



HAL
open science

Machine Learning Approaches to Predicting Corporate Green, Social, and Sustainability Bond Issuance

Riadh Ben Jelili

► **To cite this version:**

Riadh Ben Jelili. Machine Learning Approaches to Predicting Corporate Green, Social, and Sustainability Bond Issuance. 2025. <hal-04906541>

HAL Id: hal-04906541

<https://hal.science/hal-04906541v1>

Preprint submitted on 22 Jan 2025

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



HAL Authorization

Machine Learning Approaches to Predicting Corporate Green, Social, and Sustainability Bond Issuance

Riadh BEN JELILI

IAE Bretagne Sud - LEGO, Vannes, France

<https://orcid.org/0000-0002-6193-8663>

riadh.ben-jelili@univ-ubs.fr

Abstract:

This study investigates the factors driving corporate green, social, sustainability, and sustainability-linked bond issuances (GSSS bonds) through an advanced machine learning framework that balances predictive accuracy and interpretability. By analyzing GSSS bonds issued by non-financial corporations across 51 countries from 2013 to 2024, the research highlights the effectiveness of Random Forest (RF) and XGBoost for prediction and Multinomial Logistic Regression (MLR) for model transparency. Feature importance analysis using SHAP values and Partial Dependence Plots (PDPs) identifies key drivers, including firm size, governance quality, ESG performance, and macroeconomic factors such as GDP per capita and inflation. The findings demonstrate RF's superior predictive accuracy, with larger firms and robust governance frameworks emerging as dominant influences on GSSS bond issuance. Europe's leadership in sustainable finance further underscores the importance of strong regional frameworks. These insights provide practical guidance for issuers, investors, and policymakers, offering a roadmap to enhance sustainable finance strategies while contributing to global environmental and social objectives.

Keywords: Sustainable Bond Markets; Machine Learning; Governance and Sustainability; Predictive Modeling.

1. Introduction

The global financial sector has seen a remarkable rise in the issuance of green, social, sustainability, and sustainability-linked bonds (GSSS bonds). These instruments channel investments into impactful projects like renewable energy, affordable housing, and climate resilience, playing a pivotal role in advancing environmental and social progress. Aligned with frameworks like the UN Sustainable Development Goals (SDGs, 2015) and the Paris Agreement (2015), GSSS bonds have become essential for bridging funding gaps and driving sustainable development.

By mid-2024, global GSSS bond issuance reached USD 5.1 trillion, with USD 554 billion issued in the first half of the year alone—a 7% year-over-year increase (CBI, 2024). Green bonds dominated the market at 70% of total issuance, while sustainability and social bonds accounted for 17% and 13%, respectively. However, sustainability-linked bonds saw a 45% decline, raising concerns about their long-term viability. Corporate issuers remain key drivers of growth, contributing USD 145.1 billion—a 47% increase from 2023—while sovereign issuances reached USD 104 billion across 33 countries. Despite this progress, the factors guiding corporate decisions on bond type selection remain underexplored, which is critical for optimizing sustainable finance allocations.

This study investigates these factors using a dual-method machine learning framework, combining the predictive power of Non-Parametric Machine Learning (NPML) models like Random Forest (RF) and XGBoost with the interpretability of Parametric Machine Learning (PML) approaches such as Multinomial Logistic Regression (MLR). This approach ensures high predictive accuracy while maintaining model transparency, a key requirement for financial decision-making under stringent regulatory frameworks (Bacciu et al., 2019). To address the interpretability challenge of NPML models, SHAP (SHapley Additive exPlanations) is employed. This method provides insights into how features contribute to the model's predictions by assigning each feature a Shapley value, representing its marginal contribution to the prediction. Additionally, a Partial Dependence Plot (PDP) is used to visualize the relationship between one or two features and the model's predicted outcome. PDPs help to understand how the model's predictions change as a particular feature (or features) vary, while marginalizing the effects of all other features. Together, SHAP and PDP complement each other in elucidating how corporate, national, and sectoral characteristics influence bond type selection.

By integrating advanced machine learning with statistical analysis, this research identifies meaningful patterns in the sustainable finance sector and provides actionable insights. The findings fill a critical gap in the literature, offering stakeholders valuable guidance to enhance the adoption and diversification of GSSS bonds. Ultimately, this study contributes to the broader mission of leveraging sustainable finance to address global challenges while fostering economic growth.

The paper is organized as follows: Section 2 provides a review of the literature on GSSS bonds, examining their market evolution, defining features, and key determinants. Section 3 describes the dataset and methodological framework, with a focus on the integration of machine learning models and interpretability tools such as SHAP and PDPs. Section 4 presents the study's findings, highlighting the models' predictive accuracy and the primary factors influencing GSSS bond issuance. Section 5 explores the broader implications of these results for policymakers, investors, and corporate issuers. Finally, Section 6 concludes by summarizing the study's key contributions and offering directions for future research.

2. Green Bonds vs. Emerging Trends in Sustainable Finance

Driven by the global push for sustainability and mounting societal, client, and financial pressures, companies are increasingly embracing sustainable practices. They are investing in green and social projects, creating sustainable products, transforming business models, and aligning their operations with Environmental, Social, and Governance (ESG) principles or the United Nations Sustainable Development Goals (SDGs). To facilitate this transition, the financial sector has introduced a range of sustainability-oriented instruments, particularly in banking and bond markets. Among these, green bonds (GBs) have emerged as the dominant tool, outperforming alternatives like sustainability-linked bonds (SLBs), social bonds (SOBs), and sustainability bonds (SUBs). The widespread adoption of GBs is attributed to their clear purpose, standardized frameworks, and proven effectiveness in financing environmentally sustainable initiatives. While other instruments address broader sustainability goals, GBs are specifically designed to tackle critical environmental challenges, such as reducing greenhouse gas emissions, as outlined in the Paris Agreement.

Since their inception in 2018, SLBs have encouraged environmentally responsible behavior by linking financial terms to performance targets. However, GBs remain the most widely used tool

due to their transparency, targeted focus, and established reputation. Studies have underscored the financial and reputational benefits of GBs, showing that issuers often experience lower financing costs (Zerbib, 2019; Gianfrate and Peri, 2019), positive stock market responses, improved corporate social responsibility (CSR) ratings, and enhanced financial performance (Flammer, 2021; Wang et al., 2020). The “greenium” effect, where GBs yield lower interest rates due to high demand, provides issuers with cost advantages while offering investors stable returns (Gianfrate and Peri, 2019). Additionally, GBs serve as a credible demonstration of a company’s commitment to sustainability, reducing economic and reputational risks (Flammer, 2013). This combination of financial and reputational gains, along with the maturity of the GB market, has solidified GBs as the preferred choice for sustainable financing.

GBs stand out for their ability to directly fund projects with measurable environmental benefits, such as renewable energy, energy efficiency, and climate adaptation, under frameworks like the Green Bond Principles (2021). The market’s growth dates back to 2007 when the European Investment Bank introduced the Climate Awareness Bond, followed by the World Bank in 2008. By June 2024, cumulative GB issuances exceeded \$3.2 trillion, driven by societal demand, favorable regulations, and rising interest in ESG investments (CBI, 2024; Flammer, 2021). This established track record gives GBs a significant maturity advantage over SLBs, SUBs, and SOBs, which remain in early stages of development (Bhutta et al., 2022).

The structure of GBs provides clarity and accountability, requiring proceeds to be exclusively allocated to specific environmental projects. This ensures transparency for both issuers and investors. By contrast, SLBs offer more flexibility by linking financial terms to sustainability goals, but this can introduce uncertainty. For example, SLBs may include options for issuers to repurchase bonds before maturity, avoiding penalties for missed goals (Ul Haq and Doumbia, 2022). While flexibility appeals to issuers, it raises concerns about long-term sustainability commitments and investor confidence. GBs avoid these issues through strict use-of-proceeds requirements, ensuring funds are used for tangible environmental outcomes.

Globally recognized standards, such as the Green Bond Principles (GBP) by the International Capital Market Association (ICMA) and the EU Green Bond Standard, enhance the credibility of GBs by promoting transparency, comparability, and rigorous reporting. In contrast, SLBs, SUBs, and SOBs lack universally adopted guidelines, making compliance and validation more complex (Tolliver et al., 2020). Through third-party verifications and stringent criteria, GBs effectively address greenwashing concerns, providing issuers and investors with confidence in their environmental impact (Maltais and Nykvist, 2020).

The proven success and maturity of GBs have made them a cornerstone of sustainable finance, enabling governments, corporations, and institutional investors to align their financial strategies with climate goals. In contrast, the newer SLBs, SUBs, and SOBs face limited market adoption, further reinforcing the dominance of GBs in sustainable finance. Moreover, GBs deliver clear environmental benefits, with monitored and verified outcomes, ensuring compliance with their stated objectives (Zerbib, 2019). By comparison, SLBs often rely on metrics that are harder to monitor, reducing accountability (Ul Haq and Doumbia, 2022). Similarly, SUBs and SOBs, with their broader mandates, dilute their focus on environmental issues, diminishing their appeal to ESG-conscious investors (Tolliver et al., 2020). GBs' targeted project funding approach makes them an effective tool for addressing urgent challenges like climate change.

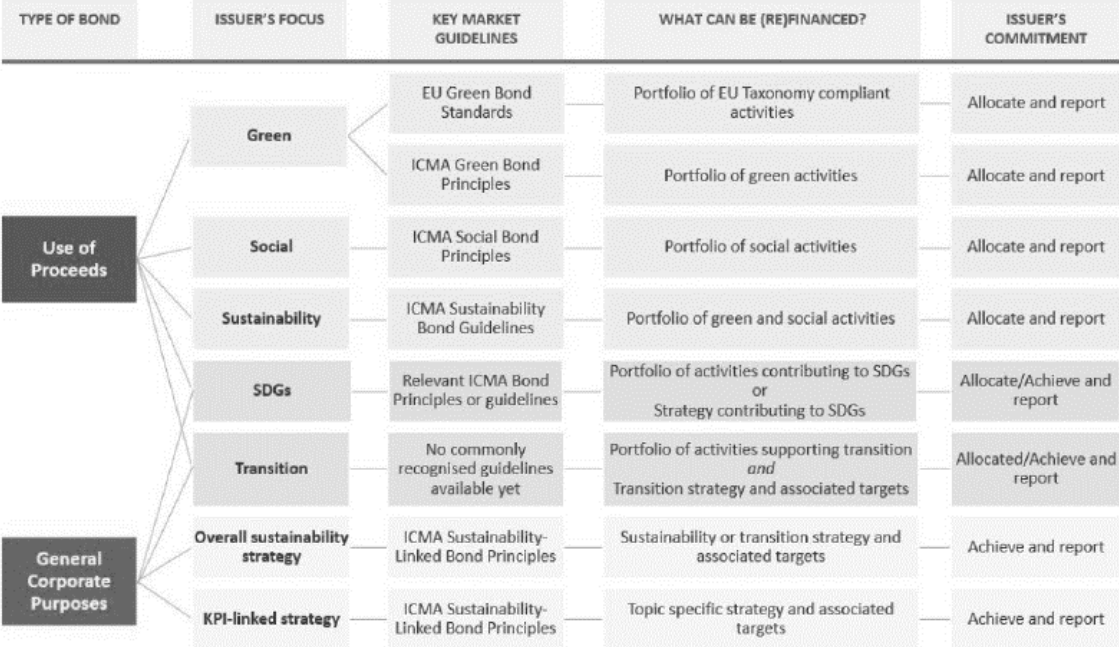
Standards and principles for GSSS bonds play a vital role in maintaining market integrity by fostering transparency and accountability. The ICMA's Green, Social, and Sustainability-linked Bond Principles provide voluntary guidelines to improve disclosure, though gaps remain for SDG-linked and transition bonds due to limited or inconsistent frameworks. For instance, GBs align with EU Green Bond Standards and ICMA Green Bond Principles, ensuring funds are directed toward eligible green activities. In contrast, SDG-linked bonds lack universal standards, reflecting broader challenges in standardization. The European Green Bond Standard addresses some of these gaps by requiring alignment with the EU Taxonomy, detailed reporting, external compliance checks, and oversight by the European Securities and Markets Authority (ESMA) (Bhutta et al., 2022). Despite progress, inconsistencies in data quality and adherence to guidelines persist, highlighting the need for standardized governance to reduce risks such as greenwashing and boost investor confidence.

While GBs continue to lead the sustainable finance market due to their transparency, focused purpose, and measurable impact, the increasing visibility of alternative instruments like SLBs, SUBs, and SOBs underscores their potential to tackle broader sustainability goals. However, these alternatives face significant challenges, including their complexity, dependence on performance-linked frameworks, and the absence of universally accepted standards, which hinder their widespread adoption (Tolliver et al., 2020).

To fully realize their potential and enhance their complementarity with GBs in driving global sustainability and climate initiatives, it is vital to deepen the understanding of the factors influencing their issuance. These factors include market dynamics, structural characteristics, and investor preferences (Maltais and Nykvist, 2020). Such an analysis is essential to pinpoint the distinctive contributions of SLBs, SUBs, and SOBs in the growing realm of sustainable

finance. By addressing these challenges, these instruments can play a more prominent role alongside GBs in tackling the pressing environmental and social issues of our time.

Figure 1 : Labelled bond criteria



Source: Harvard Law School Forum on Corporate Governance, June 2020, <https://corpgov.law.harvard.edu/2020/06/>.

3. Dual Analytical Approach: MLR and NPML

The analysis of the choice to issue a specific GSSS bond involves evaluating predictors associated with firm-specific characteristics, issuance-specific attributes, and macroeconomic contexts. The objective is to identify the factors influencing the issuance decision and accurately predict the bond type using machine learning algorithms.

Parametric Machine Learning: MLR

MLR, or multinomial logit, is an extension of logistic regression used to model outcomes with more than two discrete, unordered categories. It is particularly suitable for predicting the likelihood of categorical outcomes, such as the selection of bond types (e.g., GB, SLB, SOB, SUB), based on a set of predictors. MLR handles continuous, categorical, or mixed predictors, modeling how each influences the probability of an observation belonging to a specific category

Let Y be the categorical dependent variable with k classes ($Y \in \{1,2,\dots,k\}$), $X = [X_1, X_2, \dots, X_p]$ represent the predictor variables, and $P(Y = j | X)$ denote the probability of

class j given X . In the MLR framework, the log-odds of each class j relative to a reference class k is modeled as:

$$\log\left(\frac{P(Y=j|X)}{P(Y=k|X)}\right) = \beta_{j0} + \beta_{j1}X_1 + \beta_{j2}X_2 + \dots + \beta_{jp}X_p \quad (1)$$

where β_{j0} is the intercept for class j , and $\beta_{j1}, \beta_{j2}, \dots, \beta_{jp}$ are the coefficients for the predictors. These coefficients represent the change in the log-odds of selecting a specific bond type over the baseline category (the reference class) for a one-unit change in the corresponding predictor.

The probability of choosing bond type j is modeled as:

$$P(Y = j | X) = \frac{\exp(\beta_{j0} + \beta_{j1}X_1 + \beta_{j2}X_2 + \dots + \beta_{jp}X_p)}{\sum_{l=1}^k \exp(\beta_{l0} + \beta_{l1}X_1 + \beta_{l2}X_2 + \dots + \beta_{lp}X_p)} \quad (2)$$

MLR relies on several key assumptions: the Independence of Irrelevant Alternatives (IIA) assumes that the odds ratio between any two categories remains unaffected by the presence or absence of other categories, although this may not hold when categories are similar. The model also assumes linearity, where the log-odds of the outcome are a linear function of the predictors, and it requires minimal multicollinearity among independent variables to ensure reliable coefficient estimates.

NPMP: Random Forest (RF) and XGBoost

Non-parametric methods, such as machine learning algorithms, are highly effective in modeling complex datasets as they relax assumptions about data distribution and functional relationships, allowing for greater flexibility. These algorithms excel at capturing non-linear relationships and intricate interactions among variables, making them particularly suitable for classification tasks like identifying the factors that influence the selection of GSSS bond types in the presence of multiple interacting predictors.

RF works by creating a collection of decision trees, each built (trained) from a random sample of the data, and considering only a subset of predictors at each step to ensure variety and avoid overfitting. The final prediction comes from combining the outputs of all the trees—using majority voting for classification tasks or averaging for regression. This method is particularly effective at handling complex, non-linear data, making it ideal for exploring how factors like ESG scores, macroeconomic conditions, and company characteristics influence bond issuance

decisions. Random Forest also offers insights into which predictors are most important, helping analysts understand key drivers.

For an issuance i , let:

Y_i : represent the categorical outcome ($i = GB, SLB, SOB, SUB$).

X_j : be the set of predictors, including firm-specific (X_f), country-specific (X_c), and sectoral dummies (X_s).

The model approximates the probability of choosing bond type k given the predictors by aggregating predictions from multiple decision trees:

$$P(Y_i = k|X_j) = \frac{1}{T} \sum_{t=1}^T h_t(X_j) \quad (3)$$

where T is the number of trees in the forest; $h_t(X_j)$ is the prediction of the t -th tree for X_j .

Random Forest (RF) is highly valued for its ability to uncover complex, non-linear relationships without requiring predefined assumptions about how variables interact or behave. This flexibility makes it particularly useful for analyzing intricate dynamics, such as the interplay between macroeconomic indicators, bond issuance characteristics, and company-specific factors. Additionally, RF provides meaningful insights by identifying key factors and measuring their impact on the model's accuracy. This is achieved through metrics like the reduction in impurity (e.g., Gini impurity or entropy) at decision points, defined as:

$$Importance(X_j) = \frac{1}{T} \sum_{t=1}^T \Delta I_{j,t} \quad (4)$$

where $\Delta I_{j,t}$ is the decrease in impurity for variable X_j in tree t .

One of RF's strengths is its ability to uncover interactions between variables and generate probabilistic predictions. This allows for nuanced insights into how factors like macroeconomic conditions and firm-level characteristics influence bond type choices. As a result, RF is particularly valuable for understanding the determinants of sustainable finance instruments.

The implementation of the Random Forest (RF) model followed a clear and systematic process. First, numerical predictors were standardized to ensure consistency, while categorical variables, like sectoral affiliations, were converted into dummy variables for analysis. Second, since green bonds (GBs) dominated the dataset, undersampling was applied to balance the representation of all bond types. Third, the RF model, configured with a set number of decision trees and

balanced class weights, was trained to enhance predictions for smaller, less-represented bond categories. Fourth, the model’s performance was evaluated using metrics such as precision, recall, and F1-scores, with particular attention to accurately classifying underrepresented bond types like SLBs, SOBs, and SUBs. Finally, the model provided insights into the most important predictors, identifying factors like governance indicators and macroeconomic conditions as key drivers of bond issuance decisions.

XGBoost, or Extreme Gradient Boosting, is an advanced gradient boosting algorithm that builds decision trees sequentially, with each tree correcting the errors of the previous one. The objective function it minimizes (L) comprises two components: a loss function ($l(y_i, \hat{y}_i)$) that evaluates prediction errors (e.g., log-loss for classification), where y_i is the actual target value and \hat{y}_i is the predicted value for the i -th training example, and a regularization term ($\Omega(f_k)$) that penalizes model complexity to enhance generalization, where f_k represents the k -th decision tree or weak learner:

$$L = \sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k) \quad (5)$$

XGBoost employs additive training to iteratively reduce the loss function, incorporates L_1 and L_2 regularization to prevent overfitting, and uses column sampling to improve computational efficiency and reduce overfitting. Its ability to handle large datasets, flexibility in tuning hyperparameters (such as learning rate, tree depth, and number of estimators), and feature importance metrics make it a highly effective tool for predictive modeling.

The XGBoost algorithm starts by making initial predictions using a simple base model, like the average or log-odds of the target variable. It then calculates gradients, which represent the errors in the current predictions, to pinpoint where improvements are needed. A decision tree is built to address these errors, and the predictions are updated based on the tree’s output. This process is repeated multiple times, with each tree refining the predictions further, until a stopping criterion is reached—such as hitting a set number of iterations or triggering an early stopping rule.

4. Data, Implementation and Results

Dataset and Key Metrics for GSSS Bonds

The models are trained on financial data sourced from Bloomberg, accessed via API servers, using a dataset that integrates firm-specific, bond-specific, and market-specific features. Firm-level characteristics include sustainability indexes, profitability ratios, and solvency ratios;

bond attributes cover coupon rates, credit ratings, and maturity lengths; while market-level factors account for the country of issuance and the associated industry sector. These variables are complemented by macroeconomic indicators, which influence corporate decisions on bond issuance.

The dataset captures records from Bloomberg of all non-financial corporate GSSS bonds issued between January 2013 and October 2024, covering 51 countries. It includes detailed information on issuers, issuance amounts, maturities, and both announcement and issuance dates. Additional macroeconomic data for each country was sourced from the International Monetary Fund (IMF) and the World Bank's Worldwide Governance Indicators. Together, this comprehensive dataset offers a strong foundation for a global analysis of the factors influencing corporate GSSS bond issuance. Table 1 provides an overview of the variables included in the dataset, along with their descriptions and data types, while Table 2 summarizes key characteristics of all continuous variables.

The original dataset included 1850 bonds: 1250 GB, 305 SLB, 216 SUB, and 78 SOB, amounting to nearly USD 549 billion in total issuance. To ensure the dataset's relevance and consistency, strict selection criteria were applied. Only bonds with detailed information about the issuers and their characteristics were included. Issuances from offshore financial hubs, such as the Cayman Islands, Guernsey, and Bermuda, were excluded to avoid potential biases from their unique regulatory environments. Bonds with a minimum issuance size of USD10 million were prioritized to focus on significant market transactions, while perpetual bonds and those with unusually high coupon rates were excluded to maintain uniformity and avoid distortions caused by outliers.

After applying these criteria, the final dataset was narrowed to 1620 bonds from 47 countries, with a total issuance volume of USD 488.24 billion. This refined dataset includes 1069 GB, 290 SLB, 192 SUB, and 69 SOB. Table 3 provides a detailed breakdown of key metrics for each country, including the number of bonds issued, total issuance amounts (in USD millions), average maturities (in years), and coupon rates (average). This curated dataset ensures a solid foundation for analyzing trends and patterns in GSSS bond issuance.

To strengthen the analysis, issuer-specific variables were lagged by one period (at time $t-1$), along with macroeconomic data for the country of issuance, following the methodologies of Lin and Su (2022) and Altunbaş et al. (2010). This lagging approach accounts for the influence

of prior-year financial conditions on issuance decisions and reduces potential endogeneity concerns, making the findings more robust and reliable.

Japan leads the GSSS bond market in issuance volume, with 394 bonds, followed by China with 129 and Sweden with 124, demonstrating these nations' strong commitment to funding sustainability initiatives. The United States, despite fewer issuances (117), stands out with an average issuance size of \$753.57 million, reflecting the larger scale and strategic importance of individual bonds in its market. The highest average issuance amounts are seen in the United Arab Emirates (UAE) at \$925 million, Ireland at \$861.34 million, and the Czech Republic at \$729.90 million, highlighting significant funding needs for large-scale infrastructure or sustainability projects. In contrast, countries like Lithuania (\$22.30 million) and Hungary (\$21.74 million) exhibit smaller issuance sizes, indicating more modest financing demands.

Coupon rates vary widely, with Japan averaging the lowest at 0.62%, a reflection of its low-interest-rate environment, while Taiwan (1.19%) and Switzerland (1.26%) also benefit from favorable borrowing conditions. On the higher end, Kazakhstan has the steepest average coupon rate at 17.00%, likely driven by higher risks or inflation, followed by South Africa (9.92%) and Mexico (9.12%). Maturity lengths also show notable differences. Portugal leads with an average maturity of 29.42 years, reflecting a long-term borrowing strategy, followed by Iceland (17.97 years) and Australia (17.94 years). Conversely, Argentina exhibits the shortest average maturity at 2.13 years, pointing to a preference for short-term financing.

Globally, the average issuance size across all 1,620 bonds is \$301.38 million, with an average coupon rate of 2.90% and an average maturity of 7.40 years. These benchmarks highlight the diversity of the GSSS bond market, showcasing how advanced economies like Japan and Germany pursue lower-cost, longer-term financing, while emerging markets such as South Africa and Brazil adapt to different borrowing conditions and strategies to meet their sustainability goals.

Table1: Description of Variables

Name	Description	Data type
Issuance type (target variable)	One-hot encoding assigns each GSSS issuance category (GB, SLB, SUB, SOB) a unique binary pattern of 1s and 0s.	Float
Amount issued	The volume of GSSS bonds issued, measured in millions of dollars, is normalized to a value between 0 and 1 using the equation below: $y_i = \frac{x_i - \min(x)}{\max(x) - \min(x)}$	Float
Maturity length	The difference between the issue date and the maturity date in days.	Float
Coupon rate	The interest payment received by a bondholder from the date of issuance until the date of maturity of a bond	Float
Use of proceeds	Dummy variable is defined to indicate whether the funds raised are allocated for sustainability-related purposes.	Float
Investment grade	Dummy variable to signal strong creditworthiness, making a firm more attractive to institutional investors, particularly for ESG-focused bonds.	Float
Principal currency	Dummy variables to represent the principal currency of the bond issuance, where one dummy indicates whether the bond is issued in EUR and another dummy indicates whether the bond is issued in USD.	Float
Leadership in GSSS Bond Markets	Dummy variables are created for the country of issuance, where each dummy represents one of the four countries under consideration: China, France, Germany, Japan, Korea, Sweden and USA.	Float
ESG composite score	The average of the environmental, social, and governance disclosure scores, on 100-point scale.	Float
Return on Asset	Proxy measure of firm's profitability, measures as a ratio	Float
Leverage ratio	The ratio of debt (short and LT) to the issuer's equity; reflects the extent to which a firm relies on debt financing relative to equity.	Float
Liquidity ratio	Measures firm's ability to meet its short-term liabilities with liquid assets.	Float
Capex to total assets	Ratio assessing a firm's investment strategy, growth prospects.	Float
Firm size	Ratio of a company's market capitalization to the amount of a specific bond issuance, to assess the scale of a bond issuance relative to the company's total market value.	Float
Gender diversity	Defined as the percentage of female executives in the company; a measure of proactive approach to diversity and inclusion, which aligns with the broader objectives of GSSS bonds	Float
Sectoral dummies	Different sectors experience varying sustainability pressures and opportunities, with certain industries being more affected by regulations and investor scrutiny	Float
Governance quality index at the country level	First principal component derived from a PCA conducted on six governance-related indicators: Control of corruption, government effectiveness, political stability, regulatory quality, rule of law, and voice and accountability.	Float
Government debt	General government gross debt percent of GDP.	Float
GDP per capita	GDP per capita, in constant 2017 international USD (PPP-adjusted).	Float
Growth rate	GDP growth rate at constant prices.	Float
Inflation	Average consumer prices, percent change.	Float
Investment rate	Total investment as a percentage of GDP.	Float

Table 2: Summary statistics of continuous variables

Variable	count	mean	std	min	50%	max
Maturity length	1620	2700,02	2507,37	365	1827	22371
Amount issued	1620	0,12	0,13	0	0,0545	1
Coupon rate	1620	0,03	0,03	0	0,0237	0,1700
Leverage ratio	1620	1,41	2,00	-24,7371	0,9574	18,0084
Liquidity ratio	1620	0,07	0,07	0	0,0503	0,6471
Return on asset	1620	0,04	0,07	-0,8773	0,0359	0,5242
ESG composite score	1620	43,42	21,41	3,2511	48,4585	85,7954
Firm size	1620	1306,45	8558,83	0,5632	37,5044	171989,256
Gender diversity	1620	13,25	15,85	0	6,25	75
Capex to total assets	1620	0,05	0,05	0	0,0378	0,5531
Governance quality index	1620	0,08	2,24	-5,2758	1,1073	2,9954
Government debt	1620	116,81	81,63	0,0550	83,6440	258,2970
GDP per capita	1620	0,33	0,14	0	0,3253	1
GDP growth rate	1620	1,30	3,83	-11,1650	1,9230	13,7880
Inflation	1620	2,73	5,02	-1,2620	1,9730	133,4890
Investment rate	1620	25,93	6,11	12,5380	25,2460	43,9610

Table 3: Key metrics by country for GSSS bonds

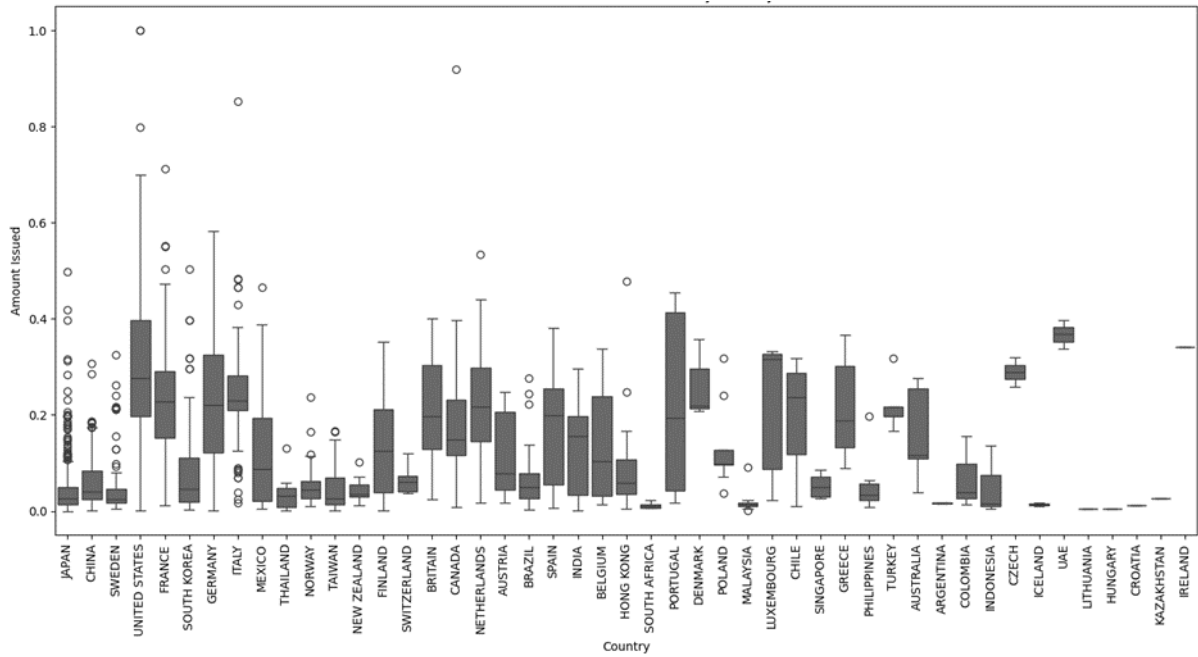
Country	# Issuance	Average issued amount (Millions USD)	Average coupon rate	Average maturity length (years)
JAPAN	394	120,24	0,62%	7,45
CHINA	129	162,60	3,18%	3,46
SWEDEN	124	124,19	4,49%	4,96
UNITED STATES	117	753,57	3,17%	9,70
FRANCE	93	590,15	2,47%	7,91
SOUTH KOREA	87	215,15	3,01%	4,64
GERMANY	83	565,95	1,74%	11,65
ITALY	53	612,17	2,41%	7,96
MEXICO	38	318,86	9,12%	7,10
NORWAY	37	149,02	6,39%	5,51
THAILAND	37	86,69	3,34%	5,96
TAIWAN	30	129,91	1,19%	4,97
FINLAND	29	344,99	3,61%	5,84
NEW ZEALAND	29	115,71	4,61%	9,66
BRITAIN	28	514,35	3,36%	7,36
SWITZERLAND	28	161,71	1,26%	7,62
CANADA	27	507,09	4,52%	15,09
NETHERLANDS	26	576,37	3,02%	8,56
AUSTRIA	24	301,24	2,19%	8,54
BRAZIL	22	189,81	6,54%	9,54
SPAIN	22	434,24	2,32%	7,45
INDIA	20	375,92	5,83%	5,65
BELGIUM	17	383,25	2,25%	7,74
HONG KONG	13	277,84	3,45%	6,85
SOUTH AFRICA	12	37,54	9,92%	5,25
DENMARK	10	654,57	3,40%	7,77
PORTUGAL	10	562,27	4,06%	29,42
MALAYSIA	9	61,90	4,98%	4,11

POLAND	9	340,04	5,68%	6,23
CHILE	7	499,65	3,83%	13,04
LUXEMBOURG	7	543,25	2,98%	6,41
GREECE	6	544,04	3,32%	6,09
PHILIPPINES	6	157,42	6,47%	6,67
SINGAPORE	6	140,09	4,24%	6,17
AUSTRALIA	5	406,69	3,08%	17,94
TURKEY	5	555,31	6,75%	5,90
ARGENTINA	4	52,05	5,94%	2,13
COLOMBIA	3	182,87	8,13%	10,34
INDONESIA	3	139,33	7,41%	4,34
CZECH	2	729,90	3,31%	6,50
ICELAND	2	45,49	1,86%	17,97
UAE	2	925,00	4,72%	11,22
CROATIA	1	40,79	4,25%	5,00
HUNGARY	1	21,74	3,00%	10,01
IRELAND	1	861,34	4,25%	12,01
KAZAKHSTAN	1	74,61	17,00%	15,01
LITHUANIA	1	22,30	6,00%	5,01
TOTAL	1620	301,38	2,90%	7,40

Figure 2 visualizes the normalized issuance amounts of GSSS bonds across countries through a boxplot, enabling a comparison of trends and variations. The X-axis represents the countries, while the Y-axis shows the normalized issuance amounts. Each box-and-whisker plot captures the range, spread, and key characteristics of bond issuances for each country.

Key observations reveal substantial differences in issuance scales. Countries like Ireland, the UAE, and the Czech Republic show higher median issuance values, reflecting their significant contributions to large-scale bonds. In contrast, Lithuania and Hungary display smaller, more uniform issuance distributions. Japan and China exhibit wider spreads and numerous outliers, indicating greater variability in issuance amounts. This figure highlights the disparities in bond issuance scales and the dominance of certain countries in high-value GSSS bond markets.

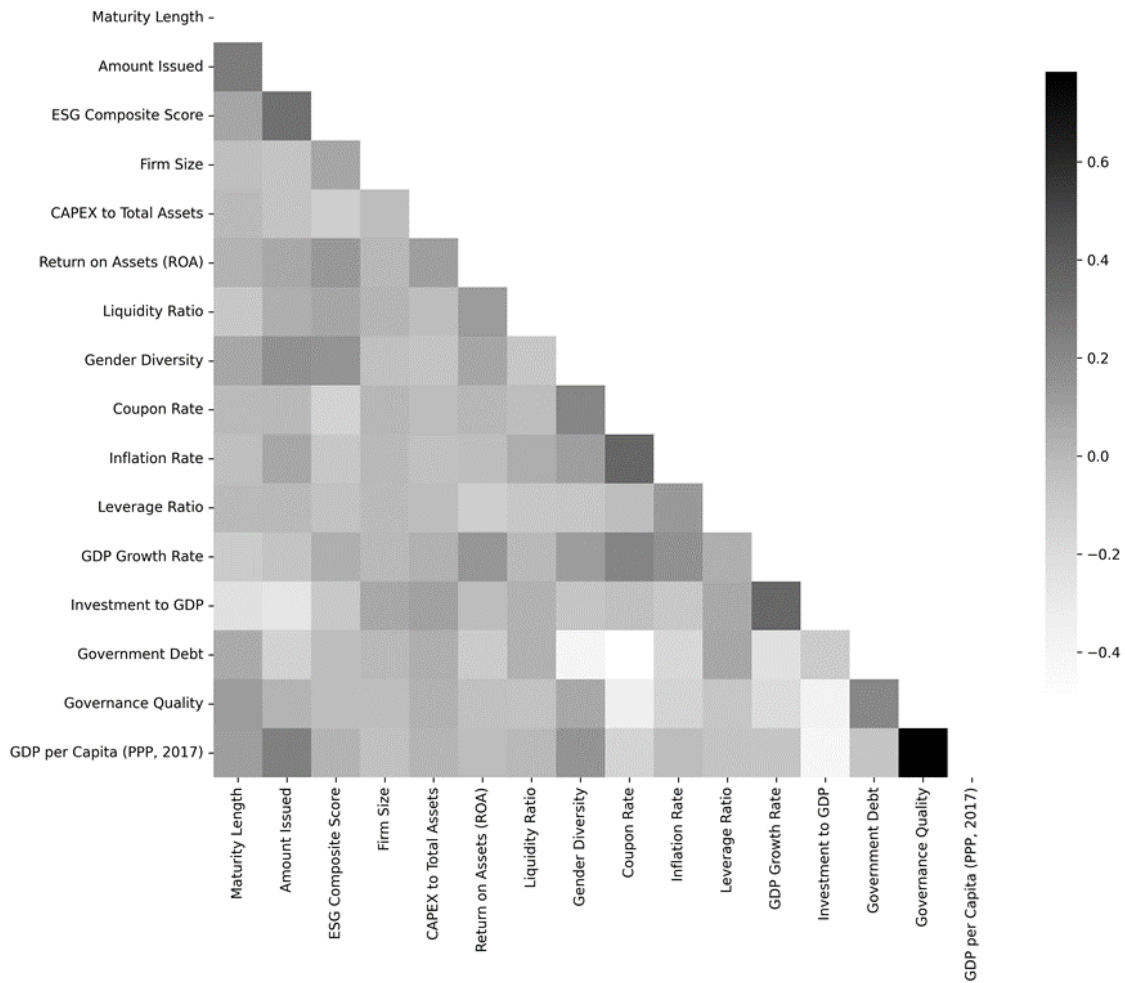
Figure 2: Normalized Issuance Amounts by Country of Issuance



The grayscale heatmap in Figure 3 reveals critical relationships among numerical variables influencing GSSS bond issuance. For instance, the positive correlation between “Firm Size” and “CAPEX to Total Assets” suggests that larger firms allocate more resources to capital expenditures, demonstrating their capacity to undertake large-scale projects. Similarly, “Governance Quality” shows a moderate positive correlation with “GDP per Capita (PPP, 2017),” highlighting the role of economic stability in fostering strong governance frameworks that drive bond issuance. Negative correlations, such as between “Leverage Ratio” and “Return on Assets (ROA),” indicate that firms with higher debt levels often face lower profitability, potentially affecting their capacity to issue bonds.

Subtle patterns also emerge, offering additional insights. For example, the moderate positive correlation between “Liquidity Ratio” and “Gender Diversity” suggests that firms with stronger liquidity management may prioritize diversity initiatives, reflecting broader organizational commitments. Meanwhile, a slight negative correlation between “Inflation Rate” and “Firm Size” implies that larger firms are better equipped to withstand inflationary pressures. Notably, the relationship between “ESG Composite Score” and “Governance Quality” reinforces the interplay between strong governance and sustainability practices in shaping bond markets. These observations provide a nuanced understanding of how financial, macroeconomic, and ESG factors collectively influence GSSS bond issuance, offering insights for issuers and investors alike.

Figure 3: Correlation Heatmap of Potential Continues Variables Influencing GSSS Bond Issuance



Implementation of MLR and NPML Methods

The implementation of MLR and NPML methods for analyzing bond type choices was conducted using Python 3.10, leveraging its robust libraries for data preparation and machine learning. The “pandas” library was employed to preprocess the dataset, including reshaping data for alternatives and creating dummy variables for categorical predictors.

The experiment begins with data preprocessing to ensure quality and consistency. The dataset includes detailed information on bond characteristics, issuer attributes, and macroeconomic data. Predictors—such as financial metrics, macroeconomic indicators, and contextual factors—are defined, with interaction terms calculated to account for potential multiplicative effects. Missing values are removed, categorical variables are one-hot encoded, and the target variable (type of GSSS bond) is label-encoded. Predictors are standardized to ensure uniform scaling, while variables with high Variance Inflation Factors ($VIF > 10$) are excluded to

mitigate multicollinearity. Winsorization is applied to handle outliers by capping extreme values.

To address class imbalance, the Synthetic Minority Oversampling Technique (SMOTE) is utilized, generating synthetic examples for underrepresented bond types to create a balanced dataset. The processed data is split into training (70%) and testing (30%) sets for model development and evaluation. Three models are employed: Multinomial Logit (MNL), Random Forest (RF), and XGBoost. The MNL model uses robust estimation techniques to derive coefficients for each predictor across bond categories. RF undergoes hyperparameter tuning with grid search and cross-validation to optimize parameters like the number of estimators and tree depth. XGBoost, configured with default settings and a multiclass objective function (mlogloss), efficiently captures complex relationships within the data.

Model performance is assessed using metrics such as accuracy, precision, recall, F1-scores, and ROC-AUC, while confusion matrices and ROC curves provide deeper insights into classification accuracy. For interpretability, RF and XGBoost include feature importance analyses to highlight key predictors, and MNL computes marginal effects to show how changes in predictors influence bond type probabilities. Additionally, SHAP offers a detailed breakdown of how individual features contribute to model predictions by assigning each feature a Shapley value, representing its marginal impact. Complementary techniques such as Partial Dependence Plots (PDPs) further enhance interpretability by visualizing the effects of predictors on the model's outcomes.

The results are compared across models, with ROC-AUC scores serving as a key metric for classification effectiveness. MNL provides interpretability through coefficients and marginal effects, while RF and XGBoost excel in capturing non-linear interactions and identifying influential predictors. This comprehensive approach ensures robust evaluation and valuable insights into the factors driving GSSS bond issuance.

Model Evaluation and Comparison

Figure 4 evaluates the performance of three models—MLR, RF, and XGBoost—in predicting bond issuance types (GBs, SLBs, SOBs, and SUBs) using Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) metrics. Each model's curve is visually distinguished by unique line styles and thicknesses, with the baseline for random guessing (AUC = 50%) represented by a dashed diagonal light gray line. The MLR model achieves an AUC of 82.89%, reflecting moderate predictive capabilities. While its performance is limited

by an inability to capture complex, non-linear relationships in the dataset, MLR remains valuable for its interpretability and baseline comparisons. The RF model achieves exceptional accuracy with an AUC of 98.79%. Its nearly perfect ROC curve highlights its strength in modeling non-linearities and feature interactions, making it the most effective tool for this task. XGBoost also performs impressively with an AUC of 96.18%. Although slightly behind RF, it demonstrates strong capabilities in balancing bias and variance, handling complex data structures effectively.

All three models significantly outperform the baseline, confirming their utility in accurately classifying bond types. RF emerges as the top performer, followed closely by XGBoost, while MLR provides reasonable, if less sophisticated, accuracy. This analysis highlights the superiority of advanced ensemble models like RF and XGBoost in addressing multi-class classification problems, reinforcing their importance for understanding complex datasets in sustainable finance.

Figure 5 offers another meaningful overview of the models' overall predictive performance without focusing on specific bond types. It illustrates how confident and consistent the predictions are across all categories. The higher median prediction values (horizontal line within each box) for RF and XGBoost suggest greater confidence in their predictions compared to MNL, which shows a lower median. Additionally, the narrower interquartile ranges (height of the boxes) for RF and XGBoost indicate more consistent predictions, reflecting better calibration and stability.

In contrast, Multinomial Logit exhibits greater variability in its predictions, possibly due to challenges in handling certain cases or capturing non-linear patterns effectively. Prediction extremes across all models, ranging from very low to very high probabilities, show instances of both high confidence and uncertainty. However, Random Forest and XGBoost consistently produce higher probabilities, reinforcing their stronger predictive capabilities. Overall, this comparison highlights Random Forest and XGBoost as superior in both confidence and consistency, outperforming Multinomial Logit.

Figure 4: ROC Curve Comparison of Models for Bond Type Prediction

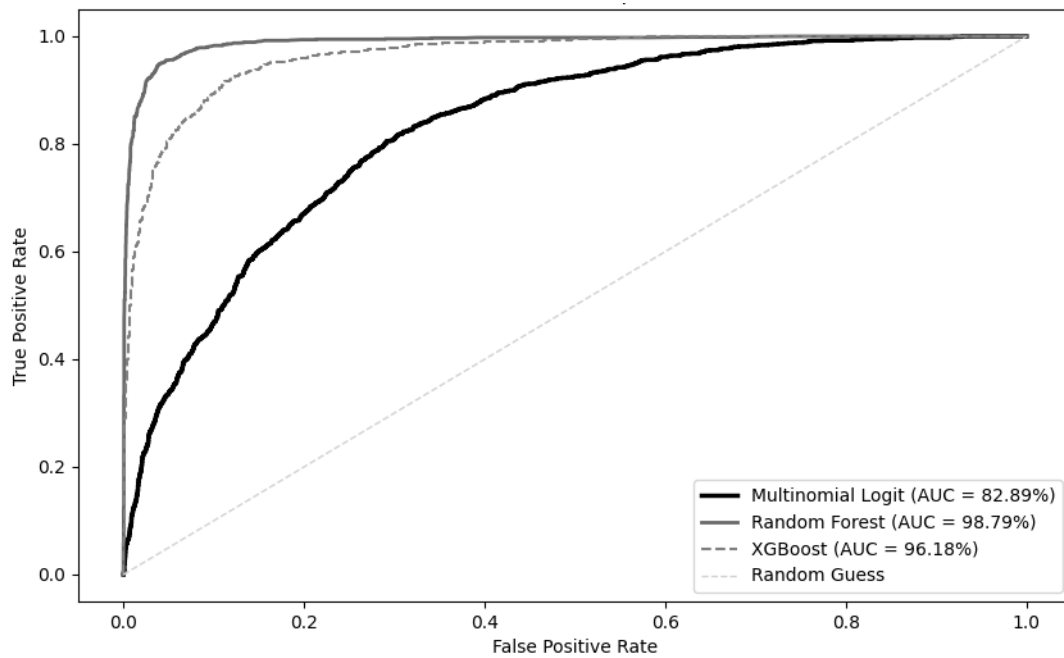


Figure 5: Predictive Confidence and Consistency Across Models

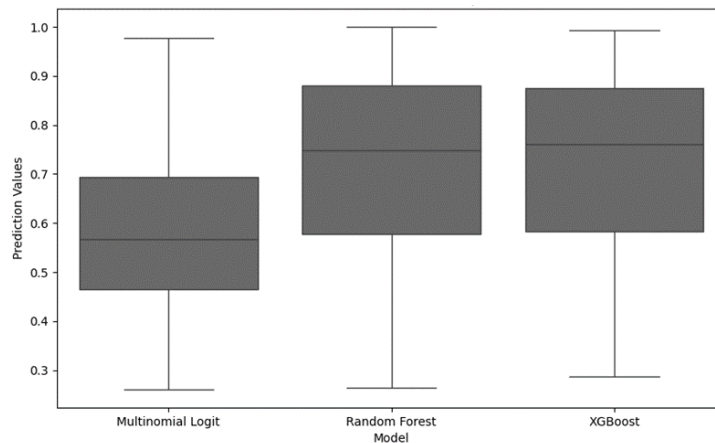


Table 4 provides a summary of the performance metrics for the three models—MLR, RF, and XGBoost—evaluated using five key indicators. Root Mean Square Error (RMSE) measures the average magnitude of prediction errors, while Mean Absolute Error (MAE) reflects the average absolute difference between predicted and actual values. The F1 Score combines precision and recall to assess overall classification performance, Accuracy represents the proportion of correctly classified cases, and Log Loss evaluates how well the predicted probabilities are calibrated. Together, these metrics offer a detailed assessment of each model’s predictive accuracy and overall robustness.

RF stands out as the best-performing model across all metrics. It achieves low error rates (RMSE: 0.5457, MAE: 0.1387), exceptional accuracy (91.97%), an excellent F1 Score

(0.9193), and well-calibrated probabilities (Log Loss: 0.4005). These results highlight its ability to effectively capture complex patterns in the data while maintaining a strong balance between precision and recall. XGBoost follows closely with strong overall performance. It shows intermediate error values (RMSE: 0.8043, MAE: 0.3055), solid accuracy (82.31%), and a high F1 Score (0.8217). However, it lags slightly behind RF in precision and probability calibration, placing it as the second-best model. In contrast, MLR demonstrates the weakest performance. It records the highest error rates (RMSE: 1.2274, MAE: 0.7272), low accuracy (56.59%), and poorly calibrated probabilities (Log Loss: 0.9794). This underperformance highlights its struggle to handle the dataset’s complexity and potential class imbalances.

Table 4: Performance Metrics of MLR, RF, and XGBoost

Model	RMSE	MAE	F1 Score	Accuracy	Log Loss
Multinomial Logit	1,2274	0,7272	0,5645	0,5659	0,9794
Random Forest	0,5457	0,1387	0,9193	0,9197	0,4005
XGBoost	0,8043	0,3055	0,8217	0,8231	0,4965

RF stands out as the best model for further explanation of predictions due to its superior performance across multiple evaluation metrics. With an AUC of 98.79%, RF excels at capturing complex, non-linear relationships in the data, significantly outperforming MLR and XGBoost in accuracy (91.97%), precision, and calibration. Its low error rates (RMSE: 0.5457, MAE: 0.1387) and high F1 Score (0.9193) further emphasize its robustness and reliability. Additionally, RF consistently demonstrates narrow interquartile ranges in prediction confidence, reflecting exceptional stability and well-calibrated probabilities. These strengths, combined with its ability to handle intricate interactions among features, make RF the most effective model for understanding how corporate, national, and sectoral factors influence bond type predictions.

Insights from the RF Model’s Predictions

Based on the previous evaluation, RF proves to be the most reliable model for delving deeper into prediction patterns and understanding how features contribute to the outcomes. Its outstanding performance across key metrics and ability to handle complex data relationships make it a clear choice for explaining the factors influencing bond type predictions.

The confusion matrix in Figure 6 provides valuable insights into the model’s performance across the four bond issuance types: GBs (class 0), SLBs (class 1), SOBs (class 2), and SUBs (class 3). The evaluation, based on a balanced dataset of 1,283 test observations using SMOTE,

ensures fair representation of each bond type. The model performs well overall but reveals some areas for improvement. For GB, it correctly classified 294 instances but showed confusion with SLB and SUB, misclassifying 53 cases and falsely predicting 23 from other classes as GB. Similarly, SLB performance was strong, with 273 correct classifications, though there was overlap with GB and SUB, resulting in 46 misclassifications and 31 false positives. The results for SOB were exceptional, with 301 correctly classified cases and minimal errors, making it the most reliably predicted class with the highest precision and recall. SUB classifications were generally good, with 273 correct predictions, but noticeable confusion with GB and SLB indicates opportunities for refinement.

The classification report for the Random Forest model complements the insights from the confusion matrix by showing strong overall performance, with an accuracy of 89% and consistent precision, recall, and F1-scores across all bond issuance types. The model excels in predicting SOBs, achieving the highest precision (97%) and recall (96%), reflecting its strong ability to distinguish these bonds. Performance for GB, SLB, and SUB is also high, with precision, recall, and F1-scores ranging from 85% to 88%. The balanced metrics across classes, along with the close alignment between precision and recall, indicate a well-trained and reliable model, although further refinement could enhance predictions for GB, which has the largest support.

While the model handles the dataset effectively overall, challenges persist in distinguishing between classes with shared characteristics, such as GB and SLB or SUB and GB.

Figure 6: Confusion Matrix of Bond Issuance Types

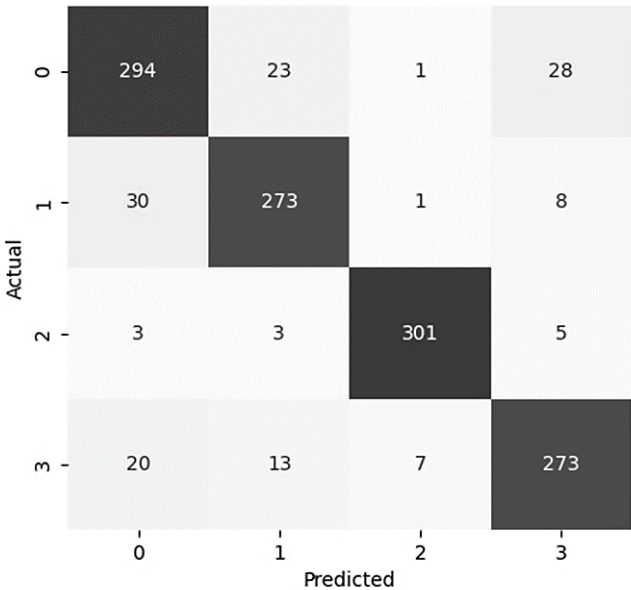


Figure 7 highlights the top 20 features influencing bond issuance predictions, ranked by their mean absolute SHAP values for each bond type: GB, SLB, SOB, and SUB. These SHAP values represent the average contribution of each feature to the model's predictions, offering insights into the most critical factors for each issuance type.

For GB, firm size emerges as the most significant factor, contributing roughly 25% to predictions. This underscores the dominant role that larger firms play in GB issuance. The use of proceeds for sustainability is the second most important feature, highlighting the strong alignment of GBs with environmental goals. Governance quality at the country level also plays a crucial role by shaping institutional and regulatory environments. Countries with high governance quality typically have robust frameworks, clear enforcement of laws, and effective environmental policies. These factors inspire confidence among investors and reduce risks. For instance, stringent carbon emission regulations or incentives for renewable energy projects, often present in well-governed countries, enhance the appeal of GBs.

For SLBs, the use of proceeds for sustainability emerges as the most influential factor, reflecting their strong alignment with purpose-driven objectives. Firm size is another critical determinant, underscoring the role of larger firms in SLB issuance. The liquidity ratio also plays a key role, as it signals the financial health of issuers and their capacity to meet the performance targets linked to these bonds. Governance quality, evaluated at the country of issuance level, significantly impacts SLB issuance by ensuring a transparent and reliable institutional environment. Countries with strong governance frameworks often establish robust reporting standards, third-party auditing mechanisms, and accountability processes, which enhance investor confidence in the credibility of sustainability performance targets. Additionally, macroeconomic conditions such as inflation and the size of the issuance contribute to SLB issuance decisions, further shaping their market dynamics.

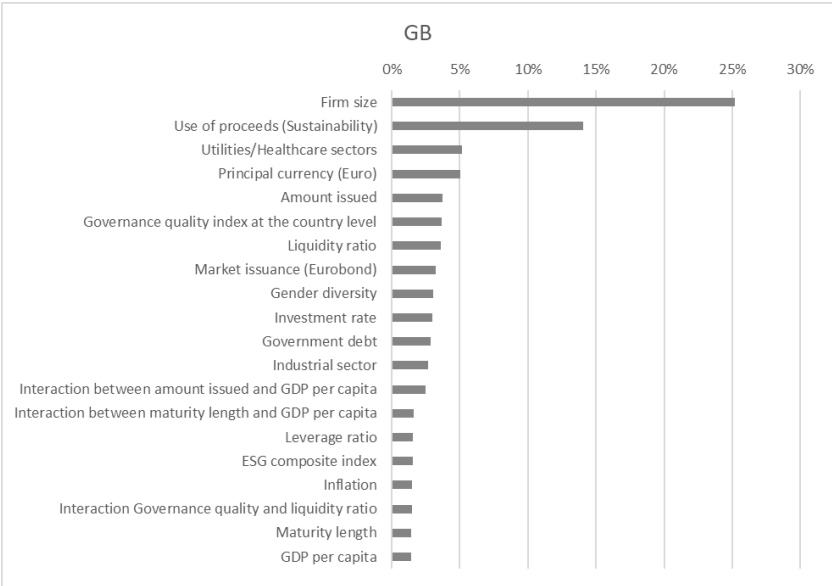
For SOBs, firm size once again leads as the most critical predictor, emphasizing the tendency of larger firms to issue these bonds. The investment rate is another influential factor, pointing to efficient resource allocation as a key driver. ESG composite index performance aligns closely with SOB issuance, highlighting the importance of sustainability and governance standards. The Euro continues to play a significant role, reflecting the concentration of SOB markets in Europe. Broader economic factors, such as bond maturity and GDP per capita, further shape SOB issuance patterns.

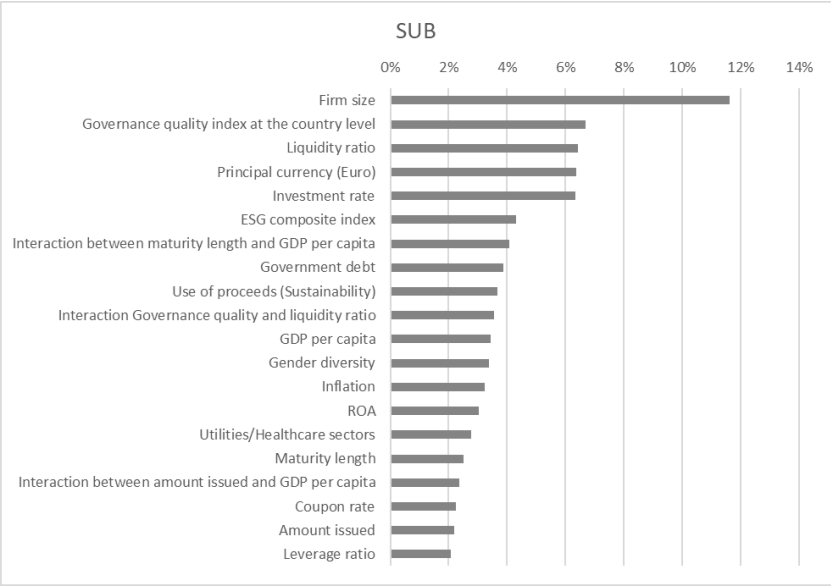
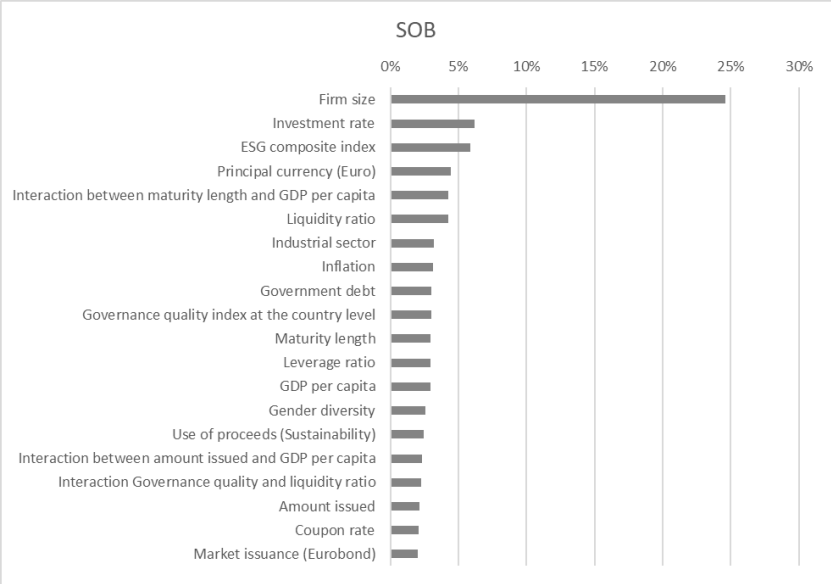
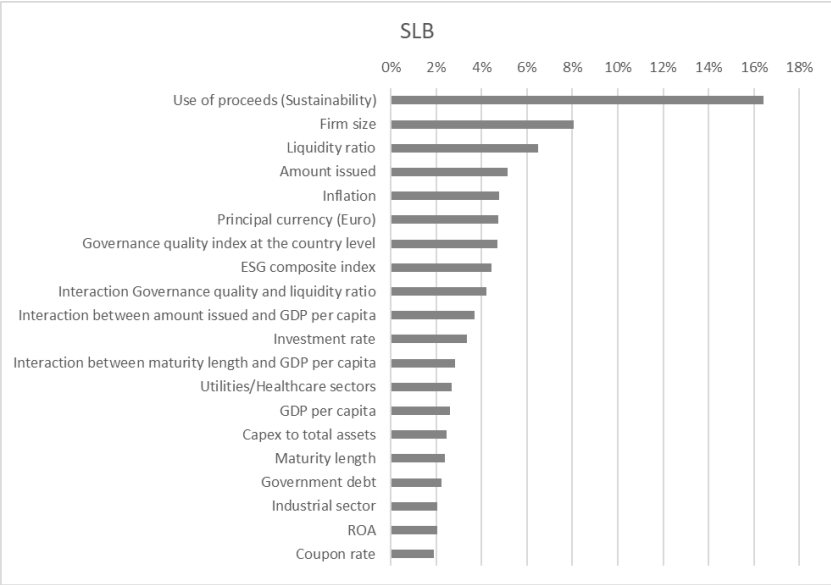
SUB issuances are also strongly influenced by firm size, reinforcing the advantage that larger firms hold in issuing these bonds. Governance quality at the country level is another critical

factor, reflecting the importance of stable and effective institutional frameworks. The liquidity ratio indicates the financial health of issuers, while the Euro again underscores the geographical focus of these markets. The investment rate completes the list of top drivers, highlighting its role in sustaining SUB issuance.

Across all bond types, firm size consistently emerges as the most significant predictor, underlining the prominence of larger firms in the GSS+ bond market. Sustainability and ESG-related factors, such as the use of proceeds and ESG index performance, are particularly relevant for GB, SLB, and SOB. Governance quality serves a dual purpose: directly supporting the alignment of bonds with sustainability goals and indirectly fostering trust by creating reliable market conditions. The recurring role of the Euro highlights the geographic concentration of these markets in Europe. Economic indicators, such as GDP per capita, inflation, and investment rates, further shape the issuance landscape. These findings provide invaluable insights for issuers, investors, and policymakers, offering a comprehensive understanding of the dynamics driving GSS+ bond markets.

Figure 7: Top 20 Features by SHAP Values for Each Issuance Type





Partial Dependence Plots (PDPs) offer a detailed view of how key predictors influence the likelihood of selecting specific bond types while holding other factors constant. These plots are particularly useful for interpreting non-linear models like RF and focus on the top five predictors identified in the analysis. In multi-class classification problems, PDPs require specifying a target class, which allows relationships to be plotted individually for each bond type—Green Bonds (GBs), Sustainability-Linked Bonds (SLBs), Social Bonds (SOBs), and Sustainability Bonds (SUBs). This targeted approach provides valuable insights into the distinct dynamics of each bond type.

Figure 8 provides an overview of the factors influencing the issuance of Green Bonds (GBs). Firm size, measured as the ratio of a company's market capitalization to the amount of a specific bond issuance, stands out as a key factor. Smaller firms, where bond issuances represent a substantial share of their market value, are more likely to issue GBs. This observation aligns with Lin and Su's (2022) conclusion that companies with longer-term financing needs tend to favor conventional bonds, while smaller firms often prioritize GBs to address immediate growth objectives. The sharp decline in partial dependence for larger firms underscores the role of GBs as a strategic financing tool for smaller organizations focused on sustainability.

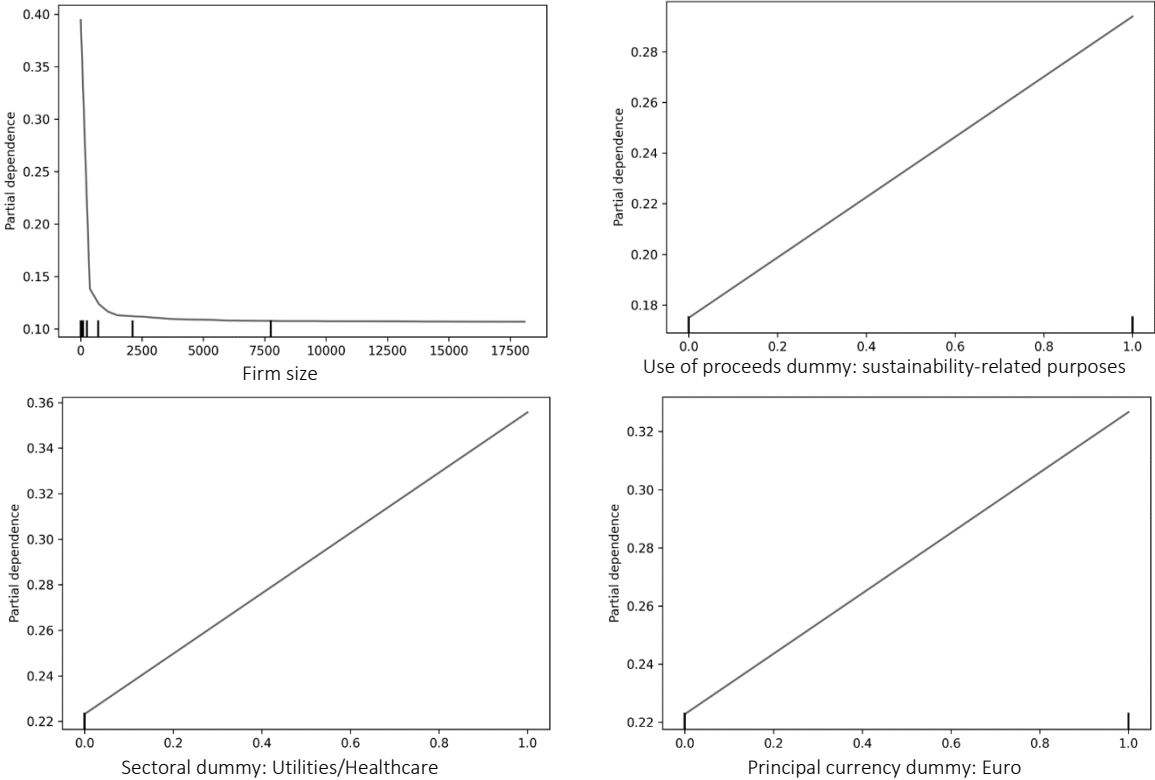
The allocation of proceeds to sustainability purposes shows a clear positive relationship with GB issuance, reaffirming the bond's alignment with projects explicitly targeting sustainability. Sectoral focus also emerges as a significant driver, with Utilities and Healthcare sectors exhibiting strong positive associations due to their involvement in environmental and social benefit initiatives. The steady rise in the Euro currency dummy further highlights Europe's leadership in sustainable finance markets, consistent with Lin and Su's (2022) findings that European Central Bank (ECB) collateral eligibility enhances the appeal of GBs within the region.

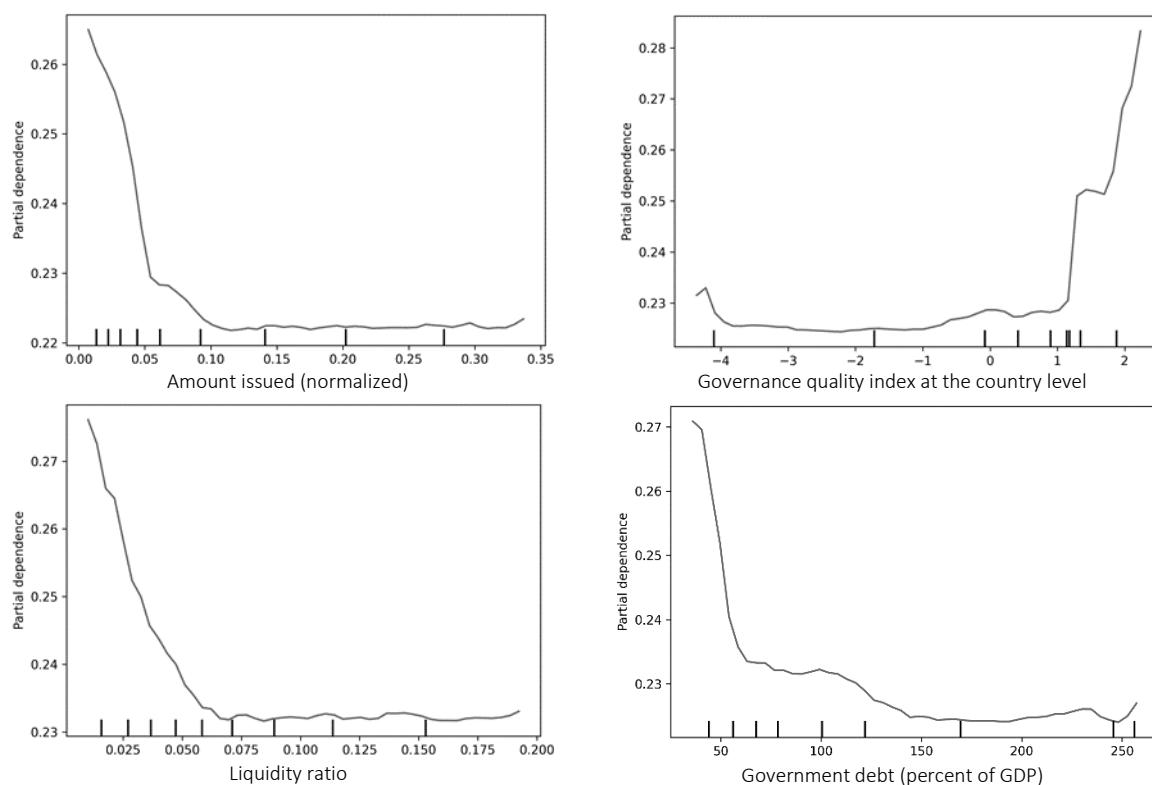
The analysis of issuance amounts reveals a distinct trend. Smaller issuances correlate with a reduced likelihood of GB issuance, while larger amounts stabilize, suggesting GBs are often employed for targeted projects with moderate funding needs. Liquidity also plays an important role. Firms with tighter liquidity constraints may turn to GBs as a means of accessing sustainability-focused finance markets. This perspective adds to Gianfrate and Peri's (2019) findings that firms with higher current ratios and long-term debt are more likely to issue GBs, suggesting that GBs also serve as a resource for liquidity-constrained firms aiming to pursue sustainability goals.

Governance quality at the country level exhibits a nuanced relationship, with partial dependence initially declining before increasing significantly in countries with high governance standards. This pattern underscores the role of strong governance frameworks in promoting GB issuance by enabling effective enforcement of sustainability regulations. These findings align with Liao et al.'s (2015) observations on the positive influence of governance structures, such as larger boards and independent directors.

Macroeconomic factors further contribute to GB issuance dynamics. Countries with higher levels of government debt show an increased likelihood of GB issuance, supporting Gianfrate and Peri's (2019) conclusion that higher government bond interest rates create favorable conditions for sustainable investment. Additionally, the U-shaped relationship identified in our findings suggests that both low-debt and high-debt countries have distinct motivations for promoting GBs, ranging from attracting sustainability-conscious investors to diversifying funding sources.

Figure 8: Marginal Impact of Key Predictors on GBs through PDPs





The analysis of PDPs in Figure 9 explores the factors influencing SLBs, highlighting the importance of firm size, financial health, and macroeconomic stability in shaping issuance likelihood. Larger firms are more likely to issue SLBs, as indicated by a flattening trend in partial dependence beyond a firm size threshold of approximately 2,500 units. This finding aligns with Kölbl and Lambillon (2022) and Berrada et al. (2022), who find that SLB issuers tend to be larger, more leveraged, and more profitable compared to non-issuers. Larger firms have the resources and operational capacity to handle the financial and performance obligations tied to SLBs, as well as the scrutiny associated with their sustainability targets. Smaller firms, on the other hand, face challenges in meeting SLB performance obligations due to their limited resources and market presence.

The results indicate that SLBs are closely tied to overarching corporate sustainability strategies rather than specific projects, as reflected in the negative relationship observed between SLB issuance and the use of proceeds allocated explicitly to sustainability-related purposes. Berrada et al. (2022) emphasize that unlike green bonds, which are tied to specific environmental projects, SLBs offer issuers flexibility in fund allocation while linking financial penalties or rewards to sustainability outcomes.

Liquidity emerges as a critical factor influencing the likelihood of Sustainability-Linked Bond (SLB) issuance, with firms possessing higher liquidity more likely to issue these bonds. Financial stability enables such firms to manage the operational and performance-linked

obligations tied to SLBs, while also capitalizing on features like callable options. Callable bonds, which constitute 66% of the SLB market, provide issuers with the flexibility to adjust financing terms under changing market conditions, thereby reducing risks associated with unmet sustainability targets (Kölbel and Lambillon, 2022). This flexibility is particularly advantageous in inflationary environments, as firms can use SLBs to secure fixed-cost financing when prices are rising, a finding consistent with the positive relationship observed between inflation and SLB issuance (Flammer, 2021).

Moreover, liquidity also aligns with the financial stability required to leverage the benefits of the sustainability premium, which reduces capital costs for issuers (Berrada et al., 2022). By combining financial flexibility with the potential cost savings offered by SLBs, firms with strong liquidity profiles are well-positioned to navigate the demands of sustainability-linked financing while mitigating associated risks.

Macroeconomic conditions significantly influence SLB issuance. The positive relationship between inflation and SLB issuance suggests that firms leverage these instruments to secure fixed-cost financing during inflationary periods. This is supported by Berrada et al. (2022), who note that SLBs' ability to adjust payouts based on sustainability performance provides issuers with a strategic advantage in uncertain economic environments. Governance quality also fosters SLB issuance, although its incremental impact diminishes at very high levels, reflecting the saturating effect of well-established governance frameworks. This finding aligns with evidence that well-governed firms are better positioned to adopt innovative financing mechanisms like SLBs. Regional dynamics further emphasize governance's role, with Europe accounting for 68% of global SLB issuances, underscoring the region's leadership in sustainable finance and the importance of robust institutional frameworks in supporting these markets (Kölbel and Lambillon, 2022).

Firms with robust ESG performance are strongly inclined to issue SLBs, as indicated by the positive relationship with the ESG composite index. This aligns with Flammer's (2021) findings on the dual role of SLBs in signaling sustainability commitments and enhancing a firm's reputation. Berrada et al. (2022) further highlight that SLBs contribute to improved sustainability outcomes, particularly in decarbonization, with issuing firms reducing greenhouse gas emissions 6-7 percentage points faster than non-issuers. This underscores the effectiveness of SLBs in incentivizing meaningful sustainability progress. However, the non-linear relationship between investment rates and SLB issuance suggests that moderate investment levels are most conducive to adoption. At very high levels, competing financial

priorities or increased risk aversion may discourage firms from issuing SLBs, as some prioritize financial considerations over sustainability signaling (Flammer, 2021).

Figure 9: Marginal Impact of Key Predictors on SLBs through PDPs

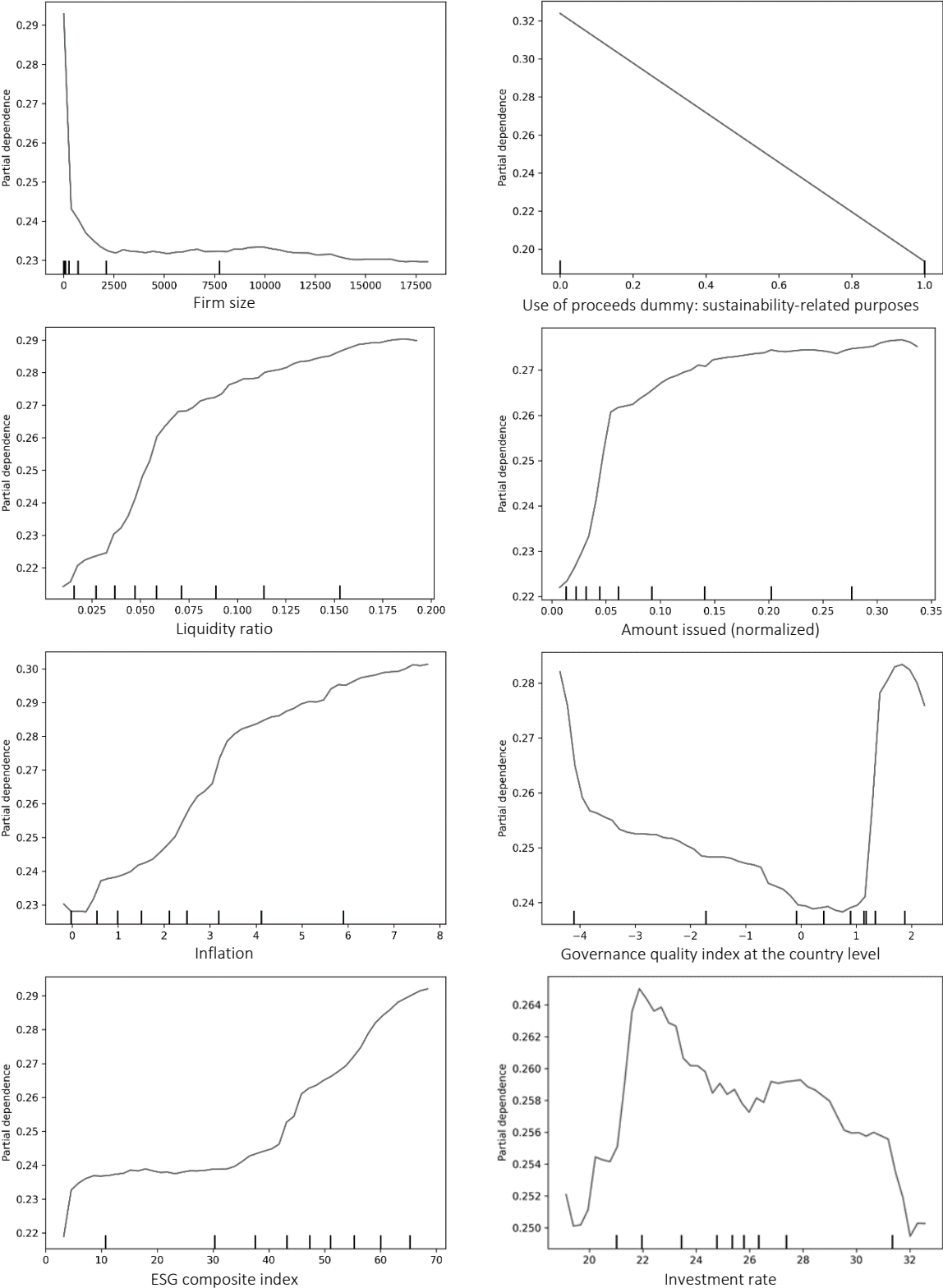


Figure 10 highlights the factors influencing the issuance of SOBs, which are often used to fund socially impactful projects. Larger firms are significantly more likely to issue SOBs, as indicated by a steep rise in partial dependence at smaller firm sizes. This reflects the capacity of larger organizations to allocate resources toward substantial social initiatives, consistent with Torricelli and Pellati (2023) findings that government and financial sectors dominate the SOB market due to their ability to support large-scale projects.

The investment rate shows a non-linear relationship with SOB issuance. Firms with moderate to high investment rates are more likely to issue SOBs, as these levels align with a focus on impactful social projects. However, very high investment rates correlate with fluctuating and declining issuance likelihoods, likely reflecting competing financial priorities or constraints. Interestingly, firms with higher ESG scores are less inclined to issue SOBs, as evidenced by a negative relationship with the ESG composite index. This suggests that SOBs are more commonly employed by firms targeting specific social initiatives rather than those with broader, well-established ESG commitments.

Currency plays an important role in SOB issuance dynamics. Firms issuing in Euros are less likely to classify their bonds as SOBs, which aligns with Torricelli and Pellati (2023) findings that Euro-denominated social bonds exhibit a small negative social premium compared to bonds in other currencies. This may reflect regional differences in demand and investor preferences.

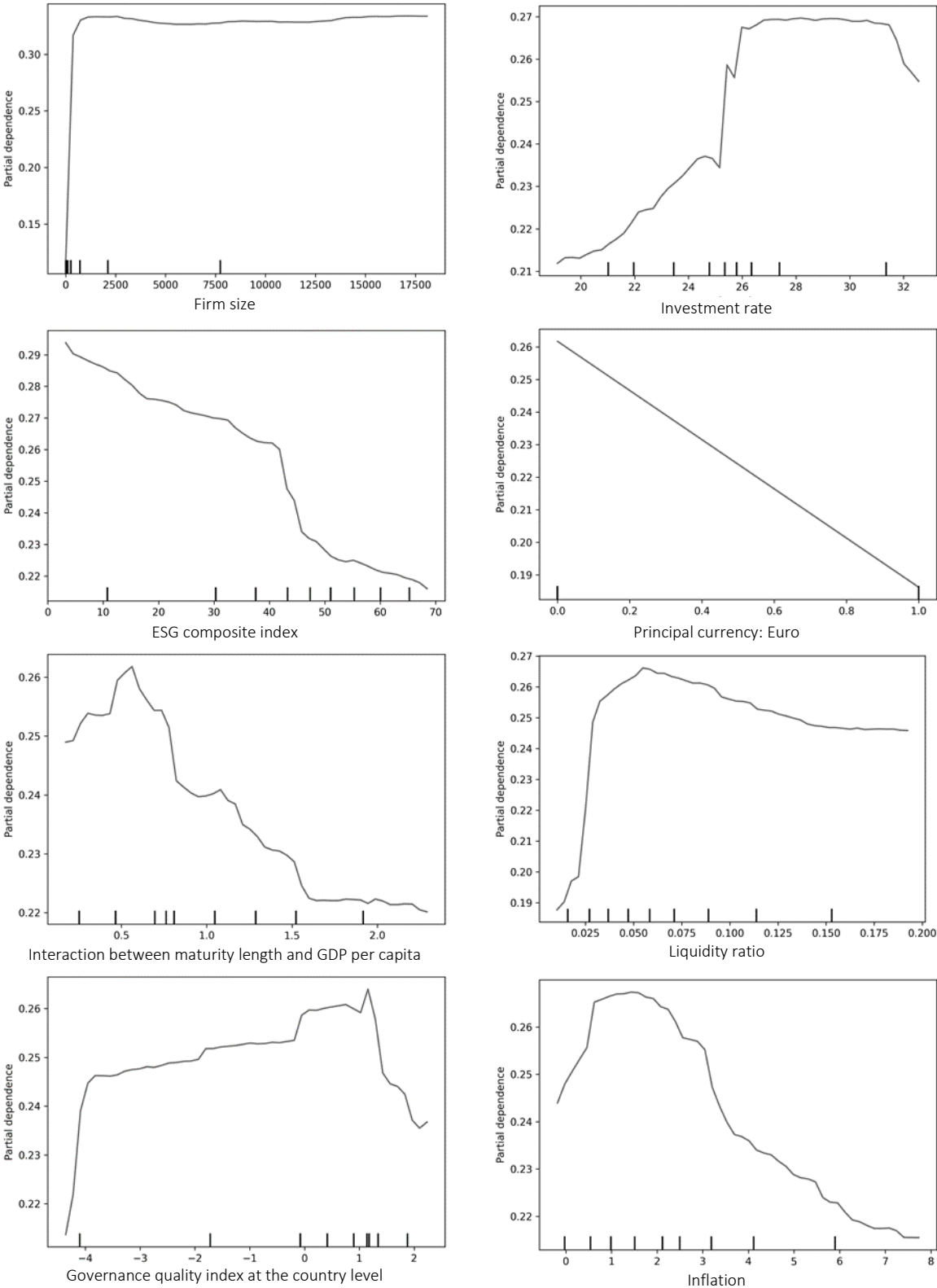
The interaction between bond maturity length and GDP per capita reveals a complex relationship. SOB issuance is more likely in countries with moderate GDP per capita and longer maturities, supporting Torricelli and Pellati's observation that longer maturities are positively associated with the social premium. However, at very high interaction values, the trend reverses, potentially reflecting limited demand for SOBs in highly developed economies.

Liquidity and governance quality further shape SOB issuance. Firms with higher liquidity are more likely to issue SOBs, highlighting the financial stability required to support social projects. This finding aligns with Torricelli and Pellati's evidence that liquidity plays a crucial role in determining yield spreads, with illiquid bonds exhibiting higher yields. Governance quality exhibits an initial positive relationship with SOB issuance but diminishes at higher levels, suggesting that while good governance fosters social bond markets, its incremental effects lessen in well-governed environments.

Finally, inflation demonstrates a strong negative relationship with SOB issuance, as financial instability and uncertainty associated with inflation discourage socially driven bond markets.

The role of SOBs in addressing urgent social needs, as observed during the COVID-19 pandemic, highlights the importance of macroeconomic stability in fostering these instruments for critical social initiatives.

Figure 10: Marginal Impact of Key Predictors on SOBs through PDPs

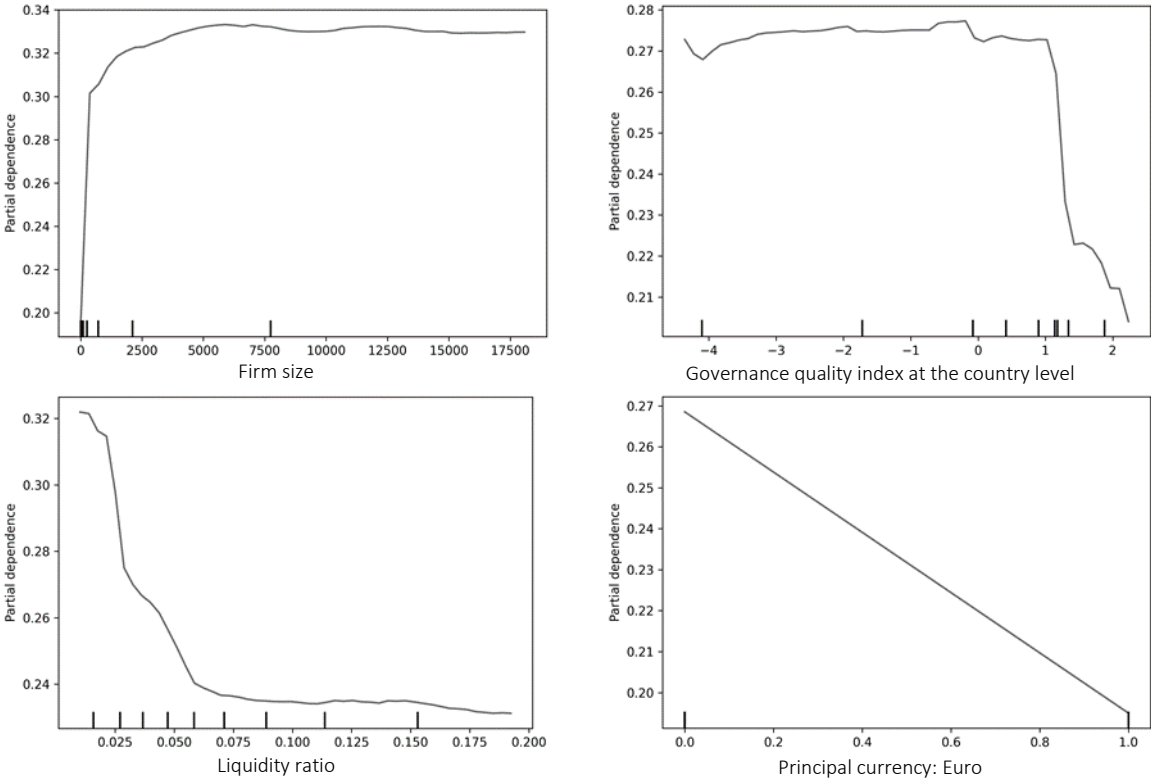


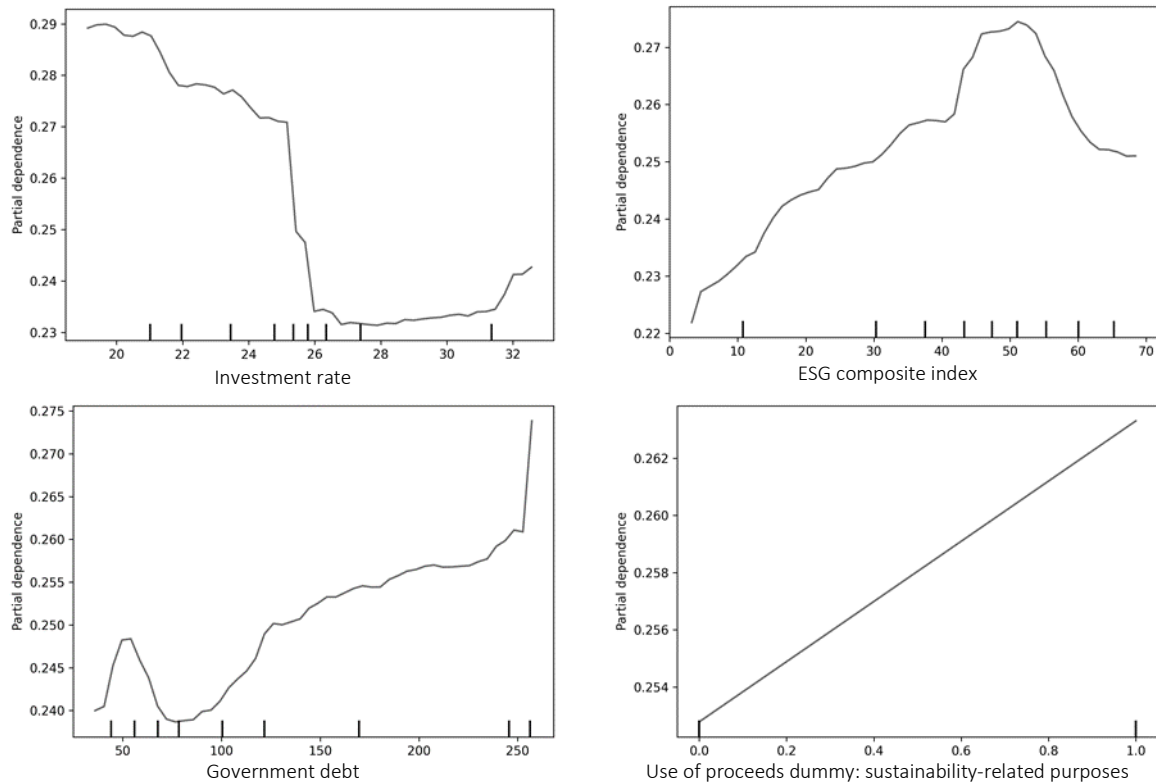
The PDPs in Figure 11 highlight the predictors influencing SUBs, which are tailored to support sustainable development goals. Larger firms are more likely to issue SUBs, as shown by a sharp rise in partial dependence before plateauing. This suggests that firm size plays a key role in enabling organizations to undertake large-scale sustainability projects.

Governance quality exhibits a steady increase in partial dependence before tapering off, indicating that SUB issuance is most common in moderately strong governance environments. Liquidity trends diverge from other bond types, with lower-liquidity firms showing a higher likelihood of SUB issuance. This reflects the strategic use of SUBs as a financing option during periods of financial constraints. A declining trend in Euro currency issuance highlights regional diversification, with non-European markets playing a greater role in SUB activities.

Moderate investment rates are associated with a higher likelihood of SUB issuance, reflecting a balanced approach to integrating sustainability into growth strategies. ESG performance shows a strong positive trend, with firms with higher ESG scores more inclined to issue SUBs, aligning with the goals of these bonds. Finally, government debt follows a U-shaped curve, with SUB issuance more likely in countries with either very low or very high debt levels. This suggests that SUBs serve diverse purposes, from development initiatives in less-indebted countries to debt restructuring in highly indebted economies.

Figure 11: Marginal Impact of Key Predictors on SUBs through PDPs





5. Discussion

Advances in non-parametric machine learning, particularly RF, have revolutionized the ability to analyze complex datasets, making RF an ideal tool for understanding bond issuance patterns. RF's reliability and ability to capture non-linear interactions provide nuanced insights into the drivers of GBs, SLBs, SOBs, and SUBs.

Firm size consistently emerges as the most critical determinant across all bond types, reflecting the dominance of larger organizations in sustainable finance due to their capacity to handle regulatory, financial, and operational demands. Smaller firms, however, use bonds like GBs to align financing with sustainability goals, balancing growth and environmental priorities.

For GBs, the allocation of proceeds to sustainability projects is a key driver, complemented by strong sectoral focus in areas like Utilities and Healthcare. Governance quality also plays a significant role by fostering confidence through clear regulations and institutional stability. The Euro's prominence highlights Europe's leadership in green finance, while liquidity constraints drive smaller firms toward GBs to access specialized markets.

SLBs differ by linking financial terms to sustainability performance targets, making them attractive for firms seeking flexibility and cost savings through mechanisms like the sustainability premium. Larger, financially stable firms dominate this market, leveraging features like callable bonds for risk management, especially in inflationary environments.

Governance quality supports transparency in SLB markets, with Europe maintaining its leadership.

SOBs target social projects like affordable housing and healthcare, with larger firms leading due to resource availability. Investment rates show a non-linear relationship, with moderate levels driving issuance. Surprisingly, ESG performance negatively correlates with SOB issuance, suggesting a focus on targeted social goals over broader strategies. Euro-denominated SOBs are less prevalent, reflecting regional demand variations. Macroeconomic factors like GDP per capita and longer maturities also influence issuance, while inflation discourages socially driven investments.

SUBs combine environmental and social objectives, with larger firms and strong governance frameworks driving issuance. Interestingly, lower-liquidity firms are more likely to issue SUBs, using them as strategic financing tools during financial constraints. Moderate investment rates and strong ESG performance further enhance SUB issuance, while government debt shows a U-shaped relationship, reflecting varied motivations from development to debt restructuring. The declining role of the Euro underscores growing non-European participation.

Across all bond types, firm size, governance quality, and sustainability factors like ESG performance and the use of proceeds are critical drivers. Europe remains a leader in sustainable finance, supported by robust frameworks and investor demand. Macroeconomic indicators, including inflation and GDP per capita, further shape issuance patterns. These findings offer valuable guidance for advancing sustainable finance through informed decision-making by issuers, investors, and policymakers.

6. Conclusion

This analysis highlights the critical role of non-parametric machine learning, particularly Random Forest (RF), in uncovering the drivers behind sustainable bond issuance. RF's ability to capture non-linear interactions and its interpretability make it an invaluable tool for analyzing Green Bonds (GBs), Sustainability-Linked Bonds (SLBs), Social Bonds (SOBs), and Sustainability Bonds (SUBs). Its performance enables a deeper understanding of the key factors influencing these instruments.

Firm size is the most significant determinant across all bond types, reflecting the dominance of larger organizations in sustainable finance due to their capacity to meet regulatory, financial, and operational demands. Smaller firms, however, use bonds like GBs to align growth with sustainability goals. Governance quality and sectoral focus also play key roles, with robust

institutional frameworks and leading sectors such as Utilities and Healthcare enhancing the appeal of GBs. Europe's leadership in green finance further underscores the importance of strong governance structures.

SLBs distinguish themselves with flexibility, linking financial outcomes to sustainability performance targets. Larger firms benefit from mechanisms like the sustainability premium and callable features, particularly valuable in managing risks during inflationary periods. SOBs cater to social projects like housing and healthcare, with issuance shaped by macroeconomic factors like GDP per capita and inflation. SUBs appeal to lower-liquidity firms, serving as strategic financing options during constrained periods and combining environmental and social objectives.

The consistent importance of firm size, governance quality, and sustainability-related factors like ESG performance and the use of proceeds illustrates the alignment of these bonds with broader sustainability goals. Macroeconomic indicators, including GDP per capita and inflation, further contextualize issuance patterns, providing valuable insights for optimizing sustainable finance.

Future research could enhance these findings by exploring alternative machine learning models, such as gradient boosting and neural networks, to improve predictive accuracy and uncover additional complexities. Longitudinal studies could examine how regulatory reforms and sustainability incentives shape GSSS bond markets over time, clarifying their effectiveness and identifying areas for improvement. Additionally, a deeper investigation into issuer-specific characteristics, including corporate sustainability strategies and governance practices, could reveal why certain firms are more inclined to issue these bonds, offering a clearer link between organizational behavior and sustainable finance outcomes.

References

- Altunbaş, Y., Kara, A., & Marques-Ibanez, D. (2010). Large debt financing: Syndicated loans versus corporate bonds. *The European Journal of Finance*, 16(5), 437–458.
- Bacciu, D., Biggio, B., Lisboa, P. J., Martin Guerrero, J. D., Oneto, L., & Vellido Alcacena, A. (2019). Societal issues in machine learning: When learning from data is not enough. In ESANN 2019, 27th European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning: Bruges, April 24-25-26, 2019: proceedings (pp. 455-464). European Symposium on Artificial Neural Networks (ESANN).
https://upcommons.upc.edu/bitstream/handle/2117/179507/printout_es2019-6.pdf?sequence=1
- Barua, S., & Chiesa, M. (2019). Sustainable financing practices through green bonds: What affects the funding size? *Business Strategy and the Environment*, 28(6), 1131–1147.
- Berrada, T., Engelhardt, L., Gibson, R., & Krueger, P. (2022). The economics of sustainability linked bonds. *Swiss Finance Institute Research Paper*, (22-26).
- Bhutta, U.S., Tariq, A., Farrukh, M., Raza, A., & Iqbal, M.K. (2022). Green bonds for sustainable development: Review of literature on development and impact of green bonds. *Technological Forecasting and Social Change*, vol. 175, article 121378.
- Climate Bonds Initiative (CBI). (2024). Sustainable Debt Market Summary H1 2024. Retrieved from www.climatebonds.net.
https://www.climatebonds.net/files/reports/cbi_mr_h1_2024_02e_1.pdf
- Dawson, L. M. (1997). Ethical differences between men and women in the sales profession. *Journal of Business Ethics*, 16(11), 1143–1152.
- Denis, D. J., & Mihov, V. T. (2003). The choice among bank debt, non-bank private debt, and public debt: Evidence from new corporate borrowings. *Journal of Financial Economics*, 70(1), 3–28.
- Diamond, D. W. (1991). Debt maturity structure and liquidity risk. *The Quarterly Journal of Economics*, 106(3), 709–737.

Flammer, C. (2013). Corporate social responsibility and shareholder reaction: The environmental awareness of investors. *Academy of Management Journal*, 56(3), 758–781.

Flammer, C. (2021). Corporate green bonds. *Journal of Financial Economics*.

Frank, M. Z., & Goyal, V. K. (2009). Capital structure decisions: Which factors are reliably important? *Financial Management*, 38(1), 1–37.

Gianfrate, G., & Peri, M. (2019). The green advantage: Exploring the convenience of issuing green bonds. *Journal of Cleaner Production*, 219, 127–135.

Green Bond Principles. (2021). Voluntary process guidelines for issuing green bonds. International Capital Market Association (ICMA).

<https://www.icmagroup.org/assets/documents/sustainable-finance/2021-updates/green-bond-principles-june-2021-100621.pdf>

Kölbel, J. F., & Lambillon, A. P. (2022). Who pays for sustainability? An analysis of sustainability-linked bonds. *Swiss Finance Institute Research Paper*, (23-07).

Liao, L., Luo, L., & Tang, Q. (2015). Gender diversity, board independence, environmental committee and greenhouse gas disclosure. *The British Accounting Review*, 47(4), 409–424.

Lin, B., & Su, T. (2022). Green bond vs conventional bond: Outline the rationale behind issuance choices in China. *International Review of Financial Analysis*, 81, 102063.

Maltais, A., & Nykvist, B. (2020). Understanding the Role of Green Bonds in Advancing Sustainability. *Journal of sustainable finance & investment*, pp. 1-20,

Myers, S. C. (1977). Determinants of corporate borrowing. *Journal of Financial Economics*, 5(2), 147–175.

Tolliver, C., Keeley, A. R., & Managi, S. (2020). Drivers of Green Bond Market Growth: The Importance of Nationally Determined Contributions to the Paris Agreement and Implications for Sustainability. *Journal of Cleaner Production*, vol. 244, p. 118643.

Torricelli, C., & Pellati, E. (2023). Social bonds and the “social premium”. *Journal of Economics and Finance*, 47(3), 600-619.

Ul Haq, I., & Doumbia, D. (2022). Structural loopholes in sustainability-linked bonds. World Bank Policy Research Working Paper Series.

Wang, J., Chen, X., Li, X., Yu, J., & Zhong, R. (2020). The Market Reaction to Green Bond Issuance: Evidence from China. *Pacific-Basin Finance Journal*, vol. 60, article 101294,

Zerbib, O. D. (2019). The effect of pro-environmental preferences on bond prices: Evidence from green bonds. *Journal of Banking & Finance*, 98, 39–60.

Zhou, X., & Cui, Y. (2019). Green Bonds, Corporate Performance, and Corporate Social Responsibility. *Sustainability*, vol. 11, no. 23, article 6881.