



Decoupling Energy Intensity for Sustainable Development: The Role of Information and Communication Technology Exports and R&D in G7 Economies Using a CS-ARDL Approach

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ABSTRACT

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This study analyzes the factors influencing energy intensity in the G7 economies including Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States from 2000 to 2022, emphasizing the long-term decoupling effects of Information and Communication Technology (ICT) exports and Research and Development (R&D) investments. The analysis utilizes advanced second-generation panel econometric techniques, such as Pesaran cross-sectional dependence test, CIPS unit root test, Westerlund cointegration test, and Cross-Sectional Augmented Autoregressive Distributed Lag (CS-ARDL) model to guarantee robust inference. Diagnostic results validate the existence of cross-sectional dependence and slope heterogeneity, hence warranting the application of the CS-ARDL methodology. The results indicate a consistent long-term cointegrating link between energy intensity and its determinants. Long-term projections indicate that a 1% rise in R&D expenditure and ICT exports decreases energy intensity by roughly 0.155% and 0.082%, respectively, underscoring the significance of innovation and digitalization in enhancing energy efficiency. GDP per capita demonstrates the most significant impact, exhibiting a negative elasticity of -0.650%, whereas industrial value added amplifies energy intensity. The error correction term signifies a swift realignment towards long-term balance. The results emphasize the significance of continuous R&D, together with ICT-driven innovation, in attaining energy efficiency in developed economies.

1. INTRODUCTION

The international dedication to sustainable development fundamentally relies on enhancing energy efficiency, as outlined in Sustainable Development Goal (SDG) Target 7.3, which requires a doubling of the average worldwide rate of improvement in energy intensity by 2030. Energy intensity is defined as the ratio of energy supply to gross domestic product, measured in megajoules per dollar of 2021 purchasing power parity GDP. To achieve the SDG 7.3 target, the global rate of energy intensity improvement must increase to 4% annually [1]. Despite advancements in energy efficiency within industrialized nations, attaining this objective necessitates the identification and vigorous exploitation of the particular economic and technological elements that facilitate decoupling.

The G7 countries, namely, Canada, France, Germany, Italy,

Japan, the United Kingdom, and the United States, constitute a vital subset for this analysis. These advanced economies have predominantly exhibited absolute decoupling, marked by sustained economic growth accompanying a reduction in primary energy intensity over the last twenty years.

The reduction in EI in these developed economies is attributed to both passive structural shifts and proactive policy-induced technology advancements. Passive impacts arise from the intrinsic transition to service-oriented economic frameworks, which are fundamentally less energy-intensive than manufacturing. Active impacts entail intentional investment in technology. Research and Development (R&D) expenditures, encompassing both fundamental and applied research, serve as the primary means for advancing energy productivity improvements and fostering sustainable energy systems. The proliferation of Information and Communication Technology (ICT), especially as indicated by ICT goods

exports, enhances industrial and commercial processes, resulting in dematerialization and increased efficiency in production and distribution.

Comprehending the distinct impact of technological variables (R&D and ICT) in relation to structural elements (industrial value added) is crucial for formulating a successful energy strategy. This study acknowledges that merely advocating for general economic expansion, which inherently diminishes EI through structural transformations, is probably inadequate. The quantification of certain technology elasticities is essential for directing targeted investments towards policy areas that enhance efficiency beyond inherent economic trends.

A major difficulty in analyzing the G7 as a group is the profound interconnection of these countries. Technological, economic, or regulatory shocks often disseminate throughout the group, creating unobserved common characteristics that result in cross-sectional dependence [2]. Moreover, national variations in energy composition, regulatory strictness, and R&D goals (for instance, Japan's persistently elevated R&D intensity relative to Italy's) require consideration of slope heterogeneity [3]. Disregarding cross-dependence and heterogeneity leads to biased coefficient estimates, which may inaccurately reflect the long-term efficacy of policy interventions.

This research utilizes the Cross-Sectional Augmented Autoregressive Distributed Lag (CS-ARDL) model [4] to address these methodological limitations for the G7 panel from 2000 to 2022. This second-generation method effectively estimates stable long-term coefficients by explicitly modeling and eliminating common associated effects, thus offering dependable policy guidance for policymakers seeking to enhance decoupling via technological innovation.

2. LITERATURE REVIEW

2.1 Theoretical framework

Investment in R&D is divided into three phases: basic research, applied research, and experimental development, all intended to enhance knowledge and create new applications. The impact of R&D techniques should reduce EI by facilitating improved energy management and the advancement of high-efficiency, low-carbon technology. The empirical ambiguity, however, stems from the possible rebound effect. Although R&D enhance energy efficiency, the consequent decrease in the relative cost of energy services may encourage increased overall consumption, thereby exacerbating total energy demand; nevertheless, this phenomenon is often less pronounced in highly developed economies that prioritize tertiary sectors.

Exports of ICT goods act as a quantifiable indicator of an economy's technology sophistication and specialization. The theoretical connection to EI is propelled by optimization and structural transformation. The dissemination of ICT enables the management of intricate industrial processes with enhanced accuracy, minimizing waste and optimizing energy usage, so directly contributing to energy efficiency. Research indicates that the utilization of ICT enhances environmental quality in affluent nations, however findings differ about its effect on gross energy consumption [5].

Economic growth, as measured by GDP per capita, is anticipated to facilitate a reduction in environmental impact.

This is intrinsically associated with the Environmental Kuznets Curve (EKC) hypothesis, which asserts an inverted U-shaped correlation between income and environmental degradation [6]. The G7 economies, having attained elevated average income levels (about \$32,000 to \$64,000 per capita in 2022), are situated on the declining segment of the curve. At this juncture, economic maturity results in increased dominance of the service sector, more stringent environmental rules, and adequate capital accumulation for substantial efficiency investments, indicating a considerable negative elasticity on EI.

Industrial activity, which includes mining, manufacturing, construction, electricity, water, and gas industries, is characterized by inherent energy needs. Even after de-industrialization, the remaining industry exerts a positive pressure on EI due to the intensity of its operations. In contrast, urbanization (URB) in developed regions often promotes efficiency. High population density allows for economies of scale in infrastructure, leading to centralized, efficient energy provision and better utilized public transportation, consequently reducing energy intensity.

2.2 Empirical studies on the energy-technology-economy nexus

Empirical studies on the correlation between ICT goods exports and energy intensity yield inconclusive results, frequently emphasizing indirect influences via technological progress or trade dynamics instead of direct causality. Briglauer et al. [7] conducted an analysis of OECD countries from 2002 to 2019 employing two-way fixed-effects panel estimation with instrumental variables, revealing that ICT goods exports exert an insignificant net effect on CO₂ emissions, a proxy for energy intensity, indicating a minimal impact on the reduction or augmentation of energy consumption per unit of output. Wang et al. [8] analyzed 25 technologically advanced nations from 2009 to 2018 using ordinary least squares regression with fixed effects, concluding that exports of ICT goods positively influence carbon intensity, serving as a proxy for energy intensity, by enhancing high-energy manufacturing and trade. Conversely, Li et al. [9] examined 46 countries from 2007 to 2021 using two-way fixed effects and panel threshold regression models, concluding that exports of ICT goods, as a component of digital trade, indirectly reduce carbon emissions by improving productivity and energy-efficient technologies, suggesting a negative impact on energy intensity at elevated digital trade thresholds. Murshed et al. [10] provided supplementary evidence about South Asian countries from 1990 to 2018, utilizing augmented mean group (AMG) estimators, which revealed non-linear effects of ICT-trade openness on energy efficiency, indicating that increased openness diminishes energy intensity by facilitating transitions to renewable energy sources. Additionally, Zhou et al. [11] examined global ICT trade from 2000 to 2018 using input-output analysis, demonstrating that ICT exports from rich nations shift CO₂ emissions to emerging countries, thereby indirectly elevating world energy intensity by 15-20%. Li and Wang [12] analyzed panel data from 30 Chinese provinces spanning 2005 to 2020 using spatial Durbin models, revealing that ICT exports diminish regional energy intensity by 8-12% through enhancements in digital infrastructure. Briones-Bitar et al. [13] conducted a bibliometric analysis and systematic review of smart buildings, revealing that ICT technologies, such as IoT

and communication networks, reduce energy intensity by optimizing consumption and enabling efficient HVAC and lighting systems in urban environments, with up to 30% decreases in energy use in LEED-certified structures.

Multiple studies indicate that R&D expenditures typically diminish energy intensity by fostering technical innovations and efficiency improvements, but the extent of this effect varies by geography and context. Huang et al. [14] investigated 30 Chinese provinces from 2000 to 2013 employing fixed effects estimators, feasible generalized least squares, and panel threshold models, demonstrating that R&D expenditure intensity significantly reduces energy intensity via threshold effects that amplify technology spillovers. Meng et al. [15] analyzed data from 30 Chinese provinces between 2004 and 2014 using the logarithmic mean Divisia index, demonstrating that R&D intensity emerged as a significant factor, contributing -114.59% to the reduction in carbon emissions. Briglauer et al. [7] utilized two-way fixed-effects panel estimation with instrumental variables in OECD countries from 2002 to 2019, revealing that R&D expenditure exerts a positive yet statistically insignificant influence on CO₂ emissions in the majority of models, suggesting a constrained direct impact on diminishing energy intensity. Huang et al. [16] categorized China into Eastern, Central, and Western regions from 2000 to 2014 utilizing DEA-Malmquist and spatial panel estimations, concluding that R&D facilitates technological advancement that markedly reduces energy intensity, with more pronounced effects in Eastern and Central regions. Garrone and Grilli [17] analyzed OECD nations from 1980 to 2004 using dynamic panel GMM, demonstrating that public R&D in energy industries decreases energy intensity by 0.5-1% for each percentage point increase in investment. Azhgaliyeva et al. [18] examined 44 nations from 1990 to 2016 using common correlated effects mean group estimators, observing that R&D-oriented policy tools such as grants diminish energy intensity by 5-10%. Petrović and Lobanov [19] utilized panel VAR in G6 economies from 2000 to 2015, demonstrating that R&D reduces energy intensity by enhancing environmental performance. Rabhi et al. [20] reviewed Algeria's energy policies and regulations, concluding that increased R&D expenditure is essential for reducing energy intensity through renewable energy adoption, efficiency enhancements, and addressing knowledge gaps in policy effectiveness for diversification and emission reduction.

The correlation between GDP per capita and energy intensity is frequently negative, consistent with the EKC concept, which posits that increased income levels promote efficiency and structural transformations, while positive correlations may emerge during initial phases of growth. Filipović et al. [21] conducted a panel data study using fixed-effects estimators on EU-28 member states from 1990 to 2012, revealing that a rise of EUR 1000 in GDP per capita correlates with a reduction in energy intensity by 1.74 kgoe/1000EUR. Azhgaliyeva et al. [18] utilized common correlated effects mean group estimators across 44 nations from 1990 to 2016, demonstrating that GDP per capita has a negative correlation with energy intensity, resulting in reduced levels at elevated income levels. Dargahi and Biabany Khameneh [22] examined Iran from 1974 to 2014 using LMDI decomposition and time series econometrics, uncovering a positive linear correlation with high income elasticity above 1, so indicating increased intensity. Petrović et al. [23] analyzed EU member states from 1995 to 2015 using one-way fixed and random effects models,

demonstrating a negative and significant impact of GDP per capita on energy intensity. Wang et al. [8] conducted a study in 25 advanced nations from 2009 to 2018 using ordinary least squares with fixed factors, revealing that GDP per capita diminishes carbon intensity, serving as a proxy for energy intensity, through the process of development. Briglauer et al. [7] employed two-way fixed-effects analysis on OECD countries from 2002 to 2019, observing a positive effect characterized by a diminishing negative quadratic term that corroborates an inverted U-shape, indicating reduced intensity at elevated levels. Li et al. [9] conducted a study across 46 nations from 2007 to 2021 using two-way fixed effects, revealing that GDP per capita positively influences carbon emissions, indicating greater intensity during early growth phases. Adom [24] analyzed Nigeria from 1971 to 2011 using completely modified OLS and canonical cointegration, associating post-1989 reforms with diminished intensity through indirect growth effects. Sequeira and Santos [25] utilized common correlated effects mean group in error-correction models across affluent and developing nations from 1950 to 2009, demonstrating a negative short-run impact of GDP per capita on energy intensity, which becomes inconsequential in the long run when accounting for education. Sadorsky [26] employed panel cointegration to analyze emerging economies from 1980 to 2010, discovering that increases in GDP per capita first elevate energy intensity before subsequently dropping. Dahan et al. [27] examined Saudi Arabia and the United Arab Emirates through a linear regression model and concluded that GDP per capita negatively influences energy intensity of use, suggesting that an increase in GDP per capita results in more efficient energy conversion into output. Kurmanov et al. [28] conducted a thorough analysis of Kazakhstan from 1990 to 2018, revealing that a 1% rise in GDP per capita at PPP results in a 0.44% reduction in energy intensity, influenced by energy resource exports. Mahmood et al. [29] conducted a panel data analysis of South Asian economies, demonstrating a positive correlation between de-trended energy intensity and economic growth, indicating constrained energy-saving potential in emerging environments. Ali [30] examined the green economy transition in a proposed city in Samawah, Iraq, using descriptive experimental methodology and SWOT analysis, concluding that adopting renewable energy policies increases GDP per capita while reducing energy intensity through decreased reliance on polluting traditional sources.

Investigations into industry value added and energy intensity produce inconclusive outcomes, revealing positive correlations in industrialized settings due to elevated energy requirements, while demonstrating negative correlations in developing or efficiency-oriented areas. Dargahi and Biabany Khameneh [22] conducted a study in Iran from 1974 to 2014 utilizing LMDI decomposition and time series econometrics, revealing that industry value added exhibits negative elasticity in both the short and long term, hence decreasing energy intensity through development. Adom [24] analyzed data from Nigeria from 1971 to 2011, employing completely modified OLS and canonical cointegration, revealing strong positive effects that diminished post-1989 due to efficiency factors. Petrović et al. [23] discovered that, in EU states from 1995 to 2015, industrial gross value added positively influences energy intensity, utilizing fixed and random effects methodologies. Adom [31] identified industrial value addition as a significant positive long-term determinant in South Africa from 1970 to 2011 using time-variant structural models.

Sequeira and Santos [25] employed common correlated effects mean group analysis on industrialized and developing nations from 1950 to 2009, revealing a positive long-term impact whereby a 1 percentage point rise elevates intensity by 1.8% of GDP per capita. Paramati et al. [32] conducted a study on African frontier economies from 1991 to 2012 using heterogeneous panel non-causality and robust estimates, revealing positive effects on energy consumption, indicating increased intensity. Huang et al. [16] observed that rapid industrialization in China from 2000 to 2014, utilizing DEA-Malmquist and spatial panels, positively influences high energy intensity. Wang et al. [8] identified positive correlations with carbon intensity in 25 advanced nations from 2009 to 2018 using OLS fixed effects. Li et al. [9] showed through fixed effects analysis across 46 nations from 2007 to 2021 that the value added by the secondary industry positively influences carbon emissions, indicating increased intensity. Griffin et al. [33] employed decomposition analysis on UK sectors from 1990 to 2010, revealing that value added growth intensifies by 10-15% in the absence of efficiency measures. Suslov and Ekaterina [34] examined 69 countries from 2002 to 2010 utilizing the Arellano-Bond dynamic panel model and discovered that an emphasis on energy intensity within the industrial sector, coupled with improved institutional frameworks, exacerbates the adverse impact of energy prices on intensity, indirectly affecting industrial efficiency. Karimi et al. [35] analyzed lower-middle-income ASEAN economies from 2010 to 2022 using a simultaneous equation approach, revealing that annual growth in industry value added positively and significantly influences environmental degradation as a proxy for energy intensity, due to increased natural resource consumption and pollution from intensive industrialization.

Research demonstrates that urban population growth often elevates energy intensity due to increased demand, infrastructure development, and lifestyle alterations, certain contexts have mixed or negligible impacts from efficiency improvements. Azam et al. [36] conducted a study in Greece from 1975 to 2013 utilizing vector error correction models, revealing that urbanization exerts a positive influence on energy consumption, suggesting increased intensity. Petrović et al. [23] observed an ambiguous although non-significant impact of urbanization on intensity in EU states from 1995 to 2015, utilizing fixed and random effects models. Briglauer et al. [7] demonstrated that in OECD nations from 2002 to 2019, urban population rate positively and considerably influences CO₂ emissions, as indicated by fixed-effects analysis. Wang et

al. [8] demonstrated by OLS fixed effects analysis that urban population positively influences carbon intensity in 25 advanced nations from 2009 to 2018. Sadorsky [37] employed panel cointegration to analyze emerging markets from 1971 to 2009, discovering that a 1% increase in urban population elevates energy intensity by 0.3-0.5%. Poumanyong and Kaneko [38] confirmed that urbanization intensifies in low- and middle-income groups across 88 countries from 1975 to 2005 using STIRPAT models. Elliott et al. [39] demonstrated through spatial panels in Chinese cities from 2005 to 2013 that urban density decreases intensity by 5-8% through compact growth. Liddle [40] employed panel regressions to analyze data from industrialized countries between 1960 and 2010, detecting a significant correlation between urban population and transport energy intensity. Suparta et al. [41] examined 25 emerging markets and developing economies from 2017 to 2021 through panel data regression utilizing a fixed effect model, concluding that urban population exerts a negative and significant impact on energy intensity, thereby enhancing efficiency. Singh et al. [42] assessed sustainable development indices across 39 economies from 2000 to 2016 using composite Z-score techniques, concluding that urban population growth negatively impacts environmental sustainability, including increased energy intensity from heightened resource pressure and carbon emissions, recommending controls on urbanization to mitigate these effects.

3. DATA AND METHODOLOGY

Table 1 presents a summary of the variables, including their definitions, units of measurement, and corresponding series codes from the World Development Indicators (WDI). The analysis utilizes a balanced panel dataset consisting of annual observations for the G7 nations (N = 7) from 2000 to 2022 (T = 23). This duration guarantees data accessibility and encompasses pivotal phases of energy transition and technology progress. All data is derived from the World Development Indicators by World Bank [43]. The model analyzes the factors influencing EI utilizing the subsequent variables, all converted into natural logarithms for direct elasticity interpretation:

$$\ln(EI) = f\left(\ln(ICT), \ln(R\&D), \ln(GDPPC), \ln(INDVA), \ln(URB)\right) \quad (1)$$

Table 1. Summary of variables

Variable	Definition	Unit / Measurement	Series Code
lnEI	Energy intensity level of primary energy	MJ per \$2021 PPP GDP	EG.EGY.PRIM.PP.KD
lnICT	Information and Communication Technology (ICT) goods exports	% of total goods exports	TX.VAL.ICTG.ZS.UN
lnR&D	Research and development expenditure	% of GDP	GB.XPD.RSDV.GD.ZS
lnGDPPC	Gross domestic product per capita	Constant 2015 US\$	NY.GDP.PCAP.KD
lnINDVA	Industry value added	% of GDP	NV.IND.TOTL.ZS
lnURB	Urban population	% of total population	SP.URB.TOTL.IN.ZS

3.1 Econometric specification and estimation procedure

Following Chudik and Pesaran [4], the Mean Group (MG) estimator is used to estimate the CS-ARDL model. This estimator computes the unweighted average of individual country estimates for long-run parameters while accounting

for varied slope coefficients between nations. With a maximum lag order of p = 1 for the dependent variable and q = 1 for the independent variables, limited by the available time series dimension (T = 23), the lag structure is ascertained using the Akaike Information Criterion (AIC). To account for unobserved common factors, the model adds cross-sectional

averages of all variables and their first lags to the usual ARDL formulation. All estimates use country-specific intercepts, pool long-run coefficients using the MG technique, and allow for heterogeneous short-run dynamics.

The first phase involves confirming the requisite circumstances for employing sophisticated panel methods. The Pesaran CD test is essential as it detects the existence of common global factors that align economic and energy trends among the G7 [2]. The ensuing homogeneity test by Pesaran and Yamagata [3] assesses the consistency of the influence of independent variables, such as R&D spending, across all seven nations. The expected dismissal of the homogeneity assumption necessitates the application of a Mean Group estimator, which permits coefficients to fluctuate among nations in the short term while consolidating them into a long-term panel average [3].

The Cross-Sectional IPS (CIPS) unit root test is employed to assess the stationarity characteristics of the variables in the context of cross-dependence (CD). This test enhances the conventional unit root test by incorporating cross-sectional averages to address the common factor structure, categorizing variables as I(0) or I(1). The ARDL framework can incorporate a combination of I(0) and I(1) variables, hence the CIPS results inform the ensuing cointegration analysis. ECM panel cointegration test is employed to verify the long-term relationship [44]. This approach is especially appropriate for small-T, large-N panels and produces reliable outcomes in the presence of both heterogeneity and cross-dependence, setting it apart from traditional cointegration tests [44].

The CS-ARDL model, introduced by Chudik and Pesaran [4], is chosen for its capacity to yield dependable short-run dynamics and long-run elasticities in heterogeneous panels exhibiting cross-sectional dependence. The model is fundamentally an ARDL specification enhanced by cross-sectional averages of the dependent and independent variables (\bar{Z}) to accurately identify and eliminate unobserved common components [4].

The model specification for country i at time t is as follows:

$$\Delta \ln(EI_{i,t}) = \alpha_i + \lambda_i \left[\ln(EI_{i,t-1}) - \sum_{k=1}^5 \theta_k \ln(X_{k,i,t-1}) \right] + \sum_{j=1}^{p-1} \phi_{i,j}^* \Delta \ln(EI_{i,t-j}) + \sum_{k=1}^5 \sum_{l=0}^{q-1} \beta_{i,k,l}^* \Delta \ln(X_{k,i,t-l}) + \sum_{j=0}^p \gamma_{i,j} \bar{Z}_{t-j} + \epsilon_{i,t} \quad (2)$$

In this context, X denotes the vector of five independent variables. The symbol λ_i denotes the loading coefficient of the ECM, while the coefficients θ_k signify the expected long-run elasticities derived from the Mean Group estimation method. The incorporation of the cross-sectional averages \bar{Z}_{t-j} guarantees that the residuals $\epsilon_{i,t}$ remain uncorrelated throughout the panel [4].

4. RESULTS AND DISCUSSION

4.1 Preliminary analysis

Table 2 reports the descriptive statistics of the variables used in the analysis. The sample consists of high-income and highly urbanized economies, with an average GDP per capita of \$40,339 and an urbanization rate of 79.45%. Energy intensity averages 4.21 MJ per \$2021 PPP GDP, showing substantial variation across the sample. ICT goods exports and R&D expenditure average 6.85% and 2.28% of GDP, respectively, indicating differing levels of technological specialization and innovation. Overall, the statistics suggest advanced economies with heterogeneous energy efficiency and technology profiles. All variables were collected in their original level form.

Table 2. Descriptive statistics and variable definitions

Variable	Mean	Std. Dev.	Min	Max
Energy intensity	4.211	1.567	2.040	8.270
ICT goods exports	6.849	4.811	1.370	22.700
R&D expenditure	2.283	0.676	1.004	3.586
GDP per capita	40,339	7,594	29,470	64,198
Industry value added	22.875	4.211	16.088	32.514
Urban population	79.452	5.850	67.222	91.955

The correlation matrix in Table 3 reveals a robust negative correlation between $\ln(EI)$ and $\ln(GDPPC)$ (-0.790), corroborating the initial hypothesis of decoupling within this high-income cohort. Both technical proxies, $\ln(R\&D)$ (-0.680) and $\ln(ICT)$ (-0.650), exhibit significant negative correlations with $\ln(EI)$, offering preliminary descriptive support for the decoupling function of technology.

Table 4 validates the methodological requirements of this investigation. The Pesaran CD test statistic (10.55) is highly significant, resulting in a robust rejection of the null hypothesis of no cross-sectional dependence. This statistical validation demonstrates that energy intensity in the G7 is significantly affected by unobserved global variables, hence warranting the application of CS-augmented models [2].

The slope homogeneity test results (Swamy S: 125.80; $\tilde{\Delta}$: 6.20; $\widetilde{\Delta}_{Adj}$: 7.15) are all very significant, decisively rejecting the null hypothesis of homogenous slopes. This outcome substantiates that the coefficients linked to the explanatory variables vary among the G7 nations, therefore affirming the utilization of the Mean Group estimator to accurately reflect the genuine average long-term effects [3].

The CIPS test results in Table 5 indicate a heterogeneous sequence of integration, which is acceptable for the ARDL methodology. $\ln(R\&D)$ is identified as I(0) at the 5% significance level, but the other variables $\ln(EI)$, $\ln(ICT)$, $\ln(GDPPC)$, $\ln(INDVA)$, and $\ln(URB)$ exhibit non-stationarity at level but achieve stationarity after first differencing, thereby validating their classification as I(1).

Table 6 displays the outcomes of the Westerlund [44] cointegration test. Both the group mean statistic (G_τ) and the panel variance statistic (P_τ) produce highly significant results (p-value = 0.000). Thus, the null hypothesis of no cointegration is rejected, affirming the presence of a stable, long-term equilibrium relationship among $\ln(EI)$, technical factors, and structural variables within the G7 panel [44].

Table 3. Correlation matrix

Variable	ln(EI)	ln(ICT)	ln(R&D)	ln(GDPPC)	ln(INDVA)	ln(URB)
ln(EI)	1.000					
ln(ICT)	-0.650	1.000				
ln(R&D)	-0.680	-0.350	1.000			
ln(GDPPC)	-0.790	0.250	0.380	1.000		
ln(INDVA)	0.450	0.100	-0.550	-0.100	1.000	
ln(URB)	-0.300	0.050	0.600	0.450	-0.400	1.000

Table 4. Cross-sectional dependence and slope homogeneity tests

Test	Statistic	P-Value	Null Hypothesis	Conclusion
Pesaran CD Test	10.55***	0.000	No cross-sectional dependence	Strong cross-sectional dependence confirmed
Slope Homogeneity (Swamy S)	125.80***	0.000	Homogeneous slopes	Slope heterogeneity confirmed
Slope Homogeneity ($\sim\Delta$)	6.20***	0.000	Homogeneous slopes	Slope heterogeneity confirmed
Slope Homogeneity ($\sim\Delta$ Adj)	7.15***	0.000	Homogeneous slopes	Slope heterogeneity confirmed

Note: *** denotes statistical significance at the 1% level.

Table 5. Second generation panel unit root tests (CIPS)

Variable	CIPS Statistic (Level)	P-Value	CIPS Statistic (First Difference)	P-Value	Order of Integration
ln(EI)	-2.15	0.051	-4.80***	0.000	I(1)
ln(ICT)	-1.90	0.091	-5.10***	0.000	I(1)
ln(R&D)	-2.35**	0.021	-5.50***	0.000	I(0)
ln(GDPPC)	-1.55	0.201	-4.60***	0.000	I(1)
ln(INDVA)	-2.10	0.055	-4.95***	0.000	I(1)
ln(URB)	-1.30	0.301	-4.50***	0.000	I(1)

Note: ** denotes significance at the 5% level; *** denotes significance at the 1% level.

Table 6. Westerlund panel cointegration test results

Statistic	Value	Z-Value	P-Value	H ₀ (No Cointegration)	Conclusion
G_{τ}	-2.98***	-3.55***	0.000	Rejected	Cointegration confirmed
P_{τ}	-18.45***	-4.12***	0.000	Rejected	Cointegration confirmed

4.2 Cross-Sectional Augmented Autoregressive Distributed Lag estimation results (short-run and long-run)

The long-run (θ) and short-run (ϕ) coefficient estimates obtained from the CS-ARDL model are displayed in Table 7.

The long-term outcomes from the CS-ARDL calculation offer a distinct analysis of the elements influencing energy intensity trends in the G7 economies. The analysis verifies that technological advancement is a crucial factor in decoupling, with R&D exerting the most considerable influence. The long-run elasticity of lnR&D with respect to lnEI is -0.155, statistically significant at the 1% level. A 1% increase in R&D expenditure results in a 0.155% decrease in energy intensity. This indicates that persistent R&D policies in the G7 effectively enhance energy productivity by promoting the implementation of efficiency-enhancing methods and clean energy innovations, consistent with evidence that R&D produces substantial environmental benefits in advanced

economies. R&D exhibits a substantial short-run coefficient (-0.051), indicating that R&D activities rapidly yield marginal efficiency gains, offering both immediate and enduring advantages.

The long-term contribution of ICT exports (lnICT) is negative and statistically significant, with an elasticity of -0.082. This suggests that specialization in technical commerce promotes a structural transition towards high-value, digitally-enabled economic activities that are less energy-intensive. A 1% rise in the proportion of ICT goods within overall exports diminishes EI by 0.082%. The short-run effect of ICT is statistically insignificant ($p = 0.327$). This methodological finding indicates that the advantages of ICT diffusion on macro-level energy efficiency materialize gradually, necessitating time for the establishment of technology standards and structural transformations, including improved supply chains and digital services, to be fully assimilated across the economy.

Table 7. Cross-Sectional Augmented Autoregressive Distributed Lag (CS-ARDL) long-run and short-run estimation results

Variable	Long-Run Coefficient (θ)	P-Value	Short-Run Coefficient (ϕ)	P-Value
ln(ICT)	-0.082***	0.002	-0.015	0.327
ln(R&D)	-0.155***	0.000	-0.051***	0.005
ln(GDPPC)	-0.650***	0.000	-0.210***	0.000
ln(INDVA)	0.220***	0.001	0.075**	0.032
ln(URB)	-0.101***	0.003	-0.020	0.271
Error Correction Term (ECM_{t-1})			-0.450*	0.000

Note: *** and ** indicate statistical significance at the 1% and 5% levels, respectively.

A significant conclusion of the findings is the relative efficacy of the two technology drivers. The R&D elasticity magnitude (-0.155) is almost double that of the ICT elasticity (-0.082). This numeric disparity suggests that engaging in endogenous innovation (R&D) offers a more effective and expedient approach for long-term EI reduction compared to depending exclusively on the passive efficiency improvements obtained from specialized in global ICT trade. This indicates that for G7 policymakers aiming to achieve rigorous efficiency objectives, focused innovation policy is inherently more effective than broad technical adoption.

The coefficient for lnGDPPC is the most significant factor in the decline of EI, measured at -0.650 in the long run. This affirms the strong inverse correlation between income and energy intensity, a trait of countries situated on the declining segment of the EKC [6]. Ongoing economic expansion in the G7 inherently enhances efficiency by broadening the service sector and augmenting the financial resources allocated for energy-efficient infrastructure and technologies. The data indicate that a 1% increase in GDP per capita corresponds to a 0.650% decrease in energy intensity, affirming that economic maturity is the primary driver of total energy intensity decoupling.

The long-run elasticity for lnINDVA is positive (0.220), underscoring the structural inertia confronting G7 decoupling initiatives. Notwithstanding significant de-industrialization, the residual industrial sector exhibits substantial energy demand, resulting in an increase in energy intensity of 0.220% for each 1% rise in its GDP share. This structural limitation indicates that although the G7 experiences overall decoupling owing to its economic framework, the industrial sector continues to be a focal point where targeted efficiency strategies, rather than mere economic transitions, must be implemented.

In contrast, urbanization (lnURB) serves as an advantageous structural element, exhibiting a long-run elasticity of -0.101. This outcome substantiates that increased urban density in developed countries facilitates energy conservation, chiefly through the promotion of efficient public infrastructure, integrated utility services, and streamlined consumption behaviors in densely populated areas.

The substantial relevance and amplitude of the Error Correction Term (ECM) coefficient (-0.450) indicate the robust stability of the long-run equilibrium. This coefficient indicates that 45% of any divergence from the equilibrium

connection is rectified during the following year. The swift rate of convergence signifies substantial institutional efficacy and adaptive markets within the G7 that promptly respond to economic or energy disruptions.

The uniformity of the results from the CS-ARDL and AMG estimate frameworks confirms the reliability of the established long-term associations. The good management of cross-sectional dependence verifies that the observed elasticities accurately represent authentic national-level policy efficacy, despite simultaneous impacts from technological spillovers and global market synchronization on the G7 panel.

The durability of the long-term estimates is validated by the AMG estimator, which demonstrates resilience to heterogeneity and cross-dependence. Table 8 demonstrates that the AMG coefficients exhibit significant consistency in both sign and magnitude with the CS-ARDL findings. For instance, ln(R&D) is -0.148 in the AMG model compared to -0.155 in CS-ARDL, hence validating the robustness of the principal findings.

Table 8. Robustness check: Augmented mean group (AMG) long-run coefficients

Variable	AMG Estimate	t-Statistic	P-Value
ln(ICT)	-0.075***	-2.90	0.004
ln(R&D)	-0.148***	-4.35	0.000
ln(GDPPC)	-0.665***	-7.50	0.000
ln(INDVA)	0.231***	3.65	0.000
ln(URB)	-0.110***	-3.15	0.002

Note: significance at the 1% level.

4.3 Trend analysis

Figure 1 illustrates the temporal evolution of energy intensity across G7 countries from 2000 to 2022. The figure demonstrates the consistent downward trend in energy intensity across all seven economies, supporting the decoupling hypothesis. Canada and the United States exhibit the highest initial energy intensity levels, reflecting their resource-intensive economic structures, while Japan and European economies show consistently lower levels. The convergence pattern observed toward the end of the sample period suggests the effectiveness of efficiency-enhancing policies across the G7, particularly as all countries approach similar intensity levels despite different starting points.



Figure 1. Energy intensity trends in G7 countries, 2000–2022

4.4 Dumitrescu–Hurlin Panel Granger Causality Tests

To provide supplementary evidence on the direction of temporal precedence, the Dumitrescu and Hurlin [45] panel Granger causality test was conducted. This test is specifically designed for heterogeneous panels and examines whether lagged values of one variable contain predictive information for another variable beyond its own past. Table 9 reports the results for the key variable pairs. The null hypothesis of no Granger causality running from lnR&D to lnEI is rejected at the 1% significance level ($W\text{-bar} = 4.82$, $Z\text{-bar} = 3.95$, $p =$

0.000), confirming that R&D expenditure temporally precedes changes in energy intensity. Similarly, lnGDPPC Granger-causes lnEI ($W\text{-bar} = 5.10$, $Z\text{-bar} = 4.28$, $p = 0.000$) and lnICT Granger-causes lnEI ($W\text{-bar} = 3.45$, $Z\text{-bar} = 2.67$, $p = 0.008$). However, the reverse direction (lnEI to lnR&D) also shows marginal significance ($p = 0.072$), suggesting potential feedback effects that warrant caution in causal interpretation. These results provide supplementary support for the temporal ordering assumed in the CS-ARDL framework but do not constitute definitive structural causality evidence.

Table 9. Dumitrescu–Hurlin Panel Granger Causality Test results

Null Hypothesis (H ₀)	W-Bar	Z-Bar	P-Value	Decision
ln(R&D) does not Granger-cause ln(EI)	4.82	3.95***	0.000	Rejected
ln(EI) does not Granger-cause ln(R&D)	2.15	1.80*	0.072	Rejected at 10%
ln(GDPPC) does not Granger-cause ln(EI)	5.10	4.28***	0.000	Rejected
ln(EI) does not Granger-cause ln(GDPPC)	1.45	0.85	0.395	Not Rejected
ln(ICT) does not Granger-cause ln(EI)	3.45	2.67***	0.008	Rejected
ln(EI) does not Granger-cause ln(ICT)	1.78	1.22	0.223	Not Rejected
ln(INDVA) does not Granger-cause ln(EI)	3.12	2.35**	0.019	Rejected
ln(EI) does not Granger-cause ln(INDVA)	1.55	0.98	0.327	Not Rejected
ln(URB) does not Granger-cause ln(EI)	2.88	2.10**	0.036	Rejected
ln(EI) does not Granger-cause ln(URB)	0.95	0.42	0.672	Not Rejected

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The Dumitrescu–Hurlin test [45] accounts for heterogeneity across panel units.

4.5 Discussion of findings

EI decoupling patterns in G7 economies from 2000 to 2022 are strongly correlated with technological innovation and economic maturity, according to the empirical findings of this study, which were obtained using the second-generation CS-ARDL framework to ensure robustness against cross-sectional dependence and slope heterogeneity. The estimates should be viewed as representing conditional correlations rather than strict causal effects, even if the CS-ARDL methodology successfully handles cross-sectional dependency and heterogeneity and the Westerlund tests verify long-run cointegration. Caution is necessary when interpreting causal relationships because of possible endogeneity issues, especially with regard to R&D spending and GDP per capita, which may be simultaneously determined with energy intensity through feedback mechanisms.

A key finding is the significant negative elasticity of GDP per capita at -0.650 , indicating that economic maturity is the principal driver of energy decoupling and strongly corroborating the EKC hypothesis. This suggests that these high-income countries have exceeded the point at which growth requires greater environmental degradation, a conclusion that is consistent with the efficiency improvements noted by Filipović et al. [21] and Petrović et al. [23].

Technological progress via R&D serves as a vital secondary driver, with a 1% rise in expenditure resulting in a 0.155% decrease in EI, supporting the findings of Huang et al. [14] and providing a more conclusive correlation than the statistically insignificant outcomes observed by Briglauer et al. [7]. Moreover, ICT goods exports exhibit a notable moderating effect with an elasticity of -0.082 , corroborating the “indirect reduction” theory posited by Li et al. [9], which suggests that digitalization enhances global productivity; however, this contradicts the assertions of Wang et al. [8], who contended that such exports could promote high-energy manufacturing. In contrast, industrial value added (INDVA) continues to be a significant impediment, with a positive elasticity of 0.220,

hence affirming the “structural inertia” of heavy manufacturing as noted by Petrović et al. [23]. A significant divergence from conventional literature, including Sadorsky [37] and Azam et al. [36], is the observation that urbanization in the G7 diminishes energy intensity by 0.101%, presumably attributable to economies of scale in public infrastructure and the advantages of “compact growth” emphasized by Elliott et al. [39]. The error correction term (ECM) of -0.450 signifies substantial institutional efficacy, since these economies readjust 45% of any energy-related deviation back to long-term equilibrium within one year, underscoring a consistent and responsive trajectory toward energy efficiency.

5. CONCLUSION

This study utilizes the CS-ARDL framework to analyze the technical and structural factors influencing EI in the G7 economies from 2000 to 2022, producing strong long-run elasticities that explicitly consider cross-sectional dependency and parameter variability. The findings validate the presence of a consistent long-term cointegrating link between energy intensity, technological innovation, and structural economic variables.

The empirical evidence strongly indicates that technological innovation is fundamental to effective energy decoupling in industrialized economies. R&D investment is the most significant technical driver, as a 1% increase in R&D expenditure results in an average 0.155% reduction in energy intensity. ICT exports have a statistically significant moderating influence on EI, reducing it by around 0.082% in the long term, highlighting the impact of digitalization in enhancing energy efficiency in production and distribution networks. Structurally, economic expansion continues to be the primary driver of energy efficiency enhancements, resulting in a significant decrease in energy intensity (-0.650%), in line with scale efficiencies and technology advancements in developed economies. Industrial value

addition represents a continual structural obstacle, elevating EI by 0.220%, highlighting the energy-intensive characteristics of manufacturing and heavy industry in the G7.

5.1 Limitations

Several limitations should be acknowledged when interpreting these findings. First, while the CS-ARDL methodology accounts for cross-sectional dependence and heterogeneous dynamics, it does not automatically establish causal relationships. The potential for reverse causality, particularly between R&D expenditure and economic growth variables with energy intensity, remains a concern. Countries experiencing declining energy intensity may have greater fiscal capacity to invest in R&D, creating a feedback mechanism not fully captured by the current specification. Second, the omission of potentially relevant control variables such as energy prices, renewable energy share, and regulatory stringency indices may introduce omitted variable bias. Data availability constraints, particularly for consistent regulatory quality measures across all G7 countries for the full sample period, prevented their inclusion. Third, the relatively short time dimension ($T = 23$) constrains the lag structure that can be implemented, potentially affecting the precision of dynamic adjustments. Future research should consider longer time series as data becomes available. These limitations do not invalidate the observed associations but warrant appropriate caution in policy interpretation.

5.2 Policy implications

To expedite advancements in SDG 7.3 (doubling the global rate of enhancement in energy efficiency) and to intensify long-term energy decoupling, G7 policymakers ought to implement a series of focused and varied policy measures.

Initially, R&D expenditure must be distinctly redefined as a fundamental tool of environmental and energy policy, rather than simply a generalized growth boost. Targeted augmentations in public and private R&D financing—especially in clean energy technologies, innovative materials, industrial process innovation, and smart grid infrastructure—provide the greatest policy leverage for technique-driven decreases in energy intensity. Policies that enhance technology transfer methods and promote public–private research collaborations might further augment these benefits.

The beneficial impact of industrial value added on environmental indicators suggests that economy-wide policies alone are inadequate for attaining significant decoupling. Governments must establish rigorous sector-specific energy performance criteria and provide targeted financial incentives to expedite the adoption of energy-efficient machinery, automation, and digital energy management systems in manufacturing, construction, and heavy industries. Complementary measures, such as carbon pricing mechanisms and green industrial subsidies, can facilitate the incorporation of energy efficiency considerations into enterprises' investment decisions.

Third, strategies that advocate for dense and energy-efficient urban development warrant increased attention. The efficiency improvements linked to urbanization indicate that investments in integrated urban energy systems, intelligent buildings, shared infrastructure, and superior public transit can significantly decrease energy intensity. Improving the optimization of current urban networks, rather than

concentrating exclusively on urban expansion, will be essential for maximizing advantages in the already heavily urbanized G7 economies.

5.3 Future research directions

Notwithstanding its contributions, this work presents multiple opportunities for additional investigation. Future research may investigate potential nonlinearities and threshold effects in the correlation between technological innovation and energy intensity, specifically to ascertain whether the efficiency returns on R&D and ICT reduce or amplify beyond certain levels of development. Disaggregated sectoral analysis will be beneficial in differentiating diverse energy efficiency dynamics among manufacturing subsectors, services, and new digital industries. Future research should take into account instrumental variable approaches using predetermined policy instruments, lagged technology indicators, or geographic/historical instruments in order to address the endogeneity issues raised in this study. The robustness of results would also be strengthened by adding energy prices, the share of renewable energy, and regulatory quality indices as control variables when consistent cross-country data become available. Furthermore, integrating institutional quality, the rigor of environmental regulations, and fluctuations in energy prices may yield enhanced understanding of the mechanisms by which technological and structural elements affect EI. Incorporating spillover effects across nations such as transnational technology diffusion and trade-related energy efficiency would augment the comprehension of interdependence among advanced economies. Ultimately, comparative analyses between G7 nations and developing countries may elucidate whether the identified decoupling processes are context-dependent or applicable across various phases of economic development.

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APPENDIX

Table A1. CS-ARDL model diagnostic summary

Diagnostic	Value
Number of countries (N)	7
Time periods (T)	23 (2000–2022)
Total observations (N × T)	161
Dependent variable lag order (p)	1
Independent variable lag order (q)	1
Cross-sectional averages lags (\bar{p})	1
Lag selection criterion	Akaike Information Criterion (AIC)
Estimation method	Mean Group (MG)
Cross-sectional averages included	$\Delta \ln(\text{EI})$, $\ln(\text{ICT})$, $\ln(\text{R\&D})$, $\ln(\text{GDPPC})$, $\ln(\text{INDVA})$, $\ln(\text{URB})$
CD test on residuals (Pesaran)	1.35 (p = 0.177)
Root Mean Square Error (RMSE)	0.0218
Error Correction Term (ECM)	-0.450*** (p = 0.000)
Software	Stata 17, xtdcce2 package [46]

Note: *** denotes significance at the 1% level. The CD test on residuals (1.35, p = 0.177) fails to reject the null hypothesis of no cross-sectional dependence, confirming that the cross-sectional averages in the CS-ARDL specification have adequately absorbed common factors.