Identifying the most relevant peers for benchmarking waste management performance: a conditional directional distance Benefit-of-the-Doubt approach

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Abstract

The paper demonstrates that the outcome of the robust and conditional directional distance version of the BoD model not only contains information on the overall efficiency score and rank, but also enables a region to identify its genuine peers, disentangle the overall effect of the background conditions on the performance and assess one's relative strengths and relative weakness vis à vis its most relevant peers when evaluating its municipal solid waste management. We illustrate how this information can be retrieved from the outcomes of DEA/BoD based efficiency and performance benchmarking studies by applying the methodology to the case of the Brussels Capital Region. The results show that Freiburg, Darmstadt and the province of Limburg are in general the most interesting peers for the Brussels Capital Region. In addition, the analysis reveals that Darmstadt and Freiburg are identified as the most instructive peers if the region is interested in improving its composting and recycling rate, respectively.

Keywords: Composite Indicators; Benefit-of-the-Doubt; Regional Social Inclusion; Conditional BoD; Municipal Solid Waste; European Union.

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Abbreviations: Brussels Capital Region (BCR), Benefit-of-the-Doubt (BOD), municipal solid waste (MSW), composite indicator (CI), Externality Index (EI), Individual Index (II).

1. Introduction

Inspired by the growing need for local and regional decision makers to constantly assess and adjust their municipal solid waste (MSW) management, we demonstrate how the output of the well-known DEA/BoD based efficiency and performance benchmarking methodology contains (besides an overall efficiency score and rank) crucial information that can assist the regions in identifying those management choices or policy initiatives that have the potential to improve achievements of local waste management.

The study of efficiency in MSW management has gained interest both in political and academic circles. Examples of academic studies include De Jaeger, Eyckmans, Rogge and Van Puyenbroeck (2011), De Jaeger and Rogge (2013, 2014) and Rogge and De Jaeger (2013) for Belgium and Flanders, Dijkgraaf and Gradus (2004) for the Netherlands, Marques and Simões (2009), Simões, De Witte and Marques (2010) and Simões and Marques (2012) for Portugal, Bosch, Pedraja and Suárez-Pandiello (2000), Mateu-Sbert, Ricci-Cabello, Villalonga-Olives and Cabeza-Irigoyen (2013) for Spain, Guerrini et al. (2017) for Italy, Worthington and Dollery (2001) for the UK, Greene and Tonjes (2014) for the United States, and Johnstone and Labonne (2004), Picazo-Tadeo, Castillo-Giménez and Beltrán-Esteve (2014) and Rogge, De Jaeger and Lavigne (2017) for international studies. Examples of policy studies are BiPRO (2012), BiPRO/CRI (2015), European Commission (2008), Eurostat (2012), and Forfás (2008). Most efficiency and benchmarking studies of MSW management performances use non-parametric techniques such as the Data Envelopment Analysis (DEA) methodology or the DEA based Benefit-of-the-Doubt (BoD) methodology to capture the complexity and the multidimensionality of the MSW management process. DEA is a non-parametric efficiency measurement technique originally developed by Farrell (1957) and put into practice by Charnes, Cooper and Rhodes (1978) in the Operations

Research and Management Science literature. They measure the relative efficiency performance of a set of similar entities (organizations, production lines, regions, etc.) which employ (possibly) multiple inputs to produce (possibly) multiple outputs in complex operating settings typically characterized by a lack of reliable information on the prices of inputs and outputs and/or no (exact) knowledge about the ‘functional form’ of the production or cost function.² The BoD model is tantamount to the DEA model in a ‘pure output setting’ in that one looks only at ‘achievements’ (i.e., outputs) without taking into account the input side. Whereas the DEA-model evaluates the efficiency/productivity of a MSW management process by estimating a ratio of weighted outputs to weighted inputs, the BoD model assesses the performance of a MSW management process by constructing a composite (performance) indicator (CI, hereafter) using sub-indicators that typically contain numerical information concerning relevant aspects of the MSW management process, such as waste generation and treatment. The most important advantage of the DEA/BoD model is its non-parametric nature. It allows for an endogenous (i.e. decided by the model instead of predetermined) and optimal (i.e. a weighting that results in the highest possible ranking) weighting of the multiple inputs and outputs (or, in case of the BoD model, the set of sub-indicators). More specifically, the DEA/BoD model reconstructs ‘implicit’ weights (‘shadow’ prices for the inputs and outputs in a DEA-setting or ‘implicit’ policy weights for the sub-indicators in the BoD setting) from the observed data thereby looking for the set of weights that maximize for each evaluated entity the relative performance score (efficiency score in DEA setting, composite policy performance score in BoD setting). Stakeholders in a decision-making process often have different opinions on the relative importance of the sub-indicators which makes deciding on a joint

² Other techniques are the parametric Stochastic Frontier Analysis (SFA)-method (Simões and Marques, 2011). For an extensive overview of different techniques, we refer the interested reader to Daraio and Simar (2007) or Fried, Lovell and Schmidt (2008).

weighting scheme a difficult task. For example, one stakeholder may put more emphasis on waste prevention while another wants to give a high weighting to proper waste treatment such as incineration with energy recovery as opposed to without recovery. Also the trade-offs between the importance of waste management inputs such as infrastructure, staff and the required surface area and outputs such as waste processed and waste recycled are challenging in a multi-stakeholder setting. This is therefore an attractive second best route in the absence of full information about the true input/output prices (DEA setting) or policy priorities (BoD setting).

The large majority of efficiency and performance benchmarking studies of MSW management provide policy makers and stakeholders with an efficiency/performance score and rank, which denote how well each entity (region, municipality, etc.) is performing vis-à-vis the other entities. In addition, some studies provide other more general insights such as how the operating environment affects the efficiency/performance of MSW management (Simões & Marques, 2011; Rogge & De Jaeger, 2012, 2013; Rogge et al., 2017), how the (cost) efficiency of MSW management varies by the different MSW components (Rogge & De Jaeger, 2012; 2013), how different waste reduction and/or collection policies relate to the (cost) efficiency in collecting and processing MSW (De Jaeger et al., 2011; Bosch et al., 2000) and how the size of waste management utilities, waste pricing policies and/or incentive regulations impacts (cost) efficiency in MSW services (Carvalho & Marques, 2014; Carvalho, Marques & Dollery, 2015; De Jaeger & Rogge, 2013; Marques & Simões, 2009). Whereas such general measures and results are particularly helpful for officials and policy makers at the higher policy levels (i.e., European Commission), results of DEA based efficiency and benchmarking studies of MSW services also comprise more detailed performance information and insights that are very useful and informative for regional MSW management and policy makers. As opposed to the above papers, our approach

consists in demonstrating how existing techniques in the BOD/DEA literature can be applied for identifying peers in the context of waste management in addition to a general ranking of the decision making units. Note that this approach has been applied in other fields of policy decision-making such as city performance in well-being and quality of life (Morais & Camanho, 2011; Bernini, Guizzardi & Angelini, 2013; Morais, Miguéis & Camanho, 2013), promotion of sustainable tourism (Blancas, Caballero, González, Lozano-Oyola & Pérez, 2010; Pérez, Guerrero, González, Pérez & Caballero, 2013; Salvati & Carlucci, 2014), urban water sector performance (Mbuvi, De Witte & Perelman, 2012), urban green space use (Lopes & Camanho, 2013), cities' livability (Zanella, Camanho & Dias, 2015b), and public e-services (Reggi et. al, 2014). But to the best of our knowledge, this has not yet been used in the context of regional waste management evaluations.

As point of departure we take the outcomes of Rogge, De Jaeger and Lavigne (2017) which advocated the use of a robust and conditional directional distance version of the BoD model to measure (MSW) management performance of the NUTS2 regions in the EU³. It is elaborately described in their paper how this adjusted version of the BoD model enables to properly deal with the several methodological, conceptual and practical problems usually involved in the construction of a composite MSW management performance scores. The model is applied to European NUTS2 regions which is a geographical hierarchy level coinciding with a level between the national and municipality level. In short, this particular version of the BoD model allows to (1) treat sub-indicators measuring the different aspects of MSW management having different measurement units, while (2) adopting a flexible weighting method in an evaluation setting with no consensus among experts, policymakers and other stakeholders regarding the exact level of importance of

³ As our paper builds on the same dataset (including the data manipulations), we refer Rogge et al. (2017) for a detailed description of the dataset

different aspects of MSW performance. It (3) makes it possible to consider desirable indicators (e.g., recycling rate) and undesirable indicators (e.g., disposal rate) in the measurement of regional MSW performance and (4) reduces the impact of measurement errors and atypical observations in the data set. Furthermore, it (5) accounts explicitly for differences in the background conditions under which the NUTS2 regions have to operate (given that the literature indicates that observed differences in regional MSW performance may be partially driven by differences in background conditions such as tourism or population density). However, whereas in the discussion of the outcomes, Rogge et al. (2017) predominantly focused on describing the general results which are informative predominantly for policy makers and stakeholders at higher policy making levels, the present study delves deeper into the outcomes generated by the robust and conditional directional distance version of the BoD model to look for insights and policy messages which are more useful for regional policy makers, MSW management and stakeholders.

The key objective of the present paper consists in demonstrating how the outcomes of DEA/BoD based efficiency and performance benchmarking studies of regional MSW services, besides computing an overall efficiency score and rank for each region, contain also information that enables to (1) identify peers for the evaluated region within and outside the policy maker's jurisdiction, (2) identify which regions outperform other regions in terms of MSW management, (3) interpret the region's MSW performance relative to the operating environment, and (4) identify the basic functionalities of the regional MSW management on which the region performs relatively highly and poorly (i.e. the basic functions of relative strength and relative weakness in the evaluated MSW management's functioning). Note that the four types of information might seem unrelated on first sight. In this paper we will however argue that combining 1-3 will allow a region to identify its genuine peers in terms of performance, overall or partial superior performance and

contextual characteristics while 4 will enable a region to assess one's relative strengths and relative weaknesses vis à vis its most relevant peers. By combining all information (i.e. 1-4) a region will be able to tell for each aspect of its MSW management which regions should be investigated in more detail. Throughout, we illustrate how useful and informative information can be retrieved from the outcomes of DEA/BoD based efficiency and performance benchmarking studies of regional MSW services and performances with the case study of the Brussels Capital Region (hereafter BCR with NUTS2 code BE10).

We selected the case of the BCR to illustrate the added value of identifying one's genuine peers when selecting those management choices or policy initiatives that have the potential to improve the region's waste management performance. In countries with (partly) decentralized waste management competencies (such as Belgium), national environmental authorities are typically interested in the peer comparability (and indeed comparison) of the (groups of) regions within their jurisdiction. For instance, a first look at some key figures for the BCR seems to reveal that the region is outperformed by the two other Belgian regions Flanders and Wallonia. In particular, the percentage of municipal solid waste that is collected separately for recycling or recovery, is considerably lower in the BCR compared to the other Belgian regions (see for instance Franklin, 2014). However, for the BCR, it remains difficult to assess the true bearing of such comparisons. On the one hand differences in contextual characteristics (such as the prevailing metropolitan context in the BCR with a higher population density and a higher level of tourism in the region) might invalidate the comparison, but on the other hand it is important to understand which other regions can indeed be seen as the region's genuine peers. Environmental authorities in the BCR therefore (correctly) point out that a benchmarking exercises of regional waste management performance should include 'comparable' peers. Nonetheless in many benchmarking exercises the

pool of potential peers is confined to regions operating within the same country (or same overarching jurisdiction). This paper describes how a benchmarking study can be performed amongst regions with a variety of operating environments while at the same time accounting for their differences in the selection of peers.

This paper is organized as follows. Section 2 briefly presents the robust and conditional directional distance version of the BoD model that was used in Rogge et al. (2017). Section 3 describes four methods in which a detailed analysis of the outcomes of BoD based performance benchmarking studies can be used by local policy makers when assessing their municipal solid waste (MSW) management performance. Finally Section 4 concludes.

2. Conditional directional distance BoD model

In the previous paper, Rogge et al. (2017) employed a robust⁴ directional distance version of the BoD model to measure and benchmark the MSW performances of NUTS2 regions in the EU. The regions' MSW management performance was evaluated by constructing a composite indicator derived from five sub-indicators which represent the different steps of the waste hierarchy ladder (reduce, reuse, recycle, recover, landfill). The regional performance data originate from the municipal waste generation and treatment dataset which is part of the 'Regional environmental questionnaire Data' compiled by Eurostat, the statistical office of the EU⁵. The reduce step is represented by the average municipal waste generation per capita. Unfortunately, no proper waste

⁴ The model was robustified using the order-m approach presented by amongst others Cazals et al. (2002). An alternative to the order-m approach of Cazals et al. (2002) is the order- α approach of Daouia and Simar (2007). The order-m approach was chosen as it enables an appealing economic interpretation, as it gives a clear indication of how well a region is performing relative to a subset of m regions.

⁵ The data are publically available via the Eurostat database via <http://ec.europa.eu/eurostat/web/regions/data/database>. Metadata for this dataset can be downloaded via http://ec.europa.eu/eurostat/cache/metadata/en/env_rwas_gen_esms.htm

181 reuse data was available on a European NUTS2 level. For the next step however, i.e. recycling,
182 two sub-indicators were used: the recycling rate and the composting rate. The fourth sub-indicator
183 is the percentage of incinerated municipal waste which is treated with energy recovery (denoted
184 ‘Recovery’) (i.e. incineration that fulfils the energy efficiency criteria laid down in the Waste
185 Framework Directive, Annex II, recovery operation R1). Finally we included the proportion of
186 municipal waste which is landfilled (denoted ‘Landfilling’) which is the least favourable option.
187 Although these sub-indicators make sense in a European setting, different contexts may require
188 including alternative sub-indicators. For example in developing countries, when conducting a
189 waste management benchmarking study, using sub-indicators such as collection coverage and
190 disposal in controlled facilities versus open dumps could be more appropriate depending on the
191 local realities.

192 As this measurement involved a mixture of both desirable and undesirable performance criteria of
193 MSW performance, an additional adjustment of the model after Zanella, Camanho and Dias
194 (2015a) was implemented. The result was the following model (see also, Rogge et al., 2017 p. 24;
195 Zanella et al., 2015a p. 523):

$$\begin{aligned}
D_k &= \min_{w_{k,r}^+, u_{k,l}^-} \left(- \sum_{r=1}^s w_{k,r}^+ y_{k,r}^+ + \sum_{l=1}^m u_{k,l}^- y_{k,l}^- + v \right) & (1) \\
s.t. & \\
\sum_{r=1}^s w_{k,r}^+ g_r^+ + \sum_{l=1}^m u_{k,l}^- g_l^- &= 1 \\
- \sum_{r=1}^s w_{k,r}^+ y_{j,r}^+ + \sum_{l=1}^m u_{k,l}^- y_{j,l}^- + v &\geq 0 & (j = 1, \dots, N) \\
w_{k,r}^+ &\geq 0 & (r = 1, \dots, s) \\
u_{k,l}^- &\geq 0 & (l = 1, \dots, m) \\
v &\in \Re
\end{aligned}$$

196 With $D_k(\mathbf{y}_k^-, \mathbf{y}_k^+, \mathbf{g}_l^-, \mathbf{g}_r^+)$ the optimal directional distance value and $CI_k = 1/(1 + D_k)$ the
 197 associated composite MSW performance score for the evaluated region k ; $y_{k,r}^+$ ($r = 1, \dots, s$) and $y_{k,l}^-$
 198 ($l = 1, \dots, m$) the performance values of the region k on respectively the desirable MSW
 199 performance criteria (i.e., ‘Recycling’, ‘Composting’, and ‘Recovery’, indexed r) and the
 200 undesirable MSW performance criteria (‘Waste generation’ and ‘Landfilling’, indexed l); $y_{j,r}^+$ and
 201 $y_{j,l}^-$ the performance values of all N regions in the sample ($j = 1, \dots, k, \dots, N$) on the same performance
 202 criteria; $w_{k,r}^+$ and $u_{k,r}^-$ the optimal BoD weights for region k for the desirable and undesirable
 203 performance criteria; and $(g_l^-, g_r^+) \in \mathbb{R}^{m+s}$ the direction vector which specifies for each MSW
 204 performance criterion the exact direction in which improvements may be sought. The direction
 205 vector was determined by the performance indicators for the region k under evaluation.

206 In an attempt to fine-tune the model so as to obtain more realistic benchmarking results, Rogge et
 207 al. (2017) appended the model in two ways. Firstly, two sets of weight restrictions were
 208 implemented so as to mitigate an important downside to the large flexibility in weighting inherent
 209 in the BoD model, i.e. CIs being constructed using improper weights. A first set of weight
 210 restrictions imposed that all performance criteria should receive an importance weight of at least
 211 5% so as to avoid (quasi-) zero BoD weights. Formally,

$$\frac{w_{k,r}^+ \overline{y_r^+}}{\sum_{r'=1}^s w_{k,r'}^+ \overline{y_{r'}^+} + \sum_{l=1}^m u_{k,l}^- \overline{y_l^-}} \geq 0.05 \quad (r = 1, \dots, s) \quad (2)$$

$$\frac{w_{k,l}^- \overline{y_l^-}}{\sum_{r=1}^s w_{k,r}^+ \overline{y_r^+} + \sum_{l'=1}^m u_{k,l'}^- \overline{y_{l'}^-}} \geq 0.05 \quad (l = 1, \dots, m)$$

212 This implies the overall MSW performance score cannot be constructed while disregarding one or
 213 more of the constituent performance criteria, a minimalist position which was taken to reflect the

214 underlying idea that all performance criteria are considered as providing valuable MSW
 215 performance information. A second set of weight restrictions was implemented so as to incorporate
 216 the current policy stance in waste management in the EU. More specifically, this set of restrictions
 217 imposed a rank ordering on the BoD importance weights for the MSW performance criteria that
 218 corresponds to the waste hierarchy: the most important MSW performance criterion being ‘Waste
 219 Generation’ followed by the MSW performance criteria ‘Composting’ and ‘Recycling’ and the
 220 MSW performance criterion ‘Recovery’. Following Zanella et al. (2015a), both types of weight
 221 restrictions are imposed on the ‘artificial’ region representing the average performance values on
 222 the desirable and undesirable criteria as computed across all regions in the sample. This ensures
 223 that all regions are evaluated relative to a unique best practice frontier as weight restrictions are
 224 uniform for all regions. Formally,

$$\begin{aligned} w_{k,1}^-\overline{y_1} &\geq w_{k,2}^-\overline{y_2}, w_{k,1}^-\overline{y_1} \geq w_{k,1}^+\overline{y_1^+}, w_{k,1}^-\overline{y_1} \geq w_{k,2}^+\overline{y_2^+}, \\ w_{k,1}^-\overline{y_1} &\geq w_{k,3}^+\overline{y_3^+}, w_{k,2}^+\overline{y_2^+} \geq w_{k,1}^+\overline{y_1^+}, w_{k,3}^+\overline{y_3^+} \geq w_{k,1}^+\overline{y_1^+} \end{aligned} \quad (3)$$

225 A second way in which the BoD model as in (1) was fine-tuned was by using conditional (as
 226 opposed to unconditional) version of this model (after insights of Cazals, Florens & Simar, 2002;
 227 Daraio & Simar, 2007; De Witte & Kortelainen, 2013; Bădin et al., 2010, 2012) so as to address
 228 another important concern in the measurement and benchmarking of the MSW performances of
 229 NUTS2 regions in the EU. NUTS2 regions perform under considerably different background
 230 conditions including population density, GDP per capita, the number of nights spent at tourist
 231 accommodation establishments per 1000 residents, the average wage for a worker in the MSW
 232 sector and the number of enterprises (or part thereof) active in the regional MSW sector expressed
 233 per 1000 inhabitants. This means that some regions work in more favorable and other regions in
 234 less favorable operating environments. Such differences should be properly accounted for in the

performance benchmarking analysis, which this method does. Otherwise, the regions may (not entirely unjustifiably) criticize the outcomes of a comparative analysis and question the credibility and validity of the assessment and benchmark instrument in general. The selection of background characteristics is quite context-driven. Although these selected characteristics are relevant in a European setting, a similar study on a different continent will probably require different background characteristics to be taken into account. For example, studies analyzing both developed and developing countries should probably include income levels as the size of local MSW management budgets has an impact on a region's capability to implement the necessary infrastructure to perform well in terms of MSW management. Furthermore the affordability of more extensive waste management schemes impacts the willingness of the public to join the schemes (in case of a voluntary scheme) or adhere to the rules (in case of a mandatory scheme). The method for finding and evaluating peers however remains the same regardless of the chosen background characteristics and the selected sub-indicators.

As noted in the introduction, Rogge et al. (2017) predominantly focused on describing the general results, i.e. the BoD estimated MSW performance scores and ranks for the NUTS2 regions and the relation between the regional MSW performance scores and operational environment. Regarding the regional MSW performance scores and ranks, it was reported that (1) considerable differences exist in the aggregate MSW performances of the regions, (2) the potential gains are considerable for the waste sectors of many regions in the EU, (3) the NUTS2 regions in Austria, Belgium, and Germany generally perform well in terms of MSW management and (4) the sub-indicator recycling rate is the main factor differentiating the best performing countries from the worst. It was also found that, except for the number of tourist overnight stays, background conditions are not

significantly related to the MSW management performance of the waste sectors in the NUTS2 regions.

In the remainder, we delve deeper into the outcomes generated by the robust and conditional directional distance version of the BoD model and, using as case study the BCR, illustrate how these results can be used to look for insights and policy messages that could be useful for regional policy makers, MSW management and stakeholders.

3. MSW management performance evaluation

3.1. Identifying peers

Local and regional environmental authorities are typically interested in looking at best practice regions which operate under similar contextual characteristics as the ones of their own region. Less informative for regions are best practices which operate under contextual conditions that are largely dissimilar to the own conditions, as part of the MSW management choices and performance may be due to the different operating conditions. As discussed above, the robust and conditional version of the BoD model evaluates MSW performances of each region predominantly in relative perspective to the MSW performances of regions in the sample with similar operating environments (i.e., comparing like with like). As a measure of comparability between two regions in terms of their background conditions, the conditional model generates Kernel density estimates. For the calculation of the estimates, we refer the interested reader to Daraio and Simar (2007). In doing so, the model assigns high Kernel density estimates (in this case a maximum of 0.1592) to regions j ($j = 1, \dots, k, \dots, N$) with (very) similar background conditions to those of the evaluated region k and small (or even zero) Kernel density estimates to regions with (very) dissimilar contextual characteristics.

Table 1 lists the NUTS2 regions with the highest BoD generated Kernel density estimates or, in other words, the regions in the sample of N regions with contextual characteristics that are overall most similar to the contextual characteristics of the BCR. The region most similar to the BCR is the BCR itself which is why it has the highest Kernel density estimate. The last two columns show the regions' unconditional and conditional (taking into account the operating environment) BOD-scores which represent their MSW management performance. In brackets, a number is provided which shows where the region is situated in the ranking in terms of the performance score of the 176 regions under study. There is no standard procedure to determine the number of regions that should be retained for detailed investigation. However, an interesting practical guideline consists in looking at the graphical representation of the regions sorted in decreasing order of their Kernel density estimate. Often, this graphical representation shows an “elbow”-function, with the graph displaying at first a steep drop in the Kernel density estimates up until the elbow point and a slow to very slow decline beyond this elbow point. The idea is to focus predominantly on those regions that are situated at the left of the elbow point as these regions operate under contextual characteristics more similar to the ones of region k . Figure 1 shows the graphical representation for the BCR. The plot displays an “elbow” around the 0.05-level, with 17 NUTS2 regions, including the BCR itself, having Kernel density estimates higher than this level.

Table 1 around here

Figure 1 here

Without information on how relevant the other regions are for constituting one's benchmark, the above Kernel density estimates remain insufficient to identify potential best practices. In addition to comparability of the operating environment, relevant peers should perform better than the region k under study. A useful outcome of the BoD based performance benchmarking studies to

complement the Kernel density estimates is the composition of the benchmark against which the MSW performance of region k is assessed⁶.

When constructing the composite indicator for a NUTS2 region, a hypothetical peer with its own sub-indicator values is created. Region k 's performance is assessed by evaluating how far away region k is from this hypothetical peer. This hypothetical peer is given sub-indicator values that would result in the highest possible score when applying region k 's optimal weightings. But at the same time, we are comparing region k to the other 175 regions which is why it also has to be a linear combination of the 176 regions in the study. The model provides for each region a hypothetical peer and accompanying coefficients for its linear combination. The coefficients of all regions' linear combinations are N vectors of intensities obtained from the dual version of the BoD model. The BoD model hereby generates for each evaluated region k a vector of intensities $\lambda_k = (\lambda_{k,1}, \dots, \lambda_{k,N})$ which indicate how relevant other (observed) regions are for constituting the benchmark against which the MSW performance of region k is assessed. For a mathematical formulation of the dual version and a detailed description of the intensity values, the interested reader is referred to Zanella et al. (2015a).

As is described by Zanella et al. (2015a), this linear combination has typically only non-zero lambda's for a small number of regions as the efficient frontier consists of facets in the hyperplane. The previous study used a robust version of the BOD benchmarking analysis. The results were robustified by creating $B (=2500)$ composite indicators per region in which each iteration a subsample of the $n (=176)$ regions is selected (the order-m approach). The final composite

⁶ Note that we used a simple version of the model in which the hypothetical peer is located at the cross-section between the efficient frontier and the directional distance vector (in our case the sub-indicator values of the NUTS2 region itself). Alternative techniques exist where a peer is selected which is closest to the region under evaluation in terms of the sub-indicators in order to find a direction of improvement which is easier to achieve, i.e. closest targets (see for instance Portela, Borges and Thanassoulis (2003) and Aparicio, Ruiz and Sirvent (2007)).

indicators are calculated as the average of the B scores. The λ 's presented in the intensity matrix are the average values of the B λ 's calculated for each region. Therefore, multiple (as opposed to just a small number of) regions can be identified as peers as different subsamples will generate different hypothetical peers. Furthermore, in the conditional version which takes into account the operating environment, the selection of a subsample is not random, but based on how alike regions are to the region for which we are constructing a composite indicator. Regions that are more alike have a higher probability of being selected for subsamples.

The intensity matrix is the N by N matrix collecting the $(I \times N)$ vectors of intensities for all N NUTS2 regions in the sample. In the interpretation of the intensity values, non-zero values indicate that a region acts as a peer of region k , with higher values indicating that this peer is a more important role model for the region k not only in terms of comparability of its operating environment, but also in terms of its MSW management performance. In this case study, the intensity matrix as computed by the robust and conditional BoD model is a 176x176 matrix. Due to the vastness of the matrix, only one relevant part is presented in Table 2. Table 2 displays the part of the intensity matrix that is associated with the BCR and the other Belgian NUTS2 regions (next to the BCR there are ten NUTS2 regions in Belgium: Antwerpen (BE21), Limburg (BE22), Oost-Vlaanderen (BE23), Vlaams-Brabant (BE24), West-Vlaanderen (BE25), Brabant Wallon (BE31), Hainaut (BE32), Liege (BE33), Luxembourg (BE34), and Namur (BE35)).

Table 2 around here

Table 2 shows that the BCR is an important peer for its own MSW performance evaluation. Other Belgian NUTS2 regions which are considered to some degree as benchmarks in the assessment of the BCR's MSW performance are in decreasing order of importance Limburg (BE22), Namur (BE35), Antwerpen (BE21), and Vlaams-Brabant (BE24). The intensity values displayed in Table

2 indicate that the BCR is not a peer for the other Belgian NUTS2 regions (column 1). The diagonal elements in Table 2 show that in Flanders, three out of five regions (i.e., Limburg BE22, Vlaams-Brabant BE24, and West-Vlaanderen BE25) act to some degree as their own peers in the measurement of their overall MSW performance. This can in part be attributed to their MSW management performance, but also to the fact that the region with the most comparable operating environment is itself. Furthermore, BE22, a region with comparable operating environment to the BCR (see Table 1) acts as a peer for the BCR while the opposite does not hold. We can therefore attribute a large part of intensity value 0.09 to BE22's MSW management performance. In addition, the intensity values for the Flemish NUTS2 regions reveals that BE24 plays the role of peer in the assessment of the MSW performance of one Flemish region (Oost-Vlaanderen BE23) and three Walloon regions (Brabant Wallon BE31, Hainaut BE32, and Liege BE33). Walloon regions only occasionally act as a peer for Belgian regions other than themselves (the only exception is Liege BE33 which acts to some extent as peer of Hainaut BE32).

Note though that the robust intensity values of most Belgian NUTS2 regions for the BCR are rather low as they can range between 0 and 1. This suggests that other NUTS2 regions might be more interesting peers for the BCR. In the case of the BCR, a closer inspection of the entire BoD estimated intensity matrix⁷ in fact shows that the intensity estimates range between 0 and 0.33. The BCR's highest intensity value is for the BCR itself. In addition to BE22, the regions DE13 (Freiburg) and DE14 (Tübingen) with intensity values of 0.07 and 0.11 are two important peers in the evaluation of the MSW performance of the BCR, followed by DE12 (0.06), AT34 (0.06), DE11 (0.05) and BE35(0.04). Hence when the ambition of a benchmarking analysis extends beyond the construction of a pure ranking exercise and the ultimate goal is to identify those

⁷ The full intensity matrix is available upon simple request.

management choices or policy initiatives that have the potential to improve achievements of local waste management, the analysis shouldn't be confined to the peers within one's own jurisdiction. Note that combining the Kernel density estimates with the intensity values could help to identify the most interesting peers in terms of waste management performance and waste management policy choices. The first column of Table 1 shows the intensity levels that were obtained from the BoD based performance benchmarking of the BCR (i.e., $\lambda_{BCR,j}$) for the 17 selected regions. It can be readily observed from Table 1 that from this set of 17 regions with high Kernel density estimates, the NUTS2 regions Freiburg (DE13) and Limburg (BE22) combine the highest intensity levels with high unconditional and conditional BoD based MSW performance scores. This makes these two regions potentially interesting and informative best practice regions in MSW performance for the BCR. That is, in the design of reforms to improve MSW performance, the BCR could look to the MSW management of these regions (and search for what makes the MSW managements of these regions so successful).

3.2. Dominance analysis

When selecting the best practice regions it is important to consider the weighing scheme applied. The BoD model endogenously calculates for each region k the set of weights which optimizes its performance score vis-à-vis the other regions in the study. This results in N (here 176) sets of optimal weighting schemes. Generally, a region is said to dominate another region in its MSW performance if that region is always ranked higher than the other region, irrespective of the optimal weighting scheme applied in the evaluation of the MSW performances. In terms of improving the own MSW performance, it is interesting for a region to look at regions by which it is dominated, particularly in combination with the outcomes of the peer analysis (section 3.1). The outcomes of the BoD based performance benchmarking exercise can be used to assess different levels of

dominance. As the BoD model is computed for each region k ($k = 1, \dots, N$) and, in each of these computations, optimal BoD weights of region k are applied to all N regions in the sample, each region obtains N BoD generated composite MSW performance scores and ranks. The $N \times N$ cross-efficiency score and rank matrices group all these scores and ranks, respectively. A detailed study of these matrices allows identifying which regions dominate other regions in their MSW performance.

Figures 2a and 2b portray for all NUTS2 regions in the sample the range of composite MSW performance scores and ranks as retrieved from the cross-efficiency matrices.⁸ The black dot and the blue cross on the intervals denote the arithmetic and the geometric means of the N composite MSW performance scores and ranks as computed for each region. For the BCR and the 16 NUTS2 regions with contextual characteristics similar to the ones of the BCR, ranges of scores and ranks are presented in red.

Figure 2 around here

Note in Figure 2a that in terms of the composite MSW performance scores, one region is close to being dominated by the BCR. Almost in all of the N BoD computations, Basse Normandie (FR25) obtains a composite MSW performance score that is lower than the score of the BCR. As to the MSW rankings, Figure 2b shows that one region, i.e. Border, Midland and Western Ireland (IE01), is fully dominated by the BCR. There are also two NUTS2 regions, Basse Normandie (FR25) and Martinique (FR92), that are dominated by BCR in a large majority of the N BoD computations (the range of the BCR only overlapping marginally with the predominantly lower positioned ranges of BoD based ranks for these regions). Figures 2a and 2b also show that no region in the

⁸ The figures display the composite MSW performance scores and ranks as computed by the unconditional version of the BoD model. The reason for doing so is that, when using the outcomes of the conditional BoD model, applying a region's optimal set of weights to a very dissimilar region, may result in extremely high or low scores. This is due to the fact that dissimilar regions are almost never selected in the sample when calculating the conditional scores.

sample fully dominates the BCR, neither in terms of composite MSW performance score and rank. Nonetheless, region Freiburg (DE13) with a relatively small range of the MSW performance rankings (indicating that its rank is not much affected by the weights) is close to dominating the BCR.

An alternative way to look for dominance results is less strong as the one discussed above. In particular, instead of looking at dominance across all N computations, one could also look for dominance by comparing the BoD estimated composite MSW performance score of the evaluated region k with the MSW performance score as computed for the others regions when applying the optimal BoD derived weights of the former region. In case that the evaluated region k receives the highest composite MSW performance score one could say that this region acts as its own benchmark when being evaluated using the optimal evaluation parameters (i.e., using most favorable weights). In the other scenario in which the evaluated region k does not attain the highest composite MSW performance score, a strong case (and a rather intuitive interpretation) can be provided for the idea that the region k is outperformed. In addition, the outperforming (set of) region(s) can be regarded as best-practice benchmark(s) for the evaluated region k . Table 3 shows how the composite MSW performance score of the BCR compares to the composite MSW scores as computed for the other 16 regions with similar contextual characteristics (Sub-section 3.1) when applying the optimal weights of the BCR. As can be seen in this table, BCR obtains a relatively high composite MSW score which suggest that the BCR is identified as a relatively strong MSW performer when being evaluated using its most optimal weights. On the other hand, Table 3 also demonstrated that two other regions, Limburg (BE22) and Freiburg (DE13), do obtain higher composite MSW performance scores even while using the BCR's optimal set of weights. Clearly these regions outperform the BCR in terms of their MSW performance and are therefore interesting

peers. Consequently, the above results of the peer and dominance analysis in mind, a policy recommendation for the BCR would be to focus on Limburg (BE22) and Freiburg (DE13) for further investigation.

Table 3 around here

3.3. Decomposing composite MSW performance scores

The identification of peers resulting from the above discussed peer and dominance analyses might indeed signal to regional policy makers which peers are best-in-class and can thus provide examples of well-performing sets of policies. Although the above discussed procedure already accounts for contextual differences, so far the procedure did not reveal how well (poorly) the regions under consideration and its peers are coping with the background conditions under which they have to operate. Nevertheless, such information could constitute key insights into potential successful adaptation strategies. Fortunately an analysis of the ratio of the conditional and unconditional composite MSW performance scores for the regions enables to disentangle the overall effect (positive or negative) of the background conditions on the regional MSW performance. The procedure of Daraio and Simar (2006, 2007) decomposes this ratio into three components: an internal or managerial MSW performance score, an ‘Externality Index’ and an ‘Individual Index’. The internal or managerial MSW performance score is captured by the unconditional composite MSW performance score. The Externality Index (EI_k) represents the overall effect of region k ’s operating environment (measured by the set of contextual characteristics) on its MSW management performance. The Individual Index (II_k) on the other hand, indicates how the region is able to cope with the background conditions. An $EI_k > 1$ indicates that region k ’s background conditions are favorable for its MSW management performance. An $EI_k < 1$ on the other hand, implies that the background conditions of region k are unfavorable for

its MSW management performance. In the interpretation of the II_k values, an II_k larger than one indicates that region k performs better than the average region with similar background conditions. In other words, region k manages to take advantage of favorable background conditions or suffers less from an unfavorable operating environment than what is to be expected. Regions with an $II_k < 1$ on the other hand underperform compared to the average region with similar background conditions.

Figure 3a and 3b respectively present the 95% confidence intervals of the mean EI_k 's and the mean II_k 's as computed by the robust versions of the BoD model for the NUTS2 regions in the sample. The intervals for the BCR and the 16 regions with similar contextual characteristics highlighted in red. Figure 3a shows that the EI_k values of the BCR and these 16 regions are quite similar, which is to be expected as they indeed have similar background conditions. Figure 3b demonstrates that the II_k values for the NUTS 2-regions with contextual characteristics most similar to the BCR are quite dispersed, with Freiburg (DE13) having the highest II_k -value and Hamburg (DE60) the lowest II_k value. As to the interpretation of the EI_k and II_k values for the BCR, the $II_k < 1$ shows that the BCR appears not to be able to take advantage of a mildly beneficial operating environment. Other regions such as Freiburg (DE13), Limburg (BE22), NiederÖsterreich (AT12) and Noord-Brabant (NL41) cope better with contextual characteristics similar to the ones of the BCR. On the other hands, similarly to the BCR, regions such as Martinique (FR92), Zahodna Slovenija (SI02), Hamburg (DE60), Southern & Eastern Ireland (IE02) and Border, Midland, Western Ireland (IE01) cope less well with similar contextual conditions. In order to evaluate whether EI_k and II_k values for the BCR differ statistically significantly from the values realized by the NUTS2 regions in the sample with similar contextual characteristics, one could inspect closely the intervals depicted in Figure 3a and 3b. The impact of the contextual characteristics is with high statistical significance

more (less) favorable for MSW performance for region k as compared to region j if the interval for EI_k values for region k is fully positioned above (below) the interval of the region j . Similarly, region k is said to outperform another region j in terms of coping better (worse) with the background conditions if the interval for II_k values for region k is fully positioned above (below) the interval of the region j . Figure 3b shows that in terms of coping with the contextual characteristics, the BCR only seems to outperform Martinique (FR92), Zahodna Slovenija (SI02) and Hamburg (DE60). However, the graph also shows that most of the NUTS2 regions with similar contextual characteristics cope better with these conditions.

Figure 3 around here

3.4. Identifying strengths and weaknesses

Identifying one's genuine peers in terms of general performance, overall or partial dominance and contextual characteristics is indeed a first and crucial step. Clearly for any benchmarking exercise to be useful for policy makers aiming at improving (regional) MSW performance, an overview of the aspects or sub-indicators where the region is performing strongly (poorly) compared to the other regions, is imperative. By combining such information with the results from the peer selection one will also be able to assess one's relative strengths and relative weakness vis à vis its most relevant peers. Given the multi-dimensional nature of the BoD based performance benchmarking methodology, the key building blocks for such analysis are to a large extent already endogenously determined in the model. Because of BoD's data-oriented and benevolent weighting of the sub-indicators in the construction of the composite MSW performance indicator, valuable insights on relative strengths and weaknesses can be inferred from looking at BoD estimated sub-

indicator importance weights.⁹ In general, sub-indicators for which the BoD model assigns relatively low importance weights (hence minimizing the impact of such sub-indicators) can be considered as relative weaknesses in the region's MSW performance. The opposite holds for sub-indicators for which the BoD model assigns relatively high importance weights, i.e. aspects of relative strength in the region's MSW performance. This practical advantage of BoD weighting is illustrated in Table 4 for the BCR and the regions that are most similar in terms of the operation conditions. Although the peer and dominance analysis singled out Limburg (BE22) and Freiburg (DE13) as interesting peers for the BCR, lessons can still be learned from an investigation of the strengths and weaknesses of the other similar regions under evaluation. Some valuable insights can be retrieved from Table 4. First, one readily notices that BoD obtained importance weights of the sub-indicators can be quite diverse across the regions. This illustrates that the benefit of the doubt principle in weighting plays an important role in the construction of the composite MSW performance scores for the NUTS2 regions.

As to the identification of aspects of relative strength and relative weakness in the BCR's MSW performance, the sub-indicator importance weights for the BCR show that a very high relative weight is assigned to the sub-indicator measuring the proportion of MSW which is landfilled (denoted 'Landfilling'). This indicates that the BCR is doing well on this MSW aspect, i.e. only a very small fraction of MSW is landfilled by the BCR. The sub-indicator importance weight also indicate that the BCR is doing relatively well in terms of waste generation and incineration with energy recovery (minor relative strength). This shows that the comparative strengths and weaknesses using sub-indicator importance weights are a good representation of reality as BCR's

⁹ For the desirable and undesirable sub-indicators, percentage contributions can be computed as respectively $w_{k,r}^+ y_r^+ / (\sum_{r=1}^s w_{k,r}^+ y_r^+ + \sum_{l=1}^m u_{k,l}^- y_l^-)$ and $u_{k,l}^- y_l^- / (\sum_{r=1}^s w_{k,r}^+ y_r^+ + \sum_{l=1}^m u_{k,l}^- y_l^-)$. Note that, for the ease of interpretation, the weight restrictions were omitted when calculating relative strengths and weaknesses.

MSW that is not recycled or composted is incinerated with energy recovery in an incinerator located on its territory. Furthermore, the sub-indicator importance weights show that the BCR is performing relatively poorly on the aspects of composting and recycling MSW. From the point of view of improving the overall MSW performance, the local policy makers in the MSW sector in the BCR should aim at improving performance on the aspects of the MSW performance of relative weaknesses while maintaining the good performance on the aspects of relative strength. In other words, the BCR should particularly aim at increasing the composting and recycling of MSW. In an attempt to gain knowledge on state of the art in composting and recycling, the BCR could learn from regions with similar contextual characteristics that compost and/or recycle a high proportion of their MSW. Looking at the sub-indicator importance weights for the sixteen regions that were identified in the peer analysis as region with contextual characteristics that resemble the ones of the BCR, we note that Hamburg (DE60) has a relative strength in waste generation and, to a lesser extent, incineration with energy recovery, recycling and landfilling, while composting is its relative weakness. Hamburg also has a lower composite MSW performance score. Note also that Freiburg (DE13), which was in the peer and dominance analysis identified as one of the most interesting peers to the BCR, has primarily a relative strength in recycling, but also, in decreasing order, in incineration with energy recovery, composting and waste generation. When looking for improvements in the composting policy, the BCR could have a look at Darmstadt (DE71).

Figure 4 visualizes the composite MSW performance scores and the sub-indicator importance weights for the BCR and four peer regions. The pie share representation for the composite MSW performance score of the BCR, clearly indicates that the BCR is performing very strongly on landfilling as it disposes only a marginal (quasi zero) fraction of its MSW in landfilling and relatively well in waste generation and incineration with energy recovery (both minor relative

strengths). The (quasi-)zero importance weight for the other two sub-indicators ('composting' and 'recycling') in the construction of the BoD based composite MSW performance score indicate that for the BCR these aspects of MSW are relative weaknesses.

Before concluding this paper, it is important to remark that one should be cautious in the interpretation of the BoD generated sub-indicator importance weights as indications of MSW aspects of relative strength and weakness. This because high (low) sub-indicator importance weights may sometimes identify MSW-aspects as relative strengths or relative weaknesses in a way that is difficult to justify. In particular, a sub-indicator might be identified by the BoD model as a relative strength for a poorly-performing region and as a relative weakness in the MSW performance of a highly-performing region, while the latter region performs better in absolute terms on this sub-indicator. As an example, the BoD model identifies for Hamburg (DE60) the sub-indicator 'waste generation' as a relative strength in the MSW performance largely because of the region's performances on the other sub-indicators which are relatively even worse. For the BCR, the sub-indicator 'waste generation' is identified only as a minor relative strength, even though the BCR has lower waste generation per capita as compared to Hamburg. As argued by Rogge (2011), such misinterpretations can be avoided by interpreting the BoD estimated sub-indicator importance weights for the MSW sub-indicators in relation to the composite MSW performance score.

Table 4 around here

Figure 4 around here

4. Concluding remarks

574 In this paper we demonstrated how the output of the well-known DEA/BoD based efficiency and
575 performance benchmarking methodology can be used to identify the most interesting and
576 informative best practice regions when aiming to improve one's MSW performance.

577 Applying this methodology to the case of the BCR indeed revealed which regions are the most
578 interesting peers in terms of waste management performance. Looking at the sub-indicator
579 importance weight additionally revealed that the BCR is performing relatively poorly on
580 composting and recycling of MSW. One could therefore argue that, if the BCR is interested in
581 improving its overall MSW performance, the BCR should primarily aim at increasing composting
582 and recycling rates of MSW. As most of Freiburg's strengths are found to be the BCR's relative
583 weaknesses and vice versa, an exchange of experiences between the two regions would be
584 mutually beneficial. Thus, in an attempt to improve recycling rates, looking at how Freiburg is
585 organizing the recycling of MSW might be a good place to start. When looking for improvements
586 in the composting policy, Darmstadt seems an interesting peer. Although Darmstadt is evaluated
587 with a lower composite MSW performance score, exchanging views on composting could prove
588 beneficial for the BCR. While being beyond the scope of this paper, but still a logical extension of
589 this research, we undertook a brief examination of the regions' waste management policies and
590 practices, which seems to confirm this observation. Upon inspection of the waste management
591 programs in place in Belgium and Germany, stricter resource-specific recycling targets were found
592 for packaging waste in Germany (Verordnung über die Vermeidung und Verwertung von
593 Verpackungsabfällen, 2017, Germany; Gesetz zur Fortentwicklung der haushaltsnahen
594 Getrennterfassung von wertstoffhaltigen Abfällen, 2017, Germany; Samenwerkingsakkoord van 4
595 november 2008 betreffende de preventie en het beheer van verpakkingsafval, 2008, Belgium).

596 Furthermore, separate collection of municipal solid bio-waste is mandatory in Germany (Gesetz

zur Förderung der Kreislaufwirtschaft und Sicherung der umweltverträglichen Bewirtschaftung von Abfällen (Kreislaufwirtschaftsgesetz), Germany, 2012). Both Freiburg and Darmstadt are located in the federal state (bundesland) Baden-Württemberg. As the federal states have a considerable degree of autonomy in, among others, their waste management policies, the Baden-Württemberg waste management plan (Abfallwirtschaftsplan Teilplan Siedlungsabfälle, 2017, Germany) sets explicit targets for the separate collection of 60 kg per capita per year for biodegradable kitchen waste and 90 kg for green garden waste to be attained by 2020. In the Brussels Capital Region however, although some green garden waste is collected separately and a pilot project for food waste collection is under execution, separate collection of bio-waste remains on a voluntary basis resulting in low collection rates. The above observations suggest that stricter resource-specific targets for packaging waste accompanied with the introduction of a mandatory separate collection of bio-waste could be a first step towards a more high-performing waste management in the BCR.

This paper focused on identifying a region's most relevant peers rather than pinpointing the most promising policy choices (or even operational decision). Clearly, identifying one's genuine peers is a crucial first step, but when the ultimate goal is indeed to single out the best waste management policy choices for the BCR, a more in-depth analysis of the selected peers is imperative. If one is interested in assessing which policies might work and which policies are probably less suitable for the BCR, the above analysis should be complemented with a more qualitative approach in which the regional and local choices of the benchmarking regions are assessed and compared to the BCR via for instance in-depth interviews with representatives of the regional environmental authorities. By reducing the set of promising peers (and sub-aspect of each peers' MSW policy) via the DEA/BoD based methodology proposed and elaborated in this paper, such typically time

620 consuming approaches become a feasible option, thus facilitating and significantly improving
621 decision-making processes in municipal solid waste management. As a logical extension to this
622 study, a more in-depth analysis is a very promising route for further research.

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Table 1: Similarity and performance of the Brussels Capital Region and similar regions

Region	Kernel density estimate	Intensity levels $\lambda_{k,j}$	Unconditional BoD score (rank)	Conditional BoD score (rank)
Brussels Capital Region (BE10)	0.1592	0.332	0.967 (45)	0.980 (42)
Hamburg (DE60)	0.1562	0.000	0.815 (105)	0.853 (104)
Oberpfalz (DE23)	0.1421	0.005	0.990 (40)	0.975 (45)
Noord-Brabant (NL41)	0.1368	0.000	0.948 (50)	0.920 (73)
Zahodna Slovenija (SI02)	0.1289	0.000	0.815 (106)	0.849 (106)
Overijssel (NL21)	0.1223	0.001	0.915 (68)	0.900 (81)
Southern & Eastern Ireland (IE02)	0.1180	0.000	0.709 (155)	0.726 (149)
Gelderland (NL22)	0.1138	0.004	0.961 (47)	0.934 (64)
Luxembourg (LU)	0.1040	0.000	0.747 (133)	0.742 (142)
Darmstadt (DE71)	0.1027	0.001	0.974 (41)	0.958 (53)
Limburg (BE22)	0.1022	0.090	1.104 (10)	1.043 (7)
Freiburg (DE13)	0.0946	0.066	1.098 (11)	1.046 (6)
NiederÖsterreich (AT12)	0.0890	0.000	1.021 (29)	0.989 (39)
Martinique (FR92)	0.0819	0.000	0.712 (150)	0.747 (138)
Basse-Normandie (FR25)	0.0676	0.000	0.693 (163)	0.696 (162)
Mittelfranken (DE25)	0.0658	0.000	0.928 (61)	0.925 (70)
Border, Midland, Western Ireland (IE01)	0.0508	0.000	0.693 (162)	0.709 (155)

Table 2: Intensity sub-matrix for the BCR and other Belgian NUTS2 regions

	BE10	BE21	BE22	BE23	BE24	BE25	BE31	BE32	BE33	BE34	BE35
BCR (BE10)	0.33	0.03	0.09	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.04
Antwerp (BE21)	0.00	0.09	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Limburg (BE22)	0.00	0.00	0.55	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
East Flanders (BE23)	0.00	0.00	0.02	0.03	0.25	0.00	0.07	0.00	0.00	0.00	0.03
Flemish Brabant (BE24)	0.00	0.00	0.00	0.01	0.83	0.00	0.04	0.00	0.00	0.00	0.02
West Flanders (BE25)	0.01	0.01	0.06	0.00	0.00	0.31	0.00	0.00	0.00	0.00	0.01
Walloon Brabant (BE31)	0.00	0.00	0.00	0.00	0.59	0.00	0.22	0.00	0.00	0.00	0.05
Hainaut (BE32)	0.00	0.00	0.00	0.00	0.38	0.00	0.07	0.00	0.22	0.00	0.06
Liège (BE33)	0.00	0.00	0.00	0.00	0.64	0.00	0.02	0.00	0.13	0.00	0.05
Luxembourg (BE34)	0.00	0.00	0.10	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00
Namur (BE35)	0.00	0.01	0.03	0.01	0.10	0.00	0.01	0.00	0.01	0.00	0.27

Table 3: Composite MSW performance scores for the BCR and its peers as computed using BCR's optimal BoD-derived weights

Region	Composite MSW-performance score using the BCR's weights
Brussels Capital Region (BE10)	0.982
Hamburg (DE60)	0.728
Oberpfalz (DE23)	0.848
Noord-Brabant (NL41)	0.796
Zahodna Slovenija (SI02)	0.597
Overijssel (NL21)	0.841
Southern & Eastern Ireland (IE02)	0.460
Gelderland (NL22)	0.851
Luxembourg (LU)	0.572
Darmstadt (DE71)	0.847
Limburg (BE22)	1.003
Freiburg (DE13)	0.983
NiederÖsterreich (AT12)	0.755
Martinique (FR92)	0.502
Basse-Normandie (FR25)	0.408
Mittelfranken (DE25)	0.782
Border, Midland, Western Ireland (IE01)	0.382

Table 4: Sub-indicator importance weights for Brussels Capital Region and its peers

Region	Conditional BoD-score	Recovery	Composting	Recycling	Waste Generation	Landfilling
Brussels Capital Region (BE10)	0.980	4.8%	0.0%	0.2%	5.0%	90.1%
Hamburg (DE60)	0.851	11.4%	0.1%	4.1%	77.1%	7.2%
Oberpfalz (DE23)	0.976	14.5%	38.5%	5.6%	40.4%	1.0%
Noord-Brabant (NL41)	0.921	0.7%	64.9%	6.3%	9.1%	19.0%
Zahodna Slovenija (SI02)	0.847	33.7%	0.0%	23.9%	42.0%	0.4%
Overijssel (NL21)	0.900	3.2%	36.4%	1.4%	39.6%	19.4%
Southern & Eastern Ireland (IE02)	0.726	88.6%	0.0%	10.4%	0.8%	0.2%
Gelderland (NL22)	0.935	0.3%	51.9%	1.5%	27.0%	19.3%
Luxembourg (LU)	0.741	93.8%	0.9%	4.8%	0.1%	0.4%
Darmstadt (DE71)	0.958	35.2%	12.1%	37.5%	14.4%	0.7%
Limburg (BE22)	1.044	0.6%	20.5%	0.6%	5.7%	72.6%
Freiburg (DE13)	1.046	22.3%	11.9%	57.3%	7.1%	1.5%
NiederÖsterreich (AT12)	0.988	9.2%	83.6%	0.0%	2.0%	5.2%
Martinique (FR92)	0.744	99.7%	0.0%	0.0%	0.2%	0.1%
Basse-Normandie (FR25)	0.696	98.5%	1.1%	0.3%	0.1%	0.0%
Mittelfranken (DE25)	0.925	22.7%	26.1%	16.0%	34.7%	0.5%
Border, Midland, Western Ireland (IE01)	0.710	89.1%	0.0%	10.2%	0.6%	0.1%