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Factors That Determine the Efficiency of Public Environmental Protection Expenditures of OECD Countries: Super Efficiency DEA and Panel Data Analysis

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ABSTRACT

One of the most crucial tools used by governments in addressing environmental issues is public environmental protection expenditure. This study aims to assess the efficiency of public environmental protection expenditures and identify the factors influencing this efficiency. In this study, we use environmental data of 30 OECD countries between 2008-2020 employing a two-stage Data Envelopment Analysis (DEA) methodology. In the first stage, we utilize the super-efficiency DEA model. Public environmental protection expenditures are considered as inputs, while carbon dioxide emissions, renewable energy production, forest area percentage, and particulate matter concentration in the air are treated as outputs. In the second stage, we conduct a classical panel data analysis, using the efficiency scores obtained in the first stage as the dependent variable. Independent variables include population density, urbanization, industrialization, per capita national income, and primary energy intensity. The empirical findings reveal a negative relationship between efficiency scores and both population density and primary energy intensity. Conversely, urbanization and industrialization exhibit a positive relationship with efficiency scores. No significant relationship is found between per capita national income and efficiency scores. These results suggest that urbanization and industrialization may affect the efficiency of public environmental protection expenditures. The study contributes to the literature by combining Super-Efficiency DEA with panel data analysis and by addressing a notable gap in empirical research on the efficiency of public environmental protection expenditures specifically in OECD countries, offering policy-relevant insights for sustainable fiscal planning.

INTRODUCTION

Environmental protection expenditures made by the public sector are critical in combating environmental pollution and ensuring sustainable growth and development. These expenditures clearly show the policies and strategies that states implement for environmental issue protection. Considering that environmental problems cause negative externalities and need to be solved, environmental protection and the effectiveness of environmental policies are the most important in terms of public interest. Negative externalities from environmental issues make the market mechanism's activities inadequate for addressing environmental concerns protection. Public environmental protection expenditures are at the forefront of these intervention tools. For this reason, the role of environmental protection expenditures in the effectiveness of environmental policies can be discussed. However, despite the growing importance of environmental expenditures in shaping green policy agendas, little is known about how efficiently these public resources are used, particularly within OECD countries. Assessing this efficiency is crucial for ensuring fiscal sustainability and maximizing environmental impact amid limited budgets and increasing ecological risks.

In this context, the study aims to calculate the effectiveness of environmental protection expenditures and to determine the factors that will determine effectiveness. To achieve this, we prefer a two-stage approach: DEA is used to measure relative efficiency among countries, while panel data analysis identifies the main explanatory factors behind efficiency differences. The study employs a two-stage data envelopment analysis (DEA) method to examine the effectiveness of public environmental protection expenditures and the factors determining this effectiveness. In this study, a two-stage analysis was conducted. In the first stage, Data Envelopment Analysis (DEA), which is a non-parametric mathematical method, was applied. In the second stage, panel data analysis, an econometric method, was employed to examine the factors affecting efficiency scores. During the construction of the dataset, special attention was paid to ensuring data continuity across all countries and years, and to avoiding missing data in the selected variables. In this context, the application part of the study covers 30 OECD countries and the data set for the years 2008-2020.

The DEA model in the analysis is the super-efficiency model. Unlike traditional DEA, the super efficiency model also allows for evaluating decision-making units at 100% efficiency. While there are decision units with the same efficiency level in traditional DEA, the ranking can be done more clearly with the super-efficiency model.

For the econometric model in the research, we first apply the F test to evaluate the suitability of the classical model. Then, we perform the LM test to determine the suitability of the random effects model. Finally, we use the Hausman test to choose between the fixed and random effects models. As a result of these tests, we did estimates based on the random effects in the applied model. In addition, based on the results of the model specification tests, the presence of issues such as heteroscedasticity, autocorrelation, and cross-sectional dependence was detected. Despite these problems, the random effects model was selected for the analysis, as it was found to be the most appropriate specification for the data. Against these deviations, we follow the Driscoll-Kraay (DK) method, which is one of the effective estimation methods.

The structure of this article is organized as follows: Chapters 1 and 2 provide the introduction and a review of the relevant literature. Chapter 3 outlines the research methodology. Section 4 presents the empirical findings along with a detailed discussion. Finally, Section 5 concludes the paper with a summary of the main results and offers policy recommendations.

2. LITERATURE REVIEW

Governments focus on achieving sustainable development and preventing environmental pollution with environmental protection expenditures within public expenditures. Researching the factors that de-termine the effectiveness of these expenditures is important information for public authorities. Various studies have been conducted within this framework and some of them can be summarized as follows. To comprehensively under-stand the efficiency of environmental protection expenditures, this section reviews the relevant literature by grouping studies into three thematic categories: (1) studies using DEA only, (2) studies using DEA combined with regression analysis, and (3) studies focusing on OECD versus non-OECD countries.

Taskin and Zaim (2001) calculated environmental efficiency for selected years using DEA, incorporating employment and capital as inputs and GDP and CO2 emissions as outputs. He et al. (2018) conducted a super-efficiency DEA to evaluate China's provincial ecological efficiency between 2013–2018. Similarly, Zhang et al. (2019) employed DEA to measure environmental protection expenditure efficiency in China using pollution reduction outputs. Barrell et al. (2021) applied DEA to 30 EU countries (2005–2015), showing that higher spending does not always result in better environmental outcomes.

Zaim (2004) applied pooled least squares alongside DEA to examine structural changes in the U.S. manufacturing sector. Li and Wang (2014) used Tobit regression to explore how economic development, fossil fuel usage, and trade openness influence environmental efficiency. Lacko and Hajduová (2018) applied a two-stage DEA to EU countries, analyzing greenhouse gases and GDP per capita. Wang (2018) studied Chinese provinces using DEA and Tobit regression, identifying GDP per capita as positively associated with efficiency, while urbanization and industrialization showed negative effects.

Shuai & Fan (2020) used a super-efficiency DEA and Tobit model to evaluate regional green economic efficiency in China. Jialu et al. (2022) applied a super-efficiency SBM model with OLS to assess government spending on environmental protection in China, finding that urbanization and population size negatively affect efficiency. Iram et al. (2020) used DEA-SBM and panel regression to assess OECD countries, noting that energy efficiency is a stronger determinant than economic growth.

Le Gallo and Ndiaye (2021) applied a spatial Durbin model on 28 OECD countries, revealing that nations often adjust environmental expenditures based on regional peers. Arjomandi et al. (2023) used PMG-ARDL to explore the dynamic effect of environmental policy stringency on environmentally adjusted GDP in OECD countries, showing that environmental spending boosts short-term output but may slow long-term green produc-tivity growth. Yasmeen et al. (2023) analyzed energy efficiency in OECD countries using Malmquist-Luenberger and super SBM-DEA models, finding that green technology adoption and environmental taxes significantly enhance energy productivity while reducing energy intensity across countries with varying efficiency levels.

3. MATERIALS AND METHODS

In the two-stage DEA, firstly the relative efficiency of each decision-making unit is calculated, in the second stage the efficiency score is subjected to regression using potential dependent variables to determine the factors that have a statistically significant effect on efficiency. Banker and Natarajan (2008) stated that using classical panel models instead of the widely used Tobit regression model in the second stage of two-stage DEA, the econometric model estimation would yield more consistent results. McDonald (2009) obtained results that support the study of Banker and Natarajan (2008) and argued that the use of Ordinary Least Squares (OLS) would be sufficient in two-stage DEA. Simar and Wilson (2011) criticized the regression models suggested by both McDonald (2009) and Banker and Natarajan (2008) in their study. They stated that applying OLS directly without performing the necessary econometric pre-tests would render the model inconsistent. In this study, we apply both the super-efficiency Data Envelopment Analysis (DEA) model and conventional panel data techniques.

In this study, the Simar and Wilson (2011) critique regarding the use of DEA efficiency scores in second-stage regressions is acknowledged. Although bootstrapping is a commonly proposed remedy to address the serial correlation and bias concerns in DEA-based efficiency scores, this study employs a super-efficiency DEA model, which is based on a different theoretical foundation than traditional DEA models. As noted in recent literature (e.g., Shuai & Fan, 2020; Jialu at al., 2022), the super-efficiency approach enables a complete ranking of fully efficient decision-making units, making it suitable for second-stage econometric analysis. Furthermore, to mitigate econometric issues such as heteroscedasticity, autocorrelation, and cross-sectional dependence, robust estimation was conducted using the Driscoll-Kraay standard errors in the panel regression. Therefore, instead of applying the Simar and Wilson bootstrapping procedure, this study follows a two-stage DEA methodology with established econometric controls to ensure reliable inference.

3.1. Super Efficiency Model

Data envelopment analysis is an approach developed by Charnes et al. in 1978 to measure the relative efficiency of decision-making units and has two basic assumptions. These assumptions are constant returns to scale developed by Charnes, Cooper and Rhodes (CCR) and variable returns to scale developed by Banker, Charnes and Cooper (BCC) (Charnes et al., 1978, Banker et al., 1984). In data envelopment analysis, CCR and BCC assumptions are applied as input-oriented and output-oriented. While the aim is to obtain the current output with minimum input in input-oriented data envelopment analysis, the aim is to obtain maximum output with current input in output-oriented data envelopment analysis. While both approaches give the same results under the constant returns to scale assumption, the results may differ under the variable returns to scale assumption (Coelli, 2005).

In addition to the models mentioned, the super efficiency model developed by Andersen and Petersen (1993) ranks the effective decision-making units among themselves, thus providing a clearer result in the efficiency ranking. Since the use of super-efficiency models increases the sensitivity of the data envelopment analysis, more stable and unique results are obtained. In addition, it can be more clearly revealed how the changes to be made by the decision-making units will affect the efficiency scores in question (Zhu, 2001). In this context, by using the super-efficiency model in the study, the effective decision-making units are also ranked within themselves, allowing for a more comprehensive evaluation.

The Super-Efficiency model is a method derived from classical Data Envelopment Analysis (DEA) and allows effective Decision-Making Units (DMUs) to be compared with each other. It allows ranking of effective units by allowing their efficiency scores to take values greater than 1 (Cooper vd.,2006). In the super-efficiency model, the decision-making unit being evaluated is removed from the model, providing a differentiation between the effective units. In this case:

$$\min_{\theta,\lambda} \theta$$

Restrictions: (1)

$$\sum_{j\neq 0}^{n} \lambda_j x_{ij} \leq \theta x_{i0}, \quad \forall i$$

$$\sum_{j\neq 0}^{n} \lambda_j y_{rj} \geq y_{r0}, \quad \forall r$$

$$\lambda_j \geq 0, \quad \forall j \neq 0$$

For a given n number of decision-making units (DMUs), each DMU j (j=1,…, n) uses the following inputs and outputs:

x_{ij}: Use of i input by j DMU

y_{rj} : Production of r output by j-th DMU

λj : Weights of DMUs

θ: Efficiency Score

In this model:

• If θ∗>1, the unit is considered super-efficient and performs better compared to other efficient units.

• If θ∗=1, the unit is efficient and is at the same level as other efficient units.

• If θ∗<1, the unit is not efficient.

Super efficiency is used to rank especially efficient DMUs. Because in classical DEA, all efficient units have θ∗=1, while thanks to super efficiency analysis, it is possible to distinguish between these units.

3.2. Panel Regression Analysis and Driscoll Kraay Estimator

There are 3 models in the classical panel data method: pooled least squares, fixed effects (FE) and random effects (RE) models.

In this context, the F test is used to determine the appropriate one between the fixed effects model and the pooled least squares (PLS) model, while the Breusch - Pagan, (1980) LM Test is used to compare the random effects model and the pooled least squares regression model. If the null hypothesis is not rejected in both tests, the classical least squares model is preferred. In comparing fixed and random effects models, if the Hausman test rejects the null hypothesis that individual effects are unrelated to other independent variables, the fixed effects model is preferred to the random effects (Das, 2019).

$$F = \frac{\frac{RRSS - URSS}{N-1}}{\frac{URSS}{N(T-1)-k}} \qquad (2)$$

H0: PLS Model Valid

H1: FE Model Valid

It is formulated as F test. In the F test formula, RRSS indicates the remaining sum of squares under the null hypothesis, and URSS indicates the remaining sum of squares under the alternative hypothesis. (Pesaran, 2015).

$$LM = \frac{NT}{2(T-1)}\left[1 - \frac{\widehat{u'}(I_N \otimes J_T)\hat{u}}{\widehat{u'\hat{u}}}\right]^2 \qquad (3)$$

H0: PLS Model Valid

H1: RE Model Valid

Breusch - Pagan, (1980) LM Test is formulated as above. If the estimated statistics reject the null hypothesis, the random effects model would be an appropriate model choice since it can be concluded that the heterogeneity present in the panel data and the nature of the heterogeneity are random. (Das, 2019).

$$H = \left(\widehat{\beta_{RE}} - \widehat{\beta_{FE}}\right)' \left[\mathrm{Var}\left(\widehat{\beta_{FE}}\right) - \mathrm{Var}\left(\widehat{\beta_{RE}}\right)\right]^{-1} \left(\widehat{\beta_{RE}} - \widehat{\beta_{FE}}\right) \quad \begin{matrix} \text{H0:RE Model Valid} \\ \text{H1: FE Model Valid} \end{matrix} \tag{4}$$

Hausman, (1978) test is formulated as above. The null hypothesis underlying the Hausman test is that the fixed effects and random effects estimators are not significantly different. This test statistic has an asymptotic $\chi 2$ distribution. If the null hypothesis is rejected, the random effects model will consequently be inappropriate; instead, the fixed effects model would be more appropriate. (Gujarati, 2003).

When performing panel data analysis, it is also important to check the existence of heteroscedasticity, autocorrelation and cross-sectional dependence errors in addition to model determination tests. Because the presence of these deviations will prevent the effectiveness of the estimation.

In this context, one of the tests recommended to determine whether there is a heteroscedasticity problem in the model is the Levene, Brown and Forsyth test. In this test, the hypothesis “H0 = There is no heteroscedasticity” is tested.

In addition, the Durbin-Watson and Baltagi-Wu tests are used to test whether there is an autocorrelation problem in the established model, and the hypothesis “H0 = There is no autocorrelation” is tested, and it is decided whether H0 will be accepted or rejected according to the critical value of the statistical value obtained (<2).

The last of the deviations that disrupts the effectiveness is the existence of cross-sectional dependence. Pesaran-CD and Fees tests can be used to test whether there is cross-sectional dependence. In these tests, the hypothesis “H0 = There is no cross-sectional dependence” is tested.

$$y_{it} = \beta_0 + \beta_1 x_{1it} + \beta_2 x_{2it} + \beta_3 x_{3it} + \beta_4 x_{4it} + \beta_5 x_{5it} + u_{it} \tag{5}$$

In a panel data model, the random effects model is expressed as follows, with the dependent variable y_{it}, the independent variables x_{it} and the error term u_{it}. In the context of testing for biases that distort efficiency, the Driscoll-Kraay estimator is used in fixed and random effects models in cases where there are heteroscedasticity, autocorrelation and heteroscedasticity problems in the model. This method was developed by Driscoll and Kraay (1998) to avoid biased estimators for consistent coefficient analysis.

4. RESULTS

In the first stage of the study, the effectiveness of public environmental protection expenditures will be calculated with using DEA. Environmental protection expenditures will be used as an input in the DEA. Verifying the effects of public environmental protection expenditures is important in the context of the discussion on the impact of fiscal policy on sustainable development (Krajewski, 2016). While assessing public environmental protection expenditures as inputs, the studies by Jialu et al. (2022), Sun et al. (2016), Wang (2018), and Zhang et al. (2019) were used. In calculating the effectiveness of public environmental protection expenditures, P: M. 2.5 particulate matter exposure (Ma et al., 2021; Özkan & Özcan, 2018; Wu & Guo, 2021), forest areas of countries (Arltová & Kot, 2023; Barrell et al., 2021), renewable energy production of countries (Barrell et al., 2021; Koçak, Kınacı, & Shehzad, 2021) and carbon dioxide emissions (Gómez-Calvet, Conesa, Gómez-Calvet, & Tortosa-Ausina, 2020; Lacko et al., 2023; Peng Zhou, Poh, & Ang, 2016) were determined as outputs. All variables are shown in table 1.

Table 1: Variables Used in the Super Efficiency Model and Their Explanations

Variables	Indicators	Values	Source
Output 1- Renewable Energy Production	Renewable Energy Production	Twh	Energy Institute
Output 2- Forest	Forest Area	Km^2	World Bank
Output 3- P.M. 2.5.	Average P.M. 2.5 per capita exposure	M^3 microgram	OECD
Output 4- CO_2	CO2 Emissions	CO2 equivalent, thousand tonnes	OECD
Input 1- EPE	Environmental Protection Expenditures	% GDP	IMF

The study initially aimed to calculate the effectiveness of central government environmental protection expenditures in 30 OECD countries between 2008-2020. These countries are Australia, Austria, Belgium, Chile, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom. In the study, the effectiveness analysis of environmental protection expenditures of 30 OECD countries for 2008-2020 was carried out using the DEA method. Canada, Costa Rica, New Zealand, Colombia, Estonia, the United States, Mexico, and Korea from OECD countries were not included in the study due to various deficiencies in data. The data to be used as an input was obtained from the IMF database, and the data to be used as outputs were obtained from the World Bank, OECD and Energy Institute databases

After the efficient frontier is determined in DEA, the inefficient DMU (can improve its performance to reach the efficient frontier by increasing current output levels or decreasing current input levels. Efficiency calculations are usually based on the assumption that inputs should be minimized, and outputs should be maximized. However, especially in studies on environment and energy, undesirable outputs that should be minimized are included in the production model (Scheel, 2001). Efficiency analyses using undesirable outputs will provide legislators with the opportunity to determine policies on how to manage desired outputs and improve environmental standards (Zofio and Prieto, 2001). Therefore, in studies using DEA, both desired (good) and undesirable (bad) factors are present (Seiford and Zhu, 2002). The factors in question in this study are P.M. 2.5. exposure and CO2 emission outputs. These outputs are defined as "undesirable output" or "bad output". This is because it is not desired to maximize these outputs. In addition, in studies on energy and the environment (estimation of efficiency with pollutants or modelling environmental performance), DEA using undesirable outputs seem to be quite popular (Zhou et al., 2008). For this reason, in the study the undesirable output (u) of CO2, emission and P.M. 2.5 exposure was converted into the desired output with the transformation f (u) = 1/u (Golany and Roll, 1989; Koçak et al., 2021; Scheel, 2001).

Since a significant part of the studies on environmental protection strategies focuses on inputs rather than outputs, input-oriented DEA models were preferred in this study (Barrell et al., 2021). To determine the effectiveness of OECD countries' environmental protection expenditures, the EMS 3.1 program was used in the study, considering its ease of use and access.

The Table 2 below calculate the effectiveness of OECD countries' environmental protection expenditures using the Super Efficiency model for each year between 2008-2020. The difference between the super-efficiency model and traditional DEA is that it also evaluates the effective decision-making units. Therefore, it is possible that they cannot provide full effectiveness for decision-making units with an efficiency score below 100% in the analysis. However, decision-making units with an efficiency score above 100% can determine the most effective decision-making unit according to how much they exceed the efficiency limit. While decision-making units share the same efficiency order in traditional DEA, the order can be established more clearly in DEA using the super-efficiency model.

According to the super efficiency scores obtained as a result of the analysis, Chile, Finland, Germany and Iceland (except for 2008) stand out among 30 countries in terms of the efficiency of public environmental protection expenditures. Germany, in particular, has demonstrated a very successful performance in terms of the efficiency of environmental protection expenditures in all years except 2018. On the other hand, Turkey experienced a break in 2008, and its efficiency scores were largely stable between 2009-2017. However, Türkiye's efficiency scores have continuously increased remarkably since 2017. It is seen that the average efficiency scores of public environmental protection

	KVB	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
1	Australia	0.9267	0.9406	0.8023	0.7433	0.6652	0.665	0.7138	0.8682	0.8798	0.8473	0.7969	0.8894	0.8989
2	Austria	0.2486	0.2233	0.1955	0.2283	0.2415	0.266	0.3036	0.2935	0.3136	0.3012	0.2845	0.2749	0.2988
3	Belgium	0.1108	0.1098	0.0876	0.0782	0.0781	0.0842	0.1032	0.0983	0.1026	0.0837	0.0853	0.0889	0.0945
4	Chile	1.9897	1.7571	2.0039	1.9164	2.0551	2.04	1.9004	1.6743	1.6833	1.7354	1.8065	1.5961	1.6469
5	Czech Republic	0.1044	0.1426	0.0789	0.0678	0.0671	0.091	0.0923	0.0788	0.1103	0.0898	0.0838	0.0917	0.096
6	Denmark	0.3511	0.401	0.3956	0.431	0.4391	0.3932	0.4307	0.435	0.4439	0.4092	0.4027	0.4374	0.4994
7	Finland	0.826	0.8017	0.8476	1.0847	1.1761	1.3429	1.3557	1.6003	1.8502	2.0584	1.902	2.1857	2.3342
8	France	0.1656	0.1811	0.1786	0.1914	0.1991	0.2001	0.2182	0.2051	0.2182	0.2032	0.209	0.2195	0.2481
9	Germany	2.6987	2.8052	2.8491	3.0434	2.6878	2.472	3.0951	2.8925	2.317	2.104	1.7478	1.9008	1.839
10	Greece	0.0878	0.1027	0.1025	0.0958	0.0811	0.06	0.0741	0.0663	0.0654	0.0626	0.0651	0.0688	0.0723
11	Hungary	0.1482	0.1667	0.1444	0.1305	0.1469	0.1122	0.0935	0.0782	0.1872	0.1281	0.1389	0.1264	0.1389
12	Iceland	1.9549	0.4841	1.2326	2.7755	2.7132	2.7687	2.3301	2.4578	2.0122	1.7953	1.9376	2.0495	1.4929
13	Ireland	0.1516	0.1706	0.1764	0.2294	0.2523	0.3122	0.3366	0.37	0.3621	0.3525	0.3872	0.3999	0.4389
14	Israel	0.1192	0.1422	0.1214	0.1351	0.1407	0.1363	0.1535	0.1296	0.1397	0.1263	0.132	0.1261	0.1368
15	Italy	0.1981	0.2327	0.2507	0.2784	0.3123	0.3203	0.3133	0.2678	0.2761	0.253	0.2489	0.2449	0.2451
16	Japan	0.2269	0.2105	0.2442	0.2115	0.2155	0.2312	0.2455	0.2598	0.259	0.2642	0.2877	0.3036	0.3161
17	Latvia	0.3606	2.5161	0.8829	0.3756	0.3855	0.3821	0.4532	0.4285	0.5288	0.5829	0.5411	0.5147	0.7012
18	Lithuania	0.2475	0.1325	0.1404	0.2732	0.239	0.3579	0.3522	0.3302	0.3788	0.4401	0.4401	0.3865	0.4685
19	Luxembourg	0.3382	0.1862	0.2935	0.2989	0.3133	0.2795	0.3577	0.3247	0.3566	0.3361	0.3269	0.307	0.3537
20	Netherlands	0.0825	0.0898	0.0843	0.0874	0.0888	0.0905	0.0994	0.0916	0.0896	0.0797	0.0845	0.0909	0.1107
21	Norway	0.3411	0.2784	0.2642	0.2524	0.2887	0.2793	0.2735	0.2301	0.2158	0.1867	0.1975	0.1846	0.1798
22	Poland	0.1183	0.1374	0.1212	0.1453	0.1886	0.1757	0.1879	0.1864	0.2623	0.2456	0.1803	0.1954	0.2112
23	Portugal	0.2443	0.3065	0.2443	0.2466	0.2891	0.2919	0.3409	0.2831	0.3064	0.2349	0.243	0.2468	0.2471
24	Slovakia	0.1258	0.1054	0.1059	0.1242	0.1202	0.1142	0.1401	0.1068	0.1308	0.12	0.1221	0.1262	0.1331
25	Slovenia	0.205	0.1198	0.2308	0.1864	0.2091	0.1961	0.1824	0.1557	0.2735	0.374	0.3245	0.3176	0.3596
26	Spain	0.341	0.4041	0.3993	0.3767	0.3984	0.4594	0.4074	0.347	0.3528	0.3055	0.3058	0.3094	0.3333
27	Sweden	0.4983	0.5699	0.5515	0.5478	0.5779	0.5724	0.6102	0.6167	0.5883	0.472	0.4187	0.45	0.5053
28	Switzerland	0.2391	0.2113	0.2149	0.2298	0.2392	0.2272	0.2874	0.2296	0.2246	0.2234	0.2434	0.2445	0.2645
29	Republic of Türkiye	0.263	0.3096	0.2915	0.2624	0.2981	0.3349	0.3787	0.347	0.3716	0.3675	0.4096	0.5668	0.7408
30	United Kingdom	0.2184	0.2427	0.2376	0.2746	0.3092	0.3818	0.3923	0.4182	0.4291	0.4327	0.5126	0.5425	0.5873
	OECD	0.46438	0.48272	0.45912	0.510733	0.513873	0.521273	0.540763	0.529037	0.52432	0.507177	0.495533	0.516217	0.533097

Table 2: Super Efficiency Analysis on Public Environmental Protection Expenditures

expenditures of OECD countries that applied DEA between 2008-2020 are in the range of 50%. This means that although there are serious differences in efficiency scores between countries, it is possible to say that the OECD has caught a trend for the relevant period.

The second stage of the study, the panel data analysis will be used to determine the factors determining the efficiency of public environmental protection expenditures of 30 OECD countries. The literature review conducted to determine the variables for the econometric method to be applied in this section of the study has been guiding. In the econometric model to be applied to estimate the determinants of the effectiveness of public environmental protection expenditures, super efficiency scores (Jialu et al., 2022; Shuai and Fan, 2020) were determined as the dependent variables and population density (Antonelli and De Bonis, 2019; Iram et al., 2020; Jialu et al., 2022; Tu et al., 2017), GDP per capita (Jia and Liu, 2012; Jialu et al., 2022; Yasmeen et al., 2023), urban population (Wang, 2018; Tu et al., 2017), industrialization (Wang, 2018) and primary energy intensity (Shuai and Fan, 2020) were determined as the independent variables. The econometric model to be used in the study within the framework of the determined variables.

$$\log SES_{it} = \beta 0_{it} + \beta 1 \log PD_{it} + \beta 2 \log\_GDPPC_{it} + \beta 3\, UP_{it} + \beta 4\, I_{it} + \beta 5\, PIE_{it} \quad (6)$$

Table 3: Variables Used in the Panel Regression Analysis and Their Explanations

Variable	Abbreviated	Definition	Source
Super Efficiency Scores	SES	Environmental Protection Expenditure Efficiency Score	Our Own Calculation
Population Density	PD	Number of people per km2	World Bank
GDP per Capita	GDPPC	GDP per capita in dollars	World Bank
Industrialization	I	Percentage in GDP	World Bank
Urban Population	UP	Percentage of total population	World Bank
Primary Energy Intensity	PIE	Ratio of primary energy consumption to GDP	Energy Institute

Information about the variables used in the model is given in Table 3.

Table 4: Model Determination Tests

	F Testi	Breusch-Pagan LM Testi	Hausman Testi
Test Statistics	132.64 (0.00)*	1918.38 (0.00)*	2.31 (0.8052) *

Note: The values in parentheses are significance (prob.) values.
**: Indicates statistical significance at the 1% level.*

In Table 4, the results of the tests performed to decide on the estimation method of the model are given in the table. According to the results of the F test conducted to decide between the classical model and the fixed effects model, the H0 hypothesis suggests the classical model is rejected, and the fixed effects model comes to the fore.

According to the Breusch-Pagan LM test results conducted to decide between the classical model and the random effects model, the H0 hypothesis suggests the classical model is rejected, and the random effects model comes to the fore. Finally, according to the results of the Hausman test conducted to decide between the fixed effects model and the random effects model, the H0 hypothesis suggests the random effects model is accepted. Thus, the fixed effects model is invalid. As a result of this evaluation, it was decided that the most appropriate model for the study was the random effects model.

Table 5: Deviations That Deteriorate Effectiveness

Deviations That Deteriorate Effectiveness	Tests	Test Statistics	p-values	Null Hypothesis	Decision
Heteroscedasticity	Levene, Brown ve Forsyth	W0 = 4.72	0.000000	H_0: No Heteroscedasticity	Rejected
		W50= 3.375	0.000000		
		W10 =4.146	0.000000		
Autocorrelation Test	Durbin-Watson	0. 96803598	0.000	H_0: No Autocorrelation	Rejected
	Baltagi–Wu LBI	1.1447572	0.000		
Cross-sectional dependency test	Pesaran -CD	2.703	0.0069	H_0: No Cross-Section Dependence	Rejected
	Frees	*2.332*	*0.000*		

**The critical value used for Durbin-Watson and Baltagi-Wu tests is 2.*
***The critical value for the Frees test at a 95% confidence level is 0.2620.*

The results of the tests conducted on heteroscedasticity, autocorrelation and cross-sectional dependency of the model used in the study are given in the table 5. According to the Levene, Brown, and Forsyth test results conducted to determine whether there is a heteroscedasticity problem, H0 was rejected because the variances of the units were not equal, and it was seen that there was a heteroscedasticity problem. Durbin-Watson and Baltagi-Wu tests were applied to test whether there was an autocorrelation problem in the model used. The statistical values obtained because of the tests are less than 2, which is the critical value for the random effects model. In this case, it is possible to talk about the existence of first-degree autocorrelation in the random effects model used in the study. Finally, the existence of inter-unit correlation, i.e., cross-sectional dependency, in the model was tested using the Pesaran-CD and Fees tests. According to the results obtained, both the Pesaran-CD and Fees tests gave the same result; it was concluded that there was cross-sectional dependency in the model used in the study.

As a result of the model determination tests, all deviations (heteroscedasticity problem, autocorrelation, and cross-section dependency) that disrupted the effectiveness of the random effects model that was decided to be used in the study were detected. Therefore, in the study, an estimate was made using the Driscoll-Kraay (DK) method, which is one of the effective estimation methods, against these deviations.

Table 6: Determinants of the Effectiveness of Environmental Protection Expenditures; RE and DK Estimation Results

Depended var: logSES; sample (N):30 countries; T: 13 years (2008-2020); N*T= 390		
Variables	**RE (Random Effect)**	**DK (Driscoll-Kraay)**

constant	-2.234 (0.123)	-2.234 (0.152)
logPD	-0.465 **(0.000) ***	-0.465 **(0.000) ***
logGDPPC	0.0879 (0.394)	0.088 (0.499)
UP	0.0285 **(0.001) ***	0.0285 **(0.011) ***
I	0.027 **(0.000) ***	0.027 **(0.025) ***
PIE	-0.1555 **(0.000) ***	-0.1555 **(0.019) ***
R^2	0.3596	0.3453

Note: The values in parentheses are significance (prob.) values.
**: Indicates statistical significance at the 1% level.*

The analyses conducted to estimate the determinants of the effectiveness of public environmental protection expenditures are given in the table 6. According to the results obtained from both estimation methods, population density, urbanization, industrialization, and primary energy density yielded significant results. In this context, the independent variables of population density (logPD) and primary energy density (PIE) in the model have a negative and significant relationship with the dependent variable super-efficiency scores (logSES). This result, which is in line with expectations, shows us that as countries' population density and primary energy density increase, the expected level of effectiveness from environmental protection expenditures decreases. According to the analysis results, a 1% increase in population density will cause a 0.47% decrease in environmental protection expenditures. In comparison, a 1% increase in primary energy density will cause a 0.15% decrease in the effectiveness of environmental protection expenditures.

Urbanization (UP) and industrialization (I) in the model have a positive and significant relationship with the dependent variable super efficiency scores (logSES). This result shows us that a 1% increase in urbanization in OECD countries will provide a 0.029% increase in the effectiveness of environmental protection expenditures. At the same time, a 1% increase in industrialization will give a 0.027% increase in the effectiveness of environmental protection expenditures. It is seen that the logGDPPC variable, another variable in the model, the results suggest that the variable in question has no meaningful impact on the effectiveness of environmental protection expenditures. When the results obtained are compared with the literature, it is noteworthy that there are results consistent with the literature and that differ.

Population density, one of the independent variables used in the study, has a negative and significant relationship with super-efficiency scores. According to the analysis, a 1% increase in population density causes a 0.47% decrease in the effectiveness of environmental protection expenditures. Another independent variable used in the study is primary energy density. According to the results of the analysis, a negative and significant relationship exists between primary energy density and super-efficiency scores. The analysis results indicate that a 1% increase in primary energy density causes a 0.15% decrease in the effectiveness of environmental protection expenditures.

It is seen that there is a significant and positive relationship between urbanization, one of the variables included in the analysis, and the effectiveness of environmental protection expenditures. According to the results of the analysis, a 1% increase in urbanization will provide a 0.029% increase in the effectiveness of environmental protection expenditures. Therefore, it is possible to say that the increase in urbanization increases the effectiveness of environmental protection expenditures.

Another variable included in the analysis is industrialization. According to the results obtained from the analysis, there is a positive and significant relationship between the effectiveness of environmental protection expenditures and industrialization. According to the results of the analysis, a 1% increase in industrialization rates provides a 0.027% increase in the effectiveness of environmental protection expenditures.

The last variable used in the analysis is GDP per capita, and it did not show a significant result on the effectiveness of environmental protection expenditures. Although per capita national income is seen as one of the factors causing environmental problems, it was found in the study that it did not affect the effectiveness of environmental protection expenditures. The most important reason for this is that the effectiveness of expenditures was measured, not environmental effectiveness. However, significant results were obtained in the studies using this variable in the literature.

5. DISCUSSION AND CONCLUSIONS

Public environmental protection expenditure is the main object of protecting the environment and encouraging the sustainable use of natural resources. Also, there is a main contribution of the public environmental protection expenditure as fiscal policy on sustainable development. As a result, the research validates which factors affect the efficiency of public environmental protection expenditure. For this purpose, we focus on what determines the effectiveness of environmental protection expenditures. Therefore, it is significant to have metrics that measure the effectiveness of environmental protection expenditures and include information about the results. Using the data envelopment analysis (DEA) methodology, it is possible to measure the efficiency of these expenditures. DEA also allows comparing performance measures of countries with similar scores and determining which countries are performing best given the inputs they use and the outputs they produce.

The functional classification system of public expenditures (COFOG) has divided environmental protection expenditures into six main headings. Countries classify each environmental protection expenditure they make under this heading and transparently share the purpose of these expenditures: These expenditures are waste management, wastewater management, pollution abatement, biodiversity protection, R&D expenditures related to environmental protection, and expenditure on environmental protection not elsewhere classified (n.e.c.). The subject of this study is how the effectiveness of the expenditures made with this classification affects environmental problems.

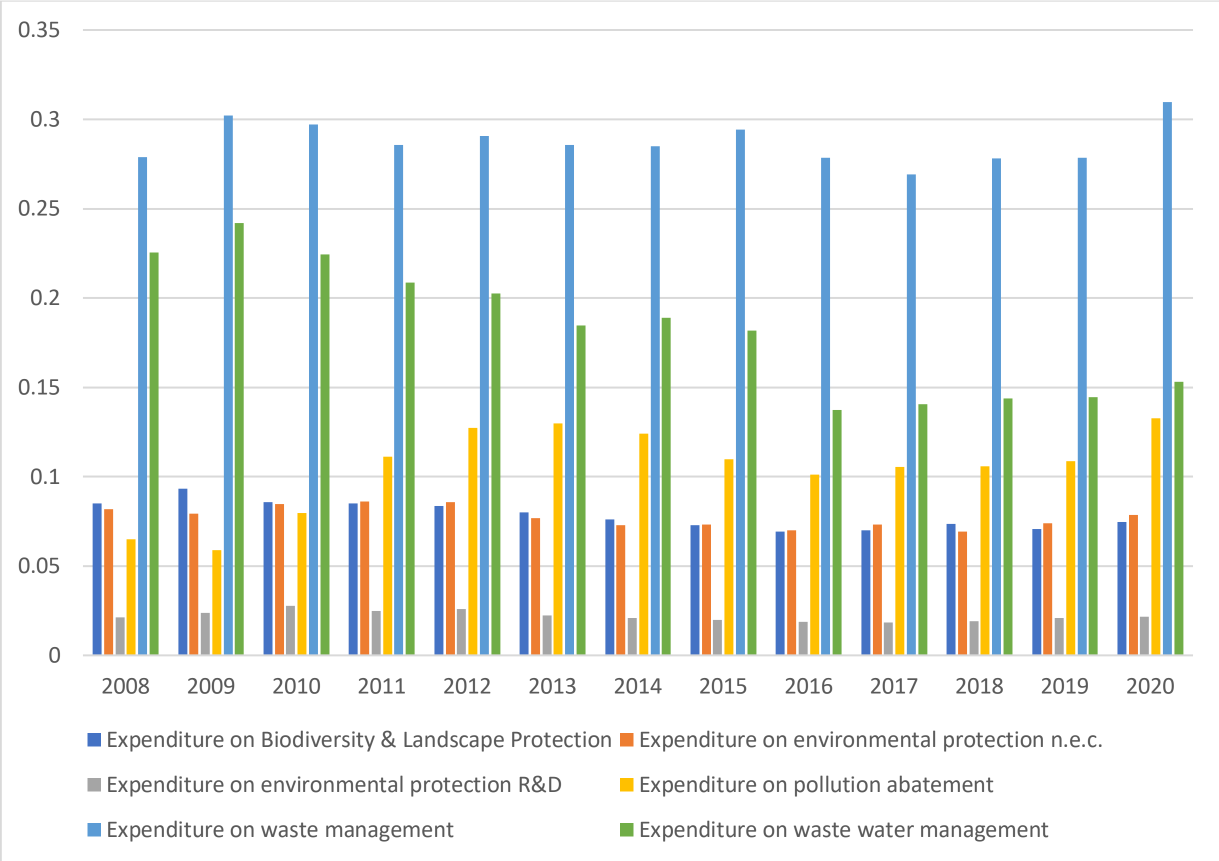

Figure 1: OECD Averages of Types of Environmental Protection Expenditures, 2008-2020

As shown in Figure 1, the average composition of environmental protection expenditures in OECD countries reveals that waste management and wastewater management consistently represent the largest share of total spending between 2008 and 2020. This indicates a clear prioritization of basic environmental services within public expenditure structures.

Increasing population density, on the other hand, has adverse impact on the effectiveness of environmental protection expenditures. Because of resource use, infrastructure needs and environmental degradation accelerate in regions with more people. This requires environmental protection expenditures to be more extensive and comprehensive. In addition, environmentally friendly solutions such as public transportation systems and green areas may be insufficient as the population density increases, and environmental protection expenditures may be insufficient to solve these problems. Wang (2018), Jialu et al. (2022), and Le Gallo & Ndiaye (2021) also emphasized in their studies that the priority of expenditures to be made in regions with high population density will change towards other needs of the population. Moreover, the control difficulties brought by the dense population in highly populated regions also reduce the effectiveness of environmental expenditures

In other words, increasing primary energy density negatively affects the effectiveness of environmental protection expenditures. Primary energy density expresses the ratio of primary energy resources used in production to national income. The primary resources mentioned here are fossil fuels, primarily oil. In today's world, where the importance of green transformation, green industrial zones, and combating waste is discussed, the fact that production is carried out with primary energy resources also reduces the effectiveness of environmental protection expenditures. Shuai & Fan (2020), Li & Wang (2014), and Lacko et al. (2023) also showed in their studies that primary energy density has a negative effect on environmental efficiency. However, Donkor et al. (2022) observed that fossil fuel consumption does not significantly affect environmental quality.

With increasing urbanization, the efficient use of resources in cities, the need for green infrastructure, the fight against waste, and environmental investments in environmentally friendly technologies have increased. In addition, urbanization increases environmental awareness by providing more economic and social development; thus, society's demand for environmental protection expenditures increases, and these expenditures reach wider audiences. In line with the results obtained in Le Gallo & Ndiaye's (2021) studies, they stated that countries with high urbanization rates make more environmental expenditures, increasing the demand for environmental quality by increasing public awareness. However, while our findings reveal a statistically significant positive relationship between urbanization and industrialization and efficiency scores, it is important to interpret this cautiously. Urbanization and industrialization can also exert additional pressure on the environment through increased pollution, land use, and resource consumption. For instance, Shuai & Fan (2020) highlight that the environmental effects of urbanization vary significantly across regions. Therefore, for environmental expenditures to be effective under growing urbanization and industrialization, they must be supported by strong environmental regulations and targeted investments in green technologies and infrastructure.

There are a number of research in the existing literature inconsistent with our results (Wang, 2018; Li and Wang, 2014). According to these studies, increasing industrialization will increase environmental pressures, negatively affecting expenditures' effectiveness. Nevertheless, He et al. (2018) have obtained consistent results with our study. Accordingly, the support of green organized industrial zones by countries with growing production capacities, the support of companies to zero-emission policies, and the public, encouraging companies to use renewable energy by making various public expenditures, are activities that can positively affect the effectiveness of environmental protection expenditures.

According to Wang (2018) and Li and Wang (2014), economic growth has both positive and negative effects on environmental effectiveness and the efficiency of protection expenditures. Indicated by Donkor et al. (2022) and Jialu et al. (2022), while the increase in per capita GDP contributes to environmental improvements, excessive economic growth in some regions can lead to environmental degradation, such as CO_2 emissions. Noted by He et al. (2018), a balance should be established between economic growth and environmental policies, and environmental protection expenditures should be aligned with sustainable development goals.

According our research, environmental protection expenditures made by states are used more effectively in places where urbanization and industrialization increase; however, the situation is vice versa in cases where population density and primary energy density increase. Environmental protection expenditures made to combat problems such as waste management, infrastructure investment or air pollution, which increase with urbanization and industrialization, may produce more successful results in urbanizing and industrializing regions since they try to meet social needs. Although urbanization and industrialization are seen among the factors that positively affect the effectiveness of environmental protection expenditures in the econometric model, an important point that draws attention is the smallness of the coefficient in the effect they create (for both determinants, nearly 0.028). This situation indicates that urbanization and industrialization are determinants of the effectiveness of environmental protection expenditures, but this effect is not sufficient.

These findings offer policy-relevant implications. For instance, in regions with high population density and primary energy intensity—where expenditure efficiency is lower—governments may focus on improving public transport systems, optimizing energy use, and implementing environmental regulations tailored to local needs. Conversely, in urbanized and industrialized areas, expanding green infrastructure and supporting clean technologies can enhance the marginal impact of environmental expenditures.

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