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EFFECTS OF GREEN FINANCE ON NON PERFORMING LOAN OF BANKS: EVIDENCE FROM BANGLADESH

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ABSTRACT

The banking sector in Bangladesh has been suffering from a high level of non-performing loans (NPLs). In recent years, incorporating green finance (GF) practices within banking institutions has received considerable attention as a potential solution to improve their loan performance. However, despite the extension of GF practices, there have been very few studies on the impact of GF on NPL and the relationship between GF and NPL in Bangladesh. This study, therefore, seeks to examine the effects of bank's green finance schemes on their loan performance. This quantitative study employs the panel data of the banks from 2015 to 2023 and focuses on variables related to GF and NPL to serve this objective. Data validity was justified using the unit roots and collinearity tests, such as variance influence factor and tolerance level. Accordingly, this study employs the panel least square (PLS), panel ordinary least square (POLS) and fixed effect model (FEM), and quantile regression to examine the impact between these sets of variables. The correlation between GF schemes and NPL has been determined. The study reveals that GF has significant effects on NPL since p values for the significant green finance variables are less than 0.10 ($P \leq .10$) at the 0.10 level, less than 0.05 ($p \leq 0.05$) at the 0 .05 level and less than 0.01 ($p \leq 0.01$) at the 0.01 level. The results of this study suggest that taking the GF scheme into the banking investment would reduce NPLs and help design the policymaking of the government, banks, and other stakeholders.

INTRODUCTION

GF is a sustainable financial practice aimed at promoting environmentally friendly investments. In Bangladesh, it has emerged as a vital device for addressing environmental challenges while fostering economic growth. This study investigates the potential link between GF schemes and the diminution of NPLs, highlighting improved risk management practices within banks. NPLs are often a direct effect of financial risks, and understanding the connection between GF and NPLs could provide valuable insights into enhancing loan performance and reducing financial risks. Al-Qudah et al. (2022) underline the impact of green industry investments in reducing credit risk and improving banks' financial health through decreased NPL ratios. For example, European nations strive for energy safety while pursuing sustainable development goals by reducing energy consumption and transitioning to renewable resources. Green bonds are essential in financing these initiatives (Mavlutova et al., 2023). Similarly, research by Hui et al. (2024) indicates that the acceptance of green practices positively influences the performance of business operations.

At the intersection of GF and the issue of NPLs lies the challenge of borrowers failing to meet repayment obligations. Financial organizations that fail to account for these risks in their portfolios may face a rise in NPLs, jeopardizing their financial performance. Banks can drive sustainable loan improvements by implementing strategic approaches while advancing environmental stewardship. Given this perspective, the present study aims to identify the effects of green project investments on banks' NPLs. Purposely, it examines the impact of green finance on annual NPLs, the non-performing loan to total loan ratio (NPLTLR), and the writing-off of bad debt (WBD). Rehman et al. (2021) underscore the

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significant influence of investment decisions on integrating environmentally sustainable banking practices. Green investment impacts NPL proportion, highlighting the connection between environmental sustainability, improved financial performance, and enhanced financial stability, thereby reducing risks in the financial system (Yang et al., 2020).

To achieve these objectives, this study employs Partial Least Squares (PLS) and panel Ordinary Least Squares (OLS) methods to explore the effects of green finance on NPLs based on their mean values. Additionally, quantile regression is utilized to discover the conditional effects, linking endogenous and exogenous variables. The Fixed Effects Model (FEM) is further applied to inspect the specific impacts of green finance on the NPLs of banks.

The arrangement of this article is prepared as follows: It begins with the literature review. Afterward, this article contains facts, materials, and methods, followed by the display of results, discussions, and goes to conclusions.

LITERATURE REVIEW

The recovery of non-performing loans (NPLs) faces diverse challenges. Stijepović (2014) proposes addressing these issues by thoroughly examining borrowers' financial situations and exploring the likelihood of debt restructuring. In addition, Wu (2023) highlights the financial stability of renewable energy investments, noting that stronger performance in this sector can contribute to a decline in NPLs. Rasoulinezhad and Taghizadeh-Hesary (2022) analyze the relationship among Co2 emission, energy efficiency, green energy index, and green investment in the economies that grant green finance.

The link between investment in alternative energy (AE) and the performance of banks, particularly regarding non-performing loans (NPL), highlights the potential for sustainable practices to allay financial risks. For example, Fan et al. (2024) demonstrate that investments in clean and affordable energy promote sustainable development and lessen the risk of default loans by aligning financial support with environmentally responsible initiatives. Similarly, Ozili (2023) argues that banks financing sustainable projects tend to experience lower volatility and improved asset quality, contributing to reduced levels of NPL. While specific studies on the effects of waste management (WM) on NPLs are narrow, existing literature suggests that operational efficiency improvements, including better waste management, can positively impact loan repayment rates and lower financial risks for banks. Bressan (2024) finds that banks involved in waste management and environmental ideas, such as addressing waste generation, can improve their financial health, enhance profitability ratios, and reduce NPL levels.

High levels of NPLs constrain banks' capacity to invest, as they may accept a more cautious approach to lending when faced with a significant proportion of defaulted loans. However, the circular economy positively influences bank performance, with recycling industries contributing to lower default risks (Ghisellini et al., 2016; Krings et al., 2024). This evidence underscores the significance of integrating sustainable and environmentally focused strategies into banking operations to enhance financial stability and performance. Banks engaged in environmentally sustainable investments, such as recycling plans, often experience lower non-performing loan (NPL) rates due to green industries' inherent stability and reliability. Similarly, Song (2021) investigates the effects of green credit on the operational efficiency of banks, providing insights into how green investments support financial stability.

Building on this foundation, this study hypothesizes that transitioning to eco-friendly brick production can mitigate environmental impairment while improving businesses' financial stability. As banks increasingly adopt environmental criteria in their lending practices, green financing in sustainable brick production can lead to lower NPL rates (Islam et al., 2023). Loans linked to green projects consistently confirm lower NPL ratios than traditional loans (Al-Qudah et al., 2022). Furthermore, improved management practices, including robust health and safety protocols, shrink financial distress in firms, thereby decreasing the risk of loan defaults (Gjeçi et al., 2023). A manufacturing sector that prioritizes safety and health promotes economic resilience, minimizing the occurrence of NPLs (Manz, 2019). In the broader context, Arduini and Beck (2024) provide a structural review of NPL trends, while Guan et al. (2017) and Shi et al. (2024) investigate the relationship between carbon-intensive loans and renewable energy investments. Energy preservation, a vital issue for sustainability, has been emphasized since the work of Hu Kao (2007). Addressing solid waste management challenges in developing cities remains critical for financial and environmental sustainability (Lohri et al., 2014). Moreover, using industrial by-products and waste materials in environmentally friendly construction has gained significant attention (Surul et al., 2020). Lastly, Alnabulsi et al. (2023) offer a comprehensive review of the factors influencing NPLs in literature published between 1987 and 2022, offering valuable insights for future research on sustainable banking practices. Purposely, this study examines the impacts of GF on annual NPL, non-performing loan to total loan ratio (NPLTLR), and writing of bad debt (WBD). This study, therefore, considers the following hypotheses.

H_1: Green finance significantly reduces annual non-performing loan (ANPL).

H_2: GF significantly reduces the non-performing loan to total loan ratio (NPLTLR).

H_3: GF significantly reduces written-off bad debt (WBD).

The study's conceptual framework is presented below in Figure 1.

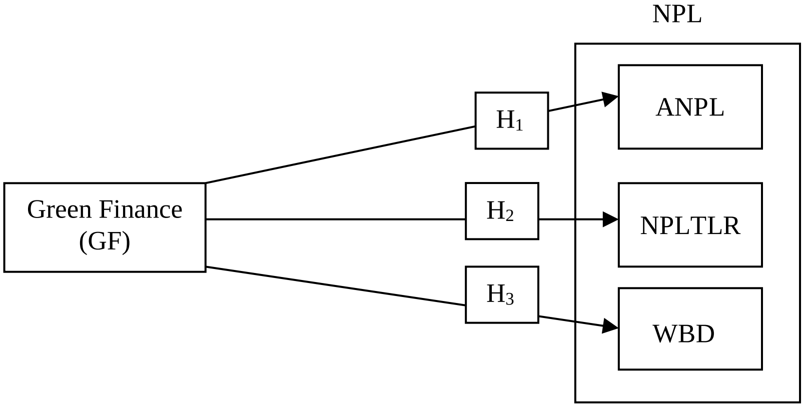

Figure 1. Conceptual Framework

MATERIALS AND METHODS

The samples were selected considering data accessibility and included banks from Bangladesh Bank's annual report. The data cover different categories of banks, including state-owned, specialized, private, and foreign commercial banks. This study uses the balanced panel data set spanning four categories of banks: SCB has 6 banks, SB has 3 banks, PCB has 43 banks, and FCB has 5 banks and focused on 9 years from 2015 to 2023. The variables are considered and divided into exogenous (independent) and endogenous (dependent) categories. The independent variables are 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). Besides, the dependent variables are annual non-performing loan (ANPL), non-performing loan to total loan ratio (NPLTLR), and writing of bad debt (WBD). The raw data value is the investment amount of these independent variables in GF sectors. Table 1 clarifies the variables.

Table 1. Variable Explanation

Var.	Sectors of green investment	Explanation
	RE	Renewable energy utilizes sunlight, wind, and water to breed sustainable power. As essential drivers of economic development, renewable energy sources play a key role in addressing environmental challenges (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 modern times, energy development is marked by a growing weight on alternative energy sources, particularly solar and wind power (Baitanayeva et al., 2020).
	WM	Waste management involves collecting, transporting, and disposing of waste (Panchal et al., 2021).
	RMRG	Recycling entails retrieving packaging materials from waste and transforming them into novel products through reprocessing (Filyaw, 2022).
GF	GIE	Green industry extends beyond eco-friendly industrial development to cover the implementation of integrated, holistic, effective, and efficient industrial systems (Aryani Siregar et al., 2020).
	EFBP	Eco-bricks offer further benefits, such as improved thermal and acoustic insulation, durability, and ease of recycling (Jha & Kewate, 2024)
	GOFI	It includes manufacturing, the factory's safety, and other green investments in the project. Ensuring safety in manufacturing also involves technological and managerial strategies (Pačaiová et al., 2024)
	ANPL	A loan where payments are overdue by 90 days or more, specifying an upper risk of non-payment within a year. NPLs are a key metric of loan risk, reflecting the likelihood of loan repayments failing (Alnabulsi et al., 2023).
NPL	NPLTLR	It measures the loan ratio not compared to the total loan portfolio, indicating credit risk. It reflects the proportion of loans within a bank's portfolio that need to generate income due to delayed repayments or defaults (Alnabulsi et al., 2023).
	WBD	WBD focuses on the portion of accounts receivable deemed uncollectible, which signifies debts unlikely to be recovered. WBD arises due to default failure of loan payment (Alnabulsi et al., 2023).

Model Selection Criterion and Methods

Panel Ordinary Least Squares (POLS) are perfect for estimating the mean effects of independent variables across all entities and periods without explicitly modeling individual or time-specific characteristics. This study selected POLS based on collinearity test results, including tolerance level (TOL) and variance inflation factor (VIF). Panel Least Squares (PLS) were utilized since they leverage the advantages of panel data to improve estimation accuracy, explain dynamic relationships, and provide richer insights. PLS also serves as both a standalone method and a foundation for sophisticated panel data techniques like Fixed Effects Models (FEM) or Random Effects Models (REM). The Fixed Effects Model (FEM) was selected for this study based on the results of the Hausman test and the Redundant Fixed Effect Likelihood Test. Quantile regression was employed to evaluate the impact of GF on NPL at different percentiles of the data distribution. Correlation analysis was conducted to assess the relationship between GF and NPL. Moreover, a cross-sectional dependence test was used to determine whether there was dependence or correlation between cross-sectional units in the panel data. Finally, a unit root test was performed to check the panel data's stationary, ensuring the econometric analysis's validity.

Panel Ordinary Least Squares (POLS)

POLS method for regression is used in our panel data. The exogenous variables are GF, and the endogenous variables are NPL; accordingly, the equation for the Panel Ordinary Least Squares regression is:

$$\mathrm{NPL_i} = \beta_0 + \beta_1 \mathrm{GF_i} + \varepsilon_i \qquad (1)$$

Where:
NPL_i is an endogenous variable for the ith observation.
GF_i is the explanatory variable for the ith observation.
β_0 is the intercept.
β_i is the coefficient of explanatory variables.
ε_i is the error term.

Panel Least Squares (PLS)

The Panel Least Squares (PLS**)** method for regression is used in our panel data, where multiple cross-sections (entities) are identified over time. The independent variable is GF, and the dependent variable is NPL; accordingly, the equation for the Panel Least Squares regression is:

$$\mathrm{NPL_{it}} = \alpha + \beta.\mathrm{GF_{it}} + u_{it} \qquad (2)$$

Where
NPL_{it} is the endogenous variable for entity i at the time t.
GF_{it} is the exogenous variable for entity i at time t.
α is the intercept term that varies across entities (fixed effect) or is constant (pooled OLS).
β is the coefficient of GF, which measures the effect of GF on NPL.
u_{it} is the error term that captures unobserved factors affecting NPL.

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 & NPL; and NPL & ESRM.

$$\mathrm{NPL_{it}} = \alpha_0 + \mathrm{GF_{it}}\beta + \gamma_{it} + \varepsilon_{it} \qquad (3)$$

Where
NPL_{it} is the endogenous variable for individual i at time t.
α_i is the intercept, also known as the fixed effect.
GF_{it} is a vector of exogenous variables for individual i at the time *t*.
β is a vector of coefficient.
γ_t stands for the time-fixed effects, accounting for time-specific influences.
ε_{it} is the error term for individual i at time t.

Quantile Regression

NPL is heterogeneous, allowing us to observe how GF influences not just the central tendency but also the extremes or other specific quantiles of NPL, thus offering a deeper insight into the variability and distributional aspects of NPL. The equation for quantile regression is:

$$\mathrm{Q\tau(NPL/GF)} = GF'\beta\tau \qquad (4)$$

Where
$\mathrm{Q\tau(NPL/GF)}$ defines τ th conditional quantile of the response variable NPL given the predictors GF.
$\beta\tau$ is the vector of coefficients for the τ^{th} quantile

RESULTS

This study uses the statistical software- Eview-12 for data analysis**.** Econometric models have been used to serve the research objective, and they are detailed in the materials and methods section. This section presents the results of correlation analysis, cross-section dependent tests, unit root tests, the Houseman test, and the redundant likelihood ratio test. Next, this section illustrates the POLS, PLS, EFM, and quintile regression results.

Correlation Analysis

After logarithm ($\log_{10}$) transformation, the data were used in our analysis. The correlation matrix is detailed in Table 2, presenting that within the case of dependent variables, ANPL has the highest correlation (r=.93) with WBD, while NPLTLR has the lowest correlation (r=.06) with WBD. Next, within the case of independent variables, GIE has the highest correlation (r=.83) with WM, while RE has the lowest correlation (r=.14) with GOF. Besides, within GF and NPL variables, ANPL has the highest correlation (r=.83) with EFBP, while NPLTLR has the lowest correlation (r=-.-6) with RE. Furthermore, The Variance Influence Factor (VIF) falls below 5.0, while the tolerance value (TOL) exceeds 0.20, affirming the absence of multicollinearity issues among our explanatory variables. Omri et al. (2019) employed control variable to condense the heteroscedasticity within the model. In econometrics, it is customary to address heteroscedasticity by applying a natural logarithm transformation to the variables for analysis, as outlined by Charfeddine and Ben Khediri (2016).

Table 2. Results of Correlation and collinearity test of GF and NPL

Var.	Correlation Matrix											Collinearity Statistics	
	RE	EE	AE	WM	RMGM	GIE	EFBP	GOFI	ANPL	NPLTLR	WBD	TOl	VIF
RE	1.0											.41	2.5
EE	.61	1.0										.46	2.2
AE	.58	.6	1.0									.44	2.3
WM	.56	.43	.46	1.0								.23	4.3
RMRG	.45	.36	.37	.72	1.0							.44	2.3
GIE	.65	.59	.46	.83	.64	1.0						.20	5.0
EFBP	.26	.34	.55	.27	.35	.18	1.0					.59	1.7
GOFI	.14	.33	.33	.41	.39	.43	.38	1.0				.64	1.6
ANPL	.38	.38	.63	.53	.54	.40	.83	.43	1.0				
NPLTLR	-.6	-.3	-.2	-.2	-.1	-.3	.39	.05	.28	1.0			
WBD	.57	.49	.6	.73	.63	.64	.74	.37	.93	.06	1.0		

Note: TOl and VIF are tolerance and variance influence factors, respectively. The endogenous variables for the collinearity diagnostics are ANPL, NPLTLR, and WBD.

Cross-Section Dependence Test

Table 3 illustrates that in the case of the impact of GF on APL, NPLTLR, and WBD follow the cross-section dependence under BPLM and PCD. However, under PSLM and BCSLM, the effect of GF on NPLTLR follows the cross-section independence. Moreover, under BCSLM, the effects of GF on WBD follow the cross-section independence. The first-generation tests, which assume that data across sections are independent, include those developed by Im et al. (2003) and Maddala and Wu (1999).

$$\mathrm{BPLM} = \mathrm{Y}\sum_{k=1}^{N-1}\sum_{j=k+1}^{N}\hat{p}\ _{ij}^{2} \tag{5}$$

$$\mathrm{BPCD} = \frac{\sqrt{2\mathrm{Y}}}{\mathrm{N(N-1)}}\sum_{k=1}^{N-1}\sum_{j=k+1}^{N}\hat{p}\ _{ij}^{2} \tag{6}$$

$$\mathrm{PSLM} = \frac{\mathrm{Y}}{\sqrt{\mathrm{N}}}\sum_{j=1}^{N}\frac{1}{\mathrm{N}}\sum_{k=1}^{N}\hat{p}\ _{i,j} \tag{7}$$

$$\mathrm{BCSLM} = \frac{\mathrm{n}}{\sigma^{2}}\left(\frac{1}{\mathrm{Y}}\sum_{t=1}^{T}\hat{e}\ _{t}^{2}\right) \tag{8}$$

Where

N is cross-sectional units (e.g., firms).

$\hat{p}\ _{k,j}$ Estimated is the estimated correlation between the residuals from the k-th and j-th cross-sectional units.

n is no. of observations.

σ^2 is the estimated variance of the errors.

Y is the number of periods or data points.

$\hat{e}\ _{t}$ represents the residuals from the model.

Table 3. Results of Cross Section Dependence test of NPL

Variables	BPLM	PCD	PSLM	BCSLM
ANPL	.0039*** (19.136)	.0410* (-2.0439)	.0001*** (3.792)	.0004*** (3.542)
NPLTLR	.2135 (8.3506)	.0423* (-2.030)	.4974 (.6786)	.6682 (.4286)
WBD	.0535* (12.405)	.0180** (-2.365)	.0645* (1.8489)	.1098 (1.5989)

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

Note: BPLM stands for Breusch Pagan Lagrange Multiplier, PCD stands for Pesaran Cross-sectional Dependence, PSLM denotes Pesaran Scaled Lagrange Multiplier, and BCSLM stands for Biased Corrected Scaled Lagrange Multiplier.

Unit Root Test

The unit root test results indicate significant evidence against unit roots for all indicators examined. Henry Ntarmah et al. (2019) used the unit root test to determine the stationary behavior of their studied variables on a level and first difference basis. Table 4 shows the unit root test results of GF, ANPL, NPLTLR WBD, and GF. It has been based on the second difference, which has individual effects of exogenous variables followed by the Newey-West automatic bandwidth selection and Bartlett kernel system. PP Fisher chi-square test statistics range from 25.5 to 53.00, with connected p-values ranging from 0.0000 to 0.0019, which implies a firm rejection of the null hypothesis of unit roots. Similarly, PP Choi Z test statistics range from -6.229 to -2.814, with linked p-values all below 0.05, further ensuring the rejection of the unit root hypothesis. These findings imply that data for all indicators are not prone to exhibiting non-stationary behavior.

$$P = -2\sum_{i=1}^{n} ln(P_{\ i}) \tag{9}$$

$$\text{Z} = \frac{1}{\sqrt{\text{n}}}\sum_{i=1}^{n}(\pi_{\ i}) \tag{10}$$

Where

P_i is the unit root test's probability value concerning the i-th cross-section.

n is the no. of cross-sections in the panel.

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

Table 4. Result of Individual Unit Root Test of GF and NPL

Indicators	PP Fisher Chi-square	P -P-value	PP Choi ZZ sta.	P-value.
ANPL	30.92	0.000***	-3.78	0.000***
NPLTLR	37.30	0.000***	-4.29	0.000***
WBD	39.44	0.000***	-4.85	0.000***
RE	41.44	0.000***	-4.63	0.000***
EE	25.50	0.001***	-3.27	0.000***
AE	31.37	0.000***	-4.73	0.000***
WM	28.49	0.000***	-2.81	0.002***
RMRG	46.23	0.000***	-4.88	0.000***
GIE	52.94	0.000***	-6.23	0.000***
EFBP	20.97	0.002***	-3.00	0.000***
GOFI	33.44	0.000***	-3.83	0.000***

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

Hausman Test

Hausman's (1978) test for panel data serves as a general specification test, indicating that rejection of the null hypothesis signifies misspecification rather than endorsing the fixed effects estimator, while non-rejection supports the random effects estimator, which is efficient under the null hypothesis (Baltagi, 2024). Both the fixed effects model(FEM) and random effects models (REM) suggest a spatial Hausman test to compare these two models while considering spatial autocorrelation in the errors (Mutl & Pfaffermayr, 2011) to fix if a time-varying covariate is exogenous in REM for panel data (Mainzer, 2018). The Hausman test judges against the estimators from the REM and the fixed effects model (FEM). The equation for the Hausman test statistic (Ha) is:-

$$\text{Ha} = (\hat{B}_{\ FE} - \ \hat{B}_{\ RE})'\,[\text{Var}(\hat{\beta}_{\ FE}) - \text{Var}(\hat{B}_{\ FE})]^{-1}(\hat{B}_{\ FE} - \ \hat{B}_{\ RE}) \tag{11}$$

Where:

$(\hat{B}_{\ FE})$ is the estimated coefficient for FEM,

$(\hat{B}_{\ RE})$ is the estimated coefficient for REM,

Var$(\hat{B}_{\ FE})$ & Var$(\hat{B}_{\ RE})$ are the variances of the coefficients for the respective model.

Table 5 represents Hausman test results that indicate which model is appropriate for our data set since Chi-square. Statistic value with the corresponding p-value tells that for NPLTLR and WDB, FEM is suitable, while for ANPL, REM is appropriate.

Table 5. Result of Hausman Test of NPL

Variables	Chi-sq. Stat.	P- value.	Model Specification
ANPL	26.59	0.000***	**REM**
NPLTLR	1.24	0.990	**FEM**
WBD	11.03	0.137	**FEM**

'***' '**' and '*' imply the significance at the 1%, 5 % and 10% levels, respectively.

Redundant Fixed Effect Likelihood Test

Likelihood ratio tests for FEM terms are suggested for analyzing linear mixed model with residual maximum likelihood estimation, along with Bartlett-type adjustments for the test statistics based on an approximate data decomposition (Welham & Thompson, 1997). However, a redundant fixed effect likelihood test (RFELT) was done to confirm the model specification. The equation of RFELT is:-

$$\text{RFELT} = -2(\text{Log } L_{restricted}) - \text{Log } L_{unrestricted}) \qquad (12)$$

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).
RLRT follows the (χ2) distribution with a degree of freedom equal to the no. of restrictions.

Table 6 presents the results of RLRT in p values of all dependent variables are 0.000, which means FEM is appropriate.

Table 6. Redundant Fixed Effect Likelihood Ratio Test Result of NPL

Variables	Statistic	Prob.	Model specification
ANPL	88.75	0.000***	**FEM**
NPLTLR	34.96	0.000***	**FEM**
WBD	36.45	0.000***	**FEM**

'***' '**' and '*' imply the significance at the 1%, 5 % and 10% levels, respectively.

Impact through POLS and PLS

Table 7 depicts that the significant factors contain a t value greater than ±3.70 at the 0.01 level, more excellent than ±2.10 at the 0.05 level, and more critical than ±1.83 at the 0.10 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, GIE, EE, RE, and RMGM impact ANPL, RE, and EFBP significantly impact NPLTLR, and WM & EFBP also affect WBD as per the POLS approach. Next, RE and GOFI have an effect on ANPL, AE & EFBP have an impact on NPLTLR, and RE, GOFI & EFBP have an effect on WBD as per the PLS method.

Table 7. Effect of GF on NPL using the Least Square Method

Models	GIE	EE	AE	WM	RMRG	RE	GOFI	EFBP
POLS (ANPL)	.039** (2.17)	.001*** (3.74)	.027** (2.34)	.890 (.139)	.044** (2.11)	.276 (-1.11)	.274 (-1.11)	.195 (-1.33)
POLS (NPLTLR)	.486 (.706)	.353 (-.94)	127 (-1.58)	.710 (.376)	.481 (-.715)	.001*** (-3.70)	.550 (-.605)	.000*** (5.45)
POLS (WBD)	.154 (1.466)	.431 (-.800)	.116 (1.623)	.014** (2.628)	.746 (.327)	.699 (.391)	.133 (-1.55)	.000*** (6.52)
PLS (ANPL)	.120 (-1.604)	0.1818 -1.369	.1071 -1.66)	0.7733 (.291)	.890 (-.134	.000*** (25.42)	.013** (2.670)	.130 (-1.56)
PLS (NPLTLR)	0.6079 (-0.518)	0.137 (-1.527)	.011** (-2.74)	.7967 (0.260)	.4149 (-.827)	0.0163 (2.555)	0.224 (1.244)	.000*** (4.164)
PLS (WBD)	0.2659 (-1.135)	0.1739 (-1.395)	0.1347 (-1.54)	0.4520 (.762)	0.7679 (-.297)	.000*** (26.10)	.048** (2.072)	0.066* (1.914)

'***' '**' and '*' imply the significance at the 1%, at the 5 % and at the 1o% level respectively.

Fixed Effect

After the Hausman test and RFELT, the effects of green finance on non-performing loans are determined. Furthermore, the fixed effect of GF on NPLs is also determined. Table 8 shows the finding of the fixed effect of GF on NPLs. The study finds that significant factors contain a t value greater than ±2.91 at the .01 level, more critical than ±2.17 at the .05 level, and greater than ±1.76 at the .10 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, RMGM and EFBP have a significant fixed effect on ANPL, GIE, RMGM, and EFBP, substantially impacting NPLTLR. Furthermore, EFBP impacts on WBD.

Table 8. Effect of GF on NPL using FEM

Var.	GIE	EE	AE	WM	RMRG	RE	GOFI	EFBP
ANPL	.9829 (.0217)	.3613 (.9397)	.8604 (.1787)	.2497 (1.195)	.0240** (2.492)	.9435 (-.072)	.7160 (-.370)	.010*** (2.919)
NPLTLR	.0791* (1.136)	.4357 (-.799)	.4144 (-.8380)	.5158 (.6646)	.097* (1.761)	.5882 (-.553)	.7052 (-.385)	.000*** (4.480)
WBD	.2725 (.3311)	.8916 (-.138)	.1806 (1.400)	.7044 (-.386	.2660 (-1.15)	.2756 (-1.13)	.5854 (.556)	.045** (2.176)

'***' '**' and '*' imply the significance at the 1%, 5 % and 10% levels, respectively.

Impact through Quarantine Regression

Table 9 illustrates that RE significantly impacts ANPL, NPLTLR, and WBD in Q_1 and Q_3. Next, AE significantly impacts ANPL, NPLTLR, and WBD in the Q_3. Next, in both quartiles, EFBP significantly impacts NPLTLR, whereas GOFI significantly impacts APNL, NPLTLR, and WBD in Q_3. However, GIE and GOFI affect ANPL only in Q_1.

Table 9. Impact of GF on NPL Using Quantile Regression

IV	25thquartile (p-value)			75thquartile (p-value)		
	ANPL	NPLTLR	WBD	ANPL	NPLTLR	WBD
RE	.000***	.0013***	.0000***	.0000***	.0003**	.000***
EE	.9514	.2645	.8883	.7484	.2423	.4328
AE	.8868	.0057***	.9578	.0351**	.0000***	.0971*
WM	.9449	.9960	.7588	.6858	.7345	.4857
RMRG	.9715	.8779	.9264	.3997	.3335	.2948
GIE	.0884*	.1100	.1942	.7548	.8100	.8012
EFBP	..8860	.0019***	.6819	.8286	.0000 ***	.6533
GOFIs	.0683*	.1026	.2155	..0210**	.0132**	.0664*

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

DISCUSSIONS

In the context of green finance in connection to banks' non-performing loans, the results of econometric models exhibit that green finance has significant impacts on decreasing ANPL, NPLTLR, and WBD, respectively. The findings that green finance significantly impacts reducing ANPL, NPLTLR, and WBD carry reflective implications. First, these results underline the strategic importance of incorporating sustainable financial practices into lending portfolios. Managers in financial institutions can leverage green finance to improve credit quality by prioritizing environmentally sound projects that exhibit lower default risks due to better risk management and compliance with sustainability regulations. This aligns with H_1, which establishes that green finance significantly reduces ANPL, indicating that sustainable projects contribute positively to loan performance. Bressan (2024) finds that GF influences the reduction of NPL levels. A study on the circular economy by Ghisellini et al. (2016) confirms its positive impact on bank performance and reduces default risks. Second, the reduction in NPLTLR, as per H_2, signals that a higher proportion of loans in green portfolios remain performing, leading to improved financial condition and stability of lending. For managers, this insight encourages the adoption of green credit policies and emphasizes the potential for enhancing banking reputation and investor confidence through sustainable practices. Rahman et al. (2016) identified that credit-deposit ratio, loans to sensitive sectors, and net interest margins positively contribute to NPLs. However, capital adequacy ratio, return on assets, and investment-deposit ratio negatively influence them. Lastly, the evidence supporting H_3, which emphasizes the reduction in WBD due to green finance, points to enhanced recovery rates and lower credit losses. This is crucial for strategic planning, as it reduces the requirement for extensive provisioning, freeing up capital for further investment and innovation. This finding aligns with the research of Li and Lin (2024), who analyzed the impact of green financing on the financial performance of environmentally conscious companies in China. Their findings exposed that banks financing sustainable industries experience lower loan risks due to the steady nature of these investments. Collectively, these findings suggest that green finance not only drives environmental benefits but also enhances financial sustainability and operational efficiency. Managers should consider incorporating robust green financing frameworks and promoting awareness among stakeholders about their dual benefits for financial performance and sustainability objectives.

Green finance, which focuses on financing projects with positive environmental outcomes, tends to promote more sustainable and resilient economic activities. This, in turn, reduces the likelihood of default loans, as these investments are often more stable and less vulnerable to market fluctuations. By promoting environmentally responsible projects, green finance supports long-term financial health, reducing the incidence of non-performing loans (NPLs). A lower NPLTLR suggests that banks are managing their loan portfolios more effectively, possibly due to better risk assessment and the prioritization of sustainable investments. Al-Qudah et al. (2022) found that green investment influences NPL ratios, underscoring the link between environmental sustainability, financial performance, and reduced financial instability. Additionally, reducing WBD directly results in fewer defaults, suggesting that integrating environmental criteria in lending practices can improve creditworthiness. Moreover, studies by Ganda et al. (2015), Iwata and Okada (2011), and King and Lenox (2001) support the positive influence of green finance on financial outcomes. Theoretical implications indicate that the banking sector's focus on environmental sustainability could reshape traditional risk management strategies, emphasizing the importance of considering environmental factors in loan assessments. The results underline the need for policy reforms and incentives to promote green finance, which could lead to healthier financial systems and contribute to the global transition to sustainability. .

Table 10. Significant Findings of this Study

Proposed hypotheses	P -value	Major Finding	Support the proposed hypotheses or not	Literature
H_1: Green finance influences significantly in reducing ANPL	.000≤P≤.044 at 1% -5% Level.	Green finance has significant effects on the reduction of ANPL	Supported	Similar to the findings concluded by Bressan (2024)

H_2: Green finance influences significantly in reducing NPLTLR	.000≤P≤.013 at 1% -5% Level.	Green finance has significant effects on the reduction of NPLTLR	Supported	Similar to the findings concluded by Al-Qudah et al. (2022)
H_3: Green finance influences significantly in reducing WBD	.000≤P≤.048 at 1% -5% Level.	Green finance has significant effects on the reduction of WBD	Supported	Similar to the finding concluded by Fan et al. (2024)

Source: Synthesis of the authors

CONCLUSIONS

This study investigates the influence of investment in green sectors on banks' non-performing loans. Enhancing green finance is crucial for reducing non-performing loans as it enhances a bank's reputation and attracts clients with a strong commitment to sustainability. This can lead to a more stable and loyal customer base, reducing exposure to high-risk borrowers. Green investments help banks foster sustainable growth while mitigating financial risks, contributing to a reduction in non-performing loans. Therefore, examining the green finance variables that influence NPL is crucial. This research examines how green finance influences none performing loans of banks by using POLS, PLS, FEM, and quantile regression.

The key findings of this study can be outlined as follows: - Firstly, it was found that ANPL is influenced by investment in AE, EE, RE RMRG, GIE, EFBP, and GOFI, indicating reducing in ANPL with a relationship statistically significant. Secondly, it was observed that NPLTLR is deceased through the investment in AE, RE, RMRG, GIE, EFBP, and GOFI, having statistically significant results. Thirdly, WBD is negatively influenced by AE, RE, WM RMRG, GIE, EFBP, and GOFI, implying WBD is reduced due to green investment.

While green finance has garnered significant attention for its environmental and sustainability benefits, this study provides empirical insights into how investments in environmentally sustainable projects influence the financial health of banks, particularly in reducing NPLs. The article examines whether banks that prioritize green finance are less likely to experience high levels of default on loans due to the long-term viability of green projects, which may reduce risk exposure. Furthermore, it assesses whether green finance enhances financial stability by promoting better risk management and fostering more substantial, resilient loan portfolios. This unique contribution provides a novel perspective on the intersection of environmental finance and banking stability, offering insights for policymakers, financial institutions, and academics interested in promoting sustainable finance practices while mitigating financial risks related to non-performing loans.

The theoretical implications of this study explore how investments in environmentally sustainable projects, supported by green finance, may influence the risk profile of banks, particularly about non-performing loans (NPLs). Moreover, it suggest that incorporating green finance into a bank's portfolio reduces the likelihood of defaulted loans, given their connection with stable, long-term, and resilient sectors. This perspective contributes to the theoretical frameworks in risk management, emphasizing how green finance strategies may lower the risk of NPLs over time. From a managerial standpoint, incorporating green finance can positively influence the financial health of banks by reducing the occurrence of non-performing loans. Bank managers would be able to understand how investments in environmentally sustainable projects can lower credit risk, enhance the quality of their portfolios, and attract socially conscious investors. Promoting green finance helps banks align with global sustainability goals and alleviates the risks associated with traditional high-risk lending practices. Moreover, this study recommends that banks assess their borrowers' environmental risk profiles to reduce potential defaults linked to unsustainable business practices. Banks should also improve their risk management frameworks to account for environmental factors. Furthermore, by promoting green finance for environmentally sustainable businesses, banks can further reduce the incidence of non-performing loans, fostering a more stable financial environment.

This study focuses on some restrictions that must be addressed in future studies. First, the study relies heavily on secondary data, which may only partially confine the complexity of green finance and its effects on non-performing loans (NPLs). Future research 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 green finance over more extended periods and across different regions to assess its global applicability. Furthermore, the study focuses primarily on financial institutions, leaving out other industries that could benefit from green finance. Future research should inspect the impact of green finance on sectors beyond banking.

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