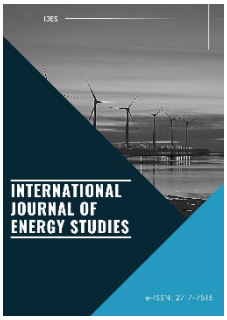
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# Heterogeneous effects of green technology innovations on renewable energy supply share: A dynamic panel evidence

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**Highlights**

- Dependence-robust and common-factor estimators reveal a stable positive association between green technology innovation and renewable energy supply share.
- The panel exhibits strong persistence, indicating that renewable energy supply share adjusts only gradually over time.
- Average short-run effects of economic growth and energy taxes are weak, but substantial heterogeneity emerges across country groups.
- Panel causality results suggest feedback between renewable energy supply, economic growth, and energy tax, while innovation effects appear to operate through longer or more conditional pathways.

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## ABSTRACT

This study examines the determinants of renewable energy supply share (RES) in a balanced panel of 17 countries (1995–2021), focusing on green technology innovations (GTI), economic growth (EG), and energy tax (ET). The analysis accounts for heterogeneity, common shocks, and dynamic adjustment by combining two-way fixed effects with dependence-robust and dynamic common correlated effects (CCE) estimators using Driscoll–Kraay inference. The results show strong persistence in RES and a robust positive association between GTI and RES in the preferred common-factor framework, while the average effects of EG and ET are weaker and model-sensitive. Dumitrescu–Hurlin panel causality tests indicate feedback between RES and EG and bidirectional linkages between RES and ET at the level, whereas innovation dynamics are asymmetric. Overall, the evidence supports innovation-centered transition strategies and emphasizes evaluating policy instruments over multi-year horizons given strong persistence and cross-country heterogeneity.

**Keywords:** Renewable energy supply share, Green technology innovations, Energy tax, Economic growth

## 1. INTRODUCTION

In globalized economic systems, energy security and sustainability have become increasingly important for countries seeking to manage climate risks and restructure their energy systems. In this context, the share of renewable energy in total energy supply is a strategic indicator because it reflects the extent to which national energy systems are transitioning away from fossil-fuel dependence.

Thus, governments need not only appropriate technological capabilities but also coherent policy frameworks that can support the expansion, diffusion, and integration of renewable energy. At this point, environmental innovations and their contributing applications might serve as leverage to achieve the desired energy independence, security, and resource management. In this context, outstanding and environmentally focused innovations can strengthen technological readiness, reduce implementation costs, and accelerate the adoption of renewable energy solutions. Therefore, it can be said that the concept of Green Technology Innovation (GTI) has gained more strategic importance in the 21st century.

GTI is assessed using indicators such as patents and sustainable innovation, with a focus on environmental technologies and applications that protect ecosystems. It generally focuses on the efficiency of renewable energy transitions [1]. It is stated that innovative approaches based on GTI can help reduce energy costs and improve integration between locations in distribution networks [2].

Nonetheless, nations cannot achieve their sustainable energy goals solely through GTI activities. In the renewable energy sector, which has a dynamic system structure, restrictive measures, fiscal policies, and investments are also of strategic importance in terms of energy supply share [3]. It is emphasized that if governments effectively use fiscal policy tools such as energy or environmental taxes, businesses and individuals can switch to renewable energy sources rather than fossil fuels due to the resulting relative price advantages [3,4].

Regardless, the effectiveness of activities carried out within the framework of sustainable energy goals also depends on the overall financial performance of countries. Indicators such as countries' Gross Domestic Product (GDP), Foreign Direct Investment (FDI), and investment capacity might be pivotal components [5]. GDP, a frequently preferred indicator for expressing economic growth

and overall performance, can influence demand for renewable energy, economic decision-making processes in this area, and the efficiency levels of renewable energy [6].

Although researchers have explored the topic from various angles and with different methods, no consensus exists on how economic growth, fiscal policies like energy taxes, and GTI activities influence the share of renewable energy. These issues have been examined in only a limited number of studies, each using different tools and variables. Most research tends to focus on just one or a few of these factors, mainly analyzing average panel effects without explicitly addressing cross-sectional dependence, continuity, or heterogeneity.

Accordingly, we believe there is a research gap in the related field. In our current study, we aim to address this gap by investigating how green technology innovations, economic growth, and energy taxes impact renewable energy supply in selected countries. To achieve this, we have thoroughly reviewed relevant research regarding the methods employed and the results obtained. Based on prominent frameworks and theoretical knowledge, we have identified key indicators for our current research. We also included new indicators that reflect evolving financial systems to offer a different perspective.

Based on the information provided, we evaluated the variables GTI, Energy Tax (ET), Economic Growth (EG), and Renewable Energy Supply Share (RES) together within a single balanced panel framework. Robust inference regarding dependence, robustness against dynamic common factors, group-based heterogeneity analysis, and heterogeneous panel causality tests, as well as two-way fixed effects analyses, were performed on a balanced panel dataset covering the years 1995-2021 for 17 countries whose secondary data are available online. In addition to reporting the results, a comparative assessment of how the link between innovation and renewable energy changes under different initial renewable energy conditions is presented.

## 2. LITERATURE REVIEW

When examining studies related to the subject and the literature, it is seen that various studies are included, encompassing different country groups. However, these studies emphasize the frequent examination of renewable energy production and consumption.

In one such study, Menegaki [7] examined the relationship between renewable energy and growth variables within the European context. This research drew attention to the supply levels and insufficient exploitation of renewable energy sources on a European scale. Similarly, Shakouri and Khoshnevis Yazdi [8] stated that the correlations between renewable energy use and growth are more visible under strong structural pressures.

Looking at a similar theoretical context, Apergis and Payne [9] noted that with potential economic expansions, financial barriers to cleaner energy investments could almost completely disappear. However, they cautioned countries to be careful, as the use of fossil fuels could increase to meet the growing energy demand.

Addressing the issue, particularly during a period when research focusing on some developing countries was increasing, Salim and Rafiq [10] argued that the shift towards renewable energy could happen faster if the right growth policies and suitable investment conditions were provided. Indeed, Sadorsky [11] presented findings supporting this claim in his study.

On the other hand, it is not possible to state that the aforementioned empirical relationship is the same for all country groups or countries. Marinaș et al. [12] stated that the direction and/or level of impact of this relationship may be shaped according to the financial contexts, income sources, and energy usage habits of nations. As one of the related studies, Amri [13] showed that the relationships between renewable energy and macroeconomic indicators such as trade and growth may differ according to the level of development of countries.

Correspondingly, it is a misconception to state that economic growth has a direct positive impact on renewable energy sources or the level of renewable energy adoption. While research generally mentions this positive impact, there are limitations such as the diversity of national economic contexts and the neglect of country heterogeneities that would reveal differences in relevant studies.

When examining research that includes green technology innovations, which is another variable of the study, it is seen that those who evaluate financial policies in relation to innovation systems stand out. In one of these, Johnstone et al. [14] demonstrated that renewable energy policies can encourage technological innovation and that this support can be made sustainable with appropriate

policies. Equivalently, Jacobsson and Johnson [15] showed that the level of diffusion varies depending on the renewable energy supply, learning processes, institutional support, and market formation.

Nevertheless, Blohmke et al. [16] have shown that, despite the difficulty of technology adoption in fragmented innovation systems, innovation can increase the use of renewable energy if appropriate supporting structures are in place. Therefore, they have pointed out that improvements in renewable energy supply can occur. Surely, Bointner [2], who reported that R&D efforts and patent activities strengthen the knowledge base in the energy sector, has shown that the share of renewable energy can be improved with the right innovations.

Noticeably, it is understood that green technology innovation is generally a significant driving force for renewable energy supply and use, and that these effects can be enhanced with the right policies and innovations that reinforce one another. While using the right innovation channel is important, appropriate fiscal tools are equally critical in increasing the importance given to renewable energy [17].

Contrarily, Xu and Yang [18] stated that in some environments, strong policy pressures can support the transition to renewable energy, while in others, the expected gains from innovation may be weak, and that pricing policies are a critical criterion in this regard. Hence, it is important to remember that the GTI effect should be interpreted carefully, especially in heterogeneous policy environments, and that developments towards renewable energy among countries should be carefully considered [19].

Consequently, Sharif et al. [20], addressing how green technology innovation, economic growth, and environmental taxation interact in dynamic environments, demonstrated that fiscal instruments play a key role in the transition to renewable energy. While Aydın and Bozatlı [21] suggest that green technology innovations and environmental taxes can support renewable energy consumption, Degirmenci and Yavuz [22] argue that fiscal instruments do not produce the same results in all jurisdictions. According to this approach, fiscal instruments such as environmental taxes are dependent on tax design, exemptions, and market structure.

Following a similar line of reasoning, Fang et al. [3] reported that even if short-term effects remain weak or negative, environmental taxes can encourage renewable energy supply and consumption in the long term. Yet, these findings in related studies show that appropriate environmental taxation will not work in isolation; rather, it needs to be supported by more appropriate policy moves and suitable green technology innovations.

Supporting this conclusion, Sen et al. [23] conducted a study demonstrating that environmental management and technological innovation can mediate the impact of environmental taxes on renewable energy production and consumption. García-Álvarez et al. [4] argued that policy effectiveness depends on competitive markets and supportive energy policies, noting that environmental taxes are more effective when institutions are trustworthy, and incentives for green technology innovation are well-targeted. Also, recent machine-learning-based studies on solar power forecasting have offered a complementary methodological perspective, showing how data-driven approaches can support renewable energy planning and operational decision-making [24].

In countries with institutions that have broader governance and an efficient innovation environment, it is possible to see that such taxation is successful. Therefore, incentives for green technology innovations alone are not sufficient. They need to be supported by the right fiscal tools. It is considered that this policy mix not only serves environmental goals but also has positive effects on economic growth.

When effective governance structures, innovation capacity, and appropriate tax regulations are integrated, it facilitates firms' transition to cleaner energy sources, enhances resource efficiency, and elevates productivity levels over the long term. This situation contributes to establishing a balance between environmental sustainability and economic growth, while also strengthening the competitiveness of countries. Thus, the success of green technology innovations depends not only on the existence of environmentally focused incentives, but also on the integration of these incentives with institutional and financial frameworks that support economic growth.

Based on the information provided, there is no generally accepted view on the effects of GTI, ET, and EG on RES. In fact, some studies argue that these effects may be short-term, while others claim they may be long-term. Therefore, to conduct a more effective literature review, the

variables, findings, and samples discussed in the accessed sources were examined. Thus, a summary of the literature review was created, as shown in Table 1.

**Table 1.** Literature review

| Studies | Sample | Variables | Findings |
|---|---|---|---|
| [5] | OECD countries (1985-2005) | RES and EG | RES ↔ EG (+C) |
| [7] | European countries (1997-2007) | RES and EG | RES ↔ EG (C) |
| [25] | G7 countries (1980-2009) | RES and EG | EG ↔ RES (C) |
| [9] | Selected countries (1999-2007) | RES and EG | EG ↔ RES (+C) |
| [26] | Türkiye (1990-2010) | RES and EG | EG ↔ RES (C) |
| [27] | 20 OECD countries (1990-2008) | RES and EG | RES ↔ EG (+C) |
| [28] | OECD countries (1980-2011) | RES and EG | EG → RES (+C) |
| [29] | Selected countries (1990-2011) | RES and EG | RES → EG (+) |
| [30] | Emerging economies (1980-2012) | RES and EG | EG ↔ RES (C) |
| [8] | South Africa (1971-2015) | RES and EG | EG ↔ RES (C) |
| [12] | Selected countries (1990-2014) | RES and EG | EG ↔ RES (C) |
| [31] | Emerging countries (1990-2016) | RES and EG | EG ↔ RES (C) |
| [3] | Selected countries (1998-2019) | RES and ET | ET → RES (±) |
| [21] | Selected countries (1994-2019) | ET, GTI, and RES | ET → RES (+)<br>GTI → RES (+) |
| [4] | European countries (2008-2019) | ET and RES | ET → RES (+) |
| [22] | Selected countries (1995-2019) | ET and RES | ET → RES (±) |
| [20] | OECD countries (1995-2018) | GTI and RES | RES → GTI (+) |
| [32] | Selected countries (2000-2020) | GTI and RES | GTI → RES (+) |
| [17] | European countries (1994-2019) | ET and GTI | ET → RES (±)<br>GTI → RES (±) |

**+:** Positive effect; **-:** Negative effect; **C:** Causality

Table 1 demonstrates that research concerning the subject employs diverse sample groups. Certain studies concentrate on specific organizational structures, such as organization of economic co-operation and development (OECD) countries, group of seven (G7) nations, and emerging economies, while others focus on specific countries. When analyzing the relationships among the variables investigated, a predominantly positive correlation between EG and RES is evident. Nevertheless, it is noteworthy that some studies suggest differing directions of relationships within the groups of ET and RES, as well as GTI and RES. Therefore, as previously mentioned, there is no consensus regarding the relationship between the independent and dependent variables in this study. Consequently, this original study examines different countries compared to previous studies in order to provide a different perspective.

## 3. METHODOLOGY

Based on the information obtained from the literature review, the aspects highlighted and those considered lacking in the literature were evaluated. Accordingly, in this section of the study, information regarding the variables used, estimation methods, and the dataset is provided.

### 3.1. Variables, Dataset, and Econometric Model

In accordance with the research objectives, multiple databases were examined for the variables EG, ET, GTI, and RES. Promising instruments capable of accurately measuring these variables were identified. Secondary data were recorded and documented from the correlation databases. Details regarding the dataset employed in the study are provided in Table 2.

**Table 2.** Dataset of the research

| Variables | Code | Instrument | Time Period | Source |
|---|---|---|---|---|
| Green Technology Innovation | GTI | Patents about Environment-Related Technologies (Index) | 1995-2021 (Annual) | [33] |
| Energy Taxes | ET | Environmental Taxes (Percentage of GDP) | 1995-2021 (Annual) | [34] |
| Economic Growth | EG | Real GDP Growth Rate (Period on Period) | 1995-2021 (Annual) | [35] |
| Renewable Energy Supply Share | RES | Renewable Energy Supply (Percentage) | 1995-2021 (Annual) | [36] |
| **Countries:** Australia, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Luxembourg, Mexico, Norway, Portugal, Sweden, and United Kingdom | | | | |

As indicated in Table 2, data for the GTI, ET, EG, and RES variables were accessed from the International Monetary Fund (IMF) and OECD databases. Annual data for the selected appropriate instruments were obtained for a time period covering 1995 to 2021. A balanced panel dataset was created covering 17 countries (N=17) and 27 years of data (T=27), namely Australia, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Luxembourg, Mexico, Norway, Portugal, Sweden, and the United Kingdom. To evaluate this data, the econometric model in Equation (1) was constructed in light of the information obtained from the literature.

$$RES_{it} = \beta_0 + \beta_1 GTI_{it} + \beta_2 EG_{it} + \beta_3 ET_{it} + \mathcal{u}_{it} \quad (1)$$

where $i\ (1, \dots, 17)$ denotes country index, $\mathcal{u}_{it}$ represents the idiosyncratic error term, and $t\ (1, \dots, 27)$ indicates year index. $\beta_0, \beta_1, \beta_2$, and $\beta_3$ are the coefficients of the model. To account for time-invariant country characteristics (such as geography and institutional endowments) and common global shocks (including global technology trends and commodity cycles), a two-way fixed effects (TWFE) model was implemented, as shown in Equation (2).

$$RES_{it} = \alpha_i + \lambda_t \ + \beta_0 + \beta_1 GTI_{it} + \beta_2 EG_{it} + \beta_3 ET_{it} + \varepsilon_{it} \quad (2)$$

where $\alpha_i$ indicates country fixed effects and $\lambda_t$ denotes year fixed effects.

### 3.2. Estimation Methodologies

As a preliminary diagnostic, pairwise correlations were inspected, followed by variance inflation factors (VIF). VIF for regressor $x_k$is defined as shown in Equation (3).

$$VIF_k = \frac{1}{1 - R_k^2} \quad (3)$$

where $R_k^2$ is obtained from regressing $x_k$ on the remaining regressors. VIF diagnostics were interpreted conservatively, consistent with the recommendation that rule-of-thumb cutoffs should be contextualized rather than applied mechanically [37]. However, macroeconomic panels often exhibit interdependence across countries due to common shocks and spillovers [38]. Cross-

sectional dependence was therefore assessed using Pesaran's CD framework (Equation (4)), which is based on the average of pairwise correlations of residuals.

$$CD = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \tag{4}$$

where $\hat{\rho}_{ij}$ denotes the sample correlation between residuals of cross-sectional units $i$ and $j$. Because CD was detected in both the raw series and the TWFE residuals, inference and robustness were designed explicitly to remain credible under cross-sectional dependence [39]. Since persistence and nonstationarity can affect interpretation and inference, panel unit-root diagnostics were implemented using Fisher-type approaches that combine country-specific augmented dickey-fuller (ADF) p-values. Maddala and Wu's Fisher test combines p-values as shown in Equation (5) under the null of a unit root [40].

$$P = -2 \sum_{i=1}^{N} \ln(p_i) \sim \mathcal{X}^2(2N) \tag{5}$$

Choi's panel unit-root framework provides related Fisher-type statistics and asymptotic logic for panel settings with heterogeneous time spans and stochastic components. Given the evidence of cross-sectional dependence, an additional robustness step was applied by removing common time components prior to testing, via year demeaning as shown in Equation (6).

$$\tilde{y}_{it} = y_{it} - \frac{1}{N} \sum_{i=1}^{N} y_{it} \tag{6}$$

This procedure is consistent with the broader cross-section augmentation intuition that common factors should be accounted for when panels are influenced by shared shocks [41].

Baseline estimates were produced under pooled OLS, fixed effects, and random effects. Country fixed effects were evaluated against pooled OLS using an F-test. Fixed vs. random effects were assessed using the Hausman specification test, which evaluates whether the difference between FE and RE coefficient vectors is systematic under the null that RE is consistent. Given typical energy-

transition data properties and the diagnostic evidence on heterogeneity and dependence, TWFE was retained as the baseline structure, with robust inference layered on top [42].

Because residual dependence can invalidate conventional standard errors, two complementary inference strategies (Driscoll–Kraay (DK) standard errors and two-way (country and time) clustered standard errors) were used. The combination of DK and two-way clustering was adopted to ensure that statistical conclusions are not driven by a single variance estimator [43, 44].

Since the renewable energy supply share tends to adjust gradually due to infrastructure inertia and cumulative capital formation, a dynamic TWFE model, as shown in Equation (7), has been estimated to capture its persistence.

$$RES_{it} = \alpha_i + \lambda_t + \rho RES_{i,t-1} + \beta_1 GTI_{it} + \beta_2 EG_{it} + \beta_3 ET_{it} + \varepsilon_{it} \quad (7)$$

Inclusion of a lagged dependent variable in a fixed-effects panel can lead to a problem such as finite sample bias. Although this bias decreases as T increases, in order to report economically significant magnitudes, long-term effects were calculated under the standard partial adjustment interpretation as shown in Equation (8).

$$LR(\beta_k) = \frac{\beta_k}{1-\rho}, k \in \{GTI, EG, ET\} \quad (8)$$

In addition to this transformation, which reflects the cumulative effect of a continuous change in the explanatory variable after dynamic adjustment convergence [45], the Common Correlated Effects (CCE) approach was used as a robustness layer to directly address unobserved common shocks and multifactor error structures. Within the CCE framework, regressions are supported by cross-sectional means of the dependent variable and regressors to represent unobserved common factors [46].

Although finite-sample Nickell bias should not be completely ignored, since the dynamic specification includes both lagged dependent variable and fixed effects, the bias is expected to be significantly smaller than in shorter T-panels due to the moderate time dimension of the panel (T = 27). For this reason, the dynamic TWFE estimates are interpreted as persistence-oriented

benchmark estimates rather than definitive structural parameters. In addition, the analysis is complemented with dynamic CCE estimates to assess whether the main conclusions remain stable when common shocks and multifactor error structures are modelled more explicitly. Long-run effects are computed using the standard partial-adjustment formula (Equation 8), and the corresponding standard errors are obtained using the delta method.

Dynamic extensions of CCE for heterogeneous panels with weakly exogenous regressors were also used to validate results under persistence and common shocks [47]. Operationally, the dynamic CCE specification can be expressed as shown in Equation (9).

$$RES_{it} = \alpha_i + \rho RES_{i,t-1} + \beta' X_{it} + \gamma' \bar{Z}_{it} + \omega_{it}\,, \qquad X_{it} = [GTI_{it}, EG_{it}, ET_{it}] \tag{9}$$

where $\bar{Z}_t$ includes cross-sectional averages. This specification is designed to reduce bias from omitted common factors and to improve robustness when cross-sectional dependence persists after TWFE.

Because policy and innovation effects are not expected to be homogeneous across countries, heterogeneity was examined by allowing slopes to differ across country groups defined by baseline renewable energy supply share.Country groups are formed according to baseline renewable energy supply share. This design allows the marginal effects of GTI, EG, and ET to differ systematically between lower-baseline and higher-baseline renewable-energy settings. That approach is also implemented via interaction models as presented in Equation (10).

$$RES_{it} = \alpha_i + \lambda_t + \sum_k \left(\beta_k X_{kit} + \delta_k (X_{kit} \times G_i)\right) + \varepsilon_{it} \tag{10}$$

where $G_i$ is a group indicator such as high and low baseline RES. The marginal effect for the reference group is $\beta_k$, while for the comparison group it is $\beta_k + \delta_k$. Statistical inference for group-specific effects was conducted using standard linear-combination logic under the chosen robust variance estimator.

To complement the panel regression evidence for the baseline model, panel causality was examined using the Dumitrescu–Hurlin (DH) heterogeneous panel Granger causality test. The DH

approach is suitable for macro panels in which slope parameters and causal responses may differ across cross-sections [48]. The test evaluates whether past values of a regressor $x$ provide incremental predictive content for an outcome $y$, conditional on the past of $y$, while allowing the coefficients to vary by country as shown in Equation (11).

$$y_{it} = \alpha_i + \sum_{k=1}^{p} \gamma_{i,k}\, y_{i,t-k} + \sum_{k=1}^{p} \beta_{i,k}\, x_{i,t-k} + \varepsilon_{it} \tag{11}$$

The null hypothesis is homogeneous non-causality ($\beta_{i,k} = 0$ for all $i$), while rejection implies that at least a subset of countries exhibits Granger causality from $x$ to $y$. Given the presence of common shocks and documented cross-sectional dependence in the raw series (notably for RES, EG, and ET), the main results are reported for year-demeaned series. With this executed transformation aims to reduce the misleading predictability arising from shared global dynamics.

## 4. EMPIRICAL RESULTS

In the estimation part of the research, the effects of the independent variables (GTI, EG, and ET) on the dependent variable (RES) were examined by following the steps in the method described. First, descriptive statistics were obtained, as presented in Table 3.

**Table 3.** Descriptive statistics

| Variable | N | Mean | Max | Min | Std |
|---|---|---|---|---|---|
| RES | 459.00 | 14.246 | 53.230 | 0.790 | 12.635 |
| GTI | 459.00 | 1.080 | 3.074 | 0.306 | 0.319 |
| EG | 459.00 | 2.057 | 24.624 | -10.047 | 3.241 |
| ET | 459.00 | 1.688 | 3.220 | -1.760 | 0.629 |

**Std:** Standard Deviation

As indicated in Table 3, the statistics for the RES variable, exhibiting a significant distribution (std ≈ 12.64) and a wide range of values (0.79–53.23), suggest a significant heterogeneity between country-time observations. In addition, relatively less dispersed GTI (std ≈ 0.32), EG with negative values (economic contractions), and significantly variable ET stand out. Hence, it is understood that policy measures, green technology innovations, economic growth, and the share of renewable energy supply are variable across the sample. Subsequently, correlation analysis was performed, resulting in the data presented in Table 4.

**Table 4.** Results of the correlation analyses

| Variable | RES | GTI | EG | ET |
|---|---|---|---|---|
| RES | 1.000 | 0.157 | -0.071 | 0.065 |
| GTI | 0.157 | 1.000 | -0.079 | 0.138 |
| EG | -0.071 | -0.079 | 1.000 | -0.062 |
| ET | 0.065 | 0.138 | -0.062 | 1.000 |

According to the results in Table 4, RES shows a positive correlation with GTI (0.157) and ET (0.065), and a negative correlation with EG (-0.071). These unconditional correlations are not sufficient for a causal interpretation, but they indicate the absence of strong linear collinearity patterns. The VIF diagnostics results in Table 5 were then obtained.

**Table 5.** Results of VIF diagnostics

| Factor | Constant | GTI | EG | ET |
|---|---|---|---|---|
| VIF | 18.521 | 1.024 | 1.009 | 1.022 |

Examining the findings presented in Table 5, it is seen that the VIF values for all explanatory variables included in the model are approximately at the level of 1. This result indicates that there is no high level of linearity between the independent variables, and therefore no multicollinearity problem in the basic model specification. In other words, the fact that the regressors do not strongly explain each other contributes to obtaining more reliable and stable coefficient estimates. Thus, the dependence of the horizontal section is investigated. The relevant results are presented in Table 6.

**Table 6.** Results of Pesaran's CD test

| Factor | RES | GTI | EG | ET |
|---|---|---|---|---|
| CD | 40.184* | -0.604 | 39.602* | 19.746* |
| p | 0.001 | 0.545 | 0.001 | 0.001 |
| ***:** $p < 1\%$ | | | | |

According to the results in Table 6, strong cross-sectional dependence is detected in RES, EG, and ET, consistent with common shocks or spillovers across countries. In contrast, GTI does not exhibit statistically significant cross-sectional dependence. This diagnostic motivates robust inference and/or estimators designed for common. In this context, Fisher ADF panel unit root tests were performed. The results of these analyses are presented in Table 7.

**Table 7.** Results of panel unit root tests

| Variable | I(0) | I(1) | I+T(0) | I+T(1) |
|---|---|---|---|---|
| RES | 12.936 | 222.986* | 43.219 | 223.316* |
| GTI | 89.589* | 302.369* | 62.449* | 125.496* |
| EG | 316.724* | 363.465* | 294.734* | 187.146* |
| ET | 53.010** | 198.523* | 47.152*** | 211.127* |

**I:** Intercept, **T:** Trend, **(0):** Level, **(1):** First Difference
***:** $p < 1\%$, ****:** $p < 5\%$, *****:** $p < 0.10$

The tests suggest that RES is not stationary at levels under the constant-only specification, while differencing yields stationarity. GTI and EG appear stationary at levels, whereas ET is borderline, depending on the specification. These mixed indications are consistent with the presence of common time dynamics and motivate testing under time-demeaning. The pooled model tests were then conducted. The results of these tests are presented in Table 8.

**Table 8.** Results of the pooled model tests

| Test | Format | Statistic | df | p |
|---|---|---|---|---|
| F Test | Country FE vs Pooled | 190.322* | (16, 439) | 0.001* |
| Hausman | FE vs RE | 0.927 | 3 | 0.818 |
| Residual CD | Two-way FE | -2.808* | Normal | 0.005* |

**df:** degree of freedom, ***:** $p < 1\%$

The diagnostic test results reported in Table 8 primarily reveal that the combined model is strongly rejected in favor of country fixed effects. This finding indicates that country-specific heterogeneous elements affecting the dependent variable and remaining constant over time should be considered in the model. On the other hand, the Hausman test does not reject the consistency of the random effects (RE) estimator. This result theoretically makes it difficult to make a direct and definitive exclusion between fixed effects (FE) and random effects models. However, in panel data models, simply distinguishing between FE and RE is not sufficient; the inter-unit interaction structure must also be considered. Indeed, the cross-sectional dependence test performed on the residuals of the two-way FE model shows that the assumption of cross-sectional independence is rejected.

In such a case, the reliability of standard inferences based on classical FE or RE estimators may be weakened. In particular, standard errors and significance levels can produce misleading results when cross-sectional dependence is not considered. Therefore, it becomes necessary to correct or

supplement model results with approaches that take into account the common factor structure, especially methods such as Common Correlated Effects (CCE). In line with these diagnostic assessments, static baseline regression estimations were performed to initially reveal the fundamental relationships between variables, and the relevant empirical findings are presented in Table 9.

**Table 9.** Static baseline regression estimations

| **Pooled OLS** ($R^2$: 0.030 \| Adjusted $R^2$: 0.024) | | | | |
|---|---|---|---|---|
| **Variable** | **Coefficient** | **SE** | **z** | **p** |
| GTI | 5.829 | 4.979 | 1.171 | 0.242 |
| EG | -0.225 | 0.212 | -1.061 | 0.289 |
| ET | 0.830 | 2.454 | 0.338 | 0.735 |
| **FE** ($R^2$: 0.878 \| Adjusted $R^2$: 0.873) | | | | |
| **Variable** | **Coefficient** | **SE** | **z** | **p** |
| GTI | 1.237 | 3.460 | 0.358 | 0.721 |
| EG | -0.188 | 0.080 | -2.352 | 0.019** |
| ET | -2.652 | 2.280 | -1.163 | 0.245 |
| **TWFE** ($R^2$: 0.954 \| Adjusted $R^2$: 0.949) | | | | |
| **Variable** | **Coefficient** | **SE** | **z** | **p** |
| GTI | 2.802 | 2.244 | 1.249 | 0.212 |
| EG | 0.037 | 0.059 | 0.625 | 0.532 |
| ET | 0.129 | 0.681 | 0.190 | 0.849 |
| **RE** ($R^2$: 0.878 \| Adjusted $R^2$: 0.877) | | | | |
| **Variable** | **Coefficient** | **SE** | **z** | **p** |
| GTI | 1.285 | 0.830 | 1.549 | 0.121 |
| EG | -0.188 | 0.071 | -2.672 | 0.008* |
| ET | -2.597 | 0.550 | -4.717 | 0.001* |

**Dependent Variable:** RES, **SE:** Standard Error, ***:** p < 1%, ****:** p < 5%, *****:** p < 0.10

The static pooled and FE results in Table 9 provide limited evidence for GTI. EG appears to have a negative effect on RES for both the FE and RE estimation models. Similarly, ET appears to have a statistically significant negative effect on RES. However, under the pooled OLS and TWFE estimation models, the independent variables show no significant effects. This indicates that the inference is susceptible to error structure and previously documented dependency models. Therefore, robustness checks with dependency-resistant covariance estimators are necessary. Thus, the results of the static TWFE inference comparison analysis are presented in Table 10.

**Table 10.** Static TWFE inference comparison

| Variable | Two-Way Cluster | | | Driscoll–Kraay | | |
|---|---|---|---|---|---|---|
| | **SE** | **Statistic** | **p** | **SE** | **Statistic** | **p** |
| GTI | 2.297 | 1.220 | 0.223 | 0.657 | 4.267 | 0.001* |
| EG | 0.053 | 0.698 | 0.485 | 0.046 | 0.814 | 0.416 |
| ET | 0.633 | 0.204 | 0.838 | 0.772 | 0.167 | 0.867 |

**SE:** Standard Error, ***:** p < 1%

According to Table 10, when dependence-robust Driscoll–Kraay inference is employed, the GTI coefficient becomes highly significant, while EG and ET remain insignificant. This divergence indicates that conventional clustered inference may understate precision under cross-sectional dependence and serial correlation, and supports reporting DK-based inference for the TWFE model. A coefficient comparison analysis was also performed for TWFE based on two-way clusters and Driscoll-Kraay in terms of static and dynamic. The relevant results are presented in Table 11.

**Table 11.** Static and dynamic comparison of TWFE

| **Dynamic** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | **TWFE (Two-Way Cluster)** | | | | **TWFE (Driscoll–Kraay)** | | | |
| | **Coefficient** | **SE** | **Statistic** | **p** | **Coefficient** | **SE** | **Statistic** | **p** |
| RES (-1) | 0.830 | 0.118 | 7.011 | 0.001* | 0.830 | 0.058 | 14.196 | 0.001* |
| GTI | 0.589 | 0.449 | 1.311 | 0.190 | 0.589 | 0.183 | 3.213 | 0.001* |
| EG | 0.007 | 0.022 | 0.313 | 0.754 | 0.007 | 0.017 | 0.398 | 0.691 |
| ET | 0.047 | 0.159 | 0.296 | 0.767 | 0.047 | 0.178 | 0.265 | 0.791 |
| **Static** | | | | | | | | |
| **Variable** | **TWFE (Two-Way Cluster)** | | | | **TWFE (Driscoll–Kraay)** | | | |
| | **Coefficient** | **SE** | **Statistic** | **p** | **Coefficient** | **SE** | **Statistic** | **p** |
| GTI | 2.802 | 2.244 | 1.249 | 0.212 | 2.802 | 0.657 | 4.267 | 0.001* |
| EG | 0.037 | 0.059 | 0.625 | 0.532 | 0.037 | 0.046 | 0.814 | 0.416 |
| ET | 0.129 | 0.681 | 0.190 | 0.849 | 0.129 | 0.772 | 0.167 | 0.867 |

**SE:** Standard Error, ***:** p < 1%, **(-1):** the one-period lag of the variable

According to the results in Table 11, the dynamic specification reveals a significant continuity in renewable energy supply share. This indicates that the renewable energy supply adjusts slowly over time. Under DK inference, GTI shows a positive and statistically significant short-run association with RES, whereas the average short-run effects of EG and ET remain statistically insignificant. Given the high persistence coefficient, the implied long-run association of GTI with RES is economically meaningful, suggesting that innovation-related gains may accumulate over

time. By contrast, the long-run magnitudes associated with EG and ET are comparatively small in the average specification.

These findings reveal that the dynamic model not only reports short-term coefficients but also provides an important analytical framework for assessing the cumulative effects of variables over time. In particular, the high persistence in the dependent variable indicates that the share of renewable energy supply is strongly influenced by past values, and therefore, some effects that appear limited in the short term may have more significant consequences in the long term. In this context, interpreting short-term coefficients alone is insufficient; long-term multipliers must also be considered within the dynamic structure. This allows for a more holistic assessment of the effects of green technological innovation, economic growth, and environmental taxation variables on renewable energy supply.

Correspondingly, the dynamic results strengthen the evidence that green technological innovation is a significant indicator of renewable energy supply share. The dynamic fixed-effects estimator is subject to a downward bias of order 1/T, as noted by Nickell [48].The remaining bias is expected to be at a reasonable level, amounting to approximately 7% for a persistence parameter of 0.83. A bias of this magnitude is unlikely to reverse the sign or statistical significance of our main coefficients. Nevertheless, this conclusion should be interpreted with caution, since Basu et al. [49] suggest that fixed-effects dynamic panel estimators may remain inconsistent under certain conditions even when the time dimension is relatively large. In addition, the consistency of the GTI coefficient across both the TWFE and CCE models supports the robustness of our findings.

At this point, it is necessary to examine the dynamic TWFE model specifically to determine the long-term effects of the independent variables. Upon evaluation, due to its high persistence ($\varphi \approx 0.832$), the implied long-run effect of GTI is sizable ($\approx 3.463$), suggesting that innovation-driven changes may accumulate over time. In contrast, under the estimated coefficients, the implied long-run effects for EG ($\approx 0.041$) and ET ($\approx 0.277$) are small. Therefore, a CCE robustness analysis was performed for the dynamic model. The relevant results are presented in Table 12.

**Table 12.** Dynamic CCE comparison

| | Dynamic | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | **TWFE (Two-Way Cluster)** | | | | **TWFE (Driscoll–Kraay)** | | | |
| | **Coefficient** | **SE** | **Statistic** | **p** | **Coefficient** | **SE** | **Statistic** | **p** |
| RES (-1) | 0.804 | 0.130 | 6.189 | 0.001* | 0.804 | 0.061 | 13.265 | 0.001* |
| GTI | 0.673 | 0.484 | 1.392 | 0.164 | 0.673 | 0.184 | 3.668 | 0.001* |
| EG | 0.009 | 0.017 | 0.535 | 0.593 | 0.009 | 0.017 | 0.531 | 0.595 |
| ET | 0.048 | 0.160 | 0.300 | 0.764 | 0.048 | 0.193 | 0.247 | 0.805 |

**SE:** Standard Error, ***:** p < 1%, **(-1):** the one-period lag of the variable

According to Table 12, GTI is positive and statistically significant, consistent with the dynamic TWFE result under Driscoll–Kraay inference. EG and ET remain insignificant. This robustness check supports the conclusion that GTI is a key correlate of RES when common dependence is addressed more comprehensively. Thus, a similar result to that of TWFE is observed. To examine this estimation on a country basis, groups were formed using median splits based on the initial RES level (RES0) and country means of GTI, EG, and ET. Each grouping yields a low and a high group, as shown in Table 13.

**Table 13.** Country grouping

| **Countries** | **RES0** | **$GTI_m$** | **$EG_m$** | **$ET_m$** |
|---|---|---|---|---|
| Australia | H | L | H | L |
| Austria | H | H | L | L |
| Belgium | L | L | H | L |
| Denmark | H | H | L | H |
| Finland | H | L | H | H |
| France | H | L | L | L |
| Germany | L | H | L | H |
| Greece | L | H | L | H |
| Ireland | L | L | H | L |
| Italy | L | L | L | H |
| Japan | L | H | L | L |
| Luxembourg | L | H | H | H |
| Mexico | H | H | H | L |
| Norway | H | H | H | L |
| Portugal | H | H | L | H |
| Sweden | H | L | H | H |
| United Kingdom | L | L | H | H |

**$_m$:** mean, **H:** High, **L:** Low

As shown in Table 13, countries were divided into high (H) and low (L) groups based on the mean values of the RES0, GTIm, EGm, and ETm variables. This classification reveals that the countries

in the sample do not have a similar structure in terms of all variables; rather, they exhibit different profiles in each indicator.

In this context, the extent to which the TWFE model and the CCE model capture heterogeneous structures differently was examined by comparing the estimated effects based on country groups. Thus, the aim was to both make visible within-group differences and to reveal how the coefficients change when cross-sectional dependence is taken into account. The summary results of these important comparisons are presented in Table 14.

**Table 14.** Comparisons between countries

| Model | Grouping | Variable | High-Low (Δ) | p (Δ) |
|---|---|---|---|---|
| TWFE | RES0 | GTI | 0.911 | 0.012** |
| TWFE | RES0 | EG | 0.065 | 0.017** |
| TWFE | RES0 | ET | -0.635 | 0.073*** |
| TWFE | $GTI_m$ | ET | -0.488 | 0.012** |
| TWFE | $ET_m$ | ET | -0.805 | 0.006* |
| CCE | RES0 | GTI | 0.803 | 0.022** |
| CCE | RES0 | EG | 0.060 | 0.018** |
| CCE | RES0 | ET | -0.736 | 0.038** |
| CCE | $GTI_m$ | ET | -0.502 | 0.021** |
| CCE | $ET_m$ | EG | -0.064 | 0.079*** |
| CCE | $ET_m$ | ET | -0.856 | 0.009* |

**$_m$:** mean, ***:** $p < 1\%$, ****:** $p < 5\%$, *****:** $p < 0.10$

**Note:** Δ denotes the difference between the estimated marginal effects in the high and low groups.

Looking at the information in Table 14, for the TWFE model, GTI and EG's effects on RES are significantly larger in the high-RES0 group than in the low-RES0 group ($\Delta = 0.911$, $p = 0.012$), indicating that innovation translates into higher renewable energy supply, particularly in countries that already had relatively higher initial RES. However, ET's impact on RES is significantly more negative for high-RES0 group countries, showing a negative effect for both the TWFE and CCE models. On the other hand, the negative impact of ET on RES is relatively less in high-$GTI_m$ group countries compared to high-RES0 group countries. Furthermore, the negative impact of EG on RES in the high-$ET_m$ countries is also noteworthy.

The negative ET coefficient observed in some high-baseline renewable-energy groups should not be taken as proof that taxation is always counterproductive. Instead, it likely indicates differences in how taxes are designed, targeted, and how the revenue is used. When energy taxes are broad,

only weakly recycled, or not well aligned with activities that produce carbon emissions, they might increase costs for production and investment without leading to a proportionate increase in renewable energy deployment. In well-developed renewable energy systems, additional tax pressure can actually hinder investment unless paired with effective revenue recycling, grid support, storage funding, and risk-reduction measures.

The final step of the estimation methodologies, the causality test, aimed to investigate causal relationships and determine the connections between variables. The long-run results of the analysis are presented in Table 15.

**Table 15.** Results of the causality test (long-run)

| DV | IV | W-stat | Zbar | p | Summary |
|---|---|---|---|---|---|
| RES | EG | 1.670 | 1.954 | 0.025** | |
| RES | ET | 1.905 | 2.638 | 0.004* | EG ↔ RES |
| ET | RES | 2.690 | 4.926 | 0.001* | ET ↔ RES |
| EG | RES | 2.525 | 4.445 | 0.001* | RES → GTI |
| GTI | RES | 1.824 | 2.402 | 0.008* | |

**DV:** Dependent Variable, **IV:** Independent Variable, ***:** p < 1%, ****:** p < 5%

According to the results in Table 15, a causal relationship exists between all independent variables and the dependent variable in the long term. It appears that the variables EG and ET have a bidirectional causal relationship with RES. However, in the long term, RES causes GTI, not the reverse. Looking at short-term causal relationships, the results in Table 16 are noteworthy.

**Table 16.** Results of the causality test (short-run)

| DV | IV | W-stat | Zbar | p | Summary |
|---|---|---|---|---|---|
| ΔRES | ΔEG | 2.045 | 3.046 | 0.001* | ΔEG ↔ ΔRES |
| ΔEG | ΔRES | 1.576 | 1.679 | 0.047** | |

**DV:** Dependent Variable, **IV:** Independent Variable, ***:** p < 1%, ****:** p < 5%

According to the results in Table 16, a statistically significant bidirectional causal relationship exists only between economic growth and renewable energy supply. No significant short-term causal relationship is observed between other variables and RES.

Although regression and causality findings appear contradictory, these two approaches measure different dimensions of the relationship between variables. Regression models estimate the

direction and magnitude of the conditional relationship between variables, considering fixed effects, common shocks, and dynamic structure, while the Dumitrescu-Hurlin causality test examines whether lagged values of one variable under a specific lag structure statistically contribute to the prediction of another variable. Therefore, a positive and significant GTI coefficient within the regression framework does not mean that GTI is a Granger cause of renewable energy in the short term.

This situation can be explained, in particular, by the fact that the effects of innovation processes often appear with a delay. The impact of green technological innovations on renewable energy supply may not be fully observable in the short term due to factors such as the commercialization process, investment requirements, financing conditions, regulatory approvals, and country-specific absorption capacity. Thus, determining the predictive power of RES to GTI within the selected short lag horizon, but not statistically supporting an inverse relationship, should be considered a methodologically consistent finding.

## 5. CONCLUSION

Innovations, traditionally considered a strategic tool for national development, are vital in financial systems, particularly in the energy sector, for maintaining a balance between supply and demand, directing investments to appropriate sectors, and implementing necessary measures to achieve desired outcomes. In contemporary commercial environments where the supply share of renewable energy sources is gaining increasing importance, innovations focused on the more optimal management of these resources are needed.

This study, focusing on the impact of green technology innovations on renewable energy supply, examines RES and their potential key drivers (GTI, EG, and ET) using a balanced panel dataset covering 17 countries between 1995 and 2021. The results of analyses using appropriate estimation and diagnostic techniques on this panel dataset show significant differences between countries and a strong continuity in RES.

According to the results of tests considering cross-sectional dependence, continuity, and common shocks, GTI stands out as the most consistent positive correlation of RES across preferred specifications. In contrast, the average short-term effects of EG and ET appear weaker and more context-dependent. Overall findings, with notable differences across country groups, suggest that

changes in renewable energy supply are influenced not only by general macroeconomic conditions but also by innovation capacity, policy design, and fundamental system characteristics.

When dynamic specifications were evaluated, the lagged renewable energy supply share (RES) coefficient was found to be highly significant and statistically meaningful ($\varphi \approx 0.80–0.83$). This model, consistent with the concepts of energy system inertia, infrastructure lock-up, and the cumulative nature of renewable capacity growth, demonstrated that renewable energy supply is adjusted gradually, not instantaneously. Because this result suggests that short-term coefficients may underestimate the overall effect of explanatory variables, long-term effects were calculated using the standard partial adjustment method. The results showed that the implied long-term effect of GTI is significantly larger and more persistent than its short-term effect.

In both static and dynamic two-way fixed-effects models, the effect of GTI was found to be statistically significant under Driscoll-Kraay inference, and this effect was confirmed to be positive within the dynamic CCE robustness framework. These findings suggest that, when common shocks and dependency structures are appropriately managed, green technology innovations can be consistently associated with the expansion of renewable energy supply.

Conversely, EG and ET did not exhibit stable average short-run effects. However, noteworthy heterogeneity was observed. In fundamental dynamic models, EG and ET were generally not statistically significant on average. Nonetheless, interaction-based heterogeneity tests revealed that their marginal effects differ systematically across country groups. Specifically, the effects of GTI and EG were markedly more pronounced in the high-initial-RES (High RES0) group, suggesting that green technology innovation and economic growth may be more effective at increasing renewable energy supply in contexts where related institutional, infrastructural, and absorptive capacities are already more developed.

Contrarily, sign-switching patterns were observed for ET. ET was positive and significant in the low-initial-RES group but became negative in the high-initial-RES group, with the high–low difference reaching conventional significance levels in both TWFE and CCE heterogeneity models. Moreover, heterogeneity in ET was also detected when countries were grouped by mean GTI and mean ET, with ET tending to become more negative in higher-tax and/or higher-innovation environments. These findings collectively indicate that fiscal instruments do not exert

a uniform marginal effect across settings. Instead, their impact appears conditional on baseline renewable supply and the broader policy/innovation context.

Regression findings show that GTI is consistently a positive predictor of RES, while the mean effects of EG and ET appear either weaker or contextually variable. This suggests that the supply of renewable energy is primarily driven by technological progress and implementation capacity, while macroeconomic conditions and fiscal tools may have heterogeneous effects across different country groups and policy regimes.

Correspondingly, findings of the causality test suggest that renewable energy supply is embedded in a broader feedback system. The EG–RES relationship exhibits robust bidirectional dynamics in both levels and short-run changes, indicating mutual reinforcement. The ET–RES relationship also shows bidirectional dynamics in levels, indicating a policy–transition feedback loop that is less visible in short-run differences. However, the RES → GTI result suggests that renewable energy supply share itself stimulates innovation, whereas the opposite direction (GTI → RES) is not detected at short horizons, implying that green technology innovation may influence renewable energy supply through longer lags or conditional pathways.

On the other hand, the study has some limitations. The analysis was conducted on a moderate-sized macro panel (N=17, T=27), and while robust inference and common-factor robustness were implemented, residual dependence signals indicate that unobserved global components may not be fully eliminated. In addition, dynamic fixed-effects models with lagged dependent variables can be subject to finite-sample bias, and the empirical relationships should not be interpreted as definitive effects in the absence of additional identification strategies (external instruments, policy timing designs, or carefully specified GMM validations). Also, the absence of short-run GTI → RES causality should not be interpreted as evidence against the strategic relevance of innovation. Rather, it suggests that innovation works through cumulative and delayed channels, including commercialization, regulatory adaptation, financing processes, and deployment capacity. Thus, policy frameworks aimed at expanding renewable energy supply should treat green innovation as a medium- and long-term strategic instrument rather than expecting immediate short-run effects.

Despite its limitations, this research adopts dependency-robust inference and common factor estimators, which are considered suitable for future macro-panels. Furthermore, the research

reveals how the relationships between macroeconometric indicators differ according to the basic renewable energy conditions of countries through heterogeneity analyses.

In evaluating the results, the necessity of prioritizing innovation-focused transition strategies stands out as a key practical takeaway. Given the strong positive correlation between GTI and RES, it is considered that supportive mechanisms for green technology innovation could include R&D incentives, commercialization pathways, and diffusion policies. It is argued that considering these fundamental tools for increasing renewable energy supply together with fiscal policies will yield significant long-term benefits. The slow adaptation observed depending on the continuity of RES reveals that the effectiveness of innovation and fiscal tools should be evaluated over multi-year horizons. Therefore, it is understood that long-term outcome measures such as capacity increase, grid integration performance, and investment continuity should be prioritized over short-term fluctuations.

As an alternative implication, it is suggested that decision-makers implement additional reforms (increasing grid connection capacity, simplifying permitting processes, improving financing conditions, and ensuring regulatory predictability) to encourage investments, improvements, and expansions toward renewable energy supply, which could also encourage reliance on fossil fuels, and to explicitly link this to readiness status.

Standing out in these contexts, it is important to remember that country-specific variability and sign-shifting effects can either encourage or hinder renewable energy supply in the proposed energy tax design. Taxes that directly target carbon-intensive sources and provide clear relative price signals are considered to be more compatible with renewable energy growth targets. In implementing the transition to renewable energy or expanding renewable energy supply, it is recommended that a transparent revenue return mechanism be implemented to direct funds towards grid improvements, storage, renewable energy supply, and risk mitigation measures. It is believed that this approach will improve supply response and prevent negative investment effects.

To maintain policy viability and sustain investment credibility, it is recommended to implement targeted compensation mechanisms and establish predictable tax trajectories, particularly in scenarios where the rollover of energy costs could constrain industrial investment or impact household welfare. Energy policies need to be tailored to baseline renewable energy conditions,

paying attention to the more pronounced GTI and EG effects observed in countries with high levels of renewable energy sources. It is necessary to consider the fact that absorber capacity and existing renewable energy infrastructure influence renewable energy supply processes. For regions with low initial renewable energy sources, it is recommended to prioritize fundamental investments (such as grid readiness, regulatory capacity, and project financing) and take effective steps to maximize outputs achieved through green technology innovations.

Given that implemented financial and innovative policies vary among different country groups, it is considered highly unlikely that innovation incentives alone will be sufficient for countries with low initial renewable energy share unless fundamental implementation conditions are improved first. It is believed that key priorities should include investments in grid readiness, storage capacity, simplified permitting processes, predictable regulatory frameworks, concessional or hybrid financing, and project risk mitigation mechanisms that enhance banking opportunities.

Future research could extend the present framework by refining measurement and modelling choices to better represent the innovation-to-deployment channel. The GTI-RES nexus may be re-examined using alternative indicators that more directly reflect deployment-relevant progress, such as technology-class-specific green patent families, citation-weighted patents, renewable-focused R&D intensity, and commercialization proxies including venture financing and technology adoption rates. In addition, the observed heterogeneity motivates explicit testing for nonlinear and threshold dynamics through approaches such as threshold panel models, quantile regressions, or regime-switching specifications, which can assess whether the effects of green innovation and energy taxation become stronger only after minimum conditions in grid readiness, institutional quality, or renewable penetration are satisfied.

## DECLARATION OF ETHICAL STANDARDS

The authors of the paper submitted declare that nothing which is necessary for achieving the paper requires ethical committee and/or legal-special permissions.

## CONTRIBUTION OF THE AUTHORS

**Oğuz Emre Balkar:** Research, conceptualization, data analysis, methodologies, writing and editing.

**Okan Alkan:** Research, conceptualization, data analysis, methodologies, writing and editing.

**Yunus Emre Özenoğlu:** Research, conceptualization, data analysis, methodologies, writing and editing.

## CONFLICT OF INTEREST

There is no conflict of interest in this study.

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