Assessing Environmental Efficiency in High-Income Nations: A Panel Data Approach Using DEA and Sustainability Indicators

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Abstract

This paper investigates the determinants of environmental efficiency in high-income countries from 1995 to 2022, focusing on the balance between economic development and environmental sustainability. It examines the relationships between GDP, energy consumption, and CO_2 emissions to identify key trade-offs for sustainable development. The study employs Data Envelopment Analysis (DEA) with CCR and BCC models on panel data from OECD countries (excluding Australia, Korea, and Turkey). The analysis uses three inputs—gross capital formation, population, and energy consumption—and two outputs—GDP and CO_2 emissions—to assess changes in relative environmental productivity. The findings show wide cross-country variation in converting investment and energy use into sustainable economic outcomes. Some countries achieve strong economic performance and lower emissions, while others are less efficient due to high energy use or weak emission control. The study highlights opportunities and ongoing challenges for sustainable growth. Policy implications stress the need to improve energy efficiency and lower carbon intensity, aligning national strategies with the United Nations Sustainable Development Goals (SDGs). The results offer useful benchmarks for low-income countries pursuing environmentally efficient development. The study contributes by applying an integrated DEA framework that captures economic, demographic, and environmental performance dimensions.

Keywords: Capital Formation, Population, Energy Consumption, GDP, CO_2 Emissions.

Introduction

Environmental issues like global warming, resource depletion, and biodiversity loss now dominate the concerns of global businesses, civil society organisations, and policymakers. High-income countries can lead the way toward a sustainable future through high consumption and advanced technologies, given their strong economies (York et al., 2003; Rosa et al., 2004). However, these countries also face an unwarranted burden of global environmental degradation due to their historical ecological footprint and significant contribution (Stern, 2011).

This indicates the ability to realise economic benefits at minimal environmental cost. This is normally termed environmental efficiency. High-income countries have sought ways to separate economic growth from environmental harm, moving beyond mere resource protection. These nations have established various laws and technologies. Their aim is to advance environmental outcomes, including reducing carbon emissions, improving energy efficiency, implementing

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circular-economy principles, and promoting sustainable urban development. Nevertheless, efforts face challenges, such as consumer behaviour, political opposition, and the need for socially oriented, sustainable solutions (Dyckhoff & Allen, 2001).

This research aims to investigate the concept of environmental efficiency in high-income countries by examining the technologies and policies adopted by campaigns to minimise environmental impacts without compromising economic stability. The study will help determine the achievements and challenges these countries face in their quest to become more sustainable by analysing key case studies and data (Zhou et al., 2008; Kumar & Khanna, 2009; Matsumoto et al., 2020). This study will contribute to the current debate on how wealthier countries can optimise their environmental performance and move closer to a more sustainable and fair future for everyone.

The main goal of the thesis is to assess the environmental efficiency of high-income OECD nations between 1995 and 2022. Specifically, it examines how efficiently these nations convert capital formation, population, and energy consumption into economic output, while reducing CO2 emissions, using Data Envelopment Analysis (DEA) (Reinhard et al., 2000; Hu & Wang, 2006).

The remainder of this paper is organised as follows: Section 2 presents a review of the relevant literature. Section 3 outlines the model specification, data, and methodology. Section 4 reports the empirical findings and includes a discussion. Finally, Section 5 concludes the study and offers policy recommendations.

Literature Review

This section provides a review of past research on environmental efficiency and sustainable economic performance in high-income nations. The conducted studies are summarised in Table 1, which analyses the correlation between resource utilisation, environmental policies, and efficiency outcomes in the context of high-income OECD countries.

Table 1: Summary of the Studies on Environmental Efficiency

Author(s)	Country	Time/Frame	Methodology	Main Findings
Taskin & Zaim (2000)	Mixed (High-income, low–middle income)	1977, 1980, 1985, 1990	Non-parametric DEA with undesirable outputs	Trade–environment link; CO_2 as undesirable output; significant inefficiencies across countries.
Hermoso-Orzáez et al. (2020)	28 EU countries	2005–2012	DEA (two variants)	Varying eco-efficiency; environmental policies improving outcomes in some EU states.
Moutinho et al. (2017)	26 EU countries	2001–2012	DEA (CCR & BCC); Quantile regression	Pollution/resource taxes significantly affect eco-efficiency; material consumption tied to inefficiency.
Lacko & Hajduova (2018)	26 EU countries	2008–2016	Two-step DEA + double bootstrap	GHG emissions strongly influence efficiency; climate and socio-economic factors explain variations.
Rakshit & Mandal (2018)	Global (High-, middle-, low-income)	1993–2013	DEA (joint, by-production)	Large disparities in Environmental Energy

				Efficiency; emissions significantly reduce efficiency.
Matsumoto et al. (2019)	27 EU countries	2000–2017	Window DEA + Global Malmquist–Luenberger Index	Long-term increase in eco-performance but mixed patterns across EU countries.
Li et al. (2019)	31 Chinese cities	2013–2016	CCR/BCC DEA; SBM; Meta-frontier	Strong regional differences; air pollution (AQI, PM2.5) negatively affects environmental performance.
Dyckhoff & Allen (2001)	Conceptual	—	Generalized environmental DEA	Introduces formal treatment of good vs bad outputs in DEA to improve environmental modeling.
Gatimbu et al. (2019)	Kenya (Tea processors)	Panel data	Inverse DEA + Tobit	Environmental efficiency low (~49%); high costs and profit orientation hinder eco-efficiency.
Zhang et al. (2016)	30 Chinese provinces	2005–2011	SBM-DEA + Tobit	Economic structure, technology, and government regulation shape inefficiency; clusters regions.
Castellano et al. (2019)	24 Italian ports	2016	DEA (eco-economic model)	Green port policies improve both environmental and economic performance.
Yang & Li (2018)	30 Chinese provinces	2007–2016	SBM-DEA + Regression	Exports and FDI have U-shaped effect on eco-efficiency; strong need for stricter early regulation.
Zhou et al. (2008)	Multi-country	—	DEA (CRS, VRS, NIRS)	Proposes efficiency metrics with variable returns to scale for environmental performance.
Chen et al. (2017)	30 Chinese provinces	2005–2014	Cross-efficiency DEA (game-theoretic)	Inter-provincial interactions affect efficiency; spatial clustering important for policy.
Chu et al. (2019)	China (Provinces)	—	Two-stage DEA	Pollution controls a major driver; major regional differences in eco-efficiency.
Balitskiy et al. (2016)	26 EU countries	1997–2011	Panel cointegration, ECM	Positive energy–GDP link; diminishing returns to natural gas; energy efficiency affects growth.
Mukherjee (2008)	United States (Industrial sector)	1970–2001	DEA	Sectoral differences in energy efficiency; DEA better than simple energy-intensity metrics.
Halkos & Tzeremes (2009)	17 OECD countries	1980–2002	DEA window + GMM	No EKC pattern; efficiency adjusts quickly to optimum level; income not tied to efficiency.

Reinhard et al. (2000)	Netherlands (Dairy farms)	—	DEA vs SFA	DEA finds lower environmental efficiency than SFA; emissions strongly reduce efficiency.
Hu & Wang (2006)	29 Chinese regions	1995–2002	DEA (TFEE index)	Energy efficiency increasing but large regional gaps; U-shaped income–efficiency link.
Shi et al. (2010)	28 Chinese regions	2000–2006	DEA with undesirable outputs	Eastern/Central China more energy-efficient; heavy industries cause inefficiency.
Wu et al. (2012)	Chinese counties	—	Dynamic DEA with undesirable outputs	Efficiency improvements mainly driven by technological progress.
Oggioni et al. (2011)	Global cement industry	—	DEA + DDF	Technology and reduced CO_2 improve eco-efficiency; cement industry highly polluting
Zofio & Prieto (2001)	OECD manufacturing	—	Regulatory DEA	Emissions constraints cause congestion; environmental regulation creates opportunity costs.
Soares et al. (2017)	60 major world economies	2010	GINI; Meta-frontier DEA	Developed countries have higher EE but also higher emissions; tech gaps cause inefficiency.
Vaninsky (2018)	Global	—	Stochastic DEA + perfect-objective method	Proposes restructuring global economy to maximize clean energy and minimize CO_2.
Madaleno et al. (2016)	26 EU countries	2001–2012	DEA (input/output oriented)	Efficiency rankings depend on DEA model; renewable energy policies drive performance.
Tsai et al. (2016)	13 Asian countries	—	Meta-frontier SBM-DEA	Energy efficiency tied to governance; recommends strong top-down carbon policies.
Banker et al. (1984)	Conceptual	—	CCR DEA	Foundational model for technical/scale efficiency; differentiates CRS vs VRS.
Singh & Khanna (2009)	38 countries	1971–1992	DEA + regression	EE follows EKC-like pattern only in Annex-I countries; trade openness improves efficiency.
Zhou et al. (2020)	China (31 industries)	2001–2015	Three-stage DEA	Eco-efficiency initially fell then rose; scale inefficiency main issue; profit & FDI improve EE.
Chen et al. (2019)	30 Chinese provinces	2012–2016	Super SBM + Malmquist	Technology drives positive changes; pollution-control investment sometimes reduces efficiency.
Youg et al. (2018)	China (Provinces)	—	DEA + Fuzzy C-Means + Rough sets + ANN	Identifies key determinants of energy efficiency; clusters provinces by efficiency levels.
Xiaoli et al. (2014)	China (Industrial sectors)	—	TFEE Index	Technology largest driver of TFEE; regional disparities remain wide.

Wu et al. (2019)	China (38 industries)	—	Two-sided non-homogeneous DEA	Waste/recycling industry most efficient; clusters sectors for tailored policy.
Ye et al. (2023)	China	1991–2020	QARDL econometric model	Sharing economy & energy efficiency support sustainable development; urbanization also positive.
Knox Lovell et al. (1995)	19 OECD countries	1970–1990	LP frontier analysis	Adding emissions alters macroeconomic rankings; Europe performs worse when pollution included.
Banker & Morey (1986)	Conceptual	—	Extended DEA with exogenous variables	Introduces DEA with non-discretionary inputs; improves real-world applicability.

Table 1 despite a few studies being conducted on environmental performance, eco-efficiency and impacts of environmental policies in various countries, there still exists considerable gaps especially with regard to the situation in high-income OECD countries. First, majority of the current studies target individual countries or short time ranges hence offering little information on the long-term trends in efficiency. The absence of a holistic study to measure the efficiency of the environment within a long period like 1995-2022 is also evident particularly on the case of the advanced economy. Second, although in the past the utilization of the variables like energy use, GDP or emissions is often analyzed few studies combine the inputs of capital formation, populations and the use of energy with the desirable (GDP) and undesirable (CO2) outputs. This multi-dimensional model is crucial in the correct measurement of the impact of resource use on the environmental outcomes in more developed countries. Third, the majority of the previous research is based on the conventional econometric models that fail to reflect the relative efficiency variations between nations. The use of DEA (CCR and BCC models) is still not common in high-income OECD settings although it is appropriate to measure efficiency under a variety of inputs and outputs without any given functions. Lastly, the high-income countries have been world leaders in technological development and environmental policy but the lack of empirical investigation on the translation of such policies and innovations to environmental efficiency exists. This leaves a knowledge gap in regards to whether the advanced economies are attaining sustainable growth or merely transferring the environmental burdens.

Data and Methodology

The purpose of this study measured the environmental efficiency in high income countries. The measurement of efficiency is created on assessing how well resources are being used to achieve a specific goal or output. This section outlines the data and methodology used to measure technical efficiency and develops the DEA model for the analysis.

Model

The model estimated the technical efficiency of environmental efficiency in high income Countries. This model involves the use of two outputs, GDP, Carbon dioxide (CO2) two inputs, Gross Capital Formation (GCF), Population and Energy use.

Table 2: Inputs and Outputs used in the study

Inputs	Outputs
Gross Capital Formation (GCF)	Gross Domestic Product (GDP)
Population	Carbon Dioxide (CO2)
Energy Use	

Data

We have used data of OECD countries excluding Australia, Kora and Turkey from 1995 to 2022 and we used Data Envelopment Analysis (DEA) methodology. This study is important as it explores the crucial link between economic growth and environmental sustainability. By analyzing the environmental efficiency of high-income countries this research provides valued visions into the effectiveness of existing ecological rules and identifies areas for improvement. This study can inform policymakers and stakeholders to maximize their resource allocation to minimize environmental degradation and encouraging sustainable development in the long run in support of the realization of the United Nations Sustainable Development Goals (SDGs). Moreover, this study may be used as a reference point to even low- and middle-income countries so that they could study the experience of the high-income states and formulate their own approaches to the environmentally friendly economic development.

Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) is an approach to measuring efficiency, which relies on mathematical programming rather than on regression. It does not require a given form of the production function to be specified and has few assumptions based on underlying technology. Farrell (1957) proposed a linear programming model of determining the technical efficiency of a firm against a given standard technology with constant returns to scale as benchmarks. The efficiency measure is connected with the coefficient of resource utilization as defined by Debreu (1951). DEA was then formalized in 1981 by Charnes, Cooper and Rhodes as an efficiency measure of decisions making units (DMUs) that have numerous inputs and outputs, and have no market prices. They used the term decision making units to refer to the industries where measurable products are manufactured using measurable inputs but they do not have market prices. The most popular model of DEA, the Charnes, Cooper and Rhodes (CCR) model, is a model that assumes constant returns to scale (CRS). The generic formulation of the CCR model is as below:

Results and Discussion

In this section, we discuss the results of DEA, CCR and BCC models are used in this study to determine the overall environmental efficiency of OECD countries. We discuss the results of DEA listed OECD countries. The results are concerned with the environmental performance of high-income nations in the period between 1995 and 2022, in terms of Data Envelopment Analysis (DEA). The descriptive statistics and efficiency trends are reported and the analysis of variations at the country level. A special focus is placed on the correlation between the economic growth energy consumption gross capital formation population and environmental performance. In this way one can find some information about how the high-income countries have managed to cope with the issue of economic performance and sustainability.

CRS Descriptive Analysis by Year

The CRS descriptive analysis from 1995–2022 in Table 3.

Table 3: CRS Descriptive Analysis by Year

Years	Mean Efficiency	Standard Deviation	Minimum Efficiency	Maximum Efficiency	No. of efficient units
1995	0.614	0.260	0.219	1	8
1996	0.628	0.260	0.215	1	9
1997	0.613	0.255	0.206	1	7
1998	0.620	0.256	0.200	1	8
1999	0.605	0.256	0.228	1	8
2000	0.601	0.256	0.227	1	8
2001	0.428	0.394	0.015	1	9
2002	0.616	0.244	0.231	1	7
2003	0.619	0.243	0.234	1	7
2004	0.633	0.240	0.268	1	7
2005	0.639	0.240	0.271	1	7
2006	0.647	0.238	0.274	1	7
2007	0.652	0.233	0.277	1	7
2008	0.640	0.235	0.271	1	7
2009	0.638	0.233	0.279	1	7
2010	0.622	0.238	0.279	1	7
2011	0.628	0.233	0.263	1	7
2012	0.644	0.232	0.273	1	7
2013	0.641	0.233	0.275	1	7
2014	0.650	0.232	0.268	1	7
2015	0.658	0.232	0.279	1	7
2016	0.650	0.234	0.274	1	7
2017	0.651	0.232	0.275	1	7
2018	0.655	0.231	0.277	1	7
2019	0.655	0.230	0.279	1	7
2020	0.653	0.229	0.287	1	7
2021	0.650	0.230	0.280	1	7
2022	0.654	0.230	0.280	1	7

Table 3 summarizes efficiency scores from 1995 to 2022 revealing a major outlier in 2001 where the mean efficiency dropped sharply to 0.428 and variability spiked, indicating significant disruption. For all other years mean efficiency remained stable between 0.60 and 0.66 with a slight improving trend over time. The standard deviation gradually decreased reflecting more consistent performance across units and the number of top-performing units stabilized at 7 annually after 2002. The data confirms that 2001 was an anomalous year while the long-term trend shows mild improvement and greater homogeneity in efficiency scores.

CRS Descriptive Analysis by Countries

In these results present the descriptive analysis by countries individually. Table shows the mean, minimum maximum and standard deviation. In these results some countries maximum efficiency is 1.

Table 4: CRS Descriptive Analysis by Countries

Countries	Mean Efficiency	Standard Deviation	Minimum Efficiency	Maximum Efficiency	No. of Efficient values
Austria	0.487	0.074	0.116	0.523	0
Belgium	0.371	0.057	0.130	0.418	0
Canada	0.261	0.045	0.041	0.287	0
Chile	0.894	0.065	0.799	1.000	13
Colombia	0.971	0.140	0.259	1.000	26
Costa Rica	0.602	0.101	0.457	1.000	1
Czechia	0.970	0.158	0.162	1.000	28
Denmark	0.867	0.081	0.769	1.000	6
Estonia	0.606	0.098	0.505	1.000	1
Finland	0.347	0.038	0.173	0.376	0
France	0.518	0.092	0.052	0.549	0
Germany	0.745	0.136	0.081	0.833	0
Greece	0.455	0.075	0.191	0.536	0
Hungary	0.645	0.102	0.304	0.757	0
Iceland	0.615	0.098	0.181	0.708	0
Ireland	1.000	0.000	1.000	1.000	28
Isreal	1.000	0.000	1.000	1.000	28
Italy	0.297	0.142	0.200	1.000	1
Japan	0.599	0.104	0.078	0.655	0
Lativa	0.996	0.023	0.880	1.000	28
Lithuania	1.000	0.000	1.000	1.000	28
Luxembourg	0.607	0.127	0.391	1.000	1
Mexico	0.668	0.114	0.110	0.744	0
Netherland	0.381	0.059	0.100	0.419	0
New Zealand	0.517	0.066	0.207	0.588	0
Norway	0.371	0.037	0.218	0.414	0
Poland	0.680	0.114	0.307	0.804	0
Portugal	0.443	0.062	0.157	0.539	0
Slovak Republic	0.600	0.064	0.480	0.698	0
Slovenia	0.705	0.073	0.502	0.837	0
Spain	0.519	0.094	0.085	0.588	0
Sweden	0.288	0.045	0.069	0.333	0
Switzerland	0.567	0.102	0.095	0.647	0
United Kingdom	0.437	0.069	0.337	0.753	1
United State	0.965	0.186	0.015	1.000	27

Table 4 shows a country-level efficiency analysis revealing stark disparities in performance across 35 nations. A clear hierarchy emerges with a small group of top performers demonstrating exceptional results. Ireland, Israel and Lithuania show perfect consistent efficiency across all observed periods while Latvia the United States, Colombia, Czechia and Chile also exhibit very high mean efficiency frequently achieving the maximum score. In stark contrast countries like Canada, Sweden, Italy, Finland and Norway form a low-efficiency tier with mean scores below 0.38 indicating persistent performance challenges. The analysis also highlights volatility top performers like the United States and Colombia have high standard deviations signifying significant fluctuations between very high and much lower scores over time. A broad middle band of countries including Austria, France and Spain displays moderate and relatively stable efficiency. The data confirms that sustained perfect efficiency is rare with most countries even some high performers experiencing considerable variation underscoring the dynamic nature of relative national performance over the long term.

Stem and leaf table of CRS

The stem and leaf table of CRS. The OTE scores shows that the years having value of 1 are on the efficient frontier under constant return to scale (CRS) technology assumption and those having values less than 1 are below the frontier.

Table 5: Stem and leaf of CRS 1995-2022

CRS	95	96	97	98	99	00	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22
1	8	9	7	8	8	8	9	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7
0.90-0.99	1	0	2	1	0	0	0	1	1	1	2	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
0.80-0.89	0	0	0	0	1	1	1	1	0	1	0	2	2	1	1	0	1	2	1	4	4	4	3	3	3	2	2	3
0.70-0.79	3	3	2	2	1	2	1	2	2	1	2	2	2	2	1	2	3	4	5	3	2	2	3	5	4	5	5	5
0.60-0.69	5	3	4	2	3	0	1	2	5	7	6	7	9	8	8	6	5	5	4	4	6	6	6	4	6	5	6	5
0.50.0.59	4	8	8	11	7	9	1	9	8	6	6	5	4	6	7	8	8	8	9	8	7	7	7	7	6	7	6	6
0.40-0.49	5	4	3	2	6	7	0	6	5	5	5	4	5	4	4	4	4	3	2	4	4	4	4	4	4	4	4	4
0.30-0.39	6	5	6	6	6	5	2	4	4	4	4	5	3	4	4	5	4	3	5	4	4	2	3	4	4	4	4	4
0.20-0.29	3	3	3	3	3	3	3	3	3	3	3	2	2	2	2	2	3	3	2	1	1	3	2	1	1	1	1	1
0.10-0.19	0	0	0	0	0	0	17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 5 the CRS distributions show clear shifts over time. In the mid-1990s there were relatively few candidates scoring in the higher CRS ranges such as 0.90–0.99 or 0.80-0.89 with most observations concentrated in the middle bands around 0.50–0.69 and 0.40–0.49. As the years progressed into the 2000s the middle ranges (0.50–0.69) continued to dominate but there was also more consistency in the lower bands (0.30–0.39 and 0.20–0.29) suggesting that many candidates clustered around average to below-average CRS scores. Interestingly from around 2010 onwards the higher ranges (0.80–0.99) became more visible and slightly more frequent indicating gradual improvement in top performers. At the same time the lowest category (0.10–0.19) which showed spikes in some earlier years disappeared completely reflecting fewer extremely low scores. By the late 2010s and early 2020s the distribution shows a more stable pattern with most candidates spread between 0.30–0.69 but with a stronger presence of candidates in the 0.70–0.89 range compared to the early years.

VRS Descriptive Analysis in Years

The VRS Descriptive Analysis from 1995-2022 in Table 6.

Table 6: VRS Descriptive Analysis in Years

Years	Mean Efficiency	Standard Deviation	Minimum Efficiency	Maximum Efficiency	No. of Efficient Units
1995	0.633	0.253	0.230	1	8
1996	0.624	0.258	0.231	1	9
1997	0.617	0.255	0.222	1	8
1998	0.625	0.256	0.216	1	9
1999	0.611	0.256	0.246	1	8
2000	0.608	0.257	0.245	1	8
2001	0.463	0.413	0.015	1	12
2002	0.623	0.246	0.250	1	7
2003	0.626	0.244	0.254	1	8
2004	0.640	0.241	0.274	1	8
2005	0.645	0.241	0.273	1	8
2006	0.653	0.239	0.277	1	8
2007	0.659	0.233	0.280	1	8
2008	0.648	0.236	0.277	1	8
2009	0.644	0.234	0.281	1	8
2010	0.630	0.240	0.283	1	8
2011	0.637	0.235	0.266	1	7
2012	0.653	0.232	0.275	1	7
2013	0.650	0.233	0.277	1	7
2014	0.660	0.233	0.270	1	7
2015	0.668	0.233	0.281	1	7
2016	0.659	0.234	0.276	1	7
2017	0.662	0.231	0.277	1	7
2018	0.665	0.230	0.279	1	7
2019	0.665	0.229	0.281	1	7
2020	0.662	0.229	0.288	1	7
2021	0.660	0.230	0.282	1	7
2022	0.664	0.230	0.282	1	7

Table 6 shows the annual performance under the Variable Returns to Scale (VRS) model from 1995 to 2022 reinforcing the critical outlier status of 2001 where the mean efficiency collapsed to 0.463 and variability surged indicating a severe disruptive event that caused a sharp divide between high and low performers. Outside of this anomaly, the long-term trend reveals a consistent narrative of gradual improvement, with the mean efficiency climbing from the 0.61-0.63 range in the late 1990s to approximately 0.66-0.67 in recent years. Accompanying this rise in average performance is a notable convergence among units as evidenced by a steadily declining standard deviation which signifies that the efficiency gap between the top and bottom performers has been narrowing over time. Furthermore, the VRS model, being less restrictive consistently yields slightly higher mean scores and a greater number of efficient units annually compared to the CRS model confirming that it provides a more forgiving assessment by accounting for differences in operational scale. Overall, the data underscores a post-2001 recovery and a long-term trajectory toward higher and more homogenous efficiency levels across the board.

VRS Descriptive Analysis in Countries

We have analyzed the VRS Descriptive analysis for OECD countries individually. The table similarly shows the mean minimum maximum and standard deviation.

Table 7: VRS Descriptive Analysis in Countries

Countries	Mean Efficiency	Standard Deviation	Minimum Efficiency	Maximum Efficiency	No of Efficient Values
Austria	0.494	0.075	0.116	0.534	0
Belgium	0.377	0.057	0.130	0.424	0
Canada	0.263	0.046	0.041	0.288	0
Chile	0.959	0.044	0.880	1.000	13
Colombia	0.971	0.140	0.259	1.000	26
Costa Rica	0.609	0.099	6.000	28.000	1
Czechia	1.000	0.000	1.000	1.000	28
Denmark	0.871	0.080	0.771	1.000	6
Estonia	0.610	0.097	0.506	1.000	1
Finland	0.350	0.038	0.173	0.379	0
France	0.525	0.093	0.052	0.556	0
Germany	0.760	0.135	0.097	0.848	0
Greece	0.460	0.076	0.191	0.540	0
Hungary	0.651	0.102	0.304	0.762	0
Iceland	0.619	0.098	0.181	0.711	0
Ireland	1.000	0.000	1.000	1.000	28
Isreal	1.000	0.000	1.000	1.000	28
Italy	0.315	0.139	0.216	1.000	1
Japan	0.613	0.102	0.105	0.668	1
Latvia	1.000	0.000	1.000	1.000	28
Lithuania	1.000	0.000	1.000	1.000	28
Luxembourg	0.608	0.127	0.391	1.000	1
Mexico	0.682	0.117	0.110	0.758	0
Netherland	0.388	0.061	0.100	0.429	0
New Zealand	0.521	0.067	0.207	0.591	0
Norway	0.373	0.038	0.218	0.415	0
Poland	0.711	0.124	0.307	0.844	0
Portugal	0.446	0.063	0.157	0.557	0
Slovak Republic	0.604	0.064	0.483	0.698	0
Slovenia	0.707	0.073	0.502	0.838	0
Spain	0.530	0.095	0.085	0.598	0
Sweden	0.289	0.045	0.069	0.334	0
Switzerland	0.572	0.101	0.095	0.651	0
United Kingdom	0.479	0.120	0.346	1.000	1
United States	0.965	0.186	0.015	1.000	27

In the Table 7 VRS Countries Table reveals a distinct hierarchy of national efficiency sharply dividing countries into top and bottom tiers while demonstrating the impact of the more flexible Variable Returns to Scale model. A group of exceptional performers including Czechia, Ireland, Israel, Latvia and Lithuania, achieved perfect efficiency across all observed periods joined by other high-efficiency nations like the United States, Colombia and Chile which frequently reached the performance frontier. In stark contrast countries such as Canada, Sweden and Belgium form a low-efficiency tier with mean scores below 0.38 and no periods of perfect performance. The data further highlights significant volatility exemplified by the United States, which despite being efficient in 27 of 28 periods has a high standard deviation due to one extremely low score. When compared to the CRS model the VRS results show a slight increase in efficiency scores for nearly all countries confirming that the model provides a more forgiving assessment by accounting for differences in operational scale thereby offering a clearer picture of pure technical efficiency apart from scale related inefficiencies.

Stem and leaf of VRS 1995-2020

Now discuss about the stem and leaf of VRS

Table 8: Stem and leaf of VRS 1995-2022

VRS	95	96	97	98	99	00	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22
1	8	9	8	9	8	8	12	7	8	8	8	8	8	8	8	8	7	7	7	7	7	7	7	7	7	7	7	7
0.90-0.99	1	0	1	0	1	1	0	1	0	0	1	0	0	0	0	0	1	1	0	1	1	1	1	1	1	1	1	1
0.80-0.89	0	0	0	0	0	0	0	1	1	1	0	2	2	1	1	0	0	2	3	3	4	4	3	3	3	2	2	2
0.70-0.79	3	3	2	2	1	2	0	2	1	2	2	2	3	3	2	3	4	3	3	4	2	2	3	4	3	4	4	5
0.60-0.69	6	4	4	4	3	1	1	4	6	6	6	7	8	7	7	7	5	5	5	3	5	5	5	5	6	6	6	5
0.50-0.59	7	7	8	10	9	9	1	7	7	7	6	6	4	6	7	6	8	8	8	8	8	8	8	7	7	7	7	7
0.40-0.49	2	4	3	2	4	6	0	6	5	4	5	5	6	4	4	4	4	4	4	4	3	3	3	3	3	3	3	3
0.30-0.39	5	5	6	5	6	5	2	4	4	4	5	3	3	4	5	5	4	3	3	4	4	3	3	4	4	4	4	4
0.20-0.29	3	3	4	3	3	3	3	3	3	3	2	2	1	2	1	2	2	2	2	1	1	2	2	1	1	1	1	1
0.10-0.19	0	0	0	0	0	0	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 8 presents a yearly frequency distribution of scores likely related to a performance or retention metric such as a Volunteer Retention Score (VRS) from 1995 to 2022. The structure groups observations into score ranges or bins, from the highest (1.00) down to the lowest (0.10–0.19). Over the entire period the majority of observations consistently fall within the mid-range scores specifically between 0.40 and 0.69 indicating that the bulk of the assessed individuals or units typically received average to moderately above-average ratings. The highest performance tier (0.90–0.99) consistently has very few entries each year suggesting that top scores were rare while the lowest bin (0.10–0.19) was almost entirely vacant except for a single, dramatic outlier. The year 2001 stands out as a significant anomaly. It features an extreme concentration of 16 observations in the lowest score bin a stark contrast to every other year which has zero or one observation in that range. Simultaneously, the perfect score bin (1.00) for 2001 shows a notably high count of 12. This unusual distribution could point to a data entry error a fundamental change in the scoring system that year or a real-world crisis that caused a severe polarization in outcomes resulting in a bimodal distribution with clusters at both the very high and very low ends. Following 2001 the score distributions become more stable and consistent, with a noticeable decline in the highest scores in recent years (2015–2022) and a continued concentration in the 0.50–0.69 range.

Scale Efficiency Descriptive Analysis by Year

In table we find the Scale Efficiency descriptive analysis by year.

Table 9: Scale Efficiency Descriptive Analysis by Year

Years	Mean Efficiency	Standard Deviation	Minimum Efficiency	Maximum Efficiency	No. of Efficient Values
1995	0.963	0.040	0.856	1	9
1996	0.987	0.016	0.931	1	9
1997	0.991	0.013	0.928	1	9
1998	0.990	0.015	0.926	1	8
1999	0.988	0.019	0.919	1	9
2000	0.987	0.019	0.916	1	8
2001	0.952	0.155	0.162	1	30
2002	0.987	0.019	0.914	1	8
2003	0.989	0.017	0.921	1	7
2004	0.988	0.017	0.921	1	7
2005	0.988	0.018	0.921	1	8
2006	0.988	0.018	0.923	1	8
2007	0.988	0.018	0.922	1	7
2008	0.987	0.018	0.925	1	7
2009	0.989	0.016	0.936	1	9
2010	0.987	0.018	0.920	1	8
2011	0.986	0.020	0.910	1	8
2012	0.985	0.022	0.909	1	8
2013	0.984	0.026	0.886	1	7
2014	0.984	0.027	0.876	1	9
2015	0.984	0.026	0.883	1	7
2016	0.983	0.029	0.860	1	7
2017	0.983	0.031	0.840	1	8
2018	0.982	0.035	0.815	1	7
2019	0.983	0.036	0.809	1	8
2020	0.985	0.032	0.828	1	10
2021	0.983	0.035	0.816	1	8
2022	0.983	0.035	0.816	1	10

Table 9 shows that scale efficiency remained consistently high over the years with mean values mostly above 0.95. At least one unit achieved perfect efficiency (1.0) each year serving as a benchmark for others. In the earlier years such as 1995, efficiency was slightly lower with a minimum of 0.855 and greater variation among units. Over time, the minimum efficiency values improved to above 0.92 reflecting better performance of the weaker units. Standard deviation also declined in later years indicating more uniformity in efficiency across the system. Additionally, the number of fully efficient units increased, reaching up to 14 in some years.

Scale Efficiency Descriptive Analysis by Countries

Discuss the scale Efficiency descriptive analysis by countries individually.

Table 10: Scale Efficiency Descriptive Analysis by Countries

Countries	Mean Efficiency	Standard Deviation	Minimum Efficiency	Maximum Efficiency	No. of Inefficient values
Austria	0.986	0.024	0.869	1	1
Belgium	0.985	0.015	0.913	1	1
Canada	0.992	0.003	0.988	1	1
Chile	0.932	0.031	0.905	1	3
Colombia	1.000	0.001	0.995	1	27
Costa Rica	0.987	0.015	0.914	1	1
Czechia	0.970	0.158	0.162	1	27
Denmark	0.995	0.003	0.990	1	6
Estonia	0.993	0.027	0.856	1	4
Finland	0.992	0.008	0.955	1	1
France	0.986	0.003	0.981	1	1
Germany	0.976	0.028	0.835	0.98	0
Greece	0.990	0.004	0.979	1	1
Hungary	0.991	0.009	0.948	1	1
Iceland	0.994	0.008	0.966	1	1
Ireland	1.000	0.000	1.000	1	28
Isreal	1.000	0.000	1.000	1	28
Italy	0.938	0.017	0.921	1	1
Japan	0.970	0.045	0.743	0.98	0
Latvia	0.996	0.023	0.880	1	27
Lithuania	1.000	0.000	1.000	1	28
Luxembourg	0.999	0.001	0.993	1	9
Mexico	0.981	0.005	0.975	1	1
Netherland	0.982	0.006	0.974	1	1
New Zealand	0.993	0.007	0.956	1	1
Norway	0.994	0.009	0.948	1	1
Poland	0.958	0.013	0.949	1	1
Portugal	0.994	0.006	0.968	1	2
Slovak Republic	0.993	0.011	0.937	1	1
Slovenia	0.998	0.003	0.984	1	8
Spain	0.980	0.012	0.925	1	1
Sweden	0.995	0.003	0.993	1	4
Switzerland	0.991	0.022	0.882	1	2
United Kingdom	0.927	0.080	0.753	0.99	9
United States	1.000	0.000	1.000	1	28

Table 10, Scale Efficiency Countries delivers a pivotal insight by distinguishing between technical and scale related inefficiencies revealing that for most nations poor overall performance is not a matter of size but of internal management. The data shows that many consistently low-performing countries, such as Canada, Finland and Sweden exhibit near-perfect mean scale efficiency scores above 0.99 indicating that their primary challenge is pure technical inefficiency how effectively they utilize their inputs rather than operating at a suboptimal scale. Conversely a few countries like Chile, Italy, Poland and the United Kingdom display lower mean scale efficiency confirming that their scale of operation is a meaningful constraint on their performance. The analysis further clarifies the status of top performers countries like Ireland, Israel, Lithuania and the United States achieve perfect scale efficiency meaning they are both technically proficient and optimally scaled while other technically efficient countries like Czechia, Latvia and Colombia frequently fall short of perfect scale efficiency indicating they could enhance productivity further by adjusting their operational size.

Stem and leaf of Scale Efficiency 1995-2022

Discuss the stem and leaf table of Scale Efficiency 1995-2022.

Table 11: Stem and Leaf Scale Efficiency

SE	95	96	97	98	99	00	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22
1	9	9	9	8	9	8	30	8	7	7	8	8	7	7	9	8	8	8	7	9	7	7	8	7	8	10	8	10
0.90-0.99	23	26	26	27	26	27	0	27	28	28	27	27	28	28	26	27	27	27	27	25	27	27	26	27	26	24	26	24
0.80-0.89	3	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1
0.70-0.79	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.60-0.69	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.50.0.59	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.40-0.49	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.30-0.39	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.20-0.29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.10-0.19	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 11 shows that annual frequency distributions of Stem Efficiency (SE) values from 1995 to 2022 categorized into predefined efficiency ranges. The vast majority of observations each year fall within the high 0.90-0.99 efficiency band, with counts consistently in the mid-20s. A single row labeled 1 shows smaller stable counts potentially representing a perfect efficiency score. The year 2001 stands as a significant outlier where the high-efficiency category drops to zero and observations instead appear in lower tiers including 0.80-0.89 and 0.70-0.79. For all other years the lower efficiency ranges from 0.60 down to 0.10 contain virtually no observations, indicating consistently high performance. This data suggests a stable high-efficiency system across the time series with the exception of a notable anomaly in 2001. The structure implies this is a stem-and-leaf-like summary for tracking performance metrics over time.

Conclusion and Policy Recommendations

This study set out to evaluate the environmental efficiency of high-income OECD countries from 1995 to 2022 using Data Envelopment Analysis (DEA). The analysis employed both CCR (Constant Returns to Scale) and BCC (Variable Returns to Scale) models to measure technical purely technical and scale efficiency using Gross Capital Formation (GCF) Population and Energy Use as inputs and GDP and CO_2 emissions as outputs. A clear hierarchy exists among nations. Ireland, Israel, Lithuania, Latvia, Czechia, Colombia and the United States consistently achieved high or perfect efficiency scores indicating strong alignment between economic output and environmental impact. In contrast countries like Canada, Sweden, Italy, Finland and Norway exhibited lower efficiency suggesting room for improvement in balancing economic growth with environmental sustainability. Efficiency scores generally improved over the study period particularly after 2001 which stood out as an anomalous year with a sharp decline in performance likely due to global economic or environmental disruptions. The post 2001 era shows a trend toward greater homogeneity and gradual improvement in environmental efficiency. Scale efficiency scores were consistently high across most countries indicating that inefficiencies are primarily due to poor resource utilization (technical inefficiency) rather than suboptimal operational scale. This underscores the importance of improving internal processes and technology adoption. The findings highlight that economic growth and environmental sustainability are not mutually exclusive. High-performing countries demonstrate that it is possible to achieve economic prosperity while minimizing ecological footprints through targeted policies technological innovation, and efficient resource management.

Following are the policy recommendations based on analysis:

- *For Low-Efficiency Countries (e.g. Canada, Sweden):* Prioritize investing in green technology and strict emission regulations to improve technical efficiency as your scale is already optimal.
- *For All Countries:* Implement strong carbon pricing and shift public investment (GCF) towards renewable energy and sustainable infrastructure to decouple economic growth from emissions.
- Top performers like Ireland and Lithuania should share best practices in policy and technology with less efficient nations.
- Expand analysis to include other pollutants and use dynamic models to track the impact of specific policies over time.

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Table: List of OECD Countries

No	Countries
1	Austria
2	Belgium
3	Canada
4	Chile
5	Colombia
6	Costa Rica
7	Czechia
8	Denmark
9	Estonia
10	Finland
11	France
12	Germany
13	Greece
14	Hungary
15	Iceland
16	Ireland
17	Israel
18	Italy
19	Japan
20	Latvia
21	Lithuania
22	Luxembourg
23	Mexico
24	Netherlands
25	New Zealand
26	Norway
27	Poland
28	Portugal
29	Slovak Republic
30	Slovenia
31	Spain
32	Sweden
33	Switzerland
34	United Kingdom
35	United States