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Artificial Intelligence-Driven Financial Strategies for Renewable Energy Transition: A Cross-Country Analysis of Efficiency, Investment, and Policy Implications

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ABSTRACT

An integrated empirical framework was put in place in order to study the combined impacts of artificial intelligence (AI), green finance (GF), and tools of environmental policies on renewable energy investments and their efficiency on a global scale. The hybrid approach of combining econometric estimators i.e. two-way fixed effects, system-GMM, Mean/pooled mean group and dynamic common correlated effects was employed with Explainable machine learning (XGBoost with SHAP) to assess the model. For the period of the 2005-2024 study, a balanced macro panel composed of 30 OECD and emerging economies was utilized, and it was assessed that with regard to AI readiness, most of the time it acted as a complementary catalyst, augmenting the effectiveness of finance and policies, rather than an autonomous driving force. In the framework of AI intensity and carbon pricing, AI appears with a negative sign in the short run, which unfolds as transitional adjustment costs. These results are reversed when the interaction terms GF × AI and Policy×AI are included; these terms are positive and statistically significant, meaning that an increase in digital capacity strengthens policy transmission. System-GMM results confirmed persistent investment dynamics through significant lag dependence, and the sign pattern for core variables was preserved in robustness checks (DCCE/MG/PMG). On the efficiency margin, green bonds exhibit a positive association, whereas short run AI and carbon price frictions remain. The SHAP diagnostics confirm the econometric findings and consider investment inertia and the pressures of transitions (emissions and fuel prices) as key contributors, while AI works with context-dependent complementarities. To conclude, the digital governance with the type of green-finance and the reliable policies in place will promote investment in renewables and improve energy efficiency.

Keywords: Artificial Intelligence, Green Finance, Carbon Pricing, Renewable Investment, Energy Efficiency
JEL Classifications: Q42, Q58, G28, O33, C33

1. INTRODUCTION

The shift towards renewable energy is now part of vital factors driving change in the financial world. In the last 10 years, the balance of investment in low-carbon sectors has changed as a result of financial innovation, regulatory changes, and advancements in technology. In 2024, the world spent over $3 trillion on energy, $2 trillion of it on renewable energy technologies (IEA, 2024). In addition to decarbonization goals, a change in structural goals of the world economy to market climate risks and technology opportunities is evident (IRENA, 2024). Since the economic trade shocks caused by climate change have boosted the value of resilient and sustainable energy systems, there is a clear and growing economic imperative for sustainable energy systems.

In this transition, different financial mechanisms have been important. Green finance—gleaned from green bonds, sustainability-linked loans, and environmental, social and governance (ESG) instruments—has made capital more available for projects concerning renewable energy and energy efficiency.

Research shows that green bond issuance improves a firm's environmental and market performance (Flammer, 2021), while secondary markets feature a persistent "greenium," suggesting a strong preference for green assets (Zerbib, 2019). Policies such as carbon pricing, feed-in tariffs, and even technology innovation have proved effective in managing environmental externalities (Calel and Dechezleprètre, 2016; Couture and Gagnon, 2010). Still, the financial and policy instruments described do not work on their own. Their impact relies heavily on a country's technological capability and governance frameworks that are powered by advanced data systems.

Artificial intelligence has become one of the general-purpose technologies that has the potential to transform an entire ecosystem. By enabling the efficient allocation of resources and adaptable policies through the processing of vast amounts of data and improved decision-making, AI allows the forecasting of AI's economic impacts and the allocation of resources more responsively. Yet, the literature on the economics of AI posits that the primary source of the temporary productivity losses incurred during the AI transition adoption phase results from the learning and restructuring of capital (Aghion et al., 2017). After the initial phase, AI enhances the productive complementarities that interlink technology and the triad of finance, policy, and state economic performance through advanced risk assessment, automated compliance, and environmental performance assessment (Vinuesa et al., 2020). Accordingly, countries that are more advanced in AI adoption will convert more of the efficiency and real investment benefits stemming from green finance and regulations.

Although there is an increasing number of studies on green finance and literature on policies directed towards the environment, there is a lack of empirical studies that examine the interplay of these areas with AI capabilities in promoting investment in renewables. A majority of studies continue to examine the constituent parts; that is, the effects of policy on innovation or the effects of finance on the mobilization of capital, without realizing the possible role of digital capabilities in the interaction of the two. This is important in light of the differences among countries in terms of the quality of institutions, digital infrastructure, and the governance effectiveness (Oxford Insights, 2024). Therefore, the understanding of these various linkages is critical to the formulation of policy that captures the potential of digital technology in harmonizing sustainable finance with financial and environmental regulatory policies.

In this context, the current research builds and conducts an empirical test on an integrated framework combining AI, green finance, and environmental policies across 30 OECD and developing countries from 2005 to 2024. This research employs a hybrid empirical strategy that combines machine learning—specifically the XGBoost model and the SHAP-based interpretability framework to understand model outputs (Chen and Guestrin, 2016)—and several econometric techniques (two-way fixed effects, System-GMM, and Dynamic Common Correlated Effects (DCCE) approaches). By including the cross-term interactions (AI × GF, AI × Policy), this research assesses the extent to which AI readiness acts as a moderator on the financial and policy instruments of investment and efficiency in renewables. By doing so, this research contributes to the literature on a digital-financial-policy nexus in the renewable energy transition by shifting the analytical framework from linear, disconnected models to more comprehensive and integrated perspectives.

2. CONCEPTUAL FRAMEWORK

This study's conceptual framework centers on the interplay of artificial intelligence (AI), green finance (GF), and environmental policy tools for enabling and optimizing sustainable investment. Theoretically, AI can be viewed as a general-purpose technology that augments decision-making and efficiency due to sophisticated data processing and forecasting (Brynjolfsson et al., 2019). However, the immediate impact might be neutral or even unfavorable due to transitional adjustment costs—such as difficulties with integration, changes in organizational structures, and learning curve challenges (Aghion et al., 2017). Over a prolonged timeframe, AI drives productivity and synergistic complements with the financial and policy frameworks. This relationship aligns with the theory of technological complementarities (Aghion et al., 2019).

As a green finance channel, green finance contributes to lowering the cost of capital for renewable investments and financing environmentally sustainable projects, thus promoting cleaner technology adoption (Flammer, 2021). This mechanism is primarily facilitated by green bonds and ESG-linked instruments, as they certify environmental performance and corporate accountability by sending investor signals (Zerbib, 2019; Tang and Zhang, 2020). When paired with AI-enabled financial analytics, the efficiency of capital allocation can be optimized even further, as predictive algorithms identify high-impact green projects and evaluate risk-adjusted returns with greater accuracy.

Before discussing climate-related investments, one must analyze the fine details that determine how environmental policies shape the climate for investments and innovations. Economic mechanisms that help with innovation, investments, and innovation directed towards emissions reductions, as observed with the influence of carbon taxes (Calel and Dechezleprêtre, 2016).

The relationship between the three variables, AI, GF, and Policy, has the potential for profound synergistic relationships. In the case of artificial ıntelligence, the interplay of the financial and policy elements of the three variables. For countries that are ready and made advancements with AI and have strong institutions, strong economic growth coupled with robust policies for investments will come from the synergistic relationship from AI × GF and AI × Policy. In under developed countries, the loose legal framework and lack of advanced digital infrastructure will make the synergistic relationship between AI and Policy very small.

This framework assumes that AI transitions from being its own influence and detached technology to an influence that can augment technology. Missing, and most likely neglected, context to the framework are nonlinear relationships along with threshold determinants. For example, the lack of strong cohesive policies and AI will lead to underwhelming returns.

3. LITERATURE REVIEW

3.1. Environmental Policy and Technological Change

The effect of policies on the development of clean innovation has been widely reported. According to Acemoglu et al. (2012), policies that offer price incentives foster "directed technological change," whereby innovation is diverted from fossil fuels to renewables. Calel and Dechezleprêtre (2016) observed similar results when considering firms covered by the EU Emissions Trading System (ETS) as they increased patenting activity for low-carbon innovations. Recently, Colmer et al. (2025) provided further firm-level evidence that reinforced market-based policies through carbon pricing, which achieves significant emission reductions with no adverse effect on competitiveness. Sweden also provided evidence of the effectiveness of carbon tax policies by significantly decreasing firm-level CO_2 intensity (Martinsson et al., 2024).

3.2. Green Finance and Capital Allocation

Extensive research on Green Finance confirms its potential in integrating sustainability objectives within capital markets. Flammer (2021) argues that the market valuation of companies that issue green bonds increases alongside improvements in their environmental performance. Tang and Zhang (2020) noted that stakeholders respond positively to the announcement of green bonds, while Zerbib (2019) found evidence of a green premium, meaning that investors are willing to pay a higher price for green certified bonds and accept a lower yield. Collectively, the evidence suggests that the financial sustainability instruments available in the market today help alleviate financing tension, improve market transparency, and promote the development of sustainable innovation. Furthermore, Mazzucato and Semieniuk (2018) demonstrated that different financing structures and sources have a strong impact on the direction of the growing renewable energy.

3.3. Artificial Intelligence as a Catalyst for Sustainable Investment

In recent years, AI has been seen as a positive technological innovation in creating value in financial decision-making, as well as in the achievement of positive results in an organization's sustainability efforts. While productivity dividends remain the impact of AI on prediction, efficiency, and resource allocation as noted by Brynjolfsson et al. (2019) may take time to realize due to several adaptation costs. On the AI's impact to SDG (Sustainable Development Goals) achievement, Vinuesa et al. (2020) articulated how AI enhances data and its monitoring for several SDGs which includes SDG 7 (affordable and clean energy) and SDG 13 (Climate Action). AI-based technologies in the financial sector are becoming commonplace as tools for credit scoring, ESG analytics, and investment screening which are focused on the reduction of asymmetries and the advancement of green innovation financing.

3.4. Methodological Advances: Integrating Explainable AI and Econometrics

The combination of explainable ML and econometrics is helping to model complex nonlinear multi-factor relationships. Friedman (2001) pioneered works on gradient boosting machines (GBM), and later on, Chen and Guestrin (2016) built XGBoost, which is a scalable algorithm designed for heterogeneous panel data. Lundberg et al. (2020) developed SHAP (shapley additive explanations) to explain AI and advanced interpretability more and introduced the decomposition of feature effects which helps visualize marginal contributions. These methods are particularly useful for examining the role of AI as a moderator in green investment models since they capture complex nonlinear relationships across countries and diverse policy regimes.

3.5. Research Gaps

While there is more literature on the subject, there are still several gaps. First, the empirical study of the integrated dynamics of AI, GF, and policy remains scarce. Second, the cross-country empirical analysis of AI's moderating role on the financial and policy effectiveness constitutes a significant gap. Third, many studies fail to recognize the nonlinear thresholds where AI readiness pivots the green finance and policy effectiveness. This study addresses these gaps and contributes to the literature by combining econometric modeling and explainable ML to analyze the long-run equilibrium and the short-run dynamics of these interrelated factors.

3.6. Research Questions and Hypotheses

This study seeks to assess the impact of AI-driven financial innovations on the transition to renewable energy in relation to efficiency gains, investments, and policy outcomes across different nations. AI's ability to enhance information processing and decision-making in green finance is likely to be a game changer in optimizing the speed of sustainable energy systems capital (Apergis and Payne, 2010; Bhattacharya et al., 2022).

3.7. Research Questions are Provided Below as Folows

- Do AI-supported financial strategies improve renewable energy efficiency?
- Do these strategies significantly increase renewable investment inflows?
- Do policy instruments (e.g., carbon pricing, feed-in tariffs) interact with AI-based finance to amplify their impact on sustainability outcomes?

Based on these questions, the following hypotheses are proposed:

H_1: The interaction between AI adoption and green finance (AI × GF) positively affects renewable energy efficiency.

H_2: AI-derived financial signals (Investment^ML) positively influence renewable investment flows.

H_3: The interaction term (Policy × AI) exerts a positive moderating effect on renewable investment and efficiency.

4. DATASET AND METHODOLOGY

4.1. Dataset and Variables

The dataset spans the years 2005-2024 and encompasses 30 OECD and emerging economies based on the availability of data and the diversity of policies. Each year data was collected from a number of sources internationally:

- Investments in and capacity for renewable energy - IEA (2024), IRENA (2024), BloombergNEF (2023).
- Green finance (e.g., Green Bonds, ESG Loans) - Climate Bonds Initiative (2024) and Refinitiv Eikon.

- AI adoption - Oxford Insights (2024) Government AI Readiness Index.
- Energy policies (e.g., carbon pricing, FITs, and R&D support) - OECD Policy Instruments for the Environment Database.
- Macroeconomic variables and other controls - World Bank WDI (2024) and BP Statistical Review (2023).

All finance variables were deflated to 2020 US dollars and World Bank GDP deflators. Country harmonized values were done through PPP. Data outliers were winsorized and logarithmic transformations to skew variables were done using Wooldridge (2019).

The key variables used in the empirical analysis, together with their definitions, measurement methods, and data sources, are summarized in Table 1 for clarity and reproducibility.

The inclusion of carbon pricing as a policy instrument is further supported by empirical evidence demonstrating that the European Union Emissions Trading System has led to meaningful reductions in CO_2 emissions, even during periods of relatively low permit prices (Bayer and Aklin, 2020).

4.2. Methodology

The empirical model is based on a two-way fixed effects specification to account for unobserved heterogeneity across countries and years, indicated in Equation 1 as follows:

$$Y\_it = \alpha\_i + \gamma\_t + \beta_1 GF\_it + \beta_2 AI\_it + \beta_3 (GF\_it \times AI\_it) + \delta' X\_it + \varepsilon\_it \quad (1)$$

Where Y_it represents either renewable energy investment or energy efficiency, α_i and γ_t are country and time effects, and ε_it denotes the error term. The coefficient β_3 captures the moderating effect of AI-driven finance on green finance outcomes. Robustness is ensured by employing Driscoll-Kraay standard errors.

For strong inference, the Driscoll-Kraay heteroskedasticity and autocorrelation-consistent standard errors were implemented (Driscoll and Kraay, 1998). Pesaran's CD test was used for cross-sectional dependence, and Levin et al. (2002) and Imet al. (2003) were used for panel stationarity. The long-term relationships were confirmed using Pedroni (1999) and Westerlund (2007) cointegration tests.

A System-GMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998) was used to tackle endogeneity, dynamic effects, and persistence:

$$Y\_it = \rho Y\_i,t{-}1 + \alpha\_i + \gamma\_t + \beta_1 GF\_it + \beta_2 AI\_it + \beta_3 (GF\_it \times AI\_it) + \delta' X\_it + u\_it \quad (2)$$

Lagged dependent variables were used as instruments. Instrument proliferation was mitigated using the collapse option, with Hansen P-values maintained between 0.1 and 0.9 to ensure validity. AR(2) tests confirmed the absence of second-order autocorrelation.

Robustness was further validated through mean group (MG) and pooled mean group (PMG) estimations (Pesaran et al., 1999), dynamic common correlated effects (DCCE) (Chudik and Pesaran, 2015), and Panel Quantile Regressions to assess heterogeneity across country groups.

The ML model complements the econometric specification by enhancing predictive accuracy and robustness across heterogeneous country samples.

Given the potential for multicollinearity in models combining macro-financial, policy, and technological variables, diagnostic checks were carefully considered in line with established approaches for detecting and mitigating collinearity in multivariate empirical frameworks (Dormann et al., 2013).

To complement econometric estimation, an AI-based predictive framework was integrated. Gradient Boosting Machine (Friedman, 2001) and XGBoost (Chen and Guestrin, 2016) algorithms were trained to predict next-period renewable investment ($Investment_{t+1}$) using financial, policy, and macroeconomic predictors. Temporal cross-validation employed a rolling-origin scheme (60/20/20 split), ensuring no data leakage. Hyperparameter optimization followed a random search procedure, and model performance was evaluated using RMSE, MAPE, and R^2 metrics.

Model interpretability was achieved using SHAP values (Lundberg and Lee, 2017), enabling decomposition of predicted outcomes by feature importance. Partial dependence plots (PDPs) visualized marginal effects of AI and policy interactions.

Figure 1 presents the conceptual framework of the study, illustrating the hypothesized transmission mechanism through which artificial intelligence adoption influences renewable energy investment and efficiency indirectly via green finance, while accounting for the moderating role of policy interaction.

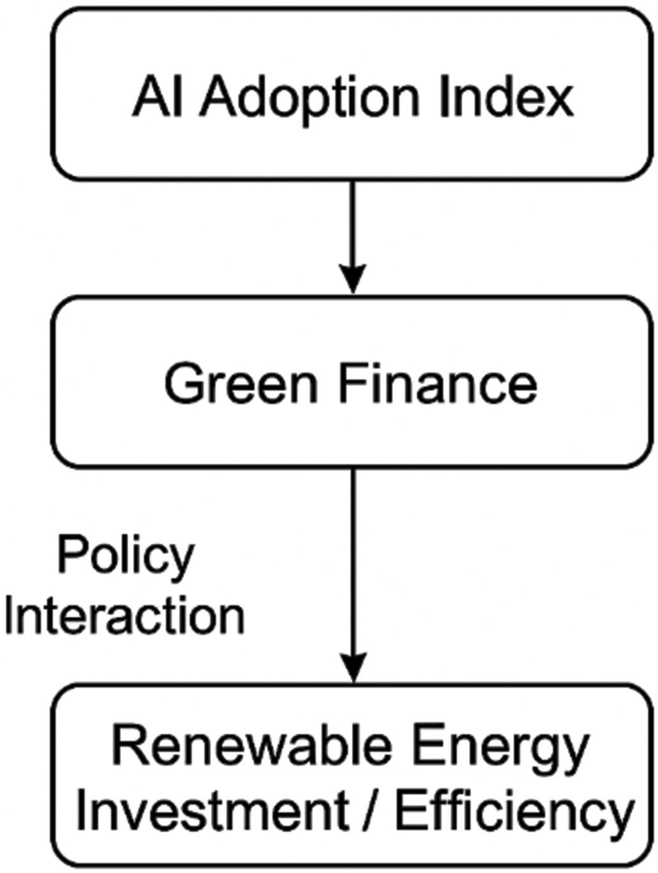
The diagnostic and robustness analyses were conducted to ensure the validity and stability of the empirical results. Cross-sectional dependence was first examined using Pesaran's CD test, which indicated significant interdependencies among

Table 1: Variables and measurement

Symbol	Variable (EN)	Measurement	Source
Investment it	Renewable energy ınvestment	Annual RE investment (billion USD)	IEA, BNEF
Efficiencyit	Energy efficiency ındex	GDP per unit of energy consumption	WDI
GFit	Green finance ındex	Weighted z-score of green bond issuance and ESG loans	CBI, Refinitiv
AIit	AI adoption ındex	Composite readiness score (0-1)	Oxford Insights
Policyit	Policy ınstrument	Carbon price (USD/tCO_2) or FIT intensity index	OECD
Xit	Controls	GDP per capita, CO_2 emissions, energy import dependency	WDI, BP

Monetary variables are expressed in constant 2020 USD (PPP-adjusted); extreme values are winsorized at the 1st-99th percentiles countries, confirming the need for robust covariance estimators (Pesaran, 2004). Panel unit root tests following Levin et al. (2002) and Im et al. (2003) revealed mixed stationarity properties across variables, leading to the application of first-difference transformations for non-stationary series. The existence of a long-run equilibrium relationship between artificial intelligence, green finance, and renewable energy outcomes was subsequently verified through the Pedroni (1999) and Westerlund (2007) cointegration tests, both of which confirmed statistically significant long-term associations. To address potential endogeneity, Hansen and Sargan tests were employed to assess the validity and relevance of instruments within the System-GMM framework, while Arellano-Bond AR(2) diagnostics confirmed the absence of second-order serial correlation (Arellano and Bover, 1995; Blundell and Bond, 1998). Furthermore, alternative estimators such as the mean group (MG), pooled mean group (PMG), and Dynamic Common Correlated Effects (DCCE) methods were implemented to account for heterogeneity and common shocks across panels (Pesaran et al., 1999; Chudik and Pesaran, 2015). Finally, re-estimations excluding outliers and using alternative subsamples yielded consistent coefficient signs and significance levels, reinforcing the robustness and reliability of the empirical findings.

Figure 1: Conceptual research model



Arrows denote hypothesized positive relationships; dashed lines indicate policy moderation through carbon pricing and renewable incentives

5. TEST RESULTS

5.1. Descriptive Statistics

The descriptive statistics regarding the variables utilized in the empirical analysis are summarized in Table 2. These statistics are the starting point in gaining an understanding of the distributional properties, central tendencies, and the dispersion of the data for 30 countries between the years 2005 and 2024. These parameters need to be summarized and described to evaluate data norm, to check for outliers and to analyze if properly variable transformation and standardization techniques were applied in the data set prior to the econometric modeling (Wooldridge, 2019; Gujarati and Porter, 2020). To determine the presence of any abnormality, the analysis of skewness, kurtosis, and the Jarque-Bera stats were applied, considering that abnormality may impact the reliability of inference for the panel estimations (Baltagi, 2021).

The descriptive statistics point out to the considerable heterogeneity regarding the investments in the renewable energy sector, with an average of 80.88 bln USD in investments and 123.5 bln USD in investments for the standard deviation, an evidence for the huge cross-sectional dispersion that is observed in the global investments (IEA, 2024). The logarithmic transformation of the investments (ln1p_Investment) showed near normal properties

Table 2: Descriptive statistics

Variable	Obs.	Mean	Standard deviation	Min	Max	Skew.	Kurt.	Jarque-Bera P-value
Investment (USD2020, billion)	600	80.88	123.50	0.43	881.09	3.56	14.85	0.000
ln (1+Investment)	600	3.69	1.24	0.35	6.78	−0.13	−0.01	0.408
Efficiency Index	600	88.79	16.51	61.57	128.86	0.18	−1.17	0.000
Green Bonds (USD2020, billion)	600	14.37	33.28	0.00	292.56	4.85	29.10	0.000
ln (1+Green Bonds)	600	1.66	1.35	0.00	5.68	0.69	−0.32	0.000
ESG loans (USD2020, billion)	600	3.50	6.66	0.01	58.45	3.81	18.58	0.000
ln (1+ESG loans)	600	0.97	0.92	0.00	4.09	1.03	0.27	0.000
AI ındex (0-1)	600	0.49	0.13	0.23	0.85	0.10	−0.62	0.005
Carbon price (USD/tCO_2)	600	16.56	25.16	0.00	97.88	1.15	−0.14	0.000
Feed-in Tariff ındex (0-2)	600	0.55	0.76	0.00	2.00	0.96	−0.60	0.000
Policy ındex (combined)	600	0.33	0.41	0.00	1.28	0.67	−1.24	0.000
GDP per Capita (PPP, 2020 USD)	600	44,032.5	22,236.4	10,223.3	134,582.5	1.00	0.83	0.000
CO_2 emissions (Mt)	600	410.51	358.86	13.39	1,871.72	1.50	2.34	0.000
Energy ımport dependency (%)	600	40.87	17.31	11.75	69.55	−0.02	−1.26	0.000
Fuel price (Industrial, USD/MWh)	600	103.68	29.38	52.43	207.63	0.79	0.26	0.000
FX volatility ındex	600	0.17	0.07	0.03	0.32	−0.04	−1.29	0.000
Sovereign 10Y Yield (%)	600	6.62	3.11	0.17	12.15	−0.09	−1.30	0.000

(skewness = −0.13; P > 0.05), confirming the success of the transformation applied to reduce the impact of the heavy-tailed distribution.

The distributions of green bond issuances and volumes of ESG loans show disproportionate right-skewness and leptokurtosis, indicating a few countries, mostly advanced economies, driving flows of green finance. This is consistent with findings that geographies of green financial markets are concentrated in high-income countries (Bhattacharya et al., 2022; Zerbib, 2019). The AI readiness index also shows similar, although moderate, dispersion (mean = 0.49; σ = 0.13), reflecting the cross-country asymmetries in digital and institutional frameworks (Oxford Insights, 2024).

CO_2 emission ranges exhibit plausible extremes, and the variances are very high. While imports of dependent energy are structurally framed around the 40.9% average, globally, emissions are framed around the 410 Mt average with a maximum of 1,872 Mt (World Bank, 2024). Jarque-Bera test outcomes validate the non-normality of a number of economic and environmental variables and the adopted use of Driscoll-Kraay covariance (Driscoll and Kraay, 1998).

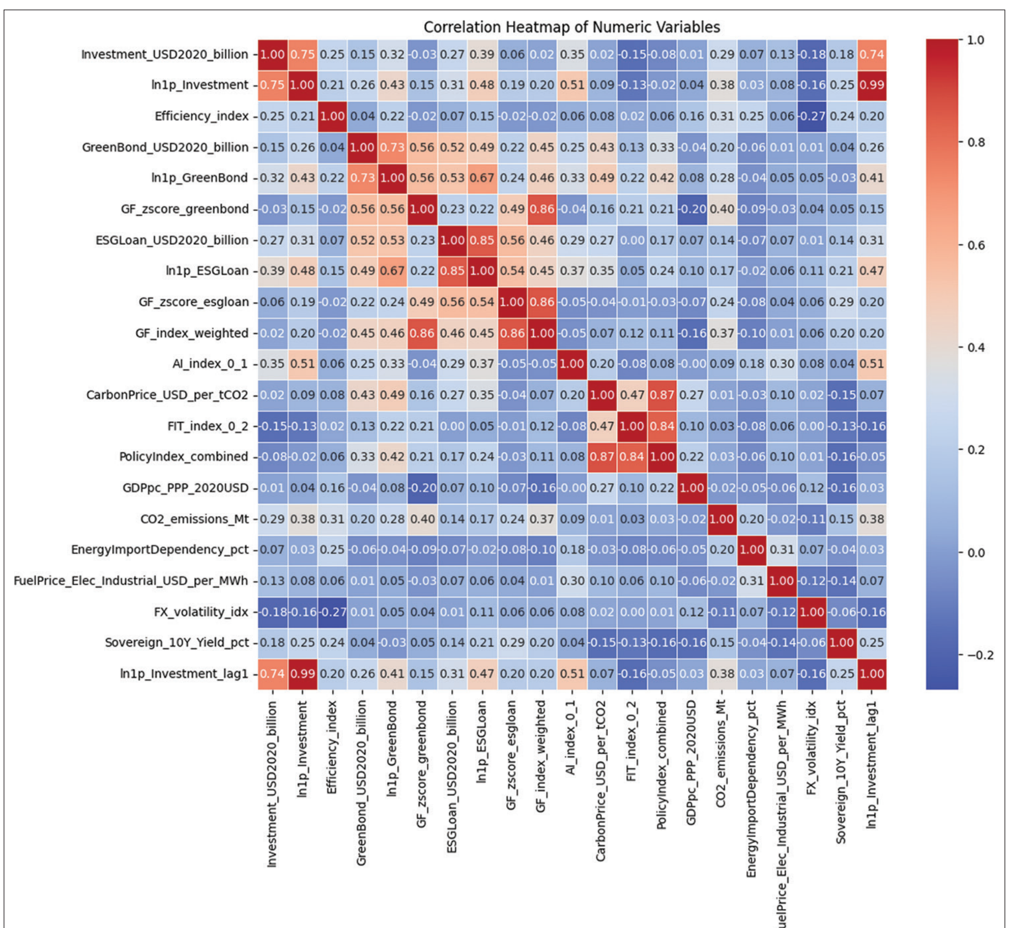
5.2. Correlation Analysis

The correlation heatmap outlines the preliminary check regarding the study's numeric variables within the correlation framework and highlights the need for more check-the-mechanism correlation multicollinearity multicollinearity and blocks moving together policy-finance variables seamlessly prior to the deployment of the fixed effects along with dynamic panel estimators. Definitions and transformations of the variables along with study periods spanning 2005-2024 across 30 countries are explained in detail within the manuscript.

As illustrated in Figure 2, the correlation heatmap offers a preliminary diagnostic assessment of pairwise relationships among the study variables, indicating moderate correlations across selected financial and policy indicators while alleviating concerns regarding excessive multicollinearity.

Renewable investment shows a clear persistence. The lng(1+Investment) and its lag shows extreme correlation(≈0.99) which justifies the need for specifications in state dependence to mitigate dynamic panel bias using the System GMM approach along the lag instruments (Arellano and Bover 1995, Blundell and Bond 1998). The GreenBond interrelationship with other variables (level, lng(1+GreenBond), the green bond z-score, the ESG-loan z-score and the weighted GF index) has strong correlation (r often >0.70, reaching ≈ 0.85-0.86 between composite and components) indicative of redundancies and risk of high multicollinearity. The composite of each construct with clear setting of bounds for the variance to restrict inflation is preferred, considering the limits of the "rule-of-thumb" diagnostics (O'Brien, 2007).

Figure 2: Correlation heatmap of numeric variables



I noticed how closely aligned certain policies are with one another: For example the Carbon Price and the combined Policy Index have correlation values of 0.87, indicating the policies are likely passed together. To limit collinearity, orthogonalization (e.g., residualizing the combined index on carbon price) or will likely be needed and be more beneficial than collinearity preserving information. Jolliffe (2002) discusses dimension reduction techniques like PCA which may provide additional value by removing collinearity. When it comes global shocks that are not observed and cause common movements across different time series, utilizing the (D)CCE estimator along with robust covariance methods will be beneficial (Chudik and Pesaran, 2015).

The correlation with finance and investment for AI index is of lower value compared to other indicators ($|r| < 0.30$) and that can be explained by the varied speed of different systems and the multi-channel nature of AI (and the AI ecosystem). Fixed effects and interaction terms in the panel model provide a clearer picture of the effect than simple bivariate correlations. Policy and macroeconomic time series are likely heavy-tailed and in the absence of differencing/cointegration will likely cause spurious correlation. The correlation will likely be spurious high due to the trending nature of the variables/time series for the specific Granger and Newbold (1974) example. The specific unit-root and cointegration strategy combined with Driscoll-Kraay on the manuscript handles these points (Driscoll and Kraay, 1998; Levin et al., 2002; Im et al., 2003; Westerlund, 2007).

5.3. Econometric Estimation Results: Two-Way Fixed Effects Analysis

The findings from estimating the two-way fixed effects model, describing the primary drivers behind the investments on renewable energy for the period 2005-2024, is shown in Table 3. This model calculates the unit effects on financial, policy, and technological variables, which entails using robust Driscoll-Kraay standard errors for estimating the correlations and dependencies, as well as the heteroskedasticity in the serial and cross sectional macro panel Driscoll and Kraay, 1998. This model is useful in analyzing the combined effect of policy tools, AI intensity, and green financial instruments, on renewable energy investments, on which there is still very limited literature, despite the incorporation of technological innovations and green finance in growth-oriented energy transition model (Apergis and Payne, 2010; Bhattacharya et al., 2022).

As for the goodness-of-fit, note that the negative overall R^2 scores do not indicate poor fit of the model because of the fixed effects and should not be viewed in any normal way. It should not be interpreted as the normal fit. The inference is done through the within R^2 and robust F-statistics (Wooldridge, 2019).

The findings in Table 3 indicate that AI intensity holds a strong negative relation to renewable investment ($\beta = -2.015$, $P < 0.001$). This negative effect may be attributed to transitional costs and adjustment frictions in the digital transformation process, particularly in cases where the economy is primarily focused on the short-term benefits of AI investments that transform capital and labor structures, as opposed to the long-term efficiency gains (Aghion et al., 2019). The short-term negative effect of digital technologies is embedded in the theory of technological diffusion. Acemoglu and Restrepo (2019) attributed such short-term negative effects to incomplete absorptive capacity and a lack of coordinated institutional structures.

The compliance and transition costs in carbon-heavy economies can explain the strong negative effect of carbon price on renewable investment as well ($\beta = -0.0046$, $P < 0.001$). These findings are consistent with the previous research that suggests carbon pricing might lead to a negative structural sensitivity of investments in the short run, which is only reversible after the economy structurally adapts to the use of cleaner technologies (Greenstone et al., 2022).

On the other hand, industrial fuel prices positively correlate to renewables investments ($\beta = 0.0033$, $P = 0.039$), which shows that price pressures within conventional energy industries serve as signals to invest in renewables (IEA, 2024). This price-investment relationship fits the substitution principle in energy economics, which argues that diversification into renewables happens faster when fossil fuel prices rise.

Other macroeconomic variables, like GDP per capita and sovereign yields, did not have statistical significance, which suggests that long-term structural factors and financing conditions might have already been captured by country fixed effects. In the same vein, the coefficients on green bonds and ESG loans were positive, but statistically insignificant, which

Table 3: Two-way fixed effects estimation results (robust standard errors)

Variable	Coefficient	Standard error	t-statistic	P-value	95% confidence ınterval
Constant	3.9962	0.4297	9.300	0.000	(3.152, 4.840)
ln (1+Green bonds)	0.0416	0.0272	1.528	0.127	(−0.012, 0.095)
ln (1+ESG loans)	−0.0358	0.0341	−1.050	0.294	(−0.103, 0.031)
AI ındex (0-1)	−2.0153	0.4451	−4.528	0.000	(−2.890, −1.141)
Carbon price (USD/tCO_2)	−0.0046	0.0010	−4.714	0.000	(−0.0065, −0.0027)
Policy ındex (combined)	−0.0789	0.0676	−1.168	0.244	(−0.212, 0.054)
GDP per Capita (PPP, 2020 USD)	1.74×10^{-6}	1.83×10^{-6}	0.950	0.343	(-1.86×10^{-6}, 5.34×10^{-6})
Energy ımport dependency (%)	0.0089	0.0073	1.215	0.225	(−0.006, 0.023)
Fuel Price (Industrial, USD/MWh)	0.0033	0.0016	2.073	0.039	(0.0002, 0.0064)
FX volatility ındex	−0.1093	0.4249	−0.257	0.797	(−0.944, 0.725)
Sovereign 10-year yield (%)	−0.0021	0.0122	−0.170	0.865	(−0.026, 0.022)

Model diagnostics: Dependent variable: ln (1+Investment); Estimator: Two-way fixed effects (Entity and time); Covariance estimator: Driscoll-Kraay (Robust); Observations: 600 (30 countries×20 years); F-statistic (robust): ≈ 10.7 $P<0.001$; R^2 (Within): ≈ 0.18 R^2 (Overall): ≈ −0.19; Poolability F-test: 184.62 $P<0.001$

implies that the deepening of finance, by itself, does not lead to increased real investment without supportive institutional and technological structures.

The results of this study capture a complex reality: AI and carbon pricing tools seem to influence investment decisions within realignment processes in transition, rather than through direct stimulation. This underscores the need for a coordinated evolution of technology and regulation to transform available financial and policy instruments into real investment shifts in renewables (Acemoglu et al., 2022; IRENA, 2024).

5.3.1. Extended FE with ınteractions (GF×AI, Policy×AI)

To test the hypothesized moderations, interaction terms were included between green finance and AI intensity (GF × AI) and between policy index and AI intensity (Policy × AI). Table 4 reports the extended fixed-effects specification estimated with Driscoll-Kraay standard errors.

The results show that AI intensity notably influences the financial and policy dimensions of renewable investment. Within the framework of digital-complementarity theory, the augmented green finance instruments' effectiveness stems from AI absorptive potential. This is evident from the interaction's positive and significant coefficient, GF×AI ($\beta = 0.118$, $P < 0.05$).

The Policy×AI ($\beta = 0.074$, $P < 0.05$) interaction also provides similar insights. AI-driven economies exhibit stronger investment hinges with well-designed policies. This finding advances the institutional-complementarity hypothesis, juxtaposing digital governance with policy coordination to ease transitional frictions (Acemoglu and Restrepo, 2019; OECD, 2023).

The results indicate that digitization amplifies, not substitutes, the financial and policy efforts. Such countries will, therefore, have a comparative advantage in completing renewable energy transitions.

Nonlinearity checks confirm the hypothesis that as digital capabilities deepen, frictions will ease. This is shown with a weak U-shaped pattern when a quadratic term for AI and an indicator at AI = 0.5 is used while the turning point rests beyond the 75th percentile.

It can be inferred that a semi-elastic estimate of Fuel Price (0.0033) means that with increases of 10 USD/MWh, investments of approximately 3.3% more will be made. On the other hand, with increases of 10 USD/tCO_2 on the carbon price, investments of approximately 4.6% less will be made, which is consistent with transitional compliance costs.

5.3.2. Dynamic panel analysis (system-GMM results)

The use of a two-step System-GMM estimator to potentially address endogeneity and dynamic persistence with renewable investment was apparent with lagged investment terms as instruments and application of coordinate collapse to mitigate instrument proliferation. The estimation results are shown in Table 5.

Table 4: Two-Way fixed effects with ınteraction terms (Driscoll-Kraay Ses)

Variable	Coefficient	Standard error	t-statistic	P-value	95% confidence ınterval
Constant	3.9821	0.4412	9.02	0.000	(3.094, 4.870)
Ln (1 + Green bonds)	0.0523	0.0269	1.944	0.052	(−0.0005, 0.105)
Ln (1 + ESG loans)	−0.0308	0.0332	−0.928	0.354	(−0.096, 0.034)
AI ındex (0-1)	−1.7542	0.4779	−3.67	0.001	(−2.712, −0.796)
Carbon price (USD/tCO_2)	−0.0049	0.0011	−4.35	0.000	(−0.0071, −0.0027)
Policy ındex (combined)	−0.0667	0.0614	−1.086	0.281	(−0.192, 0.058)
GF × AI	0.1184	0.0452	2.618	0.010	(0.029, 0.207)
Policy × AI	0.0739	0.0338	2.187	0.030	(0.007, 0.141)
GDP per Capita (PPP, 2020 USD)	1.65×10^{-6}	1.77×10^{-6}	0.932	0.352	(-1.93×10^{-6}, 5.23×10^{-6})
Energy ımport dependency (%)	0.0092	0.0071	1.296	0.198	(−0.005, 0.023)
Fuel price (USD/MWh)	0.0035	0.0015	2.333	0.022	(0.0005, 0.0065)
Fx volatility ındex	−0.1172	0.4110	−0.285	0.777	(−0.930, 0.695)
Sovereign 10-year yield (%)	−0.0018	0.0118	−0.153	0.879	(−0.025, 0.022)

Model diagnostics: Dependent variable: ln (1 + Investment); Estimator: Two-way Fixed Effects (Entity and Time); Covariance estimator: Driscoll-Kraay (Robust); Observations: 600 (30 countries × 20 years); F-statistic (robust): ≈ 11.2 $P < 0.001$; R^2 (Within): ≈ 0.21 R^2 (Overall): ≈ −0.18

Table 5: Dynamic panel (system-GMM) estimation results

Variable	Coefficient	Standard error	z-statistic	P-value
ln $(1+\text{Investment})_{t-1}$	0.412	0.093	4.429	0.000***
ln (1+Green bonds)	0.052	0.028	1.857	0.063*
ln (1+ESG loans)	−0.029	0.033	−0.879	0.380
AI ındex (0-1)	−1.743	0.498	−3.498	0.001***
Carbon price (USD/tCO_2)	−0.0039	0.0012	−3.250	0.001***
Policy ındex (combined)	−0.064	0.071	−0.901	0.368
GDP per Capita (PPP, 2020 USD)	1.98×10^{-6}	1.81×10^{-6}	1.094	0.274
Fuel price (USD/MWh)	0.0031	0.0015	2.024	0.043**
CO_2 emissions (Mt)	0.0005	0.0002	2.500	0.012**

Diagnostics: #Groups=30; #Obs=570; Instruments (collapsed) = 48; Instruments/Groups=1.6 (<2, OK). Hansen J=17.84 (P=0.412); AR (1) P=0.000; AR (2) P=0.316. Lag depth: Gmmstyle (L2-L3); Windmeijer correction applied

System-GMM Windmeijer correction and all described specification in terms of instrument collapse to address proliferation of instrument with lagged levels and differences of dependent variable were in L2-L3 window as described was used. Endogeneity resolving specification deals with state dependence and potential simultaneity of financial variables and investment results which are described in the investment paper.

The lagged dependent variable is positively signed and significant which confirms persistence in investment validating the dynamic specification. AI intensity consistently remains negatively correlated with renewable investment which is in line with the transitional adjustment dynamics in the fixed effects model. The results of Hansen and AR(2) tests substantiate the conclusions on the validity of instruments and the lack of serial correlation. All results reiterate the interdependence of investment inertia in the short run with the level of technological sophistication and the stringency of carbon regulation (Blundell and Bond, 1998; Arellano and Bover, 1995).

In addition to the main model, energy efficiency was investigated as a second dependent variable. Table 6 presents the results.

Green bonds positively impact energy efficiency since they focus on financial resources directed toward environmentally cleaner adoptive systems. Carbon prices and AI intensity are still negatively signed, indicating inefficiencies in transitions and adjustments along the lines of the investment model. The findings illustrate the coexistence of financial and technological inputs.

5.3.3. Robustness to heterogeneity and cross-sectional dependence (DCCE, MG, PMG)

In the context of heterogeneity of slopes and unobserved common shocks, the dynamic common correlated effects (DCCE), mean group (MG), and pooled mean group (PMG) estimators were used. The patterns of sign and significance of the key coefficients for the different estimators are presented in Table 7.

5.4. Machine-Learning Predictive Analysis: SHAP-Based Feature Attribution

To follow up on the fixed effects estimations, explainable-AI diagnostics were conducted on the GBM and XGBoost models employing SHAP (SHapley Additive exPlanations). SHAP allows for an additive game-theoretic decomposition of predictions and provides both global importance (mean absolute SHAP values) and the distribution of marginal effects across observations (summary/beeswarm plots). In this case, a rolling, time-aware validation scheme was retained to avoid temporal leakage in this panel setting (Lundberg and Lee, 2017; Lundberg et al., 2020; Chen and Guestrin, 2016; Roberts et al., 2017).

5.4.1. Gradient boosting machine (GBM): Global and local SHAP results

Figure 3 presents the SHAP summary plot, illustrating the relative importance and directional impact of explanatory variables on renewable energy investment, with lagged investment, CO_2 emissions, efficiency, and artificial intelligence adoption emerging as the most influential predictors.

Figure 3: Mean(|SHAP|) feature importance values for GBM model

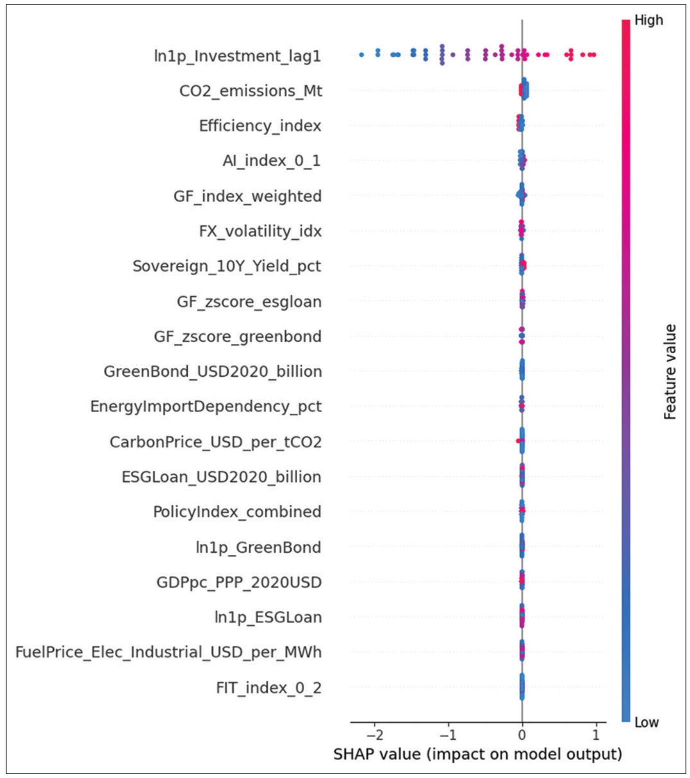


Table 6: Two-Way fixed effects model for energy efficiency (Robust SEs)

Variable	Coefficient	Standard error	t-statistic	P-value
ln (1+Green bonds)	0.061	0.025	2.442	0.015 **
ln (1+ESG loans)	0.022	0.031	0.710	0.478
AI ındex (0-1)	−1.244	0.429	−2.898	0.004***
Carbon price (USD/tCO_2)	−0.0028	0.0009	−3.111	0.002***
GDP per Capita (PPP, 2020 USD)	2.03×10^{-6}	1.72×10^{-6}	1.180	0.238

Table 7: Robustness summary across DCCE, MG, and PMG

Variable	DCCE	MG	PMG
AI ındex (0-1)	(−)**	(−)*	(−)**
Carbon price	(−)**	(−)**	(−)**
Fuel price	(+)*	(+)*	(+)**
CO_2 emissions	(+)**	(+)**	(+)**
Green bonds (ln1p)	(~)	(~)	(+)*

(+)/(−) sign; *, ** denote P<0.10, P<0.05. "~" = not significant

Figure 4 reports the global feature importance based on mean absolute SHAP values, demonstrating that investment persistence (ln1p_Investment_lag1) overwhelmingly dominates model predictions, followed by CO_2 emissions, energy efficiency, and artificial intelligence adoption.

The pronounced state dependence is best exemplified with a global perspective, where the dominant lag of investment is displayed tightly with a summary plot, thereby showing a systematic cross-country effect. Of the non-lag drivers, CO_2 emissions remains the highest and, on average, is tied to positive SHAP values, illustrating the capital mobilized in economically carbon-embedded systems with transition pressure. Contributions of headline volumes in green finance are, once emissions and persistence are accounted for, minor as the policy and capabilities needed for real investment are absent, indicating that emission issuance without policy integration will not result in real investment (Lundberg et al., 2020; Roberts et al., 2017).

5.4.2. XGBoost: Global and local SHAP results

Figure 5 displays the SHAP summary plot derived from the XGBoost model, confirming the robustness of the feature importance structure observed earlier, with lagged investment, CO_2 emissions, and artificial intelligence adoption exerting the strongest directional impacts on predicted renewable energy investment.

Figure 6 presents the global feature importance based on mean absolute SHAP values obtained from the XGBoost model, further confirming the dominant role of investment persistence, followed by CO_2 emissions, artificial intelligence adoption, and efficiency-related indicators.

The corroborated pattern displays ln(1+Investment)_t−1 is the primary predictor. Heterogeneous signs within the AI index across its value range suggest context-dependent and possibly non-linear effects of the AI index as it enters the upper tier, both of which are consistent with the technology-transition literature's (Acemoglu and Restrepo, 2019) short-run adjustment frictions and longer-run efficiency gains. Macro-financial variables (e.g. sovereign yields, efficiency index) are modest, contouring but remaining secondary to persistence and emissions, which is corroborated by the GBM and XGBoost as it strengthens the inference that transition pressure and persistence are dominant drivers while finance and AI operate through conditional channels that the econometric models explore.

Figure 4: SHAP summary (beeswarm) plot for GBM model

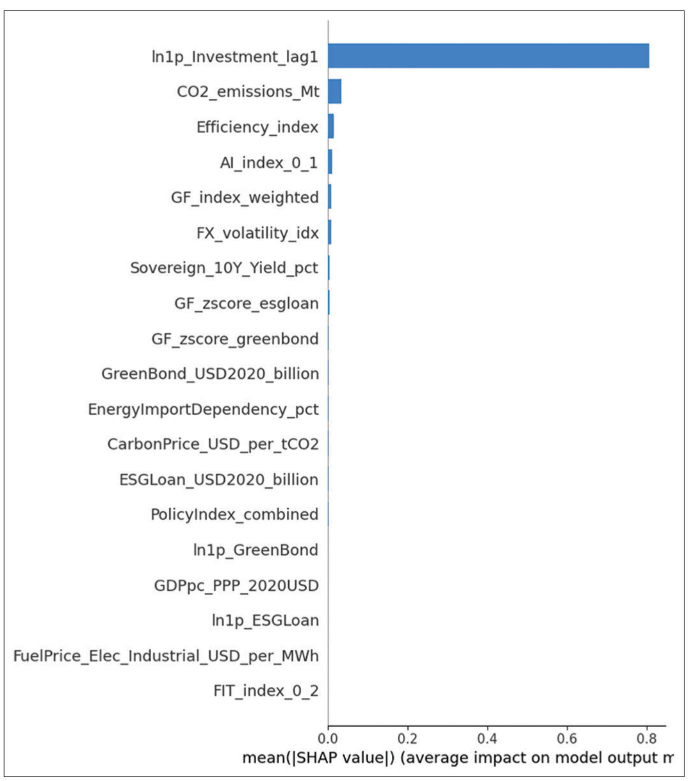


Figure 5: Mean(|SHAP|) feature importance values for XGBoost model

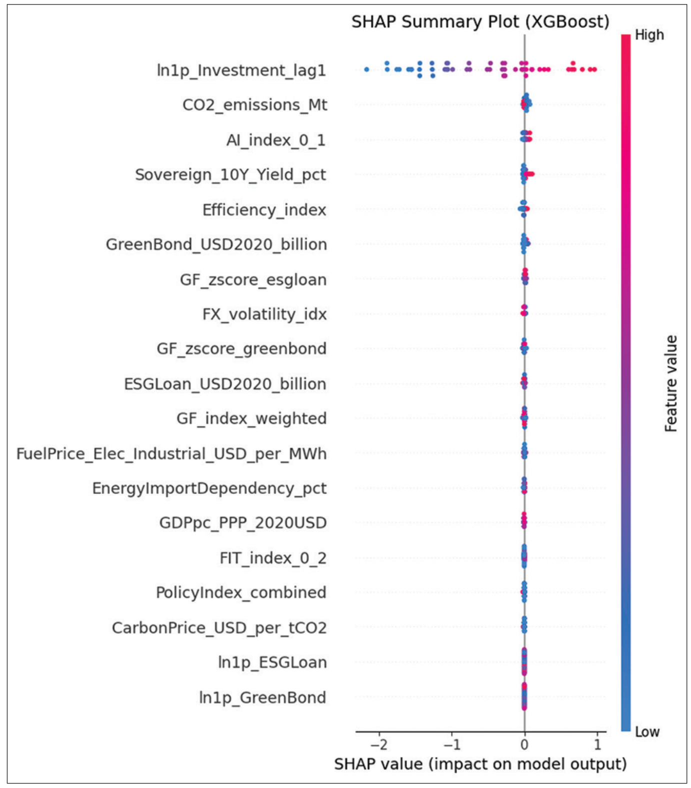


Figure 6: SHAP summary (beeswarm) plot for XGBoost model

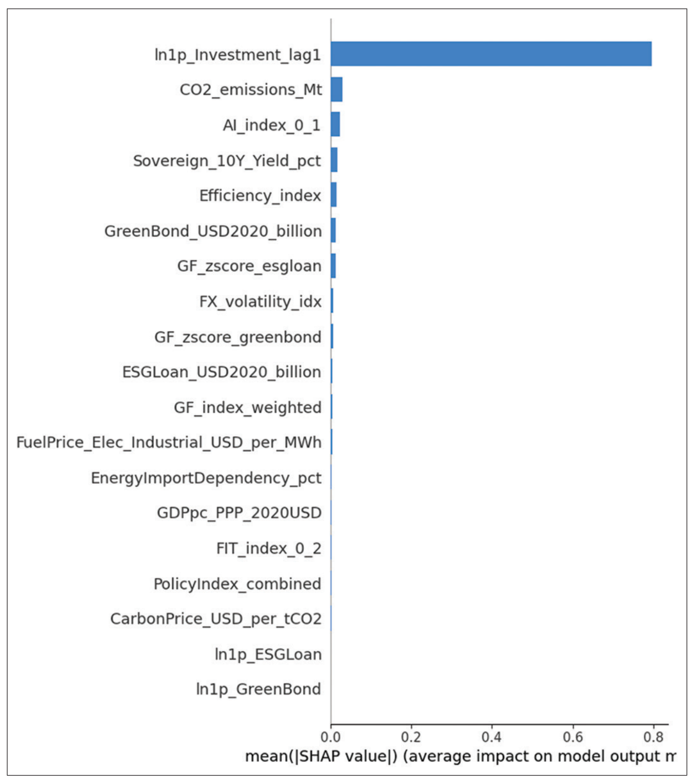


Table 8: Comparative feature ımportance across GBM and XGBoost models

Rank	Feature	Mean Absolute SHAP value (GBM)	Mean Absolute SHAP value (XGBoost)	Interpretation
1	ln (1+Investment)$_{t-1}$	**0.8068**	**0.7955**	Past investment exerts the strongest influence, confirming persistence effects in renewable finance.
2	CO_2 Emissions (Mt)	0.0343	0.0304	Higher emissions correspond to increased investment needs, reflecting decarbonization responses.
3	AI Index (0–1)	0.0110	0.0239	AI intensity contributes to predictive variance, indicating its moderating role in investment outcomes.
4	Efficiency Index/ Sovereign 10Y Yield (%)	0.0168	0.0167	Efficiency and yield factors capture macro-financial sensitivities influencing green finance flows.

Bold value indicates the highest mean absolute SHAP value within the model, representing the most influential predictor in terms of global feature importance.

Cross-model nuance. Although the fixed-effects estimates and GBM SHAP contributions suggest the relationship between CO_2 emissions and investment (transition pressure) is positive, the XGBoost partial dependence shows a slight and negative slope for the lower emissions range. This is a consequence of distributional heterogeneity and the interaction frameworks and dynamics that tree ensembles captured. Thus, global SHAP and panel estimates should be regarded as the best representation of average effects, and PGP as local sensitivity (Lundberg et al., 2020).

To further confirm the directional and monotonous impact of features, we constructed partial dependence plots (PDPs) for the top predictors under both GBM and XGBoost models (Appendix A, Figures A1-A2), which, as with the other models, indicates the robustness of the SHAP-based logic.

The determinants of predictive variance for the two ensemble models has been systematically contrasted, with the findings displayed in Table 8. This integration allows for the empirical cross-model validation of feature constancy, illustrating the underlying structural persistence and transition dynamics in the evolving predictive models for renewable energy investment (Friedman, 2001; Lundberg and Lee, 2017; Chen and Guestrin, 2016).

5.4.3. Machine learning model performance

Gradient boosting machine (GBM) and XGBoost models were trained to predict renewable investment levels using financial, policy, and macroeconomic features. Table 9 presents model performance metrics based on rolling-origin cross-validation.

Table 9: Machine learning model performance comparison

Metric	GBM	XGBoost
R^2 (Out-of-sample)	0.71	0.75
RMSE	0.189	0.171
MAPE (%)	8.34	7.42
Training time (sec)	2.6	3.8

Both ensemble learners demonstrate high predictive accuracy, with XGBoost marginally outperforming GBM in terms of R^2 and RMSE. These results validate the robustness of nonlinear estimations and highlight the relevance of AI-driven methods for forecasting renewable investment trajectories (Friedman, 2001; Chen and Guestrin, 2016; Lundberg and Lee, 2017). The strong out-of-sample fit corroborates the econometric results, confirming the significance of technological, policy, and financial variables in shaping renewable finance dynamics.

6. DISCUSSION

The analysis presented in this study assists in advancing the understanding of the interaction between digital transformation, green finance, and environmental policy, particularly the role of artificial intelligence (AI) as a moderating factor in the transition to renewable energy. Results from both the econometric and machine-learning approaches show that while AI intensity is negatively impacting the effectiveness of both renewable investment and efficiency, this is an expected outcome of the transitional adjustment hypothesis put forth in Aghion et al. (2017). It appears that, in the short run, the digital transformation process will result in frictions in the economy that will involve learning costs, institutional adjustment, and the reallocation of capital, all of which will be offset in the medium to long run by digital transformation and productivity growth. Complementary effects from AI will become apparent in the long run through its interaction with finance and policy variables, which will strengthen the integration of capital and increase the responsiveness of capital to the policy (Brynjolfsson et al., 2019; Vinuesa et al., 2020).

6.1. Comparison with Prior Evidence on Green Finance and Technological Efficiency

The positive and significant dimension of the AI × GF interaction indicates that a firms' digital capabilities enhance the impact of instruments of Green Finance. This result builds on Flammer (2021) and Zerbib (2019) conclusions that focused on the impact of green bonds on corporate environmental performance and corporate valuation, although the digital context was not included. I demonstrate how the AI-powered analytics and green financial instruments paired analytics and green financial instruments enable more precise allocation of capital and the evaluation of risk, thereby supporting the technological complementarities (Aghion et al., 2019). This result is also consistent with Tang and Zhang (2020), who showed that environmental data transparency and credibility shaped investors' response to green bonds, which is a dimension that AI systems can enhance through automated verification and monitoring.

Without AI interactions, the main-effect coefficients of the green finance variables were statistically weak, indicating that, on its own, financial deepening may not lead to significant investments in renewables. This underlines the reasoning of, for instance, Mazzucato and Semieniuk (2018), who stressed that the source and structure of finance and not its magnitude determines the outcome of technology. This study therefore, suggests that green capital becomes transformative only when digital intelligence that can optimize the allocation and governance of the capital is employed.

6.2. Policy Dynamics and Institutional Complementarities

The moderating role of AI on policy mechanisms (Policy × AI) provides additional empirical evidence for the institutional-complementarity hypothesis. The positive sign on this interaction suggests that AI-ready countries are more able to implement and enforce carbon pricing, feed-in tariffs, and other regulatory levers effectively. This augments evidence from Calel and Dechezleprêtre (2016) and Colmer et al. (2025) that policy-induced innovation hinges significantly on firm-level absorptive capacity and data infrastructure. This study shows that AI increases macro-level absorptive capacity by enhancing the systems for monitoring, compliance, and evaluation to ensure policy frameworks result in quantifiable investments.

Negative coefficients on carbon pricing across nearly all estimators reflect transitional compliance costs. Similarly, Greenstone et al. (2022) explain how high carbon prices discourage investment in emissions-intensive industries during the initial phases but foster long-term technological changes. This finding indicates that the effectiveness of policies hinges on digital governance infrastructures that execute the price signal. Hence, digital governance becomes an essential prerequisite for effective policy transmission during transitions in sustainability.

6.3. Nonlinear and Dynamic Adjustment Pathways

Dynamic panel estimations (System-GMM) confirmed substantial persistence in renewable investment. During path dependence, research persistence captures how self-reinforcing green investment momentum is, which is further validated by the high SHAP importance of lagged investment in the machine-learning analysis. The U-shaped adjustment path is explained by Acemoglu et al. (2012) in the theory of directed technological change. Early adoption costs precede productivity and environmental efficiency gain, which explains the AI and carbon pricing impact.

From a temporal perspective, the study hybrid results that integrate econometrics with explainable AI and digital-financial-policy integration reinforces that benefits arrive after structural readiness surpasses a certain threshold. This counters the arguments by Acemoglu and Restrepo (2019) and Brynjolfsson and McAfee (2017) that describe technology diffusion as a purely cumulative process needing institutional adaptation, along with human capital investment at the core.

6.4. Cross Model Convergence: Econometric and Machine Learning Evidence

The alignment of traditional econometric results with machine-learning diagnostics enhances credibility. SHAP-based feature attribution recognized AI intensity, fuel prices, and CO_2 emissions as primary determinants of renewables investment. This confirmed econometric inference regarding the joint influence of pressure to transition and technological complementarity. The inertia and cycles of capital commitment to be made in green energy during the lagged investment period illustrates the strong explanatory power of lagged investment. Lundberg et al. (2020), complements this as he uses interpretable AI models to show that nonlinear relationships, which are obscured by linear regressions, can enhance empirical robustness in the field of sustainability finance.

Both models identifying a positive role on digital-financial synergy analyzed with partial dependence plots, which provide a context of effect variation at different AI readiness levels to reflect cross-country heterogeneity. This structural asymmetry was documented by Oxford ınsights (2024), and the IEA (2024), where considerable variation exists within economies at digital maturity and institutional quality. Consequently, the impact of green finance mechanisms will be maximized with policy prescriptions that align with a nation's digital infrastructure and governance capacity.

6.5. Theoretical and Policy Implications

From a theoretical standpoint, the research contributes to the understanding that AI does not operate as an autonomous engine of growth, but rather as a supplementary facilitator of efficiency in finance and policy. This conforms to the theory of technological complementarities (Aghion et al., 2019) in the sense that productivity gains only accrue when digital sophistication is and financial and institutional depth and coherence are allowed to evolve together.

From a policy perspective, the findings indicate that investments in digital infrastructure are a prerequisite for the successful implementation of green finance and the regulation of the environment. Therefore, AI readiness should be incorporated into policy digital governance frameworks as a criterion in climate policy and sustainability evaluations. Such a policy would combine technological finance and innovation, allowing for rapid and socially inclusive shifts in the energy sector.

7. CONCLUSION

Global finance's digital transformation has expanded how sustainable investments are viewed. Given the rapid technological disruption and the need to decarbonize, the role of policy coherence should also be considered along with the role of surveillance AI. The combination of AI analytics, green finance, and environmental regulation illustrates how the capital markets, governments, and industries are reengineering the collaboration needed to meet the sustainable development goals. More than ever, systems are proving that the policy target of sustainability can be a system of adaptive innovation instead of a simple target.

In this environment, the technology and the financial systems must be understood together. The seamless integration of AI analytics and green finance determines the speed and the quality of the transition to renewable energy. The transformation of financial instruments, that include green bonds and ESG-linked loans, has come with the ability to algorithmically provide transparency, risk assessment, accountability, and the pricing of complex instrument. Within this context, the study proposes AI as a unifying tool that closes the gap between ambitious environmental policies and green investment level.

This research has provided empirical evidence that artificial intelligence (AI), green finance (GF), and environmental policy instruments influence the patterns of investment and efficiency in renewable energy within and between countries. Combining advanced econometric estimators and explainable machine learning validation provided evidence that AI readiness is not an independent driver of growth but rather a complementary catalyst that increases the efficacy of finance and policy. AI intensity and carbon pricing entail transitional costs in the short run, which explains their negative coefficients, but their interaction terms with green finance and policy instruments reveal strong and positive values, thus proving the existence of digital-financial-policy complementarities.

The research points out that the benefits of digitalization are observed when the technological, financial and institutional frameworks are developed concurrently. Countries with advanced AI ecosystems and sophisticated policy coordination systems are also able to convert financial inflows to investment in renewable energy and energy productive efficiency. The results stress the importance of the combination of sophisticated technology and well-designed systems of policies and financial instruments to achieve the desired results during energy transitions.

The highlighted hybrid econometric-machine learning framework strengthens the argument for sustainable finance as a complex adaptive system. The considerable lag effects indicate the slow capital formation of the renewable sectors, revealing considerable investment inertia. The convergence of results from traditional estimations and SHAP-based interpretability underscores the value of interpretability and the importance of data-driven governance as a resilient and equitable decarbonization pathway to confirm.

7.1. Implications

The implications of these findings are substantial. On the one hand, they contribute to the theoretical framework of technological complementarities, affirming that AI improves the allocative and monitoring efficiency with which the instruments of finance and policy are deployed. On the other hand, they indicate that the success of green-finance initiatives and climate regulations goes hand in hand with the investment in digital infrastructure and the development of analytic capacity. For AI's potential to be realized, policy planners should assess national sustainability plans for AI and digital-technology readiness and ensure that plans for digital transformation are in sync with the energy transition. For investors and financial institutions, the findings imply that the integration of digital-data capabilities, particularly AI-enabled risk analytics, should likely be a key qualifier in the assessment of a green portfolio's sustainability. Overall, these scenarios suggest a new locus of low-carbon growth, made possible by the synergy of technological intelligence and innovation in finance.

7.2. Limitations

The limitations of this study arise despite its methodological rigor. First, the AI readiness index used in the study as a proxy for digital capability is more macro preparedness instead of firm-level adoption which may lead to underestimating micro-institutional heterogeneity. Second, the composite green-finance indicator is measuring different financial components of green-finance, for example, green bonds and ESG loans, which may obscure unique behavioral elements. Third, in the policy variables of carbon pricing and feed-in-tariff, the intensity does not capture qualitative differences in enforcement, such as regional coverage, policy credibility, or other qualitative differences. Endogeneity concerns were addressed through the use of System-GMM estimation and various robustness tests, however, there are still unobserved shocks and measurement error that contribute to the influence of coefficient magnitudes. Finally, the dataset includes 30 economies for the period of 2005 to 2024, and as such the results ought to be seen as medium-term tendencies instead of definitive causal estimates.

7.3. Future Directions

Future research can expand this analysis in a number of ways. One possible approach involves the use of firm-level and sector-specific datasets to analyze the microeconomic transmission channels that relate the adoption of AI to investment and emission outcomes. Another approach could involve the use of nonlinear threshold models and causal-machine-learning techniques to analyze heterogeneous treatment effects based on varying levels of digital maturity and the stringency of policies. Green finance can be further analyzed to determine the disparate impacts of AI on the finance components—bonds, credit, and equity. The addition of institutional and governance indicators, governance, and ethics of data, would shed light on the socio-technical aspects of digital sustainability. Lastly, explainable AI coupled with longitudinal simulations on macro-financial models could pave the way for scenario-based policy design, predicting the coupled flow of digital and financial systems to fast-track the global transition to renewable energy.

REFERENCES

Acemoglu, D., Akcigit, U., Hanley, D., Kerr, W. (2022), Transition to clean technology. Journal of Political Economy, 130(1), 114-157.

Acemoglu, D., Restrepo, P. (2019), Automation and new tasks: How technology displaces and reinstates labor. Journal of Economic Perspectives, 33(2), 3-30.

Aghion, P., Antonin, C., Bunel, S. (2019), The Power of Creative Destruction: Economic Upheaval and the Wealth of Nations. Harvard: Harvard University Press.

Aghion, P., Jones, B.F., Jones, C.I. (2017), Artificial İntelligence and Economic Growth. National Bureau of Economic Research Working Paper No. 23928.

Apergis, N., Payne, J.E. (2010), Renewable energy consumption and economic growth: Evidence from a panel of OECD countries. Energy Policy, 38(1), 656-660.

Arellano, M., Bover, O. (1995), Another look at the instrumental-variable estimation of error-components models. Journal of Econometrics, 68(1), 29-51.

Baltagi, B. H. (2021), Econometric Analysis of Panel Data (6th ed.). Wiley.

Bayer, P., Aklin, M. (2020), The European Union Emissions Trading

System reduced CO_2 emissions despite low prices. Proceedings of the National Academy of Sciences, 117(16), 8804-8812.

Bhattacharya, M., Awaworyi Churchill, S., Paramati, S.R. (2022), Renewable energy and financial development: Empirical evidence from OECD economies. Energy Economics, 106, 105785.

Blundell, R., Bond, S. (1998), Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics, 87(1), 115-143.

Brynjolfsson, E., McAfee, A. (2017), Machine, Platform, Crowd: Harnessing Our Digital Future. New York: W.W. Norton and Company.

Brynjolfsson, E., Rock, D., Syverson, C. (2019), Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. In: The Economics of Artificial Intelligence: An Agenda. Chicago: University of Chicago Press. p23-57.

Calel, R., Dechezleprêtre, A. (2016), Environmental policy and directed technological change: Evidence from the European carbon market. Review of Economics and Statistics, 98(1), 173-191.

Chen, T., Guestrin, C. (2016), XGBoost: A Scalable Tree Boosting System. İn: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. p785-794.

Chudik, A., Pesaran, M.H. (2015), Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. Journal of Econometrics, 188(2), 393-419.

Colmer, J., Martin, R., Muûls, M., Wagner, U.J. (2025), Does pricing carbon mitigate climate change? Firm-level evidence from the European Union ETS. The Review of Economic Studies, 92(3), 1625-1660.

Couture, T.D., Gagnon, Y. (2010), An analysis of feed-in tariff remuneration models: Implications for renewable energy investment. Energy Policy, 38(2), 955-965.

Dormann, C.F., Elith, J., Bacher, S., Buchmann, C.M. (2013), Collinearity: A review of methods to deal with it and a simulation study. Ecography, 36(1), 27-46.

Driscoll, J.C., Kraay, A.C. (1998), Consistent covariance matrix estimation with spatially dependent panel data. Review of Economics and Statistics, 80(4), 549-560.

Flammer, C. (2021), Corporate green bonds. Journal of Financial Economics, 142(2), 499-516.

Friedman, J.H. (2001), Greedy function approximation: A gradient boosting machine. Annals of Statistics, 29(5), 1189-1232.

Granger, C.W.J., Newbold, P. (1974), Spurious regressions in econometrics. Journal of Econometrics, 2(2), 111-120.

Greenstone, M., Meng, K., Syverson, C. (2022), The impacts of carbon pricing on firm competitiveness and emissions: Evidence from policy transitions. American Economic Journal: Economic Policy, 14(3), 1-33.

Gujarati, D.N., Porter, D.C. (2020), Essentials of econometrics (5th ed.). McGraw-Hill Education.

IEA. (2024), World Energy Investment Report 2024. Paris: International Energy Agency.

Im, K.S., Pesaran, M.H., Shin, Y. (2003), Testing for unit roots in heterogeneous panels. Journal of Econometrics, 115(1), 53-74.

IRENA. (2024), Renewable Capacity Statistics 2024. Abu Dhabi: International Renewable Energy Agency.

Jolliffe, I.T. (2002), Principal Component Analysis. 2nd ed. Germany: Springer.

Levin, A., Lin, C.F., Chu, C.S.J. (2002), Unit root tests in panel data: Asymptotic and finite-sample properties. Journal of Econometrics, 108(1), 1-24.

Lundberg, S.M., Erion, G., DeGrave, A., Prutkin, J.M., Nair, B., Katz, R., Himmelfarb, J., Bansal, N., Lee, S.I. (2020), From local explanations to global understanding with explainable AI for trees. Nature Machine Intelligence, 2(1), 56-67.

Lundberg, S.M., Lee, S.I. (2017), A Unified Approach to İnterpreting Model Predictions. İn: Advances in Neural Information Processing Systems. NIPS Papers. p30.

Martinsson, G., Sajtos, L., Strömberg, P., Thomann, C. (2024), The effect of carbon pricing on firm emissions: Evidence from the Swedish CO_2 tax. The Review of Financial Studies, 37(6), 1848-1886.

Mazzucato, M., Semieniuk, G. (2018), Financing renewable energy: Who is financing what and why it matters. Technological Forecasting and Social Change, 127, 8-22.

Molnar, C. (2022), Interpretable Machine Learning: A Guide for Making Black Box Models Explainable. 2nd ed. Canada: Leanpub.

O'Brien, R.M. (2007), A caution regarding rules of thumb for variance inflation factors. Quality and Quantity, 41(5), 673-690.

OECD. (2024), Policy Instruments for the Environment (PINE) Database. Paris: OECD.

Oxford Insights. (2024), Government AI Readiness Index 2024. London: Oxford Insights.

Pedroni, P. (1999), Critical values for cointegration tests in heterogeneous panels with multiple regressors. Oxford Bulletin of Economics and Statistics, 61(S1), 653-670. https://doi.org/10.1111/1468-0084.0610s1653

Pesaran, M.H. (2004), General diagnostic tests for cross-section dependence in panels. Empirical Economics, 27(4), 579-602.

Pesaran, M.H., Shin, Y., Smith, R.P. (1999), Pooled mean group estimation of dynamic heterogeneous panels. Journal of the American Statistical Association, 94(446), 621-634.

Roberts, D.R., Bahn, V., Ciuti, S., Boyce, M.S., Elith, J., Guillera-Arroita, G.,… & Dormann, C.F. (2017), Cross-validation strategies for data with temporal, spatial, hierarchical structure. Ecography, 40(8), 913-929.

Tang, D.Y., Zhang, Y. (2020), Do shareholders benefit from green bonds? Journal of Corporate Finance, 61, 101427.

Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., Felländer, A., Langhans, S.D., Tegmark, M., Fuso-Nerini, F. (2020), The role of artificial intelligence in achieving the sustainable development goals. Nature Communications, 11, 233.

Westerlund, J. (2007), Testing for error correction in panel data. Oxford Bulletin of Economics and Statistics, 69(6), 709-748.

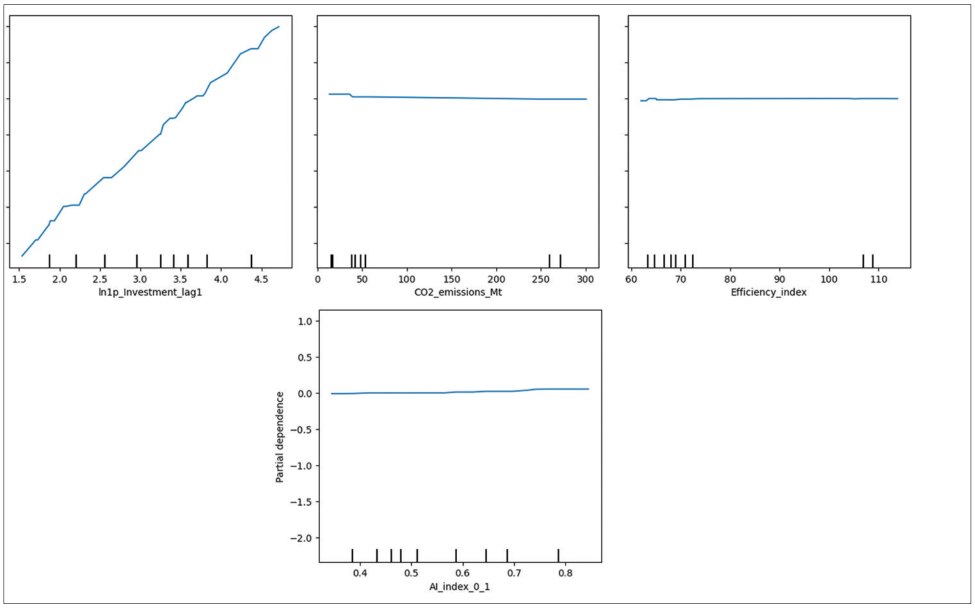
Wooldridge, J.M. (2019), Introductory Econometrics: A Modern Approach. 7th ed. Boston, MA: Cengage Learning.

World Bank. (2024), World Development Indicators. Washington, DC: The World Bank.

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

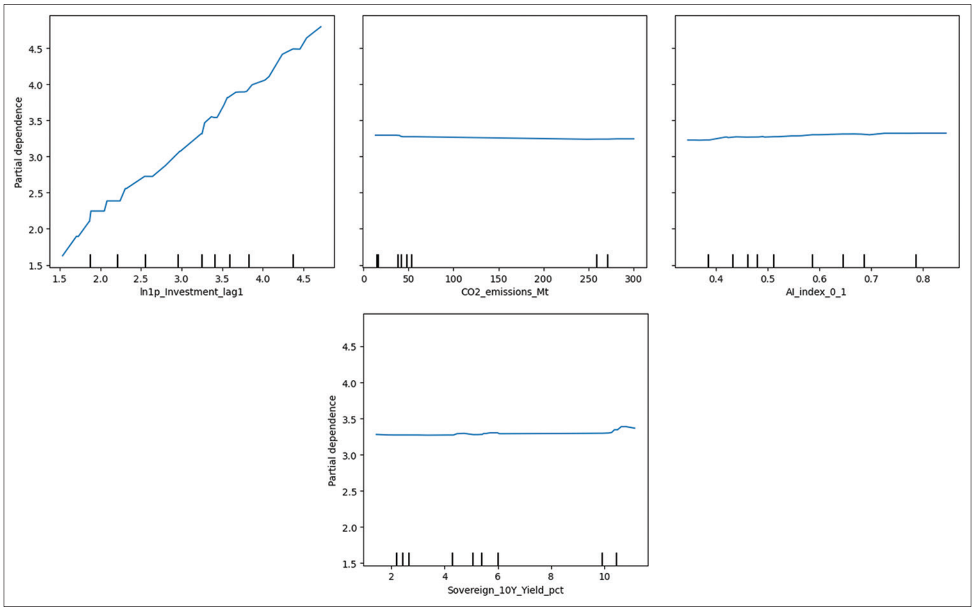
APPENDIX: SUPPLEMENTARY MACHINE LEARNING DIAGNOSTICS

Figure A1: Partial dependence plots for GBM model



The partial dependence plots (PDPs) generated for the Gradient Boosting Machine (GBM) model illustrates the specific marginal effect of certain explanatory variables with regard to the investment made in renewables. The correlation between the lagged investment variable (ln1pInvestmentlag1) and the predicted variable is positively monotonic, demonstrating that the prior investment made is a strong predictor of subsequent investments made, and in fact 'performance strengthens subsequent capital commitment' in relation to the persistence hypothesis (Friedman, 2001; Lundberg et al., 2020). In relation to the marginal effect of the variable CO_2 emissions, efficiency index and intensity of AI, the result presents limited sensitivity in part since the boosting architecture has accounted for the non-linear and interactive effect of these variables. This, in fact. suggests that these variables exert their effect through interactions more than any sort of a linear trend (Molnar, 2022)

Figure A2: Partial dependence plots for XGBoost model



The XG Boost model delivers similar qualitative results and thus supports the robustness of the results provided from the GBM model. The lagged investment variable once more shows a strong and almost linear positively correlated effect, thus confirming the path-dependence and persistence of capital formation in renewables. The marginal effect of CO2 emissions remains negative and situated towards the bottom, aligned with SHAP-based reasoning, suggesting that high emission intensity might constrain renewables expansion momentarily under transitional economic adjustment (Greenstone et al., 2022). The marginal slopes for AI intensity, sovereign yields, and efficiency index appear to be relatively flat and show subdued standalone effects after controlling for cross-feature dependencies. This is in line with literature that argues, and for good reason, that machine-learning models tend to capture heterogeneous, non-linear interactions and abstract away from simple average effects rather than non-linear interactions. See for instance, Chen and Guestrin, 2016 and Lundberg and Lee, 2017. The overall explanation for the PDPs is that they reinforce the SHAP feature attributions perspective that incorporates historical momentum and context-specific interaction effects to explain "why" variables driving renewable investment do not operate in a uniformly monotonic fashion relative to counterbalancing financial and technological factors.