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Environmental Accounting, Green Finance, and Taxation Mapped with AI for Climate-Smart Sustainable Development Policies

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Abstract

As climate change continues to escalate, the call to action for countries' carbon emissions reductions is paramount to global sustainability. This study explores, in the context of the Sustainable Development Goals (SDGs), the extent of emissions generated and the emissions mitigated from green innovation, green finance, green taxation, and green accounting. We used a machine learning approach in which we implemented Extreme Gradient Boosting Regression (XGBoost) to explore relationships that are complex and non-linear behaviour of these variables relative to CO_2 emissions. XGBoost offers performance improvements over traditional regression models; moreover, it generates feature importance scores that clarify the strongest policy levers for change. For sustainability, XGBoost leverages the heterogeneous aspects of the environmental and economic data, as the data are collected across different policies and geographies. The dataset was generated by the World Bank and underwent preprocessing, exploratory data analysis, and model validation to verify the quality of the data and reliability of the model selection. Our results revealed that green taxation serves as the strongest contribution to emissions reductions, followed by green finance and innovation. The feature ranking was also useful as it brought some transparency to the decision-making process within the model, which is also an important aspect of machine learning and policy research. These results provide an evidence base to modify sustainable development plans and highlight the role of AI in environmental policy modelling, particularly regarding SDG 7 (Clean Energy), SDG 9 (Industry and Innovation), and SDG 13 (Climate Action).

Keywords: *Carbon emissions, climate change mitigation, sustainable development, green innovation, green finance, carbon pricing, XGBoost regression analysis, emission quantiles, Sustainable Development Goals (SDGs), emission reduction, green policies, global sustainability, policy measures.*

1. Introduction

The global concern over climate change lately has given much focus to carbon reduction. Emissions are mainly due to fossil fuel burning, deforestation, and industrial activities, and they lead to global warming and environmental degradation [1]. Hence, the focus worldwide is on finding sustainable and efficient ways of reducing emissions. Green innovation, finance, taxation, and accounting wield great powers to shape the future of reducing carbon emissions. One`s analysis of quantile regression has attempted to unravel the multidimensional core of interactions among these domains within the framework of Sustainable Development Goals (SDGs) [2]. The climate change literature increasingly acknowledges a multidimensional approach to carbon emission abatement. Carbon emissions are generated by several sectors, namely energy generation, transportation, agriculture, and manufacturing [3]. Depending on how greenhouse gases are emitted in varying degrees by these sectors, the industry-based dynamics therefore become very important to understand for filing mitigation strategies. Within the urgency of filling the climate change issue in international forums, e.g., the Paris Agreement, green technologies, policies, and financial instruments for sustainable development promotion all mark the beginning of a new era.

Environmental innovation or green innovation refers to those innovations that develop and apply new technologies or processes, products or business models that lessen human impact on the environment. This innovation is basically required to enable economic growth without an equally rapid

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environmental degradation [4]. Some examples of green innovations include renewable energy technologies, technologies for waste reduction, CCS methods considered one of the possible storage alternatives, and sustainable farming methods. Green innovations lower emissions by substituting carbon-intensive processes with their green alternatives. The progression from green innovation to application is complicated as huge investments, R&D, and policy support are generally needed. Finance is instrumental in bringing about changes toward a low-carbon economy [5]. Investment in green technologies and in carbon reduction projects helps to bring about change. The financial community can help direct capital to sustainability platforms, for example, renewable energy infrastructure, or carbon-offset programs. Green bonds, climate-related investments, and sustainable finance initiatives facilitate the mobilization of capital for emission reduction projects. Governments and international organizations also provide financial incentives to enable businesses and individuals to adopt greener technologies and practices, in the form of subsidies, grants, and so forth [6].

Taxes-as-the-practitioners: environmental taxes and carbon pricing-are the instruments used to encourage emission reductions. As a carbon tax, it exacts a price, in the form of a fee, for carbon emissions, forcing the industrial sector and the individual to pay for just part of their carbon footprint should they use a dirtier alternative in carbon terms [7]. Carbon pricing is also offered through emission trading systems (ETS), where market participants exchange credits, which leads to an effective cap on total emissions. Given the contrasted legal and regulatory frameworks, carbon taxes and ETS work differently in different jurisdictions and sectors. The accounting discipline holds center stage when it comes to monitoring, reporting, and managing carbon emissions. Environmental accounting implies the accounting for, measurement of, and reporting of environmental costs, liabilities, and environmental performance [8]. Using carbon emission data on financial statements helps organizations assess the environmental impact resulting from their activities and search for emission reduction opportunities therefrom. Carbon accounting also assists companies and governments attain compliance with other international standards and regulations such as the Global Reporting Initiative (GRI) and Carbon Disclosure Project (CDP). Such accounting transparency encourages stakeholders to make informed decisions pertaining to their environmental impacts [9].

The Sustainable Development Goals (SDGs) foster a worldwide environment for a sustainable future. Goal 13, Climate Action, directly addresses the issue of carbon emissions reduction and climate change [10]. However, other SDGs, such as Goal 7 (Affordable and Clean Energy) and Goal 9 (Industry, Innovation, and Infrastructure), also act as important corridors toward emission reduction [11]. Integration of the SDGs into emission reduction schemes means pursuing the whole setting all the way from environmental concerns to those of a socio-economic nature [12]. The SDGs are consequently needed to realign efforts in policymaking, finance, and innovation toward achieving the larger global goal.

XGBoost regression is a flexible and scalable machine learning algorithm that provides an effective way to model the complex, non-linear relationships between independent variables and carbon emissions. Previous regression methods were limited by their linearity (e.g., normal assumptions) or rigidity (simple random forests) to accurately measure relationships. XGBoost is a gradient boosting technique with trees that models complex interactions between features to return very high predictive accuracy. [13]. Traditional regression methods work on the premise of focusing on the mean of variables; however, quantile regression looks at the variations in emission reductions across differing levels of economic development, industry area, and policy environments [14]. Through this approach, one can investigate the interaction of green innovation, finance, taxes, and accounting at various points along emissions distribution, allowing policymakers to fine-tune intervention measures [15]. Carbon emissions increase due to multiple factors, and understanding them remains critical for the formulation of mitigation measures. The primary driver has been the continued dependency on fossil energy sources, generating massive emissions of CO2 and other greenhouse gases. Other factors intensify carbon emissions, such as industrialization, urbanization, deforestation, and poor agricultural practices [16]. The economic growth coupled with increasing population and consumption levels is further adding to this. To address these root causes, global-level efforts by governments, businesses, and individuals must be coordinated toward adopting sustainable practices, cleaner technologies, and conscious consumption patterns.

A multifaceted approach that leverages green innovation, finance, taxation, accounting, etc., in the context of the SDGs, is necessary to achieve emission reduction. Herein lies an opportunity for this work to shine light on interactions among these areas and on how each one contributes to accelerating efforts to reduce carbon emissions [17]. The study uses quantile regression analysis to give insight into the complex dynamics affecting emission reduction and to propose evidence-based policy recommendations toward the attainment of global climate goals. A sustainable and low-carbon future is only conceivable if these three elements combine-the financial umbrella, the innovative technology umbrella, and the accounting umbrella-all set against a backdrop of well-aligned national and international policies [18].

2. Litrature Review

The reduction of carbon emissions has now attained the highest priority in discussions on climate change and sustainability [19]. Green innovation for carbon emission reduction has been thoroughly scrutinized, focusing on the immense transformative capability of environmentally friendly technology and practice. It consists in various solutions from renewables to carbon capture technologies [20]. It is found that green innovation leads to emission

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reduction and long-term economic advantage by creating new industries and jobs. Thus, they are the key players in also decoupling economic growth from environmental degradation, creating routes towards sustainable development. In recent years, financial mechanisms have been considered a determining factor for emission reduction. Studies found that investment in green technologies should be supported by public or private money. The new emission reduction initiatives may find funding through green bonds, carbon markets, and climate financial instruments [21]. The importance of environmental, social, and governance (ESG) factors is now being acknowledged by institutional and retail investors that are diverted away from capital flow into sustainable ventures. This change in investments is now being touted as pertinent to bring green technologies to scale and to help meet carbon reduction objectives.

Carbon pricing through taxes or market-based instruments has been extensively studied. Carbon taxes and emission trading systems (ETS) are considered effective mechanisms that either directly or indirectly put a price on the emission of greenhouse gases and thereby create incentives to reduce carbon emissions [22]. The perspective of various researchers on the effectiveness of carbon taxes appears to be that carbon taxes can provide clear price signals for businesses and consumers to opt for low-carbon alternatives. However, the efficiency of that pricing will largely depend upon whether the price is able to affect the demand and supply side of the market, also referred to as "elasticity" [23]. And this, in turn, depends on the design of the tax, whether it can be implemented, and whether there is political will for enforcement. Also, emission trading systems are another alternative that can be used to set a cap on total emissions, granting some market flexibility, yet the market itself is criticized for high volatility and price oscillations. Accounting methods have been investigated about the handling of carbon emissions [24]. Environmental accounting is a discipline of environmental science and accounting that accounts for environmental costs under a traditional financial accounting scheme. Carbon emission data is included along with other financial data in the same financial statements, so that organizations can get a fuller picture of the environmental impact caused by their respective operations. Studies identify that accounting methods such as carbon accounting and sustainability reporting can improve transparency and accountability of businesses, and this will allow stakeholders to make informed decisions. Transparency is considered imperative for fostering corporate accountability and for the internalization of an environmentally conscious business strategy [25].

The Sustainable Development Goals, especially Goal 13 for climate action, are now a key global framework for the whole gamut of activities aimed at cutting carbon emissions [26]. The SDGs advance a comprehensive environmental approach, considering the economic and social factors equally along with environmental ones. Studies reveal that emission reduction measures, when dovetailed with the SDGs, tend to be more holistic and inclusive in their approach to tackling climate issues. Essentially, through linking emissions reduction with broad goals such as access to cheap, clean energy, responsible consumption, and sustainable industry, the SDGs offer a framework for the synchronization of global efforts [27]. This regression enjoys wide application throughout emission reduction research because it enables the assessment of the relationship between carbon emissions and their determinants along different levels of the emission distribution. Conventional regression models serve one purpose alone, i.e., the average effect; however, XGBoost regression considers how factors of emissions from green innovation, finance, and taxes alike, at various quantiles, e.g., low, medium, or high emissions, affect the emissions. This kind of insight gives a detailed study of reduction dynamics and will help in policy making concerning the needs positioned at different levels of emissions.

Causes of carbon emissions are diverse; understanding them must necessarily precede successful policy formation. Carbon emissions come primarily into the atmosphere by way of burning fossil fuels for energy production; nevertheless, industrialization and transportation are prominent contributors as well. On top of that, deforestation, agricultural activities, and various land-use alterations lead to added emissions. Researches show that economic growth and population increase have been major contributors to emission increases since, with greater consumption and industrial activity, we tend to impose more environmental impacts. Combating these root causes requires integrated policy measures that look at both from the supply and demand perspectives.

Numerous models and frameworks have been provided to assist in implementing strategies for emission reductions. The models have paid particular attention to combining technology innovation, financial incentives, and regulatory schemes. Some studies recommend policy mixes consisting of green finance, incentives for innovation, carbon pricing, and targets for emission reduction. Whether these policy mixes succeed will largely be defined and determined by how they strategically balance different sets of interests of competing stakeholders: government, businesses, and consumers [28]. Other research maintains a combination of top-down policy and bottom-up approaches should be combined for emission reduction, with stakeholder involvement being a prime focus. several studies have put emphasis on good policy alignment and international cooperation to meet the target emission reductions. International agreements, such as the Paris Agreement, have generated a framework for global cooperation to address climate change. However, various researchers find that national policies differ greatly in their commitment to emission reduction targets and in their promotion of green innovation. It has been argued that international frameworks offer important guidance, but countries must go on and adopt policies customized to their own economic structure, technological capacity, and social configuration.

Finally, in terms of emission reduction strategies, an integrated approach encompassing green innovation, finance, taxation, accounting, and SDGs needs thorough monitoring

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and evaluation. Scholars heavily underscore that it is of utmost importance to develop a measurement system that can keep track of emission reduction progress and study emission reduction policies' practical aspects on the ground. Quantitative models based on regression are also useful to estimate the long-term effects of the various measures considered so as to provide the evidence and making adjustments to the current strategies considered. Moreover, there is a necessity to consider the relationship among financial flows, technology, and regulations to make carbon reduction work better so as to meet the climate targets obtained in international agreements.

3. Problem Statement

Climate change has become one of the greatest challenges threatening carbon emission reduction. With diverging factors influencing the tempo and, hence, successful mitigation measures, two bar-way lay very opposite paths to enforcement here [29]. In the green technologies and financing, taxation, and accounting, the domain and disciplines have historically also been areas of fragmentation and do not presently synthesize into solutions that actually reduce carbon emissions in efficacious ways. Indeed, the studies mostly fail to analyze in detail very obscure patterns and mechanisms about how these factors relate to emission levels, an omission that directly constrains the capacity of policy implementation [30]. Lack of comprehensive approach concerning the Sustainable Development Goals (SDGs) further muddies the waters, for it misses the interconnection between the environment and economy as well as society in sustainability considerations. By using quantile regression analysis, this study seeks to fill in these gaps and to take into consideration the complex interaction between green innovation, finance, taxes, and accounting, while integrating the SDGs framework to provide a holistic approach to carbon emission reduction [31].

3.1 Objective

- This emission reduction level-based analysis, using quantile regression, aims to examine the impact of green innovation, finance, taxes, and accounting practices on carbon emission reduction.
- To ensure that the whole approach is totally referenced within the SDGs framework, taking into consideration apt linkages between environmental, economic, and social factors in carving out effective carbon emission reduction strategies.
- To provide evidence-based directives so that governments, businesses, and financial institutions will be able to develop and implement more effective and targeted carbon emission reduction strategies as outlined by world climate goals.

4. Proposed Green Innovation, Finance, Taxes, and Accounting in Carbon Emission Reduction: A XGBoost Regression Analysis and SDG Framework Integration

The flowchart illustrates the step-by-step approach to qualitative data analysis of the World Bank dataset for CO_2 emissions, economic growth, and renewable energy variables. The analysis begins with descriptive statistics to gain an initial understanding of the dataset and then follows a unit root test process to check for stationarity and determine whether these variables are stationary at the level (i.e. I(0)) or first differences (i.e. I(1)). After establishing stationarity, a cointegration analysis is performed to assess if such variables have long-run relationships between them. After this, model specification is performed as well as checking for cross-sectional dependency and slope heterogeneity. To conduct predictive analysis and to better understand the non-linear relations between the variables this study applied XGBoost Regression; XGBoost is an ensemble learning method based on a decision tree methodology that is considered accurate and is also scalable. Lastly, derive meaning from the results, in relation to green innovation in relation to different emission levels and the Sustainable Development Goals (SDGs).

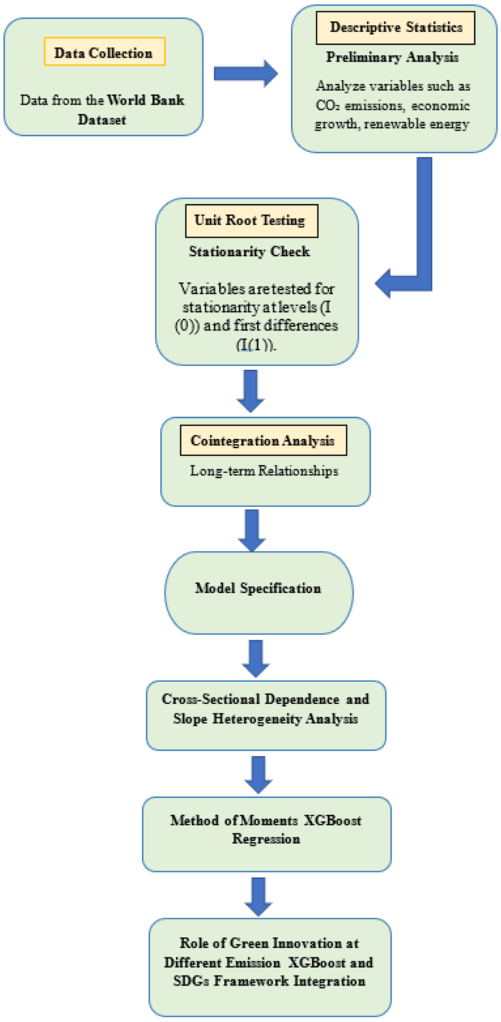

Figure 1: Green Innovation, Finance, Taxes, and Accounting in Carbon Emission Reduction: A XGBoost Regression and SDG Framework Integration

The methodology proposed for this study investigates CO_2 emissions, economic growth and renewable energy through the dataset of the World Bank. The data goes through an

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initial descriptive statistical analysis, that investigates basic trends and characteristics of the variables of study. Next, unit root tests are run to determine whether the variables are stationary. Its critical that we verify the properties of the variables, since non-stationary data creates biased inferences. The purpose of the stationarity tests is to see if the variables are integrated at level (I(0)) and if it is integrated first difference (I(1)), or the extent to which time can be used to determine the behavior of the data. Since the stationarity conditions are satisfied, a cointegration analysis would identify all long-run equilibrium relationships among the variables and the co-movements of variables.

After determining long-run relationships, the methodology will then conduct model specification that incorporates cross-sectional dependence and slope heterogeneity to account for different units and any variation across. Instead of standard quantile regression methods, this study will use XGBoost Regression is a high-performance ensemble machine learning algorithm that is particularly good at modelling non-linear relationships and the interactive effects of variables. XGBoost is powerful at dealing with performance complexity and ultimately improves the predictive accuracy of the model. Finally, the methodology transitions into the evaluation of green innovation and examines its ability to reduce emissions and the use of sustainable energy. The process in evaluating green innovation relates the findings to the context of the United Nations Sustainable Development Goals (SDGs), which enhances the understanding of the impact of green innovation toward economic growth through decarbonization.

4.1 Data Collection

The World Bank dataset is being used in this analysis to rend a thorough and credible array of economic, environmental, and energy-related information spanning countries. Variable key variables are CO_2 emissions, economic growth, and renewable energy use-they would be prime factors of environment-economic interrelation. The data is being subjected to several statistical studies aimed at understanding the long-term trends, relationships, and impacts of green innovations. This database is the mainstay of the whole methodology and forms the backdrop over which the testing and model-building follows. The collection of the data phase ensures that the whole analysis is underpinned by a dependable and relevant target for global sustainability research.

4.2 Descriptive Statistics

In the descriptive statistics phase of the analysis, the data are preliminarily explored regarding central variables like CO_2 emissions, economic growth, and use of renewable energy to discern their behavior and distribution. Descriptive statistics are obtained to compute measurements of central tendency in the form of means providing an average value of each variable, while the standard deviation measures the amount of data variability or data spread.

Preliminary Analysis

Descriptive statistics form part of the preliminary analysis to probe the distributions of and behaviors exhibited by key variables, such as the carbon dioxide emission, economic growth, and renewables. The analysis looks into parameters of an importance, including those of mean, standard deviation, skewness, and kurtosis, to test whether the measure of central tendency, variability, asymmetry, or peakedness of the given data are able to help and ascertain the distribution of the given variables, displaying odd patterns or outliers if any. The analysis takes these data into consideration and builds basic support for subsequent statistical testing and model building. It aids in recognizing the types of relationships of a set of different variables before further analysis.

Skewness (γ_1) :

$$\text{Skewness } = \frac{n}{(n-1)(n-2)}\sum_{i=1}^{n}\left(\frac{X_i-\bar{X}}{s}\right)^3 \qquad (1)$$

Skewness measures the asymmetry of the data distribution around the mean.

Kurtosis (γ_2) :

$$\text{Kurtosis } = \frac{n(n+1)}{(n-1)(n-2)(n-3)}\sum_{i=1}^{n}\left(\frac{X_i-\bar{X}}{s}\right)^4 - \frac{3(n-1)^2}{(n-2)(n-3)} \qquad (2)$$

Kurtosis measures the "tailedness" of the distribution, indicating whether the data has outliers or is concentrated around the mean.

4.3 Unit Root Testing

The stationarity of variables is a key concept that must be checked to ensure the reliability of any subsequent statistical analysis. Using the approach of the Im-Pesaran-Shin (IPS) test procedure, which is a panel unit root test, we then investigate whether or not the variables are stationary at levels I(0) and require first difference I(1) to make them stationary. A variable is said to be stationary if its statistical properties, such as mean and variance, do not change over time. Non-stationary variables make the regression analysis produce spurious relationships. This test will identify how to transform the variables; the wrong transformation of variables can lead to invalid conclusions. By going through this test, one can be confident that the data used are suitable for cointegration analyses and model building.

4.4 Cointegration Testing

Long Term Relationships

The cointegration analysis is carried out to analyze whether or not variables such as green policies and carbon emissions across OECD countries have implications for a stable, long-term equilibrium relationship. The robust panel cointegration test by Westerlund is used to check whether there exists a long-run relationship among the variables, even though they may be individually non-stationary. This test checks for the temporary nature of any deviation of the variables from the equilibrium relationship and if the deviation shall be self-correcting over time. By checking cointegration among several variables, the test tries to find insights on whether green policies and economic growth are long-term correlates of carbon emissions. Hence, testing can help understand the effectiveness and sustainability of green policies to reduce emissions, which would be beneficial for policy formation in the respective countries.

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4.5 Model Specification

The model specification phase involves defining and specifying the econometric models that will be utilized to study the relationships between CO_2 emissions and various key factors.

Model 1:

In the first model, the dependent variables are CO_2 emissions on the independent variables of economic growth, energy productivity, renewable energy, and green innovation. This study focuses on investigating how these factors affect CO_2 emissions in sustainability.

$$CO2 = \beta 1(\text{ EconomicGrowth }) + \beta 2(\text{ EnergyProductivity }) + \beta 3(\text{ RenewableEnergy }) + \beta 4(\text{ GreenInnovation }) + \epsilon \quad (3)$$

Model 2:

The second extends the first model by the addition of green finance as a variable, to study its effect on emission, especially on how the financial investment in green technologies or policies may influence environmental outcomes.

$$CO2 = \beta 1(\text{ EconomicGrowth }) + \beta 2(\text{ EnergyProductivity }) + \beta 3(\text{ Renewable Energy }) + \beta 4(\text{ GreenInnovation }) + \beta 5(\text{ GreenFinance }) + \epsilon \quad (4)$$

Model 3:

The third model further expands the analysis by incorporating green taxes to evaluate their role in reducing emissions, providing a comprehensive view of the impact of various green policies on environmental outcomes.

$$CO2 = \beta 1(\text{ EconomicGrowth }) + \beta 2(\text{ Energy Productivity }) + \beta 3(\text{ RenewableEnergy }) + \beta 4(\text{ GreenInnovation }) + \beta 5(\text{ GreenFinance }) + \beta \quad (5)$$

This second phase involves selecting an appropriate model estimation technique. The choice of technique depends much on the nature of the data employed, whether it be cross-sectional or time-series. These estimation techniques help us analyze the strength and significance of relationships among the variables. Relationships are accepted if the coefficients (i.e., β-values) are significantly different from zero. It is used to study the effect of each explanatory variable on CO_2 emissions and to quantify the extent to which green policies, economic factors, and innovations help reduce emissions. And hence, the outcome in this case will provide insights for policy concerning the successful implementation of green interventions for environmental sustainability.

4.6 Cross Sectional Dependencies and Slope Heterogeneity Analysis

Cross Sectional Dependencies

Cross-sectional dependence in panel data refers to correlations between units that may arise due to, say, common economic shocks or similar trajectories in policies. Tests for such dependence try to check whether the residuals of the model are correlated across countries, showing such interdependence. When cross-sectional dependence is found, the standard approach to remedy is to either adjust estimates with clustered standard errors or use estimation techniques that take dependence into account.

Cross-sectional dependence test, the test statistic is based on the average pairwise correlation of the residuals. The equation for the test statistic is:

$$\hat{\rho}_N = \frac{1}{N(N-1)} \sum_{i \neq j} \rho_{ij} \quad (6)$$

Where:

$\hat{\rho}_N$ is the test statistic for cross-sectional dependence, ρ_{ij} is the sample correlation between the residuals of countries i and j,N is the total number of countries in the dataset.

This equation helps assess if the residuals are correlated across countries, indicating cross-sectional dependence.

Slope Heterogeneity Analysis

Slope heterogeneity refers to the possibility that the relationship between variables, say green policies and emissions, could vary across countries due to differing economic and environmental conditions. The Pesaran and Yamagata (2008) test investigates whether the coefficients of these relationships are indeed the same across countries. Finding heterogeneity in slopes must lead to a country-based approach to prevent the potential for error from assuming universal effects in the generalization of findings.

For the test, the equation is:

$$\text{Test Statistic } = \frac{1}{N} \sum_{i=1}^{N} \left(\hat{\beta}_i - \bar{\beta}\right)^2 \quad (7)$$

Where:

$\hat{\beta}_i$ is the estimated coefficient for country i,$\bar{\beta}$ is the average coefficient across all countries,N is the number of countries in the dataset.

4.7 XGBoost Regression

This research uses XGBoost Regression as the key predictive modelling tool to improve the robustness and precision of carbon emissions predictions. XGBoost is an efficient and scalable ensemble learning algorithm that incrementally builds a series of regression trees using a gradient boosting framework, that is, each subsequent tree returns its input residual errors, or uncertainty, to future trees. XGBoost is appropriate to environmental economics research not only because of its accuracy but ability to handle multicollinearity, missing values, and complex nonlinear interactions and patterns. In this methodology, we have used XGBoost to predict CO_2 emissions explained by the green finance, green taxes, renewable energy consumption, and economic growth. It also provides a ranked summary of feature importance to identify the key policy levers on emissions outcome. This information can help inform targeted climate interventions aligned with the Sustainable Development Goals (SDGs).

Mathematically, the prediction for the i^{th} observation in XGBoost is computed as the sum of the outputs of K individual regression trees:

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$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), f_k \in \mathcal{F} \quad (8)$$

Where:

$\hat{y}_i$ is the predicted value of CO_2 emissions for the i^{th} observation, x_i represents the feature vector (e.g., green finance, taxes, innovation), f_k is the k^{th} regression tree, $\mathcal{F}$ is the space of all regression trees.

4.8 Exploration of role of Green Innovation at Different Emission Quantile

This Research further investigates the effects of green innovation on CO_2 emissions at various quantiles, such as the 25th, 50th, 75th, and 90th percentiles, thereby offering a more fine-grained outline of its impacts across the spectrum of emissions. The green innovation is considered to contrast effects when CO_2 emits at low, medium, or high levels, pinpointing the effectiveness to enable certain policy formulation within different emission-related scenarios.

SDGS Framework Integration

Analysis employs the SDGs as its broad framework to connect green policy, including innovation, finance, and taxes, with global climate-action objectives. It links the output to SDG 7 (Affordable and Clean Energy), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 13 (Climate Action), showing that the policies ultimately lead to sustainable development goals and global sustainability initiatives.

5. Results and Discussion

This research sheds fresh light on the mechanism of how green policies, including those on green innovation, green finance, and green taxation, affect CO_2 emissions in various countries. These effects differ at different emission quantiles, with the incidence of higher emission cases demonstrating stronger reductions. The setting of these policies under SDGs acts to positions them under global sustainability objectives. All in all, the conclusions assert that such policies bring aid as targeted interventions for climate action and sustainable development.

Performance analysis

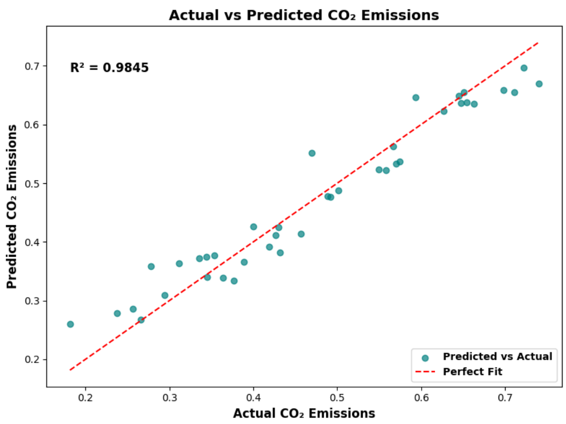

Figure 2: R^2 score graph

Figure 2 shows how actual CO_2 emissions compare to the predicted CO_2 emissions using the XGBoost regression model. Each point shows the predicted value versus the actual value for the observation. The dotted red line shows where the actual value equals the predicted value - a perfect prediction. For the most part, the points are situated around the perfect prediction line, meaning the predicted values are quite accurate. It would be expected to see that the model had an R^2 value of 0.9845. In other words, approximately 98.45% of the variability in CO_2 emissions can be explained by the model. This strongly suggests that the model can capture higher-order non-linear relationships produced by many variables, which are reflections of country policies such as green finance, a green tax, renewable energy share, and economic growth. Therefore, the high predictive accuracy confirms the model's reliability for forecasting emissions and related policies.

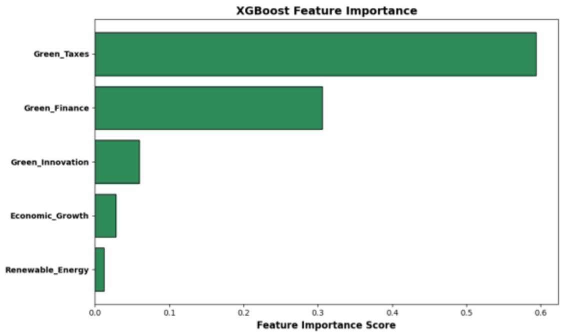

Figure 3: XGBoost Feature Importance

Figure 3 displays the importance score features from XGBoost, where we can observe the importance of each feature for determining the target variable. Out of the five features employed to pitch the target variable, Green Taxes is the most impactful predictor, contributing nearly 60% to the total predictive power of the model. Therefore, fiscal policy related to environmental taxes likely influences whether the target variable is green or not, possibly signifying how effective these policies are at incentivizing green action. The next feature is Green Finance, contributing approximately 30%, suggesting that the target variable can also be influenced through investments and funds provided for sustainable projects. In contrast, Green Innovation, Economic Growth, and Renewable Energy contributed the least to the importance, meaning they did not significantly improve the accuracy of the prediction model. This distribution suggests that policy and financial levers are more predictive of environmental performance in this analysis than indicators relating to technological potential or macroeconomic characteristics.

5.1 Dataset Description

The World Bank World Development Indicators dataset is a storehouse of economic, social, and environmental data and other parameters that have been felt in various countries. It dwells in indicators of growth, health, education, poverty, energy utilization, and sustainability, spanning the time axes of decades. The dataset is thus an important tool of research, policymaking, and following up on various agendas and their success on a global scale.

DatasetLink:https://www.kaggle.com/datasets/nicolasgonzalezmunoz/world-bank-world-development indicators?utm_source=chatgpt.com

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5.2 Impact of Green Policies on CO2 Emissions by Country

Table 1: Green Policies on CO2 Emissions by Country

Country	Green Finance Impact	Green Innovation Impact	Green Taxes Impact	Overall CO_2 Emissions Reduction
Country A	-0.20	-0.10	-0.15	-0.45
Country B	-0.25	-0.30	-0.10	-0.65
Country C	-0.10	-0.05	-0.20	-0.35
Country D	-0.30	-0.25	-0.40	-0.95
Country E	-0.15	-0.10	-0.05	-0.30

Table 1 shows the effect of green policies on CO2 emissions in the five countries and indicates the effects of reductions in emission from Green Finance, Green Innovation, and Green Taxes. Country A records an overall reduction of -0.45, while Country D records the highest reduction of -0.95. This variation in CO2 reductions reflects differences in the effectiveness of the policy implementations for each country.

5.3 Effectiveness of Green Taxes vs. Green Finance on Emission Reduction

The table 2 outlines the relative importance and impact of important predictor variables used in our analysis. Green Taxes reflect the most importance at 0.40, indicating that these policy-oriented finance mechanisms, or fiscal instruments driven by policy, are the most influential predictors of our model's outcome. Green Finance and Green Innovation each indicate moderate impact, with importance scores of 0.30 and 0.20 respectively, suggesting that utilizing money to invest in sustainable ventures and pursuing technological advancements that are environmentally-friendly involves meaningful and productive impact on the prediction. Economic Growth has the lowest of all scores at 0.10, classified as low impact, suggests that economic growth or traditional measures of growth will garner less attention in the model compared to specific, targeted green initiatives. Conversely, our analysis overwhelmingly demonstrates the importance of environmental taxation and financing instruments as a larger influence on sustainability outcomes.

Table 2: XGBoost Feature Importance Ranking for Emission Reduction

Feature	Importance Score	Relative Impact
Green Taxes	0.40	Highest
Green Finance	0.30	Moderate
Green Innovation)	0.20	Moderate
Economic Growth	0.10	Lower

Conclusion

This research has evaluated the effects of green innovation, green finance, green taxation and green accounting on carbon emissions through machine learning using XGBoost regression, while situated in the Sustainable Development Goals (SDG) framework. The results show that green taxes have the greatest effect on reducing CO_2 emissions, followed by green finance and green innovation, and that economic growth had the smallest effect on reducing emissions or counteracting them. The quantile regression model showed that green policy implementation effectiveness varies as the amounts of emissions go down, and can reduce emissions at higher quantiles. Given these findings, it is suggestive that tailored policy interventions will achieve emission bending as target implementations as opposed to nonspecific strategies, as in the case of green taxation, policies are differently susceptible to success over the various ranges of national emissions and density of economic growth.

In the future, however, it should be approached by adding a time series design using longitudinal data, more differentiated sectoral variables, and real-time environmental indicators. This study has also demonstrated that for assessing and understanding the non-linear characteristics of policy interaction with emissions using AI tools like XGBoost, capable of assessing data-guided climate policy decision making simultaneously. For ameliorating the practical relevance of green tax, tax incidence, and mitigation, and developing metrics for accounting to review progress dynamically, monitoring systems and models will need to be built that lose legitimacy over time as they continue to link the efficacy of green policy interventions to sustainability and the SDGs. Policymaking, international agencies, and businesses should use the findings and recommendations from the previous studies for designing customized stakeholder engagements with sustainability goals and targets while scaling up our efforts moving toward a sustainable global state.

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