) distribution with degrees of freedom equal to the number of restrictions.

Fixed Effect Model

Fixed effects method with time-fixed effects allows us to control for unobserved entity-specific characteristics, focus on within-entity changes, account for time-specific factors, and provide consistent estimates of the relationship between GF & ESRM GF & PI, and PI & ESRM.

$$\mathrm{ESRM_{it}} = \alpha_0 + \mathrm{GF_{it}}\beta + \gamma_{\mathrm{it}} + \varepsilon_{\mathrm{it}} \tag{9}$$
$$\mathrm{PL_{it}} = \alpha_0 + \mathrm{ESRM_{it}}.\beta + \gamma_{\mathrm{it}} + \varepsilon_{\mathrm{it}} \tag{10}$$

Where

$\mathrm{PI_{it}}$ is the dependent variable for individual i at time t.
α_i represents the individual-specific intercept, also known as the fixed effect.
$\mathrm{GF_{it}}$ is a vector of independent variables for individual i at time t.
β is a vector of coefficients representing the effect of independent variables on the dependent variable.
γ_t stands for the time-fixed effects, accounting for time-specific influences.
ε_{it} is the error term for the individual i at time t, representing unobserved factors affecting the dependent variable.

Random Effect Model

Random Effects Model (REM) is commonly used in econometrics and statistics when dealing with panel or hierarchical data structures. The general form of a random effects model can be written as:-

$$\mathrm{ESRM_{\,it}} = \mathrm{B_0} + \mathrm{GF}_{\mathbf{it}}\beta + \mathrm{u_i} + \varepsilon_{\mathrm{it}} \tag{11}$$
$$\mathrm{PI_{it}} = \mathrm{B_0} + \mathrm{ESRM_{it}}\beta + \mathrm{u_i} + \varepsilon_{\mathrm{it}} \tag{12}$$

Where

$\mathrm{RP_{it}}$ $\mathrm{PM_{it}}$, and $\mathrm{SLREAP_{it}}$ are the dependent variables for individual i at time t.
B represents the individual-specific intercept, also known as the fixed-effect.
$\mathrm{GF_{it}}$ is a vector of independent variables for individual i at time t.
β is a vector of coefficients representing the effect of independent variables on the dependent variable.
u_i is the random effect, capturing unobserved heterogeneity specific to individual i (assumed to be normally distributed.
ε_{it} is the idiosyncratic error term.

Panel Generalized Method of Moments

PGMM is more flexible and accounts for potential endogeneity (when the independent variable correlates with the error term). This makes PGMM useful if GF is suspected to be endogenous.

$$ESRM_t = \alpha_0 + \alpha_i \sum GF_{it} + \eta_{it} \quad (13)$$

$$PI_{it} = \gamma_0 + \gamma_1 ESRM_t + e_{it} \quad (14)$$

Where

$\beta_0, \alpha_0, \gamma_0, \beta_i, \alpha_i, \gamma_i$ are the parameters to be estimated

Moment condition

$E[Zi\ (ESRM_i - \alpha_0 - GF_i) = 0$

$E[Zi\ (PI_i - \gamma_0 - ESRM_i) = 0$

Z is the instrument that is correlated with GF and correlated with error terms: ε, η, and e

RESULTS

Correlation Analysis between GF, ESRM, and Performance

In the realm of econometrics, it's customary to address heteroscedasticity by using a natural logarithm transformation to the variables for analysis, as outlined by Charfeddine and Ben Khediri (2016). The data, after logarithm (log10) transformation, were utilized in our analysis. Mean, standard deviations, and the correlation matrix are detailed in Table 2. Furthermore, the Variance Inflation Factors (VIF) falls below 5, while the tolerance (TOL) value exceeds 20%, affirming the absence of multicollinearity issues among our explanatory variables. EE has the largest variability (SD: 11.8) while AE has the lowest variability (SD: 1.10). ESRM has the highest positive correlation (r=0.816) with RE and the lowest positive correlation (r=0.194) with EFBP. Among the independent variables, a positive correlation exists. Table 3 illustrates the correlation between ESRM and performance in which ESRM has the highest positive correlation (r=.710) with ROA and negative correlation (r= -.72) with EIR.

Table 2. Correlation between GF and ESRM along with collinearity result

Var.	MN and SD		Correlation Matrix									Collinearity statistics	
	MN	SD	RE	EE	AE	WM	RMGM	GIE	EFBP	GOFI	ESRM	TOL	VIF
RE	7.95	1.10	1.0									.405	2.47
EE	-1.27	11.8	.606	1.0								.456	2.19
AE	-8.06	10.6	.583	.597	1.0							.439	2.28
WM	2.07	10.8	.556	.430	.456	1.0						.233	4.28
RMRG	1.25	10.1	.447	.357	.370	.724	1.0					.439	2.28
GIE	1.96	11.4	.648	.590	.458	.829	.638	1.0				.201	4.98
EFBP	0.23	11.6	.257	.340	.539	.271	.345	.175	1.0			.585	1.71
GOFI	7.18	4.24	.139	.328	.328	.41	.392	.429	.378	1.0		.642	1.55
ESRM	10.86	1.19	.816	.525	.601	.72	.643	.790	.194	.210	1.00	1.00	1.00

Note: MN means mean; SD stands for standard deviations; TOL and VIF are tolerance and variance influence factor, respectively.

Table 3. Correlation between ESRM and performance

Var.	MN and SD		Correlation matrix				
	MN	SD	ROA	ROE	EIR	NPL	ESRM
ROA	.0003	.019	1.0				
ROE	.003	0.14	.838	1.0			
EIR	.88	0.40	-.96	-.69	1.0		
NPL	11.1	.570	-.09	-.15	-.04	1.0	
ESRM	10.86	1.19	.710	.668	-.72	.440	1.0

Results of Unit Root Test

Table 4 shows the unit root test results of GF, ESRM, and performance. The analysis is based on the second difference, accounting for the individual effects of exogenous variables, and applies the Newey-West automatic bandwidth selection with the Bartlett kernel system. The PP Fisher chi-square test statistics range from 16 to 60.11, with p-values between 0.0000 and 0.015, strongly rejecting the null hypothesis of unit roots. Likewise, the PP Choi Z test statistics range from -6.48 to -2.11, with p-values below 0.05, confirming stationarity across all indicators.

Table 4. Individual unit root process

Indicators	PP Fisher Chi-square	P-value.	PP Choi Z stat	P-value
AE	31.869	0.0000***	-4.733	0.0000***
EE	25.502	0.0013***	-3.270	0.0005***
RE	41.439	0.0000***	-4.629	0.0000***
WM	28.489	0.0004***	-2.814	0.0024***
RMRG	46.227	0.0000***	-4.878	0.0000***
GIE	52.939	0.0000***	-6.229	0.0000***

EFBP	20.974	0.0019***	-2.999	0.0014***
GOFI	33.441	0.0001***	-3.833	0.0001***
ESRM	18.254	0.0194**	-2.429	0.0080***
ROA	51.7830	0.0001***	-5.877	0.0000***
ROE	60.1057	0.0000***	-6.477	0.0000***
EIR	39.3571	0.0000***	-4.664	0.0000***
NPL	30.9200	0.0000***	-3.780	0.0000***

'***' '**' and '*' signify the significance at the 1%, at the 5 % and at the 10% level respectively.

The Effect of GF on ESRM Influencing Performance Based on Mean

POLS has been used to identify the effect of GF on ESRM based on the mean distribution of ESRM and to examine the impact of ESRM on performance-ROA, ROE, EIR, and NPL based on the mean distribution of these dependent variables. Table 5 depicts that the significant factors containing t value greater than ±2.11 at the 5% level of significance and p values p≤ 0.01 or p≤ 0.01 or p<≤0.10 at the 0.01 or at the 0.05 or the 0.10 level have ensured those findings. Accordingly, RE, AE, RMRG, and GIE have a significant positive impact on ESRM. Moreover, ESRM significantly impacts ROA, ROE, and EIR at the 0.01 level.

Table 5. Impact of GF on ESRM on performance

DV	IV	t-statistic	p-value	IV	DV	t-statistic	p-value
ESRM	RE	3.744	.001***	ESRM	ROA	5.884	.000***
	EE	-1.112	.276		ROE	5.240	.000***
	AE	2.341	.027**		EIR	-6.030	.000***
	WM	.139	.890		NPL	2.853	.007***
	RMRG	2.113	.044**		-	-	-
	GIE	2.167	.039**		-	-	-
	EFBP	-1.329	.195		-	-	-
	GOFI	-1.117	.274		-	-	-

Note: DV stands for the dependent variable, and IV stands for the independent variable.

Conditional effect of GF on ESRM influencing performance

Quantile regression allows for modeling different conditional quantiles of GF and ESRM indicators. Accordingly, in the quartile regression, this section presents the impact of GF on ESRM on performance across the distribution's Q1, Q2, and Q3. Table 6 displays the t-statistic (t>±2.230), which provides the significant impact of GF on ESRM performance. Furthermore, the p-value confirmed that it was a significant finding. As a result, RE positively influences ESRM at the 0.01 level of significance. Furthermore, ESRM as a mediating factor influences ROA, ROE, EIR, and NPL at the 1% significance level.

Table 6. Conditional impact of GF on ESRM having impact on performance

IV	DV	Ist Q		2nd Q		3rd Q	
		t-statistic	p-value	t-statistic	p-value	t-statistic	p-value
AE	ESRM	0.466	0.645	-0.320	0.751	-1.256	0.220
EE		-1.285	0.209	-0.916	0.368	-0.569	0.574
RE		59.378	0.000***	37.799	0.000***	36.664	0.000***
WM		-0.026	0.980	-0.415	0.682	0.285	0.778
RMRG		1.093	0.284	0.529	0.601	0.459	0.650
GIE		-0.232	0.819	0.662	0.514	0.415	0.681
EFBP		0.562	0.579	0.241	0.811	-0.199	0.848
GOFI		-0.152	0.880	0.166	0.870	0.717	0.480
	ROA	-1.469	0.151	1.167	0.251	3.222	0.003***
	ROE	3.772	0.001***	2.230	0.033**	8.853	0.000***
	EIR	6.010	0.000***	6.628	0.000***	3.772	0.001***
	NPL	39.331	0.000***	34.345	0.000***	26.857	0.000***

'***' '**' and '*' signify the significance at the 1%, at the 5 % and at the 10% level respectively.

Result of the Hausman Test and Redundant Fixed Effect Likelihood LM Ratio Test

Table 7 illustrates the results of the Hausman test in that Chi-Square statistics in the corresponding p-value specifies the selection of REM because, at the 1% level, this study rejects the alternative hypothesis. Besides, a redundant fixed effect likelihood LM ratio test (RFELT) was done to confirm the model specification. Table 8 presents the results of RFELRT where the p-values of all dependent variables are 0.000, which means FEM is appropriate.

Table 7. Hausman test result of ESRM and performance

Variables	Chi-square statistics	p-value	Model specification
ESRM	2.724	0.951	Random Effect Model (REM)
ROA	0.569	0.451	REM
ROE	0.112	0.738	REM
EIR	1.315	0.252	REM

Variables	Chi-square statistics	p-value	Model specification
NPL	0.036	0.849	**REM**

'***' '**' and '*' signify the significance at the 1%, at the 5 % and at the 10% level respectively.

Table 8. Redundant fixed effect likelihood ratio test result

Variables	t-Statistic	p-value	Model specification
ESRM	70.626	0.000***	**FEM**
ROA	76.060	0.000***	**FEM**
ROE	40.889	0.000***	**FEM**
EIR	79.851	0.000***	**FEM**
NPL	133.199	0.000***	**FEM**

'***' '**' and '*' signify the significance at the 1%, at the 5 % and at the 10% level respectively.

Fixed and Random Effect of GF on ESRM Influencing ESRM

After the Hausman test and RFELT, the effect of GF on ESRM that influences the performance of banks is determined. Table 9 shows the findings of the fixed and random effects of GF on ESRM performance. Here, the researcher finds that the significant factors contain a t-value greater than ±2.00 at the 10 % significance level, more significant than ±2.17 at the 5 % significance level, and greater than ±2.96 at the 1 % significance level. Finally, p-value p≤ 0.01 or p≤ 0.01 or p<≤0.10 at the 0.01 or the 0.05 or the 0.10 level have ensured those findings. Accordingly, EE has a significant fixed effect at the 0.10 level, RMRG at the 0.05 level, and EFBP at the 0.1 level on ESRM. Besides, RE and RMGM have random effects on ESRM at .01 and .10 levels. Moreover, ESRM has a significant random effect on profitability and non-performing loan-ROA, ROE EIR, and NPL at 0.010 level.

Table 9. Fixed and random effect of GF on ESRM influencing performance

DV	IV	FEM		REM		IV	DV	FEM		REM	
		t-statistic	p-value	t-statistic	p-value			t-statistic	p-value	t-statistic	p-value
ESRM	RE	0.321	0.752	2.647	.030**	**ESRM**	ROA	-0.891	0.382	8.770	0.000***
	EE	-2.960	.009***	-.819	.437		ROE	-0.651	0.522	9.331	0.000***
	AE	0.989	0.337	1.543	.161		EIR	-0.621	0.540	-8.920	0.000***
	WM	-1.033	0.317	.143	.590		NPL	1.247	0.225	7.333	0.000***
	RMRG	2.175	0.045**	2.235	.056		-	-	-		
	GIE	1.690	0.110	1.434	.190		-	-	-		
	EFBP	-2.002	0.0625*	-1.024	.336		-	-	-		
	GOFI	-0.684	0.504	-1.105	.301		-	-	-		

'***' '**' and '*' signify the significance at the 1%, at the 5 %, and at the 10% level respectively.

Dynamic Effect of GF on ESRM Influencing Performance

PGMM has been used to determine the dynamic effect of GF on ESRM that influences the performance of banks. Table 10 shows the results of the dynamic effect of GF on ESRM and the dynamic effect of ESRM on performance. Here, the researcher finds that the significant factors contain a t-value greater than ±10.00 at the 1 % significance level. Finally, p-value p≤ 0.01 at the 0.01 has ensured those findings. Accordingly, AE, RE, and GOFI significantly affect ESRM at the 0.010 level. Moreover, ESRM significantly affects ROA, ROE, EIR, and NPL at the 0.01 level.

Table 10. Dynamic effect of GF on ESRM on performance

DV	IV	t-statistic	p-value	IV	DV	t-statistic	p-value
ESRM	**RE**	74.699	0.000***	**ESRM**	**ROA**	11.173	0.000***
	EE	-0.640	0.527		**ROE**	2.997	0.005***
	AE	4.428	0.001***		**EIR**	3.159	0.003***
	WM	-1.167	0.251		**NPL**	61.070	0.000***
	RMRG	0.687	0.497		-	-	-
	GIE	1.045	0.303		-	-	-
	EFBP	0.119	0.906		-	-	-
	GOFI	10.393	0.000***		-	-	-

'***' '**' and '*' signify the significance at the 1%, at the 5 %, and at the 10% level respectively.

Discussion of GF, ESRM, and Performance

The findings of this study align closely with the evolving discourse in the literature regarding the ESRM frameworks within financial institutions and their broader implications for sustainability, economic performance, and risk management. The POLS method, quantile method, EFM, and PGMM approaches collectively elucidate the nuanced relationships between ESRM and various financial indicators. Zhang et al. (2022) emphasize the positive effects of environmentally friendly schemes within the banking sector, demonstrating significant improvements in environmental performance and green financing development. The findings in this study echo these insights by revealing ESRM's significantly positive impact on variables such as ROA, ROE, and EIR.

The quantile method findings, which show ESRM as a mediator influencing variables like ROA, ROE, and other performance indicators across multiple quantiles, align with the results (Mavlutova et al., 2023). Their cluster analysis revealed a positive correlation between economic performance and overall ESG (Environmental, Social, and Governance) risk across European OECD nations. This underscores the growing recognition of ESG factors as pivotal drivers of financial performance. Yang et al. (2020) identified the adverse effects of financial instability on carbon emissions in developing economies, highlighting the intricate relationship between financial systems and environmental outcomes. Similarly, this study demonstrates ESRM's role in mitigating adverse impacts on variables like ANPL and NPLTLR while positively influencing green investment practices. This suggests that robust ESRM practices can address systemic risks, improve financial stability, and contribute to environmental sustainability goals.

Qian and Yu (2024) find that GF policies positively impact ESG performance, highlighting the broader societal and environmental benefits of aligning the financial system. This resonates with the study’s EFM method findings, which indicate that variables such as RMGM and EFBP significantly and positively influence ESRM, leading to enhanced performance in areas like TA and sustainable investment programs.

Xi et al. (2021) GF schemes safeguard ecosystems and support RE implementation, which directly correlates with ESRM. These outcomes emphasize the transformative potential of ESRM in fostering RE adoption and ecological preservation, thereby advancing financial and environmental objectives. Ngwenya and Simatele (2020) highlight the significant influence of green lending on banks' environmental performance. This theme parallels this study's findings on ESRM's role in driving positive outcomes in sustainable lending programs. The lagged variable impacts identified in the PVAR method, such as the influence of GF on other performance metrics, underscore the dynamic connection between green finance and financial performance. Interestingly, Guan et al. (2017) point out the dual role of carbon intensity loans (CIL) in meeting societal emission reduction goals while elevating credit risk. This aligns with the study's findings that ESRM negatively affects variables like NPL.

Additionally, the PGMM results demonstrate that ESRM exerts significant dynamic effects on a wide range of performance indicators, ROA, and ROE, substantiating its key role in integrating sustainability into financial systems.

CONCLUSIONS

This study aims to examine ESRM's impact on banks' performance. The POLS method reveals that ESRM has a significantly positive impact on variables such as TA, DA, SIA, SID, ROA, ROE, and NPL, while it negatively affects EIR. In the quantile method, RE shows a positive influence on ESRM. Additionally, ESRM acts as a mediator, significantly influencing ROA, ROE, EIR, and NPL. The EFM and REM indicate that EE, RE, RMGM, and EFBP have significant effects on ESRM that have a significant random effect on performance.

The PGMM method shows that AE, RE, and GOFI have significant multi-effects on ESRM. Furthermore, ESRM exerts a significant dynamic effect on ROA, ROE, EIR, and NPL.

The findings significantly contribute to the theoretical understanding of ESRM. The positive impact of ESRM on variables such as NPL challenges existing frameworks by suggesting that effective ESRM practices can drive financial performance and steadiness. Furthermore, the mediating role of ESRM across different quartiles supports the idea that it might influence financial outcomes differently across various levels of company performance. The negative connection with EIR and positive connection with NPL add a nuanced layer to understanding how ESRM can impact financial risk, offering new avenues for future research on the link between sustainability practices and risk management.

The results underline the importance of integrating ESRM practices into organizational strategies for managers. The significant positive effects on financial indicators like ROA, ROE, and NPL imply that improving ESRM can lead to better profitability and risk management. The adverse effects of EIR suggest that overemphasis on certain ESRM practices may result in financial efficiencies. However, managers should aim for a balanced approach, leveraging ESRM to enhance long-term value while mitigating potential drawbacks.

Companies should consider incorporating ESRM practices to force performance and sustainability. The mediation effects emphasize that ESRM influences key financial outcomes, such as ROE and ROA, emphasizing its role in shaping long-term organizational success. The identified relationships between ESRM and financial indicators indicate that implementing robust ESRM strategies could enhance financial stability and operational efficiency, particularly in performance matrix- profitability and NPL.

This study focuses on some restrictions that must be addressed in future studies. First, the study relies heavily on secondary data, which may not entirely confine the complexity of GF and its effects on future research performance. It could promote primary data collection through surveys or interviews to add deeper insights. Second, the study is limited by the data's time frame and geographical span and suffers from long-term impacts. Future studies should investigate the extensive effects of GF over longer periods and across different regions to assess its global applicability. Furthermore, the study focuses primarily on financial institutions, leaving out other industries that could also benefit from the GF system. Future research should inspect the impact of GF on sectors beyond banking.

Author Contribution: Conceptualization, M.J.A.S., AHM.Z.H.; Methodology, M.J.A.S., AHM.Z.H., S.P., H.B. and R.F.; Software, M.J.A.S., Validation, M.J.A.S., AHM.Z.H., S.P., H.B. and R.F.; Formal analysis, M.J.A.S., AHM.Z.H., S.P., H.B., and R.F.; Investigation, M.J.A.S., AHM.Z.H., S.P., H.B. and R.F.; Data Curation, M.J.A.S., AHM.Z.H., S.P., H.B. and R.F.; Writing-Original draft preparation, M.J.A.S., AHM.Z.H., S.P., H.B. and R.F.; Writing-Review and Editing, M.J.A.S., AHM.Z.H., S.P., H.B. and R.F.; Supervision, M.J.A.S. and AHM.Z.H., Funding acquisition, M.J.A.S., AHM.Z.H., S.P., H.B. and R.F. Authors have read and agreed with the published version of the manuscript.

Institutional Review Board Statement: Ethical review and approval were waived for this study because the researcher does not involve vulnerable groups or sensitive issues.

Funding: Authors received no funding for this research.

Acknowledgment: Not Applicable.

Data Availability Statement: Data presented in this study are available at the request of corresponding authors, and data are not publicly available due to restrictions.
Conflict of interest: Authors declare no conflict of interest.

REFERENCES

Abuatwan, N. (2023). The impact of Green Finance on the sustainability performance of the banking sector in Palestine: The moderating role of female presence. *Economies*, *11*(10), 247. https://doi.org/10.3390/economies11100247

Alnabulsi, K., Kozarević, E., & Hakimi, A. (2023). Non-performing loans as a driver of banking distress: A systematic literature review. *Commodities*, *2*(2), 111–130. https://doi.org/10.3390/commodities2020007

Aryani Siregar, S., Napitupulu, H., & Ginting, R. (2020). Identification of factors affecting a green industry: A literature review. *IOP Conference Series: Materials Science and Engineering*, *801*(1), 012097. https://doi.org/10.1088/1757-899x/801/1/012097

Adeusi, S. O., Akeke, N. I., Adebisi, O. S., & Oladunjoye, O. (2014). Risk management and financial performance of banks in Nigeria. *Risk Management*, *6*(31), 123-129. https://doi.org/10.9790/487x-1465256

Baitanayeva, B., Yerezhepova, A., Nurmanova, B., & Andabayeva, G. (2020). Current state and problems of alternative energy development in the world. *E3S Web of Conferences*, *159*, 07004. https://doi.org/10.1051/e3sconf/202015907004

Baltagi, B. H. (2024). Hausman's specification test for panel data: Practical tips. *Advances in Econometrics*, 46, 13–24. https://doi.org/10.1108/s0731-905320240000046002

Banani, A., & Sunarko, B. (2022). Nexus between Green Finance, Creativity, Energy Accounting and financial performance: Banks Sustainability Analysis from developing country. *International Journal of Energy Economics and Policy*, *12*(6), 447–455. https://doi.org/10.32479/ijeep.13806

Charfeddine, L., & Ben Khediri, K. (2016). Financial Development and Environmental Quality in UAE: Cointegration with structural breaks. *Renewable and Sustainable Energy Reviews*, *55*, 1322–1335. https://doi.org/10.1016/j.rser.2015.07.059

Chi, Y., & Yang, Y. (2023). Green Finance and green transition by enterprises: An exploration of market-oriented governance mechanisms. *Borsa Istanbul Review*, *23*(3), 628–646. https://doi.org/10.1016/j.bir.2023.01.003

Crane, A. D., Michenaud, S., & Weston, J. P. (2016). The effect of institutional ownership on Payout policy: Evidence from index thresholds. *Review of Financial Studies*, *29*(6), 1377–1408. https://doi.org/10.1093/rfs/hhw012

Dai, X., Siddik, A. B., & Tian, H. (2022). Corporate Social Responsibility, Green Finance and Environmental Performance: Does green innovation matter? *Sustainability*, *14*(20), 13607. https://doi.org/10.3390/su142013607

Dikau, S., & Volz, U. (2021). Central Bank mandates, sustainability objectives and the promotion of Green Finance. *Ecological Economics*, *184*, 107022. https://doi.org/10.1016/j.ecolecon.2021.107022

Dunlop, T. (2022). Energy efficiency: The evolution of a motherhood concept. *Social Studies of Science*, *52*(5), 710–732. https://doi.org/10.1177/03063127221096171

Esposito, L., Mastromatteo, G., & Molocchi, A. (2022). Green mortgages, EU Taxonomy and Environment Risk Weigthed Assets: A key link for the transition. https://doi.org/10.2139/ssrn.4021389

Fan, M., Mo, Z., Fu, H., Wu, T.-H., Chen, Z., & He, Y. (2024). Does climate policy uncertainty matter for bank value? *Economic Change and Restructuring*, *57*(2). https://doi.org/10.1007/s10644-024-09651-8

Fauzi, S. A., & Nurasik, N. (2023). *Influence of Total Asset Turnover, Net Profit Margin, Return on Investment, Equity Multiplier and Return on Equity on Company Value*. https://doi.org/10.21070/ups.3651

Feng, H., Liu, Z., Wu, J., Iqbal, W., Ahmad, W., & Marie, M. (2022). Nexus between government spending's and green economic performance: role of green finance and structure effect. *Environmental Technology & Innovation*, *27*, 102461. https://doi.org/10.1016/j.eti.2022.102461

Filyaw, M. H. (2022). Recycled plastics in food contact. *Global Legislation for Food Contact Materials*, 193–202. https://doi.org/10.1016/b978-0-12-821181-6.00010-7

Guan, R., Zheng, H., Hu, J., Fang, Q., & Ren, R. (2017). The higher carbon intensity of loans, the higher non-performing loan ratio: The case of china. *Sustainability*, *9*(4), 667. https://doi.org/10.3390/su9040667

Hausman, J. A. (1978). Specification tests in Econometrics. *Econometrica*, *46*(6), 1251. https://doi.org/10.2307/1913827

Henry Ntarmah, A., Kong, Y., & Kobina Gyan, M. (2019). Banking System Stability and economic sustainability: A panel data analysis of the effect of banking system stability on sustainability of some selected developing countries. *Quantitative Finance and Economics*, *3*(4), 709–738. https://doi.org/10.3934/qfe.2019.4.709

Hossain, M. A., Rahman, M. M., Hossain, M. S., & Karim, M. R. (2020). The effects of green banking practices on financial performance of listed banking companies in Bangladesh. *Canadian Journal of Business and Information Studies*, *2*(6), 120-128. https://doi.org/10.34104/cjbis.020.01200128

Hasan, S. M., Islam, K. M. A., Tawfiq, T. T., & Saha, P. (2025). Triple pillars of sustainable finance: the role of green finance, CSR, and digitalization on bank performance in Bangladesh. *Banks and Bank Systems, 20*(1), 38-50. http://dx.doi.org/10.21511/bbs.20(1).2025.04

Husna, A., & Satria, I. (2019). Effects of return on asset, debt to asset ratio, current ratio, firm size, and dividend payout ratio on firm value. *International Journal of Economics and Financial Issues*, *9*(5), 50–54. https://doi.org/10.32479/ijefi.8595

Jha, A. K., & Kewate, S. P. (2024). Manufacturing of eco bricks: A sustainable solution for construction. *International Conference on Innovative Product Design and Intelligent Manufacturing Systems, 66(1)*, 28. https://doi.org/10.3390/engproc2024066028

Kwan, S., & Eisenbeis, R. A. (1997). Bank Risk, capitalization and inefficiency. https://doi.org/10.2139/ssrn.1188

Li, Z., Kuo, T. H., Siao-Yun, W., & Vinh, L. T. (2022). Role of green finance, volatility and risk in promoting the investments in Renewable Energy Resources in the post-covid-19. *Resources Policy*, *76*, 102563. https://doi.org/10.1016/j.resourpol.2022.102563

Liu, Z., Tang, Y. M., Chau, K. Y., Chien, F., Iqbal, W., & Sadiq, M. (2021). Incorporating strategic petroleum reserve and welfare losses: a way forward for the policy development of crude oil resources in South Asia. *Resources Policy*, *74*, 102309. https://doi.org/10.1016/j.resourpol.2021.102309

Mainzer, R. (2018). The effect of a preliminary Hausman test on confidence intervals. *Bulletin of the Australian Mathematical Society*, *98*(3), 518–519. https://doi.org/10.1017/s0004972718000655

Mavlutova, I., Spilbergs, A., Verdenhofs, A., Kuzmina, J., Arefjevs, I., & Natrins, A. (2023). The role of Green Finance in fostering the sustainability of the economy and renewable energy supply: Recent issues and challenges. *Energies*, *16*(23), 7712. https://doi.org/10.3390/en16237712

Milojević, N., & Redžepagić, S. (2020). Current trends and future progress in the banking risk and Capital Management. *Economic Analysis*, *53*(2), 79–94. https://doi.org/10.28934/ea.20.53.2.pp79-94

Mutl, J., & Pfaffermayr, M. (2011). The hausman test in a cliff and Ord Panel model. *The Econometrics Journal*, *14*(1), 48–76. https://doi.org/10.1111/j.1368-423x.2010.00325.x

Ngwenya, N., & Simatele, M. D. (2020). The emergence of green bonds as an integral component of Climate Finance in South Africa. *South African Journal of Science*, *116*(1/2). https://doi.org/10.17159/sajs.2020/6522

Pačaiová, H., Turisová, R., Glatz, J., & Onofrejová, D. (2024). *Sustainability Assessment of Machinery Safety in a Manufacturing Organisation – Supporting Machinery Safety Decision Making with AHP and CART Methods*. https://doi.org/10.20944/preprints202403.0868.v1

Panchal, R., Singh, A., & Diwan, H. (2021). Does circular economy performance lead to sustainable development? – A systematic literature review. *Journal of Environmental Management*, *293*, 112811. https://doi.org/10.1016/j.jenvman.2021.112811

Park, H., & Kim, J. D. (2020). Transition towards green banking: role of financial regulators and financial institutions. *Asian Journal of Sustainability and Social Responsibility*, *5*(1), 1-25. https://doi.org/10.1186/s41180-020-00034-3

Poyser, A., & Daugaard, D. (2022). Indigenous Sustainable Finance as a research field: A systematic literature review on indigenizing ESG, Sustainability and Indigenous Community Practices. https://doi.org/10.2139/ssrn.4130710

Indriani, Y. P., Erfandi, E., Murdianingsih, D., & Setiani, T. Y. (2022). Analysis of the Effect of Asset Growth and Total Asset Turnover (Tattoo) on Return on Asset (ROA) with Capital Structure as an Intervening Variable (Case Study on Kpri Dwija Karya Bantarbolang 2017-2021). *Return: Study of Management, Economic and Business*, *1*(4), 176-182. https://doi.org/10.57096/return.v1i4.60

Qian, S., & Yu, W. (2024). Green finance and environmental, social, and governance performance. *International Review of Economics & Finance*, *89*, 1185–1202. https://doi.org/10.1016/j.iref.2023.08.017

Shaumya, K., & Arulrajah, A. (2017). The impact of green banking practices on bank's environmental performance: Evidence from Sri Lanka. *Journal of Finance and Bank Management*, *5*(1), 77-90. https://doi.org/10.15640/jfbm.v5n1a7

Shinwari, R., Yangjie, W., Payab, A. H., Kubiczek, J., & Dördüncü, H. (2022). What drives investment in renewable energy resources? evaluating the role of Natural Resources Volatility and Economic Performance for China. *Resources Policy*, *77*, 102712. https://doi.org/10.1016/j.resourpol.2022.102712

Siddikee, M. J. A., Haq, A. Z., Parvin, S., Ahammed, M. M. U., & Zabin, S. (2024). Effects of green finance on non-performing loan of banks: evidence from Bangladesh. *Bangladesh Journal of Multidisciplinary Scientific Research*, *9*(6), 47–57. https://doi.org/10.46281/bjmsr.v9i6.2263

Taneja, S., & Özen, E. (2023). To analyse the relationship between Bank's Green Financing and Environmental Performance. *International Journal of Electronic Finance*, *12*(2), 163. https://doi.org/10.1504/ijef.2023.129919

Tangen, S. (2004). Performance measurement: From philosophy to practice. *International Journal of Productivity and Performance Management*, *53*(8), 726–737. https://doi.org/10.1108/17410400410569134

Welham, S. J., & Thompson, R. (1997). Likelihood ratio tests for fixed model terms using residual maximum likelihood. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, *59*(3), 701–714. https://doi.org/10.1111/1467-9868.00092

Xi, B., Wang, Y., & Yang, M. (2021). Green Credit, green reputation, and corporate financial performance: Evidence from China. *Environmental Science and Pollution Research*, *29*(2), 2401–2419. https://doi.org/10.1007/s11356-021-15646-z

Yan, M., & Gong, X. (2024). Impact of green credit on Green Finance and corporate emissions reduction. *Finance Research Letters*, *60*, 104900. https://doi.org/10.1016/j.frl.2023.104900

Yang, B., Ali, M., Nazir, M. R., Ullah, W., & Qayyum, M. (2020). Financial instability and CO2 emissions: Cross-country evidence. *Air Quality, Atmosphere & Health*, *13*(4), 459–468. https://doi.org/10.1007/s11869-020-00809-7

Yu, C.-H., Wu, X., Zhang, D., Chen, S., & Zhao, J. (2021). Demand for green finance: Resolving financing constraints on green innovation in China. *Energy Policy*, *153*, 112255. https://doi.org/10.1016/j.enpol.2021.112255

Zhang, X., Wang, Z., Zhong, X., Yang, S., & Siddik, A. B. (2022). Do green banking activities improve the banks' environmental performance? the mediating effect of Green Financing. *Sustainability*, *14*(2), 989. https://doi.org/10.3390/su14020989

Zheng, G.-W., Siddik, A. B., Masukujjaman, M., & Fatema, N. (2021). Factors affecting the sustainability performance of financial institutions in Bangladesh: The role of green finance. *Sustainability*, *13*(18), 10165. https://doi.org/10.3390/su131810165

Publisher's Note: CRIBFB stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.