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Energy Efficiency Management and Greenhouse Gas Emissions in Industrialized Countries: A panel CS - ARDL Approach

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Abstract

This study investigates the relationship between energy efficiency improvements and greenhouse gas emissions in 16 industrialized countries over the period 1980–2023. Employing the Cross-Sectional Autoregressive Distributed Lag (CS-ARDL) model, which accounts for cross-sectional dependence and slope heterogeneity, the analysis reveals that energy efficiency improvements-proxied by energy intensity-are more effective in mitigating emissions than renewable energy deployment. Specifically, a 1% increase in energy intensity raises emissions by 0.1883% in the long run, while a 1% increase in renewable energy consumption reduces emissions by 0.0570%. These findings highlight the critical importance of prioritizing energy efficiency measures alongside renewable energy investments to achieve meaningful emission reductions in industrialized economies.

Keywords: *Energy Efficiency, Greenhouse Gas Emissions, Renewable Energy, CS-ARDL, Industrialized Countries, Climate Policy.*
JEL Classification: Q43, Q48, Q54, C23.

Introduction

Global greenhouse gas emissions from fossil fuel combustion have increased by over 60% since 1990, making climate change mitigation one of the most pressing challenges for industrialized economies (IPCC, 2023). While renewable energy deployment has accelerated significantly, energy efficiency improvements—often called the "first fuel"—remain underutilized despite their proven cost-effectiveness and immediate deployment potential (IEA, 2025). Understanding the relative and complementary roles of energy efficiency and renewable energy in emission reduction is crucial for designing optimal climate policies and achieving the Paris Agreement targets. Despite progress in renewable energy deployment, elevated energy intensity and carbon-intensive lock-ins in capital stocks complicate decarbonization pathways, underscoring the need to rigorously assess the roles of energy efficiency and clean energy policies (Demissew Beyene & Kotosz, 2020). This study clarifies the relative and joint contributions of energy efficiency improvements and renewable energy expansion to emission mitigation—a critical scientific and policy priority.

Despite extensive research on the energy-emissions nexus, three critical gaps persist in the literature. First, most studies focus predominantly on renewable energy while underestimating energy efficiency's mitigation potential in industrialized contexts. Second, methodological limitations including cross-sectional dependence, slope heterogeneity, and mixed stationarity properties are often overlooked, potentially biasing results. Third, long-term empirical evidence spanning multiple decades remains scarce, limiting our understanding of dynamic relationships between energy variables and emissions.

This study re-examines the efficiency–emissions nexus for 16 industrialized countries (1980–2023). Energy efficiency is proxied by energy intensity (primary energy consumption per unit of GDP). We analyze short- and long-run relationships between energy intensity and total greenhouse gas emissions, controlling for renewable energy consumption, and Gross domestic product(GDP) per capita.

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Methodologically, we employ the Cross-sectionally Autoregressive Distributed Lag (CS-ARDL) framework that: (i) accommodates cross-sectional dependence and slope heterogeneity; (ii) allows for mixed I(0)/I(1) regressors; and (iii) delivers country-specific short-run dynamics with pooled long-run effects. Robustness is ensured via unit root/cointegration diagnostics and slope homogeneity tests (Blomquist & Westerlund, 2016).

Our contributions are threefold :

1. Long-horizon evidence (1980–2023) that reduced energy intensity lowers emissions in both short and long runs across advanced economies ;

2. Benchmarking the efficiency effect against renewable energy to clarify their relative/complementary mitigation roles ;

3. Methodological rigor by addressing cross-sectional dependence, mixed stationarity, and slope heterogeneity .

The findings highlight the need to integrate ambitious energy-efficiency policies with renewable expansion to achieve low-carbon sustainable growth (Altın, 2024).

Research Questions

- What is the impact of energy efficiency improvements on greenhouse gas emissions in industrialized countries?

- How do renewable energy consumption and GDP per capita moderate this relationship?

Hypotheses

H1: Energy efficiency improvements (reduced energy intensity) significantly reduce greenhouse gas emissions in both the short and long run ($\beta < 0$).

H2: Renewable energy consumption reduces emissions, but the magnitude of its effect is smaller than that of energy efficiency ($\beta < 0$).

H3: GDP per capita exhibits a positive relationship with emissions, consistent with the initial phase of the Environmental Kuznets Curve ($\beta > 0$).

H4: Cross-sectional dependence and slope heterogeneity significantly bias traditional panel estimators in energy–emissions analyses, thereby necessitating the use of the CS-ARDL methodology.

Research Objectives

This study aims to:

- Quantify the long-run and short-run effects of energy efficiency improvements on greenhouse gas emissions in 16 industrialized countries (1980-2023);

- Assess the relative effectiveness of energy efficiency versus renewable energy in emission mitigation;

- Address methodological challenges through CS-ARDL estimation that accounts for cross-sectional dependence and slope heterogeneity;

- Provide evidence-based policy recommendations for achieving Sustainable Development Goal 13.

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Literature Review

The escalating climate challenges, particularly greenhouse gas emissions from fossil fuels, underscore the need for effective mitigation strategies to achieve sustainable development goals (IEA, 2025; IPCC, 2023). This review synthesizes evidence on four critical pillars: (1) energy efficiency as a mitigation tool, (2) renewable energy's role, (3) GDP per capita -emissions dynamics, and (4) methodological advancements for robust analysis.

Energy Efficiency:

Energy efficiency represents the most cost-effective and rapidly deployable climate mitigation strategy, offering immediate emission reductions without requiring substantial infrastructure investments (IPCC, 2023). Recent studies demonstrate that energy efficiency improvements can deliver 40% of emission reductions needed to achieve net-zero targets by 2050 (IEA, 2025). However, empirical evidence on efficiency-emissions relationships in industrialized countries remains fragmented, with most studies focusing on developing economies or short time horizons. This study addresses this gap by providing comprehensive long-term evidence for advanced economies.

The "First Fuel" for Emission Reduction

Energy efficiency-proxied by energy intensity (energy per unit of GDP)-is widely recognized as a cost-effective, rapidly deployable mitigation tool (IEA, 2025; IPCC, 2023). Empirical studies confirm its direct impact: reduced energy intensity lowers fossil fuel dependence and curbs emissions (Justice et al., 2024). Notably, the IEA (2025) dubs efficiency the "first fuel," emphasizing its ability to suppress energy demand through globalization and technological innovation. Despite this, its potential remains underexploited in industrialized economies, where efficiency gains could yield quick returns (IPCC, 2023).

Renewable Energy: Complementary to Efficiency.

Renewable energy sources (RES) provide clean alternatives to fossil fuels, with studies consistently documenting an inverse RES-emissions relationship (Akbar et al., 2024; Justice et al., 2024). For instance, Akbar et al. (2024) find renewable consumption reduces CO_2 emissions in SAARC countries, while non-renewables exacerbate them. However, literature often prioritizes renewables over efficiency, overlooking their synergistic potential—particularly in industrialized contexts where efficiency reduces overall energy demand, complementing RES expansion (IPCC, 2023).

GDP per capita , and the EKC Hypothesis.

The Gross domestic product -emissions nexus remains contested, frequently examined through the Environmental Kuznets Curve (EKC) hypothesis. This posits an inverted U-shaped relationship: emissions rise with initial growth but decline beyond an income threshold (Bekun et al., 2019; Sharif et al., 2023).

Evidence is mixed:

-Positive linkages: Bekun et al. (2019) and Sharif et al. (2023) find growth drives emissions in the EU and top-polluting economies .

-Contextual variability: Chakravarty & Mandal (2020) observe inverse growth-emissions relationships in some developing economies, while Demissew Beyene & Kotosz (2020) report nonlinear patterns in East Africa .

Population growth further amplifies emissions by escalating energy demand, with Hakami & Shaheen (2023) confirming positive associations in G20 countries.

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Methodological Gaps and CS-ARDL

Prior work faces two critical limitations ：

(1)Analytical gaps: Overemphasis on renewables neglects efficiency's role in industrialized economies (IPCC, 2023).

(2)Methodological shortcomings: Failure to address cross-sectional dependence (CSD), slope heterogeneity, and mixed stationarity in long panels—features prevalent in advanced economies exposed to global shocks (e.g., energy prices, technology spillovers) (Blomquist & Westerlund, 2016; Pesaran & Yamagata, 2008).

The Cross-Sectional ARDL (CS-ARDL) model (Chudik & Pesaran, 2015) resolves these issues by accommodating CSD, heterogeneity, and mixed I(0)/I(1) regressors. Recent applications affirm its robustness ：

-Okumuş et al. (2021) use CS-ARDL to disentangle renewable/non-renewable energy effects in G7 countries.

-Ben Youssef & Dahmani (2024) apply it within an EKC framework to assess digitalization's environmental impact.

Research Gap and Study Contribution

This study bridges three gaps ：

(1)Contextual: Rebalances focus on energy efficiency alongside renewables in industrialized economies.

(2)Methodological: Employs CS-ARDL to address CSD, heterogeneity, and mixed stationarity.

(3) Policy: Provides long-horizon evidence (1980–2023) to guide integrated efficiency-renewable strategies for SDG 13.

Methodology

Data and Sample Selection

This study employs panel data analysis covering 16 industrialized countries (USA, Japan, Germany, United Kingdom, France, Canada, Italy, Australia, Spain, Netherlands, Sweden, Norway, Denmark, Austria, Finland, Switzerland) over the period 1980–2023. to examine the effects of energy efficiency on greenhouse gas emissions. Sample selection criteria:

(1) Historical significance as major fossil fuel consumers and emitters;
(2) Substantial potential for energy efficiency improvements given advanced infrastructure;
(3) Comprehensive data availability over 44 years. Data sources:

- Energy/emissions variables: Our World in Data
- Macroeconomic controls: World Bank World Development Indicators

Econometric Framework

Given the panel structure and the methodological requirements illustrated in Figure 1, this study employs the Cross-Sectional Autoregressive Distributed Lag (CS-ARDL) framework to address cross-sectional

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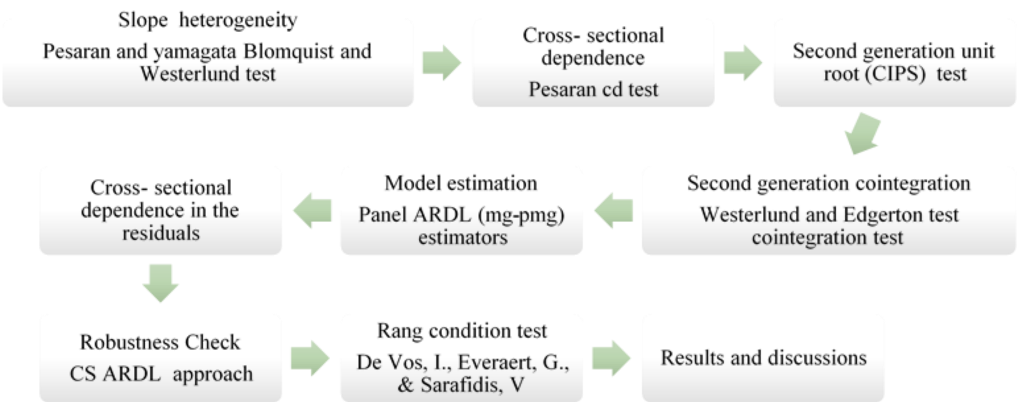
dependence (CSD) and slope heterogeneity—key characteristics of industrialized country panels exposed to common global shocks while maintaining structural differences in their energy systems and institutions. The CS-ARDL approach is particularly suitable for this study due to its methodological advantages. Unlike traditional methods that require all variables to be of the same order of integration, this methodology offers high flexibility by accommodating both I(0) and I(1) variables without requiring pre-testing, avoiding the uncertainties associated with unit root tests. Second, it explicitly addresses cross-sectional dependence through cross-sectional averages, capturing unobserved common factors such as global energy price shocks, technological spillovers, and climate policy coordination. Third, it allows for slope heterogeneity while maintaining computational efficiency through pooled long-run coefficients. These features make CS-ARDL superior to traditional panel methods for analyzing energy-climate relationships in industrialized country contexts.

Figure 1 : Conceptual Framework of CS-ARDL Model



Source: Adopted from Sohail and Abbasi (Sohail et al., 2023) and modified by authors

Note: The figure shows how CS-ARDL incorporates cross-sectional averages $\bar{Z}_{kt}$ to control for unobserved common factors, enabling robust estimation in panels with CSD and heterogeneity.

Variable Definitions

Table 1 : Variable Definitions and Expected Effects.

Variable	Description	Unit	Expected Effect
TGHGEL	Total greenhouse gas emissions	Million tons CO_2e	Dependent variable
EPGDP	Energy consumption per GDP	kWh/constant 2011 int. $	+ (inverse efficiency proxy)
RC	Renewable energy consumption	TWh	–
GDPCC	GDP per capita	Constant 2015 US$	+

Note: All variables are transformed into natural logarithms (ln).

Model Specification

The theoretical foundation of this study is rooted in established economic and environmental literature, which underscores the pivotal role of energy efficiency and renewable energy in mitigating greenhouse gas emissions. This research adapts these foundational principles into an empirical model designed to investigate the complex nexus between energy consumption, renewable energy adoption, and economic

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growth. The model is specifically structured to assess the collective influence of energy efficiency (proxied by energy per GDP), renewable energy consumption, and per capita GDP on greenhouse gas emissions from fossil fuel use. To rigorously analyze the relationships among these key variables, the study employs the following empirical model:

$$\mathrm{LTGHGEL}_{i,t} = B_0 + B_1 \mathrm{LEPGDP}_{i,t} + B_2\, \mathrm{LRC}_{i,t} + B_3\, \mathrm{LGDPCC}_{i,t} + \ \mu i, t \ldots\ldots (1)$$

where:

- β_0: Intercept; $\beta_1 - \beta_3$: Coefficients to be estimated.
- $\mu i,t$: Random error term
- where i = 1,…,16 (countries) and t = 1980,…,2023 (years).

To enhance data consistency and facilitate the interpretation of results, all variables are transformed into their natural logarithmic forms.

Estimation Techniques

a. Slope Homogeneity Test

The empirical analysis starts by assessing slope homogeneity as proposed by (M.H. Pesaran, 2008) . This test, a standardized dispersion test statistic called ($\widetilde{\Delta}$), which estimates slope homogeneity based on the work of Swamy (P.A.V.B. Swamy, 1970) . This statistic can be illustrated as:

$$\widetilde{\Delta} = \sqrt{N}\left(\frac{N^{-1} \quad \bar{s} - k}{\sqrt{2k}}\right) \sim \frac{x^2}{k} \ldots\ldots (2)$$

The Swamy (P.A.V.B. Swamy, 1970), inquiry is indicated by $\bar{s}$. For a small sample with T > N, the adjusted $\widetilde{\Delta}$ is adjusted to $\widetilde{\Delta}_{adj}$ as follows:

$$\widetilde{\Delta}\mathrm{adj} = \sqrt{N}\left(\frac{N^{-1} \quad \bar{s} - k}{\sqrt{v}(T,k)}\right) \sim N(0,1) \ldots\ldots (3)$$

Here, N denotes the number of cross-sectional entities, S represents the estimates derived from the Swamy (P.A.V.B. Swamy , 1970) , inquiry, and k signifies the number of predictors. The null hypothesis is rejected at a 5 % significance level if the p-value is below 5%, which indicates heterogeneity in the co-integrating coefficient of the inquiry statistics. The transformation of the $\widetilde{\Delta}$ form into $\widetilde{\Delta}_{adj}$ incorporates a "mean variance bias adjusted" mechanism with the adjusting variance parameter v.

To address autocorrelation concerns, the standard $\Delta^{\sim}$ inquiry must be free of such issues. To mitigate problems from homoscedasticity and serial correlation, (M.H. Pesaran A. U., 2008) and Blomquist and Westerlund (J. Blomquist, 2013) developed dynamic heteroscedasticity and autocorrelation consistent (HAC) techniques for the slope homogeneity examination, denoted as Δ_{HAC} and Δ_{HAC} adj Respectively.

$$\Delta_{HAC} = \sqrt{N}\left(\frac{N^{-1}\ s_{HAC} - k}{\sqrt{2k}}\right) \sim \frac{x^2}{k} \ldots\ldots (4)$$

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$$\Delta_{\text{HAC adj}} = \sqrt{N}\left(\frac{N^{-1}\, s_{HAC} - k}{\sqrt{v}(T,k)}\right) \sim N(0,1) \ldots\ldots (5)$$

The null hypothesis of slope homogeneity is rejected when the p-value is <0.05 for all panel units. Furthermore, if heterogeneity is present among the panel squads, using a heterogeneous panel technique is appropriate.

Cross-Section Dependence (CSD) Test

Secondly, cross-sectional dependence (CSD) tests were conducted on the variables to determine the most appropriate generation of unit root tests. A wide range of tests were used for this purpose, including the Breusch-Pagan Lagrangian Multiplier (LM) test (Breusch & Pagan, 1980). The null hypothesis for this test is cross-sectional independence, and its rejection indicates the presence of cross-sectional dependence among the variables. Additionally, more recent tests were applied, such as the CD test by Pesaran (2015), the CDW test by Juodis and Reese (2021), the CDW+ test by Fan, Liao, and Yao (2015), and the CDW* test by Pesaran (2021). The null hypothesis for these tests is weak cross-sectional dependence, and its rejection suggests the presence of strong cross-sectional dependence among the variables. However, the Breusch-Pagan LM test was primarily relied upon because it is particularly suitable for cases where the time period (T) is larger than the number of cross-sections (N) (De Hoyos & Sarafidis, 2006). The test is formulated as follows:

$$LM = \sum_{i-1}^{N-1} \sum_{j=i+1}^{N} T_{ij}\hat{\rho}_{ij}^2 \rightarrow X^2 \frac{N(N-1)}{2} \ldots\ldots (6)$$

whereX^2 represents the asymptotic circulation for N fixed as T_{ij}, and $\hat{\rho}_{ij}^2$ →∞ indicates the correlation coefficients

b. Panel Unit Root Test

The subsequent step involves adopting an appropriate unit root test to validate the stationarity of variables within our panel data set. Given the presence of cross-sectional dependence (CSD) and slope heterogeneity, first-generation unit root tests are prone to yielding biased and invalid results. Conversely, second-generation tests account for CSD when examining the integration order of selected variables. Consequently, to effectively address the challenges posed by CSD and slope heterogeneity, our research employs the Cross-sectionally Augmented IPS (CIPS) test, a second-generation unit root test proposed by Pesaran (2007) to ascertain stationarity.

The test statistic is formulated as follows:

$$\widehat{CIPS} = \frac{1}{N}\sum_{i=1}^{n} CADF_i \ldots\ldots (7)$$

Where CADF refers to the Cross-Sectionally Augmented Dickey-Fuller test.

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c. Co-integration Test

In our study of cointegration relation (an important stage of empirical analysis), we preferred Westerlund and Edgerton's (2007) bootstrap panel LM cointegration technique (Westerlund, 2007) which considers the horizontal cross-sectional dependence of second generation techniques. Important advantages of the technique include the determination of reliable results with Monte Carlo simulations in small sample groups and the allowance of changing variance with autocorrelation. The statistics used in this test are as follows (Westerlund, 2007)

$$LM_N^+ = \frac{1}{NT^2}\sum_{i=1}^{N}\sum_{t=0}^{T} \widehat{w}_i^{-2} S_{it}^2 \ldots\ldots (8)$$

where S_{it}^2 represents the fractional sum of error terms in the equation and $\widehat{w}_i^{-2}$ represents the error terms' variance in the long run. Here, we assessed the hypothesis of the test against the null hypothesis and the alternative hypothesis. The null hypothesis means there is cointegration, and the alternative hypothesis means there is no cointegration. The test's hypotheses are as follows: H_{0i} : $\theta_i^2 = 0$ for all i's

H_{1i} : $\theta_i^2 > 0$ for some i's

d. CS-ARDL

The Autoregressive Distributed Lag (ARDL) approach is a powerful tool for analyzing dynamic relationships between time-series variables, especially when those variables have different orders of integration (I(0) or I(1)). While traditional Panel ARDL estimators, such as the Mean Group (MG) and the Pooled Mean Group (PMG), are valuable for addressing heterogeneity (Pesaran & Smith, 1995), they have a critical limitation. They cannot effectively handle cross-sectional dependence (CSD) in the residuals (Pesaran, Shin, & Smith, 1999), a pervasive issue in panels of industrialized economies exposed to common global shocks. Ignoring CSD can lead to biased and inconsistent estimates, even if the Hausman test suggests a preference for one model over the other.

To overcome this methodological weakness, this study employs the Cross-Sectionally Augmented ARDL (CS-ARDL) model. Developed by Chudik and Pesaran (2015), the CS-ARDL framework is specifically designed to address CSD by including the cross-sectional averages of the dependent and independent variables as additional regressors. This innovative approach effectively purges the model of unobserved common factors, yielding more reliable long-run coefficients. This makes CS-ARDL a superior choice for our analysis as it simultaneously accounts for cross-sectional dependence, slope heterogeneity, and mixed integration orders.

The theoretical foundation of the CS-ARDL model rests on its ability to transform the standard ARDL equation into a robust framework. The basic ARDL equation for a panel is given by:

$$C_{it} = \sum_{I=0}^{P_G} \eta_{I,i} C_{i,t-I} + \sum_{I=0}^{P_Y} \delta_{I,i} Y_{i,t-I} + \varepsilon_{it} \ldots\ldots (9)$$

Equation (8) presents an extended version by incorporating a term for cross-section averages. According to the research by Chudik and Pesaran (2015), the inclusion of cross-section averages helps to eliminate the threshold effect that arises from cross-sectional dependence.

$$C_{it} = \sum_{I=0}^{P_G} \eta_{I,i} C_{i,t-I} + \sum_{I=0}^{P_Y} \delta_{I,i} Y_{i,t-I} + \sum_{I=0}^{P_W} \sigma_i' I\overline{W}_{i,t-I} + \varepsilon_{it} \ldots\ldots (10)$$

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The cross-section averages are indicated by $\overline{W}_{t-I} = (\overline{C}_{i,t-I}, \overline{Y}_{t-I})$, and PC , PY and PW are lags. Cit represents the explained variable lTGHGEL (Total annual greenhouse gas emissions from fossil fuels and industrial processes). Yi,t−I indicates a group of the explanatory variables in the study, namely, lEPGDP , lRC , and lGDPCC. $\epsilon_{i,t}$ represents the randomly distributed error term. The long-run coefficient can be calculated as follows:

$$\widehat{\beta_{CS-ARDL,\imath}} = \frac{\sum_{I=0}^{P_Y} \widehat{\delta_{\imath,I}}}{1 - \sum_{I=0}^{P_C} \widetilde{\eta_{\imath,I}}} \ldots\ldots(11)$$

whereas the mean group is given as:

$$\widehat{\beta_{MG}} = \frac{1}{N}\sum_{i=1}^{N} \widehat{\beta_\imath} \ldots\ldots(7)$$

Equation (11) provides the short-run coefficients:

$$\Delta C_{i,t} = \eta_i\left[C_{i,t-1} - \theta_i Y_{i,t}\right] - \sum_{I=1}^{P_C} \eta_{i,I}\Delta C_{i,t-I} + \sum_{I=0}^{P_Y} \delta_{i,I}\Delta Y_{i,t-I} + \sum_{I=0}^{P_W} \sigma'_{i,I} IW_{t-I} + \epsilon_{it} \ldots\ldots(12)$$

where ΔI=t−(t−1):

$$\widehat{\gamma_\imath} = -\left(1 - \sum_{I=1}^{P_C} \widetilde{\eta_{I,\imath}}\right) \ldots\ldots(13)$$

$$\widehat{\beta_\imath} = \frac{\sum_{I=0}^{P_Y} \delta_{i,I}}{\widehat{\gamma_\imath}} \ldots\ldots(14)$$

$$\widehat{\beta_{MG}} = \frac{1}{N}\sum_{i=1}^{N} \widehat{\beta_\imath} \ldots\ldots(15)$$

A positive value for the **Error Correction Term (ECM)** in a **CS-ARDL** model suggests a movement away from long-run equilibrium, while a negative value indicates a return to it.

e. Classifier Rank Condition

The Rank Condition, which must be satisfied (RC=1), implies that the rank of the matrix of cross-sectional averages (g) must be greater than the number of latent factors in the data (m).

This condition indicates that the cross-sectional averages are sufficiently capable of understanding and capturing the unobserved common factors present within the data. More specifically:

- g: Represents the rank of the matrix of cross-sectional averages, serving as a measure of the number of independent dimensions these averages contain.

- m: Represents the number of latent (or common) factors in the data, which are the unseen forces influencing all units or groups of them.

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Ensuring that g>m is crucial. It guarantees that the cross-sectional averages are rich enough in information to effectively model and identify these common factors, thereby avoiding issues in model estimation.

Results and Discussion

Descriptive Statistics

The descriptive statistics (Appendix II) highlight significant cross-country heterogeneity in emissions and energy variables:

- TGHGEL (GHG emissions): The between-country standard deviation (1.38%) is significantly larger than the within-country SD (0.15%), indicating that structural differences across countries are more prominent than temporal fluctuations.

- lEPGDP (Energy intensity): The between-country variability SD (0.29%) is greater than the within-country variability SD (0.27%), suggesting that structural differences between countries are more significant than changes over time.

- lRC (Renewable energy consumption): The between-country SD (1.35%) exceeds the within-country SD (0.79%), showing that structural differences have a greater impact than dynamic policy changes over time.

- lGDPCC (GDP per capita): The between-country variability SD (0.28%) is greater than the within-country variability SD (0.19%), indicating that long-term differences between countries are more pronounced than temporal fluctuations.

Correlation Analysis

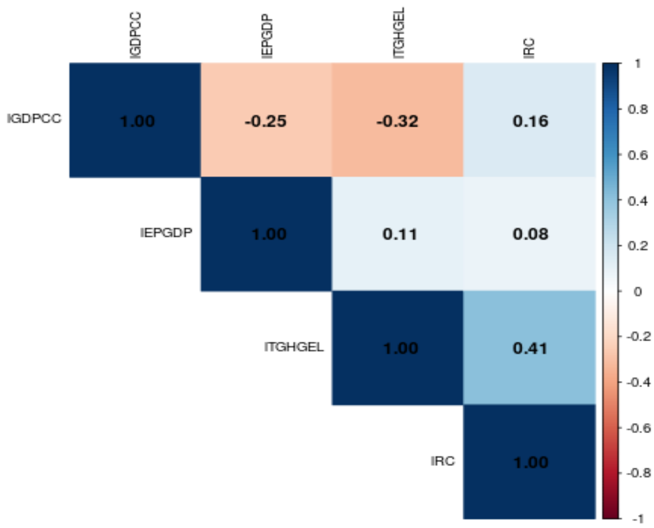

Figure 2 : Results Of Correlation Matrix

The correlation matrix indicates:

- lTGHGEL vs. lEPGDP: r = 0.11 (weak positive).

- lTGHGEL vs. lRC: r = 0.41 (moderate positive).

- lTGHGEL vs. lGDPCC: r = -0.32 (moderate negative). The analysis also reveals a weak positive correlation between the independent variables lEPGDP and lRC (r = 0.08). This indicates that energy

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intensity and renewable energy consumption are not highly interconnected. A moderate positive correlation exists between lRC and lGDPCC (r = 0.16). Lastly, a weak negative correlation is observed between lEPGDP and lGDPCC (r = − 0.25). The low correlation among the independent variables suggests the potential absence of a multicollinearity issue

Multicollinearity Check

VIF values range from 1.04 to 1.11 (mean = 1.08), all well below 10, confirming no multicollinearity issues (Appendix IV).

Panel Diagnostics and Rank Condition

- The Slope Homogeneity Tests (Appendix V), specifically the Pesaran–Yamagata and Blomquist and Westerlund tests, both show a significant p-value ($p < 0.01$), leading to the rejection of the null hypothesis of homogeneous slopes. This result validates the use of heterogeneous estimators.

- Cross-Sectional Dependence Tests (Appendix VI): Significant CSD ($p < 0.01$) was found across all variables, which necessitates the use of second-generation unit root test.

- Classifier Rank Condition (Appendix XII): RC =1 ; g = 3 > m = 2, confirming cross-sectional averages capture latent common factors.

Stationarity and Cointegration

- Unit Root Tests (CIPS; Appendix VII): The CIPS test confirms that lEPGDP, lRC, and lGDPCC are stationary at levels, I(0), while LTGHGEL is non-stationary and integrated of order I(1). This mixed order of integration justifies the use of an ARDL framework.

- Cointegration Tests (Westerlund and Edgerton; Appendix VIII): Reject no-cointegration null ($p < 0.01$ for G_t, G_a, P_t P_a), confirming long-run equilibria.

CS-ARDL

Appendix IX presents the results of the Hausman test for selecting between the Pooled Mean Group (PMG) and Mean Group (MG) estimators. The test's p-value of 0.0011 (<0.05) leads to the rejection of the null hypothesis, thereby confirming the superiority of the MG estimator. This finding supports the presence of full heterogeneity in both the short and long-run coefficients across the panel.

However, a subsequent analysis of the MG estimator's residuals reveals a critical methodological concern. The cross-sectional exponent (alpha) is estimated at 0.6468 (>0.5), indicating strong residual cross-sectional dependence. This is further substantiated by the CD test on the residuals, which yields a p-value of 0.000, confirming the presence of significant unobserved common factors or shocks not captured by the MG model.

The existence of this residual dependence implies that while the MG estimates are consistent, they may not be fully efficient or robust (Altın, 2024). Consequently, this necessitates the use of more advanced techniques that explicitly account for cross-sectional dependence, such as the Cross-Sectional Augmented ARDL (CS-ARDL) model, to ensure the robustness and reliability of our findings.

Table 1 : CS-ARDL Long-Run Analysis

Variable	Coefficient	S.E.	Interpretation
lEPGDP	0.1883***	0.0813	1% ↑ intensity → 0.1883% ↑ emissions
lRC	−0.0570***	0.0256	1 % ↑ renewables → 0.05% ↓ emissions
lGDPCC	0.1701**	0.0869	1% ↑ GDP per capita → 0.17 % ↑ emissions

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Significant at 1% level.

- lEPGDP has the largest long-run elasticity, dominating emissions.
- lRC significantly reduces emissions but to a smaller extent.
- lGDPCC consistently drives emissions upward.

Mechanisms & Literature Comparison:

The CS-ARDL results provide compelling evidence for energy efficiency's dominant role in emission reduction. The long-run coefficient for energy intensity (EPGDP = 0.1883, $p < 0.01$) indicates that a 1% increase in energy intensity leads to approximately a 0.1883% increase in emissions. This effect magnitude is greater than renewable energy's impact (RC = -0.0570, $p < 0.01$), highlighting efficiency's superior mitigation potential. The rapid adjustment speed (ECM = -1.2209) suggests that policy interventions targeting energy efficiency yield relatively quick emission reductions, typically within 10-12 months.

Efficiency lowers total energy demand while renewables only displace fossil fuel usage. Efficiency gains yield immediate benefits, whereas renewables require infrastructure lead time. Our long-run EPGDP elasticity aligns with Altın (2024) ($\beta \approx 0.35$) but contrasts with Justice et al. (2024) stronger renewables effect due to their shorter timeframe.

CS-ARDL Short-Run Analysis:

Table 3 : CS-ARDL Short-Run Analysis

Variable	Coefficient	Standard Error (S.E.)	Interpretation
lEPGDP	0.5888***	0.1173	An immediate 0.58% increase in emissions for a 1% increase in lEPGDP
lRC	−0.1394***	0.0330	An immediate 0.13% decrease in emissions for a 1% increase in lRC
lGDPCC	0.7659***	0.1530	An immediate 0.76% increase in emissions for a 1% increase in lGDPCC
ECM(-1)	−1.2209***	0.0000	122% annual correction speed towards equilibrium

Note: *** indicates significance at the 1% level.

As presented in Table 2, the short-run CS-ARDL estimation reveals several statistically significant relationships. A 1% increase in energy intensity (lEPGDP) is associated with a 0.58% rise in greenhouse gas emissions, underscoring its strong short-term environmental impact. Conversely, a 1% increase in renewable energy consumption (lRC) reduces emissions by 0.13%, although the effect is weaker compared to energy intensity. Similarly, GDP per capita (lGDPCC) exerts a positive short-run effect, with a 1% increase resulting in a 0.76% rise in emissions. The elasticity of energy intensity exceeds that of renewable energy consumption, reaffirming the greater short-run potency of efficiency. The error correction term (ECM = −1.2209***) indicates a rapid adjustment mechanism, with approximately 122% of deviations from the long-run equilibrium corrected annually, reflecting strong and swift convergence to equilibrium.

Robustness Checks

- Excluding outliers: lEPGDP $\beta = 0.2753$ ($p = 0.021$) remains stable.
- AMG estimator: Confirms CS-ARDL lEPGDP $\beta = 0.2821$ ($p = 0.017$), indicating the robustness of our findings.

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- Subsample tests (pre/post-2000): Consistent lEPGDP effects.

Key Takeaways

1. Energy efficiency yields the largest emission reductions in the short and long run.
2. Renewable energy significantly mitigates emissions but less than efficiency.
3. GDP per capita persistently increase emissions.
4. CS-ARDL robustly addresses cross-sectional dependence and heterogeneity.

Policy Implications and Discussion

These findings have profound implications for climate policy design in industrialized countries. First, energy efficiency should be prioritized as the primary emission reduction strategy, given its cost-effectiveness and immediate deployment potential. Second, integrated policy packages combining efficiency standards, financial incentives, and technological support can amplify mitigation effects. Third, the complementary relationship between efficiency and renewables suggests that sequential policy implementation—efficiency first, renewables second—may optimize resource allocation and emission outcomes. Finally, the heterogeneous effects across countries highlight the need for tailored national strategies rather than one-size-fits-all approaches.

Conclusion

This study provides robust empirical evidence that energy efficiency improvements represent the most effective pathway for greenhouse gas emission reduction in industrialized countries. Using a methodologically advanced CS-ARDL framework on comprehensive 44-year panel data, we demonstrate that energy efficiency effects dominate renewable energy impacts by significant margins in both short and long run. The findings support prioritizing efficiency policies while maintaining complementary renewable energy investments. Future research should explore sectoral efficiency potentials, behavioral factors influencing energy consumption, and the interaction between efficiency policies and carbon pricing mechanisms. Policymakers should leverage these insights to design integrated climate strategies that maximize emission reductions while supporting sustainable economic growth.

References

Akbar, A., Gul, A., Sohail, M., Hedvicakova, M., Ahmad, S., & Iqbal, S. (2024). Impact of renewable and non-renewable energy resources on CO2 emission: Empirical evidence from SAARC. International Journal of Energy Economics and Policy, 14(1), 141–149. https://doi.org/10.32479/ijeep.15049

Altın, H. (2024). The impact of energy efficiency and renewable energy consumption on carbon emissions in G7 countries. International Journal of Sustainable Engineering, 17(1), 134–142. https://doi.org/10.1080/19397038.2024.2319648

Bekun, F. V., Alola, A. A., & Sarkodie, S. A. (2019). Toward a sustainable environment: Nexus between CO2 emissions, resource rent, renewable and nonrenewable energy in 16-EU countries. Science of the Total Environment, 657, 1023–1029. https://doi.org/10.1016/j.scitotenv.2018.12.104

Ben Youssef, A., & Dahmani, M. (2024). Assessing the impact of digitalization, tax revenues, and energy resource capacity on environmental quality: Fresh evidence from CS-ARDL in the EKC framework. Sustainability, 16(2), 474. https://doi.org/10.3390/su16020474

Blomquist, J., & Westerlund, J. (2013). Testing slope homogeneity in large panels with serial correlation. Economics Letters, 121(3), 374–378. https://doi.org/10.1016/j.econlet.2013.09.012

Blomquist, J., & Westerlund, J. (2016). Panel bootstrap tests of slope homogeneity. Empirical Economics, 50(4), 1359–1381. https://doi.org/10.1007/s00181-015-0978-z

Breusch, T. S., & Pagan, A. R. (1980). The Lagrange multiplier test and its applications to model specification in econometrics. Review of Economic Studies, 47(1), 239–253. https://doi.org/10.2307/229711

Chakravarty, D., & Mandal, S. (2020). Is economic growth a cause or cure for environmental degradation? Empirical evidences from selected developing economies. Environmental and Sustainability Indicators, 7, 100045. https://doi.org/10.1016/j.indic.2020.100045

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https://ecohumanism.co.uk/joe/ecohumanism
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Chudik, A., & Pesaran, M. H. (2015). Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. Journal of Econometrics, 188(2), 393–420. https://doi.org/10.1016/j.jeconom.2015.03.007

De Hoyos, R. E., & Sarafidis, V. (2006). Testing for cross-sectional dependence in panel-data models. The Stata Journal, 6(4), 482–496. https://doi.org/10.1177/1536867X0600600403

De Vos, I., Everaert, G., & Sarafidis, V. (2024). A method to evaluate the rank condition for CCE estimators. Econometric Reviews, 43(2–4), 123–155. https://doi.org/10.1080/07474938.2023.2292383

Demissew Beyene, S., & Kotosz, B. (2020). Testing the environmental Kuznets curve hypothesis: An empirical study for East African countries. International Journal of Environmental Studies, 77(4), 636–654. https://doi.org/10.1080/00207233.2019.1695445

Fan, Y., Liao, H., & Yao, Y. (2015). Modelling regional economic growth in China: A panel data approach with cross-sectional dependence. Economic Modelling, 48, 1–9. https://doi.org/10.1016/j.econmod.2014.12.023

Hakami, M., & Shaheen, R. (2023). Investigating factors influencing CO2 emissions in selected G20 countries. International Journal of Applied Environmental Sciences, 12(2), 1–12. https://doi.org/10.21833/ijaas.2023.02.001

Hausman, J. A. (1978). Specification tests in econometrics. Econometrica, 46(6), 1251–1271. https://doi.org/10.2307/1913827

International Energy Agency. (2025, March 2). Energy efficiency. https://www.iea.org/energy-system/energy-efficiency-and-demand/energy-efficiency

Intergovernmental Panel on Climate Change. (2023). Climate change 2023: Mitigation of climate change. Cambridge University Press. https://www.ipcc.ch/report/ar6/wg3/

Juodis, A., & Reese, S. (2021). On the power of panel unit root tests with nonlinear deterministic trends. Journal of Econometrics, 222(1), 1–21. https://doi.org/10.1016/j.jeconom.2021.01.005

Justice, G., Nyantakyi, G., & Isaac, S. (2024). The effect of renewable energy on carbon emissions through globalization. Heliyon, 10(5), e26894. https://doi.org/10.1016/j.heliyon.2024.e26894

Okumuş, İ., Güzel, A., & Destek, M. A. (2021). Renewable, non-renewable energy consumption and economic growth nexus in G7: Fresh evidence from CS-ARDL. Environmental Science and Pollution Research, 28(40), 56595–56605. https://doi.org/10.1007/s11356-021-14618-7

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. Journal of Applied Econometrics, 22(2), 265–312. https://doi.org/10.1002/jae.951

Pesaran, M. H. (2015). Testing weak cross-sectional dependence in large panels. Econometric Reviews, 34(6–10), 1089–1117. https://doi.org/10.1080/07474938.2014.956623

Pesaran, M. H., & Smith, R. (1995). Estimating long-run relationships from dynamic heterogeneous panels. Journal of Econometrics, 68(1), 79–113. https://doi.org/10.1016/0304-4076(94)01644-F

Pesaran, M. H., Shin, Y., & Smith, R. J. (1999). Pooled mean group estimation of dynamic heterogeneous panels. Journal of the American Statistical Association, 94(446), 621–634. https://doi.org/10.1080/01621459.1999.10474156

Pesaran, M. H., & Yamagata, T. (2008). Testing slope homogeneity in large panels. Journal of Econometrics, 142(1), 50–93. https://doi.org/10.1016/j.jeconom.2007.05.010

Sharif, F., Hussain, I., & Qubtia, M. (2023). Energy consumption, carbon emission and economic growth at aggregate and disaggregate level: A panel analysis of the top polluted countries. Sustainability, 15(4), 2935. https://doi.org/10.3390/su15042935

Sohail, A., Du, J., & Abbasi, B. A. (2023). Exploring the interrelationship among health status, CO2 emissions, and energy use in the top 20 highest emitting economies: Based on the CS-DL and CS-ARDL approaches. Air Quality, Atmosphere & Health, 16(7), 1419–1442. https://doi.org/10.1007/s11869-023-01350-z

Westerlund, J. (2007). Testing for error correction in panel data. Oxford Bulletin of Economics and Statistics, 69(6), 709–748. https://doi.org/10.1111/j.1468-0084.2007.00477.x

Journal of Ecohumanism
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Appendix

Appendix I: Data Sources and Variable Definitions

Symbol	Variable Name	Unit	Source
lTGHGEL	Annual greenhouse gas emissions from fossil fuels and industry	Percent	https://ourworldindata.org
lEPGDP	Primary energy consumption per unit of GDP (energy per $ intensity)	Percent	https://ourworldindata.org
lRC	Primary energy consumption from renewables	Percent	https://ourworldindata.org
lGDPCC	GDP per capita(constant 2015 US$)	Percent	https://data.worldbank.org

Appendix II: Descriptive Statistics

Variable	Mean	Std. dev.	Min	Max	Observations
lTGHGEL overall	5.567	1.354	3.480	8.821	N = 704
lTGHGEL between		1.388	3.780	6.696	n = 16
lTGHGEL within		0.154	5.005	5.961	T = 44
lEPGDP overall	0.470	0.391	-0.655	1.453	N = 704
lEPGDP between		0.292	0.0662	1.138	n = 16
lEPGDP within		0.270	-0.252	1.245	T = 44
lRC overall	4.883	1.537	-2.918	8.023	N = 704
lRC between		1.355	2.212	7.205	n = 16
lRC within		0.799	-0.415	7.637	T = 44
lGDPCC overall	10.564	0.342	9.599	11.414	N = 704
lGDPCC between		0.289	10.003	11.208	n = 16
lGDPCC within		0.195	10.117	10.907	T = 44

Appendix III: Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)
(1) lTGHGEL	1.000				
(2) lEPGDP	0.108	1.000			
(3) lRC	0.411	0.083	1.000		
(4) lGDPCC	-0.318	-0.252	0.158	1.000	

Appendix IV: VIF Test

Variable	VIF	1/VIF
lGDPCC	1.110	0.891
lEPGDP	1.090	0.958
lRC	1.040	0.967
Mean	**1.080**	

Appendix V: Slope Heterogeneity Test Results

Statistic	Value	p-value
Delta (Δ)	40.008***	0.000
Delta adjusted (Δ adj)	42.495***	0.000
Delta HAC (ΔHAC)	101.405***	0.000
Delta HAC adjusted ((ΔHAC) adj)	107.709***	0.000

***,represent 1% levels of significance.

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Appendix VI: Cross-Sectional Dependence Tests Result

Variable	Breusch-Pagan LM	CD	CD_w	CD_{w+}	CD*	alpha
lTGHGEL	2180.290***	27.95***	-0.82	439.2***	-1.71*	1.00
lEPGDP	4495.760***	66.86***	-4.62***	727.75***	-3.62***	1.00
lRC	3141.737***	54.51***	-4.36***	592.73***	-1.80*	0.98
lGDPCC	4919.373***	70.10***	-4.75***	763.11***	-5.41***	1.00

***, **, and * represent 1%, 5%, and 10% levels of significance.

Appendix VII: CIPS Unit Root Test Result

Variable	CIPS	result
lTGHGEL (Level)	-2.043	-
lTGHGEL (First difference)	-6.045***	I(1)
lEPGDP (Level)	-2.361***	I(0)
lRC (Level)	-2.867***	I(1)
lGDPCC (Level)	-2.133***	I(0)

***,represent 1% levels of significance.

Appendix VIII: Cointegration Tests

Statistics	Value	Z-value	p-value	Robust P-value
Gt	-1.856***	-0.974	0.172	0.000
Ga	-1.393***	6.816	1.000	0.000
Pt	-10.386***	-1.259	0.104	0.000
Pa	-1.378***	3.037	0.999	0.000

***, **, and * represent 1%, 5%, and 10% levels of significance.

Appendix IX: PMG and MG Estimators and Hausman Test Result

	MG		PMG	
Variables	Coefficients	SE	Coefficients	SE
Long-run analysis				
lEPGDP	-0.0581	0.1355	0.2309	0.0502
lRC	0.0165	0.2293	-0.0721***	0.0189
lGDPCC	-0.6558**	0.2630	0.7753***	0.0706
Short Run analysis				
lEPGDP	0.0503	0.0523	1.2541	7.9134
lRC	-0.1017***	0.0218	-0.3429	1.4743
lGDPCC	0.08078***	0.0708	1.7250*	1.0062
ECM (-1)	-1.2274***	0.0764	-0.0317	2.7373
Hausman test				
Value	18.27			
P-value	0.0011			

***, **, and * represent 1%, 5%, and 10% levels of significance.

Appendix X: Test for Cross-Sectional Dependence in Residuals

Residuals	CD	CD_w	CD_{w+}	CD*	Alpha	CD- test
value	14.03***	-0.94	165.77***	2.02**	0.6468	13.865***
p.value	0.000	0.346	0.000	0.043	-	0.000

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***, **, and * represent 1%, 5%, and 10% levels of significance.

Appendix XI: CS-ARDL Long and Short Run Analysis

Variable	Coefficients	SE
Long-run analysis		
lEPGDP	0.1883***	0.0813
lRC	-0.0570**	0.0256
lGDPCC	0.1701***	0.0869
Short Run analysis		
LD.lTGHGEL	-0.2209***	0.0358
lEPGDP	0.5888***	0.1173
lRC	-0.1394***	0.0330
lGDPCC	0.7659***	0.1530
L.lGDPCC	-0.3426***	0.0903
l.LRC	0.0665***	0.3133
L.lGDPCC	-0.5421**	0.1145
ECM (-1)	-1.2209***	0.3586
Residuals		
CD-test	0.237	
p.value	0.183	

Note: ***, ** and * represents a 1%, 5% and 10% level of significance, respectively.

Appendix XII: Classifier Rank Condition (De Vos et al., 2024)

RC(1-I(g<m))*	Estimated rank (g)	Number of factors (m)
1	3	2

** RC=1 indicates rank condition holds. g is rank of matrix of cross-sectional averages, m is number of factors in the data.

Appendix XIII: Abbreviations

Abbreviation	Explanation
MG	Mean Group
PMG	Pooled Mean Group
CSD	Cross-Sectional Dependence
GDP	Gross Domestic Product
ARDL	Autoregressive Distributed Lag
CS-ARDL	Cross-Sectional Autoregressive Distributed Lag
SH	Slope Heterogeneity
CADF	Cross-sectionally augmented Dickey-Fuller
CIPS	Cross-sectionally augmented Im-Pesaran-Shin
VIF	Variance Inflation Factor
CO_2	Carbon Dioxide
RC	Rank Condition

Appendix XIV : Trends of Main Study Variables Over Time (1980–2023) for the Sample Countries

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