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The Influence of ESG Factors on Sovereign Credit Ratings in Sub-Saharan Africa: A LASSO and Random Forest Approach

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Abstract

This study examines the impact of Environmental, Social, and Governance (ESG) factors on sovereign credit ratings in Sub-Saharan African countries using LASSO and Random Forest models. Sovereign credit ratings, issued by major rating agencies, play a crucial role in determining a country's borrowing costs and investment attractiveness. Traditionally, these ratings have been influenced by macroeconomic factors; however, recent trends suggest that ESG considerations are becoming increasingly relevant. By applying statistical prediction models, this study assesses the relative importance of ESG factors versus non-ESG (macroeconomic) variables in credit rating determination. The results reveal that governance and macroeconomic factors are the dominant determinants of sovereign credit ratings in upper-middle-income Sub-Saharan African countries, whereas environmental factors play a crucial role in lower-income nations. The Random Forest model outperformed the LASSO regression in predictive accuracy, reinforcing the significance of non-linear relationships in credit rating determinants. The findings highlight the necessity for policymakers to integrate ESG considerations into national financial and economic strategies to improve creditworthiness and attract sustainable investments.

Subject Areas

Business Analysis

Keywords

ESG Factors, Sovereign Credit Ratings, Random Forest, Macroeconomic Variables, Sub-Saharan Africa

1. Introduction

According to research conducted by Lewin; Abeywickrama *et al.*, Modugu and Dempere [1]-[3], the International Monetary Fund (IMF), countries in sub-Saharan Africa, which are mostly considered emerging nations, heavily depend on outside funding to finance their expenses. External debt plays a crucial role in supporting developmental projects, capital investments, and economic assistance [4]. While external debt can promote growth, it may become counterproductive if there is no proper plan to manage and repay it. Because of this, international donors often require countries to demonstrate their credit ratings and financial responsibility, economic and political stability, social responsibility Gugler and Shi [5]-[9], an environment that fosters investment in order to ensure continued support and their ability to pay back [10].

As countries engage in greater financial interactions and seek external funding, the relevance of sovereign ratings becomes more apparent. Sovereign credit ratings provide a concise assessment of a government's ability and willingness to meet its public debt obligations, including both principal and interest payments within specified timeframes [11]-[14]. The importance of sovereign credit ratings stems from three key factors; firstly, these ratings influence the interest rates a country must pay when borrowing from the global financial market. Secondly, the ratings assigned to a government can impact the ratings of banks or companies within that country, potentially imposing limitations or restrictions on them. Lastly, institutional investors often have risk limits for their investments and they consider credit risk indicated by rating agencies when determining the composition of their bond portfolios [14]-[18]. As the number of countries receiving sovereign ratings increases, the information conveyed by these rating agencies becomes increasingly significant.

The growing emphasis on sustainable development worldwide has made ESG (environmental, social, and governance) investing a crucial component. Not so long ago profit, economic growth and development were the main goals for both corporates and countries; today it's certainly still the same case, but with added conditions, these conditions include integrating sustainability factors while maintaining economic value. Traditionally, credit ratings primarily focused on economic indicators such as GDP growth, fiscal discipline, and debt levels. However, the recognition of non-financial factors measured by ESG factors as critical determinants of a country's creditworthiness has grown in recent years, and efforts are being made to incorporate these factors into investment decision-making and debt management practices. This trend initially emerged in equity investments and has now extended to fixed-income markets, reshaping how investors allocate their funds.

This shift reflects the broader movement towards responsible investing and sustainable development in the financial industry and Investors now view ESG accounting as a crucial part of risk management [19]-[22].

This is because ESG indicators serve as an additional safeguard for investors when considering lending money to a country, as governments with low ESG scores are more likely to pose a higher risk of defaulting on their sovereign debt and consequently investors would demand a higher interest rate (Icaza, 2016). According to Crifo [23], a government's capacity to implement economic policies that generate sufficient revenue to service its debt has a direct impact on the country's overall risk profile, thereby influencing its ability to repay sovereign debt in both the short and long term.

When debt levels are high governments may encounter "fiscal fatigue" which could result in fewer fiscal adjustments and less fiscal capacity when the debt ceiling is reached, this tendency can be lessened if the government has a suitable political institution that enables it to secure extensive support; this capacity to carry out policies and successfully executing an economic stabilization plan during trying times enhances the government's image, which may eventually affect its sovereign risk while looking to borrow funds in the future. This could explain why Japan despite having the highest debt-to-GDP ratio faces less market pressure and lower interest rates compared to other industrialized countries [20] [24] [25].

If countries don't have strong ESG standards, it can directly affect investors financially. For instance, in 2018, South Africa faced a significant increase in long-term CDS spreads (a measure of credit risk) due to a prolonged drought period. This led to an economic crisis and social unrest, causing financial consequences for investors. Similarly, in 2011, several developed countries in southern Europe experienced rising credit spreads due to a lack of well-developed governance standards. This resulted in substantial losses for investors and had negative effects on other countries as well [26].

Most importantly, Kiesel and Lücke [27] revealed that ESG factors had a significant influence on credit-default swap (CDS) spreads, especially around the time of credit rating announcements. They also highlighted the importance of corporate governance in credit rating decisions, indicating that how well a company is governed plays a crucial role in its creditworthiness. Additionally, Broadstock Broadstock, Chan [28], studied the performance of investment portfolios in China and found that those with higher ESG ratings outperformed portfolios with lower ratings. This suggests that considering ESG factors when making investment decisions can lead to better financial outcomes.

While several papers have worked on the determinants of credit rating by only considering macroeconomic factors and governance factors and others on the significance of ESG factors in financial analysis and creditworthiness there remains a research gap concerning the direct impact of ESG on sovereign credit ratings. Our paper aims to fill the information gap by extensively examining the potential impacts of ESG factors in credit rating and in particular sub-Saharan African countries given the diverse socioeconomic landscape and governance structures across the region which previous studies have left unexplored and in a more specific way. Our methodology involves examining the distinct contribution of each ESG dimension by considering them separately. To achieve this, we employ similar variables that were used by Pineau [29] using factor analysis to obtain separate variables for Environmental (E), Social (S), Governance (G), and non-ESG (Macroeconomic factors) factors with the addition of few variables which were not included in their research. We then assess the significance of these variables within statistical shadow rating models. Governments may use the results from our study to help predict possible changes in their credit ratings and take necessary actions to maintain their ratings. On the other hand investors and financial institutions can use our findings to assess whether a country's current credit rating aligns with what would be anticipated based on its economic fundamentals by helping them to evaluate any discrepancies or deviations, which may indicate potential investment opportunities or risks.

The rest of the study is structured as follows: Section 2 literature review. Section 3 provides a detailed explanation of the data and methodology employed in the research. Section 4 presents the results and discussion of the findings. Finally, Section 5 concludes the study and offers policy recommendations based on the obtained results.

2. Literature Review

Currently, Moody's, Fitch, and Standard & Poor's are the largest credit rating agencies that assign credit ratings to various countries. In recent years, researchers have shown interest in understanding the factors that determine sovereign credit ratings (SCRs). Numerous studies have attempted to identify and analyze these factors, approaching them from various perspectives due to differences in methodology, data sources, and sample composition. Recently researchers have expanded their research by including additional political and institutional variables [14] [30]-[32]. These studies highlight the significance of considering political factors alongside economic factors when assessing sovereign credit ratings. There is a vast literature about sovereign credit rating, which covers a wide range of topics. This study will only cover relevant ones that relate to our topic.

In light of the ongoing interest in non-financial information as new drivers for financial analysis and creditworthiness assessment, it becomes increasingly evident that incorporating a country's ESG rating is crucial in enhancing credit assessment practices. A country's ESG performance shows how well it deals with environmental, social and governance risks.

From this perspective, investors may be willing to accept lower returns from countries that have strong ESG performance. This means that investors may view these countries as being better at managing potential risks and therefore consider them to be less risky to invest in.

The World Bank (2021) conducted an empirical analysis examining the relationship between credit ratings and ESG scores across high-income countries. Their findings indicate a positive correlation between these two factors, suggesting that countries with higher credit ratings tend to exhibit higher ESG scores. However, the relationship between credit ratings and ESG scores for lower-income countries is less pronounced, despite the influential role macroeconomic factors play in determining sovereign creditworthiness. This observation is particularly noteworthy for lower-income countries that share the same creditworthiness rating but demonstrate divergent ESG performance [33].

Pineau [29] researched the significance of ESG factors in sovereign credit ratings. Employing a data-driven methodology, their research examined the relative importance of ESG and non-ESG factors in determining sovereign credit ratings. Notably, their findings affirmed that ESG factors exert a more substantial influence on the credit ratings of countries experiencing higher economic growth, while their impact is relatively low for developing economies. This underscores the role of the economic context in shaping the significance attributed to ESG considerations in the assessment of sovereign creditworthiness. Fitch Solutions [34], in their study that examines how ESG factors impact sovereign credit ratings, indicates a potential impact of ESG on sovereign credit ratings, with governance aspects being the most influential.

Ciocchini *et al.* [35] have studied corruption and discovered that countries with more corruption tend to pay higher costs when they borrow money by issuing bonds. This means that countries with a higher level of corruption are seen as riskier by investors, so they charge them more money in interest rates when lending to them. Using world development indicators by Dufrénot and Paret [35], study how well a government functions and how it affects the difference in interest rates (called bond spreads) between different countries when they borrow money. The study found that when a government is more effective in its operations, it has a significant impact on the risk associated with lending to that country. This means that countries with more efficient and effective governments are seen as less risky to lend money to, so they can borrow at lower interest rates. Furthermore Cantor [36] found that countries with better measures of how well their people are doing overall (such as education, healthcare, and income equality) and lower rates of unemployment are less likely to have problems repaying their debts, which makes it cheaper for them to borrow money.

Eichler [37] focused their research on a group of emerging countries and examined how the type of political system in a nation affected the interest rates on their government bonds. The study found that countries with parliamentary systems, where the government is made up of elected representatives, tended to have higher interest rates compared to those with presidential systems, where a single elected leader holds significant power. Additionally, the study found that when the quality of governance improved, meaning that the government became more transparent, accountable, and efficient, the interest rates on sovereign bonds decreased, which means that countries with better governance faced lower borrowing costs because investors had more confidence in their ability to repay the borrowed money.

A study by Crifo [23] looked at the relationship between the interest rates on government bonds and corruption. The study found that when a country was perceived to be more corrupt according to Transparency International's Corruption Perception Index, it had a negative impact on the creditworthiness of its bonds. This means that the likelihood of repaying the borrowed money was seen as lower, leading to higher interest rates. The study found that higher ESG ratings have a significant impact in lowering government bond spreads, indicating that stronger

ESG performance is associated with reduced borrowing costs for sovereigns.

Margaretic and Pouget Margareti [38] demonstrated that countries with effective governance of their natural, human, and financial resources can implement socioeconomic measures that enhance their capacity to generate earnings and improve their ability to meet governmental obligations. Margaretic and Pouget [38] revealed that better ESG factors are linked to lower bond yields in OECD countries, particularly for long-term bonds, suggesting that incorporating ESG considerations can lead to favorable financing conditions for governments. Bouyé and Menville [39] established a negative relationship between ESG ratings and government bond CDS spreads, with this effect being more pronounced for advanced economies (AEs) compared to emerging market and developing economies (EMDEs).

Nemoto [40] in their study found that higher ESG performance, as measured by the aggregate ESG score, is associated with lower sovereign funding costs. This underscores the importance of incorporating ESG considerations in the assessment of sovereign creditworthiness and highlights the potential financial benefits for countries with stronger ESG performance. However, the analysis suggests that environmental considerations did not significantly impact credit ratings, indicating a potential gap in capturing these factors within the assessment framework.

The review on existing literature shows that, most of the studies primarily focus on macroeconomic factors and government factors such as corruption that determines the credit rating while several other studies have examined the links between sovereign credit risk and ESG. In this regard our paper aims to enrich previous by examining the relative importance of ESG and non-ESG (*i.e.* macro-economic) factors in assessing sovereign creditworthiness.

3. Materials and Methods

As recommended by Grömping and Pineau *et al.* [29] [41] this study uses statistical regression models, specifically statistical rating prediction models (Shadow rating) to predict the importance of ESG versus non-ESG (macroeconomic factors) in assessing the factors that have a greater effect on ratings.

We map the observed variables X to the rating y such that

$$Y_t^i\left(credit\ rating\right) = \beta_0 + \beta_1 Env + \beta_2 Soc + \beta_3 Gov + \beta_4 NonESG$$

After choosing the statistical regression model we choose the statistical model $F_{\varnothing}$ with parameters $\varnothing = \{\beta_i\}$, we fit the parameters with the independent variable X to the dependent variable rating y, such that $F_{\varnothing}\left(X_t^i\right) \approx Y_t^i$

Where F = model

Parameter: the correlation coefficient of independent and dependent variables.

With an appropriate model, the importance of each input variable can be accessed from ϕ using a function variable importance VI such that $VI(\varnothing) \in R$, with P the number of input variables, and

$$\sum_{k=1}^{p} VI(\varnothing)_k = \frac{|\varnothing_k|}{\|\varnothing\|_1} = \frac{|\varnothing_{Env}|}{\|\varnothing\|_1} + \frac{|\varnothing_{Soc}|}{\|\varnothing\|_1} + \frac{|\varnothing_{Gov}|}{\|\varnothing\|_1} + \frac{|\varnothing_{nonESG}|}{\|\varnothing\|_1} = 1$$

Where $\|\varnothing\|_1 = \sum_{k=1}^{p} VI(\varnothing)_k$ is called the L_1-norm and $\varnothing$ is the correlation coefficient of independent and dependent variables (the importance of the variable is rescaled to sum to 1 to make all models comparable).

Where

$VI(\varnothing)$: Importance of each variable

R*p*+: The set of positive real numbers

***P*:** Number of input variables

$VI(\varnothing)_k$: Rescaled importance values **where *k*** represents each variable

$\sum_{k=1}^{p} VI(\varnothing)_k$ The sum of rescaled importance values

3.1. Linear Model

Linear models like OLS (Ordinary Least Square) and LASSO (*Least Absolute Shrinkage and Selection Operator*) are commonly employed when it comes to statistical rating prediction Canuto *et al.* and Pineau *et al.* [29] [42]. Our Approach will be based on Variable importance (**VI**) in the statistical linear regression model (**LASSO**) to explain the importance variables between ***ESG*** and ***NON-ESG*** factors in determining a country's credit rating. LASSO is suited for linear modeling with multicollinearity, offering efficient variable selection, whereas Random Forest accommodates complex, non-linear interactions without distributional assumptions. Due to the data's complexity, both models were evaluated, with Random Forest chosen for its superior predictive performance.

In linear models, the importance of variable k may be defined as:

$$VI(\varnothing)_k = \frac{|\varnothing_k|}{\|\varnothing\|_1}$$

Which may be explained as a calculation of the Variable Importance by taking the absolute value of the coefficient for the variable in question and dividing it by the sum of the absolute values of all the coefficients in the model. The larger the resulting value, the more important the variable is in predicting the outcome in the linear model.

3.2. Non-Linear Models

Extensive research has established that the relationship between ratings and variables is non-linear, [32] [43] [44] in this case we will look into statistical non-linear regression models that include a natural definition of VI, there are the tree-based models, like random forests (RFs) [29] [45]. The Random Forest model uncovered notable non-linear interactions, with governance and macroeconomic factors strongly influencing credit ratings in upper-middle-income countries, and environmental variables playing a key role in lower-income countries. Joint effects such as renewable energy use and corruption control—were more impactful in the non-linear framework. These interdependencies, measured via a mean decrease in Gini impurity, demonstrate the model's superiority in capturing complex relationships that linear models like LASSO cannot fully identify.

We define Variable Importance in Random Forests as a measure providing the importance of a variable in the set of prediction rules. It helps us understand which variables have the biggest impact on the final prediction. It is called mean decrease in Gini (**MDG**) which refers to a mathematical concept used in Random Forests to determine the importance of a variable in making predictions. **MDG** tells us how much a variable contributes to making accurate predictions by measuring how much it improves the purity of the groups. A higher MDG score means the variable is more important in the prediction process and in this research, it is defined as follows:

$$VI(\varnothing)_k = \frac{1}{N_T}\sum_{N_T}\sum_{t\in T:V(t)=k} p(t)\Delta i(s_t,t)$$

The formula calculates the Variable Importance (***VI***) by summing up the probabilities of data points that match a specific variable (***k***) in each tree (***T***) of the Random Forest. It also considers the decrease in impurity when a data point is split based on a particular criterion. The higher the Variable Importance score, the more important the variable is in making accurate predictions within the Random Forest model.

In order to interpret the ***VI*** in terms of ***ESG*** and ***non-ESG***, it is necessary to create meta-variables respectively for Environmental (E), Social (S), Governance (G), and non-ESG based on previous knowledge by Capelle-Blancard *et al.* [46] and understanding of the meta-variables which can influence credit rating with some of the main steps they suggested which are:

1) Verifying that factorial analysis is meaningful using Kaiser-Meyer-Olkin (**KMO**) in Python as suggested by Kaiser and rice [47] as cited in [48] as a means of assessing the suitability of the sampling for factor analysis and if factor analysis is suited for our data. KMO must be greater than **0.5;** in this research, the KMO statistics for Environmental (E), Social (S), Governance (G), and non-ESG are 0.52; 0.58; 0.72, and 0.575 respectively.

2) To reduce the dimensionality of the dataset while preserving the important features we Build factors using Principal Component Analysis (PCA) plus varimax rotation to make correlations between the variables and the factors more distinct and easier to interpret [49].

3) To obtain 1-dimensional indices for E, S, G, and non-ESG, the process involves calculating the indices by examining the correlation between factors and variables.

Once the meta-variables have been computed, the next step in the research is to assess the significance of ESG factors. We will achieve this by employing statistical prediction models such as LASSO and RF. These models help us to establish the relationship between ESG and non-ESG indices as well as the credit rating. By doing so these prediction models will help us gain insights into the importance and impact of ESG factors on the ratings.

3.3. Data

This study uses panel data which provides more variability, more efficiency, and best fits to study our macro-economic variables. Therefore in order to investigate the impact and importance of Environmental, Social, and Governance (ESG) factors in sovereign credit rating initially this study chooses all sub-Saharan African countries however due to the unavailability of ratings from S&P, Moody's, and Fitch rating agencies the final sample size is restricted to 22 countries out of 49 countries during the wide range from 2010 to 2022 period. Interaction effects between ESG components were not explicitly modeled as cross-product terms, but Random Forest models inherently capture such interactions due to their structure. For example, a tree may split on governance and then on environmental variables, implicitly capturing the ESG effect. The study prioritized model interpretability and robustness over explicitly modeling all possible interactions, which would have significantly increased model complexity and potential overfitting, especially given the limited sample size of 22 countries over the 2010-2022 period.

Several sets of variables in our dataset were collected from various sources.

Table 1. Credit rating category and numerical transformation.

Rating category	Rating scale	Moody's	S&P	Fitch
Investment Grade	20	Aaa	AAA	AAA
	19	Aa1	AA+	AA+
	18	Aa2	AA	AA
	17	Aa3	AA−	AA−
	16	A1	A+	A+
	15	A2	A	A
	14	A3	A−	A−
	13	Baa1	BBB+	BBB+
	12	Baa2	BBB	BBB
	11	Baa3	BBB−	BBB−
Speculative Grade	10	Ba1	BB+	BB+
	9	Ba2	BB	BB
	8	Ba3	BB−	BB−
	7	B1	B+	B+
	6	B2	B	B
	5	B3	B−	B−
	4	Caa1	CCC+	CCC+
	3	Caa2	CCC	CCC
	2	Caa3	CCC−	CCC−
Extremely speculative	1	Ca	CC/C	CC/C
Default	0	WR	D	D

Sources: Standard & Poor's, Moody's Investors Service, and Fitch Ratings.

Dependent variables

The data for the sovereign credit rating were provided by the three rating agencies: Standard and Poor's, Moody's and Fitch.

Generally, credit ratings fall within the categories of **A, B, C**, or **D** as indicated in Table 1. Traditionally, the highest rating given by all credit rating agencies is **AAA**. As the rating decreases, it signifies a higher likelihood of default. Governments that receive ratings above "**BBB**" are regarded as having "**investment grades**", indicating a lower risk of default. Conversely, governments with ratings below "**BBB**" are considered to have "**speculative grades**," indicating a higher risk of default.

Since it is impractical to represent letter symbols exactly in our model, we adopt a linear transformation to convert credit ratings into a numerical scale [50].

3.3.1. Independent Variables

For ESG variables we employ the World Bank's Sovereign ESG Dataset.

To evaluate a nation's environmental performance the World Bank Group's World Development Indicators (WDI) are used. Halbritter & Dorfleitner and Delmas *et al.* [51] [52] raised Concerns about the unreliability, validity, and reproducibility of ESG ratings derived from publicly available data. To solve these shortcomings and provide a fresh perspective, our study directly picks and assesses observable variables rather than depending on judgments from institutions. This lowers potential biases and increases the openness of our findings by enabling a thorough and cogent analysis.

➢Strong performance in Data on trees, renewable energy, water and sanitation, air quality, etc. demonstrates a nation's dedication to protecting and improving the environment. Significantly, their desire to repay debt may be positively correlated with their long-term commitment to sustainable practices; countries with a strong commitment to sustainability may also exhibit a greater determination to honor their debt obligations.

➢The underlying idea is that a country's responsible approach toward environmental stewardship reflects its overall commitment to long-term economic stability and responsible governance [20] [53].

➢Furthermore in order to assess the level of dedication a country has towards developing and preserving its human and social resources we use data from WDI by examining factors such as gender equality, employment, and demography. This assessment allows us to gauge the extent to which a nation is committed to promoting fair and sustainable growth over the long term. The commitment demonstrated through these efforts reflects the country's investment in the well-being and advancement of its people. By prioritizing these areas, the country strives to create an environment that fosters long-term prosperity and a harmonious society [54].

➢Lastly, to assess and collect data concerning governance we used data from WDI to evaluate factors such as voice and accountability, political stability and absence of violence, government effectiveness, rule of law, control of corruption, etc.

➢This study identifies political stability as a significant contributor to the governance construct, highlighting its positive impact on credit ratings by enhancing institutional trust and a country's debt-servicing capacity.

3.3.2. Control Variables

Macroeconomic variables (non-ESG factors): To account for the economic characteristics of each country, we incorporate 10 country-specific macroeconomic variables sourced from IMF and prior research studies [55]. Economic policies like fiscal discipline and public investment can blur the true impact of ESG (Environmental, Social, and Governance) metrics on outcomes like credit ratings. Strong macroeconomic performance might hide weak ESG performance, or vice versa. To address this, the authors included detailed macroeconomic controls (e.g., GDP per capita, inflation, debt ratio) in their models to isolate the effects of ESG. However, policy feedback loops where ESG and economic policies influence each other—may still create complex dynamics that the models can't fully separate (See Table 2).

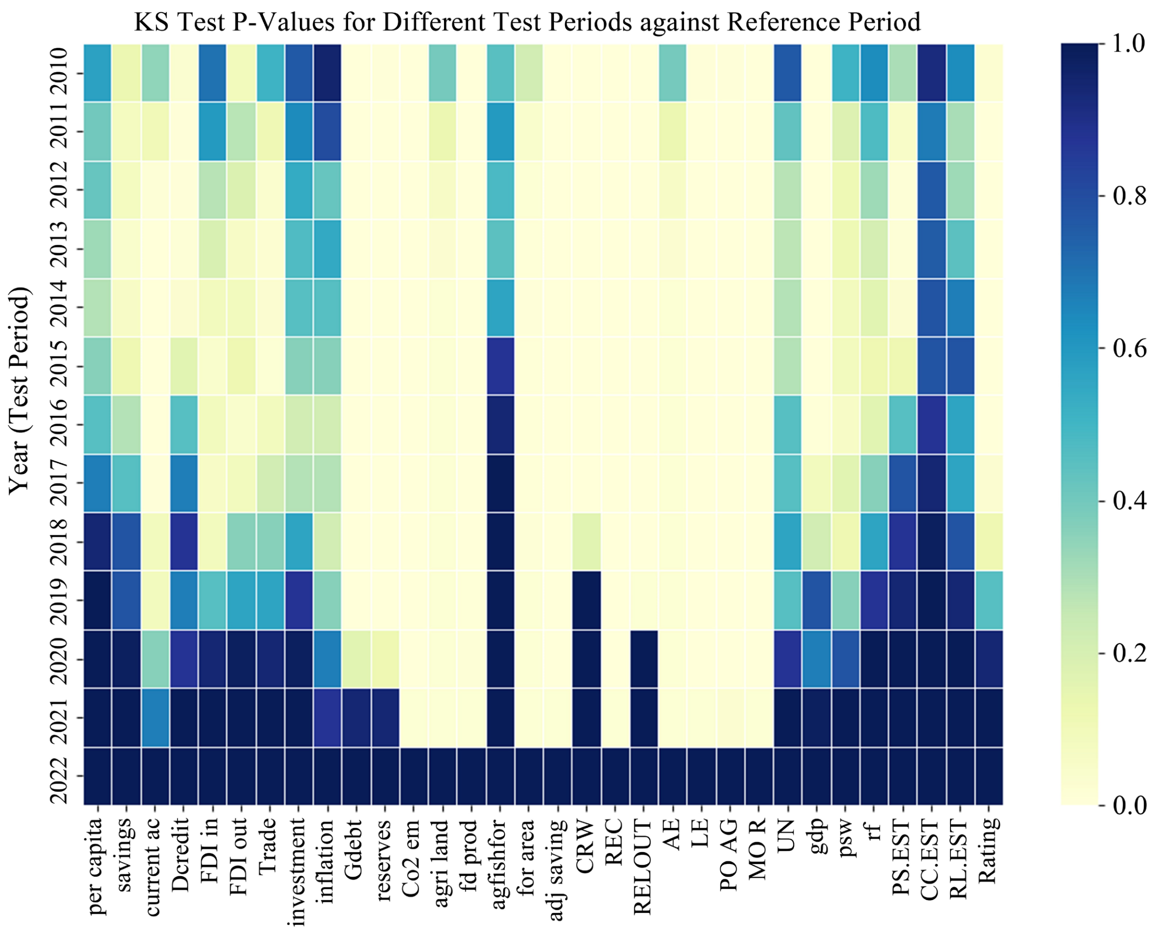

Figure 1. P-values of the KS test comparing each year to 2022.

Table 2. Observed variables from World Bank International Monetary Fund (IMF).

Dimensions	Variable	Category	Sources
Credit rating	Sovereign credit rating	Dependent variable	Moody's, S&P and Fitch
Macroeconomic variables (Non ESG)	GDP per Capita	Economy (Independent variable)	World bank
	Gross savings (% of GDP)	Economy (Independent variable)	World bank
	Gross capital investment (% of GDP)	Economy (Independent variable)	IMF
	Total reserves	fiscal strength (Independent variable)	IMF
	General government gross debt	fiscal strength (Independent variable)	IMF
	Current account balance (% of GDP)	fiscal strength (Independent variable)	World bank
	Inflation, average consumer prices	Money and Trade (Independent variable)	IMF
	Domestic credit to private sector (% of GDP)	Money and Trade (Independent variable)	World bank
	Foreign Direct Investment (% of GDP)	Money and Trade (Independent variable)	World bank
	Trade (% of GDP)	Money and Trade (Independent variable)	World bank
Environmental	CO_2 emissions (metric tons per capita)	Independent variable	Sovereign ESG, WB
	Food production index (2014 - 2016 = 100)	Independent variable	Sovereign ESG, WB
	Agricultural land (% of land area)	Independent variable	Sovereign ESG, WB
	Agriculture value added (% of GDP)	Independent variable	Sovereign ESG, WB
	Forest area (% of land area)	Independent variable	Sovereign ESG, WB
	Adjusted savings (% of GNI)	Independent variable	Sovereign ESG, WB
	Combustible renewables and waste (% of total energy)	Independent variable	Sovereign ESG, WB
	Renewable energy consumption (% of total final energy consumption)	Independent variable	Sovereign ESG, WB
	Renewable electricity output (% of total electricity output)	Independent variable	Sovereign ESG, WB
Social	Access to electricity (% of population)	Independent variable	Sovereign ESG, WB
	Life expectancy at birth, total (years)	Independent variable	Sovereign ESG, WB
	Population ages 65 and above (% of total population)	Independent variable	Sovereign ESG, WB
	Mortality rate, under 5 (per 1000 live births)	Independent variable	Sovereign ESG, WB
	Unemployment, total (% of total labor force) (modeled ILO estimate)	Independent variable	Sovereign ESG, WB
Governance	GDP growth (annual %)	Independent variable	Sovereign ESG, WB
	Proportion of seats held by women in national parliaments (%)	Independent variable	Sovereign ESG, WB
	Ratio of female to male labor force participation rate (%) (modeled ILO estimate)	Independent variable	Sovereign ESG, WB
	Patent applications, residents	Independent variable	Sovereign ESG, WB
	Political stability	Independent variable	Sovereign ESG, WB
	Control of corruption	Independent variable	Sovereign ESG, WB
	Rule of law	Independent variable	Sovereign ESG, WB

For each variable, we test the null hypothesis H_0: *same distribution* between observations on period for $t \in \{2010, \cdots, 2021\}$ and period $\{2018, \cdots, 2022\}$. A low p-value is interpreted as a rejection of H_0. We observed the non-stationarity of the samples across the years as all the variables vary across from H_0 rejection to acceptance.

From Figure 1, we conducted KS test to compare the distributions of each variable between two different periods, $t \in \{2010, \cdots, 2021\}$ and $\{2018, \cdots, 2022\}$ period.

The null hypothesis outlined that, the distributions are the same, H_0 *same distribution* between observations. If the p-value obtained from the tests is low, it indicates that we reject the null hypothesis. We found that the samples of all the variables varied across the years, with some showing a rejection of the null hypothesis and others showing acceptance. This suggests that the variables were not stationary, hence exhibited changes over time.

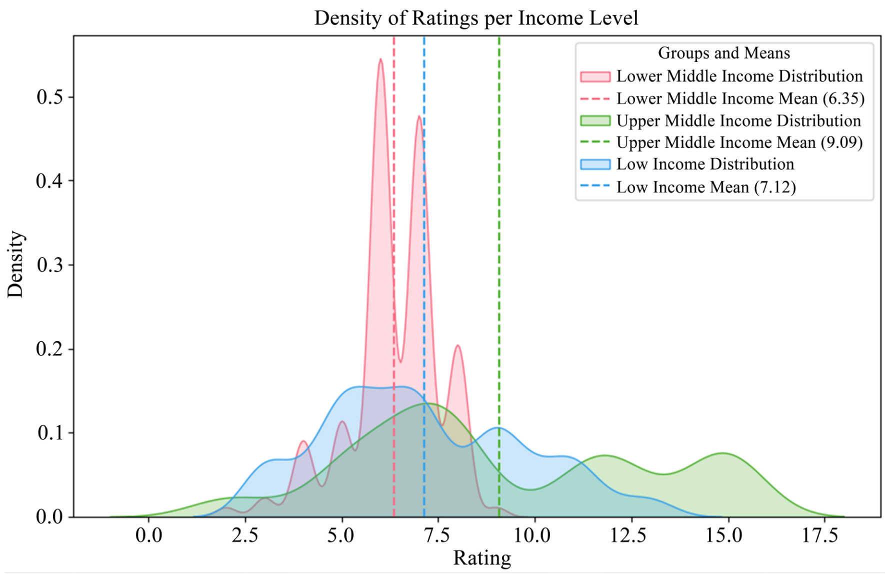

Figure 2. Density of the ratings per income level.

Figure 2 shows the density distribution of ratings per income level (low income, Low middle income, and upper middle income within the sub-Saharan countries) both computed with kernel density estimation (KDE). The KDE usually estimates the probability density function (PDF) of a random variable based on a set of observations or data points. In this context it allows us to get a clear picture/shape of the data distribution to show how the ratings are spread out and how likely different values are.

4. Result and Discussion

Figure 3 below shows Casual graph inferred with LiNGAM algorithm by Shimizu *et al.* [56] using the meta-variables from factor analysis developed by Capelle-Blancard *et al.* [46], We observe the relationship between rating, ESG and non-

ESG using the prediction model. Then this paper compares the importance of ESG factors versus non-ESG factors in the credit ratings of different income level countries within SSA countries, using regression models using RF and LASSO; the results presented in Table 3 indicate that the Random Forest (RF) model outperforms the linear model in terms of credit rating prediction accuracy. Therefore, for the remainder of this study, the analysis will exclusively utilize the Variable Importance (VIs) computed using the Random Forest model.

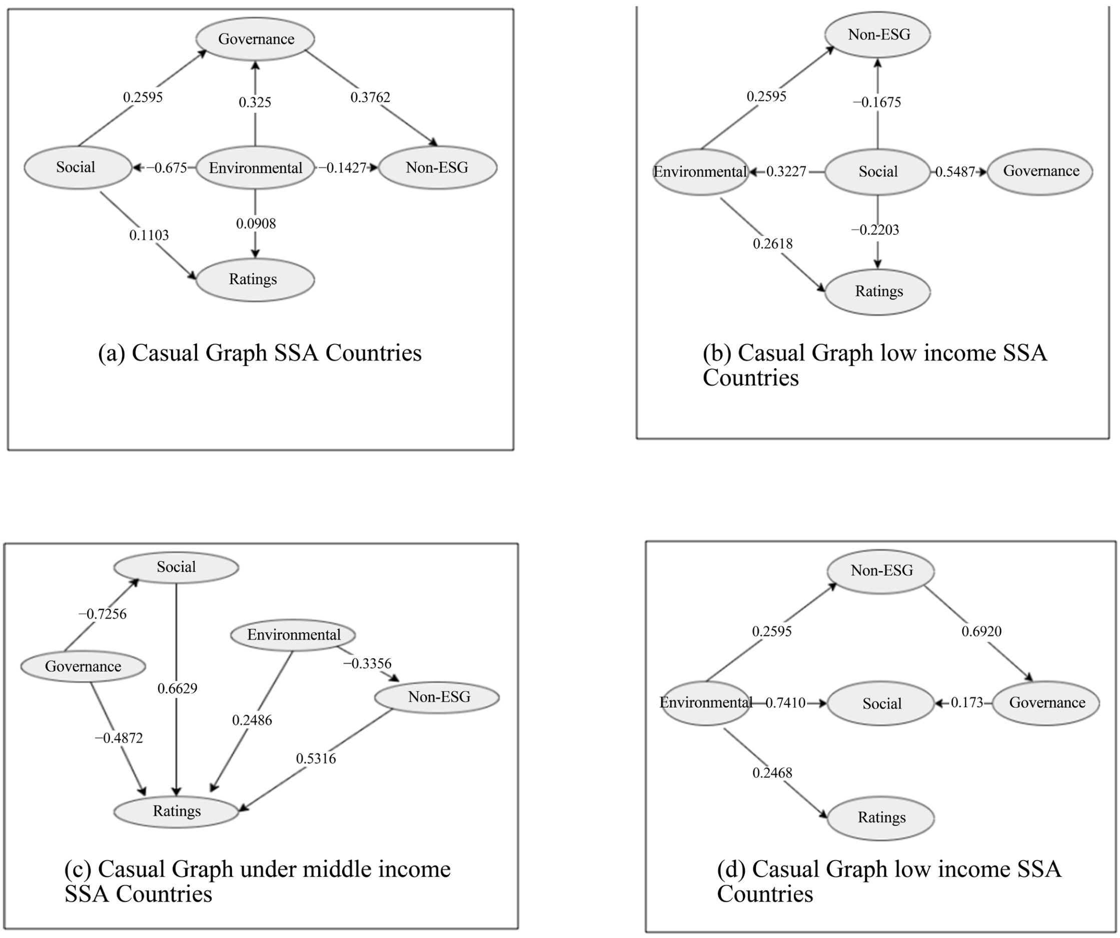

Figure 3. Casual graph inferred with LiNGAM algorithm.

Figure 3 which includes **(a), (b), (c), (d)** shows causal graphs created using the Lingam algorithm Shimizu *et al.* [56] and meta-variables developed by Capelle-Blancard *et al.* [46]. The variable "Ratings" is a leaf node or a dependent variable meaning it is influenced by other factors (ESG and non-ESG) but does not affect them back. Therefore it's appropriate to use prediction models to understand how changes in ESG and non-ESG factors might affect the credit rating. The graph also shows that for upper middle income within SSA countries the main factors influencing credit ratings are Governance (G) and non-ESG factors while for middle income and low income countries within SSA countries the main factors influencing credit ratings are the Environmental (E) factor and non-ESG.

4.1. Comparing ESG Factors and Macroeconomic Variables Using LASSO (Linear Model) and Random Forest (Non-Linear Model) (See Figure 4 and Figure 5)

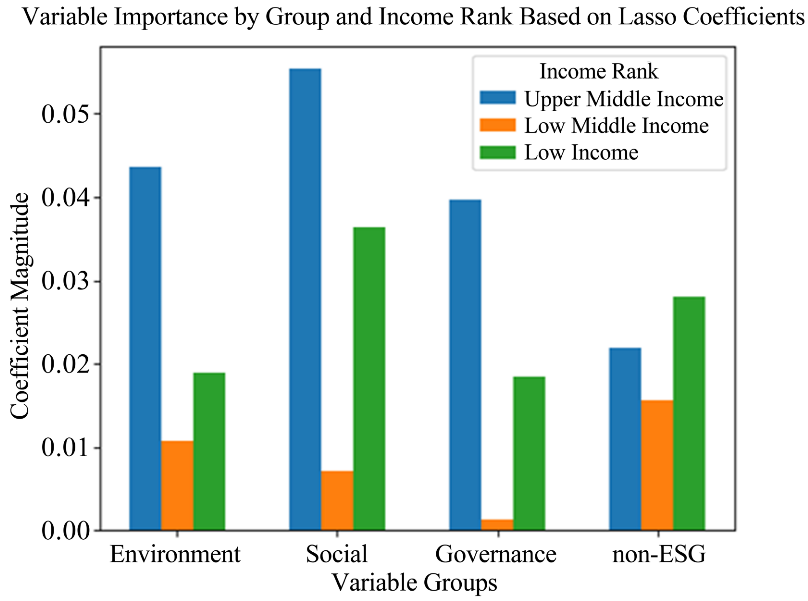

Figure 4. Comparing ESG factors and macroeconomic variables using LASSO (linear model) and random forest (non-linear model).

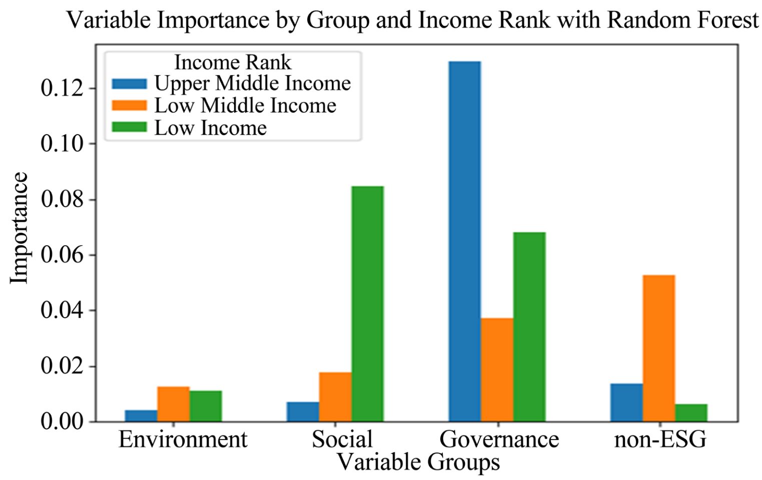

Figure 5. Meta-variable importance *VI* for LASSO and RF models.

4.2. Model Comparison between Random Forest and Lasso Regression Model

Table 3 shows accuracy computation with a tolerance of 2 ratings (on a 23 rating scale). The computation of the accuracy measure was based on the random selection of 80% of the dataset and the Mean ± standard deviations were computed by repeating 20 times. Greater accuracy and higher R^2 mean an efficient model. This is used to assess the performance of the models, the model with high performance metrics (RF) is selected for the rest of this study.

Table 3. Comparison between Random forest and Lasso regression model.

Model	Accuracy ± 2	R^2
LASSO	0.75 ± 0.05	0.56 ± 0.11
RF	0.94 ±0.03	0.86 ± 0.08

This approach allows for a more robust evaluation of the models, as it takes into account the variability in the data and the potential for random changes in the model's performance. The selection of the RF model for further studies suggests that it outperformed the other models in terms of predictive accuracy, making it a good option for more in-depth investigation and potential application in the research context. (See Figure 6)

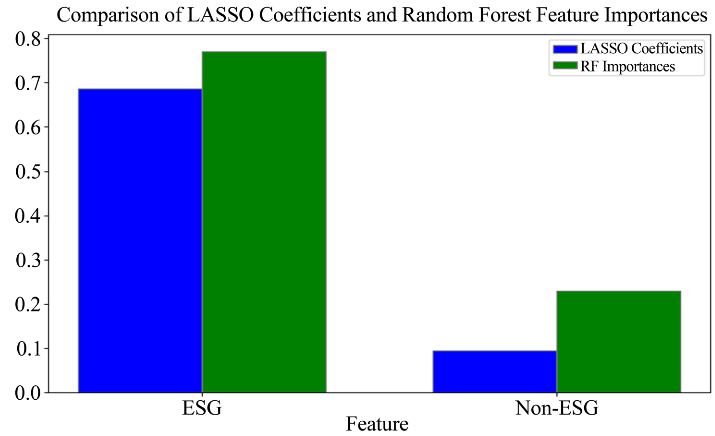

Figure 6. Comparative analysis of feature influence in Lasso and random forest models.

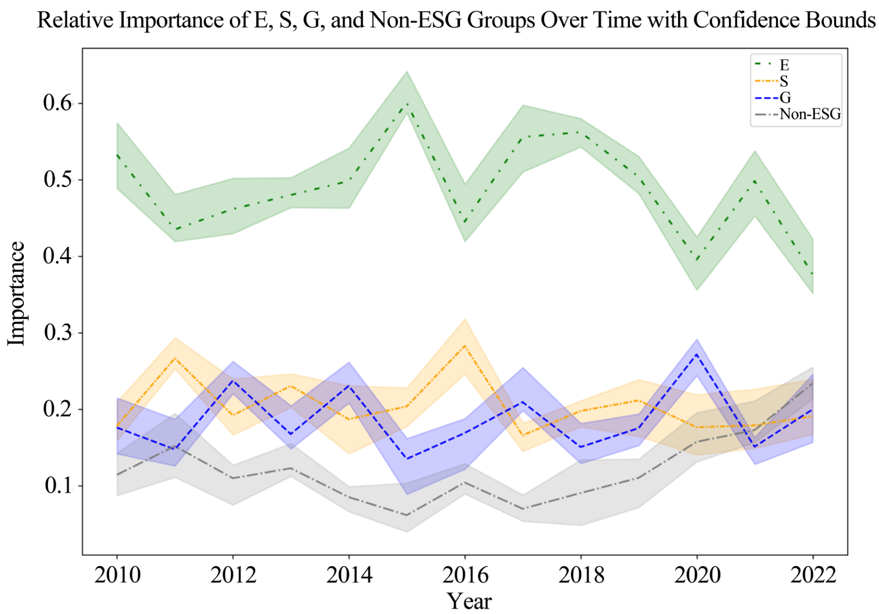

Figure 7. Relative importance of ESG and Non-ESG groups over time with confidence bounds.

In **Figure 7**, we observe that for both ESG and a non-ESG feature, the Lasso model which relies on linear relationships has a positive influence on credit rating. Also, the Random Forest model which captures non-linear relationships considers both ESG and non-ESG factors highly significant in predicting credit rating, with ESG factors having a much higher importance score. The graph indicates that while both factors are deemed important, their factors are measured differently by linear and non-linear modeling techniques.

The changing significance of environmental, social, and governance (ESG) factors considerations over the years.

5. Conclusion

In conclusion, the study underscores the growing importance of ESG factors in sovereign credit ratings within Sub-Saharan African countries. While traditional macroeconomic indicators remain crucial in credit assessments, the findings indicate that governance and environmental sustainability have significant impacts on sovereign ratings, particularly in countries with varying income levels. The findings align with prior studies by (Pineau *et al.*, 2022; Crifo *et al.*, 2017) showing that governance is a strong determinant of credit ratings. However, this study diverges slightly by finding that environmental factors play a more prominent role in low-income Sub-Saharan African countries—possibly due to the region's climate vulnerabilities and dependency on natural resources. Most prior literature focused on high-income or OECD countries where social and governance factors dominate. This study fills a critical gap by showing ESG's differentiated impact by income level within a developing region. The superior performance of the Random Forest model over the LASSO model suggests that non-linear interactions between ESG and macroeconomic factors should be considered in credit risk assessments. The study provides valuable insights for governments, investors, and rating agencies, emphasizing the necessity of integrating ESG criteria into sovereign risk analysis. As sustainability considerations continue to shape global financial markets, African policymakers must adopt strategies that enhance ESG performance to secure better credit ratings and reduce borrowing costs.

5.1. Policy Recommendations

Based on the empirical findings and conclusions provided, the authors suggest that:

1) Governments should implement policies to enhance transparency, political stability, and regulatory frameworks, as governance factors significantly influence credit ratings.

2) Countries should adopt policies that promote environmental resilience, such as investing in renewable energy, sustainable agriculture, and climate adaptation strategies, to mitigate the risks associated with climate change and environmental degradation.

3) Governments should enhance healthcare, education, and social inclusion

policies positively to impact sovereign credit ratings by fostering human capital and economic stability.

4) Governments should establish regulatory requirements for ESG performance disclosure to provide investors and rating agencies with accurate and standardized sustainability data.

5) Financial institutions and policymakers should incentivize green bonds and other sustainable investment instruments to attract responsible capital inflows.

6) Credit rating agencies and financial analysts should incorporate advanced machine learning models such as Random Forest to capture complex relationships between ESG and macroeconomic variables in sovereign risk assessments.

5.2. Future Research Directions

While this study provides valuable insights into the impact of ESG factors on sovereign credit ratings, several areas warrant further investigation as it maybe suggested same by other researchers as follows:

1) Future studies should explore the impact of ESG factors on sovereign credit ratings in other emerging economies beyond Sub-Saharan Africa to compare regional differences.

2) It is suggested that further analysis regarding how ESG factors have influenced sovereign credit ratings over a more extended period could provide deeper insights into evolving trends and policy impacts.

3) Interested authors on this subject of discussion can investigate how different sectors (e.g., energy, finance, and agriculture) contribute to national ESG performance and sovereign risk assessments could provide more targeted policy recommendations.

4) Authors can use real-time and alternative data sources such as satellite imagery, AI-driven sentiment analysis, and big data analytics could enhance the predictive power of ESG factors in credit rating models.

5) In terms of comparing the ESG Rating Methodologies**,** future research should evaluate the discrepancies in ESG ratings from different rating agencies and their respective impacts on sovereign credit assessments.

Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] Lewin, K.M. (2020) Beyond Business as Usual: Aid and Financing Education in Sub Saharan Africa. *International Journal of Educational Development*, **78**, Article 102247. https://doi.org/10.1016/j.ijedudev.2020.102247

[2] Abeywickrama, K., Perera, N., Samarathunga, S., Pabasara, H., Jayathilaka, R. and Wisenthige, K. (2024) Factors Influencing IMF Assistance in the Sub-Saharan African Region. *PLOS ONE*, **19**, e0307071. https://doi.org/10.1371/journal.pone.0307071

[3] Modugu, K.P. and Dempere, J. (2022) Monetary Policies and Bank Lending in Developing Countries: Evidence from Sub-Sahara Africa. *Journal of Economics and Development*, **24**, 217-229. https://doi.org/10.1108/jed-09-2021-0144

[4] Manasseh, C.O., Abada, F.C., Okiche, E.L., Okanya, O., Nwakoby, I.C., Offu, P., *et al.* (2022) External Debt and Economic Growth in Sub-Saharan Africa: Does Governance Matter? *PLOS ONE*, **17**, e0264082. https://doi.org/10.1371/journal.pone.0264082

[5] Gugler, P. and Shi, J.Y.J. (2009) Corporate Social Responsibility for Developing Country Multinational Corporations: Lost War in Pertaining Global Competitiveness? *Journal of Business Ethics*, **87**, 3-24. https://doi.org/10.1007/s10551-008-9801-5

[6] Sethi, S.P., Martell, T.F. and Demir, M. (2015) An Evaluation of the Quality of Corporate Social Responsibility Reports by Some of the World's Largest Financial Institutions. *Journal of Business Ethics*, **140**, 787-805. https://doi.org/10.1007/s10551-015-2878-8

[7] Bardy, R., Drew, S. and Kennedy, T.F. (2012) Foreign Investment and Ethics: How to Contribute to Social Responsibility by Doing Business in Less-Developed Countries. *Journal of Business Ethics*, **106**, 267-282. https://doi.org/10.1007/s10551-011-0994-7

[8] Campbell, J.T., Eden, L. and Miller, S.R. (2011) Multinationals and Corporate Social Responsibility in Host Countries: Does Distance Matter? *Journal of International Business Studies*, **43**, 84-106. https://doi.org/10.1057/jibs.2011.45

[9] Birindelli, G., Ferretti, P., Intonti, M. and Iannuzzi, A.P. (2015) On the Drivers of Corporate Social Responsibility in Banks: Evidence from an Ethical Rating Model. *Journal of Management & Governance*, **19**, 303-340. https://doi.org/10.1007/s10997-013-9262-9

[10] Tai, F. and Chuang, S. (2014) Corporate Social Responsibility. *iBusiness*, **6**, 117-130. https://doi.org/10.4236/ib.2014.63013

[11] Pineau, E., Le, P. and Estran, R. (2022) Importance of ESG Factors in Sovereign Credit Ratings. *Finance Research Letters*, **49**, Article 102966. https://doi.org/10.1016/j.frl.2022.102966

[12] Chee, S.W., Fah, C.F. and Nassir, A.M. (2015) Macroeconomics Determinants of Sovereign Credit Ratings. *International Business Research*, **8**, 42-50. https://doi.org/10.5539/ibr.v8n2p42

[13] Pineau, E. and Zuñiga, E. (2024) Sectoral Credit Sensitivity to Carbon Price with Value Chain Effects. *Review of World Economics*, 1-27. https://doi.org/10.1007/s10290-024-00543-7

[14] Afonso, A., Gomes, P. and Rother, P. (2010) Short- and Long-Run Determinants of Sovereign Debt Credit Ratings. *International Journal of Finance & Economics*, **16**, 1-15. https://doi.org/10.1002/ijfe.416

[15] White, L.J. (2013) Credit Rating Agencies: An Overview. *Annual Review of Financial Economics*, **5**, 93-122. https://doi.org/10.1146/annurev-financial-110112-120942

[16] White, L.J. (2002) The Credit Rating Industry: An Industrial Organization Analysis. In: Levich, R.M., Majnoni, G. and Reinhart, C.M., Eds., *The New York University Salomon Center Series on Financial Markets and Institutions*, Springer US, 41-63. https://doi.org/10.1007/978-1-4615-0999-8_3

[17] White, L.J. (2010) Markets: The Credit Rating Agencies. *Journal of Economic Perspectives*, **24**, 211-226. https://doi.org/10.1257/jep.24.2.211

[18] Langohr, H. and Langohr, P. (2010) The Rating Agencies and Their Credit Ratings: What They Are, How They Work, and Why They Are Relevant. John Wiley & Sons.

[19] Crifo, P., Escrig-Olmedo, E. and Mottis, N. (2019) Corporate Governance as a Key Driver of Corporate Sustainability in France: The Role of Board Members and Investor Relations. *Journal of Business Ethics*, **159**, 1127-1146. https://doi.org/10.1007/s10551-018-3866-6

[20] Capelle-Blancard, G., Crifo, P., Diaye, M., Scholtens, B. and Oueghlissi, R. (2016) Environmental, Social and Governance (ESG) Performance and Sovereign Bond Spreads: An Empirical Analysis of OECD Countries. *SSRN Electronic Journal*, 62.

[21] Bruno, C.C. and Henisz, W.J. (2024) Environmental, Social, and Governance (ESG) Outcomes and Municipal Credit Risk. *Business & Society*, **63**, 1709-1756. https://doi.org/10.1177/00076503231220541

[22] Billio, M., Costola, M., Hristova, I., Latino, C. and Pelizzon, L. (2024) Sustainable Finance: A Journey toward ESG and Climate Risk. *International Review of Environmental and Resource Economics*, **18**, 1-75. https://doi.org/10.1561/101.00000156

[23] Crifo, P., Diaye, M. and Oueghlissi, R. (2017) The Effect of Countries' ESG Ratings on Their Sovereign Borrowing Costs. *The Quarterly Review of Economics and Finance*, **66**, 13-20. https://doi.org/10.1016/j.qref.2017.04.011

[24] Proaño, C.R., Schoder, C. and Semmler, W. (2014) Financial Stress, Sovereign Debt and Economic Activity in Industrialized Countries: Evidence from Dynamic Threshold Regressions. *Journal of International Money and Finance*, **45**, 17-37. https://doi.org/10.1016/j.jimonfin.2014.02.005

[25] Echevarría Icaza, V. (2017) The Interaction of Fiscal and Financial Risk in the Eurozone. https://docta.ucm.es/entities/publication/db8395d8-e646-41c1-a159-59b942d0a297

[26] Alter, A. and Beyer, A. (2014) The Dynamics of Spillover Effects during the European Sovereign Debt Turmoil. *Journal of Banking & Finance*, **42**, 134-153. https://doi.org/10.1016/j.jbankfin.2014.01.030

[27] Kiesel, F. and Lücke, F. (2019) ESG in Credit Ratings and the Impact on Financial Markets. *Financial Markets, Institutions & Instruments*, **28**, 263-290. https://doi.org/10.1111/fmii.12114

[28] Broadstock, D.C., Chan, K., Cheng, L.T.W. and Wang, X. (2021) The Role of ESG Performance during Times of Financial Crisis: Evidence from COVID-19 in China. *Finance Research Letters*, **38**, Article 101716. https://doi.org/10.1016/j.frl.2020.101716

[29] Pineau, J., Pinon, L., Mesdjian, O., Fattaccioli, J., Lennon Duménil, A. and Pierobon, P. (2022) Microtubules Restrict F-Actin Polymerization to the Immune Synapse via GEF-H1 to Maintain Polarity in Lymphocytes. *eLife*, **11**, e78330. https://doi.org/10.7554/elife.78330

[30] Soudis, D. (2016) Determinants of Sovereign Bonds Ratings: A Robustness Analysis. *Bulletin of Economic Research*, **69**, 164-177. https://doi.org/10.1111/boer.12093

[31] Biglaiser, G. and Staats, J.L. (2012) Finding the "Democratic Advantage" in Sovereign Bond Ratings: The Importance of Strong Courts, Property Rights Protection, and the Rule of Law. *International Organization*, **66**, 515-535. https://doi.org/10.1017/s0020818312000185

[32] Barta, Z. and Makszin, K. (2020) The Politics of Creditworthiness: Political and Policy Commentary in Sovereign Credit Rating Reports. *Journal of Public Policy*, **41**, 307-330. https://doi.org/10.1017/s0143814x20000033

[33] Gratcheva, E. (2024) Sovereign Environmental, Social, and Governance (ESG) Investing: Chasing Elusive Sustainability. *IMF Working Papers*, **2024**, 1-39. https://doi.org/10.5089/9798400277054.001

[34] Solutions, F. (2023) Fitch Connect. Delivery Platform Financial Data.

[35] Dufrénot, G. and Paret, A. (2018) Sovereign Debt in Emerging Market Countries: Not All of Them Are Serial Defaulters. *Applied Economics*, **50**, 6406-6443. https://doi.org/10.1080/00036846.2018.1486022

[36] Cantor, R. and Packer, F. (1996) Sovereign Risk Assessment and Agency Credit Ratings. *European Financial Management*, **2**, 247-256. https://doi.org/10.1111/j.1468-036x.1996.tb00040.x

[37] Eichler, S. and Maltritz, D. (2013) The Term Structure of Sovereign Default Risk in EMU Member Countries and Its Determinants. *Journal of Banking & Finance*, **37**, 1810-1816. https://doi.org/10.1016/j.jbankfin.2012.02.002

[38] Margaretic, P. and Pouget, S. (2018) Sovereign Bond Spreads and Extra-Financial Performance: An Empirical Analysis of Emerging Markets. *International Review of Economics & Finance*, **58**, 340-355. https://doi.org/10.1016/j.iref.2018.04.005

[39] Bouyé, E. and Menville, D. (2020) The Convergence of Sovereign ESG Ratings. *SSRN Electronic Journal*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3568547

[40] Nemoto, N. and Liu, L. (2020) Measuring the Effect of Environmental, Social, and Governance on Sovereign Funding Costs., ADBI Working Paper Series.

[41] Grömping, U. (2015) Variable Importance in Regression Models. *WIREs Computational Statistics*, **7**, 137-152. https://doi.org/10.1002/wics.1346

[42] Canuto, O., Dos Santos, P.F.P. and De SÁ Porto, P.C. (2012) Macroeconomics and Sovereign Risk Ratings. *Journal of International Commerce*, *Economics and Policy*, **3**, Article 1250011. https://doi.org/10.1142/s1793993312500111

[43] Hadzi-Vaskov, M. and Ricci, L. (2019) The Non-linear Relationship between Public Debt and Sovereign Credit Ratings. *IMF Working Papers*, **19**, 1-37. https://doi.org/10.5089/9781498325059.001

[44] Hunjra, A.I., Azam, M., Bruna, M.G. and Taskin, D. (2022) Role of Financial Development for Sustainable Economic Development in Low Middle Income Countries. *Finance Research Letters*, **47**, Article 102793. https://doi.org/10.1016/j.frl.2022.102793

[45] Breiman, L. (2001) Random Forests. *Machine Learning*, **45**, 5-32. https://doi.org/10.1023/a:1010933404324

[46] Capelle-Blancard, G. and Petit, A. (2019) Every Little Helps? ESG News and Stock Market Reaction. *Journal of Business Ethics*, **157**, 543-565. https://doi.org/10.1007/s10551-017-3667-3

[47] Kaiser, H.F. and Rice, J. (1974) Little Jiffy, Mark Iv. *Educational and Psychological Measurement*, **34**, 111-117. https://doi.org/10.1177/001316447403400115

[48] Persson, I. and Khojasteh, J. (2021) Python Packages for Exploratory Factor Analysis. *Structural Equation Modeling*: *A Multidisciplinary Journal*, **28**, 983-988. https://doi.org/10.1080/10705511.2021.1910037

[49] Mellios, C. and Paget-Blanc, E. (2006) Which Factors Determine Sovereign Credit Ratings? *The European Journal of Finance*, **12**, 361-377. https://doi.org/10.1080/13518470500377406

[50] Boumparis, P., Milas, C. and Panagiotidis, T. (2017) Economic Policy Uncertainty and Sovereign Credit Rating Decisions: Panel Quantile Evidence for the Eurozone. *Journal of International Money and Finance*, **79**, 39-71. https://doi.org/10.1016/j.jimonfin.2017.08.007

[51] Dorfleitner, G., Halbritter, G. and Nguyen, M. (2015) Measuring the Level and Risk of Corporate Responsibility—An Empirical Comparison of Different ESG Rating Approaches. *Journal of Asset Management*, **16**, 450-466. https://doi.org/10.1057/jam.2015.31

[52] Delmas, M.A., Etzion, D. and Nairn-Birch, N. (2013) Triangulating Environmental Performance: What Do Corporate Social Responsibility Ratings Really Capture? *Academy of Management Perspectives*, **27**, 255-267.

https://doi.org/10.5465/amp.2012.0123

[53] Eaton, J. and Gersovitz, M. (1981) Debt with Potential Repudiation: Theoretical and Empirical Analysis. *The Review of Economic Studies*, **48**, 289-309. https://doi.org/10.2307/2296886

[54] Lins, K.V., Servaes, H. and Tamayo, A. (2017) Social Capital, Trust, and Firm Performance: The Value of Corporate Social Responsibility during the Financial Crisis. *The Journal of Finance*, **72**, 1785-1824. https://doi.org/10.1111/jofi.12505

[55] Berger, T., Grabert, S. and Kempa, B. (2015) Global and Country-Specific Output Growth Uncertainty and Macroeconomic Performance. *Oxford Bulletin of Economics and Statistics*, **78**, 694-716. https://doi.org/10.1111/obes.12118

[56] Shimizu, S., *et al*. (2006) A Linear Non-Gaussian Acyclic Model for Causal Discovery. *Journal of Machine Learning Research*, **7**, 2003-2030.