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# Disentangling the Cost Efficiency of Jointly Provided Water and Wastewater Services

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**Abstract:**

Providing operators with objective incentives for cost efficiency and continuous improvement in the provision of public services are major concerns for regulators. Measuring efficiency empirically is complex and this complexity is accentuated when the same operator is responsible for delivering more than one service (e.g. in order to explore potential economies of scope). Based on a sample of operators that provide water and wastewater services, this paper uses a shared input data envelopment analysis model to measure separately the efficiency of each service. The results show that a single measure may not provide enough information for monitoring multi-utilities. Together with other indicators, the proposed model can assist decision-makers in prioritizing efforts to improve overall efficiency.

**Keywords:** cost efficiency; multi-utilities; shared input DEA; water sector.

## 1. Introduction

Measuring the cost efficiency in the delivery of public utility services is of crucial importance. For the same level of service, higher efficiencies should lessen the burden on rate and/or taxpayers (if there is regulatory pressure). However, when the same operator delivers more than one service, performance measurement becomes more challenging (Torres and Morrison, 2006) and global efficiency measures tend to be less useful. Traditional methodologies do not always highlight in which service efficiency is lower: a key issue for both decision-makers and regulators.

In a given territory, water and wastewater services are often jointly provided by the same operator. In fact, empirical evidence supports the argument that there are economies of scope between drinking water supply and wastewater collection/treatment/disposal, especially in smaller utilities (Abbott and Cohen, 2009). Most methodologies used in the literature to evaluate the performance of water utilities only estimate overall efficiencies and do not assess the cost efficiency of each activity (e.g. see Gomez and Rubio, 2008 or Romano and Guerrini, 2011 for a general overview of the literature). It could be the case that, for example, a given operator is cost efficient in drinking water supply and inefficient in the delivery of wastewater services. Using an overall efficiency score would not highlight this conclusion in a straightforward manner. Although evaluating the overall efficiency of operators in these cases still has significant value, managing to separate the efficiency of the water and wastewater services could be of further use for decision-makers and regulators.

Several methodologies have been used to assess the performance of water and wastewater services (Berg and Marques, 2011).[1] A conventional classification is the division between parametric and nonparametric methodologies, and both have their strengths and limitations (for a more detailed discussion see Fried, 2008). Despite being widely used in the literature,

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[1] For simplicity, in this paper we use the term ‘water utilities’ to refer to operators that jointly provide drinking water and wastewater services in a given territory.

parametric methodologies require an *a priori* definition of the cost or production function and the acceptance of various assumptions derived from economic theory (which may reduce the acceptability of the results by some members of the scientific community). Nonparametric methodologies use the information 'within the data' to estimate efficiency scores and they do not require as many assumptions or constraints[2]. Among the many methodologies available, the data envelopment analysis (DEA) is the most frequently used by researchers. By means of linear programming, DEA estimates a best practice frontier using the inputs and outputs of all observations and computes efficiencies using the most favorable weights for each decision-making unit (DMU).

The information asymmetries between regulators (independent agencies or local authorities) and operators (public or private) hinder the effectiveness of the regulatory framework (Berg, 2000). Frequently, the lack of transparency and sufficient detail in the annual statements of the operators do not allow the proper design and monitoring of incentives for cost efficiency. Although there are several operators that already do this explicitly in their financial statements, incurred costs (operations and capital) and staff are not typically allocated to the corresponding service (in our case, water and wastewater). To the best of our knowledge, this is the first application of a nonparametric model designed to estimate the cost efficiency of each output (i.e. each service) in the water sector, when both services are jointly provided by the same operator.[3]

The objective of this paper is to propose a model for estimating not only the overall efficiency of water utilities, but also the cost efficiency in each of the services provided. In this case, the

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[2] However, nonparametric methodologies also have some drawbacks. For instance, they are very sensitive to extreme data and outliers, they suffer from the 'curse of dimensionality' problem and they are deterministic methodologies with a non-statistic nature.

[3] Evidently, we are referring to the use of the shared input DEA model (see section 3.3). There are several cases where regulators use (partial) performance indicators to assess the cost efficiency of each service. See, for instance, the case of the Portuguese regulator (ERSAR, 2010).

two services under analysis are drinking water and wastewater services. Using a shared input DEA methodology (see Beasley, 1995; Cook and Green, 2004; and Cook et al., 2000), the authors are also able to report estimates for the cost shares that correspond to each service. Naturally, this methodology could prove to be very useful for regulators and decision makers who wish to benchmark their services against the best practices of the sector.

This article is organized in the following manner. After this introduction, section 2 briefly describes the importance of economic regulation in the water sector. It addresses some international experiences and the difficulties of putting in place an effective framework of incentives for cost efficiency. Section 3 presents the shared input DEA model along with the data used to assess its usefulness (consisting of 253 observations from 45 Portuguese water utilities for the period 2002-2008). Section 4 summarizes the results obtained and, finally, section 5 provides a discussion, concluding the paper.

## 2. Economic regulation and incentives for cost efficiency in the water sector

The water utilities industry presents several features (market failures) that justify regulatory intervention (either implicit or explicit). Among the many concerns, the existence of economies of scale and economies of scope, the ‘essential’ character of the services and their impact on the well-being of society, the existence of asymmetric information, the need for very high (sunk) investments and long-lived assets, and the occurrence of negative (and positive) externalities, should be highlighted (Marques, 2010). These market failures might lead to mismanagement (lack of effort to improve efficiency) and/or misconduct (setting prices above cost recovery levels and thus earning abnormally high profits). Hence, the presence of regulation is crucial for the protection of customer as well as other stakeholder interests. Regulation intends to work as an “invisible hand” that provides the right incentives for the regulated companies to become more productive (Witte and Marques, 2010).

Due to the asymmetric information environment and the magnitude of other market failures, performance-based or incentive regulation is gaining importance in the water sector (Marques, 2010). This regulatory process, sometimes called ‘yardstick competition’, is based on the use of benchmarking tools and in the scorecards obtained to make judgments for the future (Shleifer, 1985). One of the main advantages is the fact that it offers strong incentives towards efficiency and innovation by the water operators, both in their operation and capital expenses (OPEX and CAPEX, respectively). In addition, this methodology also fosters transparency and the sharing of information.

Concerning the regulation of water utilities the literature distinguishes two different benchmarking approaches (Marques, 2006). The first relies on the benchmarking used to set the operators’ prices and tariffs. The types of benchmarking tools used are diverse, varying on the actors and on the features of the countries involved. The UK, Chile and Colombia are some remarkable examples of countries which apply this regulatory methodology. The second approach concerns ‘sunshine regulation’ which consists of the comparison and public discussion of the operators’ performance. Sunshine regulation is very popular in the water sector, not only because it is easily applicable but also because it is better accepted by the water utilities. Several countries, such as Portugal, Australia, Brazil or Zambia have applied this ‘name and shaming’ regulatory methodology with good outcomes.

Regarding the methodologies used in the scope of the first approach, econometric and mathematical programming methodologies are dominant, particularly frontier methodologies such as stochastic frontier analysis (SFA) or DEA. These methodologies use the best practices as benchmarks and normally encompass multiple inputs and outputs. Since these methodologies estimate overall measures of efficiency, they are known as total or global methodologies (see Fried et al., 2008). The second approach uses partial methodologies such as performance indicators (see Alegre et al., 2006), for example the number of employees per thousand of connections or number of bursts per 100 km of mains length. These indices provide only a partial portrait of the issue under analysis but due to simplicity and ease of understanding they are quite popular in the water sector, mostly among engineers and managers. Hence, partial measures are widely used by the operators for managerial purposes and by the regulators to supervise the quality of service. In this article, we will focus on the first regulatory benchmarking approach and on the costs and efficiencies of water and wastewater services (regulation of multi-utilities).

Many regulators all over the world are using benchmarking and performance-based regulatory methodologies (Marques et al., 2011). In order to oversee the quality of service and/or to set prices and tariffs watchdogs are 'using and abusing' this tool (Berg, 2010). Benchmarking allows gathering insights to perform real interpretations of the way utilities work but its careless use might be perverse (Marques and Witte, 2010). One of the major problems is the comparison of 'apples with oranges', which is particularly more serious when operators provide different services such as water, wastewater, electricity or gas (multi-utilities). This paper develops and proposes a methodology to overcome this issue by disentangling the costs and relative efficiencies per service provided.

## 3. Data and methodology

### 3.1 Background: Portuguese water sector

Currently (2012), in Portugal, as in many countries namely in continental Europe, drinking water supply and wastewater services are the responsibility of local governments. One distinctive feature of the Portuguese water sector is the significant vertical disintegration of service provision: 'wholesale' and 'retail' services are usually delivered by different operators (Cruz et al., 2012). In drinking water supply services, the 'wholesale' segment encompasses all activities from water abstraction to reservoir storage (including transportation and treatment). Regarding wastewater services, this segment includes the transportation, treatment and disposal of wastewater. The 'retail' segment of drinking water services therefore consists in the storage and distribution of water to final consumers. Residential wastewater collection corresponds to the ‘retail’ segment of this service. ‘Wholesale’ services are provided by regional operators while municipalities typically ensure the provision of ‘retail’ services in their jurisdictions. Table 1 presents a summary of the market structure of the Portuguese water sector.

[Insert table 1]

The publicly-owned regional operators in charge of ‘wholesale’ services consist of public-public partnerships where the central state is the major shareholder (and the municipalities served by these operators are minor shareholders, Marques, 2008). There is also one private concessionaire operating in the ‘wholesale’ market. Of the 21 operators in this segment, three provide water abstraction, treatment and storage services, six provide wastewater treatment and disposal services and 12 provide both types of services.

Most semi-autonomous operators in the ‘retail’ market are municipally-owned (municipal departments, municipal services or municipal companies). However, since the 1990's, private participation in the water sector has been showing a steady increase, mainly through public-private partnership (PPP) arrangements. Currently, around 21% of the Portuguese population is served by purely contractual (e.g. concessions) or institutionalized (mixed capital companies) PPP arrangements (Cruz and Marques, 2012). The majority of the ‘retail’ operators provide both drinking water and wastewater services. One should note that many of these operators also carry out some activities that are classified as ‘wholesale’ services.

Another defining aspect of the Portuguese water sector is the regulatory framework in place. Unlike most EU countries, Portugal has a sector-specific regulator: The Water and Waste Services Regulation Authority (ERSAR in the Portuguese acronym). The intervention of this regulatory agency has been mainly focused on quality of service issues (by carrying out a sunshine regulation approach, see Marques, 2006). In fact, an annual performance assessment, which covers only concessionaire companies, has been conducted since 2003 using the public disclosure of results as a 'name and shame' strategy. In addition, all 'wholesale' operators have been under explicit economic regulation. Recently, the regulatory power and jurisdiction of ERSAR was enlarged to encompass all water utilities.

### 3.2 Description of the sample

Our sample includes utilities that operate in the Portuguese ‘retail’ segment and exclusively provide drinking water (D) and wastewater (W) services.[4] The data refers to a seven-year period (2002-2008). Thus, the sample contains 253 observations from 45 water utilities serving about 4.4 million inhabitants (of a total of 10.6 million). Figure 1 provides a graphical representation of the four types of operators studied in this paper. The capital letters ‘D’ and ‘W’ are used to refer to drinking water and wastewater services, respectively. The lowercase letters are used to distinguish the operators that carry out ‘retail’ (‘r’) services and the ones that also perform ‘wholesale’ (‘w’) services.[5] For instance, Dr-Wwr operators provide drinking water supply (water ‘retail’ service) and wastewater collection and treatment (wastewater ‘wholesale’ and ‘retail’ services).

[Insert figure 1]

Since there are many more operators in the retail segment, we chose to apply the shared input DEA model to the water and wastewater ‘retail’ market. Regional operators were excluded from

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[4] Some utilities in the sample also carry out such services as water abstraction or wastewater treatment.

[5] We consider that an utility carries out ‘wholesale’ services when its own bulk water production is more than 50% of the total water used in the network (regarding the drinking water supply activity) or when it has wastewater treatment plants (regarding the wastewater treatment activity).

the analysis to maintain the consistency of the sample (moreover, the number of ‘retail’ customers is included as an output variable in the model). All 'retail' operators that also provide municipal solid waste (or other) services were equally excluded from the sample. Figure 2 displays the number of operators according to the type of services provided distributed over time (on the left) and the percentage of the total number of observations recorded throughout the period 2002-2008 (on the right).

[Insert figure 2]

This study uses total cost (in euros) as an input to the model. This variable includes capital costs (sum of depreciation and interest paid) and operational costs. As outputs we considered the number of customers of drinking water supply services and the number of customers served by wastewater collection. Table 2 presents the summary statistics of these input and output variables (overall and for the four clusters of operators). The data were obtained from the annual account reports published by the water utilities and from the annual reports of ERSAR. Since the aim of water utilities is to reduce the inputs consumed for a given level of outputs delivered (minimize costs for a predetermined level of service), in the following analysis an input orientation was adopted.

[Insert table 2]

### 3.3 A shared input DEA model

Most methodologies used in the performance evaluation literature (either parametric or nonparametric) only allow for the estimation of the global efficiencies of each DMU. If the DMU carries out several activities, the analyst is not able to learn which one is the least (or the most) cost efficient. In this paper we implement a nonparametric methodology that allows us to estimate overall and partial cost efficiencies (corresponding to each of the services provided by the DMUs). More specifically, this study intends to evaluate the cost efficiencies of the drinking water and wastewater services for the operators that provide them together. The methodology proposed also allows estimating the share of the total costs allocated to each of the two services for each water utility. This is useful because, occasionally, operators report their costs without detailing the cost shares of each service provided. The methodology is based on the DEA technique, initially developed by Charnes et al. (1978) by extending the ideas of Farrel (1957) and Debreu (1951).

Although parametric methodologies are dominant in the performance measurement literature, nonparametric models present several 'competitive advantages': there is no need to choose a functional form to represent the cost or production function, information about prices of inputs is not necessary and one does not require so many assumptions. 'Traditional' DEA, as for most methodologies in the literature, simply allows the analyst to estimate an overall efficiency $e_k$ for the DMU *k*. These efficiency measures are defined as a ratio between a weighted sum of outputs and a weighted sum of inputs. The methodology selects the optimal weights associated to the respective inputs and outputs in order to maximize the overall efficiency of each DMU. This is especially useful when the details on the exact (real) relative importance of the inputs and outputs in the production or cost function are unknown.

The first proposal for this methodology was the following. Consider that $x \in \Re_{+}^{p}$ are the *p* inputs used by *n* DMUs to produce the *q* outputs $y \in \Re_{+}^{q}$ and that $u_i$ and $v_l$ are the weights of the outputs and inputs, respectively:

$$\max\ e_k = \left(\sum_{i=1}^{q} u_i y_{ik}\right) / \left(\sum_{l=1}^{p} v_l x_{lk}\right) \tag{1}$$

s.t.

$$\left(\sum_{i=1}^{q} u_i y_{ji}\right) / \left(\sum_{l=1}^{p} v_l x_{jl}\right) \leq 1 \qquad j = 1, \ldots, n$$

$$u_i \text{ e } v_l \geq 0$$

This formulation corresponds to an input orientation; i.e. it is implicit that the DMUs aim at rationalizing/minimizing input consumption for a given level of output production. As mentioned above, this is also the orientation adopted in the present study. It is assumed that, for water utilities, demand is an exogenous variable and the objective is to deliver the services at least possible cost for the population.

The formulation presented in (1), however, has a drawback: it presents an infinite number of solutions and the computation is quite complex (Coelli et al. 2005). To overcome these problems, we consider another constraint which is to assume that the denominator of the objective function is equal to the unit:

$$\max\ e_k = \sum_{i=1}^{q} u_i y_{ik} \tag{2}$$

s.t.

$$\sum_{l=1}^{p} v_l x_{lk} = 1$$

$$\sum_{i=1}^{q} u_i y_{ji} - \sum_{l=1}^{p} v_l x_{jl} \leq 0 \qquad j = 1, \ldots, n$$

$$u_i \text{ e } v_l \geq 0$$

Later on, this formulation evolved to its dual form:

$$\min e_k \tag{3}$$

s.t.

$$y_k - \sum_{i=1}^{n} \lambda_i y_i \leq 0$$

$$-e_k\, x_k + \sum_{i=1}^{n} \lambda_i x_i \leq 0$$

$$\lambda \geq 0$$

The model described above considers the existence of constant returns to scale (CRS). According to Banker et al. (1984), to assume a variable returns to scale (VRS) technology one needs to add the constraint $\sum_{i=1}^{n} \lambda_i = 1$ to the formulation on (3).

The DEA methodology uses linear programming to construct a nonparametric piecewise linear frontier over the data. The efficiency scores of observations are computed against that frontier.[6] However, as already mentioned, DEA models have some shortcomings. On the one hand, it simply provides one overall efficiency score for operators that deliver several services or produce many outputs; this does not allow regulators to know the partial efficiencies (and cost shares) corresponding to each activity or service. On the other hand, DEA models adopt input and output weights for the computation of efficiency scores that are not necessarily real. In the current study we use and adaptation of the DEA model that allows for estimating the cost shares allocated to each output or service provided by the DMUs. This is particularly relevant for multi-utilities operating in the water sector because the annual account reports do not always present incurred costs per type of activity carried out. This information is only known by managers (if known at all).

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[6] The observations located on the frontier are considered to be cost efficient and have efficiency scores equal to the unit. Observations that lie below the ‘best practice frontier’ are regarded as inefficient, exhibiting efficiency scores below the unit.

To estimate the cost share of each activity as well as the respective cost efficiencies, we implement a shared input DEA model as suggested by Beasley (1995) and others, such as Jahanshahloo et al. (2004) and Chen et al. (2010). This adapted DEA model computes the cost shares and partial efficiencies simultaneously, envisaging the maximization of the overall efficiency. To this end, the constraints (4.4), (4.5) and (4.6) are added to the formulation shown in (3). Thus, the model goes as follows:

$$\max\ e_k = \sum_{i=1}^{q} u_i y_{ik} \tag{4.1}$$

s.t.

$$\sum_{l=1}^{p} v_l x_{lk} = 1 \tag{4.2}$$

$$\sum_{i=1}^{q} u_i y_{ji} - \sum_{l=1}^{p} v_l x_{jl} \leq 0 \qquad j = 1,\ldots,n \tag{4.3}$$

$$\sum_{i=1}^{r} u_i y_{ji} - \sum_{l=1}^{s} \alpha_i v_l x_{jl} \leq 0 \qquad j = 1,\ldots,n; i = 1,\ldots,q \tag{4.4}$$

$$\sum_{i=1}^{q} \alpha_i = 1 \qquad j = 1,\ldots,n \tag{4.5}$$

$$\varepsilon_{\min} \leq \alpha_i \leq \varepsilon_{\max} \tag{4.6}$$

$$u_i \text{ e } v_l \geq 0 \tag{4.7}$$

Where $\alpha_i$ is the ratio of inputs (costs) associated with service *i* and $e_k$ is the overall cost efficiency score of DMU *k*. As in ‘traditional DEA’, higher scores indicate higher overall cost efficiencies.

On constraint (4.4), the parcel $\sum_{i=1}^{r} u_i y_{ji}$ consists of the sum of the *r* weighted outputs concerning activity *i* and $\sum_{l=1}^{s} \alpha_i v_l x_{jl}$ the *s* weighted inputs consumed in activity *i*. In the current study, since there is only one output associated with each service and only one input for both activities (total costs), this is simplified to $u_i y_{ji} - \alpha_i v_l x_{jl} \leq 0$. The objective of this constraint is to compute the optimal cost shares for each DMU, imposing that the partial cost efficiency scores $e_{ki}$ are below the unit. Furthermore, the constraint (4.5) ensures that the total costs are fully allocated to the various activities carried out by the DMUs. Constraint (4.6) allows for the imposition of a minimum and maximum cost share to be allocated to activity *i*, which is useful when one has some knowledge regarding the actual range of these values. The methodology will look for the most favorable option within the admissible range of values in order to maximize the overall efficiency of each DMU. In the current study we opted not to include limits to the values for the cost shares. Instead, we adopted the constraint $u_1 \geq u_2$. This restriction imposes a higher weight for the drinking water services (in relation to the wastewater services). This makes sense because 1) in all Portuguese municipalities the number of drinking water customers is always higher than the number of customers of wastewater services (not all customers have a connection to the wastewater network), and 2) experience shows that, generally in Portugal, drinking water services have higher costs associated.

At last, the overall (aggregate) cost efficiency scores are determined through the partial cost efficiency estimates $e_{ki}$ weighted by the respective DEA-estimated cost shares:

$$e_k = \sum_{i=1}^{q} \alpha_i e_{ki} \tag{5}$$

Where the partial cost efficiency scores $e_{ki}$ are defined as a ratio between the weighted sum of the *r* outputs concerning service *i* and the weighted sum of the *s* inputs consumed by service *i*:

$$e_{ki} = \sum_{i=1}^{r} u_i y_{ji} \Big/ \sum_{l=1}^{s} \alpha_i v_l x_{jl} \tag{6}$$

In the following sections the partial cost efficiencies $e_{k1}$ and $e_{k2}$ refer to drinking water services and wastewater services, respectively. In a similar fashion, $\alpha_1$ and $\alpha_2$ refer to the inputs (costs) allocated to drinking water services and wastewater services, respectively.

## 4. Empirical results

Using the shared input DEA model described in the previous section we were able evaluate the cost efficiency of the different activities carried out by the water utilities (drinking water and wastewater services). During the process the estimates for the cost shares of the services were also computed for all operators. The results confirm the expectation that, typically, drinking water services are more relevant in the cost structure of the operators (i.e. $\alpha_1 > \alpha_2$ for a 95%: confidence level: *p-value* of the Kruskal-Wallis test = 5.555e-078 < 0.05). In fact, on average and regarding the Portuguese ‘retail’ segment, drinking water services are responsible for 64% of the total costs (while the remaining costs are allocated to wastewater services). Table 3 presents the overall and partial cost efficiency estimates along with the respective cost shares for all observations in the sample. As we have mentioned above, for the same DMU, the sample includes values from different years. In our formulation, the cost shares are allowed to vary freely from one year to the other and this could lead to inconsistent results. However, the results show that the cost share estimates do not change significantly for the same operator.

[Insert table 3]

Although the results reveal that, on average, drinking water services seem to be slightly more efficient than wastewater services (i.e. $e_{k1} > e_{k2}$) this difference is not statistically significant at a 95% confidence level according to the results obtained by the Kruskal-Wallis test (*p-value* = 0.729 > 0.05). As it can be seen in figure 3, the partial cost efficiencies $e_{k1}$ and $e_{k2}$ are directly correlated indicating that, in general, the operators exhibit similar partial cost efficiencies for both services, although some have higher efficiencies for drinking water services (when the average partial cost efficiency $e_{k1}$ is higher than the average of $e_{k2}$). Note that, for regulators and managers, it is interesting to learn where each operator is standing in the scatter plot of figure 3.

[Insert figure 3]

As shown in figure 4 and tables 4 and 5, if we cluster the observations by type of services provided (see figure 1) it is possible to discern that 'retail' operators that also carry out drinking water 'wholesale' services present higher overall and '$e_{k1}$' efficiencies. This could be an indication of the presence of economies of vertical integration for drinking water services. These results are in line with the literature. Indeed, economies of vertical integration have been observed in the water and wastewater sectors, particularly in smaller utilities (Abbott and Cohen, 2009). Furthermore, the 'Drw-Wrw' operators correspond to the observations that present higher cost efficiencies for wastewater services ('$e_{k2}$'). This obviously makes 'Drw-Wrw' and 'Drw-Wr' operators the most efficient ones (especially the 'Drw-Wrw' operators). Figure 4 ant table 4 also present the 'traditional DEA' CRS and VRS efficiency scores.

[Insert figure 4]

[Insert table 4]

[Insert table 5]

Figure 5 helps us to illustrate the usefulness of the model presented in this paper. To a great extent, more than drawing wide-ranging conclusions about a sector, this methodology is especially useful for evaluating each operator individually. In addition to the shared-input DEA overall and partial efficiencies, this graphical representation also shows the CRS, VRS and scale efficiency (SE) scores for each cluster of operators.[7] Note that drawing these spider charts for each individual operator would be very relevant both for regulators and managers (creating a sort of “water utility scorecard” that provides detailed information to the analyst). This way, one is able to have the perception of the overall efficiency of the operator and also learn on which services there is more room for improvement.

[Insert figure 5]

## 5. Discussion and conclusion

The results show that the major share of the total costs of multi-utilities providing water and wastewater services are allocated to drinking water supply (around 64%, on average). The shared input DEA model also allowed us to conclude that there is no statistical significant difference between the efficiencies of drinking water services and wastewater services. Furthermore, it seems that vertically integrated operators (providing ‘retail’ and ‘wholesale’ drinking water and wastewater services) have higher cost efficiencies for both services and therefore also in overall terms. This is an interesting finding with potential policy implications

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[7] SE scores are obtained by dividing CRS scores by VRS scores (using the ‘traditional DEA’ model).

(that go against recent reforms, for instance, in Portugal and the Netherlands). However, detecting the presence of economies of vertical integration is neither the major objective of this paper nor the main usefulness of the shared input DEA model. Additional research should be carried out on this topic regarding the Portuguese 'retail' water and wastewater markets.

As we have shown (for instance in figure 5), used in conjugation with 'traditional' methodologies for measuring global performance, the model proposed in this paper to disentangle the cost efficiency of water and wastewater services can generate more information that is useful for the missions of regulators and managers. Since it allows for identifying asymmetric performances in water and wastewater services when these are jointly provided by the same operator, the methodology would especially useful for the operators that are far away from the central tendency (regression), as exemplified in figure 3.

The usual lack of transparency and detailed financial information regarding the management of water utilities often hinders the effectiveness of regulation. The proposed methodology tries to cope with this reality and provides a solution to the classic problem of information asymmetry. Moreover, as the primary regulators of the water and wastewater services provided in their jurisdictions, municipalities are in need of useful tools for monitoring their utilities. Indeed, the exercise carried out in this paper could be repeated individually for all water utilities. The shared input DEA model does not only provide local governments with their 'global' picture, it also allows for the identification of those activities for which there is still room for improvements. Finally, the fact that the methodology implemented computes the most favorable cost efficiency score for each operator (as in 'traditional DEA' and given the proper constraints), increases the acceptability of the model as a performance assessment tool.

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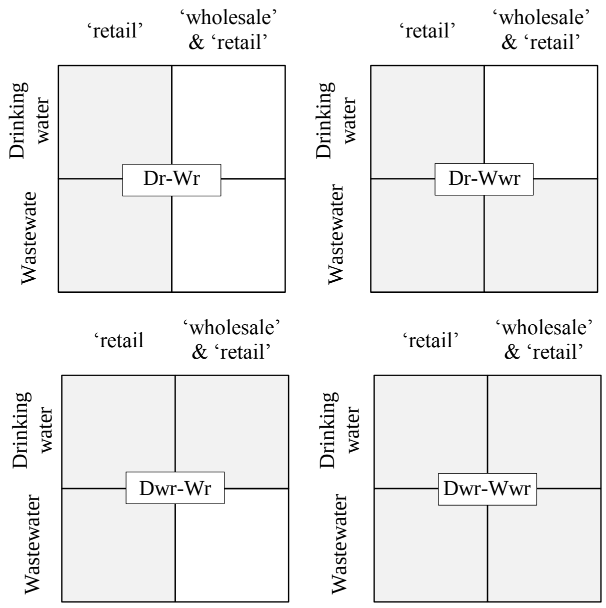

**Figure 1 – Types of water utilities in the sample according to their degree of vertical integration**

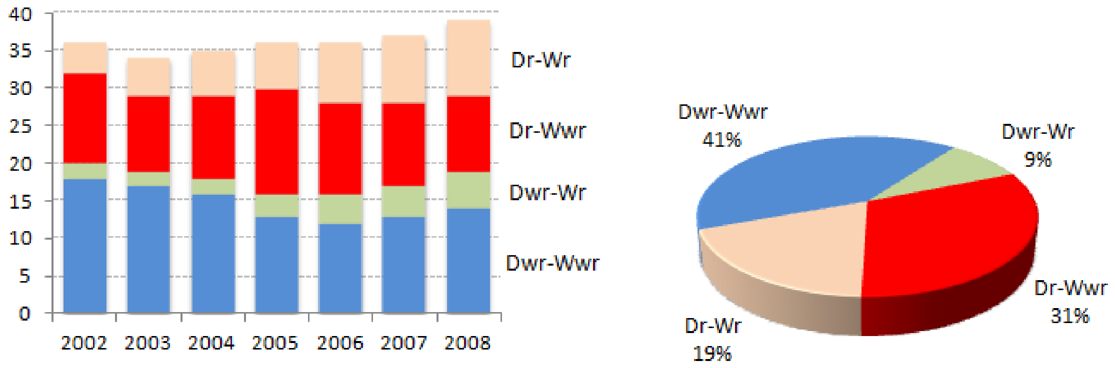

Figure 2 – Number of operators and number of observations clustered by type of service provided

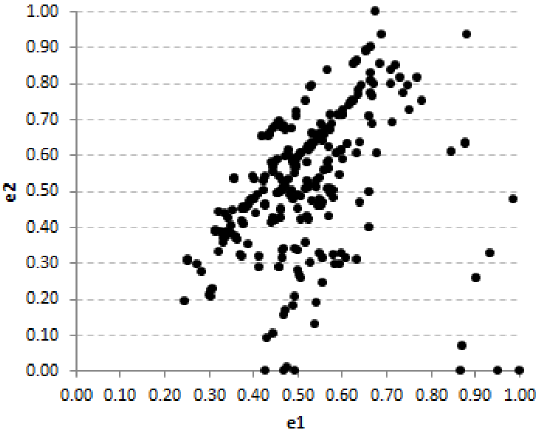

**Figure 3 – Scatter plot of the partial cost efficiency scores $e_{k1}$ and $e_{k2}$**

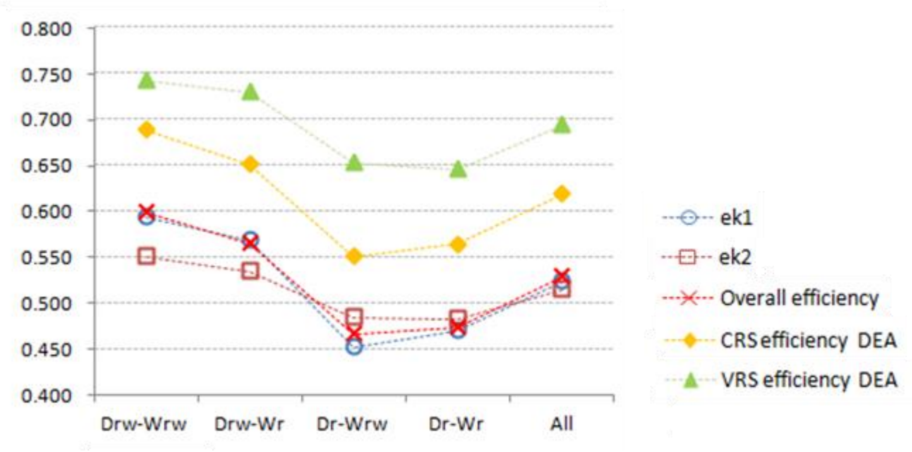

Figure 4 – Plot of shared input DEA overall and partial cost efficiency scores and DEA efficiency scores clustered by type of utility (average values)

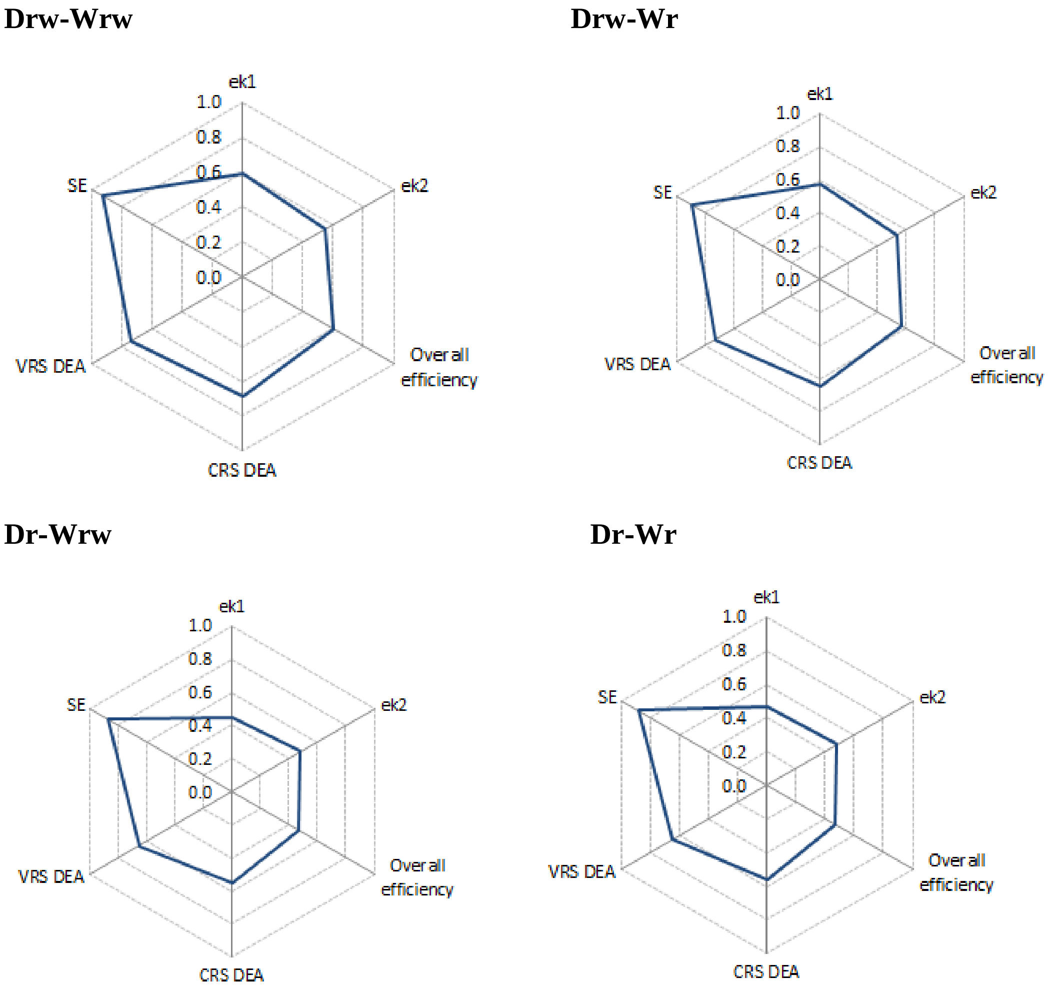

**Figure 5 – Detailed information on the cost efficiency of water utilities (average values)**

**Table 1 – Market structure of the Portuguese water sector. Source: ERSAR (2010).**

| | Management model | | |
|---|---|---|---|
| | Private (no.) | Mixed (no.) | Public (no.) |
| **‘Wholesale’ segment** | 1 | 0 | 20 |
| **‘Retail’ segment** | 28 | 5 | 246 |

Note: not all ‘retail’ segment operators are served by the wholesale operators

### Table 2 – Summary statistics of input and output variables for the utilities in the sample

|  | **Statistics** | **Average** | **Median** | **St. Deviation** | **Minimum** | **Maximum** | **Utilities (no.)** | **Obs. (no.)** |
|---|---|---|---|---|---|---|---|---|
|  |  |  |  |  | **All utilities** |  |  |  |
| Input | Total costs (€) | 12,168,457 | 7,547,850 | 12,037,577 | 895,154 | 53,061,841 |  |  |
| Outputs | Water customers | 48,359 | 30,400 | 45,290 | 4,553 | 185,784 | 47 | 253 |
|  | Wastewater customers | 36,154 | 18,672 | 39,790 | 1,222 | 185,561 |  |  |
|  |  |  |  |  | **Dwr-Wwr** |  |  |  |
| Input | Total costs (€) | 6,595,039 | 4,899,671 | 5,522,676 | 986,866 | 24,348,746 |  |  |
| Outputs | Water customers | 30,719 | 24,971 | 25,418 | 4,553 | 105,243 | 18 | 103 |
|  | Wastewater customers | 21,760 | 13,747 | 22,507 | 1,223 | 102,643 |  |  |
|  |  |  |  |  | **Dwr-Wr** |  |  |  |
| Input | Total costs (€) | 8,752,367 | 8,978,700 | 4,051,488 | 3,687,439 | 15,343,292 |  |  |
| Outputs | Water customers | 38,779 | 29,016 | 16,714 | 19,839 | 59,189 | 5 | 22 |
|  | Wastewater customers | 22,257 | 18,543 | 10,362 | 14,600 | 51,293 |  |  |
|  |  |  |  |  | **Dr-Wwr** |  |  |  |
| Input | Total costs (€) | 16,945,857 | 12,277,266 | 14,560,864 | 1,550,328 | 53,061,841 |  |  |
| Outputs | Water customers | 63,159 | 39,077 | 53,758 | 7,059 | 185,561 | 14 | 80 |
|  | Wastewater customers | 49,697 | 36,404 | 49,289 | 3,346 | 185,561 |  |  |
|  |  |  |  |  | **Dr-Wr** |  |  |  |
| Input | Total costs (€) | 17,731,457 | 10,837,313 | 14,249,212 | 895,154 | 41,896,638 |  |  |
| Outputs | Water customers | 65,937 | 35,068 | 56,569 | 4,915 | 185,784 | 10 | 48 |
|  | Wastewater customers | 50,836 | 27,616 | 46,703 | 4,464 | 147,141 |  |  |

**Table 3 – Descriptive statistics of the estimates for water utilities cost efficiencies and cost shares**

| | | **Average** | **St dev.** | **Min** | **Max** | **25 percentile** | **50 percentile** | **75 percentile** |
|---|---|---|---|---|---|---|---|---|
| **Efficiency estimates** | $e_k$ | 0.530 | 0.138 | 0.154 | 1.000 | 0.432 | 0.522 | 0.605 |
| | $e_{k1}$ | 0.523 | 0.135 | 0.246 | 1.000 | 0.444 | 0.506 | 0.592 |
| | $e_{k2}$ | 0.515 | 0.199 | 0.000 | 1.000 | 0.387 | 0.511 | 0.655 |
| **Cost share estimates** | $\alpha_1$ | 0.641 | 0.107 | 0.179 | 1.000 | 0.602 | 0.602 | 0.631 |
| | $\alpha_2$ | 0.359 | 0.107 | 0.000 | 0.821 | 0.369 | 0.398 | 0.398 |

**Table 4 – Shared input DEA overall and partial cost efficiency scores and DEA efficiency scores clustered by type of utility (average and median values)**

| | | **Drw-Wrw** | **Drw-Wr** | **Dr-Wrw** | **Dr-Wr** | **All** |
|---|---|---|---|---|---|---|
| **Average** | $e_k$ | 0.598 | 0.565 | 0.465 | 0.473 | 0.530 |
| | $e_{k1}$ | 0.593 | 0.569 | 0.452 | 0.470 | 0.523 |
| | $e_{k2}$ | 0.550 | 0.534 | 0.485 | 0.482 | 0.515 |
| | CRS-DEA | 0.688 | 0.651 | 0.551 | 0.564 | 0.618 |
| | VRS-DEA | 0.742 | 0.731 | 0.654 | 0.646 | 0.695 |
| **Medians** | $e_k$ | 0.591 | 0.527 | 0.491 | 0.444 | 0.522 |
| | $e_{k1}$ | 0.571 | 0.577 | 0.451 | 0.486 | 0.506 |
| | $e_{k2}$ | 0.605 | 0.547 | 0.491 | 0.476 | 0.511 |
| | CRS-DEA | 0.672 | 0.616 | 0.561 | 0.544 | 0.604 |
| | VRS-DEA | 0.780 | 0.777 | 0.676 | 0.586 | 0.693 |
| **number of observations** | | 103 | 22 | 80 | 48 | 253 |

**Table 5 – Results obtained by Kruskal-Wallis test when comparing the shared input DEA overall and partial cost efficiency scores clustered by type of utility**

| | Drw-Wrw | | Drw-Wr | | Dr-Wrw | |
|---|---|---|---|---|---|---|
| **Drw-Wr** | Overall eff. (0.407) = | | | | | |
| | $e_{k1}$ | $e_{k2}$ | | | | |
| | (0.856) = | (0.529) = | | | | |
| **Dr-Wrw** | Overall eff. (1.800e-9) ≠ | | Overall eff. (0.002) ≠ | | | |
| | $e_{k1}$ | $e_{k2}$ | $e_{k1}$ | $e_{k2}$ | | |
| | (3.987e-12) ≠ | (0.002) ≠ | (3.667e-6) ≠ | (0.420) = | | |
| **Dr-Wr** | Overall eff. (2.945e-7) ≠ | | Overall eff. (0.004) ≠ | | Overall eff. (0.902) = | |
| | $e_{k1}$ | $e_{k2}$ | $e_{k1}$ | $e_{k2}$ | $e_{k1}$ | $e_{k2}$ |
| | (1.921e-7) ≠ | (0.005) ≠ | (2.000e-4) ≠ | (0.330) = | (0.174) = | (0.723) = |

*p-values* in parentheses; = means that the samples are not statistically different to the 95% confidence level; ≠ means that the samples are statistically different to the 95% confidence level