Exploring the Nexus among Innovation, Green Finance, and Banks' Performance Using Machine Learning Models: International Evidence

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Abstract

This study explores the nexus among innovation, green finance, and banks' performance across 14 countries over 8 years using machine learning. It examines whether innovation and green finance influence banks' performance, explores whether innovation moderates the relation between green finance and banks' performance, and tests for cointegration among the components of the nexus. It uses a global innovation index as a proxy for innovation. Green finance has been measured by green bonds, while banks' performance has been measured by capital adequacy, profitability, liquidity, and asset quality.

The study conducts an empirical comparison between panel regression and machine learning approaches to pinpoint the most accurate and robust predictive approach. Python-based models were applied to contrast the predictive capabilities of different machine learning algorithms in forecasting key financial indicators. Using panel data with robust standard errors, the analysis reveals that green bonds have a significantly positive impact on capital adequacy, but a negative impact on asset quality in these markets. Results suggest that innovation positively impact profitability but negatively affect asset quality. Moreover, innovation plays a moderating role, exerting a negative influence on the relation between green bonds and capital adequacy, while positively moderating the relation between green bonds and asset quality. The Kao Residual Cointegration Test indicates a long-term nexus between the components. Support Vector Regression and K-Nearest Neighbors outperformed other approaches and are recommended for future financial predictions. Future research may extend this study by focusing on the effect of innovation on the firms' financial performance across Arab countries.

Keywords: *Advanced learning algorithms, Banks' performance, Cointegration test, Emerging and developed Markets, Green finance, innovation, Python-based models.*

JEL Classification: *C52, C58, G21, O30, Q50*

Introduction

Given the escalating complexity of climate-related issues, addressing the effects of climate risk and reducing carbon emissions have become essential steps to overcome its severe consequences. As a result, the financial sector has begun to take environmental considerations into account, with green finance emerging as a primary mechanism to address the challenges arising from climate-related risks. Prior research has examined the effects of green finance on financial sector (Zhang, 2018; Yasmin & Akhter, 2021; Putri et al., 2022; Abuatwan, 2023; and Mirza et al., 2023), while other studies have assessed how inno-

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vation contributes to financial performance improvement across various applications and frameworks (Ali & Saraç, 2024; Wang et al., 2024; and Sakalsız & Koç, 2024).

Despite growing interest, several challenges remain unaddressed. Based on the existing literature, there appears to be a significant gap, and thus, the present study aims to examine the nexus among innovation, green finance, and banks' performance across 14 countries over 8 years using a machine learning approach. It investigates whether innovation and green finance influence banks' performance, explores whether innovation moderates the relation between green finance and banks' performance, and tests for cointegration among the components of the nexus.

Adopting financial, environmental, and technological aspects, this study first explores the nexus among innovation, green finance, and banks' performance. It then examines whether innovation and green finance influence banks' performance, while accounting for the potential effect of climate change. This study explores whether innovation moderates the relation between green finance and banks' performance. Further, it tests for cointegration among the components of the nexus. This study uses a global innovation index as a proxy for innovation. Green finance has been measured by green bonds, while banks' performance has been measured by capital adequacy, profitability, liquidity, and asset quality.

This study conducts an empirical comparison between panel regression and machine learning techniques to pinpoint the most accurate and robust predictive approach. Using panel data with robust standard errors, the analysis reveals that green bonds have a significantly positive impact on capital adequacy, but a negative impact on asset quality in these markets. Results suggest that innovation positively impact profitability but negatively affect asset quality. Moreover, innovation plays a moderating role, exerting a negative influence on the relation between green bonds and capital adequacy, while positively moderating the relation between green bonds and asset quality. The Kao Residual Cointegration Test indicates a long-term nexus between the components. Further, the findings highlight that the machine learning-based techniques produces better prediction outcomes compared to other approaches. In the light of above discussions, this issue serves as the main motivation for this study to assess the nexus among green finance, innovation, and banks' performance in emerging and developed markets over 8 years using a machine learning approach. Future research may extend this study by focusing on the impact of innovation on the firms' financial performance across Arab countries. This study is structured as follows: Section 2 outlines the literature review, while Section 3 defines the problem statement and research objectives. Section 4 shows the development of hypotheses, Section 5 presents the methodology, Section 6 describes the results, while Section 7 summarizes the conclusions.

Literature Review

Some studies have examined the influence of green finance on financial sector (Zhang, 2018; Alonso-Conde and Rojo-Suárez, 2020; Danye, 2020; Yasmin & Akhter, 2021; Yeow & Ng, 2021; Putri et al., 2022; Abuatwan, 2023; & Baharudin & Arifin, 2023), while other studies have assessed how innovation contributes to financial performance improvement across various applications and frameworks (Ali & Saraç, 2024; Wang et al., 2024; & Sakalsız & Koç, 2024).

Prior studies on the effect of green finance on financial performance have shown mixed results, with some reporting a negative impact through higher cost of operations, while others indicate a positive effect on profitability. Zhang (2018) examine the impact of green credit on financial performance using data from and by an industrial bank in China (2005-2017) and indicate a positive impact on bank's financial performance. The study also suggests that environmental and financial factors slowed profit growth during 2013-2015. Alonso-Conde and Rojo-Suárez (2020) examine that the impact of green bond financing on profitability and credit quality using the case of the Sagunto regasification plant in Spain. They find that green bonds provides a direct financial incentive, based on financial data from 2011 - 2018 and forecasts up to 2041.

Similarly, Danye (2020) and Yasmin and Akhter (2021) assure the positive effect of green credit on banks' profitability in China and Bangladesh, respectively. While Yeow and Ng (2021) examine the effect of green bonds on firms' environmental and financial performance, using data from conventional and green bonds between 2015 and 2019. They indicate that certified green bonds improve environmental performance but have no significant effect on financial performance.

Putri et al. (2022) indicate that banks' profitability increased with the adoption of green banking-related factors such as corporate social responsibility funds and capital adequacy ratios, while the number of ATMs had no significant impact on profitability in Indonesia during 2010 - 2020. Abuatwan (2023) suggest that green finance significantly enhanced sustainability performance in both the short and long term in Palestine during January to April in 2023, based on survey data from 104 credit managers across eight banks. Further, Baharudin and Arifin (2023) find that green finance positively influenced firm value, as measured by Tobin's Q, for four banking companies listed in Indonesia during 2019-2021.

Wang et al. (2024) suggest that innovation activities improve the performance of listed financial service firms, while oraganizational innovation has mixed effects for 191 firms in Taiwan during 2014-2018. Ali & Saraç (2024) indicate that innovation has a positively significant impact on SMEs' financial performance in Upper Egypt. Sakalsız & Koç) 2024(indicate that innovation investment had no significant impact on financial performance, while intangible assets negatively impacted ROA but positively impacted ROE, based on data from 80 manufacturing firms listed on Borsa Istanbul during 2018-2022.

In the light of above discussions, this issue has attracted the interest of this study to assess the nexus among green finance, innovation, and banks' performance in emerging and developed markets over 8 years using a machine learning approach. Hence, this study departs from existing literature in six main ways: (1) this current study investigates the effect of green finance on banks' performance; (2) it examines the effect of innovation on banks' performance for 14 countries. In addition, (3) this study includes data from 2013 to 2020; (4) this study sample and period differ from other prior literature; (5) it compares panel regression with machine learning techniques to pinpoint the most accurate and robust predictive approach; and (6) it tests for cointegration among the components of the nexus. In the light of above discussions, this study seeks to address this issue by assessing the nexus among green finance, innovation, and banks' performance in emerging and developed markets over 8 years using a machine learning approach.

Research Problem and Objectives

In recent years, the financial sector, along with environmental challenges, concerns about green finance, and innovation, has become a significant issue worldwide. These concerns have prompted growing interest among researchers, who are increasingly investigating the influence of green finance on financial sector. Additionally, the role of innovation in improving the financial performance of these institutions has emerged as a key area of focus in such studies. In light of this importance, scholars and policymakers have shown a growing interest in exploring the influence of green finance on the financial sector (Zhang, 2018; Yasmin & Akhter, 2021; Putri et al., 2022; Abuatwan, 2023; & Mirza et al., 2023). While other studies focused on the relation between innovation and financial sector in specific countries (Ali & Saraç, 2024; Wang et al., 2024; Sakalsız & Koç, 2024).

Thus, this study seeks to investigate the nexus among innovation, green finance, and banks' performance in emerging and developed markets over the period from 2013 to 2020 by using a machine learning approach. It investigates whether innovation and green finance influences banks' performance, explores whether innovation moderates the relation between green finance and banks' performance. While prior studies have often examined green finance and innovation separately, this study contributes to the literature by jointly analyzing their impact on the financial sector's performance. It also considers how green finance and innovation influence financial performance, factoring in the potential effect of climate change. This study investigates the moderating role of innovation in the relation between green finance and banks' performance. Also, it tests for cointegration among the components of the nexus. Figures 1 and 2 illustrate the trends green bonds and innovation across fourteen in emerging and developed markets over the period from 2013 to 2019.

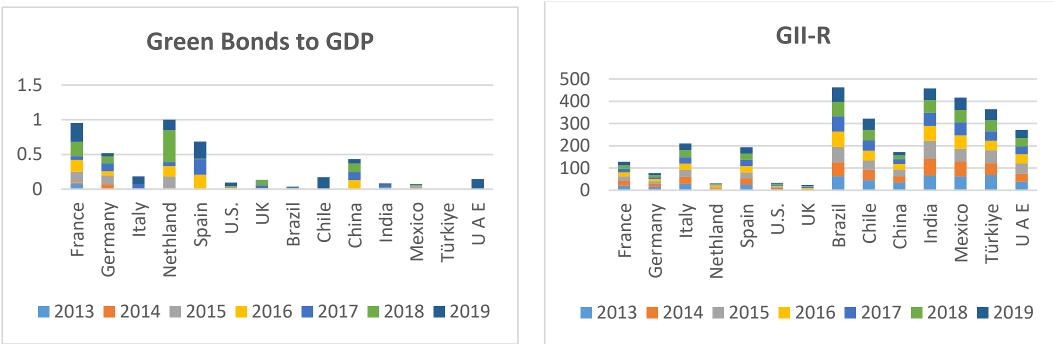


Figure 1. Green Bonds and Innovation Development in Emerging and Developed Markets

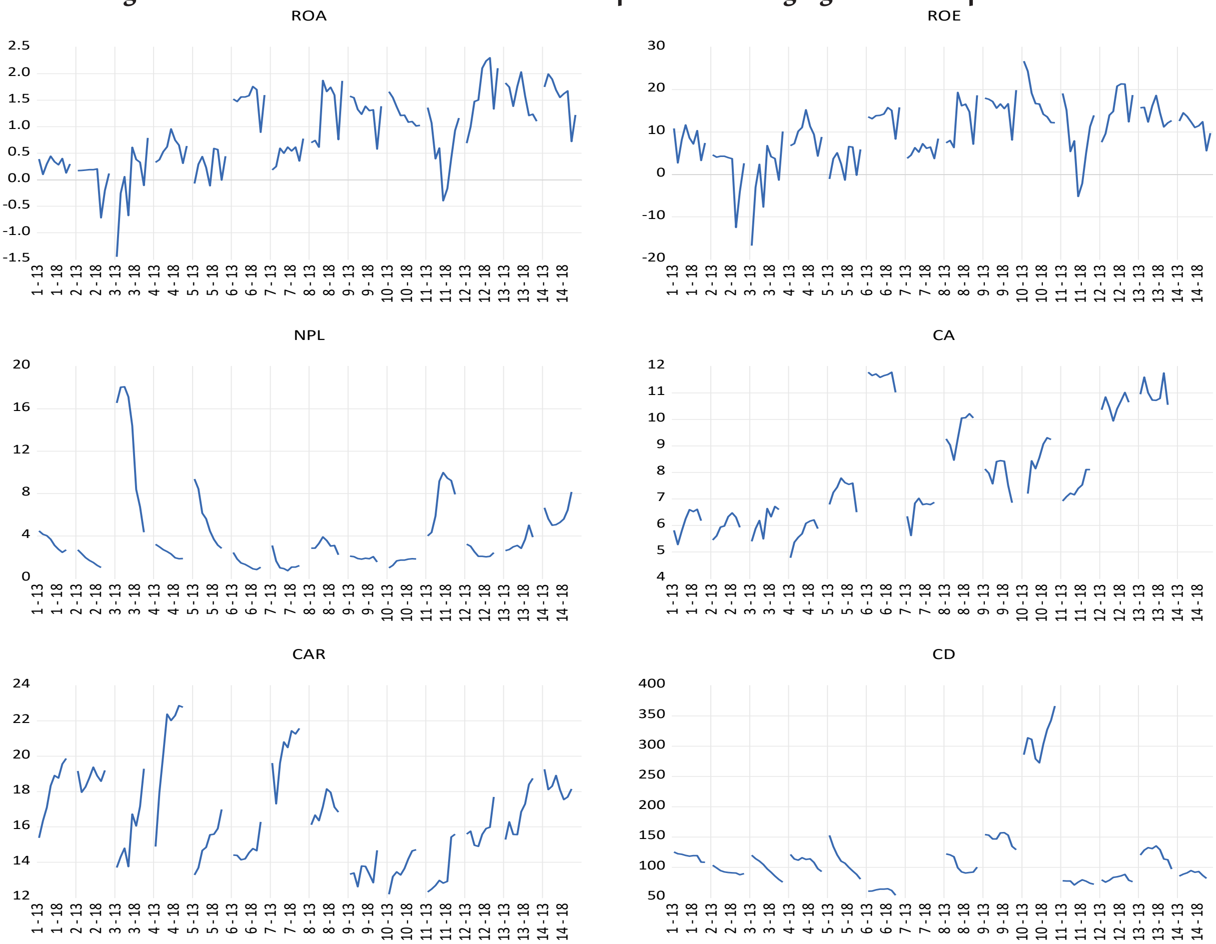


Figure 2. Innovation Development in Emerging and Developed Markets

Figure 1 illustrates the green finance across 14 countries during the specified period. Figure 2 highlights the trend in innovation from 2013 to 2019, revealing that many countries are striving to achieve a green environment and secure a better future through green financing instruments.

This study seeks to explores the nexus among innovation, green finance, and banks' performance across 14 countries over 8 years using a machine learning approach. It investigate whether green finance influences banks' performance, explores whether innovation moderates the relationship between green finance and banks' performance, and tests for cointegration among the components of the nexus. To this end, this study utilizes cross -country data covering 14 countries over the period 2013-2020. Therefore, this study's purpose is to explores the nexus among innovation, green finance, and banks' performance for 14 countries and examine this impact based on annual data from 2005 to 2014, along with multiple advanced learning techniques.

In light of the existing literature, this study provides the following contributions. First, existing studies have separately examined the relation between green finance or innovation and financial sector, focusing on specific countries. Thus, this study seeks to address this gap by exploring the nexus among green finance, innovation, and banks' performance for 14 countries over 8 years using machine learning techniques on international evidence to verify this relation and, in doing so, expand on previous studies. Also, it explores the moderating role of innovation in the relation between green finance and banks' performance. Second, this study is conducted from the perspective of finance and machine-learning techniques, comparative aspect between methods and tested using cross-country data. This study uses SVR and KNN to benchmark the results with the regression-based findings. Third, this study tests for cointegration among the components of the nexus. Fourth, it examines the factors influencing banks' performance and contrasts the predictive performance of machine learning models in assessing banks' key financial indicators.

This study is primarily motivated by growing global concerns over financial risks, environmental degradation, and the separate effects of innovation and green finance on the financial sector. A secondary motivation stems from the increasing academic interest in examining how green finance influences the financial sector under various market conditions-taking into account the role of innovation. Departing from previous literature, this current study focuses on exploring the nexus among green finance, innovation, and banks' performance during 2013 - 2020 by using a machine learning approach. Overall, this study seeks to address the following questions:

- Does green finance affect banks' performance in markets?
- Does innovation play a moderating role in the relation between green finance and banks' performance?
- Does a long-run cointegration relationship exist among green finance, innovation, and banks' performance in markets?
- Do economic and market determinants influence banks' performance?

For the objectives of the present study, a sample of 76 observations covering 14 countries was utilized. The analysis considers three categories of control variables: (a) macroeconomic factors , such as foreign direct investment, real effective exchange rate, and inflation; (b) environmental variables, represented by CO_2 emissions; and (c) market-related characteristics, including market capitalization. influence

Research Hypotheses

Given the literature review and research motivation discussed, this study is designed to test the following hypotheses:

- H_1: Banks' performance is significantly driven by green finance in markets.
- H_2: innovation moderates the relation between green finance and banks' performance.
- H3: There is a long-run cointegration relation among green finance, innovation, and banks' performance.

Criteria for Testing Hypotheses:

- H_{O1}: There is no significant impact of green finance on banks' performance.
- H_{A1}: There is a significant impact of green finance on banks' performance.
- H_{O2}: There is no evidence of a moderating impact of innovation on the relation between green finance and banks' performance.
- H_{A2}: There is a significant moderating impact of innovation on the relation between green finance and banks' performance.
- H_{O3}: There is no long-run cointegration relation among green finance, innovation, and banks' performance.
- H_{A3}: There is a long-run cointegration relation among green finance, innovation, and banks' performance.

Study Methodology

Data and Methods

To assess the nexus among green finance, innovation, and banks' performance for 14 countries, which included as follow: France, Germany, Italy, Netherlands, Spain, U.S., and UK, Brazil, Chile, China, India, Mexico, Turkey, and UAE. The countries are chosen as the most representative developed and emerging markets according to data availability during the period from 2013 to 2020. This data was collected from the Institute of International Finance (IIF), the International Monetary Fund (IMF), and World Development Indicators (WDI) database of the World Bank. For the purpose of this study, a sample of 76 observations covering 14 countries was utilized. This study uses the Kao Residual Cointegration test to examine the relation among variables of this study.

Research Variables

This study uses a global innovation index as a proxy for innovation and utilizes the green bonds to GDP ratio (GB) as a measure of green finance. Banks' performance has been measured by capital adequacy, profitability, liquidity, and asset quality. The analysis considers three categories of control variables: (a) macroeconomic factors; (b) environmental variables, represented by CO_2 emissions; and (c) market-related characteristics, including market capitalization. Overall, these variables used in the model are defined in the following Table:

Table 1. Description of Variables and Abbreviations

Type	Variable	Abbreviation
Independent	Green bonds of GDP	GB
	innovation	CII-R
Dependent	Bank capital to total assets	CA
	Bank regulatory capital to risk-weighted assets	CAR
	Bank non-performing loans to gross loans	NPL
	Bank credit to bank deposits	CD
	Bank return on assets	ROA
	Bank return on equity	ROE
Control	Carbon Dioxide (CO2) Emissions (metric tons per capita)	CO2
	Log of Foreign Direct Investment, net inflows of GDP ratio	FDI_LOG
	Log of gross domestic product	LOG (GDP)
	Inflation, GDP Deflator (annual %)	INFD
	Domestic credit to private sector (% of GDP)	DOM
	Market capitalization of listed domestic companies (% of GDP)	MC

Source: Prepared by Researcher.

Research Model

This study conducts an empirical comparison between panel regression and machine learning techniques to pinpoint the most accurate and robust predictive approach. This study uses the Kao Residual Cointegration test to examine the relation among variables of this study.

1- **Panel Regression Model**

This study utilizes models established in prior literature to test the hypotheses . This study used three statistical approaches, including the Ordinary Least Squares (OLS), Fixed Effects Model (FEM), and Random Effects Model (REM) suitable for panel data. After that, the Hausman test was used to determine whether the FEM model or the REM model were suitable for research.

- **Effect of green finance on banks' performance**

To investigate the effect of green finance on banks' performance, the following panel regression models are proposed:

$$\widehat{(CA)}_{it} = \alpha_0 + \alpha_1 GB_{it} + \alpha_2 CO2_{it} + \alpha_3 FDI\_LOG_{it} + \alpha_4 LOG(GDP)_{it} + \alpha_5 INFD_{it} + +\alpha_6 DOM_{it} + \alpha_7 MC_{it} + e_{it} \quad (1)$$

$$\widehat{(CAR)}_{it} = \alpha_0 + \alpha_1 GB_{it} + \alpha_2 CO2_{it} + \alpha_3 FDI\_LOG_{it} + \alpha_4 LOG(GDP)_{it} + \alpha_5 INFD_{it} + +\alpha_6 DOM_{it} + \alpha_7 MC_{it} + e_{it} \quad (2)$$

$$\widehat{(NPL)}_{it} = \alpha_0 + \alpha_1 GB_{it} + \alpha_2 CO2_{it} + \alpha_3 FDI\_LOG_{it} + \alpha_4 LOG(GDP)_{it} + \alpha_5 INFD_{it} + +\alpha_6 DOM_{it} + \alpha_7 MC_{it} + e_{it} \quad (3)$$

$$\widehat{(CD)}_{it} = \alpha_0 + \alpha_1 GB_{it} + \alpha_2 CO2_{it} + \alpha_3 FDI\_LOG_{it} + \alpha_4 LOG(GDP)_{it} + \alpha_5 INFD_{it} + +\alpha_6 DOM_{it} + \alpha_7 MC_{it} + e_{it} \quad (4)$$

$$\widehat{(ROA)}_{it} = \alpha_0 + \alpha_1 GB_{it} + \alpha_2 CO2_{it} + \alpha_3 FDI\_LOG_{it} + \alpha_4 LOG(GDP)_{it} + \alpha_5 INFD_{it} + +\alpha_6 DOM_{it} + \alpha_7 MC_{it} + e_{it} \quad (5)$$

$$\widehat{(ROE)}_{it} = \alpha_0 + \alpha_1 GB_{it} + \alpha_2 CO2_{it} + \alpha_3 FDI\_LOG_{it} + \alpha_4 LOG(GDP)_{it} + \alpha_5 INFD_{it} + +\alpha_6 DOM_{it} + \alpha_7 MC_{it} + e_{it} \quad (6)$$

- **Moderating effect of innovation on the relation between green finance and banks' performance**

To evaluate the moderating role of innovation in the relation between green finance and banks' performance, the following panel regression models are specified:

$$\widehat{(CA)}_{it} = \alpha_0 + \alpha_1 GB_{it} + \alpha_2 GII\_R_{it} + \alpha_3 GB * GII\_R_{it} + \alpha_4 CO2_{it} + \alpha_5 FDI\_LOG_{it} + \alpha_6 LOG(GDP)_{it} + \alpha_7 INFD_{it} + \\ +\alpha_8 DOM_{it} + \alpha_9 MC_{it} + e_{it} \quad (7)$$

$$\widehat{(CAR)}_{it} = \alpha_0 + \alpha_1 GB_{it} + \alpha_2 GII\_R_{it} + \alpha_3 GB * GII\_R_{it} + \alpha_4 CO2_{it} + \alpha_5 FDI\_LOG_{it} + \alpha_6 LOG(GDP)_{it} + \alpha_7 INFD_{it} + \\ +\alpha_8 DOM_{it} + \alpha_9 MC_{it} + e_{it} \quad (8)$$

$$\widehat{(NPL)}_{it} = \alpha_0 + \alpha_1 GB_{it} + \alpha_2 GII\_R_{it} + \alpha_3 GB * GII\_R_{it} + \alpha_4 CO2_{it} + \alpha_5 FDI\_LOG_{it} + \alpha_6 LOG(GDP)_{it} + \alpha_7 INFD_{it} + \\ +\alpha_8 DOM_{it} + \alpha_9 MC_{it} + e_{it} \quad (9)$$

$$\widehat{(CD)}_{it} = \alpha_0 + \alpha_1 GB_{it} + \alpha_2 GII\_R_{it} + \alpha_3 GB * GII\_R_{it} + \alpha_4 CO2_{it} + \alpha_5 FDI\_LOG_{it} + \alpha_6 LOG(GDP)_{it} + \alpha_7 INFD_{it} + \\ +\alpha_8 DOM_{it} + \alpha_9 MC_{it} + e_{it} \quad (10)$$

$$\widehat{(ROA)}_{it} = \alpha_0 + \alpha_1 GB_{it} + \alpha_2 GII\_R_{it} + \alpha_3 GB * GII\_R_{it} + \alpha_4 CO2_{it} + \alpha_5 FDI\_LOG_{it} + \alpha_6 LOG(GDP)_{it} + \alpha_7 INFD_{it} + \\ +\alpha_8 DOM_{it} + \alpha_9 MC_{it} + e_{it} \quad (11)$$

$$\widehat{(ROE)}_{it} = \alpha_0 + \alpha_1 GB_{it} + \alpha_2 GII\_R_{it} + \alpha_3 GB * GII\_R_{it} + \alpha_4 CO2_{it} + \alpha_5 FDI\_LOG_{it} + \alpha_6 LOG(GDP)_{it} + \alpha_7 INFD_{it} + \\ +\alpha_8 DOM_{it} + \alpha_9 MC_{it} + e_{it} \quad (12)$$

Where $\alpha_0\alpha_0$ is a constant, and $\alpha_1\alpha_1$to $\alpha_9\alpha_9$ is the coefficient of the exogenous variables. In addition, CA_{it}, CAR_{it}, NPL_{it}, CD_{it}, ROA_{it}, and ROE_{it} reflect the banks' performance of country i at time t, while GB_{it}, expresses the green finance of country i at time t, as reflected by their green finance instruments such as green bonds of GDP ratio, ii refers to the bank sector number in a certain country, but t refers to a certain year from 2013 to 2020. GII_R_{it} refers to the innovation rank in a certain country, while $CO2_{it}$, FDI_LOG_{it}, $LOG(GDP)_{it}$, $INFD_{it}$, DOM_{it}, and MC_{it} denote to the control variables, while e_{it} is the error term.

2- **Support Vector Regression (SVR)**

The SVR is formed with 10-fold cross-validation and uses Radial Basis Function (RBF) kernel type. ϵ-SVR uses an ϵ-insensitive loss function, ignoring errors below ϵ:

$$|\mathcal{Y} - f(x)|_\varepsilon \equiv max\ \{0, |\mathcal{Y} - f(x)| - \mathcal{E}\} \quad (13)$$

The model mathematics of SVR is:

$$\underset{w,b,\mathcal{E}}{Max} \quad \frac{1}{2} \parallel w \parallel^2 + C\sum_{i=1}^{n} |\mathcal{Y}_i - f(x)|_\varepsilon \quad (14)$$

The support vectors and values of the solution determine the regression form, as follows:

$$\boldsymbol{f(x)} = \sum_{i=1}^{n} \alpha_i K(x, x_i) + b \quad (15)$$

Regarding a-priory constants C, ν the dual quadratic optimization problem is:

$$\underset{\alpha,\alpha^*}{max} \quad \sum_{i=1}^{n}(\alpha_i^* - \alpha_i)\mathcal{Y}_i - \frac{1}{2}\ \sum_{i,j=1}^{n}(\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_j)\, K\ (x_i, x_j) \quad (16)$$

3- **K-Nearest Neighbors Model (k-NN)**

The Euclidean distance function is clarified as follows.

$$E(x,p) = \sqrt{\sum_a^m (x_a - p_a)^2} E(x,p) = \sqrt{\sum_a^m (x_a - p_a)^2} \quad (17)$$

Where x and p are the query point and a case from the set of examples, respectively, while m is the number of input variables. After selecting the value of k, KNN predictions are computed as the average of the outcomes (Al-Dosary et al., 2019):

$$y = \frac{1}{k}\ \sum_{i=1}^{k} y_i y = \frac{1}{k}\ \sum_{i=1}^{k} y_i \quad (18)$$

Where y_i is the i^{th} example, and y is the prediction for the query point.

Accuracy Metrics

To compare the methods used, this study calculated RMSE by using the following formula (Cao & Tay, 2001):

$$\text{Root Mean Squared Error (RMSE)} = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(y_i - \ddot{y}_i)^2} \quad (19)$$

4- **Comparative Analysis of Machine Learning Models Using Python**

- **Decision Trees (DT)**

Decision Trees (DT) are supervised learning models that recursively partition the feature space into smaller regions to create simple decision rules. For regression tasks, the model minimizes the Mean Squared Error (MSE) to determine optimal splits, as expressed by:

$$MSE = (1 / N) * \Sigma\ (y_i - \hat{y})^2 \qquad) \quad 20($$

Where y_i is the actual target value, $\hat{y}$ is the predicted mean of the target values within a region, and N is the number of samples in that region.

- **Random Forest (RF)**

Each tree is trained on a bootstrap sample with random feature selection at each split. The final prediction for regression tasks is computed by averaging the predictions of all trees, given by:

$$\hat{y} = (1 / T) * \Sigma\ f_t(x) \quad (21)$$

Where T is the total number of trees, and $f_t(x)$ is the prediction of the t^{th} tree for the input x.

- **Extreme Gradient Boosting (XG-Boost)**

This model optimizes a regularized loss function, defined as:

$$Obj = \Sigma\ l(y_i, \hat{y}_i) + \Sigma\ \Omega(f_k) \quad (22)$$

Where $l(y_i, \hat{y}_i)$ is the loss function, and $\Omega(f_k)$ is the regularization term defined as:

$$\Omega(f_k) = \gamma T + (1 / 2)\ \lambda\ \Sigma\ w_j^2 \quad (23)$$

Here, T is the number of leaves in the tree, w_j are the leaf weights, and γ, λ are regularization parameters.

- **Light Gradient Boosting Machine (Light-GBM)**

LightGBM employs leaf-wise growth and histogram-based binning to improve both speed and accuracy, with the objective function defined as:

$Obj = \Sigma\, l(y_i, \hat{y}_i) + \Sigma\, \Omega(f_k)$ (24)

Where:

- $l(y_i, \hat{y}_i)$ is the differentiable loss function, typically squared error for regression tasks
- $\Omega(f_k)$ is the regularization term that penalizes model complexity
- f_k represents the k^{th} decision tree

LightGBM employs a leaf-wise growth strategy, where at each iteration, the algorithm grows the leaf that maximally reduces the loss, rather than growing all leaves level by level. This approach allows for deeper trees in regions with high information gain, leading to improved accuracy.

- **Ridge Regression (L2 Regularization)**

Ridge Regression adds an L2 penalty to reduce overfitting and multicollinearity. The optimization problem is expressed as:

minimize: $\Sigma (y_i - X_i \beta)^2 + \lambda \Sigma \beta_j^2$ (25)

Where y_i is the observed target value, X_i is the feature vector for the i^{th} observation, β is the vector of model coefficients, λ is the regularization parameter controlling the penalty strength, and p is the number of features.

The L2 penalty term ($\Sigma \beta_j^2$) shrinks the coefficients towards zero but does not force them to be exactly zero.

- **Lasso Regression (L1 Regularization)**

Lasso Regression introduces an L1 penalty that encourages sparsity, meaning some coefficients can be exactly zero, allowing for feature selection. The optimization problem is defined as:

minimize: $\Sigma (y_i - X_i \beta)^2 + \lambda \Sigma |\beta_j|$ (26)

The symbols retain the same meaning as defined for Ridge Regression. The L1 penalty term ($\Sigma |\beta_j|$) can force irrelevant feature coefficients to exactly zero, simplifying the model and enhancing interpretability.

Empirical Results and Discussion

Table 2 presents the results of the descriptive statistics. Additionally, this study conducts correlation matrix and unit root tests to ensure that the results are strong against alternative empirical specifications and possible biases. Using panel analysis according to fixed and random effect models, results support the hypotheses on the impact of independent variables.

Descriptive Statistics Analysis and Correlation matrix

As shown in table 2, the descriptive statistics summarize the study variables. The mean value of GII_R which is the moderator is 35.67105 and the standard deviation is 23.12943, including minimum value of 3.000000 and maximum value of 81.00000.

The results uncover the mean value of GB 0.041750 with a standard deviation of 0.065463; similarly, ROA and ROE average statistics are 0.919672 and 10.46306, whereas the mean values of CA, NPL, CAR, and CD are 8.390567, 3.641121, 15.72373, and 120.6635, respectively.

The skewness result shows that ROA and ROE are skewed negatively, whereas CA, NPL, CAR, CD, GB, and GII_R are skewed positively. Meanwhile, table 3 presents a correlation matrix for all variables, as follows:

Table 2. Descriptive Statistics of Major Variables

Variable	N	Mean	Median	Minimum	Maximum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
ROA	76	0.919672	1.077902	-1.452849	2.296899	0.745845	-0.455909	2.932084	2.647412
ROE	76	10.46306	12.25051	-16.76591	24.30535	7.596545	-1.050757	4.569846	21.78913
CA	76	8.390567	8.117238	4.783922	11.77650	2.094474	0.170652	1.748148	5.331469
NPL	76	3.641121	2.795528	0.855252	18.03305	3.084517	2.751010	11.57231	328.5628
CAR	76	15.72373	15.48433	12.31822	22.37529	2.290208	0.689865	2.975975	6.030060
CD	76	120.6635	112.6772	60.51690	327.0919	59.35273	2.185030	7.538824	125.7115
GB	76	0.041750	0.007819	0.000000	0.246092	0.065463	1.610153	4.419580	39.22101
GII_R	76	35.67105	29.00000	3.000000	81.00000	23.12943	0.108608	1.634857	6.050862
CO2	76	6.064558	4.820605	1.527675	16.11119	3.725272	1.272850	4.127848	24.54999
FDI_LOG	76	1.612796	1.594034	1.572216	1.906484	0.061548	3.522782	14.96183	610.2969
LOG(GDP)	76	28.30608	28.22315	26.17519	30.62320	1.159647	0.393870	2.875443	2.014152
INFD	76	3.457359	2.065939	-0.223723	16.47582	3.408652	1.802470	6.475930	79.41264
DOM	76	95.72118	92.46590	29.01750	191.3640	43.76575	0.591022	2.546412	5.076072
MC	76	68.91545	65.49011	19.17380	164.9132	36.11738	0.830301	3.195382	8.853276

Source: Outputs of data processing using Eviews 13.

Table 3. Correlation Matrix

Variable	GB	GII_R	CO2	FDI_LOG	LOG(GDP)	INFD	DOM	MC	ROA	ROE	CA	NPL	CAR	CD
	1.000000													
GB	-----													
	-0.384173	1.000000												
GII_R	0.0006	-----												
	0.095867	-0.819162	1.000000											
CO2	0.4101	0.0000	-----											
FDI_	0.167201	-0.263299	0.157236	1.000000										
LOG	0.1488	0.0216	0.1749	-----										
LOG	0.079021	-0.455585	0.592422	-0.323391	1.000000									
(GDP)	0.4974	0.0000	0.0000	0.0044	-----									
	-0.352902	0.546179	-0.349819	-0.180110	-0.285423	1.000000								
INFD	0.0018	0.0000	0.0020	0.1195	0.0124	-----								
	0.165515	-0.721409	0.773781	0.081540	0.514863	-0.419555	1.000000							
DOM	0.1530	0.0000	0.0000	0.4838	0.0000	0.0002	-----							
	0.078502	-0.532142	0.635860	0.229685	0.372016	-0.493312	0.705561	1.000000						
MC	0.5003	0.0000	0.0000	0.0459	0.0009	0.0000	0.0000	-----						
	-0.313169	0.296248	0.066891	-0.054713	-0.004529	0.432018	0.067718	0.029613	1.000000					
ROA	0.0059	0.0094	0.5659	0.6388	0.9690	0.0001	0.5611	0.7995	-----					
	-0.181270	0.214545	0.032163	0.059509	-0.030804	0.302140	0.119134	0.086444	0.934052	1.000000				
ROE	0.1171	0.0627	0.7827	0.6096	0.7917	0.0080	0.3054	0.4578	0.0000	-----				
	-0.367606	0.302944	0.156754	-0.335560	0.206992	0.503019	0.066991	-0.002636	0.757649	0.524539	1.000000			
CA	0.0011	0.0078	0.1763	0.0030	0.0728	0.0000	0.5653	0.9820	0.0000	0.0000	-----			
	-0.131016	0.194714	-0.345202	-0.132490	-0.124082	-0.081307	-0.225836	-0.183125	-0.566074	-0.612867	-0.311526	1.000000		
NPL	0.2593	0.0919	0.0023	0.2539	0.2856	0.4850	0.0498	0.1133	0.0000	0.0000	0.0062	-----		
	0.302343	-0.299219	0.114413	0.364649	-0.065558	0.081513	-0.212043	-0.153277	-0.146217	-0.118110	-0.196200	-0.238844	1.000000	
CAR	0.0079	0.0086	0.3250	0.0012	0.5737	0.4839	0.0659	0.1862	0.2075	0.3096	0.0894	0.0377	-----	
	0.127152	-0.121319	-0.057793	-0.018505	0.117984	-0.054480	0.356550	-0.167808	0.087807	0.258787	-0.124727	-0.144153	-0.223272	1.000000
CD	0.2737	0.2965	0.6200	0.8739	0.3101	0.6402	0.0016	0.1473	0.4507	0.0240	0.2830	0.2141	0.0525	-----

Source: Outputs of data processing using Eviews 13.

Table 3 displays the correlation matrix of the study variables. All correlation coefficients are below 0.97, suggesting that multicollinearity is not a concern in this study. There some strong correlations like ROA have strong correlations with ROE, CA. GB has more correlation with CAR as compared to the CD. GII_R has more correlations with CA and ROA as compared to the ROE and NPL. ROE has strong correlation with CA.

Unit Root Tests

This study employs the Augmented Dickey and Fuller (ADF) and Phillips and Perron (PP) unit root tests to find out whether the variables contain unit root. Table 4 reports the results of the unit root tests, as follows:

Table 4. Panel Unit Root Tests

Variable	Level		First difference		
Chi–square	ADF–Fisher	PP–Fisher	ADF–Fisher	PP–Fisher	Conclusion
ROA	59.7847***	63.0513***	148.956***	161.505***	In level
ROE	55.6670***	76.5133***	158.581***	172.506***	In level
CA	53.8954***	32.6265	98.4893***	94.3102***	In level
NPL	69.0277***	88.1459***	75.0705***	77.4529***	In level
CAR	29.8861	49.1749***	87.7576***	100.477***	In level
CD	31.4918	36.8396*	66.7772***	65.2482***	In level
GB	35.6717	54.1269***	188.780***	198.608***	In level
GII_R	31.1913	42.5069**	135.439***	144.342***	In level
CO2	31.2938	41.1387*	104.984***	103.681***	In level
FDI_LOG	66.3121***	72.6883***	***155.449	***185.387	In level
LOG(GDP)	28.0428	39.4874*	***90.9208	***101.693	In level
INFD	*40.0637	*38.6672	***123.651	***119.495	In level
DOM	25.9132	21.6650	*38.2106	**39.2745	1 st Difference
MC	29.8057	29.9410	-2.53490***	***45.8709	1 st Difference

Note. ***, ** and * indicate significant levels of 1%, 5% and 10%, respectively.

Table 4 indicates that the variables ROA, ROE, CA, NPL, CAR, CD, GB, GII_R, CO2, FDI_LOG, LOG (GDP), and INFD are stationary at level, whereas the others become stationary at the first difference, reflecting varying levels of stationarity among the model variables.

The Panel Regression Results and Hypotheses Testing

To assess the effect of green finance on banks' performance in emerging and developed markets annually during 2013-2020, this study uses panel data analysis according to both fixed and random effect models with robust standard errors to mitigate the concerns of heteroscedasticity and autocorrelation. The outcomes of the panel regression are as follows:

Table 5. Models' Statistics

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Effect	ROA	ROE	CA	CAR	NPL	CD
Constant	2.901406	754.2297	-71.57761	-139.1410	-123.4492	3.724343
	(4.004085)	(243.1213)***	(23.39872)***	(49.31749) ***	(82.47652)	(358.5559)
GB	-0.315385	8.158137	1.184039	4.543457	-5.462170	-61.05443
	(0.577646)	(8.820635)	(0.871604)	(2.626251) *	(2.505366) **	(17.93486)***
CO2	0.038977	0.330002	-0.074392	0.559458	0.172491	-1.242643
	(0.021046)*	(1.391859)	(0.118315)	(0.158625) ***	(0.268224)	(1.295758)
FDI_LOG	0.308313	-0.710212	-1.302502	-2.716287	5.505312	53.49834
	(1.236624)	(14.22950)	(1.011048)	(6.943916)	(3.565181)	(34.37363)
LOG(GDP)	-0.088798	-26.12880	2.914696	5.493647	3.956225	-0.901791
	(0.124577)	(8.512345)***	(0.804030)***	(1.593701)***	(2.871812)	(12.20580)
INFD	0.002800	0.212383	-0.074898	0.040798	-0.044198	-0.422146
	(0.015630)	(0.186761)	(0.028772)**	(0.039101)	(0.060826)	(0.435040)
DOM	-0.004218	-0.086229	-0.009812	-0.034199	0.050474	0.871445
	(0.005044)	(0.062754)	(0.007539)	(0.010889)***	(0.022885)**	(0.150241)***
MC	0.001089	0.012407	0.015419	0.047781	0.011108	-0.227437
	(0.004444)	(0.055049)	(0.004605)***	(0.010982)***	(0.011422)	(0.102198)**
R-squared	0.028831	0.738356	0.977275	0.888866	0.910935	0.442529
Adjusted R-squared	0.061812	0.653955	0.969830	0.853016	0.882205	0.389073
S.E. of regression	0.395404	4.443170	0.365292	0.893068	1.031923	7.949905
F-statistic	0.318072	8.748158	131.2754	24.79429	31.70618	8.278371
Prob (F-statistic)	0.943641	0.000000	0.000000	0.000000	0.000000	0.000000

Source: Outputs of data processing using Eviews 13.

Table 5 shows the effect of GB on banks' performance. The outcomes reveal that GB has a positive effect on CAR, but a negative impact on NPL and CD. This suggests that GB positively impacts CAR by providing stable, low-risk, long-term funding that strengthens the bank's capital and improves its ability to withstand unexpected losses. The findings also reveal that GB negatively affects NPL, indicating improved asset quality and reduced credit risk, as banks increasingly finance sustainable, regulator-supported projects. Further, GB negatively impacts CD, indicating a reduced reliance on deposits as the primary source of lending. Therefore, the first hypothesis is supported.

Table 6. The Moderating Effect of Innovation on the Relation between Green Finance and Banks' Performance

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Effect	ROA	ROE	CA	CAR	NPL	CD
Constant	-1.443380	-35.31548	-53.40589	-175.5231	10.02134	131.2519
	(4.130178)	(59.22839)	(29.34145)*	(60.14681) ***	(28.70446)	(378.6768)
GB	0.918394	14.40471	5.978658	17.23104	-11.48375	-43.99189
	(1.255392)	(17.69824)	(1.158212) ***	(6.716569) **	(4.517892) **	(31.88774)
GII_R	0.017406	0.211762	-0.009756	0.036254	-0.049464	-0.148019
	(0.007905)**	(0.102595)**	(0.011751)	(0.024681)	(0.027485) *	(0.164993)
GB*GII_R	-0.039479	-0.600842	-0.175525	-0.493696	0.275755	-0.631965
	(0.046092)	(0.619467)	(0.033653)***	(0.205147)**	(0.160230) *	(0.794025)
CO2	0.060200	0.463250	-0.033982	0.581045	-0.121440	-1.606379
	(0.019889)***	(0.263008)*	(0.118110)	(0.154725) ***	(0.148423)	(1.245306)
FDI_LOG	0.561090	16.14414	-3.840742	-7.944676	4.022126	42.35128
	(1.088143)	(14.58751)	(0.923931)***	(6.940745)	(4.152725)	(40.62330)
LOG(GDP)	0.007963	0.199319	2.425995	7.031322	-0.460315	-4.413443
	(0.116085)	(1.664332)	(1.002147)**	(2.001642)***	(0.991093)	(12.55469)
INFD	0.009052	0.106843	-0.087573	0.017862	-0.022435	-0.520143
	(0.016033)	(0.174111)	(0.025815)***	(0.038506)	(0.047539)	(0.436281)
DOM	-3.63E-05	0.014674	-0.010227	-0.031305	0.031386	0.856143
	(0.005265)	(0.066583)	(0.006133)	(0.011341)***	(0.024531)	(0.147612)***
MC	0.001752	0.013845	0.013960	0.043149	0.006378	-0.244982
	(0.004522)	(0.057481)	(0.003918)***	(0.010259)***	(0.014027)	(0.106245)**
R-squared	0.087927	0.082716	0.980769	0.908585	0.177818	0.444670
Adjusted R-squared	0.024521	0.030374	0.973558	0.875066	0.076453	0.374276
S.E. of regression	0.396177	4.696730	0.341983	0.823362	1.079738	8.125752
F-statistic	0.781935	0.731417	136.0002	27.10664	1.754238	6.316876
Prob (F-statistic)	0.633545	0.678784	0.000000	0.000000	0.092073	0.000002
Cointegration Test	-1.547617*	-1.523154*	-4.126705***	-5.716203***	-1.989858**	-1.558809*

Note. Each cell contains the estimated parameters, with Std. Error between brackets, where * denotes p-value of 10%, ** indicates 5% & *** denotes 1%.

Table 6 represents the results of the main model which shows the moderating impact of GII_R on the relationship between green finance and banks' performance. The analysis employs panel data with robust standard errors to address heteroscedasticity and autocorrelation concerns. Results suggest that innovation plays a moderating role, exerting a negative influence on the relation between green bonds and capital adequacy, while positively moderating the relationship between green bonds and asset quality.

The findings indicate that green bonds have a significantly positive impact on capital adequacy, but a negative impact on asset quality in these markets. Moreover, innovation positively impacts profitability but negatively affects asset quality. The Kao Residual Cointegration Test indicates a long-term nexus between the components. In this context, this study finds that the banks' performance in markets was significantly driven by green bonds and innovation.

The results reveal that GII_R significantly and negatively moderates the relationship between GB and both CAR and CA, possibly due to the high costs associated with innovative investments. In contrast, GII_R significantly and positively moderates the relationship between GB and NPL, indicating a likelihood of increased credit risk due to exposure to green projects with relatively limited risk levels. However, GII_R has an insignificant moderate effect on the relationship between GB and profitability, which may suggest that the financial returns of innovative green projects require more time to yield actual returns.

The results indicate that the impact of green finance on capital adequacy varies depending on the level of innovation. Based on these findings, the second and third hypotheses are accepted.

Results of SVMs and k-NN in Regression

Table 7. compares the empirical outcomes of the panel data model with those of the SVR and KNN models. Both the support vector regression (SVR) and K-nearest neighbors (K-NN) models were implemented using Statistica software. The prediction from the panel data regression has an RMSE ranging between 7.6 and 4.4, whereas the SVR model achieves a lower RMSE of 19.8.The RMSE of the K-NN model falls within the range of 7.03 to 4.34.

Table 7. SVM and k-NN Regression Results

Methods Variables	Panel Regression		SVR		K-NN	
	RMSE	R^2	RMSE	R^2	RMSE	R^2
NPL	1.013	0.178	0.954	0.787	0.807	0.854
CD	7.608	0.445	19.722	0.518	7.034	0.98
ROA	0.371	0.088	0.351	0.743	0.365	0.638
ROE	4.405	0.083	4.359	0.6	4.348	0.493
CA	0.2898	0.981	0.747	0.825	0.431	0.966
CAR	0.700	0.909	0.756	0.871	0.778	0.86

Source: Outputs of data processing using Statistica software.

The comparison shows that the K-NN model achieved the best performance in predicting NPL and CD, while the SVR model provided better predictions for ROA and ROE. The Panel Regression model outperformed the others in CA and CAR. Overall, the findings reveal that the model based on the k-NN and SVR approaches outperforms the panel data model in predicting most variables.

Results of modern machine learning models

Table 8. The Comparison of Empirical Results Obtained Using Python

Model	SVR		Decision Tree		KNN		XGBoost	
Metric	rmse	r squared	**rmse**	**r squared**	**rmse**	**r squared**	**rmse**	**r squared**
ROA	0.316311577	0.848616925	0.546925486	0.547411545	0.463526536	0.674915433	0.445455233	0.699769175
ROE	5.625276075	0.578488018	6.828305493	0.378919166	6.104731492	0.503573021	6.933370643	0.359659345
CA	0.891578091	0.813906864	1.088818946	0.722461705	0.50799087	0.939587975	1.366815782	0.562647567
NPL	0.933750969	0.795473027	1.95344668	0.104858726	0.933496338	0.79558456	0.538183099	0.932056398
CAR	1.344948181	0.729742673	2.090923334	0.346805392	1.320426885	0.739507581	1.793779819	0.51926622
CD	12.84588591	0.967790541	44.46933494	0.614009534	15.21268526	0.954828234	27.84368535	0.848675675
AVG	3.659625133	0.789003008	9.496292479	0.452411011	4.09047623	0.767999467	6.486881655	0.653679063
Model	**Random Forest**		**Lasso**		**Light-GBM**		**Ridge**	
Metric	**rmse**	**r squared**	**rmse**	**r squared**	**rmse**	**r squared**	**rmse**	**r squared**
ROA	0.448776872	0.695275002	0.700427595	0.257709942	0.625789622	0.407478844	0.634226617	0.391394213
ROE	6.17841269	0.491517432	7.839540429	0.181340229	7.31329035	0.287560691	7.596454304	0.23132262
CA	0.601369079	0.915336978	1.328377324	0.586900676	1.621722684	0.384306228	1.473243229	0.491886791
NPL	0.759903672	0.864541723	2.278020369	-0.217316939	1.719240054	0.306635662	2.601598848	-0.587702478
CAR	1.381586985	0.714817522	1.733955406	0.550797442	1.817847061	0.506279617	1.559272993	0.636745765
CD	30.27826746	0.821055913	34.69675879	0.765018797	53.43037225	0.442773568	34.01252126	0.774195308
AVG	6.608052793	0.750424095	8.096179985	0.354075024	11.08804367	0.389172435	7.979552876	0.322973703

Source: Outputs of data processing using Python.

Table 8 compares the predictive performance of machine learning models in assessing banks' key financial indicators. The findings reveal that the SVR model achieved the best overall performance, with the lowest average RMSE and the highest R^2 across most financial indicators. The KNN model also performed well, especially in predicting CA, NPL, and CD. The Random Forest model provided acceptable results but was less accurate than SVR and KNN. In contrast, the Decision Tree, Lasso, LightGBM, and Ridge models showed weaker predictive performance with higher errors and lower R^2 values.

Overall, SVR and KNN proved to be the most effective models in this analysis and are recommended for future financial predictions and decision-making in similar banking and financial contexts due to their superior reliability and performance.

Conclusion and Recommendations

This study contributes to assessing the nexus among innovation, green finance, and banks' performance across 14 countries over 8 years using a machine learning approach. The study first considers whether innovation and green finance influence banks' performance. Furthermore, this study explores whether innovation moderates the relation between green finance and banks' performance, and tests for cointegration among the components of the nexus.

This study uses a global innovation index as a proxy for innovation. Green finance has been measured by green bonds, while banks' performance has been measured by capital adequacy, profitability, liquidity, and asset quality. The analysis employs panel data with robust standard errors to address heteroscedasticity and autocorrelation concerns. A comparison was conducted between panel data and two models, namely SVR and KNN, using statistical software. The study employed financial, economic, and machine learning approaches using Python to analyze banks' performance across international contexts. Python-based models were applied to compare the predictive capabilities of different machine learning techniques in forecasting key financial indicators.

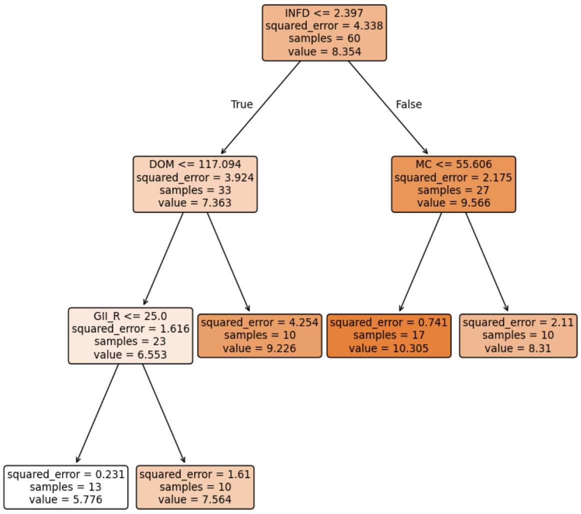
The outcomes suggest that green bonds have a significantly positive impact on capital adequacy, but a negative impact on asset quality in these markets. Results suggest that innovation positively impacts profitability but negatively affects asset quality. Moreover, innovation plays a moderating role, exerting a negative influence on the relation between green bonds and capital adequacy, while positively moderating the relation between green bonds and asset quality. The Kao Residual Cointegration Test indicates a long-term nexus between the components. The results reveal that models such as Decision Tree, Lasso, Light-GBM, and Ridge demonstrated weaker predictive capabilities, whereas SVR and KNN consistently outperformed the other models, making them preferable for future financial predictions and decision-making in similar contexts.

This study is distinguished by its comparative evaluation of machine learning models in predicting key financial indicators, highlighting the superior accuracy of SVR and k-NN compared to other models. Additionally, the study investigates the nexus among innovation, governance, and performance, with particular attention to the moderating role of innovation in influencing the relation between green finance and banks' performance.

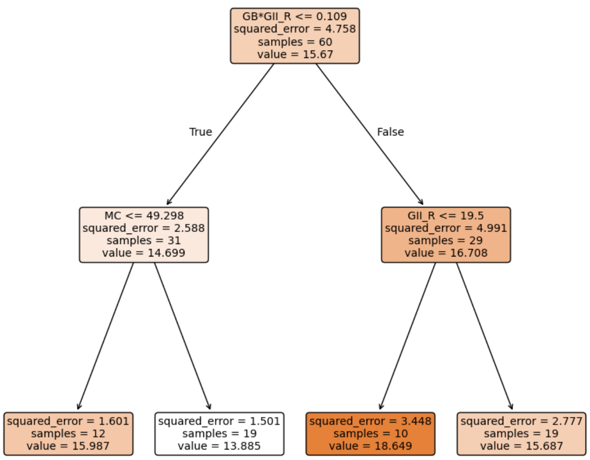
The study offers a comparative analysis of various methodologies and provides valuable insights into ongoing discussions in this area. The results suggest that there are incentives for banks to extend more green bonds to companies, which will help foster financial performance and sustainability targets. This study has certain limitations. For instance, the sample covers only 14 countries due to limited data availability, and it does not account for some bank-specific factors or country risks that may influence banks' financial performance. Future research may extend this study by focusing on the effect of innovation on the firms' financial performance across Arab countries.

Appendix 1: Decision Trees for Models

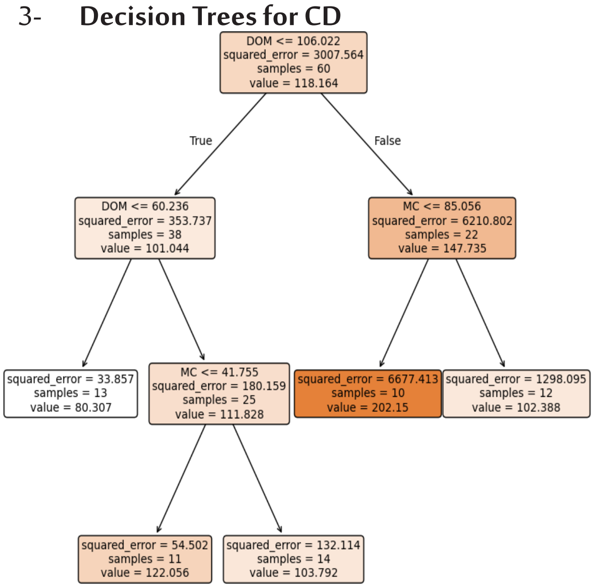
1- Decision Trees for CA



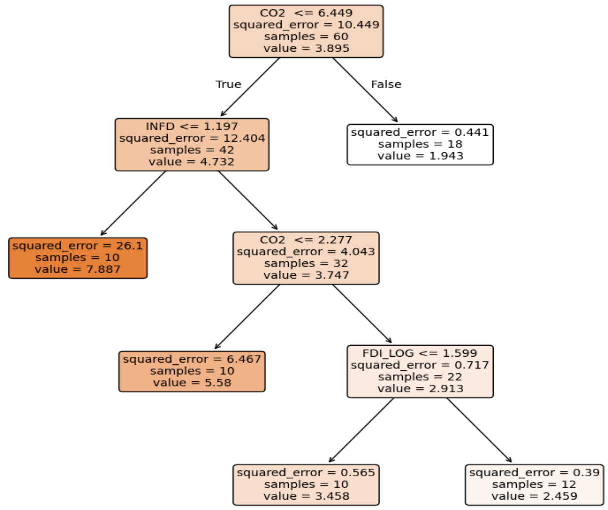
2- Decision Trees for CAR



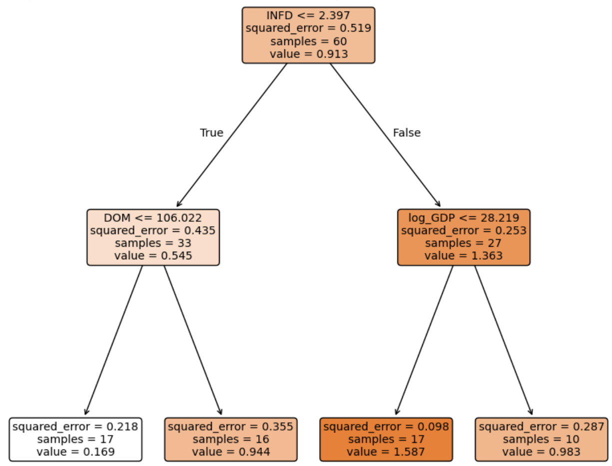
3- Decision Trees for CD



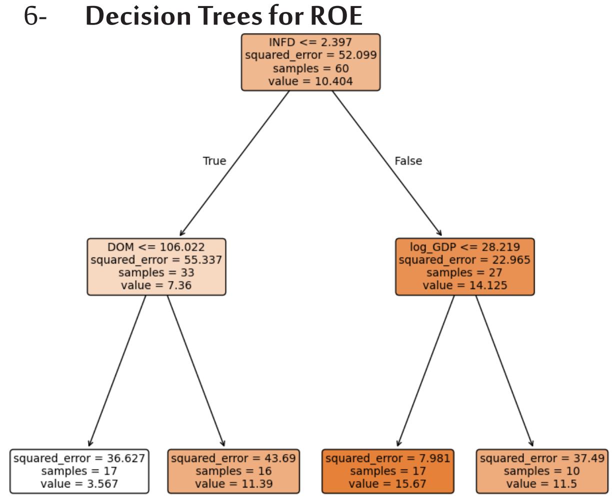
4- Decision Trees for NPL



5- Decision Trees for ROA



6- Decision Trees for ROE



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