“Assessing the efficiency of renewable energy policies: A DEA, machine learning, and panel data approach”

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ASSESSING THE EFFICIENCY OF RENEWABLE ENERGY POLICIES: A DEA, MACHINE LEARNING, AND PANEL DATA APPROACH

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Abstract

The accelerating energy transition and uneven effectiveness of renewable energy policies across OECD member, accession, and key partner countries covered by the OECD policy database highlight the need to understand which policy designs deliver efficient outcomes. This study aims to assess how different regulatory policy instruments and their combinations influence the efficiency with which countries convert policy stringency inputs into renewable electricity generation outcomes. The analysis uses panel data for 47 countries over 2000–2023, combining Data Envelopment Analysis, Random Forest modeling, and fixed-effects regressions with lagged variables. The results show that the average DEA efficiency score is 0.348 (median = 0.258), indicating substantial underperformance relative to the best-practice frontier. Random Forest results reveal that structural factors dominate, with energy intensity (IncNodePurity = 2.53×10^{-12}) and GDP per capita (1.44×10^{-12}) exhibiting the highest variable importance scores. Among policy instruments, feed-in tariffs, renewable energy auctions, and emission standards have the most robust positive associations. Interaction effects indicate complementarity, with the joint impact of feed-in tariffs and auctions being positive and significant. In contrast, most individual instruments show limited or insignificant effects, confirming that policy effectiveness depends on coordinated policy mixes and structural conditions rather than isolated measures.

Keywords energy transition, regulatory stringency, energy policy, policy mix, RE generation, cross-country analysis

JEL Classification Q42, Q48, Q58, C14

INTRODUCTION

The rapid acceleration of the global energy transition has made the effectiveness of renewable energy policies a central concern for policymakers and international organizations. Recent reports by the International Energy Agency emphasize that, despite record growth in renewable electricity capacity, global progress remains uneven and insufficient to meet net-zero targets, with persistent gaps in policy implementation and investment (IEA, 2025, 2026). Similarly, the International Renewable Energy Agency notes that although renewable capacity additions reached historic levels, structural barriers such as grid constraints, fossil-fuel lock-in, and regulatory inconsistencies continue to limit efficiency gains (IRENA, 2025). The Organization for Economic Co-operation and Development further notes that countries differ significantly in their ability to translate policy efforts into renewable energy outcomes due to variations in institutional quality and policy coherence (OECD, 2025). These findings underscore that the mere presence of renewable energy policies is insufficient; their effectiveness depends critically on design, coordination, and systemic alignment.

Recent international evidence points to a growing consensus that policy mixes, rather than individual instruments, are essential for achieving effective and sustained renewable energy deployment. The OECD (2025) and IEA (2025) highlight that combining market-based mechanisms, such as auctions, feed-in tariffs, and carbon pricing, with regulatory instruments, such as emission standards and fossil fuel phase-out policies, enhances investment certainty and improves system efficiency. Likewise, IRENA and CPI (2025) emphasize that stable, coordinated policy frameworks are necessary to mobilize long-term energy transition finance and reduce investment risks. However, despite this growing recognition, there remains a lack of rigorous empirical analysis identifying which specific policy combinations are most effective and how they interact to influence efficiency outcomes.

At the same time, recent reports increasingly emphasize the role of structural and institutional conditions in shaping policy effectiveness. The OECD (2025) points to the importance of economic development, governance quality, and regulatory capacity in determining the success of renewable energy policies. The IEA (2025) further highlights that energy system characteristics, including energy intensity and infrastructure readiness, critically influence how policies translate into actual renewable generation. In parallel, IRENA and CPI (2025) underline that institutional stability and credible long-term policy signals are essential for attracting energy-transition investment. These insights collectively indicate that policy effectiveness cannot be evaluated in isolation but must be analyzed within a broader systemic context, thereby reinforcing the need for integrated analytical frameworks that capture both policy interactions and structural determinants of renewable energy efficiency. In this study, renewable energy policy efficiency is understood as the relative efficiency with which countries transform regulatory policy stringency inputs into renewable electricity generation, measured as the share of renewable electricity in total electricity generation.

1. LITERATURE REVIEW

The effectiveness of renewable energy policies has been widely examined within the broader framework of environmental regulation, technological change, and sustainable energy transition. Early studies established that policy instruments influence technology diffusion and innovation through dynamic incentives, market signals, and regulatory pressure, but they also showed that no single instrument is sufficient to generate optimal outcomes in complex energy systems (Jaffe & Stavins, 1995; Fischer & Newell, 2008; Johnstone et al., 2009). This perspective laid the foundation for analyzing renewable energy policy not as a set of isolated measures, but as a combination of mutually reinforcing instruments. Later research confirmed that regulatory push, technology push, and market pull jointly shape eco-innovation and environmental outcomes, supporting the need to assess renewable energy policies through integrated policy-mix frameworks rather than individual tools alone (Horbach et al., 2012).

A substantial part of the literature focuses on environmental policy stringency, energy efficiency, and renewable energy deployment. Efficiency-based evidence indicates that environmental regulation may improve energy performance, though the magnitude and direction of the effects depend on sectoral conditions, regulatory design, and implementation quality (Bi et al., 2014). Cross-country and regional studies further demonstrate that policy stringency can support renewable energy production, but its effectiveness differs across institutional and territorial contexts (Godawska & Wyrobek, 2021; Vasa et al., 2024; Štreimikienė, 2024). These findings are particularly relevant for the present study because they indicate that the key question is not only whether renewable energy policies exist, but how efficiently countries transform regulatory policy stringency into renewable electricity outcomes.

Broader structural and macroeconomic conditions also shape the effectiveness of renewable energy policies. Energy intensity, resource productivity, sectoral resilience, and economic capacity influence countries' ability to convert policy efforts into measurable renewable energy outcomes (Taušová et al., 2022; Pimenow et al., 2026). This is consistent with the view that renewable energy policy efficiency depends not only on regulatory

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instruments but also on the underlying structure of the energy system. Recent evidence on energy security and renewable deployment also highlights the importance of macroeconomic stability, energy dependency, and geopolitical shocks, especially in the European context and in relation to the war in Ukraine (Wołowiec et al., 2022; Havrylenko & Myroshnychenko, 2025; Vasylieva et al., 2025a, 2025b). These studies support the inclusion of structural control variables and justify the cross-country analytical design.

Another central strand of research emphasizes policy coherence, governance, and institutional quality. Policy coordination across sectors is essential because environmental and energy instruments often interact, overlap, or generate unintended effects when implemented separately (Nilsson et al., 2012; Roelfsema et al., 2020). Recent studies show that differences in regulatory convergence, governance capacity, and institutional conditions may explain why similar environmental policies produce different outcomes across countries (Alper et al., 2026; Ferenczi Vaňová et al., 2026). Sustainable governance and green-growth frameworks further indicate that policy effectiveness depends on the quality of institutions, coordination mechanisms, and the capacity to manage long-term transition risks (Shanyazov et al., 2026; Türüç-Seraj et al., 2026). This literature directly supports the present study's focus on policy mixes and institutional conditions.

Financial instruments and investment mechanisms are another important foundation for the effectiveness of renewable energy policy. Feed-in tariffs, power purchase agreements, government expenditure, and sustainable finance mechanisms can reduce investment uncertainty and stimulate renewable energy deployment, although their effects depend on market maturity and policy stability (Lyeonov & Moroz, 2025; Shcherbakova, 2025; Fernandes et al., 2025). Broader financial-market and infrastructure-investment conditions also shape economies' ability to support the energy transition through capital mobilization and long-term investment planning (Krause et al., 2024; Patnaik & Hedau, 2026). These studies are closely linked to the empirical model because several policy inputs analyzed in this article, including feed-in tariffs and auctions, function through investment incentives and risk-reduction channels.

A related but more peripheral strand of literature broadens the discussion of renewable energy policy effectiveness by examining organizational, behavioral, public health, corporate, start-up, and digital governance channels of the sustainability transition. Green human resource management, ethical and strategic leadership, behavioral incentives, and public-health improvements are not direct components of the empirical model used in this study, but they illustrate how environmental regulation may operate through organizational adaptation, social acceptance, behavioral change, and co-benefits (AlNaqbi & Mohd Shamsudin, 2024; Barcelona, 2025; Burrell et al., 2025; Badreddine & Larbi Cherif, 2024). Similarly, research on energy entrepreneurship ecosystems, investor protection, and digitalization points to broader governance, innovation, and market-adaptation mechanisms that may indirectly influence environmental and renewable energy policy outcomes (Halynskyi & Telizhenko, 2024; Sira & Kuzior, 2025; Yu et al., 2021). Corporate reporting quality, sustainable development, and carbon tax cooperation further highlight the importance of transparency, regulatory accountability, and international coordination in shaping the effectiveness of environmental policy (To & Tran, 2025; Trinh, 2025; Yoshimori, 2024). These studies are therefore used as contextual support rather than as direct empirical foundations for the DEA-Random Forest-panel data model.

Recent literature also highlights uncertainty, informality, and macro-financial instability as factors that may weaken the transmission of environmental policies into expected outcomes. Climate policy uncertainty can affect carbon productivity and investment decisions, while financial stress may influence the performance of clean energy markets (Cui & Yuan, 2025; Sahu et al., 2026). Environmental policies may also interact with informal economic activity, compliance incentives, and governance constraints, thereby reducing the effectiveness of formal regulatory instruments (Lyeonov et al., 2025a, 2025b). This evidence suggests that renewable energy policy efficiency should be analyzed not only through direct policy effects but also through the broader institutional and economic environment in which such policies operate.

Despite these advances, several gaps remain. Existing studies often focus on individual policy instruments, specific regions, or single methodological approaches. In contrast, fewer studies combine efficiency analysis, machine learning, and panel econometrics to assess the effectiveness of renewable energy policy in an integrated manner. The interaction effects between policy instruments and the role of structural, institutional, and governance conditions also remain insufficiently explored in cross-country settings. However, recent studies emphasize that sustainable governance, green-growth strategies, institutional capacity, and leadership mechanisms are essential for effective environmental and energy transitions (Shanyazov et al., 2026; Türüç-Seraj et al., 2026; Ntshangase et al., 2024; Stadniichuk et al., 2025). This gap is particularly important when policy effectiveness is defined as the efficiency with which regulatory stringency inputs are converted into renewable electricity outcomes (Sitnicki et al., 2026a, 2026b; Kuzior et al., 2025). Therefore, this study addresses the identified gap by integrating DEA, Random Forest analysis, and fixed-effects panel modeling to identify which policy instruments and policy combinations are associated with higher renewable energy policy efficiency.

The existing scientific literature demonstrates that interactions among regulatory instruments, financial incentives, institutional quality, and structural energy-system conditions shape the effectiveness of renewable energy policy. However, the literature still lacks comprehensive empirical frameworks capable of capturing these multidimensional relationships within one analytical design. This study contributes to the literature by assessing not only which instruments matter, but also how policy mixes and structural conditions jointly shape the efficiency with which policy stringency translates into renewable electricity generation outcomes.

This study aims to assess how different regulatory policy instruments and their combinations influence the efficiency of renewable electricity generation across OECD member, accession, and key partner countries covered by the OECD policy database, and to determine the structural and institutional conditions under which these policies are most effective.

2. METHODOLOGY

This study employs a multi-stage empirical strategy to examine the effectiveness of regulatory policy instruments in promoting renewable electricity generation across a panel of 47 countries over the period 2000–2023. The analysis integrates non-parametric efficiency measurement, machine learning techniques, and panel econometric modeling to capture both relative performance and complex policy dynamics.

The dataset is constructed from multiple international sources. The core policy variables – stringency indices for ETS (electricity), carbon taxes, fossil fuel subsidies, fossil fuel excise taxes, feed-in tariffs, renewable energy auctions, renewable energy certificates, coal phase-out policies, planning for renewable expansion, air emission standards, cross-sectoral policies, and international policies – as well as renewable electricity generation (percentage of total electricity generation) and energy intensity per capita (tonnes of oil equivalent per person) are obtained from the OECD Data Explorer (OECD, n.d.). GDP per capita (constant 2015 US dollars) is sourced from the World Bank (World Bank, n.d.), while the Heritage Index of Economic Freedom is sourced from The Heritage Foundation (The Heritage Foundation, n.d.).

The sample includes the following OECD member, accession, and key partner countries, covered by the OECD policy database: Argentina, Australia, Austria, Belgium, Bulgaria, Canada, Chile, China, Colombia, Costa Rica, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Latvia, Lithuania, Luxemburg, Malta, Mexico, the Netherlands, New Zealand, Norway, Peru, Poland, Portugal, Romania, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Turkey, and the United Kingdom. The inclusion criterion was the availability of harmonized OECD policy stringency indicators and corresponding renewable electricity, energy intensity, GDP per capita, and institutional data for the period 2000–2023. Therefore, the sample includes OECD member countries as well as selected non-OECD economies covered by the OECD policy database. The initial dataset contains 1,128 country-year observations. The panel

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is unbalanced due to missing values in some variables and the construction of lagged policy variables. Fixed-effects regressions use 1,081 observations because the first year of observation for each country is lost after introducing one-year lags and because observations with incomplete transformed variables are excluded.

In the first stage, Data Envelopment Analysis (DEA) is applied to estimate the relative efficiency with which countries convert regulatory policy stringency inputs into renewable electricity generation outcomes. The decision-making units are country-year observations for 47 OECD member, accession, and key partner countries covered by the OECD policy database over the period 2000–2023. The DEA model is specified as an output-oriented model with variable returns to scale (VRS), because the purpose is to assess how far renewable electricity generation could be increased for a given level of policy stringency rather than to minimize policy inputs. The output variable is renewable electricity generation, measured as the percentage share of renewable electricity in total electricity generation. The input variables are the twelve OECD policy stringency indices: ETS – electricity, carbon tax – electricity, fossil fuel subsidies – electricity, fossil fuels excise taxes – electricity, feed-in tariffs, renewable energy auctions, renewable energy certificates, ban and phase-out on the construction of coal-fired power plants, planning for renewables expansion, air emission standards, cross-sectoral policies, and international policies. Thus, all policy stringency indices are treated as DEA inputs.

The DEA model is estimated in R using the Benchmarking package. Zero values in policy stringency indices are retained because they represent the absence of a given policy instrument or the lowest level of policy stringency and are therefore meaningful observations rather than missing values. Observations with missing values in any DEA input or output variable are excluded from the corresponding estimation. Structural and macroeconomic variables, including energy intensity, GDP per capita, and the Heritage Foundation's Economic Freedom Index, are not included in the DEA model. They are used only in the second-stage Random Forest and fixed-effects panel models to explain differences in DEA efficiency across countries and over time. The resulting output-oriented DEA scores are bounded between 0 and 1 and subsequently logit-transformed for use in fixed-effects regressions.

Because the DEA efficiency score is constructed using policy stringency indices as inputs, the second-stage models are not interpreted as independent causal tests of the same policy instruments. Instead, the Random Forest and fixed-effects models are used as diagnostic tools to examine which policy-input dimensions and structural conditions are most strongly associated with variation in the constructed efficiency score. This interpretation recognizes that policy variables enter both the DEA construction and the second-stage analysis; therefore, the second-stage results should be understood as identifying patterns of relative contribution, non-linear associations, and complementarities within the policy-efficiency framework rather than as causal estimates of policy impacts.

In the second stage, a Random Forest model is used to examine the relative contribution of policy-input dimensions and structural variables to variation in DEA efficiency scores. This non-parametric approach allows for the detection of complex nonlinear relationships and interaction effects without imposing restrictive functional form assumptions. Variable importance measures are complemented by partial dependence plots and interaction diagnostics to enhance interpretability and uncover potential threshold effects. The dependent variable in the Random Forest model is the bounded DEA efficiency score, while policy stringency indices and structural variables are used as predictors.

In the third stage, the DEA-based patterns are further examined using two-way fixed-effects panel models that incorporate both country- and year-fixed effects to control for unobserved heterogeneity and common temporal shocks. These models are interpreted as robustness and association checks rather than causal second-stage regressions. Lagged policy variables are included to account for delayed policy impacts. Additional specifications test for non-linear effects through quadratic terms and for policy complementarity through interaction terms. The dependent variable in the fixed-effects regressions is the logit-transformed DEA efficiency score.

This integrated methodological framework enables a comprehensive assessment of policy effectiveness, combining efficiency measurement, flexible modeling of complex relationships, and econometric robustness.

DEA results are sensitive to the selection and number of policy input variables; in this study, DEA uses twelve policy stringency indices as inputs and renewable electricity generation share as the only output, while structural variables are analyzed only in the second-stage models. Although lagged variables and fixed effects reduce some endogeneity concerns, the analysis should be interpreted as associative rather than strictly causal. Random Forest improves the detection of non-linearities and interactions, but does not establish causality. In addition, the sample includes OECD member, accession, and key partner countries, covered by the OECD policy database, thereby increasing heterogeneity. The use of aggregate renewable electricity generation fails to distinguish between technologies such as wind, solar, hydro, and biomass. A further limitation is that several policy variables used as explanatory variables in the second-stage models are also used as DEA inputs; therefore, the second-stage results may partly reflect the constructed nature of the DEA efficiency score and should be interpreted as diagnostic associations rather than causal effects. Future research should employ stronger causal identification strategies, include measures of policy implementation quality, and examine technology-specific outcomes of renewable energy.

3. RESULTS

The descriptive statistics presented in Table A1 (Appendix A) provide an overview of the variation in regulatory policy instruments, renewable energy outcomes, and structural control variables across OECD member, accession, and key partner countries over the period 2000–2023. The average share of renewable electricity generation amounts to 34.34%, with substantial dispersion (SD = 28.42), indicating pronounced cross-country heterogeneity in energy transitions. Policy instruments exhibit markedly different distributions. Market-based instruments, such as the emissions trading system (ETS), show a moderate average intensity (mean = 3.49) and a relatively symmetric distribution. In contrast, carbon taxes and fossil fuel excise taxes exhibit highly skewed distributions (skewness = 3.59 and 4.69, respectively), with medians equal to zero, suggesting that these instruments are implemented in only a limited subset of countries and years. Similarly, renewable energy auctions and certificates exhibit strong right-skewness and excess kurtosis, indicating episodic or uneven adoption patterns across the sample.

In contrast, regulatory and planning instruments, such as air emission standards (mean = 4.32) and planning for renewable energy expansion (mean = 2.29), appear more widely implemented and exhibit more balanced distributions, although some still show moderate skewness. Fossil fuel subsidies and cross-sectoral policies show relatively stable averages but considerable variability, reflecting differences in national policy frameworks. Importantly, several policy variables have medians equal to zero, highlighting the prevalence of non-adoption or delayed adoption across 47 OECD member, accession, and key partner countries covered by the OECD policy database and reinforcing the need to analyze policy mixes rather than individual instruments in isolation.

With respect to control variables, GDP per capita averages 28,621 USD (constant 2015 prices), with substantial dispersion, indicating wide differences in economic development. Energy intensity per capita (mean = 3.39 tonnes of oil equivalent) is strongly right-skewed (skewness = 2.84), suggesting that a small number of highly energy-intensive economies drive the upper tail of the distribution. The Heritage Index of Economic Freedom shows a relatively symmetric distribution around a mean of 68.28, reflecting moderate institutional variation across OECD member, accession, and key partner countries. The descriptive evidence points to significant heterogeneity in both policy design and structural conditions, supporting the use of flexible, non-linear modeling approaches and efficiency-based frameworks to capture the complex relationships between regulatory stringency and renewable energy performance.

The DEA results reported below are based on an output-oriented VRS specification using the twelve OECD policy stringency indices as inputs

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and the renewable electricity generation share as the output. The results indicate substantial heterogeneity in both renewable electricity outcomes and the efficiency with which regulatory policy instruments are translated into these outcomes across country–year observations in the analyzed sample. Renewable electricity generation exhibits a wide distribution, with a mean of 34.34% and a median of 25.31%, suggesting that while several countries have achieved high shares of renewables (up to 99.99%), a considerable proportion of observations remains at relatively low levels, as reflected in the first quartile of 11.41%. This confirms uneven progress in the energy transition across the sample.

The output-oriented DEA results further reinforce this heterogeneity. The raw efficiency scores (*dea_eff_out*) exhibit extreme dispersion, including infinite values, arising from observations with very low or zero renewable output relative to the policy input bundle. This indicates that, for some country-year cases, the model identifies extremely large proportional gaps between observed performance and the estimated frontier, reflecting weak conversion of regulatory stringency into renewable energy outcomes. Such behavior is typical in DEA when outputs approach zero, underscoring the presence of structurally inefficient observations.

After transformation into the bounded efficiency measure (*dea_eff_*01), the results become more interpretable. The efficiency scores range from 0 to 1, with a mean of 0.348 and a median of 0.258, indicating that the average country operates well below the best-practice frontier. In practical terms, this suggests that, given their levels of policy intensity, most countries could substantially increase their renewable electricity share if they operated as efficiently as frontier countries. The relatively high standard deviation (0.288) points to pronounced cross-country variation in policy effectiveness. At the same time, the presence of frontier observations (max = 1) confirms that certain country-year combinations successfully achieve optimal conversion of regulatory inputs into renewable outcomes. The findings highlight both the existence of best-practice policy configurations and significant inefficiencies in the majority of cases, justifying further investigation into the role of specific policy instruments and their combinations.

The Random Forest results presented in Table 1 reveal a clear hierarchy in the determinants of DEA-based efficiency in transforming regulatory policy instruments into renewable electricity outcomes. The importance measures, based on both the percentage increase in mean squared error (%IncMSE) and node purity (IncNodePurity), consistently indicate that structural and macroeconomic factors dominate policy-specific variables in explaining efficiency differences across OECD member, accession, and key partner countries. Since the DEA efficiency score is constructed from the policy stringency inputs, the Random Forest results should be interpreted as a diagnostic ranking of variables associated with efficiency variation, not as causal evidence that these instruments contribute to the construction and variation of DEA-based efficiency.

Table 1. Random Forest variable importance for DEA efficiency

Variable	%IncMSE	IncNodePurity
ln_energy_intensity	7.66e-15	2.53e-12
ln_gdp_pc	6.84e-15	1.44e-12
Heritage Index of Economic Freedom	2.97e-15	1.01e-12
Air emission standards	5.06e-15	9.92e-13
Cross-sectoral policies	2.08e-15	5.44e-13
Coal phase-out policies	2.42e-15	4.99e-13
International policies	9.74e-16	3.62e-13
Feed-in tariffs	1.03e-15	3.10e-13
Planning for renewables expansion	9.24e-16	2.72e-13
Fossil fuels excise taxes	6.35e-16	2.72e-13
Fossil fuel subsidies	9.51e-16	2.50e-13
ETS (Electricity)	6.24e-16	1.57e-13
Renewable energy certificates	4.95e-16	1.45e-13
Carbon tax	1.29e-16	6.66e-14
Renewable energy auctions	4.02e-17	4.37e-14

Among all predictors, energy intensity per capita (ln_energy_intensity) emerges as the most influential, with the highest IncNodePurity and %IncMSE values. This suggests that countries with lower energy intensity are substantially more efficient at translating regulatory efforts into renewable energy outcomes, highlighting the critical role of the underlying energy system structure. Similarly, GDP per capita (ln_gdp_pc) and the Heritage Index of Economic Freedom also display high variable-importance scores.

Among policy instruments, the most influential variables include air emission standards, cross-sectoral policies, and coal phase-out regulations, all of which have relatively high importance scores. This implies that broad regulatory frameworks and structural constraints on fossil fuel use are more effective in driving efficiency than narrowly targeted instruments. In contrast, market-based mechanisms such as renewable energy auctions, carbon taxes, and excise taxes are comparatively less important, suggesting a limited standalone impact within the broader policy mix.

Notably, feed-in tariffs, planning for renewables expansion, and international policies occupy an intermediate position, indicating that while these instruments contribute to efficiency, their effectiveness is conditional on the broader economic and institutional environment. The results underscore that policy effectiveness is not solely determined by the presence of specific instruments but by their interaction with structural economic conditions and comprehensive regulatory frameworks.

Figure 1 presents the graphical representation of variable importance derived from the Random Forest model, illustrating the relative contribution of each predictor to the explanation of DEA efficiency. The plot visually confirms the dominance of structural variables, with energy intensity and GDP per capita clearly standing out as the most influential determinants. These variables exhibit substantially higher importance scores than individual policy instruments, indicating that underlying economic and energy system characteristics strongly condition the efficiency of renewable energy transformation.

Among policy-related variables, the plot highlights air emission standards, cross-sectoral policies, and coal phase-out measures as the most relevant contributors, forming a second tier of importance. In contrast, market-based instruments such as auctions and carbon taxes appear at the lower end of the importance spectrum, reinforcing the conclusion that their effectiveness is limited when not embedded within a broader regulatory and institutional framework.

The overall pattern observed in Figure 1 suggests a multi-layered structure of determinants, with macroeconomic conditions forming the primary layer, comprehensive regulatory frameworks constituting the second layer, and specific policy instruments playing a complementary role. This visual evidence supports the argument that policy mixes, rather than individual instruments, are central to achieving high efficiency in renewable energy transitions.

Figure 2 presents the Random Forest variable importance plot, which provides a visual ranking of predictors based on their contributions to explaining DEA efficiency. It clearly demonstrates a strong concentration of explanatory power among a limited set of variables, with energy intensity per capita and GDP per capita emerging as the dominant determinants. These variables are positioned at the top of the plot with substantially higher importance scores, indicating that structural economic and energy system characteristics play a primary role in shaping the efficiency with which regulatory policies are translated into renewable electricity outcomes.

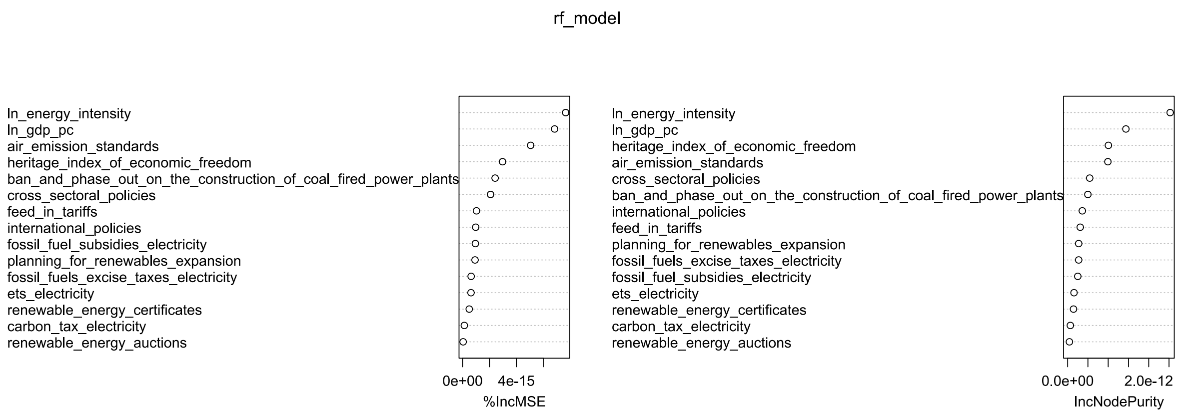

Figure 1. The graphical representation of variable importance derived from the Random Forest model

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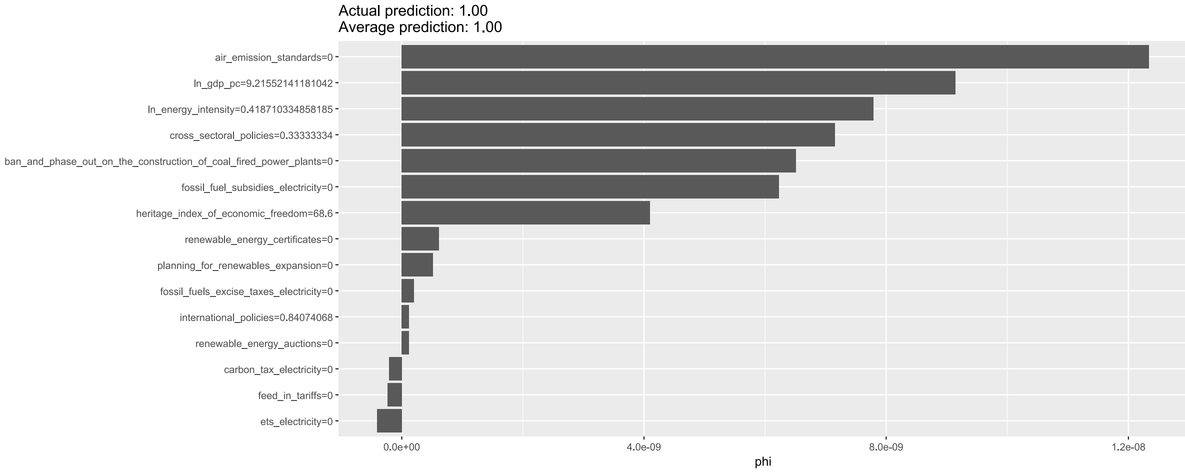

Figure 2. Random Forest variable importance plot

The second tier of variables consists of institutional quality (Heritage Index of Economic Freedom) and broad regulatory measures such as air emission standards, cross-sectoral policies, and coal phase-out regulations. Their relatively high importance suggests that comprehensive, system-wide regulatory frameworks are more effective at enhancing efficiency than isolated policy interventions. This pattern indicates that policy effectiveness is strongly embedded in the broader institutional and regulatory environment rather than driven solely by individual instruments.

In contrast, more targeted or market-based instruments, including renewable energy auctions, carbon taxes, and excise taxes, appear at the lower end of the importance ranking. This suggests that their contribution to efficiency is comparatively limited when considered in isolation, and that they likely operate through interaction effects within broader policy mixes rather than as standalone drivers.

Figure 2 highlights a hierarchical structure of determinants, in which structural factors dominate, comprehensive regulatory frameworks play a supporting but significant role, and individual policy instruments contribute marginally. This visual evidence reinforces the conclusion that achieving high efficiency in renewable energy transitions requires not only the implementation of specific policy tools but also favorable economic conditions and strong institutional foundations.

Figure 3 presents the partial dependence plot illustrating the marginal effect of a selected policy instrument on DEA efficiency, holding all other variables constant. The plot reveals a non-linear

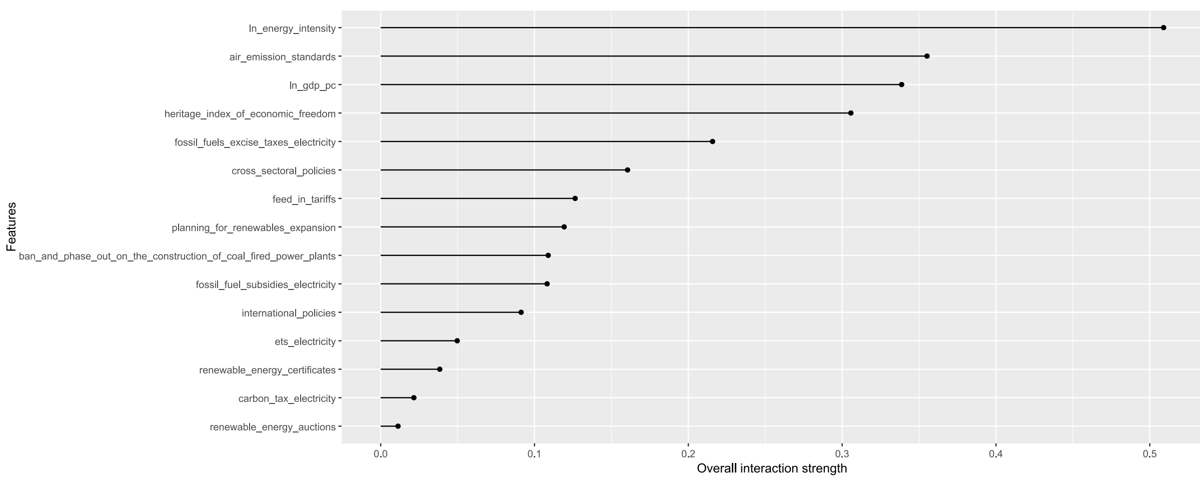

Figure 3. Partial dependence plot

Table 2. Fixed-effects quadratic model for feed-in tariffs and DEA efficiency

Variable	Coefficient	Std. Error	t-value	p-value
Feed-in tariffs (lagged)	3.236e-06	8.11e-07	3.99	<0.001
Feed-in tariffs^2 (lagged)	1.280e-07	1.22e-07	1.05	0.296
Fixed effects	Country, Year			
Observations	1,081			
Adjusted R^2	0.878			
Within R^2	0.180			

Note: The dependent variable is the logit-transformed DEA efficiency score. The model includes country- and year-fixed effects. Lagged values of feed-in tariffs are used to account for delayed policy effects. Standard errors are reported in parentheses.

relationship between the policy variable and efficiency, characterized by an initial phase of relatively weak or even negative marginal effects, followed by a gradual increase in efficiency beyond a certain threshold.

At lower levels of the policy variable, the predicted DEA efficiency remains relatively flat, suggesting that limited or fragmented policy implementation does not significantly improve countries' ability to convert regulatory stringency into renewable electricity outcomes. This may reflect insufficient scale, weak enforcement, or the absence of complementary policies necessary for effectiveness.

However, as the intensity of the policy instrument increases, the plot shows a clear upward trend, indicating that beyond a certain level, the policy exerts a stronger positive influence on efficiency. This pattern is consistent with the presence of threshold effects, where policy instruments become effective only when implemented at a sufficient scale or within an adequately developed regulatory environment.

In some segments of the plot, mild fluctuations can be observed, reflecting interaction effects and heterogeneity across 47 OECD member, accession, and key partner countries covered by the OECD policy database, which are typical in non-parametric models such as Random Forest. These variations suggest that the effectiveness of the policy instrument may depend on country-specific characteristics, including economic development, institutional quality, and energy system structure.

Figure 3 provides evidence of non-linear, threshold-dependent policy effects, reinforcing the conclusion that incremental policy adoption may be insufficient and that substantial, coordinated policy efforts are required to achieve meaningful improvements in renewable energy efficiency.

The results of the fixed-effects quadratic specification presented in Table 2 provide limited support for the presence of non-linear (threshold) effects of feed-in tariffs on DEA efficiency. The coefficient on the linear term (fit_l1) is positive and highly statistically significant (β = 3.236e-06, $p <$ 0.001), indicating that increases in feed-in tariffs are associated with higher efficiency in converting regulatory policy into renewable electricity outcomes. This suggests that, on average, stronger deployment of feed-in tariffs enhances policy effectiveness.

However, the quadratic term (fit_l1^2) is statistically insignificant ($p = 0.296$), implying that there is no robust evidence of curvature in the relationship. In other words, the data do not support the existence of a meaningful U-shaped or inverted U-shaped pattern. This is further confirmed by the inability to compute a valid turning point, as the estimated quadratic coefficient is not statistically different from zero, resulting in an undefined (NA) turning point.

The distribution of the feed-in tariff variable reinforces this conclusion. The median and first quartile are both zero, indicating that a large share of observations correspond to the absence of this policy instrument. This high concentration of zeros limits the model's ability to detect non-linear effects, suggesting that the relationship is better characterized as weakly linear within the observed data range.

The model exhibits a high adjusted R^2 (0.878), largely driven by the inclusion of country- and year-fixed effects, which capture substantial cross-

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country heterogeneity and common temporal shocks. However, the within R^2 (0.180) indicates that only a modest share of the variation in efficiency is explained by changes in feed-in tariffs over time within countries. This suggests that while feed-in tariffs have a statistically detectable effect, their overall explanatory power is limited compared to structural and time-invariant factors.

The findings indicate that feed-in tariffs exert a positive but predominantly linear effect on efficiency, with no strong evidence of threshold behavior. This contrasts with the non-linear patterns suggested by the Random Forest partial dependence plots, highlighting that these non-linearities may be driven by interaction effects or heterogeneous responses across the 47 OECD member, accession, and key partner countries covered by the OECD policy database, rather than a simple quadratic relationship.

The results of the full fixed-effects model presented in Table 3 provide robust evidence on the determinants of DEA efficiency, incorporating the full set of policy instruments alongside structural control variables. The model exhibits strong explanatory power, with an adjusted R^2 of 0.933 and a within R^2 of 0.555, indicating that the included variables capture a substantial share of within-country variation in efficiency. The fixed-effects models provide panel-based robustness evidence on associations between lagged policy-input dimensions, structural controls, and DEA efficiency. They should not be interpreted as identifying causal policy effects, because several explanatory variables are also used in constructing the DEA score.

Among policy instruments, feed-in tariffs (*fit_l1*) and renewable energy auctions (*auctions_l1*) emerge as the most influential variables associated with DEA efficiency variation. Both variables are positive and highly statistically significant ($p < 0.001$), suggesting that these instruments play a central role in enabling countries to convert regulatory policies into renewable electricity outcomes. This confirms the importance of direct financial support mechanisms and competitive allocation schemes in accelerating renewable energy deployment.

Similarly, air emission standards (*emission_standards_l1*) exhibit a strong, highly significant positive effect ($p < 0.001$), highlighting the role of regulatory constraints on emissions in driving efficiency improvements. These findings indicate that both market-based incentives and regulatory measures contribute positively to policy effectiveness when implemented at a sufficient scale.

Table 3. Fixed-effects model for DEA efficiency with lagged policy variables

Variable	Coefficient	Std. Error	t-value	p-value
ETS (lagged)	–8.35e-07	3.55e-07	–2.35	0.023
Carbon tax (lagged)	–1.01e-06	7.88e-07	–1.29	0.204
Fossil fuel subsidies (lagged)	–4.09e-08	6.89e-07	–0.06	0.953
Excise taxes (lagged)	–7.28e-07	1.27e-06	–0.57	0.571
Feed-in tariffs (lagged)	3.89e-06	2.91e-07	13.37	< 0.001
Renewable energy auctions (lagged)	4.77e-06	8.03e-07	5.94	< 0.001
Renewable certificates (lagged)	9.37e-09	5.80e-07	0.02	0.987
Coal phase–out policies (lagged)	–1.52e-06	6.81e-07	–2.23	0.031
Planning for renewables (lagged)	–9.40e-07	8.12e-07	–1.16	0.253
Air emission standards (lagged)	5.02e-06	8.23e-07	6.10	< 0.001
Cross-sectoral policies (lagged)	–1.17e-06	1.58e-06	–0.74	0.465
International policies (lagged)	–9.18e-07	1.45e-06	–0.63	0.529
GDP per capita (log)	2.22e-05	1.41e-05	1.58	0.122
Energy intensity (log)	–5.77e-05	1.53e-05	–3.76	< 0.001
Economic Freedom Index	–7.76e-07	3.60e-07	–2.15	0.037
Fixed effects	Country, Year			
Observations	1,081			
Adjusted R^2	0.933			
Within R^2	0.555			

Note: The dependent variable is the logit-transformed DEA efficiency score. The model includes country- and year-fixed effects, with standard errors clustered by country. Lagged policy variables capture the delayed effects of regulatory instruments.

In contrast, several policy instruments display either negative or insignificant effects. Notably, ETS (*ets_l1*) and coal phase-out policies (*coal_phaseout_l1*) are negative and statistically significant ($p < 0.05$), suggesting that, in the short run, these instruments may be associated with lower efficiency. This could reflect transition costs, implementation lags, or structural rigidities in energy systems undergoing regulatory tightening. Other instruments, including carbon taxes, fossil fuel subsidies, excise taxes, renewable certificates, planning policies, cross-sectoral policies, and international policies, are not statistically significant when considered independently, indicating limited direct effects.

Turning to control variables, energy intensity (*ln_energy_intensity*) is negative and highly significant ($p < 0.001$), confirming that more energy-intensive economies are less efficient in transforming policy inputs into renewable outcomes. The Heritage Index of Economic Freedom also shows a negative and significant effect ($p < 0.05$), suggesting that certain institutional characteristics may be associated with lower efficiency, potentially reflecting market-oriented structures that delay coordinated policy implementation. In contrast, GDP per capita (ln_gdp_pc) is positive but not statistically significant, indicating that economic development alone does not guarantee higher efficiency.

The results demonstrate that policy effectiveness is driven by a combination of targeted support instruments, regulatory constraints, and structural conditions, rather than by any single policy tool. Importantly, the findings are broadly consistent with the Random Forest results, particularly in highlighting the importance of feed-in tariffs, auctions, and emission standards, while confirming that several instruments exhibit limited standalone impact.

The results presented in Table 4 provide strong evidence that policy effectiveness in renewable energy transitions is driven by interactions among instruments rather than by their isolated implementation. Both feed-in tariffs (*fit_l1*) and renewable energy auctions (*auctions_l1*) remain positive and highly statistically significant ($p < 0.001$), confirming their individual importance as key policy tools. Importantly, the interaction term between these two instruments (*fit_l1* × *auctions_l1*) is also positive and statistically significant ($p < 0.01$), indicating the presence of complementarity effects. This suggests that the simultaneous use of feed-in tariffs and auction-based mechanisms enhances efficiency beyond the sum of their individual contributions, supporting the argument that coordinated policy mixes are more effective than standalone instruments.

In contrast, while planning policies (*planning_l1*) exhibit a negative and statistically significant effect ($p < 0.05$), and air emission standards (*emission_standards_l1*) remain positive and highly significant ($p < 0.001$), their interaction term is not statistically significant. This indicates that not all policy combinations generate synergistic effects, and that the effectiveness of planning instruments may depend on factors not captured by this interaction, such as implementation quality or institutional capacity.

The interaction model confirms that policy complementarity is selective rather than universal, with strong evidence for synergy between market-

Table 4. Fixed-effects model with policy interaction effects

Variable	Coefficient	Std. Error	t-value	p-value
Feed-in tariffs (lagged)	3.94e-06	3.25e-07	12.11	< 0.001
Renewable energy auctions (lagged)	3.87e-06	8.30e-07	4.67	< 0.001
Planning policies (lagged)	–1.68e-06	8.17e-07	–2.06	0.045
Air emission standards (lagged)	4.92e-06	1.07e-06	4.61	< 0.001
FIT × Auctions	4.06e-07	1.29e-07	3.16	0.003
Planning × Emission standards	1.14e-07	1.46e-07	0.78	0.438
Fixed effects	Country, Year			
Observations	1,081			
Adjusted R^2	0.919			
Within R^2	0.459			

Note: The dependent variable is the logit-transformed DEA efficiency score. Standard errors are clustered at the country level.

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Table 5. Fixed-effects quadratic models for auctions and planning policies

Variable	Coefficient	Std. Error	t-value	p-value
Panel A: Renewable energy auctions				
Auctions (lagged)	5.62e-06	1.92e-06	2.93	0.004
$Auctions^2$ (lagged)	–3.87e-07	4.10e-07	–0.94	0.345
Adjusted R^2	0.857			
Within R^2	0.040			
Panel B: Planning policies				
Planning (lagged)	–2.57e-06	1.02e-06	–2.53	0.012
$Planning^2$ (lagged)	1.72e-07	1.10e-07	1.57	0.117
Adjusted R^2				
Within R^2				

Note: All models include country- and year-fixed effects. The dependent variable is the logit-transformed DEA efficiency score.

based support mechanisms (FITs and auctions), but weaker or absent interactions among broader regulatory instruments.

The results in Table 5 further examine the presence of non-linear (quadratic) effects for key policy instruments. In renewable energy auctions, the linear term is positive and statistically significant ($p < 0.01$), indicating that higher auction activity is associated with greater efficiency. However, the quadratic term is not statistically significant, suggesting no robust evidence of curvature. This implies that the effect of auctions on efficiency is predominantly linear within the observed data range, with no clear threshold or diminishing returns.

For planning policies, the linear term is negative and statistically significant ($p < 0.05$), indicating that increases in planning-related interventions are associated with lower efficiency, potentially reflecting bureaucratic complexity or implementation delays. Although the quadratic term is positive, it is not statistically significant, providing only weak and inconclusive evidence of a potential U-shaped relationship. As a result, no statistically reliable turning point can be identified, and the relationship is best interpreted as predominantly linear and negative.

These findings indicate that non-linear effects are not a dominant feature of individual policy instruments, despite the non-linear patterns suggested by machine learning models. Instead, the results reinforce the conclusion that interaction effects between policies are more critical than simple quadratic relationships, highlighting the importance of coordinated policy design.

4. DISCUSSION

The empirical findings suggest that DEA-based renewable energy policy efficiency is associated with both the composition of policy stringency inputs and broader structural conditions. However, these results should be interpreted with methodological caution. Since several policy variables are used to construct the DEA efficiency score and are later included in the Random Forest and fixed-effects models, the second-stage analysis should not be read as a causal test of independent policy effects. Rather, it provides evidence on the internal structure of the DEA-based efficiency measure and on the associations between policy-input dimensions, structural conditions, and efficiency variation. The relatively low average DEA efficiency score of 0.348 indicates that most countries operate below the best-practice frontier, suggesting substantial gaps in converting regulatory policy stringency into renewable electricity outcomes. This is consistent with earlier findings that environmental regulation does not automatically translate into improved energy performance without appropriate policy design, implementation, and institutional support (Bi et al., 2014; Godawska & Wyrobek, 2021). The heterogeneity observed across the 47 OECD member, accession, and key partner countries covered by the OECD policy database further supports the view that renewable energy policy efficiency is conditioned by structural factors, including energy intensity, economic development, and energy-system characteristics (Taušová et al., 2022; Pimenow et al., 2026; Sitnicki et al., 2026b).

The fixed-effects results identify positive, statistically significant associations between DEA efficiency and selected policy instruments, particularly feed-in tariffs, renewable energy auctions, and air emission standards. These findings are consistent with the literature, which emphasizes the role of financial incentives, competitive allocation mechanisms, and regulatory constraints in supporting renewable energy deployment and innovation (Lyeonov & Moroz, 2025; Shcherbakova, 2025; Johnstone et al., 2009). At the same time, the absence of significant positive associations for several other instruments, including carbon taxes and renewable certificates, should not be interpreted as proof of their ineffectiveness. Rather, it suggests that these instruments do not show independent positive associations with DEA efficiency in the present specification, possibly because their influence depends on complementary policies, implementation quality, or country-specific conditions. The negative coefficients for ETS and coal phase-out policies should also be interpreted cautiously. They may reflect implementation lags, transition costs, reverse causality, or the adoption of stricter policies in countries already facing more difficult energy-transition conditions, rather than a direct negative policy effect. This interpretation is consistent with research showing that environmental policy outcomes may be shaped by structural divergence, transition frictions, and regulatory adjustment costs (Alper et al., 2026; Ferenczi Vaňová et al., 2026).

The interaction results provide evidence consistent with selective policy complementarity, especially through the positive association between the joint use of feed-in tariffs and renewable energy auctions and DEA efficiency. This suggests that coordinated policy mixes may be associated with stronger efficiency outcomes than isolated policy instruments, which corresponds to the theoretical and empirical literature on policy coherence and policy-mix design (Fischer & Newell, 2008; Horbach et al., 2012). At the same time, the Random Forest results should be interpreted separately from the fixed-effects estimates. Random Forest identifies variables with high predictive importance for DEA efficiency, particularly structural variables such as energy intensity and GDP per capita. In contrast, fixed-effects models provide panel-based evidence on associations between lagged policy-input dimensions and DEA efficiency. The results indicate that the interaction among policy input composition, structural conditions, and institutional context shapes the efficiency of renewable energy policy. This extends the current literature by offering an integrated yet cautious DEA–machine learning–panel data perspective on the efficiency of renewable energy policy (Krause et al., 2024; Ntshangase et al., 2024; Wołowiec et al., 2022).

The empirical findings provide several important implications for the design and implementation of renewable energy policies in OECD member, accession, and key partner countries. First, the results clearly indicate that policy effectiveness is driven by coordinated policy mixes rather than individual instruments. In particular, the strong and statistically significant interaction between feed-in tariffs and renewable energy auctions suggests that governments should avoid relying on a single policy tool and instead implement complementary combinations of market-based support mechanisms. Feed-in tariffs can provide investment certainty and early-stage support, while auctions enhance cost efficiency and competitive allocation, and their joint application leads to superior efficiency outcomes.

Second, the results highlight the critical role of regulatory frameworks, especially air emission standards, which consistently show strong positive associations across models. This suggests that binding regulatory constraints on emissions are essential for creating a stable environment that supports renewable energy deployment. Policymakers should therefore prioritize the development and enforcement of comprehensive regulatory standards alongside financial incentives, as these instruments reinforce one another and enhance overall policy effectiveness.

Third, the negative or insignificant effects observed for several instruments, including carbon taxes, fossil fuel subsidies, and planning policies, indicate that the presence of a policy does not guarantee its effectiveness. In particular, the negative coefficient of planning policies may reflect bureaucratic inefficiencies, regulatory complexity, or implementation delays. This implies that policy design and governance quality are as important as policy selection, and that poorly designed or weakly implemented measures may even reduce ef-

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ficiency. Governments should therefore focus on simplifying administrative procedures, improving institutional coordination, and ensuring consistent policy implementation.

Fourth, the strong influence of structural factors such as energy intensity and institutional quality underscores that policy outcomes are highly context-dependent. Countries with high energy intensity are systematically less efficient in transforming policy inputs into renewable outcomes, suggesting that energy system modernization and efficiency improvements are necessary preconditions for effective policy performance. Similarly, the role of institutional factors implies that transparent, stable, and well-functioning economic systems enhance the effectiveness of renewable energy policies.

Finally, the absence of robust quadratic effects for individual instruments suggests that there is no universal threshold level at which policies suddenly become effective. Instead, effectiveness appears to emerge through gradual improvements and, more importantly, through interactions between policies and structural conditions. This reinforces the need for a holistic, long-term policy strategy rather than short-term or isolated interventions.

The findings suggest that governments should adopt a systemic approach to renewable energy policy, combining financial incentives, regulatory measures, and structural reforms. Effective policy design should prioritize complementarity, institutional quality, and energy system transformation, rather than focusing on the optimization of individual instruments in isolation.

CONCLUSION

This study set out to evaluate how different renewable energy policy instruments and their combinations influence the efficiency with which countries convert regulatory efforts into renewable electricity outcomes, with particular attention to the role of structural and institutional conditions. To achieve this, a multi-method empirical framework was applied to panel data for 47 countries over the period 2000–2023, integrating Data Envelopment Analysis, Random Forest modeling, and fixed-effects panel regressions with lagged variables to capture both efficiency dynamics and complex policy interactions.

The results reveal substantial inefficiencies across 47 OECD member, accession, and key partner countries covered by the OECD policy database, with an average DEA efficiency score of 0.348, indicating that most economies operate well below the best-practice frontier. Structural factors, particularly energy intensity and economic development, emerge as the most influential determinants of efficiency, highlighting the importance of underlying system characteristics. Among policy instruments, feed-in tariffs, renewable energy auctions, and air emission standards demonstrate the most robust positive associations, while several other instruments show limited or insignificant standalone impact. Importantly, the positive interaction between feed-in tariffs and auctions suggests that coordinated policy mixes are associated with higher DEA-based efficiency than isolated policy measures.

These findings suggest that policymakers should prioritize integrated policy frameworks that combine financial incentives with regulatory measures, while ensuring coherence, administrative simplicity, and long-term stability. Feed-in tariffs and auction mechanisms should be designed as complementary tools rather than competing instruments. Air-emission standards should remain part of a broader regulatory framework supporting renewable electricity deployment. At the same time, improving energy efficiency, reducing energy intensity, strengthening institutional quality, and removing structural barriers are essential for increasing the efficiency with which policy stringency is converted into renewable electricity outcomes.

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REFERENCES

1. AlNaqbi, E., & Mohd Shamsudin, F. (2024). Greening the UAE workforce: Can green human resource management and domestic environmental regulations support green innovation at the workplace? *Problems and Perspectives in Management, 22*(1), 593-604. https://doi.org/10.21511/ppm.22(1).2024.47
2. Alper, F. O., Alper, A. E., Mike, F., & Kızılkaya, O. (2026). Environmental policy stringency and fossil energy trade in OECD countries. *Discover Environment, 4*(1), Article 31. https://doi.org/10.1007/s44274-026-00535-4
3. Badreddine, A., & Larbi Cherif, H. (2024). Public health improvement by reducing air pollution: A strategy for the transition to renewable energy. *Health Economics and Management Review, 5*(1), 1-14. https://doi.org/10.61093/hem.2024.1-01
4. Barcelona, R. G. (2025). Asserting business leadership: How decisionmakers shift strategic advantages and appropriate value under ambiguities. *Business Ethics and Leadership, 9*(3), 337-357. https://doi.org/10.61093/bel.9(3).337-357.2025
5. Bi, G.-B., Song, W., Zhou, P., & Liang, L. (2014). Does environmental regulation affect energy efficiency in China's thermal power generation? Empirical evidence from a slacks-based DEA model. *Energy Policy, 66,* 537-546. https://doi.org/10.1016/j.enpol.2013.10.056
6. Burrell, D. N., Wansi, T., Morin, S. L., Rahim, E., Tessema, D. B., Alemu, B. A., Harris, N., & Conley, L. (2025). Harnessing behavioral economics, green promotions, and financial incentives as catalysts for sustainable practices. *Green Transition and Sustainable Development, 1*(1), 1-16. https://doi.org/10.61093/gtsd.1(1).1-16.2025
7. Cui, T., & Yuan, W. (2025). Analysis of the nonlinear impact of climate policy uncertainty on total factor carbon productivity in Chinese cities. *Sustainability, 17*(24), Article 11069. https://doi.org/10.3390/su172411069
8. Ferenczi Vaňová, A., Krajcirova, R., Cheben, J., Munk, M., & Tóth, T. (2026). Why environmental taxation fails to converge in the European Union: Evidence of structural divergence across the EU 27. *Equilibrium. Quarterly Journal of Economics and Economic Policy, 21*(1), 95-141. https://doi.org/10.24136/eq.3933
9. Fernandes, K., Marathe, S. R., Parab, S., Amonkar, V., Vernekar, G., & Pandhre, S. S. (2025). Evaluating the role of government expenditure in promoting renewable energy and economic growth in India. *Environmental Economics, 16*(2), 162-172. https://doi.org/10.21511/ee.16(2).2025.12
10. Fischer, C., & Newell, R. G. (2008). Environmental and technology policies for climate mitiga-

http://dx.doi.org/10.21511/ee.17(2).2026.17

tion. *Journal of Environmental Economics and Management, 55*(2), 142-162. https://doi.org/10.1016/j.jeem.2007.11.001

11. Godawska, J., & Wyrobek, J. (2021). The impact of environmental policy stringency on renewable energy production in the Visegrad group countries. *Energies, 14*(19), Article 6225. https://doi.org/10.3390/en14196225
12. Halynskyi, D., & Telizhenko, O. (2024). Fair business leadership: Is protecting minority investors important to the development of start-ups in clean and digital energy? *Business Ethics and Leadership, 8*(4), 57-68. https://doi.org/10.61093/bel.8(4).57-68.2024
13. Havrylenko, O., & Myroshnychenko, I. (2025). Does renewable energy enhance energy security? Evidence from a Granger causality analysis of countries in the context of geopolitical risks and socioeconomic challenges. *SocioEconomic Challenges, 9*(2), 207-219. https://doi.org/10.61093/sec.9(2).207-219.2025
14. Horbach, J., Rammer, C., & Rennings, K. (2012). Determinants of eco-innovations by type of environmental impact – The role of regulatory push/pull, technology push and market pull. *Ecological Economics, 78,* 112-122. https://doi.org/10.1016/j.ecolecon.2012.04.005
15. International Energy Agency (IEA). (2025, October 7). *Renewables 2025*. Paris. Retrieved from https://www.iea.org/reports/renewables-2025
16. International Energy Agency (IEA). (2026, April 20). *Global Energy Review 2026*. Paris. Retrieved from https://www.iea.org/reports/global-energy-review-2026
17. International Renewable Energy Agency (IRENA), & Climate Policy Initiative (CPI). (2025). *Global landscape of energy transition finance 2025*. Abu Dhabi: IRENA. Retrieved from https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2025/Nov/IRENA_CPI_FIN_Global_landscape_energy_transition_finance_2025.pdf
18. International Renewable Energy Agency (IRENA). (2025). *Renewable capacity statistics 2025*. Abu Dhabi. Retrieved from https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2025/Mar/IRENA_DAT_RE_Capacity_Statistics_2025.pdf
19. Jaffe, A. B., & Stavins, R. N. (1995). Dynamic incentives of environmental regulations: The effects of alternative policy instruments on technology diffusion. *Journal of Environmental Economics and Management, 29*(3), S43-S63. https://doi.org/10.1006/jeem.1995.1060
20. Johnstone, N., Haščič, I., & Popp, D. (2009). Renewable energy policies and technological innovation: Evidence based on patent counts. *Environmental and Resource Economics, 45*(1), 133-155. https://doi.org/10.1007/s10640-009-9309-1
21. Krause, J., Myroshnychenko, I., Tiutiunyk, S., & Latysh, D. (2024). Financial instruments of the green energy transition: Research landscape analysis. *Financial Markets, Institutions and Risks, 8*(2), 198-212. https://doi.org/10.61093/fmir.8(2).198-212.2024
22. Kuzior, A., Kovalenko, Y., Tiutiunyk, I., & Hrytsenko, L. (2025). Assessment of the energy security of EU countries in light of the expansion of renewable energy sources. *Energies, 18*(8), Article 2126. https://doi.org/10.3390/en18082126
23. Lyeonov, S., & Moroz, A. (2025). Financial instruments for renewable energy incentives: A cluster-based analysis of feed-in tariffs and power purchase agreements. *Financial Markets, Institutions and Risks, 9*(1), 123-139. https://doi.org/10.61093/fmir.9(1).123-139.2025
24. Lyeonov, S., Kulawiecka, E., Krawczyk, D., & Oláh, J. (2025a). Decarbonisation and informality: Empirical evidence on the shadow economy response to climate policy mix. *Economics & Sociology, 18*(3), 274-295. https://doi.org/10.14254/2071-789X.2025/18-3/15
25. Lyeonov, S., Moroz, A., Dudzik, I., & Chuluunbaatar, E. (2025b). Green rules & grey markets: Do environmental policies influence the informal economy? *Economics & Sociology, 18*(1), 313-338. https://doi.org/10.14254/2071-789X.2025/18-1/17
26. Nilsson, M., Zamparutti, T., Petersen, J. E., Nykvist, B., Rudberg, P., & McGuinn, J. (2012). Understanding policy coherence: Analytical framework and examples of sector-environment policy interactions in the EU. *Environmental Policy and Governance, 22*(6), 395-423. https://doi.org/10.1002/eet.1589
27. Ntshangase, B. A., Makole, K. R., & Msosa, S. K. (2024). Overcoming the socio-economic challenges to good governance: Streamlining cooperative governance model. *SocioEconomic Challenges, 8*(4), 19-30. https://doi.org/10.61093/sec.8(4).19-30.2024
28. Organisation for Economic Co-operation and Development (OECD). (2025). *OECD Regulatory Policy Outlook 2025.* Paris: OECD Publishing. https://doi.org/10.1787/56b60e39-en
29. Organisation for Economic Co-operation and Development (OECD). (n.d.). *OECD data Explorer*. Retrieved from https://data-explorer.oecd.org/
30. Patnaik, B., & Hedau, A. (2026). Sustainable infrastructure investment: Financial drivers, policy dynamics and socio-economic challenges. *SocioEconomic Challenges, 10*(1), 27-41. https://doi.org/10.61093/sec.10(1).27-41.2026
31. Pimenow, S., Pimenowa, O., Sitnicki, M. W., Dluhopolskyi, O., & Zieliński, M. (2026). Energy use, costs and economic resilience of EU agriculture: The role and potential of CAP eco-schemes in reducing energy intensity. *Energies, 19*(4), Article 1016. https://doi.org/10.3390/en19041016
32. Roelfsema, M., van Soest, H. L., Harmsen, M., van Vuuren, D. P., Bertram, C., den Elzen, M., Höhne, N., Iacobuta, G., Krey, V., Kriegler, E., Luderer, G., Riahi, K., Ueckerdt, F., Després, J., Drouet,

L., Emmerling, J., Frank, S., Fricko, O., Gidden, M., ... Vishwanathan, S. S. (2020). Taking stock of national climate policies to evaluate implementation of the Paris Agreement. *Nature Communications, 11*(1). https://doi.org/10.1038/s41467-020-15414-6

33. Sahu, A., Kumar, A., & Kumar, A. (2026). Dynamic impact of macroeconomic and financial stress factors on clean energy index performance: Evidence from an ARDL analysis. *Investment Management and Financial Innovations, 23*(1), 424-433. https://doi.org/10.21511/imfi.23(1).2026.31

34. Shanyazov, N., Saidov, D., Babajanov, J., Karimboev, D., Niyozmetov, D., Mamadiyarov, Z., & Djumabayeva, S. (2026). Transport sustainability governance and green growth in the EU-27: Evidence from panel CS-ARDL and MMQR models. *Problems and Perspectives in Management, 24*(2), 89-102. https://doi.org/10.21511/ppm.24(2).2026.07

35. Shcherbakova, O. (2025). Do feed-in tariffs unlock green finance? A panel study of banking sector assets and renewable energy consumption across 66 countries around the world. *Banks and Bank Systems, 20*(3), 27-44. https://doi.org/10.21511/bbs.20(3).2025.03

36. Sira, M., & Kuzior, A. (2025). Digitalization of government management processes in the context of sustainable development. *Management Systems in Production Engineering, 33*(2), 289-310. https://doi.org/10.2478/mspe-2025-0029

37. Sitnicki, M. W., Iwanowska, B., Kapranov, Y., Klapkiv, J., Dluhopolskyi, O., Panasyuk, V., & Halynskyi, D. (2026a). Digitalisation and entrepreneurial ecosystems as drivers of energy start-ups: Evidence from cross-country panel data. *Sustainability, 18*(11), Article 5475. https://doi.org/10.3390/su18115475

38. Sitnicki, M. W., Serhiienko, R., Halynskyi, D., & Zhytar, M. (2026b). Economic freedom and the dynamics of energy start-ups: Cross-country evidence on green and digital entrepreneurship and financing. *Journal of International Studies, 19*(1), 255-279. https://doi.org/10.14254/2071-8330.2026/19-1/14

39. Stadniichuk, R., Popovych, R., Rahmanov, F., Garafonova, O., & Krymchak, L. (2025). Institutional mechanisms and ethical leadership as factors of reducing entropy in the system of economic security and regulation of social conflicts. *Business Ethics and Leadership, 9*(3), 211-226. https://doi.org/10.61093/bel.9(3).211-226.2025

40. Štreimikienė, D. (2024). Renewable energy penetration in Nordic and Baltic countries of the EU. *Journal of International Studies, 17*(1), 97-107. https://doi.org/10.14254/2071-8330.2024/17-1/6

41. Taušová, M., Tauš, P., & Domaracká, L. (2022). Sustainable development according to resource productivity in the EU environmental policy context. *Energies, 15*(12), Article 4291. https://doi.org/10.3390/en15124291

42. The Heritage Foundation. (n.d.). *Index of economic freedom: Explore the data – All country scores*. Retrieved from https://economic-freedom.heritage.org/

43. To, M. H., & Tran, B. M. (2025). Environmental regulatory stringency and corporate reporting quality: Evidence from waste, emissions, water, and energy regulations in Vietnamese firms. *Environmental Economics, 16*(3), 67-81. https://doi.org/10.21511/ee.16(3).2025.05

44. Trinh, L. D. (2025). Renewable energy and sustainable development: Evidence from lower middle-income countries. *Equilibrium. Quarterly Journal of Economics and Economic Policy, 20*(3), 905-926. https://doi.org/10.24136/eq.3440

45. Türüç-Seraj, F., Pervar, A., Üçışık-Erbilen, S., & Seraj, M. (2026). Green governance and energy transition: A quantile-on-quantile analysis of renewable energy, policy, and innovation effects on carbon emissions. *Sustainability, 18*(2), Article 1127. https://doi.org/10.3390/su18021127

46. Vasa, L., Kubatko, O., Sotnyk, I., Piven, V., Trypolska, G., & Pysmenna, U. (2024). Economic and environmental drivers of renewable energy transition in the EU. *Environmental Economics, 15*(2), 232-245. https://doi.org/10.21511/ee.15(2).2024.16

47. Vasylieva, T., Derkacz, A., Popp, J., & Horsch, A. (2025a). From energy dependency to energy security: How the war in Ukraine accelerated renewable deployment in Europe. *Economics and Sociology, 18*(3), 229-253. https://doi.org/10.14254/2071-789X.2025/18-3/13

48. Vasylieva, T., Gutowski, P., & Smiech, L. (2025b). Dynamic inflation responses to war-related electricity shocks: DTW-based evidence from European energy and renewables regimes. *Journal of International Studies, 18*(4), 180-203. https://doi.org/10.14254/2071-8330.2025/18-4/9

49. Wołowiec, T., Kolosok, S., Vasylieva, T., Artyukhov, A., Skowron, Ł., Dluhopolskyi, O., & Sergiienko, L. (2022). Sustainable governance, energy security, and energy losses of Europe in turbulent times. *Energies, 15*(23), Article 8857. https://doi.org/10.3390/en15238857

50. World Bank. (n.d.) *Indicators*. Retrieved from https://data.worldbank.org/indicator

51. Yoshimori, M. (2024). Global cooperation for reducing carbon emissions: The role of carbon taxes. *Financial Markets, Institutions and Risks, 8*(3), 69-79. https://doi.org/10.61093/fmir.8(3).69-79.2024

52. Yu, J., Shi, X., Guo, D., & Yang, L. (2021). Economic policy uncertainty (EPU) and firm carbon emissions: Evidence using a China provincial EPU index. *Energy Economics, 94,* Article 105071. https://doi.org/10.1016/j.eneco.2020.105071

http://dx.doi.org/10.21511/ee.17(2).2026.17

APPENDIX A

Table A1. Descriptive statistics of variables (47 OECD member, accession, and key partner countries, 2000–2023)

Variable	N	Mean	SD	Median	Min	Max	Skewness
ETS – Electricity	1,128	3.49	3.46	4.50	0.00	10.00	0.19
Carbon Tax – Electricity	1,128	0.56	1.89	0.00	0.00	10.00	3.59
Fossil Fuel Subsidies – Electricity	1,128	4.30	4.49	2.00	0.00	10.00	0.23
Fossil fuels excise taxes – Electricity	1,128	0.29	1.20	0.00	0.00	8.50	4.69
Feed-in Tariffs	1,128	1.74	2.46	0.00	0.00	9.50	1.09
Renewable energy auctions	1,128	0.35	1.11	0.00	0.00	6.00	3.35
Renewable energy certificates	1,128	1.18	2.73	0.00	0.00	10.00	2.19
Coal phase-out (construction ban)	1,128	1.20	2.18	0.00	0.00	8.00	1.53
Planning for renewables expansion	1,128	2.29	3.14	0.00	0.00	9.00	1.05
Air emission standards	1,128	4.32	3.31	5.00	0.00	10.00	-0.11
Cross-sectoral policies	1,128	2.22	1.90	1.83	0.00	8.30	0.80
International policies	1,128	2.49	1.91	2.08	0.19	8.73	1.32
Renewable electricity generation (%)	1,128	34.34	28.42	25.31	0.00	99.99	0.78
Energy intensity per capita (toe per person)	1,128	3.39	2.46	2.81	0.39	18.21	2.84
GDP per capita (constant 2015 USB)	1,128	28,621.45	22,674.88	20,664.77	756.70	112,417.88	1.22
Heritage Index of Economic Freedom	1,128	68.28	7.97	68.30	43.80	84.40	-0.35

Note: The table reports descriptive statistics for the main variables used in the analysis, based on an unbalanced panel of 47 OECD member, accession, and key partner countries covered by the OECD policy database over the period 2000–2023 (N = 1128 observations). Policy variables are measured using indices of regulatory stringency. Renewable electricity generation is expressed as a percentage of total electricity generation. GDP per capita is measured in constant 2015 US dollars. Energy intensity is measured in tonnes of oil equivalent per person. In the DEA model, the 12 policy stringency indices serve as inputs, while renewable electricity generation is the output. Energy intensity, GDP per capita, and the Heritage Index of Economic Freedom are used only in the second-stage Random Forest and fixed-effects models.