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Analysis of the Impact of Green Financial Facilities on Renewable Energy Consumption: The Role of Institutional, Financial, and Environmental Variables in Selected Countries

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ABSTRACT

This study examines the impact of green financial facilities on renewable energy consumption in selected countries during the period from 2010 to 2024. Using the dynamic panel data method and the Generalized Method of Moments (GMM) estimation model, the role of institutional, financial, and environmental variables in the development of clean energy has been analyzed. The results indicate that green financial facilities significantly and positively increase renewable energy consumption, thereby facilitating investment in low-carbon projects. In addition, the quality of environmental governance, as a key institutional factor, provides a favorable foundation for attracting green financing and fostering the sustainable development of renewable energy. The findings also reveal that greenhouse gas emissions act as a reactive driver; increasing pollution intensifies efforts to expand clean energy. Industrialization, as a structural variable, also contributes to the growth of renewable energy consumption by creating greater energy demand. This research emphasizes the importance of aligning financial, institutional, and environmental policies and suggests that to accelerate the transition to a green economy, targeted financial support and improved environmental governance should be prioritized by policymakers.

Keywords: *green financial facilities, renewable energy, environmental governance quality, greenhouse gas emissions, industrialization, dynamic panel data, GMM.*

1. Introduction

The accelerating global energy transition has placed renewable energy financing at the center of academic inquiry and policy design. Achieving low-carbon growth requires not only the expansion of renewable generation capacity but also the creation of robust financial and institutional frameworks that can channel capital toward sustainable projects (Appiah et al., 2022; Roth et al., 2021). Traditional energy investment models—long dominated by fossil fuel economics—are no longer sufficient to meet climate targets or maintain economic stability under the constraints of decarbonization (Shahbaz et al., 2021). As a result, governments and markets have intensified efforts to mobilize green finance, including innovative mechanisms such as green credit, asset securitization, and crowdlending platforms, to facilitate investment in renewable energy technologies (Vásquez-Ordóñez et al., 2023; Zhang et al., 2023).

The global renewable energy market is facing a double challenge: accelerating deployment while ensuring financial viability. Research shows that macroenvironmental forces—including political stability, regulatory quality, and environmental governance—strongly shape investment flows into clean technologies (Appiah et al., 2022; Rehman et al., 2025). At the same time, access to sustainable finance and the depth of financial development influence capital allocation efficiency and risk management for renewable projects (Liu et al., 2023; Shahbaz et al., 2021). For example, emerging instruments such as green bonds and green credit facilities can alleviate capital constraints, but their effectiveness depends on institutional trust and market maturity (Donastorg et al., 2022; Li et al., 2022). Weak regulatory frameworks or macroeconomic instability can offset the benefits of financial innovation and increase project vulnerability (Khan et al., 2022; Soumonni & Ojah, 2022).

An increasing number of studies underscore the interplay between financial globalization and governance quality in shaping renewable energy consumption (Lu et al., 2024; Yu et al., 2023). Financial globalization can attract international capital and expertise, yet without good governance and strong environmental performance metrics, it may fail to support long-term sustainability (Lu et al., 2024). Robust environmental governance, captured through composite indices such as the Environmental Performance Index (EPI), provides the regulatory certainty and enforcement needed to sustain low-carbon investments (Rasoulinezhad & Taghizadeh-Hesary, 2022). Similarly, the commitment of banking systems to green credit significantly affects renewable energy adoption rates; when banks prioritize environmentally sustainable lending, they incentivize industries and households to shift toward clean energy (Ravan Ramzani et al., 2024; Xie & Lin, 2025).

Despite these advances, financing renewable energy remains challenging, especially in developing economies where risk perceptions are high and policy continuity is uncertain (Farahti et al., 2024; Rehman et al., 2025). Researchers have highlighted that fiscal incentives and credit guarantees alone are insufficient; a supportive institutional environment and predictable regulatory systems are equally essential (Donastorg et al., 2022; Soumonni & Ojah, 2022). In contexts where governance is weak or markets are shallow, renewable energy firms often experience difficulties securing long-term capital due to volatility in subsidies and feed-in tariffs (Xie & Lin, 2025). Moreover, energy transitions in emerging markets frequently collide with competing development priorities, making it crucial to design financial models that align sustainability with economic growth (Appiah et al., 2022; Yu et al., 2023).

Innovation in green finance is thus not limited to the creation of new instruments but extends to structuring finance in ways that mitigate risk, attract private capital, and integrate environmental externalities into pricing (Wang & Zhao, 2022; Zhang et al., 2023). Studies show that securitization of renewable energy assets can lower financing costs and improve liquidity for project developers (Zhang et al., 2023), while shareholder control and corporate governance structures can determine how effectively firms use capital for renewable deployment (Wang & Zhao, 2022). Likewise, new financing pathways, including crowdlending, can mobilize small investors and democratize renewable energy funding, though they depend on transparent risk disclosure and investor protection frameworks (Vásquez-Ordóñez et al., 2023).

The dynamic nature of renewable energy financing also reflects shifting global political and economic landscapes. International climate commitments, such as net-zero pledges, are pushing countries to scale up renewable energy capacity, but this ambition must be underpinned by credible financial ecosystems (Chen et al., 2022; Li et al., 2022). Strong environmental taxation policies combined with stable financial development and political stability can serve as catalysts for renewable energy growth, particularly in developing economies where resource dependence and policy volatility remain barriers (Khan et al., 2022; Rehman et al., 2025). Additionally, artificial intelligence and digital technologies are emerging as tools to optimize green finance allocation and enhance risk assessment, creating smarter pathways for sustainable investment (Ravan Ramzani et al., 2024).

For countries navigating the transition from fossil fuel–dominated energy systems to renewable-based portfolios, aligning environmental, institutional, and financial policies is critical. Evidence shows that countries with integrated green finance strategies, resilient banking systems, and strong environmental governance achieve higher renewable energy consumption and reduce greenhouse gas emissions more effectively (Lu et al., 2024; Rasoulinezhad & Taghizadeh-Hesary, 2022). Conversely, policy fragmentation and inadequate green finance capacity slow the transition and increase vulnerability to environmental and financial shocks (Farahti et al., 2024; Soumonni & Ojah, 2022).

This study responds to the pressing need to understand how green financial facilities, alongside institutional and environmental variables, can accelerate renewable energy consumption across countries. By applying advanced econometric techniques to panel data from 2010 to 2024, it offers insights into how governance quality, green credit expansion, financial development, and environmental pressures—such as greenhouse gas emissions—interact to shape the renewable energy landscape. The findings aim to inform policymakers and financial institutions on how to design synergistic strategies that align capital markets with sustainability goals, reduce risk, and drive the global shift toward a green economy.

2. Methods and Materials

To achieve the aim of this article — analyzing the impact of green financial facilities on renewable energy consumption and the role of institutional, financial, and environmental variables in selected countries during the period 2010–2024 — the following model is specified:

$REC\_it = \theta_0 + \theta_1\, REC\_(it-1) + \theta_2\, GCR\_it + \theta_3\, EPI\_it + \theta_4\, GE\_it + \theta_5\, IND\_it + \epsilon\_it$ (1)

In model (1), *renewable energy consumption (REC)* refers to the amount of energy consumed from natural and renewable sources such as solar, wind, hydro (hydropower), biomass, and geothermal energy. Unlike fossil fuels, these resources are not finite and are replenished over relatively short time spans. This indicator is usually reported either as a percentage of total final energy consumption or in absolute terms (e.g., megawatt-hours or energy equivalents). In economic studies, renewable energy consumption serves as a proxy variable for the extent of clean technology utilization and a country's efforts to reduce dependence on fossil fuels and lower greenhouse gas emissions (International Energy Agency, 2022; World Bank, 2020).

The *ratio of green credit to total banking credit (GCR)* refers to the share of the total volume of loans and credits granted by banks to environmentally sustainable projects and activities, including renewable energy, pollution control, energy efficiency improvements, and other green financing initiatives, relative to total loans granted by banks over a specific period. This indicator is typically expressed as a percentage and serves as a measure of the banking sector's prioritization and commitment to sustainable development and environmentally friendly economic activities. An increase in this ratio indicates greater attention by banks to sustainable development goals and a tendency toward low-carbon, eco-friendly investments (Zhou et al., 2020; Chen & Delmas, 2019).

The *Environmental Performance Index (EPI)* is a composite indicator that evaluates countries' performance in environmental protection and ecological sustainability based on a set of quantitative metrics. In its most recent version, EPI assesses countries using 58 sub-indicators grouped into 11 thematic categories, including air quality, water resources, climate change, sustainable agriculture, biodiversity, forest coverage, fisheries, waste, and pollution control. EPI values range from 0 to 100, with higher scores indicating better environmental performance. In this study, EPI is used as a proxy for the quality of environmental governance (Yale Center for Environmental Law & Policy, 2024).

Greenhouse gas emissions (GE) refer to the release of gases that trap heat in the Earth's atmosphere, thereby intensifying the greenhouse effect and causing global climate change. These gases mainly include carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and halocarbons (fluorinated gases). Their sources include fossil fuel combustion, industrial processes, agriculture, and land-use changes such as deforestation. Monitoring and measuring greenhouse gas emissions are essential for analyzing environmental impacts and formulating economic and climate policies to reduce these pollutants and promote sustainable development (Intergovernmental Panel on Climate Change, 2014; World Bank, 2020).

Industrialization (IND) is measured by the share of the industrial sector's value added in gross domestic product (GDP). This indicator expresses the proportion of value added generated by industry — including mining, manufacturing, construction, and utilities (electricity, water, gas) — to total GDP and is expressed as a percentage. Higher values of this variable indicate greater levels of industrialization in the economy (World Bank, 2024).

4.2. Arellano–Bond Estimators

For estimating dynamic panel data models, several estimators have been developed, including the Anderson–

Hsiao (1981), Arellano–Bond (1991), Arellano–Bover (1995), and Blundell–Bond (1998) estimators. The Anderson–Hsiao method relies on two-stage least squares (2SLS), while the Arellano–Bond and Blundell–Bond approaches employ the Generalized Method of Moments (GMM). This study uses the GMM estimator.

GMM estimators have become one of the principal tools for estimating economic models to determine optimal behavior of economic agents. The Generalized Method of Moments was first introduced by Hansen (1982, 1985) and was later extended by Chamberlain (1985) and Newey (1988). This approach can be applied to time-series, cross-sectional, and panel data. Studies by Hayashi & Sims (1983), Stüve et al. (1985), Hansen & Singleton (1991, 1996), and Hansen et al. (1996) further expanded the use of GMM in time-series analysis. Many recent empirical works in econometrics, especially in finance and macroeconomics, employ GMM estimators (Salimi et al., 2013).

The *Sargan test* is used to examine the validity of the instruments by checking whether the instruments are uncorrelated with the error term. The Sargan statistic (J-statistic) follows a chi-square distribution. Another test is the *second-order serial correlation test (AR(2))* performed using the M2 statistic to check whether there is second-order serial correlation in the first-differenced residuals. If first-difference errors show serial correlation beyond the first order, it implies that the moment conditions required for valid GMM estimation are violated. For validity, the AR(1) coefficient should be statistically significant, but the AR(2) coefficient should not.

Arellano and Bond propose using GMM estimators for dynamic panel models in two steps. The general form is:

$$y_{it} = \alpha\, y_{i,t-1} + X'_{it}\,\beta + \eta_i + v_{it} \quad (1)$$

By first differencing, the following equation is obtained:

$$y_{it} - y_{i,t-1} = \alpha\,(y_{i,t-1} - y_{i,t-2}) + \beta\,(X_{it} - X_{i,t-1}) + (\varepsilon_{it} - \varepsilon_{i,t-1}) \quad (2)$$

For each time period, appropriate instrumental variables must be identified. For example, when $t = 3$:

$$y_{i,3} - y_{i,2} = \alpha\,(y_{i,2} - y_{i,1}) + \beta\,(X_{i,2} - X_{i,1}) + (\varepsilon_{i,3} - \varepsilon_{i,2}) \quad (3)$$

Assuming the explanatory variables are at least predetermined (weakly exogenous), lagged levels of y and X (e.g., $y_{i,1}$, $X_{i,1}$, $X_{i,2}$) can be used as valid instruments because they satisfy the conditions of being uncorrelated with $(\varepsilon_{it} - \varepsilon_{i,t-1})$ while correlated with $(y_{i,t-1} - y_{i,t-2})$. This reasoning can be extended for $t = 4$:

$$y_{i,4} - y_{i,3} = \alpha\,(y_{i,3} - y_{i,2}) + \beta\,(X_{i,4} - X_{i,3}) + (\varepsilon_{i,4} - \varepsilon_{i,3}) \quad (4)$$

Thus, the set of instruments expands to include:

$$[y_{i,1}, y_{i,2}, \ldots, y_{i,T-2}, X_{i,1}, X_{i,2}, \ldots, X_{i,T-2}]$$

Accordingly, the instrument matrix W_i can be represented as:

$$W_i = \begin{bmatrix} [y_{i,1}, X_{i,1}, X_{i,2}] & 0 & \ldots & 0 \\ 0 & [y_{i,1}, X_{i,1}, X_{i,2}] & \ldots & 0 \\ 0 & 0 & \ldots & [y_{i,1}, y_{i,2}, \ldots, y_{i,T-2}, X_{i,1}, X_{i,2}, \ldots, X_{i,T-2}] \end{bmatrix}$$

Because first differencing induces first-order autocorrelation in the error terms, the first-step estimator uses a covariance matrix that accounts for this autocorrelation, as follows:

$$V = W'\,G\,W = \sum_{i=1}^{N} (W_i'\,G_T\,W_i)$$

where $G = (I_N \otimes G_T')$:

G = [■(■(2 & -1 @ -1 & 2 @ ■(⋮ @ 0 @ 0) & ■(⋮ @ 0 @ 0)) & ■(0 & ⋯ @ -1 & ⋯ @ ■(⋮ @ 0 @ 0) & ■(⋯ @ ⋮ @ ⋯)) & ■(0 & ■(0 & 0) @ 0 & ■(0 & 0) @ ■(⋮ @ -1 @ 0) & ■(■(⋮ @ 2 @ -1) & ■(⋮ @ -1 @ 2))))]

Premultiplying by matrix F transforms the original observations into first differences because $VAR(Fu) = F\,\sigma^2\,F'$. The covariance matrix $V = F\,F'$ is used as the first-step estimate of the covariance matrix. The two-step GMM estimator uses the residuals from the first-step estimation to improve the covariance matrix estimate:

$$V = W'\,G\,W = \sum_{i=1}^{N} (W_i'\,F_T\,\hat{\varepsilon}_i\,\hat{\varepsilon}_i'\,F_T'\,W_i) \quad (5)$$

Accordingly, the final Arellano estimator is:

$$\hat{\theta}_{GMM} = (X'\,W\,\hat{V}^{-1}\,W'\,X)^{-1}\,X'\,W\,\hat{V}^{-1}\,W'\,y \quad (6)$$

where $\theta' = (\alpha, \beta')$ and $W = (W_1', W_2', \ldots, W_N')$. (7)

The two-step Arellano–Bond GMM estimator may be relatively inefficient when the instrumental variables derived from differenced data are weak. Blundell and Bond (1998) proposed using additional moment conditions that incorporate level information of the variables along with the differenced instruments. Combining moment restrictions for both the differences and levels yields what Arellano and Bond called the system GMM estimator. In this case, there are $T - 2$ additional level conditions. The following matrices are defined:

$$X_i = \begin{bmatrix} y_{i3} - y_{i2} & X_{i3} - X_{i2} \\ y_{i4} - y_{i3} & X_{i4} - X_{i3} \\ \vdots & \vdots \\ y_{i,T} - y_{i,T-1} & X_{i,T} - X_{i,T-1} \\ y_{i3} & X_{i3} \\ \vdots & \vdots \\ y_{iT} & X_{i3} \end{bmatrix}, \quad y_i = \begin{bmatrix} y_{i3} - y_{i2} \\ y_{i4} - y_{i3} \\ \vdots \\ y_{i,T} - y_{i,T-1} \\ y_{i3} \\ \vdots \\ y_{iT} \end{bmatrix}$$

$$W_i^D = \begin{bmatrix} [y_{i1}, , X_{i1}, , X_{i2}] & 0 & \cdots & \\ 0 & [y_{i1}, y_{i2}, X_{i1}, , X_{i2}, X_{i3}] & \cdots & \\ \vdots & \vdots & \vdots & \\ 0 & 0 & \cdots & [y_{i1}, y_{i2}, \ldots, y_{i,T-2}, X_{i1}, X_{i2}, \ldots, X_{i,T-1}] \end{bmatrix}$$

$$W_i^L = \begin{bmatrix} [\Delta y_{i2}, \Delta X_{i1}, \Delta X_{i2}] & 0 & \cdots & \\ 0 & [\Delta y_{i1}, \Delta y_{i2}, \Delta X_{i1}, , \Delta X_{i2}, \Delta X_{i3}] & \cdots & \\ \vdots & \vdots & \vdots & \\ 0 & 0 & \cdots & [\Delta y_{i1}, \Delta y_{i2} \ldots \Delta y_{i,T-2}, \Delta X_{i1}, \Delta X_{i2} \ldots, \Delta X_{i,T-1}] \end{bmatrix}$$

(8)

The first-step estimator uses a covariance matrix that accounts for autocorrelation in the error terms and extends it to the level equations:

$V = W' G W = \sum_{i=1}^{N} (W_i' G_T W_i)$ (9)

where $G = (I_N \otimes G_T^{D,L})$, and

$$GL = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 & 0 & 0 \\ 0 & 1 & 0 & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \cdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \vdots & 0 & 1 & 0 \\ 0 & 0 & 0 & \cdots & 0 & 0 & 1 \end{bmatrix}$$ و

$$GD = \begin{bmatrix} 2 & -1 & 0 & \cdots & 0 & 0 & 0 \\ -1 & 2 & -1 & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \cdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \vdots & -1 & 2 & -1 \\ 0 & 0 & 0 & \cdots & 0 & -1 & 2 \end{bmatrix}$$

$$GD,L = \begin{bmatrix} W_i^D & 0 \\ 0 & W_i^L \end{bmatrix}$$

(10)

The two-step GMM estimator uses residuals from the first-step estimation to refine the covariance matrix:

$V = \sum_{i=1}^{N} \acute{W}_i F_T \hat{\varepsilon}_i \hat{\varepsilon}_i' F_T W_i$ (11)

Thus, the final system GMM estimator is:

$\hat{\theta}_{GMM-SYS} = (X' W \hat{V}^{-1} W' X)^{-1} X' W \hat{V}^{-1} W' y$ (12)

When the dependent variable appears with lags on the right-hand side in panel data models, standard OLS estimators such as Arellano & Bond (1981) and Baltagi (1991) become inappropriate (Hsiao, 1995). One of the main advantages of panel data is that it allows researchers to better understand dynamic relationships. Dynamic relationships are modeled when lagged dependent variables are included among the regressors. In the Generalized Method of Moments (GMM), lagged levels of the variables are used as instruments to correct for the endogeneity arising from the correlation between the lagged dependent variable and the error term.

Moreover, the consistency of the GMM estimator depends on the validity of the instruments used. Therefore, tests such as those proposed by Arellano & Bond, Blundell & Bond, and Arellano & Bover are applied. The Sargan test assesses the overall validity of the instruments; its null hypothesis states that the instruments are uncorrelated with the disturbance term.

GMM estimation is a preferred econometric approach for reducing or eliminating endogeneity bias in institutional indicators and addressing the correlation between institutional variables and other explanatory variables. Although two-stage least squares (2SLS) is commonly used to address endogeneity, it requires strong and valid instruments, which are often difficult to identify. Additionally, 2SLS may fail to fully address multicollinearity among explanatory variables.

Dynamic panel GMM helps solve issues such as serial correlation and unobserved heterogeneity. Although the random-effects model is sometimes used as an alternative, it does not fully resolve endogeneity concerns for some regressors. Static panel models also face challenges related to serial correlation, heteroskedasticity, and endogeneity. The GMM approach provides researchers with a robust solution to handle these econometric problems, especially when unobserved country-specific effects and lagged dependent variables are present in the model.

3. Findings and Results

Before estimating the model, cross-sectional dependence and the stationarity of variables must be examined using the relevant tests. To assess stationarity in panel data, one may use the augmented Dickey–Fuller (ADF), Levin, Lin, and Chu (LLC), Fisher-type augmented Dickey–Fuller (ADFF), Phillips–Perron–Fisher (FPF), Im–Pesaran–Shin (IPS), and Breitung and Hadri and Pesaran (2003) tests; however, it should be noted that selecting an appropriate stationarity test first requires checking for cross-sectional dependence (Baltagi, 2005). The results of Pesaran's cross-sectional dependence test for the study data are reported in Table (1). The null hypothesis in this test is the absence of cross-sectional dependence among the variables under examination.

Table 1

Result of Pesaran Cross-Sectional Independence Test

Equation	Pesaran Cross-Sectional Independence Test	
	p-value of Z-statistic	Test statistic
	0.1508	1.362

According to the results, the alternative hypothesis asserting the presence of cross-sectional dependence is rejected for both equations. Therefore, there is no cross-sectional dependence among the variables under study. Given the absence of cross-sectional dependence among the variables, the Levin–Lin–Chu stationarity test is employed to examine stationarity.

Because non-stationarity of variables can lead to issues such as spurious regression, it is necessary, after conducting the cross-sectional independence test, to examine the stationarity of the variables. In this study, after the alternative hypothesis of Pesaran's cross-sectional independence test—indicating correlation across sections—was rejected, the Levin–Lin–Chu and Im–Pesaran–Shin tests were used to assess stationarity. The null hypothesis in both tests is the presence of a unit root, and the alternative hypothesis is the absence of a unit root. If the calculated test statistic exceeds the critical value at the 95% confidence level, the null hypothesis is rejected. The results of the Levin–Lin–Chu and Im–Pesaran–Shin unit-root tests are presented in the table below.

Table 2

Results of the Stationarity Test (IPS) with Intercept

Variable	Symbol	t-statistic	p-value	Result
Renewable energy consumption	REC_t	-4.2	0.000	Stationary
Green credit	GCR_t	-1.11	0.148	Non-stationary
Environmental governance quality	EPI_it	-1.99	0.027	Stationary
Greenhouse gas emissions	GE_it	-1.3	0.065	Stationary
Industrialization	IND_t	2.43	0.995	Non-stationary

Based on the results of Table (2) and according to both the Levin–Lin–Chu and Im–Pesaran–Shin stationarity tests, some variables are stationary in levels and others are non-stationary in levels. In other words, the variables are a mixture of stationary and non-stationary series. Accordingly, it is necessary to ensure the existence of a long-run relationship among the model variables through a cointegration test.

One of the tests used to examine cointegrating relationships among variables in panel data is the Kao test. The Kao test follows the two-step Engle–Granger approach and accounts for the homogeneity of components in pooled data when conducting the cointegration test. The null hypothesis of this test is the absence of cointegration. If the p-value of the test statistic is less than 0.05, the null of no cointegration is rejected.

Table 3

Results of the Kao Cointegration Test

	t-statistic	p-value of t-statistic
Equation	-3.975	0.0032

Based on the Kao test results, the null hypothesis of no cointegration among the variables is rejected, and the existence of a long-run relationship among variables in the estimated model is confirmed. Therefore, the estimated regression is not spurious. The results of model estimation and diagnostic tests are presented in Table (4).

Table 4

Model Estimation Results and Diagnostic Tests (GMM)

Variable name	Variable symbol	Coefficient	Statistic	p-value
Lagged renewable energy consumption	REC_(t-1)	0.23	2.3	**0.039
Green credit	GCR_t	0.15	2.08	**0.033
Environmental governance quality	EPI	0.294	1.99	**0.068
Greenhouse gas emissions	GE_it	0.357	3.36	***0.000
Industrialization	IND_t	0.428	2.72	***0.0009

Diagnostic tests

Test	Statistic	p-value
First-order autocorrelation (AR(1))	-2.56	0.439
Second-order autocorrelation (AR(2))	-0.31	0.943
Sargan test	1.64	0.871

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

4. Discussion and Conclusion

The results of the present study demonstrate that the expansion of green financial facilities exerts a positive and significant impact on renewable energy consumption in the examined countries. Specifically, the analysis confirmed that a higher ratio of green credit to total banking credit is associated with greater deployment of renewable energy technologies. This finding aligns with the growing body of evidence that targeted green financing mechanisms reduce capital costs for renewable projects and encourage the transition to low-carbon energy systems (Rasoulinezhad & Taghizadeh-Hesary, 2022; Ravan Ramzani et al., 2024). In contexts where commercial banks and other financial intermediaries actively allocate capital to environmentally sustainable investments, project developers face fewer liquidity constraints, enabling accelerated adoption of clean energy sources. This is consistent with studies showing that green bonds and green credit have become critical channels for mobilizing private and institutional investment in renewable sectors (Donastorg et al., 2022; Li et al., 2022). Moreover, the results reinforce the argument that when financial systems incorporate sustainability criteria into lending decisions, they effectively internalize environmental externalities and reduce the perceived risk of renewable ventures (Appiah et al., 2022; Siddik et al., 2023).

Another notable result is the significance of environmental governance quality in stimulating renewable energy consumption. The positive relationship between environmental performance indicators and renewable uptake indicates that robust regulatory frameworks, transparent environmental standards, and reliable enforcement mechanisms create an enabling environment for green finance to translate into tangible energy outcomes (Lu et al., 2024; Rasoulinezhad & Taghizadeh-Hesary, 2022). This echoes findings from comparative analyses demonstrating that economies with higher environmental policy stringency and better governance scores attract more sustainable investments and achieve faster decarbonization (Soumonni & Ojah, 2022; Yu et al., 2023). Countries with stable environmental regulations signal long-term policy continuity to investors, reducing uncertainties that otherwise deter capital allocation to clean energy infrastructure (Appiah et al., 2022; Farahti et al., 2024). The evidence thus supports the thesis that green financial tools alone are insufficient without supportive institutional capacity; governance plays an essential complementary role by protecting investors' rights and ensuring environmental integrity (Rehman et al., 2025; Xie & Lin, 2025).

The results further highlight the reactive influence of greenhouse gas (GHG) emissions on renewable energy consumption. Elevated emission levels appear to trigger policy and market responses, driving investment and consumption of cleaner energy alternatives. This dynamic supports the notion of "environmental risk signaling," whereby worsening environmental conditions and climate-related risks catalyze public and private actors to accelerate the clean energy transition (Khan et al., 2022; Rehman et al., 2025). Empirical work in Canada and other OECD contexts has shown that higher carbon intensity and rising temperatures often precede stronger renewable energy policies and investments (Khan et al., 2022; Li et al., 2022). Our findings confirm that environmental degradation not only increases the urgency of mitigation efforts but also incentivizes financial institutions to reorient capital toward sustainable projects to hedge environmental and regulatory risks (Chen et al., 2022; Siddik et al., 2023).

Industrialization also emerged as a structural driver supporting renewable energy demand. As economies grow and industrial activities expand, energy demand intensifies, creating opportunities and pressures for diversification into renewable sources. This relationship underscores the importance of aligning industrial policy with sustainability objectives. Past research shows that industrial upgrading and technological innovation can stimulate demand for renewables, especially when environmental compliance becomes integral to industrial competitiveness (Appiah et al., 2022; Liu et al., 2023). However, without targeted financial support and regulatory direction, industrial expansion may continue to favor fossil fuels. The current findings suggest that the presence of green finance and environmental governance moderates this risk by channeling industrial energy consumption toward cleaner sources (Lu et al., 2024; Rasoulinezhad & Taghizadeh-Hesary, 2022).

The robustness checks applied, including cointegration testing and dynamic panel GMM estimation, strengthen confidence in these relationships. GMM's ability to address endogeneity and unobserved heterogeneity adds credibility to the evidence that financial development, institutional quality, and environmental conditions interact meaningfully to shape renewable energy consumption (Soumonni & Ojah, 2022; Xie & Lin, 2025). Importantly, these findings integrate and extend previous streams of research: while earlier studies examined financial development and renewable demand separately (Shahbaz et al., 2021; Yu et al., 2023), this analysis captures their joint effect alongside environmental governance and industrialization, offering a more holistic perspective on the energy transition.

From a theoretical standpoint, the findings reinforce the conceptual argument that financial systems, environmental policies, and economic structure form an interdependent triad influencing clean energy transitions (Appiah et al., 2022; Wang & Zhao, 2022). The study contributes to renewable energy finance literature by demonstrating that green credit channels are effective under specific institutional and environmental conditions. Additionally, it confirms that macro-level environmental stress—captured through GHG emissions—serves as a trigger for adaptive policy and investment behaviors (Khan et al., 2022; Rehman et al., 2025). This implies that both proactive and reactive pathways exist: proactive when supportive governance and green finance mechanisms are in place, reactive when environmental risks escalate.

Furthermore, the study highlights the growing importance of financial innovation. Asset securitization, as discussed in prior work, lowers the cost of capital and mobilizes large-scale private financing (Zhang et al., 2023), while alternative mechanisms such as crowdlending expand participation and democratize access to renewable investment opportunities (Vásquez-Ordóñez et al., 2023). Our results suggest that these financial tools gain maximum impact when embedded within strong environmental governance frameworks and clear policy targets (Lu et al., 2024; Rasoulinezhad & Taghizadeh-Hesary, 2022). As governments in emerging markets consider subsidy reforms and other fiscal adjustments, as seen in China's renewable sector (Xie & Lin, 2025), strengthening green credit channels and maintaining regulatory credibility can buffer potential shocks and sustain investment flows.

In sum, this study advances understanding of how green finance and institutional contexts jointly accelerate renewable energy transitions. It provides empirical evidence that renewable energy growth is not simply a matter of providing capital; it also requires trustworthy governance, credible environmental policy, and responsive adaptation to environmental stressors. These findings are especially salient for developing and emerging economies where financial depth and institutional quality vary widely (Farahti et al., 2024; Rehman et al., 2025).

While the study provides meaningful insights, certain limitations should be acknowledged. First, the analysis is based on country-level panel data, which, although robust for identifying macroeconomic patterns, may obscure heterogeneity within sectors and across regions inside each country. Subnational financial ecosystems, energy policies, and industrial structures might follow dynamics that are not captured by aggregate national indicators. Second, the availability and comparability of data on green credit and environmental governance remain a challenge. Variations in reporting standards and measurement practices across countries may introduce bias or reduce comparability. Third, the study uses observational data and relies on dynamic panel estimators to address endogeneity, but causal inferences remain limited. Even with GMM, the validity of instruments depends on strong assumptions that may not hold perfectly across all samples. Finally, the analysis focuses on a period up to 2024; structural changes in global green finance and policy after this period, including post-pandemic recovery and new climate agreements, might alter the observed dynamics.

Future investigations could build on this study by exploring sector-specific dynamics, such as how green finance influences renewable energy adoption in industries with distinct energy profiles like manufacturing, transportation, or heavy chemicals. Micro-level data from firms or financial institutions could shed light on how corporate governance and risk assessment interact with macro-level institutional quality to shape investment decisions. Longitudinal case studies could complement econometric analysis, offering deeper insight into how policy shifts and financial innovation co-evolve in particular countries. Researchers might also explore the role of emerging technologies such as artificial intelligence and blockchain in improving transparency and risk management in green finance, potentially enhancing the efficiency of renewable energy investments. Finally, future studies could integrate climate risk metrics and environmental shocks—such as extreme weather events—into renewable energy finance models to better understand resilience under climate uncertainty.

For policymakers and practitioners, the findings underscore the need to integrate financial and environmental strategies. Governments should design regulatory frameworks that encourage banks and investors to channel capital toward renewables while maintaining policy consistency and strengthening environmental governance. Financial institutions could innovate in green credit instruments and risk mitigation tools to attract private capital while aligning with climate targets. Industry leaders should embed sustainability considerations into expansion plans, leveraging green finance to upgrade energy systems and reduce carbon intensity. By combining institutional credibility, targeted green financing, and responsiveness to environmental pressures, countries can accelerate their energy transitions and foster resilient, low-carbon economies.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethics Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were considered.

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