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Evaluating the Circular Economy Performance of European Countries: A DEA-Based Approach to Resource Management, Waste Reduction and Innovation

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Abstract

Due to the difficulties arising from the traditional model and the environmental limits of ecosystems, a new economic model emerged, known as the Circular Economy (CE). Growing population and consumption have made CE increasingly popular worldwide. It has become a major foundation for promoting sustainable development and reducing the global environmental footprint. As CE continues to expand, particularly among European Union countries, it is important not only to consider how and to what extent these countries incorporate CE into their policies, but also whether and how they achieve efficiency in terms of resource management, waste reduction, and innovation. To address this, the study applies nonparametric Data Envelopment Analysis (DEA) to evaluate the efficiency of 27 EU members based on 2022 data. Both CCR (CRS) and BCC (VRS) DEA models are used across two datasets — one focusing on input aspects (material footprint, import dependencies, and greenhouse gas emissions) and the other on output elements (innovation and recycling rates). The results indicate that countries such as Estonia, Sweden, and the Netherlands are among the most efficient, while Greece and Portugal are labeled inefficient due to high resource consumption and low recycling performance. A linked DEA analysis was also conducted, offering deeper insight into the relationship and potential impact of resource use on circular economy outcomes, particularly in waste management, and confirming that the analyzed dimensions are interrelated and constitute the CE framework. The use of two datasets enables a multidimensional evaluation of best practices and helps identify potential areas where CE policies can be improved.

Keywords

Circular Economy (CE), European Union (EU), Data Envelopment Analysis (DEA), sustainable development, resource management, efficiency.

1. Introduction

Traditional economic models are grounded in the widespread linear approach known as the „take-make-waste“ or „open-loop“ approach (Bongers & Casas, 2022). According to this approach, primary resources are extracted from nature, used in industry as a starting point for production and further processing, and later discarded as a result of taking everything that is valuable. Consequently, this approach is recognized as unsustainable because it puts great pressure on nature while generating massive amounts of waste through high consumption and processing (Neves & Marques, 2022).

Due to the difficulties arising from the traditional model and environmental limits of ecosystems, a new economic model emerged, referred to as the Circular Economy (Rizos et al., 2017). Circular economy (CE) is often described as a "closed-loop" model because it primarily focuses on reducing resource consumption and waste emissions. Unlike the "open-loop" approach, CE aims to extend the lifespan of products and services by maintaining their value through recycling and making them suitable for multiple uses. This economic model strives to optimize energy investment and reduce its impact on the environment (Roremo et al., 2021; Velenturf & Purnell, 2021).

The core principles of CE can be summarized as follows (de Oliveira & Oliveira, 2023; Kirchherr et al., 2017; European Commission, 2020):

(1) Conservation of natural resources through managing inventories and ensuring the sustainable flow of renewable resources.
(2) Resource optimization through recycling and enabling multiple uses of products and materials.
(3) Redefining processes to minimize and eliminate negative impacts from the outset.

Growing population and consumption have made CE increasingly popular around the world. CE has become a major foundation in promoting sustainable development and reducing environmental footprint around the globe. China, Japan, the European Union and a number of other countries and organizations have incorporated CE into their economic and ecological development strategies. China views the circular economy as a broader concept that includes pollution and other environmental issues, whereas the European countries focus on waste management, natural resources, and business opportunities (Bleischwitz et al., 2022; Bongers & Casas, 2022). In spite of its extensive application, it is the European Union that has shown the greatest interest in this concept (Meseguer-Sánchez et al., 2021).

In light of the Circular Economy (CE) becoming increasingly globally present over time, especially in European Union countries, it is of great value not only to consider the ways and extent to which these countries incorporate CE into their policies, but also whether and how they achieve efficiency in terms of resource management, waste reduction, and boosting innovation. Given the fact that there are many different approaches and strategies being used, it is crucial to examine the performance outcomes resulting from various implementations of CE, as well as to identify the key factors contributing to its success.

The objective of this study is to examine the performance of European Union countries regarding CE by employing Data Envelopment Analysis (DEA), with a particular focus on resource management, waste reduction, and innovation. Through this analysis, the aim is to provide deeper insight into the efficiency and sustainability of CE practices across Europe, as well as to identify the factors that significantly impact its success in reducing environmental harm and improving economic performance.

This paper is organized as follows. After the introduction, the second section contains a brief literature review on different DEA approaches used for assessing the performance of European countries in the CE. After that, the third section is dedicated to the methodology, followed by the fourth section, which presents information regarding the origin of data and the used indicators. The results of the analysis and the discussion are presented in the fifth section. Finally, the last section provides the conclusion and future research directions.

2. Literature Review on CE Performance

As predicted by Korhonen and co-authors (2018), for more than a decade, the concept of CE has been widely promoted in the European Union, mainly by a few business organizations and national governments, as a practice-oriented approach. While at first CE was primarily practical and lacked clearly defined scientific foundations, in recent years, a large number of scientific contributions focusing on providing a more precise definition of CE and its core principles, as well as analyzing the various contexts related to its implementation (Kirchherr et al., 2023; Lamba et al., 2023). Table 1 highlights key studies on the evaluation of Circular Economy performance in European Union countries using the DEA method.

Table 1: Overview of key DEA studies evaluating CE performance in EU countries

DEA model				
Reference	**Inputs**	**Outputs**	**Best ranked countries/Results**	**Observed year(s)**
BCC (VRS) DEA model				
Radovanov et al. (2023)	generation of municipal waste per capita	recycling rate of municipal waste, share of energy from renewable sources	Belgium, Sweden, Lithuania, Poland, Autria	2016 - 2019
BCC (VRS) super-efficiency DEA model (SE-BCC)				
Nazarko et al. (2022)	waste production, jobs and investments, recycling rate of special waste, recycling rate of general waste	the value added	Croatia, Netherlands, Luxembourg, Slovenia, Belgium, Denmark, Ireland	2018 - 2019
Banjerdpaiboon & Limleamthong (2023)	generation of municipal waste per capita, generation of waste excluding major mineral wastes per GDP, recycling of biowaste	recycling rate of municipal waste, recycling rate of packaging waste, circular material use rate	Germany, the Netherlands, Austria, Belgium	2018
CCR (CRS) + BCC (VRS) slack-based (SMB) DEA models				
Lacko et al. (2021)	waste generated, gross capital formation	recycling rate of municipal waste, circular material use rate	Poland was characterized as the only V4 country that succeeded in reaching the efficiency of the Euro 28 countries in terms of CE.	2010 - 2017
CCR (CRS) + BCC(VRS) assurance region (AR) DEA models + Window DEA				
Ratner et al. (2025)	private investment, number og jobs	circular material use rate, share of renewables, gross value added	Germany, Sweden, Malta, France, Austria, Italy, Luxembourg	2014 - 2021
BOD DEA model – CCR (CRS) DEA model with a single constant input				
Milanović et al. (2022)	The analysis did not utilize specific inputs and outputs for DEA, but instead calculated the index for CE.		Germany, Austria - leading in technology and high-quality recycling; Belgium, the Netherlands: significant progress in reintegrating materials into the economy.	2010, 2012, 2014, 2016

Table 1: (continued)

DEA model				
Reference	**Inputs**	**Outputs**	**Best ranked countries/Results**	**Observed year(s)**
Weight restriction approach DEA model (Yekta et al. 2018)				
Giannakitsidou et al. (2020)	basic human needs foundations of wellbeing, opportunity, MSW generated	recycling rate of MSW, circular material use rate	Belgium, Germany, Netherlands, Slovenia, Poland	2014, 2016, 2017
CCR (CRS) + BCC (VRS) DEA models				
Temerbulatova et al. (2021)	generation of municipal waste per capita, water exploitation index, final energy consumption, social progress index	circular material use rate, municipal waste recycling rate	Belgium, Estonia, Germany, Latvia, Lithuania, Malta, Netherlands, Slovenia	2019
CCR (CRS) DEA model				
Marques & Teixeira (2022)	municipal waste generated, general expenditure on wm, innovation in wm-related technologies, domestic material consumption, gross domestic product	recycling rate of municipal waste, circular material use rate	Belgium, Bulgaria, the Netherlands, Slovenia	2011 - 2019
Marjanović et al. (2025)	raw material consumption, generation of municipal waste per capita, greenhouse gas emissions intensity of energy consumption	recycling rate of municipal waste, energy productivity, share of energy from renewable sources, resource productivity, circular material use rate	the Netherlands, Sweden, Ireland	2019

Upon analyzing the literature sources listed in Table 1, it was noticed that most of the papers primarily focus on ranking countries of the European Union using various DEA models, primarily the fundamental BCC (VRS) and CCR (CRS) models (see Chapter 3). Only two papers (Giannakitsidou et al., 2020; Milanović et al., 2022) use DEA analysis as an approach to develop composite indexes for CE, for the purpose of providing a comprehensive picture and enabling easier comparison of countries.

When it comes to the input and output indicators used, the majority of the analyzed studies employed waste-related indicators, particularly the values of generated waste, both general and municipal. Alongside those indicators, which were mostly used as inputs, the recycling rate for different kinds of waste and the circular material use rate represent the main outputs used in the conducted analyses. Interestingly, even though opening new job opportunities and investments related to CE represent some of the major topics in the domain of CE (Yaroson et al., 2024), only a small portion of the analyzed studies (Nazarko et al., 2022; Ratner et al., 2025) incorporate indicators such as the number of jobs and private investment related to these themes.

Lastly, when analyzing the years in which the EU countries were observed in terms of their performance, even in the most recent studies, the latest data used originates from the year 2021. The reason for this could be the fact that the analyzed studies gathered data from the Eurostat database, which has only recently updated many datasets and incorporated data from the years 2022 and 2023.

3. Methodology

Data Envelopment Analysis (DEA) is a mathematical technique based on linear programming, designed to measure the efficiency of peer entities. The DEA approach is founded on its ability to quantify the efficiency of observed entities, commonly referred to as Decision Making Units (DMUs), by analyzing the values of the diverse inputs they use and the various outputs they produce. The DEA method enables the simultaneous consideration of multiple inputs and outputs without requiring prior assumptions about data distribution or the specification of a production function. From the DEA perspective, the process of transforming available resources into valuable results is perceived as a "black box," meaning that DEA is not concerned with how transformation occurs within an entity, but only with the observable inputs used and the outputs produced.

Owing to these characteristics, DEA is considered an analytic, non-parametric method that directly relies on data and facilitates a more flexible approach to efficiency analysis. The efficiency of decision-making units is measured as a proportional change in inputs and outputs. Based on the obtained results, DEA classifies DMUs as efficient or inefficient, while also providing insights into the operations of inefficient DMUs, allowing for the identification of business segments that can be improved (Farantos, 2015; Charnes et al., 1978; Ji & Lee, 2010; Zhu, 2020).

To assess the efficiency of DMUs in the observed set, DEA employs a frontier analysis approach. The DMUs categorized as the most efficient form the so-called efficiency frontier, which represents the "best practice" and serves as a benchmark for evaluating all other entities in the set. If a DMU operates with input and output values that place it on the frontier, it is considered relatively efficient, otherwise, it is considered relatively inefficient (Amado, Santos & Marques, 2011).

Within the DEA framework, two fundamental DEA models were developed in order to account for the assumptions of two different returns to scale. The first model, the CCR model, the acronym of which is derived from the names of its creators, Charnes, Cooper, and Rhodes (1978), operates under the assumption of constant returns to scale (CRS). The CRS assumption means that any increase in input values results in a proportional increase in output values (Mahmoudi et al., 2019). In contrast, the second model, the BCC model, created by Banker, Charnes, and Cooper (1984), allows for variable returns to scale (VRS). The VRS assumption implies that DMUs may not always operate at optimal returns to scale due to changes in the volume of their production, which impacts their efficiency (Panwar et al., 2022). The linear forms of the CCR and BCC models are listed below.

CCR model (M 1)	BCC model (M 2)
$(max)h_k = \sum_{r=1}^{s} u_r y_{rk}, k = 1, \dots, n$ (1.1)	$(max)h_k = \sum_{r=1}^{s} u_r y_{rk} + u^*, k = 1, \dots, n$ (2.1)
$p.o.$	$p.o.$
$\sum_{i=1}^{m} v_i x_{ik} = 1$ (1.2)	$\sum_{i=1}^{m} v_i x_{ik} = 1$ (2.2)
$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, j = 1, \dots, n$ (1.3)	$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + u^* \le 0, j = 1, \dots, n$ (2.3)
$v_i \ge 0, i = 1, \dots, m$ (1.4)	$v_i \ge 0, i = 1, \dots, m$ (2.4)
$u_r \ge 0, r = 1, \dots, s$ (1.5)	$u_r \ge 0, r = 1, \dots, s$ (2.5)

Each DMU (j = 1, 2, …, n) uses m inputs to produce s outputs. In the observed notation:

- x_{ij} – the amount of the i-th input used by the j-th DMU ($x_{ij} > 0$);

- y_{rj} – the amount of the r-th output produced by the j-th DMU ($y_{rj} > 0$);
- h_k – the relative efficiency of the k-th DMU;
- v_i – the weight coefficient for the i-th input;
- u_r – the weight coefficient for the r-th output.

Additionally, in the BCC model, $u*$ represents a correction factor used to adjust the efficiency assessment by defining the return to scale. Specifically:

- For $u^* < 0$, the scale is non-increasing.
- For $u^* > 0$, the scale is non-decreasing.
- For $u^* = 0$, the BCC model becomes equivalent to the CCR model, meaning constant returns to scale.

Every DMU is assessed individually by solving a linear programming model that selects the most favorable set of input and output weights in order to maximize its efficiency score. This model is subject to the constraint that no other unit in the observed set can perform better while using the same set of weights (Charnes, Cooper & Rhodes, 1978).

According to Charnes and co-authors (1994), not only is it possible to obtain different efficiency results for the same set of DMUs by employing different DEA models, but also by utilizing the same model with a different orientation. DEA models can be input- or output-oriented. In order for a DMU to improve its performance and become efficient, it needs to decrease its inputs if the model used is input-oriented, or rather increase its outputs if the model used is output-oriented (Gerami et al., 2022). Alongside the two listed orientations, in more recent literature, non-oriented DEA models have been mentioned. These are models that allow for the simultaneous decrease of inputs and increase of outputs, without the need to focus only on one group of indicators (Tohidi & Matroud, 2017).

The development of the DEA method has significantly boosted the evaluative capabilities of mathematical programming. What started with one, and later two described models, CCR and BCC, developed into an advanced method that continuously evolves. The DEA method supports parallel analyses, strategic planning, and ongoing improvements, while providing detailed insights into achieved performance (Thore & Tarverdyan, 2022). Due to the many diverse domains where it can be used to assess efficiency, DEA has become attractive to scientists and researchers from various fields. The great popularity that DEA gained resulted in a rich literature containing numerous findings and development progress, both in theory and practice (Xie et al., 2021).

In order to examine the efficiency of EU countries in the CE domain, both CCR and BCC DEA models were employed. Using both models enables a comprehensive investigation of efficiency, which is especially relevant for countries of different sizes, capacities, and strategic priorities towards the circular economy. This approach allows for a detailed assessment of efficiency while also highlighting key areas that are suitable for improvement. Since each dataset focuses on a different objective within the CE domain, models with different orientations were applied. For dataset I, which focuses on the input aspects of the circular economy, input-oriented models were used to evaluate how countries utilize their resources to achieve sustainable economic performance. For dataset II, which primarily focuses on the recycling aspect of the CE and the contribution of investments and innovations, output-oriented models were applied.

4. Data origin and indicators

For the purpose of conducting the intended DEA analysis, available data regarding the values of indicators related to CE were obtained from Eurostat, the statistical office which coordinates the majority of activities related to statistics in the Union (Eurostat, n.d.). In line with the objective of this study, as well as the principles of the DEA methodology, the gathered indicators were organized into two separate datasets, each intended to cover a different topic related to CE.

The selection and categorization of indicators for both datasets were conducted according to previous studies that were analyzed (see Table 1), as well as topics related to CE that have been widely discussed among researchers, according to Yaroson and co-authors (2024). As previously noted, the majority of the analyzed studies relied heavily on waste-related indicators (e.g., Radovanov et al., 2023; Banjerdpaiboon & Limleamthong, 2023). Therefore, in order to remain aligned with them and ensure comparability if needed, some of those indicators were incorporated into Dataset II. Alongside waste-related indicators, some of the studies (e.g., Lacko et al., 2021; Marques & Teixeira, 2022) utilized the circular material use rate and productivity, which were also used as outputs in Dataset I.

Interestingly, while CE investment and jobs are much-used phrases in CE policy discourse (Yaroson et al., 2024), comparatively few studies have incorporated private investment or CE jobs into their DEA models (e.g., Ratner et al., 2025; Nazarko et al., 2022). To fill this gap, this study includes private investment and gross value added in CE industries, as well as patents on recycling and secondary raw materials in Dataset II. This adds a focus on innovation and economic activity that hasn't received much attention so far

This study evaluates the efficiency of 27 members of the European Union based on available data for the year 2022. Although some of the most recently updated indicators include data from 2022 and 2023, most of the indicators updated closer to the end of 2024 do not contain data for the latter year. Therefore, the analysis was conducted using data from 2022, as it was available for all selected indicators.

The two datasets cover topics which can be summarized as follows:

- ***Dataset I*** – Focuses on input aspects of the circular economy, or in other words, how a country uses available resources and manages its own resource dependencies and greenhouse gas emissions. This dataset addresses resource efficiency and its sustainable usage.
- ***Dataset II*** – Focuses on output aspects of the circular economy, including activities related to waste management, recycling rates, and the application of innovations that will contribute to closing the economic loop.

The structure of both selected datasets is given in Table 2 and Table 3.

Table 2: Structure of Dataset I

Input/Output	Name of indicator	Unit of measurement	Description	Reference
Input	Raw material consumption (Material footprint)	Kilograms per capita	Total amount of raw materials required for consumption and investment by households, businesses, and governments in the EU.	Eurostat, (2025a)
	Material import dependency	%	Shows the extent to which an economy relies upon imports in order to meet its material needs.	Eurostat, (2024a)
	Greenhouse gases emissions from production activities	Kilograms per capita	Illustrates the degree to which one country is dependent on imports of materials in order to meet its needs.	Eurostat, (2024b)
Output	Circular material use rate	%	Shows the share of materials reused through recycling.	Eurostat, (2024c)
	Resource productivity	Euro per kilogram	Measures how efficiently an economy uses material resources to produce economic output.	Eurostat, (2024d)

Table 3: Structure of Dataset II

Input/Output	Name of indicator	Unit of measurement	Description	Reference
Input	Generation of municipal waste per capita	Kilograms per capita	Indicates waste collected by municipal authorities and processed through the waste management system.	Eurostat, (2025b)
	Generation of packaging waste per capita	Kilograms per capita	Refers to generated packaging waste that is not recycled but disposed of.	Eurostat, (2025c)
	Private investment and gross added value related to circular economy sectors	Milion euros	Refers to gross investment in tangible goods and gross added value in the domains of recycling, repair, reuse, and leasing.	Eurostat, (2025d)
	Patents related to recycling and secondary raw materials	Number	Represents the number of patents related to secondary raw materials and recycling.	Eurostat, (2024e)
Output	Recycling rate of municipal waste	%	Measures the proportion of recycled municipal waste to total waste generation.	Eurostat, (2025e)
	Recycling rate of packaging waste by type of packaging	%	Portraits the shares of recycled plastic packaging waste in all generated plastic packaging waste.	Eurostat, (2025f)

The use of two datasets allows for a multi-layered assessment of CE performance across EU countries across two dimensions (Figure 1). These two dimensions are interlinked: resource-efficient systems (as reflected in Dataset I) are expected to facilitate or enhance the implementation of circular economy practices (observed in Dataset II) (OECD, n.d.; EEA, 2020; OECD, 2022). Therefore, the dual-dataset approach offers both a strategic and tactical perspective on CE performance.

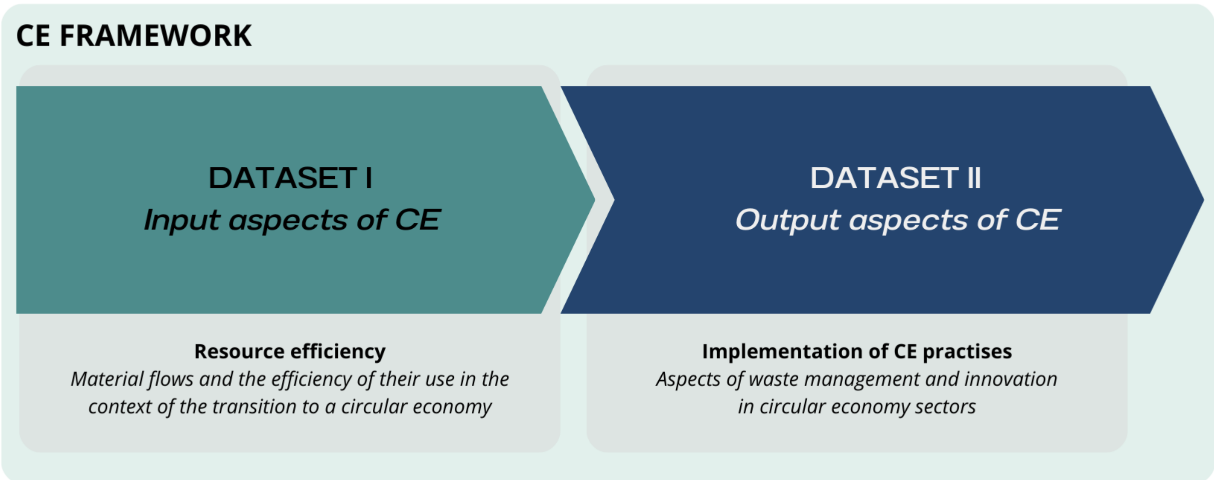

Figure 1: Interlinkage between Dataset I and II

5. Results from single DEA analysis

This section presents the key findings related to the efficiency of the 27 observed European countries. These findings highlight how each country performs in terms of efficiency, offering valuable insights for comparative analysis.

5.1. Results from Dataset I

According to the efficiency scores obtained from Dataset I, 9 out of 27 analyzed EU countries were categorized as relatively efficient under the assumption of VRS, with efficiency scores being equal to 1. Those 9 countries are: Estonia, France, Ireland, Italy, Luxembourg, Sweden, Finland, Romania, and the Netherlands (Figure 2, Table 4). For other countries, categorized as relatively inefficient, there are different causes of inefficiency which will be discussed below.

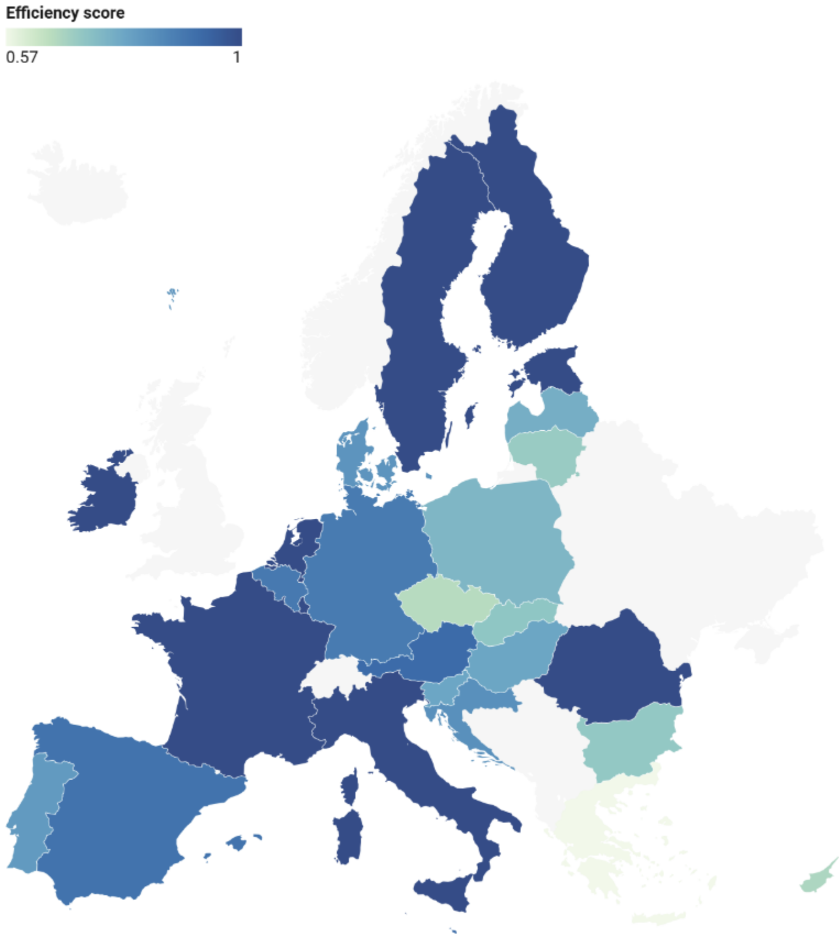

Figure 2: Efficiency scores from Dataset I (VRS)

When analyzing slack values (Annex 1) related to inputs of each DMU, it was noticed that some of the inputs were more commonly chosen than others by the majority of DMUs. In line with that, material footprint represents an indicator which wasn't the cause of inefficiency for most countries. Slack values for this indicator were 0 in the majority of cases, and therefore, correction of these values wouldn't result in any significant changes when it comes to improving the countries efficiency in the context of CE. In contrast, slack values for the indicator related to climate-altering gases originating from production activities (greenhouse gases emissions from production activities) suggest that a large number of inefficient countries still heavily rely on carbon-intensive sectors, which has a negative impact on their technical efficiency. Some of the worst-performing countries according to this indicator are Denmark, Poland, and Bulgaria, which generate more than 3800, 1900, and 500 kg per capita, respectively, more greenhouse gases from production activities than the levels required to reach technical efficiency within a circular economy framework.

Table 4: Dataset I and II result – CRS and VRS

Dataset I			Dataset II		
Country	**Overall efficiency (CRS)**	**Pure technical efficiency (VRS)**	**Country**	**Overall efficiency (CRS)**	**Pure technical efficiency (VRS)**
Estonia	1	1	Bulgaria	1	1
France	1	1	Cyprus	1	1
Ireland	1	1	Estonia	1	1
Italy	1	1	Netherlands	1	1
Luxembourg	1	1	Poland	1	1
Sweden	1	1	Slovakia	1	1
Netherlands	0,9205	1	Slovenia	1	1
Finland	0,7994	1	Sweden	0,9747	1
Romania	0,4044	1	Croatia	0,9483	1
Austria	0,9241	0,9254	Lithuania	0,9006	1
Malta	0,8845	0,9219	Germany	0,8884	1
Spain	0,8582	0,9064	Belgium	0,7861	1
Belgium	0,8292	0,8928	Romania	0,629	1
Germany	0,8569	0,8891	Austria	0,8467	0,9995
Croatia	0,4081	0,8385	Malta	0,4734	0,9988
Denmark	0,7968	0,8287	Finland	0,8476	0,9762
Portugal	0,4639	0,8151	Italy	0,919	0,952
Hungary	0,4102	0,7885	Latvia	0,9262	0,9498
Slovenia	0,5815	0,7869	Czechia	0,8188	0,9383
Latvia	0,3555	0,7666	Luxembourg	0,8428	0,9277
Poland	0,5673	0,7485	Spain	0,8235	0,9192
Slovakia	0,6114	0,7146	France	0,7256	0,8755
Bulgaria	0,291	0,7085	Denmark	0,7427	0,8566
Lithuania	0,3074	0,7009	Hungary	0,7091	0,8449
Cyprus	0,5688	0,6721	Ireland	0,7022	0,8303
Czech	0,559	0,6581	Portugal	0,6384	0,8023
Greece	0,4597	0,5704	Greece	0,6281	0,6495

Apart from slack values, projection values (Annex 2) are also important for countries that are considered to be poor performers in terms of performance improvement, as they provide a definite direction for reforms. Studying such projected values using the DEA model reveals interesting patterns that describe why a country is inefficient and pinpoint specific areas of improvement. Some of the interesting patterns that have been noticed are:

- While countries like Poland, the Czech Republic, and Bulgaria record high emissions of greenhouse gases, their projections indicate that in order to achieve relative efficiency, they would need to reduce these emissions by more than 34% (in the case of Poland, even almost 46%), which testifies to the strong dependence of these economies on carbon-intensive sectors. It is also interesting that the projected emission values are, in some cases, almost twice lower than the existing values, as is the case of Denmark (from 12,912 kg/capita to 6,874 kg/capita).
- Another notable pattern is the need for a significant increase in the circular material use rate for several countries with low efficiency scores. For example, the projection for Portugal shows that the value of this output would have to increase by as much as 266%, while Croatia records the required increase of almost 78%. On the other hand, countries like Latvia, Hungary, and Greece simultaneously show low values in several indicators, which confirms

that their inefficiency is not the result of only one weak aspect, but a combination of poor performance on different fronts.

- When looking at the similarities between countries, it is noted that Spain and Malta have very similar efficiency scores (0.91 and 0.92), and also share a similar pattern where the biggest problems are concentrated in high material footprint and material imports. However, projections related to their greenhouse gases emissions show greatly different correction needs – Spain needs a relatively mild reduction of around 9%, while Malta needs almost 8%, despite considerably different absolute values (Malta: 6,625 kg; Spain: 5,001 kg).
- It is also interesting that some countries which have very high emission values, such as Luxembourg and Ireland, still achieve efficiency, which implies that their results in other indicators (e.g., resource productivity and participation in circularity) successfully compensate for high emissions. For example, Ireland has emissions of more than 11,800 kg per capita, but at the same time has one of the best results in terms of resource productivity and circular use of materials, which allows it to remain efficient under the VRS assumption.
- An interesting observation is that some countries operate under a significant input burden, yet still manage to be considered relatively efficient. In line with that, the Netherlands has notably high values across all input indicators, but the country remains efficient due to proportionally high output values. In contrast, Romania is efficient (under the VRS assumption), but its efficiency is not driven by high productivity; rather, it reflects minimal operations within the circular economy domain. Significantly low output values (circular material use rate = 1.5%, resource productivity = €0.37/kg) are accompanied by equally low input levels. Therefore, it can be concluded that achieving VRS efficiency depends largely on maintaining a good balance and proportionality between inputs and outputs. While this balance contributes to Romania's efficiency under the VRS model, it also results in the country being one the worst performers, next to Lithuania and Latvia, under the CRS assumption with its efficiency score being just above 0.4.

Another way by which inefficient countries are able to identify ways of improving is through using peer units that are identified through DEA analysis. The peer units (Annex 3) are examples of the best practice within the group being analyzed. In both the CRS and VRS assumptions, Sweden emerges as the most valuable benchmark. Sweden was selected as a peer entity for at least 15 countries in both analyses (15 under VRS and 18 under CRS). Upon analyzing the data and results, it was concluded that this is primarily due to the fact that Sweden maintains a strong balance between input and output values. Sweden's input values (39.15 for material footprint, 24.4 for import dependency, and 3,970.89 for greenhouse gas emissions) are well below the average values (60.90, 39.88 and 7,183.35, respectively) in the analyzed set. In addition to input values, Sweden's output values (12.1 for circular material use rate and 2.03 for resource productivity) are above the average values (10.47 and 1.98, respectively). This suggests that by using relatively small amounts of inputs, Sweden has achieved significant results in the domain of sustainable resource usage. The structure of Sweden's input/output values makes the country a stable and reliable benchmark for other countries striving to improve their performance. The previously mentioned difference between efficiency scores of Romania under the CRS and VRS assumptions ($1^{VRS} - 0.4044^{CRS} = 0.5956$) resulted in different positioning of this country in those analyses. Because Romania is a part of the set of efficient DMUs in the VRS analysis and, given the fact that the proportion of its inputs and outputs is good, Romania represented the second most frequent peer entity in the VRS analysis. However, the fact that Romania struggles to maintain its efficiency under the CRS assumption and ends up performing poorly suggests that the country cannot represent a stable and reliable benchmark for sustainable resource usage to other countries. Therefore, it can be said that true peer DMUs, which show consistent and robust efficiency under both assumptions, are the countries which were labeled as efficient in both analytical models. There are six of them: Estonia, France, Ireland, Italy, Luxembourg, and Sweden.

5.2. Results from Dataset II

According to the results obtained from Dataset II, there are 13 EU members categorized as relatively efficient under the VRS assumption (Table 4). The average efficiency score of the observed dataset is 0.9452, which suggests that, in terms of innovation, the majority of EU countries are either efficient or very close to being so. This indicates that most countries have made significant progress in optimizing their resource use and fostering innovation within the framework of a CE.

Analysis of slack values (Annex 4) reveals significant patterns regarding the latent inefficiency of DMU units, or in other words, indicators whose excess could be rationalized without affecting output performance. In line with this, the results highlight one of the most obvious examples of latent inefficiency among the analyzed countries, which is Denmark. Denmark has slack values of 210 kg/capita for municipal waste and 45 kg/capita for packaging waste, surpassing all other countries in the dataset, as it is the only one with such slack for both types of waste. The only country that generates more municipal waste per capita than Denmark is Austria. Austria's slack reaches a staggering 265 kg/capita, which suggests that the absence of complete relative efficiency (i.e., an index of 0.995, very close to 1), coupled with slack values on the output side, may be a key generator of Austria's inefficiency. Along with Denmark and Austria, Ireland stands out for its slack of over 120 units of municipal waste and 104 units of packaging waste, while at the same time recording a surplus in patents. This disproportion indicates unused potential in turning resources into concrete results. Additionally, Hungary presents a special case, where the only slack is related to the recycling rate of packaging waste (14.78), while input indicators do not show any surplus. This pattern indicates a problem with the insufficient conversion of inputs into relevant outputs.

Alongside slack analysis, analyzing the projected values (Annex 5) provided better context and contributed to a greater understanding of the obtained results. Similar to Dataset I, some significant trends were also observed in Dataset II. These trends included:

- The Czech Republic and Portugal represent the clearest examples of countries that have significant room for improvement when it comes to recycling rates of both, but primarily municipal waste. In order to become relatively efficient, the Czech Republic needs to increase its municipal recycling rate by more than 60%, while Portugal needs to cease growth by approximately 40.25%. What is interesting is that these countries are both relatively stable when it comes to inputs, which indicates that the problem lies in the infrastructure of recycling processes, and not in the resources available in terms of investments and patents.
- Austria and Slovenia show that identical outputs do not imply the same efficiency when it comes to inputs. Both countries have an identical municipal waste recycling rate - 62.6% - but while Austria generates 803 kg of waste per inhabitant, Slovenia produces only 487 kg. The projection for Austria predicts an optimal input of 537.6 kg/capita of municipal waste, which represents a reduction of 33%. Since projections for Austria indicate that changes in output values are not suitable, this imbalance clearly indicates excessive inputs that have not been accompanied by a proportional increase in output.
- Malta and Romania achieve efficiency not due to high performance, but due to a small volume of activities. Romania has the lowest municipal waste input - only 303 kg/capita, and Malta 618 kg/capita, while their outputs are below average (e.g. packaging waste rate: Romania 37.3%, Malta 31.8%). The projections are almost identical to the real values, as if they are at their limit, but that limit is not particularly high. These results indicate an important distinction between pure technical efficiency (under the VRS assumption) and overall efficiency, which was penalized under the CRS assumption, given the fact that Romania is inefficient under CRS, while Malta, which is inefficient in both models, has a difference between scores of 0.5254 (0.9988^{VRS}-0.4734^{CRS}).
- On the other hand, Poland is an example of extreme input rationalization. With the lowest input in the municipal waste category (only 364 kg per capita), the country still achieves the

maximum score and records strong output performance, including a high packaging waste rate of 64%. When compared to countries that produce almost twice as much waste (e.g. Austria with 803 kg), Poland confirms that high efficiency is possible even with restrictive entry conditions.

- Denmark and Ireland show that a high amount of waste per inhabitant negatively affects efficiency, regardless of a good recycling percentage. Denmark generates 802 kg/capita of municipal waste, but the projection shows that the optimal amount would be 591 kg/capita, which means it needs to reduce the amount by 26.26%. Ireland, at 637 kg/capita, has a similar required reduction to 516 kg/capita (down by 18.96%). Both countries have projected corrections in packaging waste as well (Denmark: 24.16%; Ireland: 45.08%), which indicates a fundamental problem of excessive inputs and suboptimal use of resources.

Peer units analysis revealed a significant variation among reference units. The set of peer entities contains diverse elements, ranging from nations that are recognized as economically advanced, like Germany and the Netherlands, to countries with limited resources, like Estonia and Lithuania. In accordance with the analysis conducted on Dataset I, this also confirms that achieving efficiency is not necessarily linked to the high level of inputs used and outputs produced, but rather to the way in which resources are being utilized. For example, Estonia has sub-average levels for all four inputs monitored (input values are between ~2% and ~31% below the average) and average or above-average outputs (with the packaging waste recycling rate being approximately 11% above the average). Similarly to Estonia, Lithuania also has moderate input and output values. What is interesting is that, while Estonia is categorized as relatively efficient under both the CRS and VRS assumptions, Lithuania, which is relatively efficient under the VRS assumption and also serves as a reference unit for two other countries (Latvia and Hungary), experiences a drop in efficiency score under the CRS assumption (from 1 to 0.9006). The decrease is due to the fact that Lithuania's input values exceed the values categorized as optimal for the given amount of outputs according to the other units.

Alongside Romania, which displayed almost identical behavior as in the analysis conducted on Dataset I (manifesting in efficiency based on low functioning under VRS and inefficiency under CRS ($1^{VRS} - 0.629^{CRS} = 0.371$)), there is Belgium. Belgium served as a reference unit for 9 inefficient countries under the VRS assumption, while it is inefficient under CRS ($1^{VRS} - 0.7861^{CRS} = 0.2139$). This is caused by the assumption of constant returns to scale, indicating underutilization of fixed inputs like investments and patents, which suggests that Belgium might not utilize resources as efficiently as Bulgaria and the Netherlands, both of which were labeled as relatively efficient. Therefore, Romania and Belgium both cannot be considered stable peer units due to struggling to maintain efficiency and having significant drops in efficiency scores. When it comes to stable reference entities, both under CRS and VRS, two countries were singled out: Estonia (peer for 14 under CRS, 9 under VRS) and Slovenia. Interestingly, Slovenia is a peer for 12 countries under CRS but only for four (Denmark, Latvia, Luxembourg, Austria) under VRS. In comparison with those four countries Slovenia is a peer for, it is the one with the most proportional values of inputs and outputs, and its outputs (62.6% for both categories) are among the largest in the group.

6. Results from linked DEA analysis

As stated before, the two employed datasets are interlinked and contribute to encapsulating the overall framework of the circular economy (UNECE & OECD, 2023). Accordingly, a linked DEA approach was applied, where efficiency scores obtained from the DEA analysis on Dataset I were used as an input indicator, together with other indicators from Dataset II, in a third and final DEA analysis. This provided a methodologically consistent framework that offers a clearer view of how the initial stage of efficient resource management influences outcomes in the areas of recycling and innovation, aligning with the logic of the circular economy, where all phases are mutually dependent. The only difference in this analysis from the previous two lies in the exclusive use of the CRS (constant returns to scale) model, whereas the initial DEA assessments employed both CRS and VRS (variable returns to scale). The output-oriented CCR model was chosen for the final, linked stage to ensure methodological consistency, as it preserves proportionality between inputs and outputs when integrating efficiency scores from Dataset I into the analysis of Dataset II. This statement is particularly important from the perspective of the circular economy, whose cumulative and interactive nature across consecutive phases pleads for a steady returns-to-scale framework (Livingstone et al., 2022; Papageorgiou & Hadjiyiannis, 2023).

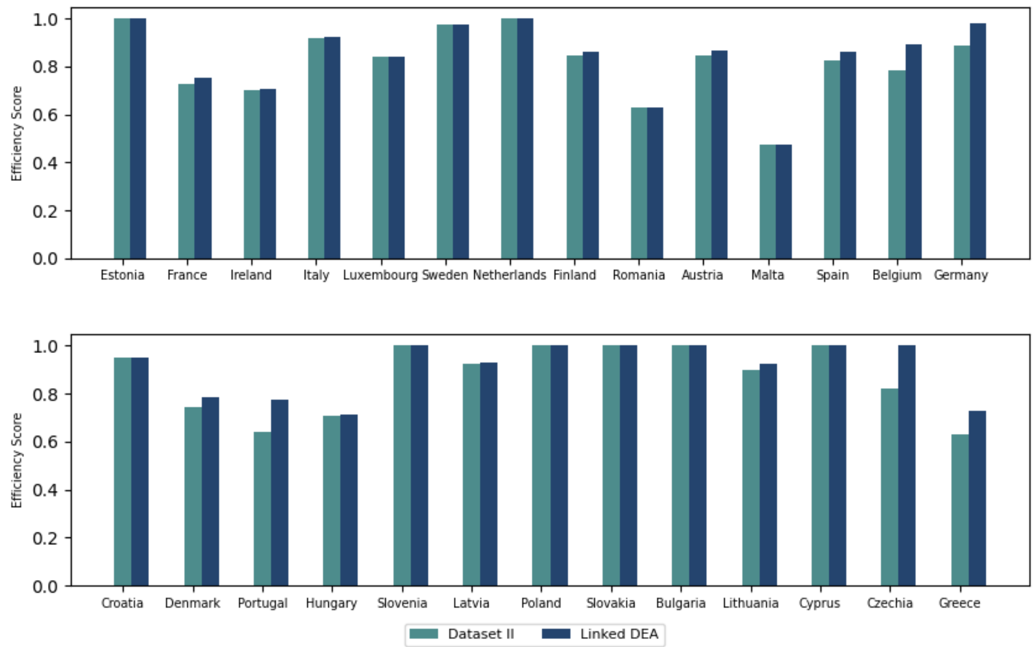

Figure 3: Efficiency scores derived from single and linked DEA analyses

By adding the efficiency score obtained from the DEA analysis conducted on Dataset I as a new input to the DEA model, some changes occurred in the performance of the 27 EU countries. Some of the countries achieved significant improvement in their efficiency scores, while others displayed some weaknesses that had not been detected by the previous model. Three countries with the most improvement and three countries with the most deterioration in rank are displayed in Table 5.

Table 5: Linked DEA countries efficiency and rank changes

Country	Score from Dataset II	Score from linked DEA	Score change	Rank from Dataset II	Rank from linked DEA	Rank change
Czechia	0.8188	1	0.1812	18	1	+17
Belgium	0.7861	0.8901	0.1040	19	15	+4
Germany	0.8884	0.9784	0.0900	13	9	+4
Ireland	0.7022	0.7044	0.0022	23	25	-2
Hungary	0.7091	0.7142	0.0051	22	24	-2
Italy	0.9190	0.9214	0.0024	11	14	-3

By adding the input to the second DEA analysis, there are clear changes that indicate its analytical value and stabilizing effect on the model. The average efficiency increased from 0.8434 to 0.8727, i.e., by 3.48%, while the standard deviation slightly decreased, from 0.1461 to 0.1376, which implies a decrease in variability and a greater clustering of DMUs around the average efficiency. The new input showed satisfactory stability — its average projection is 0.822 (which is only a -3.73% deviation from the initial value), with a relatively low standard deviation of 0.132, making it a reliable and informative contribution to the model.

The key effects of its inclusion are reflected in the reduction of required corrections in outputs: for the "rate for municipal waste," the average required improvements were reduced from 28.7% to 22.4%, while for the "rate for packaging waste," there was a reduction from 24.1% to 18.3%. This indicates that the model with the additional input generates less extreme and thus more realistic target values. Also, the observed changes in inputs show that the added input increases the visibility of the potential for resource rationalization. For example, the average required reduction of "packaging waste" increased from -8.7% to -11.4%, while for "private investment" it decreased from -7.0% to -8.9%, suggesting that the new input allows for a finer differentiation of inefficiencies in the use of input resources.

It is particularly interesting that certain DMUs, such as the Czech Republic, which was previously inefficient, has now become fully efficient (score 1), implying that the new input provided better insight into its position relative to the efficient frontier.

Interestingly, in countries like Ireland and Portugal, the output targets did not become easier after the new input was added — in fact, they stayed about the same or slightly increased. This shows that the added input allows the model to tailor requirements more precisely, depending on each DMU's unique structure.At the level of the entire sample, the variability in outputs is also reduced — the standard deviation for the packaging waste rate fell from 26.68% to 24.64%, and for the municipal waste rate from 15.77% to 15.47%, indicating a more consistent distribution of targets.

The foregoing indicates that the inclusion of the additional input not only contributes to greater differentiation among units but also enables more balanced, analytically stable, and applicably relevant projections. This further confirms the value of the linked DEA approach when the goal is optimization and evaluation in more complex systems with interdependent stages. Also, it contributes to a better illustration of the relationship and potential impact of resource manipulation on overall circular economy activities, particularly waste management.

Conclusion

Implementing and further developing the principles and practices of the circular economy provides a better response to emerging challenges than the widespread linear approach. Given the fact that the circular economy (CE) has gained great importance in defining and enforcing sustainable development policies among EU members over the past few decades, this paper provides a comprehensive efficiency analysis of the 27 European Union countries based on indicators divided into two datasets—one focusing on input aspects of CE, and the other containing indicators related to output aspects of CE.

The obtained results indicate that CE efficiency significantly fluctuates among EU member countries, whereby some countries, such as Estonia, Sweden, and the Netherlands, consistently demonstrate high efficiency results, thanks to a strong balance between input resources and output performance. On the other hand, countries such as Greece and Portugal show a need for significant improvement, whether due to high resource consumption, low recycling rates, or even lower innovation capacities.

Based on the analysis results, it is essential to point out that high efficiency does not solely depend on the size of the economy or the amount of inputs used, but more importantly, on the proportion between resources consumed and results produced. By employing the CCR and BCC models, overall efficiency was separated from technical efficiency, which contributed to an even better differentiation between countries, highlighting the strengths and weaknesses of individual economies. The conducted analysis can assist in verifying the significance of a systematic and phased approach to evaluating CE implementation.

Given the fact that the conducted analysis evaluated the performance of EU members based only on data from the year 2022, future work could involve the assessment of performance over a longer time period (e.g., 5 or 10 years), which could be analyzed through Window DEA or similar methodologies that would allow for tracking efficiency trends and better understanding of long-term CE dynamics of the EU members.

ANNEXES:

To shorten the tables presented in the appendices, the following abbreviations were applied:

Dataset I		***Dataset II***	
MF	Raw Material Consumption (Material Footprint)	**MWPC**	Municipal Waste Per Capita
MID	Material Import Dependency	**PWPC**	Packaging Waste Per Capita
GHG	Greenhouse Gases Emissions from Production Activities	**CEI**	Circular Economy Investment
CMU	Circular Material Use Rate	**PRM**	Patents on Recycling and Materials
RP	Resource Productivity	**RMW**	Recycling Rate of Municipal Waste
		RPW	Recycling Rate of Packaging Waste

Annex 1: Slack values from Dataset I (VRS)

	Slack						**Slack**				
DMU	**MF**	**MID**	**GHG**	**CMU**	**RP**	DMU	**MF**	**MID**	**GHG**	**CMU**	**RP**
Belgium	0	22,679	0	0	0	Lithuania	0	11,303	0	0,52	0
Bulgaria	0	0	508,144	0	0,184	Luxembourg	0	0	0	0	0
Czechia	0	0	0	0	0,198	Hungary	16,34	0	0	6,482	0,822
Denmark	0	0	3826,32	0	0	Malta	0	13,574	0	0	0,63
Germany	0	0	534,327	0	0	Netherlands	0	0	0	0	0
Estonia	0	0	0	0	0	Austria	0	1,05	0	0	0
Ireland	0	0	0	0	0	Poland	11,418	0	1991,52	0	0
Greece	10,438	0	0	4,684	0,174	Portugal	11,879	1,112	0	8,8	0,75
Spain	30,104	4,219	0	6,677	0	Romania	0	0	0,012	0	0
France	0	0	0	0	0	Slovenia	0	16,151	0	0,82	0
Croatia	18,498	6,456	0	5,3	0,782	Slovakia	11,128	8,331	0	0,6	0,52
Italy	0	0	0	0	0	Finland	0	0	0,066	0	0
Cyprus	0	0,734	0	0,03	0	Sweden	0	0	0	0	0
Latvia	0,707	0	0	7,527	1,071						

Annex 2: Projections from Dataset I (VRS)

	MF		**MID**		**GHG**		**CMU**		**RP**	
DMU	**Proj.**	**Diff.(%)**	**Proj.**	**Diff.(%)**	**Proj.**	**Diff.(%)**	**Proj.**	**Diff.(%)**	**Proj.**	**Diff.(%)**
Belgium	69,2702	-10,725	44,4558	-40,883	6107,03	-10,725	18,3	0	3,1213	0
Bulgaria	29,2944	-29,154	12,3271	-29,154	5699,85	-34,953	3	0	0,52634	53,542
Czechia	33,8265	-34,191	21,6513	-34,191	5929,91	-34,191	11,3	0	1,37977	16,791
Denmark	34,7944	-17,134	32,0693	-17,134	6874,21	-46,765	9,3	0	2,1551	0
Germany	56,0445	-11,085	34,4989	-11,085	6015,93	-18,338	12,5	0	2,8645	0
Estonia	36,4033	0	25,3	0	9802,41	0	21,4	0	0,6972	0
Ireland	71,2352	0	31,5	0	11896,6	0	2,1	0	3,7981	0
Greece	38,4902	-55,128	22,8731	-42,96	4052,71	-42,96	10,9839	74,347	1,85187	10,342
Spain	63,467	-38,52	34,1221	-19,333	4533,07	-9,358	16,0772	71,034	2,8456	0
France	72,1657	0	37,6	0	4734,21	0	17,5	0	3,1389	0
Croatia	39,1493	-43,057	24,3998	-33,696	3970,85	-16,153	12,0999	77,939	2,02568	62,862
Italy	93,7647	0	49	0	5347,19	0	20,6	0	3,4595	0
Cyprus	32,6522	-32,785	20,17	-35,145	5168,19	-32,785	8,53004	0,353	1,4493	0
Latvia	39,1063	-24,705	24,3001	-23,344	3976,19	-23,344	12,027	167,267	2,01433	113,586
Lithuania	31,6008	-29,913	14,4887	-60,629	5181,68	-29,913	4,52016	13,004	0,8309	0
Luxembourg	31,5358	0	90	0	11818,9	0	12,3	0	4,3123	0
Hungary	38,7253	-44,549	23,4178	-21,152	4023,51	-21,152	11,382	132,286	1,91388	75,311
Malta	91,6999	-7,814	51,1404	-27,15	6107,59	-7,814	21,5	0	3,3654	23,045

Annex 2: (continued)

	MF		MID		GHG		CMU		RP	
DMU	**Proj.**	**Diff.(%)**	**Proj.**	**Diff.(%)**	**Proj.**	**Diff.(%)**	**Proj.**	**Diff.(%)**	**Proj.**	**Diff.(%)**
Netherlands	118,091	0	82,8995	-0,001	8237,28	0	27,2	0	4,6736	0
Austria	37,386	-7,458	38,2804	-9,928	5821,01	-7,458	12,4	0	2,4653	0
Poland	34,9532	-43,582	15,5684	-25,152	5163,03	-45,986	6,7	0	0,8453	0
Portugal	39,1493	-37,467	24,3998	-22,046	3970,85	-18,493	12,0999	266,663	2,02568	58,777
Romania	32,889	-0,001	9,89993	-0,001	4748,44	-0,001	1,5	0	0,3748	0
Slovenia	36,6067	-21,31	20,4397	-56,044	4356,25	-21,31	9,11973	9,876	1,5579	0
Slovakia	39,1493	-44,353	24,3998	-46,725	3970,85	-28,537	12,0999	5,216	2,02568	34,507
Finland	19,3094	0	17,5999	0	7847,83	-0,001	5,4	0	0,9084	0
Sweden	39,1497	0	24,4	0	3970,89	0	12,1	0	2,0257	0

Annex 3: Peer units from Dataset I (VRS)

DMU	**Score**	**Rank**	**Reference units**			
Belgium	0,8928	13	Estonia	France	Luxembourg	Netherlands
Bulgaria	0,7085	23	Estonia	Romania	Finland	
Czechia	0,6581	26	Estonia	Romania	Finland	Sweden
Denmark	0,8287	16	Ireland	Luxembourg	Finland	Sweden
Germany	0,8891	14	Ireland	France	Luxembourg	Sweden
Estonia	1	1	Estonia			
Ireland	1	1	Ireland			
Greece	0,5704	27	Romania	Sweden		
Spain	0,9064	12	France	Sweden		
France	1	1	France			
Croatia	0,8385	15	Sweden			
Italy	1	1	Italy			
Cyprus	0,6721	25	Romania	Finland	Sweden	
Latvia	0,7666	20	Romania	Sweden		
Lithuania	0,7009	24	Romania	Finland	Sweden	
Luxembourg	1	1	Luxembourg			
Hungary	0,7885	18	Romania	Sweden		
Malta	0,9219	11	Estonia	Italy	Netherlands	
Netherlands	1	1	Netherlands			
Austria	0,9254	10	Estonia	Luxembourg	Finland	Sweden
Poland	0,7485	21	Estonia	Romania	Sweden	
Portugal	0,8151	17	Sweden			
Romania	1	1	Romania			
Slovenia	0,7869	19	Romania	Finland	Sweden	
Slovakia	0,7146	22	Sweden			
Finland	1	1	Finland			
Sweden	1	1	Sweden			

Annex 4: Slack values from Dataset II (VRS)

	Slack							Slack					
DMU	**MWPC**	**PWPC**	**CEI**	**PRM**	**RMW**	**RPW**	DMU	**MWPC**	**PWPC**	**CEI**	**PRM**	**RMW**	**RPW**
Belgium	0	0	0	0	0	0	Lithuania	0	0,009	0	0	0	0
Bulgaria	0	0	0	0	0	0	Luxembourg	164,646	58,041	0,685	0	0	0
Czechia	7,878	0	0,121	1,903	17,3	0	Hungary	0	20,339	1,282	0	0	14,783
Denmark	210,607	45,354	0,468	0	0	0	Malta	0	0,114	0	0	0	0,034
Germany	0	0,002	0	0	0	0	Netherlands	0	0	0	0	0	0
Estonia	0	0	0	0	0	0	Austria	265,401	2,373	2,154	0	0	0
Ireland	120,801	104,465	0	1,059	0	0	Poland	0	0	0	0	0	0
Greece	0	0	0	0,227	0	0	Portugal	0	34,075	0,518	1,242	4,716	0
Spain	0	25,154	1,268	4,461	0	0	Romania	0	0,001	0	0	0	0
France	0	30,178	2,312	5,99	0	0	Slovenia	0	0	0	0	0	0
Croatia	0,005	0	0	0	0	0	Slovakia	0	0	0	0	0	0
Italy	0	65,154	0,158	2,468	0	0	Finland	14,207	17,768	0	4,314	0	0
Cyprus	0	0	0	0	0	0	Sweden	0	0	0	0	0	0
Latvia	0	12,306	0,046	0	0	0							

Annex 5: Projections from Dataset II (VRS)

	MWPC		**PWPC**		**CEI**		**PRM**		**RMW**		**RPW**	
DMU	**Proj.**	**Diff.(%)**	**Proj.**	**Diff.(%)**	**Proj.**	**Diff.(%)**	**Proj.**	**Diff.(%)**	**Proj.**	**Diff.(%)**	**Proj.**	**Diff.(%)**
Belgium	690	0	167,1	0	8,91153	0	7,50867	0	54,7004	0,001	80,4005	0,001
Bulgaria	488	0	80,92	0	6,01127	0	5,30194	0	24,6	0	58,3	0
Czechia	562,122	-1,382	131,68	0	7,33563	-1,628	6,17758	-23,547	51,5638	60,385	75,4543	6,574
Denmark	591,393	-26,26	142,376	-24,159	7,56597	-5,829	6,51161	0	53,3488	16,737	75,7623	16,737
Germany	606	0	226,938	-0,001	10,5277	-0,002	16,1555	-0,002	69,2004	0,001	68,5004	0,001
Estonia	373	0	143,21	0	5,50126	0	5,30194	0	33,2	0	73	0
Ireland	516,199	-18,964	127,255	-45,082	6,83411	0	5,84141	-15,345	48,6561	20,436	74,309	20,436
Greece	519	0	104,95	0	5,31321	0	5,30189	-4,107	26,6347	53,958	66,8176	53,958
Spain	482	0	157,646	-13,76	7,60686	-14,286	7,40645	-37,589	46,67	8,788	75,4988	8,788
France	535	0	158,362	-16,006	7,68528	-23,124	7,0661	-45,88	47,0615	14,227	76,7604	14,227
Croatia	477,995	-0,001	82,17	0	5,81707	-0,001	5,30189	-0,001	34,2001	0	52,4001	0
Italy	486	0	167,206	-28,04	9,03842	-1,717	9,43708	-20,728	55,9859	5,039	75,5232	5,039
Cyprus	673	0	98,55	0	4,18965	0	5,30194	0	14,8	0	69,5	0
Latvia	464	0	141,134	-8,02	5,38787	-0,844	5,52897	0	53,4861	5,288	64,0149	5,288
Lithuania	465	0	151,111	-0,006	6,08432	-0,003	5,30194	0	48,4014	0,003	58,3021	0,004
Luxembourg	556,354	-22,836	150,869	-27,783	6,23856	-9,895	6,37931	0	59,936	7,799	68,6677	7,799
Hungary	407	0	146,131	-12,218	5,71661	-18,317	5,30194	0	38,8189	18,35	67,567	51,495
Malta	618	0	167,046	-0,068	4,38203	0	5,30194	0	12,5145	0,116	31,8707	0,222
Netherlands	473	0	168,78	0	9,28173	0	9,89924	0	57,6	0	75,2	0
Austria	537,599	-33,051	160,827	-1,454	6,43931	-25,067	7,85543	0	62,6289	0,046	66,2306	0,046
Poland	364	0	182,1	0	8,31777	0	10,9234	0	40,9	0	64	0
Portugal	508	0	153,385	-18,177	6,9536	-6,93	6,24174	-16,597	42,3562	40,252	76,1521	24,635
Romania	303	0	130,129	-0,001	7,03425	-0,002	7,33337	-0,002	12,3008	0,006	37,3012	0,003
Slovenia	487	0	142,12	0	4,83628	0	5,7499	0	62,6	0	62,6	0
Slovakia	478	0	108,38	0	6,29895	0	5,30194	0	49,5	0	72,2	0
Finland	507,793	-2,722	142,092	-11,115	6,8638	0	6,04745	-41,633	44,7639	2,435	75,2894	2,435
Sweden	395	0	131,46	0	7,79297	-0,003	7,23168	-0,002	39,7001	0	66,3002	0

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