Science of the Total Environment 730 (2020) 139038

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Circular economy in plastic waste - Efficiency analysis of European countries

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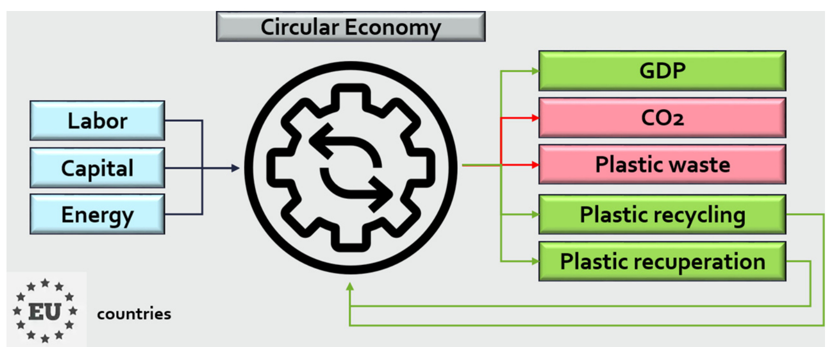
HIGHLIGHTS

- Circular economy of European countries, with plastic waste, recovery and recycling
- Efficiencies increase for most countries with time.
- Poor management of resources between 2007 and 2009, the labor is the most affected.
- Increasing capital seems to be a main driver towards efficiency.
- Difference in countries efficiency is in GDP, recovering and recycling activities.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 14 December 2019
Received in revised form 24 April 2020
Accepted 25 April 2020
Available online 1 May 2020

Editor: Konstantinos G Moustakas

Keywords:
Circular economy
Plastic waste
Efficiency analysis
European countries

ABSTRACT

The way plastics are currently produced, used and disposed does not capture the economic benefits of a more 'circular' approach and is dramatically harming the environment. It is relevant to determine which European countries can be considered more or less efficient in the end-of-life of plastic products processes, what the sources of the inefficiencies are, and how those less efficient countries could improve their performance towards a more circular economy. Although some countries have developed a variety of quantitative indicators, there is scarcity of adequate metrics for performance measurements.

This paper estimates the efficiency of 26 European countries in the context of Circular Economy, for the period 2006–2016, considering the generation of waste, recovery and recycling of plastic, with a methodology based on the Multidirectional Efficiency Analysis. Apart from identifying the most efficient countries in the studied period, results show that efficiency increases for most countries with time, and that many countries reach the full efficiency by the end of the study period, and especially by 2016. Input analysis shows that increasing capital seems to be a main driver towards efficiency, since the other inputs are used with a similar efficiency by most countries. Output analysis suggest that the difference among countries efficiency is not in their reduction of total waste or emissions, but rather in the improvement of their economic growth in a circular way, that is, improving GDP but also the recovering and recycling activities. These results could be useful to design policies towards a more efficient and circular use of plastics.

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https://doi.org/10.1016/j.scitotenv.2020.139038

1. Introduction

The Europe and Central Asia region generated 392 million tonnes of waste in 2016, or 1.18 kg per person each day. About three-quarters of this waste has the potential to be recovered through recycling or organics management, but presently, only 31% of waste materials are recovered through recycling and composting (Kaza et al., 2018). This volume of waste not only damages the place it occupies and provokes diseases to the population, but also worsens air quality and accelerates climate change. In 2016, 1.6 billion tons of carbon dioxide equivalent gases were generated by improper waste treatment processes, representing 5% of total emissions worldwide (Kaza et al., 2018).

Circular Economy (CE) models appear as a new paradigm to contribute as part of the solution to this problem. CE models maintain the added value of products for as long as possible and minimize waste, keeping the resources within the economy when products no longer serve their functions, so that materials can be used again and generate additional value (Pearce and Turner, 1990). Thus, circular business models create more value from each unit of natural resource compared to traditional linear models (Di Maio et al., 2017).

To move towards a more circular economy, in December 2015 the European Commission put forward a first Circular Economy Package, which included revised legislative proposals on waste (EC, 2019), as well as a comprehensive Circular Economy Action Plan. In this action plan, the CE is described as an economic system 'where the value of products, materials and resources is maintained in the economy for as long as possible, and the generation of waste minimised'.

The Circular Economy Action Plan (EC, 2015a) set out measures to stimulate Europe's transition towards a circular economy, that should contribute to "closing the loop" of product lifecycles through greater recycling and re-use, bringing benefits for both the environment and the economy. The Plan established a concrete and ambitious program of actions, with measures covering the whole cycle:

- Product design, for products more durable or easier to repair, upgrade or remanufacture, with special emphasis on electrical and electronic products;
- Production processes, towards a more efficient use of resources;
- Consumption, to improve, among others, the information to which consumers have access, such as the environmental footprints, energy efficiency labeling, availability of repair and spare parts, and taxation design to provide the adequate economic signals;
- Waste management, to increase high-quality recycling, or to recover its energy content rather than landfilling it, with a revised legislative proposal on waste;
- Waste-resources linkage, to reinject secondary raw materials into the market and to improve water reuse;

The plan also establishes priority areas such as plastics, food, critical raw materials, construction and demolition, and biomass and bio-based products, and ends up by setting out a timeline to complete the actions.

The revised legislative proposal on waste (EC, 2015b), which finally entered into force in June 2018 (EC, 2019), considered the following final main points (modified from the initial proposal (EC, 2015b)):

- Common EU targets: by 2030, 65% of municipal waste and 70% of packaging waste should be recycled, and landfilling of municipal waste reduced to 10%;
- Simplification and harmonization of definitions and calculation methods, and clarified legal status for recycled materials and by-products;
- Reinforced rules and new obligations on separate collection (bio-waste, textiles and hazardous waste produced by households, construction and demolition waste);
- Minimum requirements for Extended Producer Responsibility;
- Strengthened waste prevention and waste management measures, including for marine litter, food waste, and products containing critical raw materials.

In 2018, this first set of measures was complemented by the second Circular Economy Package, (EC, 2019), that included:

- The EU strategy for plastics, to transform the way plastics and plastics products are designed, produced, used and recycled, with all plastics packaging recyclable by 2030;
- A monitoring framework of indicators for the circular economy, with a set of ten key indicators that cover each phase (production, consumption, waste management and secondary raw materials, investments and jobs and innovation);
- A communication on the interface between chemicals, products and waste legislation, to assess how the rules on waste, products and chemicals relate to each other;
- A report on Critical Raw Materials, to highlight the potential to make the use of the 27 critical materials considered more circular.

In the context of the Action Plan, and included in this second Circular Economy Package (EC, 2019), other initiatives adopted in 2018 were a directive on the reduction of the impact of plastic products on the environment (with measures for single use plastics, taking into account the consumer behavior and needs and the opportunities for businesses), and a proposal for a regulation on minimum requirements for water reuse.

The European Commission identifies plastic waste as a key priority in its Action Plan for the Circular Economy (EC, 2015a). Plastic is essential in modern economies, but the way plastics are currently produced, used and disposed does not capture the economic benefits of a more 'circular' approach and is dramatically harming the environment (CIEL, 2019). Thus, there is a growing concern about the environmental problems that plastic production, use and consumption entail, such as the plastic waste that accumulates annually in the oceans.

In 2017, the European Commission confirmed its focus on the production and use of plastics and on the actions to ensure, by 2030, that all plastic packaging is recyclable (EC, 2017). The reuse and recycling rate of plastics in Europe is still very low, especially compared to other materials such as paper, glass and metals. Europe produces about 25.8 million tonnes of plastic waste annually and <30% of this waste is collected for recycling (EC, 2018). In addition, a significant part of this quantity is exported to the EU for treatment in third countries that sometimes apply different and less friendly environmental standards.

Landfill and incineration plastics disposal rates are 31% and 39% respectively, with around 95% of the value of plastic packaging materials being lost (between 70 and 105 thousand millions euros per year) after a very short duty cycle (Ellen MacArthur Foundation, 2016). The challenges associated with the production, consumption and end-of-life of plastic products can be turned into an opportunity for the EU and for the competitiveness of the European industry (EC, 2018). It is therefore relevant to determine which European countries can be considered more or less efficient in the end-of-life of plastic products processes, what the sources of the inefficiencies are, and how less efficient countries could improve these processes towards a more circular economy, in particular in those aspects related to plastic waste reduction.

There is a scarcity of adequate metrics for performance measurements, although some countries such as the European Commission have been developing a wide variety of quantitative indicators (Huysveld et al., 2019). Indicators can be useful in various implementation scales and are a necessary tool to assess CE. However, what should be measured to assess the compliance with the CE principles is a matter of debate, since CE definition is rather qualitative and ambiguous, and different indicators might lead to different or even incoherent conclusions. In this sense, some authors reviewed tools and methodologies already in use and concluded that most of them are not capable of measure all the characteristics of CE (Moraga et al., 2019). The European Commission proposed the ratio gross domestic product (GDP) divided by domestic material consumption (DMC) as an indicator of 'resource productivity' or 'resource efficiency' (EC, 2011). Material footprint indicators have been proposed by Wiedmann et al. (2015) to include the upstream raw materials related to imports and exports originating from outside the focal economy.

Most of the methodologies developed so far measure resource efficiency on the basis of the environmental burden of the resource relative to the value of the output. However, the key point of a CE is keeping resources within the economy when products no longer serve their functions, so that materials can be used again and generate more value (Di Maio et al., 2017). Nevertheless, resource efficiency can be considered one of the interpretations/consequences of Brundtland's definition of sustainable development (Di Maio et al., 2017). Eco-efficiency and CE are complementary to each other (Bi et al., 2012), but the combined analysis of eco-efficiency and CE in the empirical literature is scarce, and no works have been found on this kind of combined analysis concerning specific materials, and plastic in particular.

Most of the references that link the concepts of efficiency and CE use data envelopment analysis (DEA) applied to the country, region or cities, and most studies focus on China. For instance, Xiong et al. (2011) evaluate the CE development efficiency in Jiangsu Province, China, uses labour, resources and capital as inputs of CE development, and takes economic growth, social development, industrial “three wastes” discharge treatment compliance rate and the comprehensive utilization rate as outputs to construct the efficiency evaluation index. At city level, Liang and Wang (2011), apply DEA to calculate the city loop economic development efficiency of 17 cities of Henan province. For this analysis they use 3 input indicators: electricity consumption for GDP, energy consumption for GDP and investment in fixed assets for the proportion of GDP and 5 outputs: per capita GDP, comprehensive utilization rate of industrial solid waste, urban sewage treatment rate of living, municipal solid waste harmless treatment rate and built-up area green coverage rate. Fan et al. (2017) evaluate the eco-efficiency levels of 40 Chinese industrial parks through DEA, applying indicators relevant to resources, economy, and environment. The roles of industrial added value per capita, industrial structure, environmental policy and development scale as factors with impact on the eco-efficiency are discussed.

Other studies, also apply DEA to access efficiency in CE, but with some variants. For instance Bi et al. (2012) estimates the eco-efficiency of cities in Zhejiang Province, China, firstly using conventional DEA incorporating undesirable outputs, and in a second stage using an improved weight-set DEA model based on the weight set. This method combines the public weight method and cross-efficiency ranking method, allowing ranking the order for each city. Han et al. (2011) use TOPSIS method (based on entropy weight), and computes the resource efficiency, the environmental efficiency and the eco-efficiency as indicators for the Liaoning China Province for 19 years period. Joining DEA with emergy theory, Liu et al. (2019) adopt the SBM-Undesirable model to evaluate the eco-efficiency of the CE of the China's largest coal mining area, Shanxi Province, taking emergy flows as input and output indices, and factorizing Eco-efficiency into economic efficiency and environmental efficiency. The potential for improvement of the circular economy system is analysed based on input redundancy and output deficiency.

Wu et al. (2014) argues that the classic black-box-based data envelopment analysis DEA model may over-estimates the operation performance of a decision making unit (DMU), and proposes a novel network based on DEA model, that firstly accesses the overall efficiency of recycling systems, and then divides it into efficiencies of two subsystems, reusing undesirable output as a “new” resource input and reducing the emission of undesirable outputs at the same time. The authors estimate the traditional DEA and the novel model applied to Chinese provincial economy and compare results, concluding that a more accurate efficiency measurement is made with the new DEA model.

Given the gaps found in the literature in the application of efficiency analysis to the CE of plastics use and waste, and given the already discussed relevance of this kind of analysis, one of the main contributions of this paper is the estimation of the efficiency of 26 European countries in a context of CE, considering the generation of waste, recovery and recycling of plastic. In addition, paper contributions include the application of a non-parametric, deterministic method for measuring efficiency based in the Multidirectional Efficiency Analysis (MEA) introduced in Bogetoft and Hougaard (1999), in combination with other mathematical techniques proposed. An important index to measure the resource acquisition effort is introduced to improve comparisons along years. A characterization of efficient countries versus non-efficient ones is presented based on the so-called Group Efficiency Indicator for inputs and outputs. This indicator allows identifying those inputs whose improvements could increase the global country efficiency. On the other hand, an inefficiency index of the inputs along years is calculated individually, to assess the contribution of each variable to the efficiency. The main reason for using MEA in this study, instead of the traditional DEA, is that the latter cannot be used to assess changes in inefficiency patterns, and presents a range of issues that needed to be taken care of (such as economies of scale, percentages and other normalized data) (Dyson et al., 2001). In this sense, MEA improves data envelopment analysis, since it allows to identify improvements for each variable, turning this methodology into a more suitable approach for studying efficiency levels, differences in those levels and possible causes of those differences (Bogetoft and Leth Hougaard, 2004; Asmild and Pastor, 2010).

2. Data, methodology and techniques

2.1. Data

We study the circular economy performance of 26 European countries (see Table 1) with respect to their global plastic management in terms of total waste, recycling and recovery, during the period 2006–2016. The dataset was collected from Eurostat database.

In the Economics literature, the production process uses inputs (labour, capital, land, resources), to produce outputs (goods and services), following a production function (Samuelson and Nordhaus, 2004). In recent literature, efficiency indicators were analysed to assess the performance of economic activity, in some different strands. One of them focus on energy efficiency and evaluates the use of energy inputs and non-energy inputs (as capital and labour) to produce outputs (as GDP) (Hu and Lee, 2010). A second strand of articles analyse the environmental efficiency considering the emission of pollutants (such as CO2 emissions), as well as solid waste, waste water and gas, as undesirable outputs (Zhou et al., 2007). A third strand analyses the efficiency using, as inputs, resources (such as energy and water) and non-resources (as capital and labour) to produce at the same time desirable and undesirable outputs (Bian and Yang, 2010; Yeh et al., 2010; Zhang et al., 2011). Shi et al. (2010) state that, to analyse the efficiency

Table 1
European countries of the study and their two-letter country code.

Austria	(AT)	Finland	(FI)	Latvia	(LV)	Romania	(RO)
Belgium	(BE)	France	(FR)	Luxembourg	(LU)	Slovakia	(SK)
Bulgaria	(BG)	Germany	(DE)	Malta	(MT)	Slovenia	(SI)
Cyprus	(CY)	Greece	(EL)	Netherlands	(NL)	Spain	(ES)
Czech Republic	(CZ)	Hungary	(HU)	Norway	(NO)	United Kingdom	(UK)
Denmark	(DK)	Ireland	(IE)	Poland	(PL)		
Estonia	(EE)	Italy	(IT)	Portugal	(PT)		

Table 2
Variables definition.

	Variable	Notation	Unit	Related references
Inputs	Labor	L	Thousand workers	(Bian and Yang, 2010; Madaleno et al., 2016; Robaina-Alves et al., 2015; Shi et al., 2010; Zhang et al., 2011; Zhou and Ang, 2008; Zhou et al., 2007)
	Capital invested	K	Million euro	(Bian and Yang, 2010;Robaina-Alves et al., 2015; Yeh et al., 2010; Zhang et al., 2011; Zhou and Ang, 2008)
	Energy consumed	E	Thousand tonnes of oil equivalent (TOE)	(Moutinho et al., 2018; Robaina-Alves et al., 2015; Zhou et al., 2007)
Outputs	Gross domestic product	GDP	Million euro	(Bian and Yang, 2010; Hu and Wang, 2006; Yeh et al., 2010; Zhang et al., 2011; Zhou and Ang, 2008)
	CO2 emissions	CO2 (CCO2)[a]	Thousand tones	(Yeh et al., 2010; Zhou and Ang, 2008; Zhou et al., 2007)
	Plastic waste	W (CW)[a]	Tones	(Zhou et al., 2007)
	Plastic recycling	RC	Tones	(Wu et al., 2014)
	Plastic recovery	RP	Tones	(Wu et al., 2014)

[a] Note that, for the undesirable outputs CO2 and W, the complement variables CCO2 and CW are used instead.

according to the CE concept, it is necessary to create a new production progress, changing the undesirable outputs into useful resources (inputs), by technical promotion. According to the 3R principle of the CE (i.e. Reduce, Reuse and Recycle) (Zhang et al., 2008), the objective of production should also include reusing undesirable output as a new resource input in the production process, as well as reducing the emission of undesirable outputs at the same time (Wu et al., 2014).

In our study, we therefore focus on labour, capital and energy as inputs, and on GDP, CO2 emissions, plastic waste, plastic recycling and plastic recovery as outputs. Table 2 collects all these variables, with their respective notation, units, and related works in the literature that already used similar variables[1].

It is relevant to note that L, K and E are not related to the plastic sector only, as well as GDP and CO_2 emissions. These variables refer to the whole economy. Moreover, recovery, recycling and waste, considered in this paper, refer only to plastic as material, but not to the "plastic sector". That is, plastic recovery, recycling and waste is for the entire economy or country, and not only for the plastic sector or plastic industry. All plastic packaging placed on the market and all plastic packaging waste generated in a country are therefore covered, whether it is used or released at industrial, commercial, office, shop, service, household or any other level. Therefore what we intend to evaluate here is the performance of the country, focusing on the plastic as a material used in all economic processes. The optimization is made for the total production of the country (GDP).

In general terms, efficiency models try to minimize resources (inputs), as production (outputs) increases. However, since a greater production of the outputs CO2 emissions and plastic waste is obviously undesirable, the so-called variable complement (CC02 and CW) are used instead. Complement variables (see for instance (Jahanshahloo et al., 2005; Zhu, 2009)) are defined as the maximum value of the output variable in an entire database minus the value of the variable for the unit under consideration.

Figs. 8 and 9 in the appendix show a preliminary characterization of the selected data during the study period, for the ratios C02/GDP (carbon intensity) and Plastic waste/GDP for each country (for a fairer comparison, CO2 emissions and Plastic waste have been normalized, for each country, by dividing by the GDP). As already noted, CO2 emissions and Plastic waste are undesirable outputs, and as such should desirably decrease with time. In general, countries have been decreasing their carbon intensity and those with the high initial levels are those with the biggest descents (for instance Belgium, Estonia, Poland and Czech Republic). Norway, Finland, France and United Kingdom are among the countries with lower carbon intensities.

[1] Note that for Plastic Waste, Plastic recycling and Plastic recovery, the referred articles do not use the variables for plastic but for total materials, confirming however, the relevance of these concepts in these efficiency analysis.

When looking at the plastic waste intensity (plastic waste generated by unit of GDP produced) there is not a clear trend, which could reflect a much late awareness on plastics harm than on CO2 and a later adoption (indeed very recent) of effective policies. Among the countries with a high level of waste intensity are Denmark, France, Belgium, Norway and Portugal, and among the least waste producers are Netherlands, Luxembourg, Malta and United Kingdom.

2.2. Methodology

The methodology applied for this analysis is based on the following steps (described in the following subsections):

1) Computation of a multidirectional efficiency analysis

We perform a relative ranking to determine, characterize, and compare which are the most efficient countries, using the nonparametric method based on MEA (described in Section 2.2.1). In this work, the MEA model is applied twice. First, the algorithm is applied to the entire data set. Then, the model is reapplied to the countries with maximal efficiency, this time taking into account only the most significant input and output variables, selected using Principal Components Analysis (PCA) (Dray, 2008), in order to differentiate those countries that are on the efficiency frontier(see Section 3.1).

Once the MEA score has been calculated, we determine the level of influence of both inputs and outputs on the classification obtained by calculating the inefficiency index. This means identifying the number of times that each variable (input or output) was used inefficiently in each year, and therefore, how acting on this input could improve the MEA efficiency score.

2) Analysis of the countries effort over time

To obtain an additional comparison among the countries performance over the years, we introduce another way of characterizing the behavior of the countries during the study period, based on the assessment of the effort to acquire the resources. This is done by calculating the accumulated effort (of all countries) in each year, to acquire the inputs required for maintaining the ideal unit (the one that is able to minimize all the inputs and, at the same time, maximize all the outputs).

3) Study of the differences among different efficiency level groups

From the results obtained in step 1 of this methodology, two different groups are built: one with the countries with the highest level of efficiency, and one with the countries with the lowest level of efficiency (considered inefficient). Then, a group indicator is computed to identify the behavior of each group with respect to each variable (measuring if each particular variable was more or less used). This indicator allows to identify differences between the two groups and to suggest recommendations on those variables that can be improved in the lowest efficiency group to improve the performance of these countries.

2.2.1. Multidirectional efficiency analysis

Denoting by C the set of countries, and by T the set of years, let $n = (c,t) \in N$ be a tuple identifying the country $c \in C$ and year $t \in T$, which we call a country/year tuple. Let $[m]$ denote the set $\{1,\ldots,m\}$, for some $m \in N$. We consider that any given tuple $n \in N$ produces J outputs $y_j(n)$, $j \in [J]$, using I inputs $x_i(n)$, $i \in [I]$, where the first $1 < D \le I$ inputs are the so-called discretionary inputs, i.e. decision variables, because the non-discretionary inputs are those inputs that cannot be changed. Therefore, the discretionary inputs will be represented by the indices d such that $1 < d < I$, with $i \in [D]$, while $i \in [I]\setminus\{d\}$ will refer to the non-discretionary inputs.

Let $x(n) \in R^I$ be the vector of all the inputs $x_i(n)$,and $y(n) \in R^J$ be the vector of all the outputs $y_j(n)$, for a given country/year tuple $n \in N$. The dataset $Z = \{z(n)\} n \in N$ is then the set of values $z(n) = (x(n), y(n))$ for all $n \in N$.

Considering a variable return to scale (VRS) to develop a model for the efficiency measurement of decision-making units (see Asmild and Pastor (2010)), let's define the set:

$$\Lambda^N = \left\{ \lambda \in R^N : \sum_{n=1}^{N} \lambda_n = 1 \right\}. \tag{1}$$

The MEA score for a specific observation $z(\overline{n}) = (x(\overline{n}) \cdot y(\overline{n}))$, being $\overline{n}$ a particular value of n, is found by solving the following linear optimization programs:

$$\begin{array}{ll}
P_m^{\alpha}(z,\overline{n}) : & P_j^{\beta}(z,\overline{n}) : \\
\min \alpha_m(\overline{n}) \text{subject to} & \max \beta_j(\overline{n}) \text{subject to} \\
\sum_n (\lambda_n \cdot x_m(n)) \le \alpha_m(\overline{n}) & \sum_n (\lambda_n \cdot x_i(n)) \le x_i(\overline{n}), i \in [I] \\
\sum_n (\lambda_n \cdot x_i(n)) \le x_i(\overline{n}) i \in [I]\setminus\{m\} & \sum_n \left(\lambda_n \cdot y_j(n)\right) \ge \beta_j(\overline{n}), j \in [J] \\
\sum_n (\lambda_n \cdot y_l(n)) \ge y_l(\overline{n}), l \in [J] & \sum_n (\lambda_n \cdot y_l(n)) \ge y_l(\overline{n}) l \in [J]\setminus\{j\}
\end{array} \tag{2}$$

$$\begin{array}{l}
P_{\gamma}(\alpha,\beta,z,\overline{n}): \\
\max \gamma(\overline{n}) \text{subject to} \\
\sum_n (\lambda_n \cdot x_i(n)) \le x_i(\overline{n}) - \gamma(n)\left(x_i(\overline{n}) - \alpha_i^*(\overline{n})\right), i \in [M] \\
\sum_n (\lambda_n \cdot x_i(n)) \le x_i(\overline{n}), i \in [I]\setminus\{m\} \\
\sum_n (\lambda_n \cdot y_l(n)) \ge y_l(\overline{n}) + \gamma(n)\left(\beta_i^*(\overline{n}) - y_l(\overline{n})\right), l \in [J]
\end{array}$$

where $\lambda \in \Lambda^N$, and $\alpha_i{}^*(\overline{n})$ and $\beta_j{}^*(\overline{n})$ represent the corresponding optimal solutions to the linear optimization problems $P_i^{\alpha}(z,\overline{n})$ and $P_j^{\beta}(z,\overline{n})$.

Definition 1. For a given data set $Z = \{z(n)\}_N$ with $z(n) = (x(n), y(n))$, the MEA score of each $n \in N$ is then defined as:

$$\mathrm{MEA}_Z(n) = \frac{\dfrac{1}{\gamma^*(n)} - \dfrac{1}{D}\sum_{i=1}^{D} \dfrac{x_i(n) - \alpha_i{}^*(n)}{x_i(n)}}{\dfrac{1}{\gamma^*(n)} + \dfrac{1}{J}\sum_{j=1}^{J} \dfrac{\beta_j{}^*(n) - y_j(n)}{y_j(n)}} \tag{3}$$

where $\alpha_i{}^*(n), \beta_j{}^*(n)$ and $\gamma^*(n)$ represent the corresponding optimal solutions to the linear optimization problems $P_i^{\alpha}(z, n)$, $P_j^{\beta}(z, n)$ and $P^{\gamma}(z, n, \alpha*, \beta*)$.

The technical efficiency of each country is measured by calculating the MEA score (Eq. (3)). The value $\mathrm{MEA}_Z(n)$ varies between 0 and 1, with fully efficient countries having efficiency scores equal to 1, and null efficient countries having scores equal to 0.

Definition 1 is obtained by the directional contribution of each input and output variable. In fact, for any input $x_i(n)$, $i \in [I]$, its contribution in $Z = \{z(n)\}_N$ is given by:

$$\mathrm{meff}_i(n) = \frac{x_i(n) - \gamma^*(n)(x_i(n) - \alpha_i{}^*(n))}{x_i(n)} \chi_{[D]}(i),$$

where $\chi_{[D]}$ is the characteristic function of the set $[D]$. That means $\chi_{[D]}(i) = 1$ if $i \in [D]$; and $\chi_{[D]}(i) = 0$ if $i \notin [D]$.

For the outputs $j \in [J]$ their contribution is given by:

$$\mathrm{meff}_j(n) = \frac{y_j(n)}{y_j(n) + \gamma^*(n)\left(\beta_j{}^*(n) - y_j(n)\right)}.$$

Before continuing, we emphasize some aspects of the proposed model, for its correct application and interpretation. The performance model used in this study will be the variable scale (VRS) (Eq. (1)). A variable return on the VRS-MEA scale is an invariant translation model, which means that the model can handle negative data, see Asmild and Pastor (2010). In addition, this study uses an input-oriented model to test whether decision-making units (DMU) under evaluation can reduce its inputs while maintaining the outputs at their current levels.

One of the great advantages of MEA is that it allows estimating the level of influence of each variable individually on the model. Since we are using an input-oriented model, we introduce the following definition to compute the number of times each input was used inefficiently.

Definition 2. The inefficiency index for each given input is given by

$$R_i(n) = \frac{\sum_{n=1}^{N} \gamma(n)(x_i(n) - \alpha_i{}^*(n))}{\sum_{n=1}^{N} x_i(n)} \tag{4}$$

for $i \in [I]$ and tuple $n \in N$.

Definition 2 is based on the ideas in Bogetoft and Otto (2011), and is an average measure of what an input is lacking, for each country, to attain the optimum value. As can be seen, using MEA model the inefficiency of the three inputs variables used in this study can be analysed individually.

2.2.2. Accumulated effort

In order to measure the effort of the countries in the use of the input resources in a sequence of years, we define the accumulated effort index, introduced in Murillo and Rocha (2018).

Definition 3. Let's V as the set of countries with a MEA score ≥ 0.9. The Effort Indicator of the set V, between the period t_{j-1} and the period t_j, is defined by

$$\mathrm{EI}_{t_{j-1}} t_j(V) = -1 + \frac{1}{\bar{I}} \sum_{i \in [\bar{I}]} \frac{\min\{ x_i(c,t_j) : c \in V\}}{\min\{ x_i(c,t_{j-1}) : c \in V\}}, \tag{5}$$

where $\min\{x_i(c,t_j)\}$ represents the minima value of the input x_i in time instance t_j and $\bar{I}$ is the subset of input indices for which both minima are different from zero in the periods t_{j-1} and t_j. All inputs are non-negative. A zero on the numerator/denominator formally means that such input was introduced/removed in the second period, so it should not be used for the effort comparison.

To understand the effort made in each year to the inputs, we use the following definition.

Definition 4. The Accumulated Effort of the set V, in the time instance t_k is defined by

$$\mathrm{AEI}_{t_k}(V) = \sum_{j\epsilon\{1,\dots,k\}} \mathrm{EI}_{t_{j-1}} t_j(V). \tag{6}$$

2.2.3. Group efficiency indicator

In addition to the MEA score of each country and the inefficiency index of each variable, it is important to study the differences that can be found between groups with different levels of efficiency. For this reason, a new indicator was defined.

According to the MEA efficiency score two different groups were considered: the group G_1 corresponding to the most efficient countries (0.6 ≤ MEA score ≤ 1), and the group G_0 corresponding to the less efficient countries (0 ≤ MEA score ≤ 0.3). In order to know which variables influence the difference between groups G_1 and G_0, we defined the following indicator.

Definition 5. The Group Efficiency Indicator $\mathrm{EG}_{G1.\,G0}(x_i(n))$ for an input $x_i(n)$, i ϵ [D] is given by:

$$EG_{G1.G0}(x_i(n)) = \frac{m_{G1}(x_i(n)) - m_{G0}(x_i(n))}{m_{G0}}(x_i(n)) \tag{7}$$

where $m_{G1}(x_i(n))$ is the mean of the input $x_i(n)$,for the efficient group G_1 and $m_{G0}(V_i)$ is the mean of $x_i(n)$ for the less efficient group G_0. The group efficiency indicator represents the relative value of the difference between the groups G_1 and G_0 for each input. Following the same idea of Eq. (7), the indicator $\mathrm{EG}_{G1.\,G0}(y_j(n))$ can be defined for each output $y_j(n)$, $j \epsilon [J]$.

3. Results

The analysis performed consists in three main steps:

- (A1) general analysis using MEA efficiency score;
- (A2) analysis of input inefficiency index;
- (A3) analysis of groups with different levels of efficiency.

3.1. General analysis using MEA efficiency score (A1)

We perform a relative ranking to determine the most efficient countries, using two ranking metrics, generic and specific:

- Using the generic metric, the MEA algorithm is applied to the entire sample (for the first time) using L, K and E as inputs and GDP, CC02, CW, RC and RP as outputs.
- To distinguish those countries that result with an efficiency equal to 1 (maximum efficiency) with the generic metric, a second more specific ranking metric is used. At this stage, the MEA algorithm is again applied to those countries with maximum efficiency but for a smaller set of variables, with L and E as inputs, since these are the most significant ones (see Fig. 3), and CW, RC and RP as outputs, since these are the more relevant ones to characterize the circularity of plastic management (waste, recycling and recovery). Indeed, Fig. 5 shows that L and E are the most inefficiently used inputs, while outputs CW, RC and RP where selected for being the basic outputs needed to analyse the circularity in plastic management, which mainly implies low waste (or high CW, being CW the waste complement), high recycling (RC) and high recovery (RP). The application of Principal Components Analysis (PCA) (Dray, 2008) confirmed this variables choice. With this new application, countries that had obtained efficiency 1 in the first application have a new discrimination in the interval [0.5; 1], and countries that had efficiency <1, have a new discrimination in the interval [0; 0.5]. This technique allows one to redefine and improve the relative ranking obtained in the first application of the MEA, in particular to distinguish between those countries with maximum efficiency.

Table 3 shows the MEA scores for the twenty six countries and for the years of the study period, as a result of the composition of the two metrics described above.

As can be seen, there is a general efficiency improvement with time for most countries, becoming most of them efficient (MEA larger than 0.5) by the end of the study period, and many of them reaching the full efficiency. Six countries (CZ, DE, DK, IE, LU, MT) are fully efficient during the whole period (MEA equal to 1), but other countries such as AT, FR, NL, NO and UK show also, to a lower extent, efficient behaviours during the whole study period. No countries are inefficient (MEA score lower than 0.5) for all years, but LV reaches the null score for year 2009, being still largely inefficient at the end of the period. SK shows a similar behaviour with mostly low efficiencies all years, and still largely inefficient at the end of the period. Finally, other countries, although largely inefficient at the beginning of the period, manage to become efficient by the end, such as BG, ES, EL, and FI between the middle and the end of the period, or such as RO and PT that improve their efficiency some years earlier, with PT becoming fully efficient for the last 5 years.

Defining EFF as the subset of tuples n = (c, t) (c and t standing for countries and years respectively) such that 0.5 ≤$\mathrm{MEA}_Z(n)$ ≤ 1, that is, focusing on those countries that are efficient or fully efficient, two additional interesting ratios can be computed for each year:

a) EFFT: the percentage of the total efficiency of the sample, that is, the percentage of the countries, with respect to the total amount of counties, that are efficient or fully efficient for each year;
b) FULLEFF: the percentage of countries with MEA efficiency score equal to 1 (full efficiency) for each ear.

Fig. 1 shows how EFFT and FULLEFF evolve with time. We can see that even applying the MEA model twice, we find a considerable percentage of efficient countries per year. As can be seen, although there is a decrease in both indicators in the first two or three years, from 2008 there is a clear increasing trend, meaning that more countries managed to become efficient (or to a less extent, fully efficient).

Fig. 2, that shows the evolution of the average MEA score per year (for all countries), confirms these results, with a remarkable reduction of the average efficiency until 2007 or 2008, followed by a constant efficiency increase for the rest of the period, that reaches almost 0.8 of average efficiency by 2016.

3.2. Analysis of input inefficiency index (A2)

The contribution of each input on the model is analysed in more detail by computing their inefficiency index (see Eq. (4)). For each input variable, its inefficiency measures the average percentage of what is lacking from that input for each country to attain the optimum value.

Fig. 3 shows the percentage of times (vertical axis) that each input was used inefficiently for each year. Although the percentage of the inefficiency of the variables does not reach 20%, the labour was used inefficiently more than the other inputs, while the capital was used notably better than the other inputs, especially from 2009. Although at the beginning of the period the inefficiency of the inputs usage tends to increase, by 2008 or 2009 there is a clear tendency towards a more efficient use of the inputs, with a high efficient use at the end of the period, which is in agreement with the general efficiency improvement of most countries commented in Section 3.1.

Fig. 4 shows the minimum value of the inputs for those countries with a MEA score ≥ 0.9. During the study period, the capital used by these countries increased year after year. Meanwhile, the labor did not show a sequence of constant increase, decreasing between 2007 and

Table 3
MEA score by country and year (between 0, inefficient, and 1, fully efficient).

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
AT	1.00	0.52	1.00	1.00	1.00	1.00	1.00	0.54	1.00	1.00	1.00
BE	1.00	0.51	0.02	0.50	0.52	0.52	0.02	0.17	1.00	1.00	1.00
BG	0.07	0.01	0.03	0.12	0.50	0.01	0.50	0.02	1.00	0.50	0.51
CY	0.12	0.08	0.50	0.50	0.50	0.50	0.50	1.00	0.50	1.00	1.00
CZ	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
DE	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
DK	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
EE	0.64	0.69	0.50	0.09	0.51	1.00	0.09	1.00	0.50	0.50	1.00
EL	0.12	0.13	0.18	0.11	0.05	0.50	0.50	0.50	0.50	0.51	0.52
ES	0.06	0.06	0.06	0.11	0.06	0.10	0.10	0.62	0.75	0.64	1.00
FI	0.04	0.02	0.07	0.06	0.12	0.08	0.08	0.50	0.50	0.50	0.51
FR	0.54	0.50	0.50	0.50	0.52	0.50	0.50	0.52	0.53	0.51	0.50
HU	0.09	0.03	0.02	0.09	0.51	0.50	0.50	0.50	0.07	0.07	0.51
IE	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
IT	1.00	1.00	0.50	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
LU	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
LV	0.54	0.57	0.50	0.00	0.50	0.02	0.50	0.50	0.11	0.08	0.03
MT	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
NL	1.00	0.50	0.53	1.00	1.00	1.00	0.51	0.50	0.50	0.50	1.00
NO	0.55	0.51	0.54	0.51	0.52	0.52	0.51	0.51	0.55	0.55	0.60
PL	0.52	0.01	0.05	0.04	0.06	0.08	0.08	0.08	0.03	0.01	0.54
PT	0.13	0.08	0.10	0.51	0.52	0.50	1.00	1.00	1.00	1.00	1.00
RO	0.10	0.01	0.05	0.07	0.12	0.50	0.50	1.00	0.54	0.52	0.53
SI	1.00	1.00	1.00	0.06	1.00	1.00	1.00	1.00	1.00	1.00	1.00
SK	0.04	0.03	0.01	0.50	0.18	0.18	0.50	0.07	0.17	0.06	0.10
UK	0.53	0.51	0.50	0.50	0.50	0.52	0.53	0.56	0.60	0.50	1.00

Notes: MEA = 1 in green, MEA ∈ [0.5;1[in light green, MEA ≤ 0.1 in red, MEA ∈ [0.1;0.5[in light red; Austria (AT); Finland (FI); Latvia (LV); Romania (RO); Belgium (BE); France (FR); Luxembourg (LU); Slovakia (SK); Bulgaria (BG); Germany (DE); Malta (MT); Slovenia (SI); Cyprus (CY); Greece (EL); Netherlands (NL); Spain (ES); Czech Republic (CZ); Hungary (HU); Norway (NO); United Kingdom (UK); Denmark (DK); Ireland (IE); Poland (PL); Estonia (EE); Italy (IT); Portugal (PT)

2009, but recovering from 2011 with a larger slope from 2014. On the contrary, the energy consumption showed a flat or decreasing behavior for the whole period, with a more intense decrease from 2012, evidencing a possible concern of the more efficient countries with the energy efficiency, being able to decrease their energy consumption while still keeping or increasing their efficiency level.

Fig. 5 shows the effort of all countries (Eq. (6)) for each year, to reach the inputs required to reach the ideal country (i.e. the one that is able to minimize all the inputs and, at the same time, maximize all the outputs).

In 2009, the accumulated effort is lower than for the rest of the study period, which is directly linked to the fact that the difference between

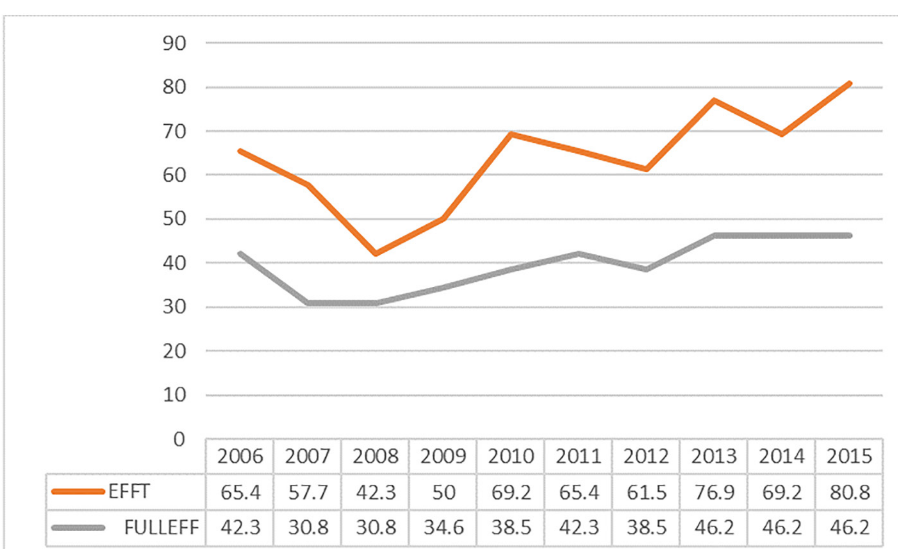


Fig. 1. EFFT and FULEFFF yearly evolution (%). Note: EFFT: percentage of countries that are efficient or fully efficient for each year; FULLEFF: percentage of countries with MEA efficiency score equal to 1 (full efficiency) for each ear.

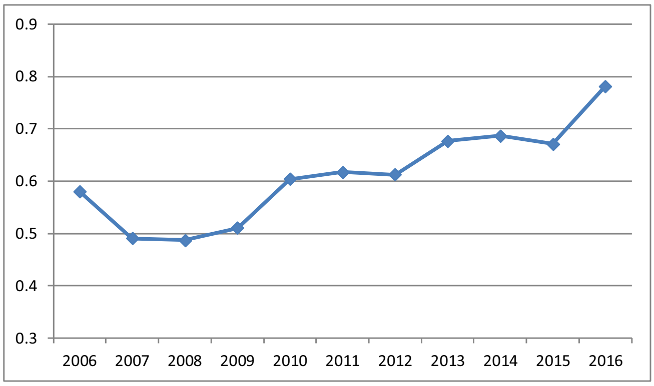


Fig. 2. MEA average yearly evolution (between 0, inefficient, and 1, fully efficient).

energy consumption (necessary to obtain high efficiency) in that year and the previous one (2008) is very low, in relation to the other variables. Moreover, it can be observed through the trend line, an increase in the accumulated effort over the years, which is coherent with the efficiency improvements seen in previous analyses.

3.3. Analysis of groups with different levels of efficiency (A3)

From the whole set of countries, we consider two groups, the group G_1 of those countries that can be considered efficient, with 0.6 ≤ MEA score ≤ 1, and the group G_0 of those countries that are inefficient, with 0 ≤ MEA score ≤ 0.3. From Table 3, if the whole study period is considered, it can be checked that there are seven countries in G_1 (CZ, DE, DK, IE, LU, MT and SI) but no countries belong to G_0. For example, EL belongs to G_0 during the period 2006–2010, but belongs also to G_1 during 2011–2016. Therefore, to better exploit the available information, it was then decided to analyse both groups G_1 and G_0 but for each year individually, and therefore, to compute the Group Efficiency Indicator $EG_{G1.\ G0}$ for each year. Its application to the inputs is in Fig. 6 and to the outputs in Fig. 7.

The Group Efficiency indicator allows giving a recommendation of the variables that could be improved to increase the efficiency. Note that the input that presents less difference in absolute value between the two groups is the variable E (2009 and 2015) with 0.03, and the input with the highest index (both in natural and absolute value) is the variable K (2016) with 4.18. In particular, the highest differences take place in the last year.

It is noteworthy a follow-up of differences between the two groups for the three variables, although labour and energy evolve closer. For capital, there is a remarkable gap between the two groups of countries that became positive from 2014 onwards. Labour and energy also became positive after this year. This means that the efficient countries are using a higher value of the inputs than the inefficient countries,

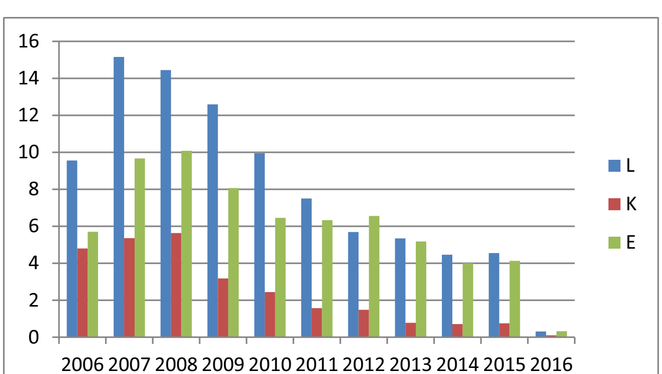


Fig. 3. Inefficiency index (all countries) by year (%). Note: L (labor); K (capital invested); E (energy consumed). Note: L (labor); K (capital invested); E (energy consumed).

and that this difference is growing, especially for capital. Note that between 2006 and 2014, the difference for labour and energy was negative, which means that the inefficient countries were using a higher value of those inputs than the efficient countries. From previous analysis, we can see that, since capital is the input that is most efficiently used, the more evident increase in overall efficiency from 2014 year onwards suggest that this input is very determinant in the efficiency of countries. Basically increasing capital seems to be a main driver towards efficiency.

Regarding the differences for the outputs, the index is near zero only for the complements of the variables C02 and W, showing that is not in total emissions or waste that countries differ the most. The biggest differences in the behaviour of the variables are seen in 2016 for RP (4.29), GDP (4.04) and RC (2.22). Again the results in 2016 are high in all the variables (except in CC02 and CW).

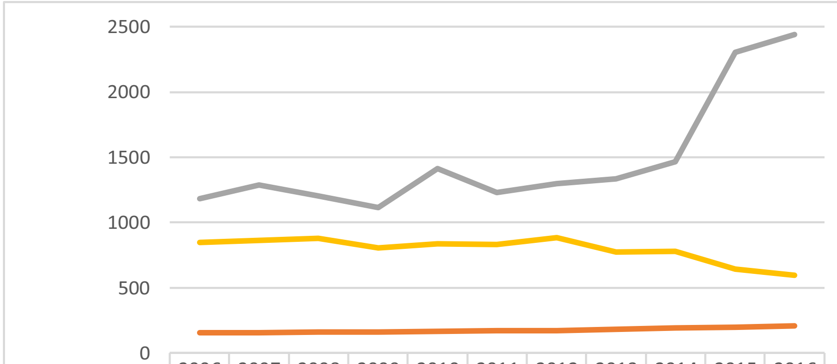
RP, RC and GDP are the output variables where there are more differences between the more efficient and the less efficient countries. In particular, after 2013, the indicator for these three variables turns positive and increase significantly. This could evidence that more efficient countries are progressing not in the reduction of total waste and emissions, but in improving the economic growth in a circular way, that is, improving GDP but also recovering and recycling activities. Note that efficiency, as used in this work, is a broad concept that tries to focus on the circularity of plastics management, but not independently of the economic growth or CO2 emissions. This approach would discard, as efficient, countries with decreasing plastic waste, recycling and recovery but due to a decrement of the economic activity (and not to a better management).

4. Conclusions and policy implications

This work uses the MEA model applied with an ad hoc methodology to study the circular economy performance of 26 European countries during the period 2006–2016, considering the generation of waste, recovery and recycling of plastic, one of the main environmental current concerns. The least and most efficient countries are identified, as well as the main characteristics of the most efficient countries in terms of the inputs and the outputs considered.

Some relevant conclusions can be drawn from the results:

- The most efficient countries throughout the study period were CZ, DE, DK, IE, LU and MT. Other countries such as AT, FR, NL, NO and UK also showed, to a lower extent, efficient behaviours during the whole study period.
- Efficiencies increase for most countries with time, as well as the total average efficiency, and many countries reach the full efficiency (which mean they become indistinguishable from other efficient countries) by the end of the study period, and especially by 2016. For example, countries BG, ES, EL, FI, RO and PT show a general efficiency improvement during the whole period (with FI, concerned with environmental causes and with good economic capacity, showing a surprising very slow improvement of its efficiency). This general improvement can also be seen in the general reduction of the inefficiency in the use of the inputs.
- Two reported extreme examples confirm some of the above findings. Indeed, while in 2016 the Czech Republic (CZ) had the highest plastic recycling rate, doubling the volume recycled in less than a decade, with plastic waste recovery rates above 59%, see Eurostat and (Linnenkoper, 2015), Finland (FI) had only 25% of recycled plastic packaging, see Eurostat and (Yle Uutiset, n.d.).
- The 26 countries studied reflected a very poor management of their resources between 2007 and 2009, the labor being the most affected, which could be due to the crisis and to the resulting austerity measures with a negative impact on different economic sectors.
- Inputs analysis basically shows that increasing capital seems to be a main driver towards efficiency, since the other inputs are used rather with a similar efficiency by most countries.
- Outputs analysis suggest that the difference between countries efficiency is not in their reduction of total waste or emissions, but rather



	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Min (K)	153.5	156.9	160.9	161	163.8	168.6	173.3	179.9	189.6	197.3	205.7
Min (L)	1183.2	1288.2	1203.1	1114.8	1411.6	1228.4	1299.8	1334.9	1465.4	2302.7	2438
Min (E)	847.7	865.2	879.7	804	836.7	831.7	881.5	772.4	776.7	641.9	594.2

Fig. 4. Minimum values of the inputs (considering all countries with MEA ≥ 0.9). Note: L (labor); K (capital invested); E (energy consumed). Note: L (labor); K (capital invested); E (energy consumed).

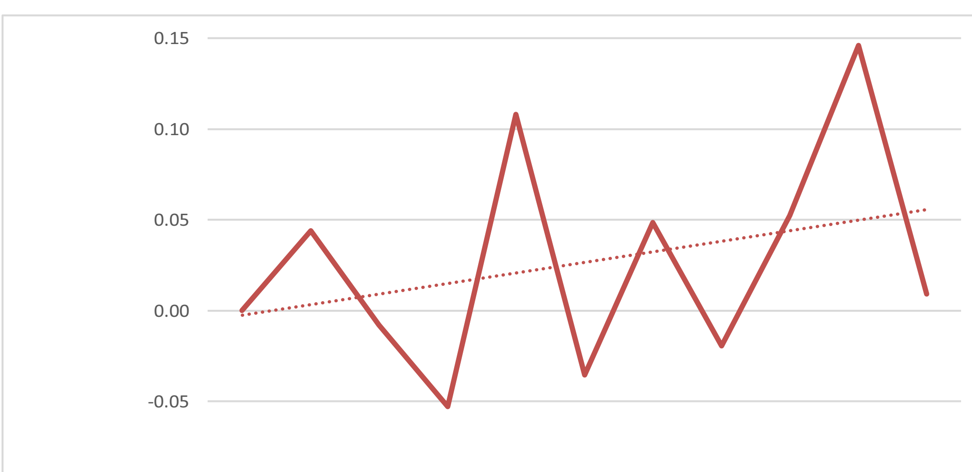
in the improvement of their economic growth in a circular way, that is, improving GDP but also the recovering and recycling activities.

Regarding this last point it can be referred that efficiency is seen as a global behaviour considering a better general management of plastic, in terms of lower waste, larger recycling and recovering, but maintaining or improving the economic growth (that is, not due to an economic deceleration). So efficiency is assessed considering all these factors together and not any of them individually, being the economic growth an important output. Efficiency can then be reached with different performances of these outputs (as well as different usages of the inputs), since there is no a standard of theoretical efficiency to be used as reference, which is at the core of these type of methodologies. Therefore, when looking at the efficient countries, considering the way this methodology determines efficiency, what we try to say is that those more efficient are such because of a larger economic growth with larger recovering and recycling activities, but similar waste. In this sense, these countries improve their economic growth in a circular way (improving GDP but also the recovering and recycling activities) even if waste is not managed in the most efficient way.

Relating the conclusions of the differences in inputs and in outputs between efficient and less efficient countries, a link between capital and the activities of recycling and recovery can be established. This link suggests that, in more efficient countries, capital investment is being canalized to recycling and recovery activities, turning its economies more efficient and more circular.

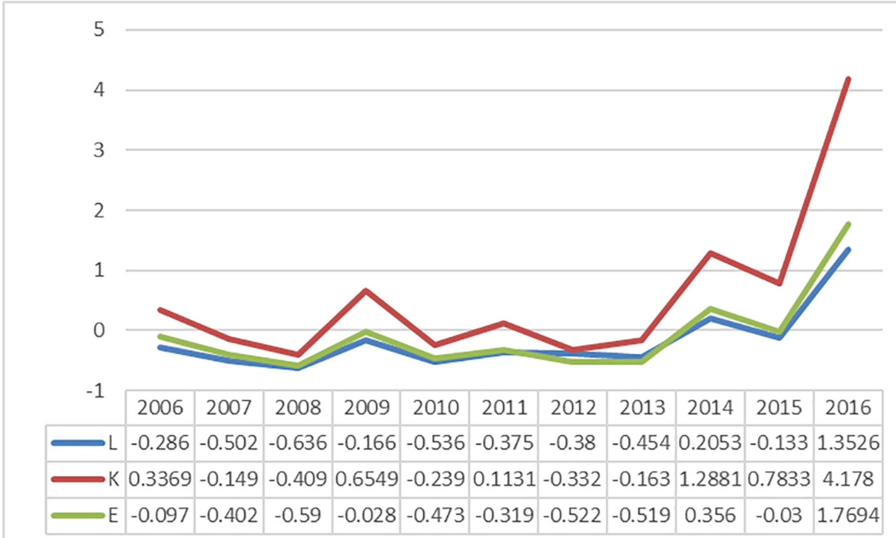
In fact, the reuse and recycling of more plastics requires more technology, and therefore more capital. As Hundertmark et al. (2018) state, the transition to a circular economy requires a massive expansion of mechanical recycling volumes and the industrial-scale launch of new technologies, such as monomer recycling and plastic waste reprocessing to produce liquid raw material in a process known as pyrolysis. Mechanical recycling is already established as a sizable and profitable business in many of the world's developed economies. According to the same report, in the United States and in Europe, redirecting plastic waste to plastic production through mechanical recycling or pyrolysis, rather than dumping it in landfills or incinerating it, can generate considerable profits.

However, access to capital can be a significant barrier to increased recycling. In fact, new technologies or processes, uncertain supply of



	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Effort Accumulated	0.0000	0.0439	-0.0080	-0.0530	0.1081	-0.0354	0.0486	-0.0196	0.0524	0.1461	0.0091

Fig. 5. Accumulated effort (all countries).



	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
L	-0.286	-0.502	-0.636	-0.166	-0.536	-0.375	-0.38	-0.454	0.2053	-0.133	1.3526
K	0.3369	-0.149	-0.409	0.6549	-0.239	0.1131	-0.332	-0.163	1.2881	0.7833	4.178
E	-0.097	-0.402	-0.59	-0.028	-0.473	-0.319	-0.522	-0.519	0.356	-0.03	1.7694

Fig. 6. Characterization of inputs, efficient versus non-efficient groups, $EG_{G1,\ G0}$ (x_i). Note: L (labor); K (capital invested); E (energy consumed); EG (Group Efficiency Indicator).

materials, fluctuating customers and fluctuating prices for goods can make the investments appear as more risky to potential investors. In this regard, public policies could develop loan programs to support projects promoting recycling and reuse of plastics to private investors.

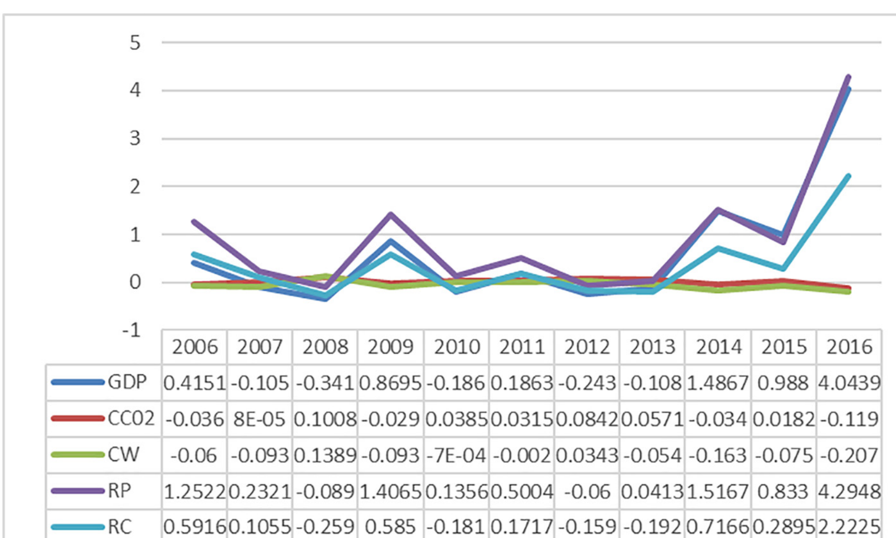
On the other hand, plastic companies should be involved in improvements in waste management technologies that facilitate collection, sorting and cleaning. Finally, plastic manufacturers should support technology development and the construction of recycling infrastructures that brings plastic waste back into the value chain.

The present study is a comparative analysis useful to suggest improvement for the less efficient countries, by comparing their performance, inputs and outputs with those of the countries that perform better. However, this approach does not allow to determine improvements for the already most efficient countries. To do so, there are other techniques, that we suggest for future works, such as Malmquist Productivity Index (MPI), a formal time series analysis technique, to analyse the efficiency evolution of decision-making units (DMUs) (Malmquist, 1953; Al-Refaie et al., 2016). MPI allows determining if the efficiency evolution of a DMU is due to changes of its input values and thus due to its own practices, or if this evolution is due to changes of the efficient DMUs used as reference, which could correspond to a technological change. In this last case, the units already in the frontier can also improve their behavior due to a technological change and a consequent change in the frontier.

The authors also suggest extending this analysis to other materials such as paper or glass, concerning also waste, recycling and recovering processes, as a further characterization of the evolution of the performance of the EU countries towards a Circular Economy.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.



	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
GDP	0.4151	-0.105	-0.341	0.8695	-0.186	0.1863	-0.243	-0.108	1.4867	0.988	4.0439
CCO2	-0.036	8E-05	0.1008	-0.029	0.0385	0.0315	0.0842	0.0571	-0.034	0.0182	-0.119
CW	-0.06	-0.093	0.1389	-0.093	-7E-04	-0.002	0.0343	-0.054	-0.163	-0.075	-0.207
RP	1.2522	0.2321	-0.089	1.4065	0.1356	0.5004	-0.06	0.0413	1.5167	0.833	4.2948
RC	0.5916	0.1055	-0.259	0.585	-0.181	0.1717	-0.159	-0.192	0.7166	0.2895	2.2225

Fig. 7. Characterization of outputs, efficient versus non-efficient groups, $EG_{G1,\ G0}$ (y_j). Notes: GDP (Gross domestic product); CCO2 (CO2 complement); CW (plastic waste complement); RP (plastic recovery); RC (plastic recycling); EG (Group Efficiency Indicator).

Acknowledgements

This work was financially supported as follows. Robaina by the research unit on Governance, Competitiveness and Public Policy (project POCI-01-0145-FEDER-006939), funded by FEDER funds through COMPETE2020 - Programa Operacional Competitividade e Internacionalização (POCI) – and by national funds through FCT - Fundação para a Ciência e a Tecnologia. Villar by National Funds through the Portuguese funding agency. FCT - Fundação para a Ciência e a Tecnologia within project: UID/EEA/50014/2019. Murillo and Rocha supported by The Center for Research and Development in Mathematics and Applications (CIDMA) through the Portuguese Foundation for Science and Technology (FCT - Fundação para a Ciência e a Tecnologia), references UIDB/04106/2020 and UIDP/04106/2020. Murillo was also supported by national funds (OE), through FCT, I.P., in the scope of the framework contract foreseen in the numbers 4, 5 and 6 of the article 23, of the Decree-Law 57/2016, of August 29, changed by Law 57/2017, of July 19.

Appendix A

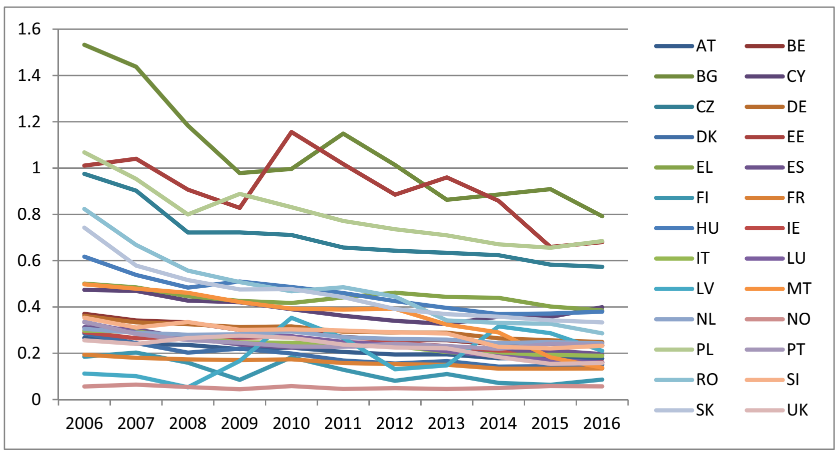


Fig. 8. C02/GDP (Thousand tones/M€) of the 26 EU for the period 2006–2016. Note: Austria (AT); Finland (FI); Latvia (LV); Romania (RO); Belgium (BE); France (FR); Luxembourg (LU); Slovakia (SK); Bulgaria (BG); Germany (DE); Malta (MT); Slovenia (SI); Cyprus (CY); Greece (EL); Netherlands (NL); Spain (ES); Czech Republic (CZ); Hungary (HU); Norway (NO); United Kingdom (UK); Denmark (DK); Ireland (IE); Poland (PL); Estonia (EE); Italy (IT); Portugal (PT).
Source: own elaboration with data from Eurostat.

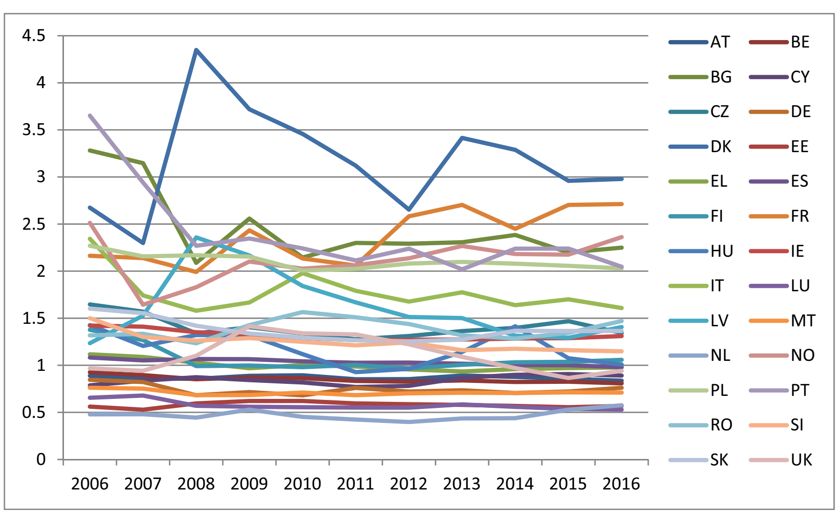


Fig. 9. Plastic waste/GDP (Tones/M€) of the 26 EU for the period 2006–2016. Note: Austria (AT); Finland (FI); Latvia (LV); Romania (RO); Belgium (BE); France (FR); Luxembourg (LU); Slovakia (SK); Bulgaria (BG); Germany (DE); Malta (MT); Slovenia (SI); Cyprus (CY); Greece (EL); Netherlands (NL); Spain (ES); Czech Republic (CZ); Hungary (HU); Norway (NO); United Kingdom (UK); Denmark (DK); Ireland (IE); Poland (PL); Estonia (EE); Italy (IT); Portugal (PT).
Source: own elaboration with data from Eurostat.

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