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THE DETERMINANTS OF MUNICIPAL SOLID WASTE MANAGEMENT EFFICIENCY IN EU COUNTRIES

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ABSTRACT: The main purpose of this paper is to assess the municipal solid waste management (MSWM) efficiency of European Union countries and to identify the determinants of this efficiency before and after introducing Directive (EU) 2018/851. The research was conducted for 23 EU Member States in order to analyse the two highest-priority waste treatment methods (material recycling and energy recovery) and the level of greenhouse gases emitted by the waste management sector. The data for 2015-2020 were extracted from the Eurostat database. The period of data was divided into two sub-periods: 2015-2017 (the period before introducing the Directive) and 2018-2020. MSWM efficiency scores were calculated using the DEA method. Later, the Tobit Regression Model (TRM) was applied to identify the determinants. The efficiency analysis showed that the countries which joined the EU before 2000 improved their MSWM efficiency in 2018-2020 compared with 2015-2017. On the other hand, the average efficiency scores of the countries that joined the EU after 2000 decreased. In 2015-2017, the following determinants of MSWM efficiency occurred to be statistically significant: population density, unemployment rate, the number of patents and the tourism intensity index, while in 2018-2020: population density, unemployment rate, Research & Development (R&D) expenditure, higher education proportion and MSW generated. A detailed analysis of these variables showed that the countries that joined the EU after 2000 should first increase their R&D expenditure and support their inhabitants in increasing their educational level.

KEYWORDS: municipal solid waste treatment efficiency, European Union, DEA, Tobit Regression Model

DOI: 10.34659/eis.2024.88.1.637

Introduction

The amount of municipal solid waste (MSW) generated globally has been increasing successively for many years. The World Bank predicts MSW generation to be on the level of 3.88 billion tons per year by 2050, about 73% more than in 2020 (The World Bank, 2022; Silpa et al., 2018).

MSW management (MSWM) in Europe promotes the circular economy based on reducing use of natural resources by delivering high quality secondary raw materials obtained from waste (European Commission, 2020). The details about MSW treatment methods were defined in the Directive (2008), which is considered one of the legal foundations for the EU waste management policy. In particular, the document introduced the waste treatment hierarchy, making prevention, then the preparation for re-use and later recycling and energy recovery the priorities of waste management. The European Commission (2018) prepared a report on the implementation of the Directive (2008), which showed that 14 EU Member States were operating at risk and should "*use EU funds more effectively to develop waste infrastructure by ensuring that co-financing supports prevention, re-use and recycling performance*" (European Commission, 2018).

Due to the fact that the regulations did not bring the expected outcomes, in 2018, Directive 2018/851 (Directive, 2018) was introduced to amend the previous one. The new document specified, e.g. new long-term policy objectives for the preparation for re-use and the recycling of municipal waste in EU countries, which shall be increased to:

- 55% (of total waste) by 2025,
- 60% by 2030,
- 65% by 2035.

Moreover, the EU justified the introduction of the document by pointing out that: "*Many Member States have not yet completely developed the necessary waste management infrastructure. It is therefore essential to set clear long-term policy objectives in order to guide measures and investments, notably by preventing the creation of structural over-capacities for the treatment of residual waste and lock-ins of recyclable materials at the lower levels of the waste hierarchy*" (Directive, 2018). Therefore, the EU Member States should focus more on the efficient use of waste treatment expenditure in line with the priorities listed in the Directive (2008). Thus, the assessment of MSWM efficiency from the perspective of this document is fully justified and necessary (Valencikova & Fandel, 2007).

MSWM can be undoubtedly considered one of the most important services delivered worldwide (Struk, 2014; Storto, 2021a). According to Guerrini et al. (2017), the improvement of MSWM efficiency is the best way to save funds and achieve a higher quality of MSWM. Molinos-Senante et al. (2023) suggested that improving MSWM eco-efficiency is essential for a sustainable economy. Lacko and Hajduova (2018) pointed out that measuring environmental efficiency is one of the key processes to improve the environment. Hence, the interest in MSWM efficiency has been increasing significantly in recent years (Valencikova & Fandel, 2007). The vast majority of papers were focused not only on assessing MSWM efficiency but also on identifying the determinants of this efficiency.

However, MSWM efficiency is calculated without considering any side effects of waste treatment, e.g. greenhouse gas emissions. In fact, waste treatment processes should be carried out with minimised negative impacts on human health and the environment (Directive, 2008). Indeed, the EU has set ambitious targets to reduce greenhouse gas emissions and reach net zero CO2 emissions by 2050 (European Parliament, 2018). As noted by the European Commission (2020), waste is the fourth largest sector of greenhouse gas emissions. So, taking greenhouse gas emissions into account while calculating MSWM efficiency is important and should be continued.

The main purpose of this paper is to assess MSWM efficiency in EU countries before and after introducing the Directive (2018). The efficiency scores were calculated taking into account the level of greenhouse gases emitted by the waste management sector. Additionally, we identified the environmental factors that affect this efficiency in a significant way before and after introducing the Directive (2018). Finally, the goal is also to measure MSWM efficiency at the level of EU countries, which is still a minority in the literature (usually limited to cities or regions). Moreover, according to the best of the author's knowledge, there are no previous studies focusing on assessing the impact of the Directive on MSWM efficiency.

DOI: 10.34659/eis.2024.88.1.637

An overview of the literature

Studies focused on MSWM efficiency were conducted in two phases. The first phase was to calculate MSWM efficiency scores, while the second phase focused on identifying factors that affect this efficiency in a significant way.

The vast majority of papers employ Data Envelopment Analysis (DEA) to evaluate MSWM efficiency scores (Lacko & Hajduova, 2018; Storto, 2021; Sala-Garrido et al., 2022). DEA allows for the calculation of the efficiency of a production process, which is described by several inputs and several outputs. In the typical DEA models, the increase in outputs and decrease in inputs are desirable from the point of view of efficiency. However, some production processes can be described as "undesirable" outputs. In relation to the "bad" outputs, we expect them to decrease, not increase. As Halkos and Papageorgiou (2014) emphasised, "*environmental production approach requires the joint production of desirable (good) and undesirable (bad) outputs*". There are three main approaches in the literature (Halkos & Papageorgiou, 2014). The first one is to treat a bad output as a regular input (Halkos & Petrou, 2018; Zhou & Zhang, 2019; Lacko & Hajduova, 2018). The second one is based on the definition of eco-efficiency and focuses on calculating the ratio between the environmental benefit – good outputs and the environmental damage – bad outputs (Rios & Picazo-Tadeo, 2021; Molinos-Senante et al., 2023). However, treating undesirable outputs as desirable inputs is perceived as not truly reflecting a production process (Seiford & Zhu, 2002). The third approach was proposed by Seiford and Zhu (2002) and relies on the transformation of a bad output using linear monotonic decreasing transformation (Halkos & Petrou, 2018; Storto, 2021).

The main advantage of the DEA is that it does not require any assumption about efficient frontier functional form (Moore et al., 2003; Zhu & Zhang, 2019; Gennitsaris & Sofianopoulou, 2022; Molinos-Senante et al., 2023). On the other hand, the lack of this assumption implies that DEA efficiency scores are sensitive to sample variation and have no statistical properties. As a consequence, DEA efficiency indicators cannot be applied to parametric regression analysis (Molinos-Senante et al., 2023). To overcome this issue, studies propose some nonparametric methods, e.g. the Kruskal-Wallis test, regression tree analysis (Sala-Garrido et al., 2022), or nonparametric smoothed regression (Guerrini et al., 2017). As an alternative approach, Simar and Wilson (2007) introduced the double-bootstrap DEA analysis (Rios & Picazo-Tadeo, 2021; Molinos-Senante et al., 2023). This method takes into account noise and uncertainty by calculating bias-corrected efficiency. Additionally, it allows us to assess the influence of some environmental variables and test their significance levels.

Many approaches assess MSWM from the cost perspective (Struk, 2014; Guerini et al., 2017; Halkos & Petrou, 2018; Yang et al., 2018; Zhu & Zhang, 2019; Storto, 2021a; Sala-Garrido et al., 2022; Molinos-Senante et al., 2023). However, instead of waste treatment methods, researchers more often take into account the amount of sorted/unsorted waste collected (Guerrini et al., 2017; Storto, 2021; Storto, 2021a; Sala-Garrido et al., 2022; Molinos-Senante et al., 2023). Collecting a large amount of sorted waste does not guarantee that it is treated in desirable ways, i.e. by following the waste treatment hierarchy established in the Directive (2008). Greenhouse gas emissions have not been considered so far, except by Halkos and Petrou (2018) and Lacko and Hajduova (2018), although the European Commission clearly pointed out that: "*The first objective of any waste policy should be to minimise the negative effects of the generation and management of waste on human health and the environment*" (Directive, 2008).

Studies in the literature test different environmental variables that can affect MSWM efficiency, too.

Struk (2014) analysed the MSWM efficiency of 600 municipalities in the Czech Republic and listed factors that significantly affect this efficiency: type of used solid waste treatment – landfill, population, a portion of the municipal population living in a flat, average area covered by "separation nests", the frequency of solid waste collection. In addition, the following factors were also analysed and found as not significant: the presence of a landfill within a municipality, public or private ownership of a waste collecting company, the presence of competition in the waste management area, and the costs of the MSW collection.

Molinos-Senante et al. (2023) performed the double-bootstrap approach to identify the factors affecting the eco-efficiency of municipal solid waste service providers (MSWSPs) in 298 municipalities in Chile. They examined the following determinants: population density, tourism index, MSW

DOI: 10.34659/eis.2024.88.1.637

generated per capita and the variable which captures the region in which MSWSPs operate. They showed that all of these factors are statistically significant.

Sala-Garido et al. (2022) focused on analysing three types of efficiency, technical, environmental and eco-efficiency, of 118 municipalities in Chile. As input, the authors picked annual operating costs; as outputs, they included the total amount of recycled waste (technical efficiency), the total quantity of unsorted waste (environmental efficiency), and the total amount of recycled and unsorted waste (eco-efficiency). As a result of the conducted research, it was found that the tourism index had a statistically significant impact on all three types of efficiency. Population density significantly influenced the technical and environmental efficiencies. In addition, the increase in MSW generated per capita affected the increase in environmental and eco-efficiency indicators.

Yang et al. (2018) showed that the impact of environmental factors on MSWM efficiency differs depending on the type of cities. They considered Quantity of Patent Authorization, Total Retail Sales of Social Consumer Goods and Excellent Rate of Urban Air Quality as potential determinants of MSWM efficiency in 33 cities in China.

Moreover, Guerrini et al. (2017) showed that the relationship between MSWM efficiency and environmental factors varies and depends on the level of these factors. They examined 40 municipalities in Italy. They found that the percentage of non-residential customers, population served, population density, and the amount of waste collected per load had a negative effect on MSWM efficiency. The average household size determined MSWM efficiency in a positive way. In the case of tourist flows, they observed a negative relationship at low values of this variable (lower than 300k tourists per year) and then a positive relationship (up to 800k tourists per year). There were more than 800k tourists, and there was no influence on efficiency.

The majority of studies examined MSWM efficiency as a dependent variable in the second stage of analysis. However, Storto (2021a) treated MSWM efficiency as the determinant of the rate of the sorted MSW collection in 258 municipalities in Italy. It turned out that the factors determining the increase were pure technical efficiency (PTE), population density and the degree of complexity of the waste collection scheme. Additionally, the study proved a negative and statistically significant influence of the following factors: the length of roads, population, as well as the total amount of waste collected per capita. The area of municipalities was not significant.

Lacko and Hajduova (2018) examined the 26 countries of the EU for 2008-2016. The authors conducted a double-bootstrap approach to identify environmental factors affecting environmental efficiency. As a result socio-economic variables (e.g. mean income, resource productivity, environmental taxes) turned out to be significant as well as the climate change variables (e.g. road freight transport, fertilizers use, waste generated).

The significance of socio-economic variables (measured by GDP per capita and GDP per capita-squared) were confirmed by Rios and Picazo-Tadeo (2021), who analysed environmental performance of the EU-28 for 2017. They found environmental awareness, economic and legal context as not significant.

To sum up, the approaches available in the literature have many gaps and limitations.

Firstly, the vast majority of papers focus on analysing MSWM efficiency across municipalities located in one country instead of other countries. There is a lack of research involving comparative analysis of countries especially of EU countries. The Directive (2018) specified new long-term policy targets for EU countries – not for municipalities. Moreover, the Directive (2018) emphasized that the targets laid down in Directive (2008) were not achieved by countries because of the lack of necessary waste management infrastructure in many EU countries. The European Commission further emphasises that "*large differences exist among Member States with respect to their waste management performance, particularly as regards recycling of municipal waste*" (Directive, 2018). The main reason for these big differences among countries was a lack of common measurement tools that could help the EU detect problems in achieving the goals formulated in the Directive (2008) early. Therefore, there is a need for a tool for measuring the MSWM efficiency of EU countries, which will allow for the early detection of problems in achieving the goals formulated in the Directive (2018), identifying the causes of these problems in order to appropriately adapt support mechanisms.

Secondly, in the literature, MSWM efficiency is analysed most often by taking into account – as the output of the MSWM process – the amount of sorted MSW collected but excluding:

- what happens next with this waste,

- how many greenhouse gases are emitted during the MSWM process?

Collecting a large amount of sorted waste does not guarantee that it is treated in accordance with the waste management hierarchy introduced in Directive (2008). Only waste treatment in accordance with the hierarchy can help countries achieve the goals laid down in the Directive (2018). Additionally, as noted by the European Commission (2020), waste is the fourth largest sector of greenhouse gas emissions. So, taking into account greenhouse gas emissions while calculating MSWM efficiency is important and should be continued.

Considering the above comments, the efficiency scores in the research presented in this paper were calculated for EU countries and by taking into account the amount of MSWM treated by recycling and energy recovery as desirable outputs of the waste management process and the total greenhouse gas emitted by the waste management sector as an undesirable output (a side effect) of this process. In addition to the factors considered in the literature, the study took into account environmental factors that have not been analysed so far, but they appeared as suggestions for further research, e.g. seniors' rate, level of education and unemployment rate.

Research methods

The conducted research consisted of several phases

The first phase was using the Data Envelopment Analysis (DEA) to calculate MSWM efficiency scores. The main reason of using DEA in calculating MSWM efficiency scores is that the DEA methods are the most popular and widely used methods among others. The main advantage of DEA is that it allows the estimation of efficiency scores of the production process, transforming several inputs into several outputs without the need to assume the shape of the efficiency frontier (Guzik, 2009).

The main purpose of the DEA models is to calculate for each DMU (Decision Making Unit) the efficiency score $0 \leq \theta \leq 1$, determining the level of inputs that maintain the results at least at the current level (θ equals 1 indicates that DMU is efficient). The DEA methods do not require any assumption about efficient frontier functional form, the shape of which depends on the DMUs taken into account while estimating the efficiency scores. The efficiency score is estimated based on some reference object calculated as a linear combination (with non-negative weights) of other objects described by their inputs and outputs.

The basic DEA model is the input-oriented, radial DEA-CCR model proposed by Charnes et al. (1978), which has undergone numerous modifications (Łozowicka & Lach, 2022). The DEA-CCR model does not make any assumptions about the weights (except being non-negative) in the linear combination. For this reason the DEA-CCR model underestimates efficiency scores just because of DMU's scale. It is said that DEA-CCR assumes a constant return to scale (CRS). The DEA-BCC differs from DEA-CCR by adding a condition to the above weights so that they need to sum to one. It is said that DEA-BCC assumes a variable return to scale (VRS). That's why the DEA-BCC model is more appropriate for a group of DMUs that has a large diversification of activity scale. More on DEA, especially on DEA-CCR, DEA-BCC can be found in some references (Guzik, 2009; Cooper et al., 2006; Cooper et al., 2011; Dellnitz et al., 2018; Pai et al., 2020).

In traditional DEA models the increase in outputs and decrease in inputs are desirable from the point of view of efficiency. One of the aims of this research was to take into account some the side effects of the waste treatment process. Thus both "desirable" and "undesirable" outputs were defined. To achieve the more reliable MSWM efficiency scores, linear monotonic decreasing transformation was used as proposed by Seiford and Zhu (2002).

Due to the fact that EU countries are characterized by great diversity of MSWM activity scales, the DEA-BCC model was applied to estimate the efficiency scores Θ^{BCC} of EU countries. The first stage of the study was carried out using R [package 'deaR' – function *model.basic()*] (Col-Serrano et al., 2023).

In the second phase, the bootstrap approach was applied to calculate the bias-corrected efficiency indicators Θ^{BCC}. As mentioned above the DEA efficiency scores Θ^{BCC} are biased, because the efficiency indicator of DMU is calculated based on the reference object being the linear combination of other DMUs. That's why the efficiency score of some DMU can rapidly change after modifying the composition of a group of DMUs. Appling the bootstrap approach allows for the calculation of the bias-corrected efficiency indicators Θ^{BCC} which include some noise and are considered more reliable

DOI: 10.34659/eis.2024.88.1.637

in the literature (Simar & Wilson, 2007). This phase of research was carried out by using the package 'deaR' – function bootstrap_basic() (Col-Serrano et al., 2023).

In the third phase, the Tobit Regression Model (TRM) was applied to identify key factors affecting these efficiency indicators. The TRM discovered by Tobin (1958) is used to analyse a limited dependent variable. In fact, the MSWM efficiency score takes value from zero to one, so it was a sufficient reason to use the TRM. The main assumption of the TRM is that the objects whose efficiency scores are equal differ from each other, which can be noticed in the differences in the independent variables. The same can be said about the objects with efficiency scores that equal zero.

Let Θ be a limited variable with a lower limit that equals 0 and an upper limit that equals 1. Let Y be a linear combination of K factors ($X_1, X_2, ..., X_K$), which are by hypothesis related with Θ. The TRM can be written as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_K X_K + \varepsilon \tag{1}$$

where:
$\varepsilon \sim N(0; \delta^2)$
Y – is a latent variable, which can be observed if, and only if, the values are greater than 0 and smaller than 1. So, the efficiency score is assumed to be as follows:

$$\theta = \begin{cases} 0, when\ Y \leq 0 \\ Y, when\ 0 < Y < 1 \\ 1, when\ Y \geq 1 \end{cases}$$

More on TRM estimation procedure can be found in some references (Tobin, 1958; Storto, 2021a; Michels & Musschoff, 2022; Kostrzewska, 2011). This phase of research was carried out by using R – package 'AER' – function tobit() (Kleiber & Zeileis, 2024) while the significance of the factors was tested usingthe bootstrap approachby applying package 'boot' – function *boot()* (Canty & Ripley, 2022).

The research was carried out for the 23 UE Members States. There were three countries that were removed from the study: Luxemburg – due to its size, Greece and Malta – because of a lack of data. The data covered the period 2015-2020, and their source was the Eurostat database. The period was divided into two sub-periods: the first one (2015-2017) referred to years before introducing the Directive (2018), and the second one (2018-2020) when countries were adapting their national policies to EU guidelines.

There was one input indicator:
- GI (good input) – the total general government expenditure on waste management (million euro),
- and three output indicators in the study:
- GO1 (good output) – the amount of MSW treated by recycling – material (thousand tonnes),
- GO2 (good output) – the amount of MSW treated by energy recovery (thousand tonnes),
- BO (bad output) – the total greenhouse gas emitted by the waste management sector (thousand tonnes).

The following ten factors were analysed:
- <u>Population density</u> (persons/km^2),
- <u>Seniors' rate</u> – Proportion of population aged 65 or more (%),
- <u>Overcrowded rate</u> – The percentage of the population living in an overcrowded household (%),
- <u>MSW generated</u> – Municipal solid waste generated per capita (kilograms per capita),
- <u>Higher education</u> – Proportion of population aged 25-64 with tertiary education level 5-8 (%),
- <u>Lower education</u> – Proportion of the population aged 25-64 with less than primary, primary and lower secondary education levels 0-2 (%),
- <u>Unemployment rate</u> – Total unemployment rate as the percentage of the population in the labour force aged 15-74 (%),
- <u>Patents</u> – Number of patents related to recycling and secondary raw materials per million inhabitants,
- <u>Research & Development (R&D) expenditure</u> – GERD as a percentage of GDP (%),

DOI: 10.34659/eis.2024.88.1.637

- Tourism intensity index – Nights spent at tourist accommodation establishments per thousand inhabitants.

The justification of environmental factors listed above is covered in the section "Discussion, limitations and future research".

Results of the research

Two DEA models were executed. The first one concerned years 2015-2017 (69 DMUs – Decision-Making Units) and the second one concerned years 2018-2020 (69 DMUs). The descriptive statistics presented in Table 1 show a great diversity of the DMUs in each of the analysed sub-periods. Therefore, using the DEA-BCC model was justified.

Table 1. Descriptive statistics of the variables used to calculate the MSWM efficiency scores

Indicator	2015-2017				2018-2020			
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
GI (mln EURO)	1834.2	3208.0	14	11289	2014.1	3311.1	19	12094
GO1 (thousand tonnes)	2691.8	5293.4	69	25435	2834.2	5176.5	83	24910
GO2 (thousand tonnes)	2193.6	3552.6	0	15946	2419.6	3790.1	1	15980
BO (thousand tonnes)	4759.2	5497.2	346	20340	4590.3	5494.7	315	20456

Source: author's work based on Eurostat [09-05-2023].

The efficiency score takes a value from 0 to 1, where value 0 means fully not efficient DMU, and value 1 – fully efficient DMU. As shown in Table 2, the average MSWM efficiency scores in 2018-2020 increased slightly vs. 2015-2017 (from 0,370 to 0,410). However, the disparities between the countries also increased.

Table 2. Descriptive statistics of the MSWM efficiency scores

Sub-period	Mean	S.D.	Min	Max	Efficient DMUs
2015-2017	0.370	0.351	0.019	1	15.9%
2018-2020	0.410	0.381	0.030	1	20.3%

Source: author's work based on Eurostat [09-05-2023].

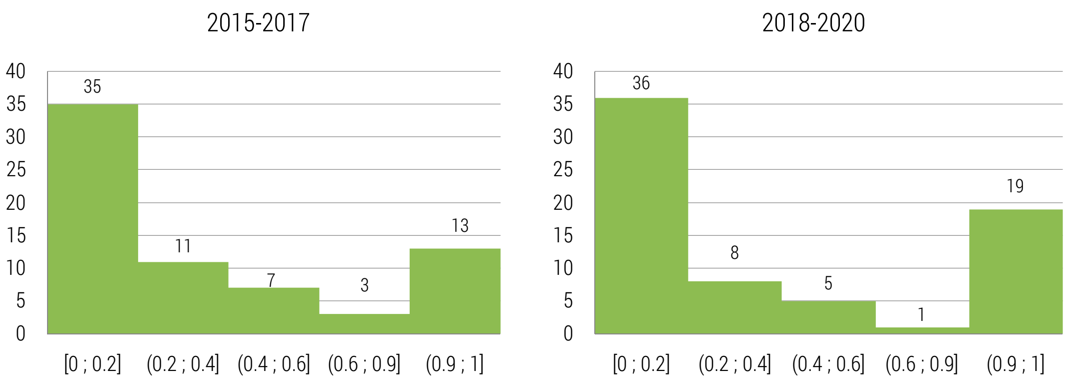

Figure 1. Histogram of the MSWM efficiency scores

Source: author's work based on Eurostat [09-05-2023].

DOI: 10.34659/eis.2024.88.1.637

The histograms (Figure 1) confirms the results described above. The MSWM efficiency scores are distributed similarly in both the analysed sub-periods. In 2018-2020 there are more countries with MSWM efficiency scores above 0,9 (the number of DMU's increased from 13 to 19). On the other hand, there are still many low efficient countries with efficiency scores below 0,2.

The differences in efficiency levels are more visible from the perspective of each of the Member States' dates of joining the EU. It can be observed that countries that joined the EU before 2000 were able to increase their mean efficiency score in 2018-2020 (0,515) compared with 2015-2017 (0,422), decreasing their disparities (from 87% to 81%). However, the countries that joined the EU after 2000 decreased their mean MSWM efficiency score (from 0,322 to 0,315). Additionally, the global minimum of the MSWM efficiency score was achieved by some countries that joined the EU after 2000 (Table 3).

Table 3. Descriptive statistics of the MSWM efficiency scores breakdown by countries that joined the EU before/after 2000

Date of joining the EU	2015-2017					2018-2020				
	Mean	S.D.	S.D./Mean	Min	Max	Mean	S.D.	S.D./Mean	Min	Max
after 2000	0.322	0.336	104%	0.019	1	0.315	0.322	102%	0.030	1
before 2000	0.422	0.365	87%	0.059	1	0.515	0.416	81%	0.052	1
Total	0.370	0.351	95%	0.019	1	0.410	0.381	93%	0.030	1

Source: author's work based on Eurostat [09-05-2023].

The detailed analysis of the histogram (Figure 1) leads to a similar conclusion. In 2018-2020, there were more countries with MSWM efficiency above 0,9 (the number of DMUs increased from 13 to 19). In the 2015-2017 results, the groups of countries with the highest (above 0,9) and with the lowest (below 0,2) MSWM efficiency scores consisted of countries that joined the EU before/after 2000 equally (Table 4). In 2018-2020, the proportions changed. The DMUs with the MSWM efficiency scores above 0,9 mostly joined the EU before 2000. In fact, there were twice as many of them as countries that joined the EU after 2000 (13 vs. 6). Unfortunately, the countries that joined the EU after 2000 made up a majority of the group of the DMUs with the lowest MSWM efficiency scores (22 DMU's joined the EU after 2000 vs. 14 DMU's joined before 2000).

Table 4. The number of DMUs by the MSWM efficiency scores achieved

Date of joining the EU	2015-2017		2018-2020	
	[0 ; 0.2]	(0.9 ; 1]	[0 ; 0.2]	(0.9 ; 1]
after 2000	15	7	22	6
before 2000	20	6	14	13
Total	35	13	36	19

Source: author's work based on Eurostat [09-05-2023].

Before running the TRM, the bias-corrected MSWM efficiency scores were calculated with 1000 bootstrap replications. The TRM is defined as follows:

$$\Theta^{BCC*} = \beta_0 + \beta_1 \cdot Population\ Density + \beta_2 \cdot Seniors'rate + \beta_3 \cdot Overcrowded\ household\ rate + \beta_4 \cdot MSW\ generated + \beta_5 \cdot Higher\ education + \beta_6 \cdot Lower\ education + \beta_7 \cdot Unemployment\ rate + \beta 8 \cdot Patents + \beta_9 \cdot R\&D\ expenditure + \beta_{10} \cdot Tourism\ intensity\ index + \varepsilon$$

DOI: 10.34659/eis.2024.88.1.637

The results of the TRM are summarised in Table 5. In 2015-2017, the disparities between countries can be explained by the following factors that occurred to be statistically significant in the analysed model:

- population density – negative influence,
- unemployment rate – negative influence,
- patents – positive influence,
- tourism intensity index – positive influence.

In 2018-2020, population density and unemployment rates occurred to be statistically significant. Additionally, the R&D expenditure turned out to be statistically significant. It can be said that introducing new technology into waste treatment processes affects the higher MSWM efficiency in both sub-periods. In 2018-2020, apart from these three variables, MSW generated and tertiary education occurred to have a positive influence on MSWM efficiency, too.

Table 5. The results the Tobit Regression Model (TRM)

Indicator	2015-2017			2018-2020		
	Coefficient	Bootstrap st. err.	z-statistic	Coefficient	Bootstrap st. err.	z-statistic
Constant	0.343	0.436	0.788	0.049	0.307	0.16
Population density	-0.001	0.000	-2.927***	-0.001	0.0002	-5.027***
Seniors' rate	-0.006	0.017	-0.360	-0.013	0.014	-0.911
Overcrowded household rate	-0.001	0.005	-0.239	-0.0002	0.003	-0.055
MSW generated	0.0004	0.0003	1.511	0.0005	0.0003	1.663*
Higher education	0.003	0.008	0.332	0.012	0.005	2.32**
Lower education	-0.002	0.004	-0.419	0.002	0.004	0.419
Unemployment rate	-0.024	0.011	-2.065**	-0.033	0.012	-2.786***
Patents	0.128	0.054	2.372***	0.028	0.045	0.634
R&D expenditure	-0.009	0.074	-0.116	0.121	0.062	1.965**
Tourism intensity index	1.19E-05	7.65E-06	1.552*	-4.7E-07	4.37E-06	-0.107

Symbols *, **, *** indicate the coefficient is statistically significant at 10%, 5% and 1% levels.
Source: author's work based on Eurostat [09-05-2023].

Table 6. Descriptive statistics of the factors affecting MSWM efficiency in a statistically significant way in 2018-2020 by countries that joined the EU before/after 2000

Statistic	Date of joining the EU	Population density	MSW generated	Higher education	Unemployment rate	R&D expenditure
Mean	before 2000	179	579.1	36.6	7.05	2.28
	after 2000	84	436.3	31.4	5.58	1.17
S.D.	before 2000	138.48	113.13	8.13	3.08	0.77
	after 2000	34.34	87.55	7.82	1.78	0.50
S.D./Mean	before 2000	77.4%	19.5%	22.2%	43.6%	33.7%
	after 2000	41.0%	20.1%	24.9%	31.9%	42.3%

Source: author's work based on Eurostat [09-05-2023].

A lower population density and a lower unemployment rate speak in favour of countries that joined the EU after 2000 (Table 6). The cause of increasing differences in MSWM efficiency scores between countries that joined the EU after 2000 compared to other countries is the lower level of

R&D expenditure. In countries that have been in the EU longer, the average share of this expenditure as part of GDP (2018-2020) is twice as large as in the countries which joined the EU later. So, the "new" countries should increase their R&D expenditure to improve the technology in the waste management sector. It is also important to support the higher education system and encourage people to invest in their education.

Discussion, limitations and future research

MSWM efficiency disparities between EU countries increased after introducing the Directive (2018). The countries that joined the EU before 2000 performed better at MSWM after introducing the new EU legacy, while other countries were left behind. In 2015-2017, there were no significant differences in MSWM efficiency between the UE countries.

From the countries grouping perspective, our results are generally consistent e.g. with results achieved by Lacko and Hajduova (2018). Although they used different variables, their results for MSWM efficiency scores obtained from the DEA-BCC model also did not differentiate countries by the date of joining the EU in the overlapping time research periods (2008-2016 vs 2015-2017).

The study showed that population density is a statistically significant factor that affects MSWM efficiency before and after introducing the Directive (2018). Moreover, the higher the density, the lower the MSWM efficiency. Also, when the population density increased, the cost of MSWM became higher, too. Molinos-Senante et al. (2023) showed a negative and statistically significant influence of population density on eco-efficiency, as well. On the other hand, Sala-Garrido et al. (2022) showed a negative and statistically significant influence on technical efficiency, and Storto (2021a) proved that population density influences sorted waste collection in a positive way. Guerrini et al. (2017) showed that, in general, the relation between population density and MSWM efficiency is negative, but the direction of this relationship may vary slightly depending on the exact value of population density.

The seniors' rate proved to be not significant in the presented model in both sub-periods. This variable has not been considered in the literature so far. The reason for including this variable in models was the assumption that older people are less likely to collect waste separately because it requires some lifestyle and habit changes. It is also more difficult for them to adapt to new circumstances. It is worth including other age groups in further research.

The overcrowded household rate turned out to not be significant both before and after introducing the Directive (2018). Including this variable was dictated by the contradictory results of earlier studies. Struk (2014) showed that the portion of the municipal population living in flats influences MSWM efficiency in a significant and negative way. According to the author, the lower levels of waste separation are typical in flats. On the other hand, Guerrini et al. (2017) proved that the relationship between the number of people per house and MSWM efficiency is, in general, negative. They explained it in two ways. Firstly, larger families are better organised to separate collected waste. Secondly, the more people per household, the lower the cost of waste transport per load.

The MSW generated per capita was statistically significant only after the introduction of the Directive (2018). Moreover, the more MSW generated per capita in the country, the higher the MSWM efficiency. This is in line with Lacko and Hajduova (2018), who showed that as a positive and statistically significant relationship in EU countries. The results presented for municipalities in the literature are inconclusive. One study showed a positive influence of this variable on MSWM efficiency (Sala-Garrido et al., 2022), while others showed a negative influence (Molinos-Senante et al., 2023). However, according to Storto (2021a), the MSW generated per capita affects the sorted waste collected in a negative way. So the more waste is produced, the less separated and less recycled it is in the end. Apart from this, we observed a positive and statistically significant relationship between the MSW generated per capita and the recycling rate in EU countries in recent years. It can explain the positive direction of this relationship in the EU.

Higher/lower education was included in this research, following Storto's suggestion (2021). Only higher education turned out to be statistically significant in explaining the variety of MSWM efficiency across EU countries in 2018-2020. The sign of the coefficient suggests that the more people with higher education in a country, the higher its MSWM efficiency. Education increases environmental awareness, which makes people more likely to change their habits.

DOI: 10.34659/eis.2024.88.1.637

The unemployment rate occurred to be statistically significant both before and after introducing the Directive (2018). Moreover, the relationship is negative. This means that the more people who do not have jobs, the lower the MSWM efficiency is. The unemployment rate has not been considered in the literature so far. However, the influence of GDP per capita and GDP per capita-squared on environmental performance was examined, and it appeared to have a positive but decreasing effect (Rios & Picazo-Tadeo, 2021). It is known that the higher the unemployment rate, the lower the GDP per capita. In other words, the lower the GDP per capita, the lower the MSWM efficiency.

The degree of technological advancement occurred to be statistically significant and affecting MSWM efficiency in a positive way. In 2015-2017, the number of patents turned out to be statistically significant, while in 2018-2020, R&D expenditure was a percentage of GDP. Yang et al. (2018) proved that the higher the level of science and technology, the more chance intelligent delivery, collection, transportation and treatment of waste modes are used. Smol et al. (2019) emphasised the high importance of innovations introduced in the waste management sector from the point of view of the circular economy transformation process. Moreover, they highlighted that these innovations include not only new technologies but also political, organisational, financial and social aspects (Smol et al., 2019).

The last variable, the tourism intensity index, proved to be statistically significant and positively explained the variety of MSWM efficiency scores across EU countries only in 2015-2017. Some researchers find this impact negative (Guerrini et al., 2017; Molinos-Senante et al., 2023; Sala-Garrido et al., 2022) however Guerrini et al. (2017) noted that the negative relationship was observed for municipalities with below 300 thousand tourists per year. Also, this study refers to municipalities.

The presented research has two key limitations. Firstly, the approach was accepted in the years 2018-2020, the period after the introduction of the Directive (2018). However, according to the document, "*Member States shall bring into force the laws, regulations and administrative provisions necessary to comply with this Directive by 5 July 2020*" (Directive, 2018), so not all the countries immediately adapted their national law to the Directive. Secondly, 2020 is considered the COVID-19 pandemic year, and there were many changes in factors that have not been observed in other years. The international situation had an impact on many aspects, e.g. nights spent at tourist accommodation establishments in 2020 were lower than in other years, and the increase of MSW generated by the EU in 2020 in relation to 2019 was the highest year-by-year change since 2012.

Considering future research, it could be interesting to analyse the impact of some other factors, e.g. the participation of private enterprises in the waste management sector, various age structures of the population, the proportion of protected areas, residents' income, etc. It could be interesting to identify not only determinants of efficiency but also factors that are affected by these efficiencies, e.g. resource productivity, circular material use rate, economic growth, etc. Moreover, multi-equation models with a more extensive network of relationships can be considered. Finally, it is worth to repeat the study once the Directive is fully implemented by each country.

Conclusions

The research presented in this paper focuses on assessing MSWM efficiency of European Union countries and identifying the determinants of this efficiency before and after introducing the Directive (2018). The research was conducted for 23 EU Member States, in order to analyse two highest-priority waste treatment methods (material recycling and energy recovery) and the level of greenhouse gases emitted by the waste management sector.

The study showed that introducing the Directive affected the MSWM efficiency of EU countries. Moreover, EU countries that joined the EU before 2000 increased their MSWM efficiency after introducing the Directive compared to the period before. So, setting up long-term objectives may have been motivating for them, and they could have had favourable conditions to introduce this Directive into their national policies as well. However, the countries that joined the EU after 2000 decreased their MSWM efficiency and probably had some issues with the full implementation of this Directive.

In the period before introducing the Directive, the following determinants of MSWM efficiency occurred to be statistically significant: population density, unemployment rate, the number of patents and tourism intensity index, while in the period after, population density, unemployment rate, Research & Development (R&D) expenditure, higher education proportion and MSW generated. A detailed analysis of these variables in the period after the introduction of the Directive showed that the countries that joined the EU after 2000 had lower education levels and R&D expenditures compared with EU countries that joined before 2000.

In view of the findings above, the following recommendations are suggested:

- EU institutions should focus more on countries that joined the EU after 2000. Introducing the Directive (2018) affected the widening MSWM efficiency gap between them and countries that joined the EU before 2000. This direction of change raises concerns in the context of the assumptions of the Cohesion policy – the EU's main investment policy. It is necessary for the EU to take action to determine whether the differences in MSWM efficiency that have deepened after the implementation of the Directive (2018) are the result of not enough funding allocated to countries that joined the EU after 2000 or perhaps management errors committed by their national governments.
- The countries that joined the EU after 2000 should take the following actions:
  - the creation of new applications in the field of MSWM infrastructure, e.g. by increasing their R&D expenditure level,
  - people's environmental awareness can be raised, e.g., by supporting the education of the inhabitants.
- Finally, studies like the one presented here could also be treated as a toolset to monitor the progress of achieving MSWM-related objectives and to trigger further initiatives.

Acknowledgements

Supported by funds granted by the Minister of Science of the Republic of Poland under the "Regional Initiative for Excellence" Programme for the 5 implementation of the project "The Poznań University of Economics and Business for Economy 5.0: Regional Initiative – Global Effects (RIGE)".

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DETERMINANTY EFEKTYWNOŚCI GOSPODAROWANIA ODPADAMI KOMUNALNYMI W KRAJACH CZŁONKOWSKICH UNII EUROPEJSKIEJ

STRESZCZENIE: Celem badania jest ocena efektywności przetwarzania odpadów przez kraje członkowskie Unii Europejskiej oraz identyfikacja determinant tej efektywności przed i po wprowadzeniu w życie Dyrektywy 2018/851. Badanie zaprezentowane w niniejszym artykule zostało przeprowadzone dla 23 krajów członkowskich Unii Europejskiej z uwzględnieniem dwóch sposobów przetwarzania odpadów uznanych przez Unię za priorytetowe, tj. recyklingu w celu odzysku materiałów i odzysku energii. Przy szacowaniu efektywności uwzględniono również poziom gazów cieplarnianych emitowanych przez sektor gospodarowania odpadami. Dane statystyczne dotyczyły lat 2015-2020 i pochodziły z bazy danych Eurostat. Okres analizy podzielono na dwa podokresy: 2015-2017 (okres przed wprowadzeniem Dyrektywy) oraz 2018-2020. Do obliczenia współczynników efektywności wykorzystano model DEA, natomiast identyfikacji determinant dokonano w oparciu o regresję tobitową. Po wprowadzeniu w życie Dyrektywy efektywność przetwarzania odpadów przez kraje włączone do Unii przed 2000 rokiem uległa poprawie, podczas gdy średnia efektywność krajów włączonych po 2000 roku spadła w stosunku do 2015-2017. Determinanty tej efektywności również uległy zmianie. W latach 2015-2017 do istotnych czynników zaliczyć można: gęstość zaludnienia, stopę bezrobocia, patenty oraz wskaźnik natężenia turystycznego, natomiast w latach 2018-2020: gęstość zaludnienia, stopę bezrobocia, wydatki badawczo-rozwojowe, wykształcenie wyższe mieszkańców oraz ilość generowanych odpadów komunalnych. Analiza szczegółowa wskaźników pokazała, że kraje włączone do Unii po 2000 roku powinny w pierwszej kolejności skupić się na podniesieniu poziomu wydatków badawczo-rozwojowych oraz wspierać mieszkańców w podnoszeniu poziomu wykształcenia.

SŁOWA KLUCZOWE: efektywność przetwarzania odpadów komunalnych, Unia Europejska, DEA, regresja to bitowa