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Economic and environmental efficiency of UK and Ireland water companies: Influence of exogenous factors and rurality

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Abstract

For water companies, benchmarking their performance relative to other companies can be an effective way to identify the scope for efficiency gains to be made through infrastructure investment and operational improvements. However, a key limitation to benchmarking is the confounding effect of exogenous factors, which may not be factored in to benchmarking methodologies. The purpose of this study was to provide an unbiased comparison of efficiency across a sample of water and sewage companies, accounting for important exogenous factors. Bias-corrected economic and environmental efficiency estimates with explanatory factors were evaluated for a sample of 13 water and sewage companies in the UK and Ireland, using a double-bootstrap data envelopment analysis (DEA) approach. Bias correction for economic and environmental efficiency changed the rankings of nine and eight companies, respectively. On average, companies could reduce economic inputs by 19% and carbon outputs by 16% if they performed at the efficiency frontier. Variables explaining efficiency were: source of water, leakage rate, per capita consumption and population density. Population density showed statistical significance with both economic (p-value 0.002) and environmental (p-value 0.001) efficiency. Consequently, a rurality factor was defined for each company's operational area, which was then regressed against normalised water company performance data. More rural water companies spend more per property (R^2 of 0.633), in part reflecting a larger number of smaller sewage treatment works serving rural populations (R^2 of

0.823). These findings provide new insight into methods for benchmarking, and factors affecting, water company efficiency, pertinent for both regulators and water companies.

Key words: Data Envelopment Analysis, Double-Bootstrap, Water Utilities, Performance Analysis, Explanatory Factors, Urbanity

1. Introduction

The water and sewage industry has fundamental links to all aspects of sustainability, those being economic, social and environmental considerations. This is through the sector being responsible for delivering potable water, a social necessity, which requires significant amounts of energy, physical infrastructure (treatment plants and pipes) and financial inputs to purify, distribute, and treat before and after usage to protect receiving waters and uphold sanitary standards (Olsson, 2015; Saleh and Gupta, 2016). Increasing economic and environmental efficiency reduces the consumption of resources and could enable a more reliable service, in line with industry, consumer and societal interests. Benchmarking is regarded as a valuable tool for increasing efficiency because it can be used to evaluate the comparative performance of companies, underpinning effective regulation. Examples where benchmarking is used by regulators arise in many different countries, such as England and Wales via Office of Water Services (OFWAT), Portugal by Entidade Reguladora dos Serviços de Águas e Resíduos (ERSAR) and Latin America via Regulación de Agua y Saneamiento en las Américas (ADERASA) (Berg, 2013), to name just a few. Even where regulators do not employ benchmarking, companies are taking it up themselves to help them perform competitively against sector leaders and to enable innovation collaborations for best practices. This is evidenced by voluntary subscriptions to organisations such as the EU Benchmarking Co-operation, South East Asia Water Utility Network (SEAWUN), and the International Benchmarking Network (IBNET), which compare key indicators from water utilities across international boundaries (Asian Development Bank, 2018; IBNET, 2018).

Benchmarking is also a topic of interest in academia. Frequent attempts have been made to refine and optimise benchmarking methodologies for the water sector as well as to validate new techniques (Daraio and Simar, 2006; Berg, 2013) and provide evidence on factors that influence efficiency (De Witte and Marques, 2010a; Lannier and Porcher, 2013; Marques et al. 2014). The most popular type of method for conducting benchmarking in the literature is production frontier analysis (Berg, 2013). A production frontier can be calculated with parametric methods (Kumbhakar and Lovell, 2004) or non-parametric methods such as data envelopment analysis (DEA), which is the most popular of the production frontier methods (Song et al. 2012). The reason for the popularity of DEA is that is has three fundamental characteristics, which make it beneficial for assessing water and sewerage companies (WaSCs). 1) It integrates multiple inputs and outputs for each unit, providing a multi-criteria analysis; 2) weightings applied to aggregate inputs and outputs are generated endogenously; and 3) it does not require a priori assumptions about the functional relationship between the inputs and outputs (Berg, 2013).

In spite of the advantages that DEA offers, it has a crucial limitation in that it is a deterministic method, meaning statistical inferences cannot be drawn from conventional DEA efficiency scores (Simar and Wilson, 2007). This is of particular relevance for WaSCs, since DEA does not allow the use of regression analysis to evaluate the explanatory factors. Cazals et al. (2002) proposed a method to overcome this limitation, referred to as ‘order-m’, which is a partial frontier method that uses a portion of the original population sample to estimate the efficiency scores. Despite the advantages of the ‘order-m’ method in terms of enabling statistical evaluation of efficiency scores, it has drawbacks (Daraio and Simar, 2006). The limitations are specifically related to the selection of ‘m’, that is the sample taken from the original larger sample – the representativeness of this sample greatly affects the efficiency scores (Da Cruz and Marques, 2014).

An alternative approach is Simar and Wilson’s (2007) double-bootstrap procedure, which allows for hypothesis-testing and statistical inferences in the DEA method, thus enabling the exploration of determinants of efficiency, whilst also bias-correcting the efficiency scores yielded from the DEA model (Yang and Zhang, 2018). As Gomez et al. (2017) note, the advantages of the bootstrap method have led to its application in an array of different areas, such as banking (Tziogkidis et al., 2018) and educational institutions (Andersson et al., 2017), as well as water companies (De Witte and Marques, 2010b; Ananda, 2014). However, the double-bootstrap DEA method has not been used extensively on water and sewage companies previously, with only one study (Molinos-Senate et al. 2018) to the best of our knowledge having done so.

Many research papers have assessed explanatory factors for the reasons behind the performance of their analysed water utilities and networks, with Conti (2005) highlighting the "role played by environmental variables in 'shaping' both the technology and the efficiency levels of the water utility industry". Examples include, but are not limited to ownership, size, technology use, energy consumption, source of water, year of construction, peak factor, and particularly relevant to this study population density (Abbott and Cohen, 2009; Guerrini et al., 2011; Molinos-Senante, et al., 2013; Molinos-Senante and Guzmán, 2018; Peda, et al., 2011; Renzetti and Dupont, 2009).

Despite there being a diverse range of exogenous factors evaluated in performance assessments of water utilities, "rurality" is a potentially pertinent differentiating factor that is rarely explored. De Witte and Marques (2010a) documented just eight academic studies prior to their 2010 publication that included customer or population density (a proxy for rurality), as an explanatory factor. Aside from those eight, there have been very few following this. A few notable studies are Carvalho and Marques (2011), Lannier and Porcher (2013), and Marques et al. (2014). Since population density is only a crude partial indicator if used to assess the influence of rurality/urbanity, a different approach is needed. There is, however, very little literature available discussing methodologies for assessing or clustering the catchments for water authorities, especially in terms of rural/urban split. Perhaps most relevant work with regard to quantifying geographic situation is Neunteufel (2017), where the use of urban classifications to aid management decisions is used. This study highlighted how leakage rate should be perceived differently in terms of acceptable performance when considering the age of piping. The analysis was conducted via a clustering exercise, with prescribed boundaries to classify between rural, urban and metropolitan (described as "Urbanity" cluster).

The reason rurality is of interest is that without accounting for it in efficiency analysis and benchmarking, it limits avenues for improvement and it may appear that companies which operate more rurally than others are performing poorly. This has relevance for all performance across water only companies (WoCs) and WaSCs operating at varying scales of urbanity furthermore, it may be relevant to regulators when evaluating whether companies are doing enough to be efficient.

There were three objectives to this study, which are discussed in order throughout the upcoming sections. Firstly, bias-corrected comparison of economic and environmental efficiency scores across UK and Irish WaSCs. Secondly, identification of key factors that may affect bias-corrected efficiency scores. Thirdly, development of a framework to assess the influence of rurality on operational efficiency across a set of English and Welsh WoCs and WaSCs. Collectively, these objectives provide novel insight for the water services industry and contribute to the academic literature on benchmarking by displaying alternative methodologies, contributing bias-corrected results and analysis of factors affecting economic and environmental efficiency across the UK and Ireland.

2. Methodology

2.1. Efficiency estimate

In order to estimate the economic and carbon efficiency of UK and Irish water and sewage companies as well as the factors affecting their efficiencies, Simar and Wilson's (2007) double-bootstrap DEA model with a truncated bootstrapped regression was used. This approach enabled bias-corrected efficiencies to be obtained, and facilitated an assessment of the variables that influence these efficiencies. The wider advantages of this method have already been mentioned above.

2.1.1. Sample and data description for efficiency estimate

The sample for the economic efficiency analysis consisted of 13 WaSCs in the UK and Ireland, whilst the environmental carbon analysis consisted of 12 WaSCs in the UK alone. The reported efficiency parameters were for the period April 2014 to April 2015. When applying a

DEA model, the sample should be as homogenous as possible; companies in this sample were all of similar size and conduct comparable operations. The source of the data was largely from Water UK (2015), a national organisation that represents and works with WaSCs throughout the UK, collating key UK water utility data from annual company reports. For data points that were missing from the Water UK set, alternative sources were accessed and are outlined as follows. Wastewater treatment volumes were largely sourced from 2017/18 data sets due to poor data availability for 2014/15; inter-annual variance in wastewater treatment volume is not significant (only 0.4% average year on year variance expected in the next 8 years according to the PR19 OFWAT data tables, data not shown). The wastewater data source for UK companies was OFWAT and their PR19 data tables (OFWAT, 2018). For Irish Water, it was their business plan document (Irish Water, 2015a) which provided the majority of their data except operational expenditure (OPEX) which came from a 2015 financial statements document (Irish Water, 2015b) and wastewater compliance information, which came from a wastewater treatment report by the Irish Environmental Protection Agency (2016). For Scottish Water, water delivered and per capita consumption data were recovered from a report from the Water Industry Commission for Scotland (2015), whilst their OPEX data were sourced from one of their own asset reports (Scottish Water, 2015). OPEX data were also acquired for Northern Ireland Water through an annual report (Northern Ireland Water, 2015). Finally, the percentage of abstracted water coming from surface water for all UK companies was obtained via direct correspondence with the British Geological Survey (M Ascott 2018, personal communication, 19 September).

The number of units (WaSCs) available for analysis in the DEA models was small relative to most studies on water utilities, and for a DEA model to avoid relative efficiency discrimination problems; the sample needs to meet a minimum size threshold. To determine a size thresholds that avoids discrimination problems, 'Cooper's rule' was used here, which states the number of units to be analysed must be ≥ max$\{m\ x\ s; 3(m+s)\}$ where m is the number of inputs and s is the number of outputs used in the model (Cooper et al. 2007). Since the samples used in this paper were 13 and 12, and both the economic and environmental assessments use two inputs and one output, ‘Cooper’s rule’ was met. Furthermore, Molinos-Senate et al. (2018) comments that utilising DEA with a bootstrap procedure ensured more accurate efficiency scores with a limited sample size.

The selection of representative inputs and outputs is imperative for a DEA model to produce valid results. The two inputs used in the economic model were OPEX and capital expenditure (CAPEX) as these accurately represent the key aspects of financial operations within a water company. OPEX in this study was made up of both wholesale and retail expenditure and excludes exceptional items, depreciation and amortisation. CAPEX was used under the assumption that the companies in the sample contribute enough for it to be sufficient to maintain and renew the distribution network long-term. Since Ireland’s currency is Euros, Irish Water’s OPEX and CAPEX figures had to be converted to GBP for the analysis using the 2011-2015 average exchange rate of 0.814 (Statista, 2018). The two inputs used in the environmental model are operational greenhouse gas (carbon dioxide equivalent) emissions and kilometres of water mains and sewage piping, which represents embedded emissions within capital assets. The length of sewage and delivery network provide a suitable proxy for embedded carbon emissions within a company given the dominance of this infrastructure in terms of material inputs. Greenhouse gas emissions, to the authors’ knowledge, has not been assessed with the DEA method within the water utility literature. However; many studies have used length of piping as a proxy to represent financial capital (Mbuvi et al. 2012; Ananda, 2014; See, 2015; Molinos-Senate et al. 2018) and fixed assets have been used to estimate carbon in other DEA literature (Zhu, 2018).

One output was used for both the environmental and economic efficiency analyses. This output is a combined volume of both water delivered and wastewater treated and combines the two key determinants of resource use within water utilities, reflecting the most common outputs used in the DEA water utility literature (De Witte and Marques, 2010a, Guerrini et al. 2013). The water delivered volumes were estimated from subtracting leakage rates away from distribution input, which is the amount of water entering the distribution system at the point of production. The wastewater treated volumes encompass all water treated at treatment plants, not just effluent from businesses and homes.

A fundamental driver of resource use within WaSCs is the quality of water they produce and the wastewater they dispose of (Plappally and Lienhard, 2012; Maziotis et al. 2015). With this in mind, companies should not be penalised in terms of efficiency assessment for producing higher quality outputs than others; therefore, this study follows Saal et al. (2007) and Molinos-Senate et al. (2015) and adjusts the two indicators used to calculate net output according to available water quality parameters. Water delivered was corrected by the quality of the water (y_1) and wastewater treated was adjusted based on wastewater discharge permit compliance (y_2). The quality indicators are reported as percentages, with 100% meaning that all legal requirements are met. For this study, they are converted to decimals and are used as multipliers for the original output data, defined thus:

$$y_1 = WD \times DWQ \tag{1}$$

$$y_2 = WWT \times DPC \tag{2}$$

Where y_1 is the quality-adjusted water delivered; WD is the volume of drinking water delivered to customers; DWQ is drinking water quality; y_2 is the quality-adjusted wastewater volume treated; WWT is the wastewater treated volume; DPC is discharge permit compliance, an appropriate wastewater discharge quality proxy. The resulting figures for the indicators y_1 and y_2 then made up the solo output of both the environmental and economic DEA analysis.

In an attempt to decipher the reasons behind companies performing the way that they do, population density, percentage of abstracted water being from surface water, leakage and consumption per capita were used as the determinant variables to evaluate. These were selected as the most likely determinants of efficiency available from the aforementioned data sources, based on results of previous studies summarised above (De Witte and Marques, 2010a; Carvalho and Marques, 2011; Marques et al. 2014; Molinos-Senate et al. 2018). The variables used for analysing the determinants of efficiency along with the inputs, outputs and quality variables used to determine the efficiency scores are summarised in Table 1.

Table 1. *Data sample description for use in DEA analyses.*

		Average	SD	Minimum	Maximum
Inputs	Operational expenditure (million£)	399.855	207.360	165.2	823.6
	Capital expenditure (million£)	446.518	327.612	155.8	1321.6
	Operational GHG emissions ($KtCO_2e$)	365.417	185.787	148	824
	Length of mains and sewage pipes (km)	82,460.167	39,081.390	30,961	139,880
Outputs	Water delivered & wastewater treated (ML/ day)	2555.944	1587.173	738.47	6338.108
Quality Variables	Drinking water quality (%)	99.9	0.1	99.5	100
	Discharge permit compliance (%)	97.2	4.7	83	99.9
Explanatory Variables	Consumption per capita (l/h/d) (excluding leakage)	138.873	16.017	115	181.159
	Population density (Population/km^2)	66.889	16.848	42.323	106.084
	Leakage (%)	24.35	8.992	12.411	49
	Surface water (%)	72.038	26.939	11.5	99.9

2.1.2. Standard DEA model

The DEA method was originally produced by Farrell (1957) and later developed by Charnes et al. (1978), and has since been frequently used to assess a vast array of water utilities (Berg, 2013). It is a non-parametric technique that employs linear programming to facilitate the creation of the efficient production frontier. The frontier develops the relative efficiency of the sample of decision-making units (DMUs), which in this case are the UK and Ireland water utilities, by comparing their inputs and outputs in relation one and other within the sample (Charnes et al. 1978). The technical efficiency of each DMU is then gauged by evaluating how far it is away from the frontier.

The model of the DEA method can orientate towards either inputs or outputs. Generally, water and sewage companies do not have much control over the quantity of their outputs, those largely being determined by demand for drinking water and sewage treatment. They do however have a large influence over their inputs, with a goal to reduce the resources going into them as much as possible, whilst still producing those outputs at the same standard; therefore, this study employed an input-orientated model. This is in line with similar literature that analyses water utilities with DEA methods (De Witte and Marques, 2010a; Berg, 2013). Furthermore, the model was based on varying returns to scale (VRS), which allows for scale effects. This is a reasonable assumption to make since the WaSCs being assessed are of various sizes and are likely to produce differing level of outputs with same level of inputs, which again, is concurrent with the majority of the literature (Berg and Marques, 2010; Peda et al. 2011; Guerrini et al. 2015; See, 2015).

Given j = 1, 2…, N units, each one using a vector of M inputs $x_j = (x_{1j}, x_{2j}, \ldots, x_{Mj})$ to produce a vector of S outputs $y_j = (y_{1j}, y_{2j}, \ldots, y_{Sj})$, the input-orientated DEA model is described as follows:

$$
\begin{aligned}
& Min\ \theta_j \\
& s.t. \\
& \textstyle\sum_{j=1}^{N} \lambda_j x_{ij} \leq \theta x_{i0} && 1 \leq i \leq M \\
& \textstyle\sum_{j=1}^{N} \lambda_j y_{rj} \geq y_{r0} && 1 \leq r \leq S \qquad (3) \\
& \lambda_j \geq 0 && 1 \leq j \leq N
\end{aligned}
$$

θ_j is a scalar whose value signifies the efficiency of the evaluated unit (WaSC), which is efficient when $\theta_j = 1$ and inefficient when $\theta_j > 1$. This subscribes to Shephard efficiency, as opposed to Farrell efficiency that has inefficient units as < 1; by following this variation, it removes the need to convert the efficiencies for the next methodology section. M is the number of inputs used, S is the number of outputs generated, N is the number of units assessed and λ_j is a set of intensity variables that symbolise the weighting of each analysed unit j within the formation of the frontier.

2.1.3. Double-bootstrap DEA method

The literature on DEA shows Tobit regression as the most popular method to analyse the effects of explanatory variables on technical efficiency. It is a two-stage approach and works by regressing the sample of explanatory variables against the technical efficiency scores, originally acquired through a DEA model (Hoff, 2007). There are, however, limitations to this method, an example being: the DEA efficiency scores are found to be serially correlated, which causes results to be biased, then explanatory variables are caused to have errors due to being derived from those efficiency estimates (Simar and Wilson, 2007).

In order to estimate the technical efficiency of a sample with DEA but without bias, whilst also assessing the influence of explanatory variables, Simar and Wilson (2007) introduced a double-bootstrap model. This method operates by simulating the sample distribution by mimicking the data-generation process (Simões et al. 2010); in this study, 2,000 bootstrap samples were generated. The DEA efficiency scores are then re-estimated with the new generated data. The difference between the original scores and the estimated frontier from the double-bootstrap method shows the amount of bias that would have potentially skewed results using other methods.

Simar and Wilson's (2007) double-bootstrap method is summarised in the proceeding steps: 1) apply the standard DEA method to estimate Shepherd's efficiency score for the WaSCs; 2) conduct a truncated normal regression with maximum likelihood method, regressing the estimated efficiency scores that are greater than one against the explanatory factors; 3) obtain bootstrap samples from the truncated normal distribution of the efficiency estimates; 4) using the bootstrap results, calculate the bias-corrected efficiency scores; 5) re-estimate the marginal effects of the explanatory factors with the bias-corrected efficiency scores in the second-stage regression; 6) apply a second bootstrap based on the empirical distribution on the second-stage bias-corrected regression; 7) for each explanatory factor attain 95% confidence intervals. The full computational procedure referred to as algorithm 2 in Simar and Wilson (2007) is encapsulated below:

1. Estimate the DEA input-efficiency scores θ_j for all of the water and sewage companies in the sample by use of equation 3.
2. Carry out a truncated maximum likelihood estimation to regress θ against a set of explanatory variables z_j, $\theta_j = z_j\beta + \varepsilon_j$, and provide an estimate $\hat{\beta}$ of the coefficient vector β and estimate $\widehat{\sigma_\varepsilon}$ of σ_ε, the standard deviation of the residual errors ε_j.
3. For each company j (j = 1, …, N) repeat the following steps (3.1-3.4) B_1 times to obtain a set of B_1 bootstrap estimates $\widehat{(\theta_{jb})}$ for b = 1, …, B_1.
   3.1. Generate the residual error ε_j from the normal distribution N (0, $\widehat{\sigma_\varepsilon^2}$).
   3.2. Compute $\theta_j^* = z_j\hat{\beta} + \varepsilon_j$.
   3.3. Generate a pseudo set (x_j^*, y_j^*) where $x_j^* = x_j$ and $y_j^* = y_j(\frac{\theta_j}{\theta_j^*})$.
   3.4. Using the pseudo set (x_j^*, y_j^*) and equation one, estimate pseudo efficiency estimates $\widehat{\theta_j^*}$.
4. Calculate the bias-corrected estimator $\widehat{\theta_j}$ for each water and sewage company j ($j = 1, \ldots, N$) using the bootstrap estimator or the bias $\widehat{b_j}$ where $\widehat{\theta_j} = \theta_j - \widehat{b_j}$ and $\widehat{b_j} = (\frac{1}{B_1} \sum_{b=1}^{B_1} \widehat{\theta_{jb}^*}) - \theta_j$.
5. Use the truncated maximum likelihood estimation to regress $\widehat{\theta_j}$ on the explanatory variables z_j and provide an estimate $\widehat{\beta^*}$ for β and an estimate $\widehat{\sigma^*}$ for σ_ε.
6. Repeat the following three steps (6.1-6.3) B_2 times to obtain a set of B_2 pairs of bootstrap estimates $(\widehat{\beta_j^{**}})$, $(\widehat{\sigma_j^{**}})$ for $b = 1, \ldots, B_2$.
   6.1. Generate the residual error ε_j from the normal distribution N (0, $\widehat{\sigma^{*2}}$)
   6.2. Calculate $\widehat{\theta_j^{**}} = z_j\widehat{\beta^*} + \varepsilon_j$.
   6.3. Use truncated maximum likelihood estimation to regress $\widehat{\theta_j^{**}}$ on the explanatory variables z_j and provide as estimate $\widehat{\beta^{**}}$ for β and an estimate $\widehat{\sigma^{**}}$ for σ_ε.
7. Construct the estimated $(1-\alpha)\%$ confidence interval of the n-th element, β_n of the vector β, that is $[Lower_{an}, Upper_{an}] = [\widehat{\beta_n^*} + \widehat{a_a}, \widehat{\beta_n^*} - \widehat{b_a}]$ with

$$Prob\left(-\widehat{b_a} \leq \widehat{\beta_n^{**}} - \widehat{\beta_n^{*}} \leq \widehat{a_a}\right) \approx 1-a$$

For solving the model, the statistical computing software 'R' with the package 'rDEA' developed by Simm and Besstremyannaya (2016) was used.

2.2. Analysing operational and rurality correlations

2.2.1. Water utility data description

So that water companies can benchmark themselves against each other in the UK, historic information about their operations, investment and performance is collated and shared. In the interests of transparency, this information is published by WaterUK, in the same format in which it was submitted by companies at the end of the 2014/15 financial year and as reported to OFWAT. The data shared by WaterUK in 2015 is the sole source for the information utilised in the rurality analysis. This information has not necessarily been through the assurance procedures and tests that would normally be applied to regulatory performance reporting data.

Including a mixture of WaSCs and WoCs within the sample could undermine the analysis due to their different operations and sizes. This issue is negated in the DEA analyses part of the study as just WaSCs were assessed. In order to minimise the impact of mixed operations and size in this part of the study, the data were normalised. Where data were reported as financial spend and total operation information by each water company, they were normalised against numbers of properties connected for that service. i.e. dividing total operation information and financial spend by the number of properties connected for water and/or sewage services as appropriate. Other already normalised data were left as originally provided. A refined version of this data is displayed below in Table 2 to provide a visual example; a full set of the data is available in supplementary information.

Table 2. *Refined indicator summary table used in rurality correlation analysis (M = million, S = sewage, GWP = Global Warming Potential, STWs = Sewage Treatment Works, 105a sewers = private lines that have become owned by water companies, size bands 1-3 = smallest group of treatment works).*

Indicator	Metric	Average	Standard deviation	Minimum	Maximum
Total company spend	£/property connected for sewage and water	205.492	78.741	90.164	372.615

Number of sewage treatment works	number/M property served S	353.205	240.323	60.941	905.097
Total length of sewers (km)	m/properties connected S	13.494	1.408	11.399	16.570
Total length of section 105A sewers (km)	m/properties connected S	10.199	1.958	7.005	13.989
Total load treated by all STWs	kg BOD5/day/M properties	135.224	43.625	59.549	176.891
Total load treated by STWs in size bands 1-3	kg BOD5/day/M properties	6,334.695	4,736.725	1,062.269	15,458.511
Total Company GWP	$kgCO_2e$/property connected for water and sewage	154.621	47.101	116.793	273.130

2.2.2. Rurality factor assessment

Water company operating area boundaries are not made publicly available by regulating bodies such as the Environment Agency, Natural Resources Wales or Drinking Water Inspectorate, due to complex licencing issues. Water companies may provide geospatial data (*i.e.* their supply boundary polygons) or maps outlining their operations at their discretion. Using published data sources (both geospatial and mapped outputs) combined with data provided in response to direct requests, the potable and wastewater operational area boundaries were georeferenced and digitised (where required) using ESRI ArcGIS 10.4 and assembled into an England and Wales coverage.

The Rural/Urban Classification is an official statistic used to distinguish rural and urban areas. The classification defines areas as rural if they are outside settlements with more than 10,000 resident population. The classification is then further divided via sparsity into whether the area is a small town, village, hamlet or conurbation of various extents (Office of National Statistics, 2013).

Geospatial data representing the 2011 Census Middle Layer Super Output Area (MLSOA) boundary polygons were obtained (in ESRI shapefile format) from the Office of National Statistics. The corresponding Rural–Urban Classification (RUC) identifiers for Small Area

Geographies data were subsequently obtained in tabular form and joined using common attributes (the MLSOA identifier codes).

The water company operational area datasets for potable and wastewater treatment were separately geoprocessed using intersection with the RUC MLSOA polygons. The resulting intersected dataset related each water company supply area to its constituent rural and urban area polygons (Figure 1). The area measures for each of the resulting polygons were re-calculated to account for any splitting and resizing of individual entities resulting from the geoprocessing, and then aggregated to their individual classes nested within each water company area using a summary statistical process. The percentages of the constituent classes were then calculated (Table 3).

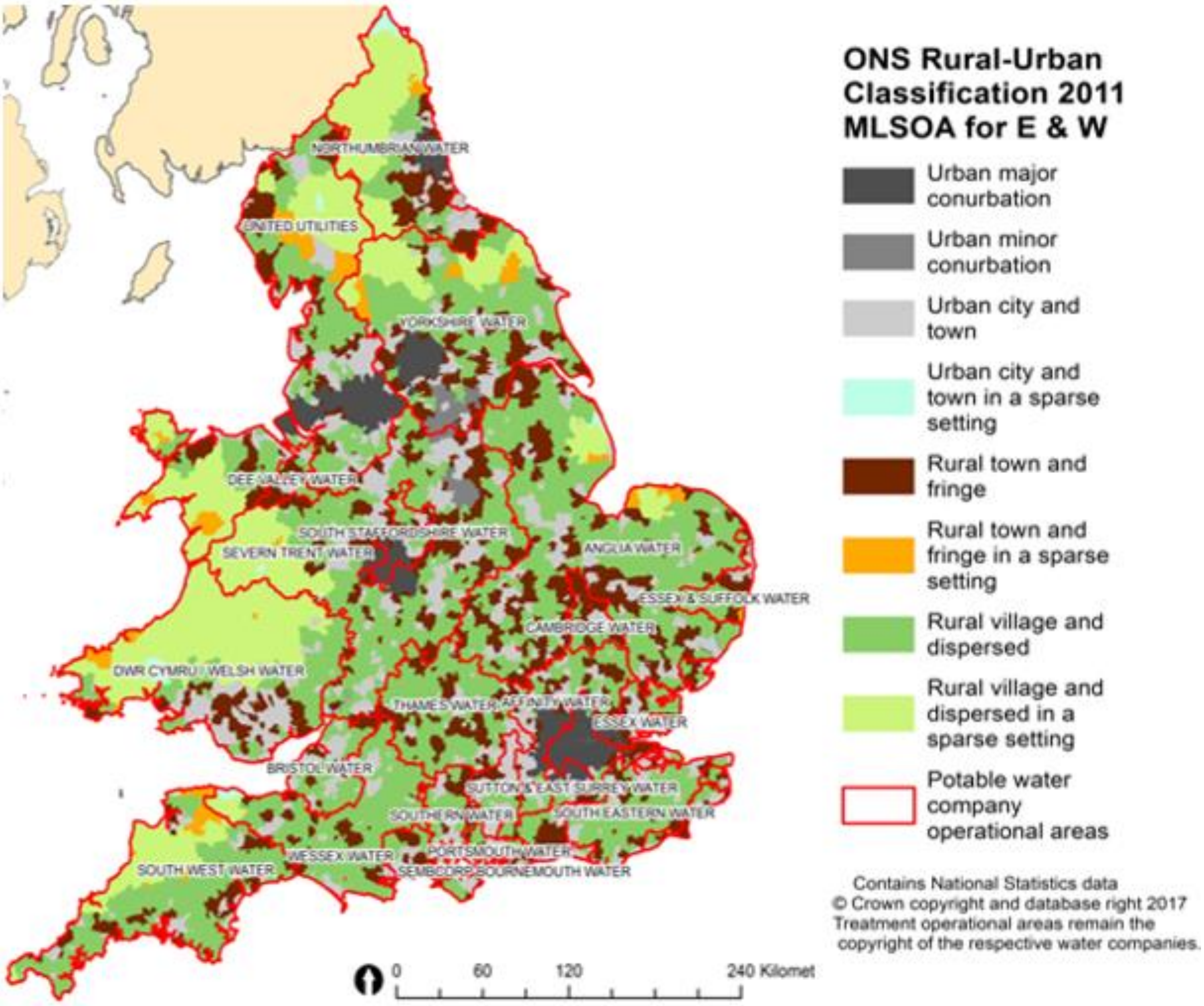

***Figure 1**. Catchment areas water supply companies in the England and Wales, showing the distribution of rural-urban classifications within them.*

Table 3. *The percentage of water and sewage supply areas of WaSCs and WoCs that fall into the primary classification of "rural".*

Water company	Water supply area: MLOSA rural-urban Index (% Rural)	Sewage supply area: MLOSA rural-urban Index (% Rural)	Total area classed as rural (%)
South West Water	91.5	91.7	91.6
Wessex Water	87.4	80.8	84.1
Welsh Water	86.9	86.2	86.6
Anglian Water	86.2	84	85.1
Essex & Suffolk Water	85.5		85.5
Cambridge Water	84.4		84.4
Northumbrian Water	81.3	81.2	81.3
Yorkshire Water	76.8	74.8	75.8
Severn Trent Water	75.6	75.2	75.4
Thames Water	71.8	60.6	66.6
United Utilities	69.2	69.3	69.3
South Eastern Water	69		69
Southern Water	68.7	71.8	70.3
Bristol Water	68		68
Bournemouth Water	64.2		64.2
Affinity Water	57.8		57.8
Portsmouth Water	55.1		55.1
South Staffordshire Water	49.1		49.1
Sutton & East Surrey Water	47.4		47.4
Essex Water	44.5		44.5
Dee Valley Water	32.2		32.2

2.2.3. Correlation methodological process

In order to evaluate if and how rurality affects water utility operations and therefore efficiency, regression analysis was undertaken. This was completed by calculating the R^2 value of the correlation between an operational parameter and the rurality percentage of the companies within the sample. The slope and intercept of the linier trendlines were also calculated to provide an average baseline from which to benchmark the performance of the utility companies assessed.

3. Results and Discussion

3.1. Economic efficiency estimate

The input-orientated Shepherd distance function that is subscribed to here regards efficiency scores higher than one as inefficient compared to the frontier, which are those operating at or closest to one. The initial DEA model, referred to in Figure 2 as ‘non-bias corrected scores’, estimated that seven of the 13 (53.8%) WaSCs are on the efficiency frontier and all have an efficiency estimate of one. This means that according this model, those seven companies cannot reduce their CAPEX and OPEX inputs, whilst also maintaining their water delivered and wastewater treated output levels. The mean efficiency was 1.140 with a standard deviation of 0.295. The implication is that an average WaSC can decrease their inputs by 12.3% (1-1/1.140) and still produce their outputs to the same standard, if they are to perform at the same level as the frontier or ‘benchmark’. For a more detailed view of the specific efficiency scores, the rank changes, and the confidence intervals, see Supplementary Information.

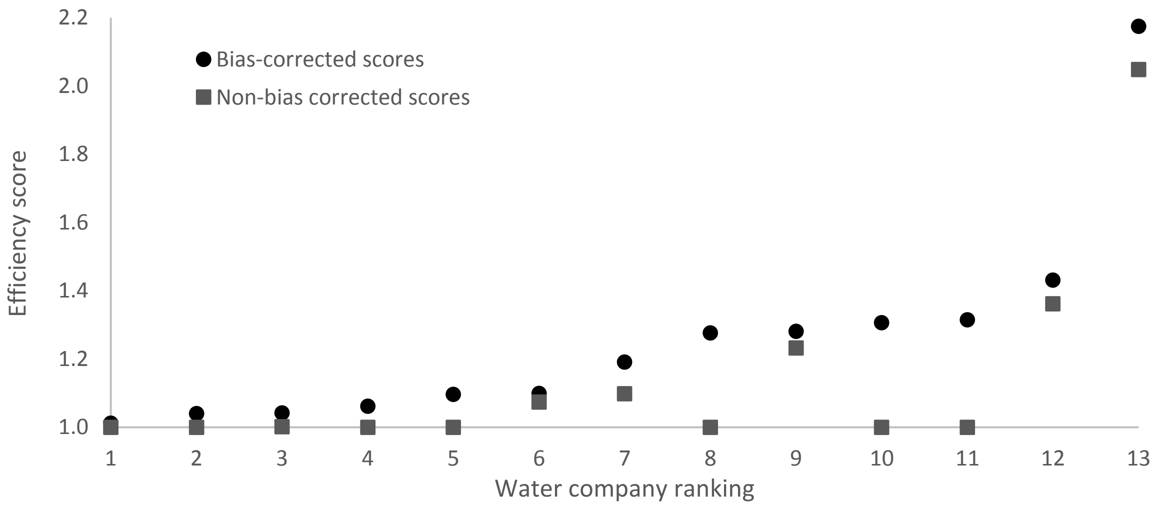

Figure 2. *Rankings based on biased standard DEA model and bias-corrected DEA estimates generated with 2,000 bootstrap iterations for the economic performance of 13 UK and Irish water and sewage companies.*

The bias for all WaSCs were zero or negative values, with mean average of bias being -0.116. This means the bias correction largely indicates that the sample are less efficient after bias-correction than in the original DEA model. This is concurrent with other studies (Ananda, 2014; See, 2015; Gomez et al. 2017; Molinos-Senate et al. 2018) and the application of the technique (Simar and Wilson, 2007).

The mean average of the efficiency scores of the sample once bias was removed was 1.256. These analyses were repeated three times to prove validity and had an average difference of

0.22% (range -0.98%-1.29% between the repeats). This result indicated that on average if the water companies could perform at the benchmark level they could reduce their financial inputs by 19.4%, whilst still maintaining the same levels of service outputs. The range of the sample was large, with the most inefficient DMU having an efficiency score of 2.175, whilst the 12th most efficient company had a score of 1.431. This result displays that most of the companies were close to each other in terms of efficiency, which was expected as the UK has quite a mature water sector that has undergone benchmarking and regulation for decades. The result also shows that one company was significantly lagging behind its peers and could likely benefit from the sharing of best practise.

The average bias was -0.116 as noted above, which is a small efficiency correction overall, but it did have a significant impact on the rank of some WaSCs. For instance, DMU 1 climbed from rank eight to three. However, large bias corrections did not necessarily mean large changes in rank; for example, DMU 12 had the largest correction of -0.315, only moving it down from seven to 11. Collectively, nine of the 13 water utilities within the sample exhibited a rank change.

3.2. Determinants of economic efficiency

The key advantage of using the double-bootstrap methodology is that it enables a review of the determinants of the WaSC efficiency scores by applying a bootstrap truncated regression model. The explanatory factors assessed in this study were consumption per capita, percentage surface water, leakage and population density; their relationship with efficiency is displayed in Table 4. The bias-corrected coefficients with the method used in this study impact the efficiency of the water utilities negatively if the value is positive and have a positive effect on efficiency scores if the coefficient is negative. A p-value ≤ 0.05 displays that the explanatory variable is significant at the 95% significance level, essentially meaning the variable influences the efficiency estimates of the WaSCs.

Table 4. Results of bootstrap truncated regression for economic efficiency analysis.

Explanatory variable	Bias-corrected coefficients	Standard error	Low	High	P-Value
Consumption per capita	0.003	0.004	-0.006	0.010	0.527
Population density	-0.018	0.006	-0.032	-0.009	0.002*
Leakage	0.029	0.008	0.014	0.044	0.000*
Surface water %	-0.008	0.003	-0.014	-0.004	0.001*

*Note: *Statistically significant at the 1%, 5% and 10% levels.*

Percentage surface water abstracted had a significant positive relationship with efficiency (p-value 0.002). This result was unexpected and goes against what is found elsewhere in the literature. Carvalho and Marques (2011) observe mixed results, with a negative influence from surface water being observed when it makes up 70-80% and over 95% of a company's total abstraction, but a positive influence between 80-95% and no influence at all below 70%. Whilst recent studies that utilise a similar methodology to the one used in this study have found insignificant relationships with surface water (Marques et al. 2014; See, 2015; Molinos-Senate et al. 2018), the expected results were that if a relationship was shown, it would be negative, such as that in Byrnes et al. (2010). The literature suggests that surface water requires purification of the water via chemical treatments that are more expensive than those used in groundwater treatment (Aubert and Reynaud, 2005; Shih et al., 2006). These costs are expected to be higher in surface water despite groundwater typically requiring pumping up to the surface, largely as a result of groundwater treatment mostly only being required for hardness and salinity (United States Geological Survey, 2016) and partially because some groundwater sources are from naturally occurring high pressure aquifers that flow to the surface without the need for pumping. It could be the case for UK and Irish companies the surface water they abstract is of a reasonably good quality and thus does not require much treatment and costs are lower.

The variable consumption per capita negatively influences the efficiency of the WaSCs to a non-significant level. Generally, the literature shows mixed results (Ananda, 2014; De Witte and Marques, 2010a; Marques et al., 2014). There is an argument that per capita consumption can affect efficiency scores positively due to links with economies of density (Byrnes et al. 2010; Carvalho et al. 2012). The indication is that once a distribution pipe network is set up, the amount of water actually running through it has minimal costs. The negative relationship found in this study may show that companies increase their efficiency via cost reductions as opposed to increasing the sale of water as noted by De Witte and Marques (2010a), however, the relationship found in this research is weak so any conclusions drawn from it are speculative (p-value 0.52).

As Table 4 illustrates, leakage is significantly negatively associated with efficiency. Logically, an increase in leakage should result in lower efficiencies since companies would have to extract, treat and pump more water to meet a specific demand. This result is concurrent with the overall trend in the literature (Corton and Berg, 2009; See, 2015; Molinos-Senate, 2018). Despite this, leakage and its equivalent indicator, non-revenue water, are not always conclusive towards causing negative effects on efficiency. Marques et al. (2014) for example, concludes that leakage shows no influence on efficiency. Furthermore, Ananda (2014) and De Witte and Marques (2010a) show there is a relationship between increased leakage and increased efficiency.

Population density showed a significantly positive relationship with the WaSC efficiency scores. This result is consistent with the overwhelming theme of results from other empirical studies from various countries (Abbott et al. 2012; Guerrini et al. 2013; Marques et al. 2014; Ananda, 2014; See, 2015; Molinos-Senate et al., 2018). The relationship between population density and efficiency is thought to be related to economy of densities (Byrnes et al. 2010; García-Sánchez, 2006). Essentially this means there is less network to install and maintain per population of customers, meaning fewer resource inputs per service output and therefore higher efficiency. Though these results concur with much of the literature, some studies still show up no significant relationship (Marques et al., 2014). Population density has particular relevance in this sample of UK and Ireland WaSCs. The water utilities compared operate in areas with a range of population densities, from 42 to 106 people/km^2, meaning certain companies have natural advantages or disadvantages in relation to each other. This should be taken into account when it comes to regulation and benchmarking to ensure fairer evaluations of performance. The un-level efficiency playing field created by population density has considerable implications for water company competitiveness and long-term viability, and is one of the key reasons that rurality/urbanity have been further investigated in this study (Section 3.5).

3.3. Environmental efficiency estimate

The results from the standard DEA model referred to in Figure 3 under 'non-bias corrected score', estimated that five of the 12 (41.6%) WaSCs are on the efficiency frontier and have an efficiency estimate of one. The mean efficiency was 1.096 with a standard deviation of 0.159. The average WaSC can decrease their carbon inputs by 8.8% (1-1/1.096) and still theoretically produce their water delivery and wastewater treatment outputs to the same standard, if they are to perform at the same level as their peers who operate at the frontier. As with section 3.1, more information on efficiency scores is available in supplementary information.

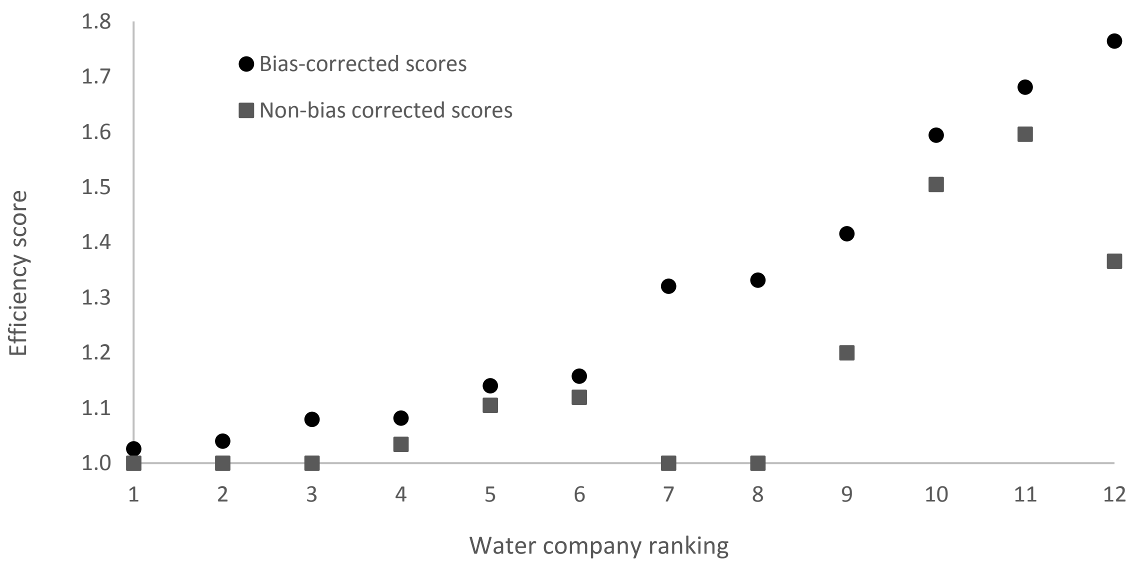

Figure 3. *Rankings based on biased standard DEA model and bias-corrected DEA estimates generated with 2,000 bootstrap iterations for the environmental performance of 12 UK water and sewage companies.*

The bias for all WaSCs were negative values, with -0.122 being the mean average of bias. As referred to in section 3.1, the double-bootstrap DEA results were expected to display a drop in efficiency within the sample. Similar to the economic efficiency analysis above, the average bias was small but again it did affect how the companies were ranked. Eight out of 12 DMUs within this sample experienced a ranking change and in total, there was 15 ranking place movements even in this small sample.

The average environmental efficiency score once bias was removed was 1.219; this analysis was repeated three times and displayed an average difference of 0.22% (range -0.98%-1.29% between the repeats). The average corrected efficiency score means on average if the WaSCs could perform at the frontier, they could reduce their carbon inputs by 15.8%, whilst still maintaining the same levels of outputs. There were no significant outliers in efficiency however, the range from 1.026-1.765 combined with the clustering of the top four performing companies (1.026-1.082), indicated that a handful of companies are leading the way in terms of carbon efficiency, and could be exemplars for various best practice techniques.

3.4. Determinants of environmental efficiency estimate

The explanatory factors assessed in the carbon efficiency analysis were the same as those evaluated for economic efficiency; consumption per capita, percentage surface water, leakage and population density. As noted in section 3.2, the bias-corrected coefficients for the explanatory variables (displayed in Table 5) are deemed to positively affect efficiency if their values are negative and adversely affect efficiency if their values are positive.

Table 5. *Results of bootstrap truncated regression for environmental efficiency analysis.*

Explanatory variable	Bias-corrected coefficients	Standard error	Low	High	P-Value
Consumption per capita	0.013	0.005	0.005	0.024	0.008*
Population density	-0.018	0.005	-0.030	-0.009	0.001*
Leakage	0.003	0.014	-0.024	0.031	0.867
Surface water %	-0.006	0.003	-0.012	-0.002	0.013*

*Note: *Statistically significant at the 1%, 5% and 10% levels.*

Consumption per capita was shown to significantly negatively influence carbon efficiency. This result matches the direction of effect on efficiency that was found in the economic analysis. The belief is that the more water each person consumes, the more treatment and energy is required, which are key sources of carbon. This relationship, like that in the economic analysis, is subject to economies of density, therefore it was not expected to necessarily show significance.

The percentage of surface water abstracted shows the same result as for the economic analysis, positively affecting efficiency to a significant degree. This is likely to be a result of lower electricity demand compared to groundwater pumping. Similar to the economic efficiency, the increased treatment usually reported for surface water may not be the case in the UK and Ireland, therefore there is a concurrent saving in carbon costs.

Population density, like surface water percentage, matched the results from the economic analysis. This was expected due to economies of density yielding naturally more efficient use of resources, as discussed in section 3.2. More pumping is required if populations are spread over a large area, as well as more infrastructure such as piping and treatment works to support those populations, which have large amounts of embodied carbon within them.

The result for leakage however diverged between environmental and economic efficiency analyses, with a non-significant relationship shown for environmental efficiency. The anticipated result was that as leakage went up, so would carbon due to more pumping and therefore more energy being required. A possible cause of this result may be that capital projects into lowering leakage rates may have been carbon intensive, therefore the relationship over a one year snapshot is not truly representative and companies who have not invested and thus have lower carbon emissions but higher leakage rates, appear to be performing better.

3.5. The role of rurality

3.5.1. Correlation results

Regression analysis was conducted on England and Wales water utilities, with a split of 10 WaSCs and 11 WoCs. The R^2 values closer to one indicate a stronger relationship between rurality and the displayed parameter. Table 6 displays the top regressions from the analysis; the total analysis results are available in supplementary information. The table displays the R^2 results, slope and intercept related to the parameter's relationship with rurality. The parameters contain data from varying areas including: economic costs, scale information, environmental performance and emissions, which are all normalised by properties connected. To make it easier to identify where a linear correlation is more likely, Table 6 has been sorted in terms of R^2 values.

Table 6*. Rurality relationship with economic cost, global warming potential, scale information, and environmental performance data normalised by property connected for that service (M = million, S = Sewage, W = Water, GWP = Global Warming Potential, STWs = Sewage Treatment Works, size bands 1-3 = smallest group of treatment works).*

Indicator	Unit	R^2	Slope	Intercept
Number of sewage treatment works	number/M property served S	0.823	24.008	-1508.887
Total load treated by STWs in size bands 1-3	kg BOD5/day/M properties	0.792	-5.139	533.304
Total company spend	£/property connected for S&W	0.633	4.035	-69.813
Properties flooded in the year	other causes/M properties	0.544	-5.139	533.304
GWP of sewage treatment	$kgCO_2e$ /property connected for sewage	0.508	0.880	-21.657
Total company GWP	$kgCO_2e$ /property connected for water and sewage	0.485	3.890	-150.956
Spend on sewage treatment	£/property connected for S	0.471	1.632	-42.806
Sewage sub-total GWP	$kgCO_2e$ /property connected for sewage	0.466	2.048	-68.807
GWP of sewage collection	$kgCO_2e$ /property connected for sewage	0.460	1.041	-46.813
Water sub-total GWP	$kgCO_2e$ /property connected for water	0.427	1.450	-17.841
Employee total	number/M properties connected W+S	0.407	8.620	717.109

The highest R^2 value from the economic data is for total company spend per property connected (0.633), indicating that as rurality percentage increases, so does the spending of the water companies. This direction of relationship is concurrent with the population density results from section 3.2, although the strengths vary. This highlights how population density is a reasonable ‘crude’ indicator to use to gauge rurality/urbanity but other methods such as the one used here, may be more accurate.

Concerning scale information and assets one of the most striking correlations found in this study was that of rurality against number of sewage treatment works (STWs) with an R^2 of 0.823 for a linear trendline and 0.963 for an exponential one (shown in Figure 4). This was reflected in the largest correlated indicator within the environmental performance information, which is total load treated by STWs in size bands 1-3 (0.792), signifying that a large number of smaller size treatment plants are distributed across more rural areas. According to these results, dispersed small treatment works are the key driver behind rurality causing economic inefficiencies across water companies. This makes sense, as economies of scale are well documented for wastewater treatment in terms of infrastructure, maintenance, energy and chemical costs (Libralato et al. 2012). The correlations described above go some way in explaining the correlations found with economic factors against the percentage rural index, such as marginal correlations in spend on sewage treatment (0.471). Future research could evaluate solutions to this, for example, assessing whether it is more financially viable within certain areas to use more extensive piping and pumping networks to move the sewage to larger treatment plants.

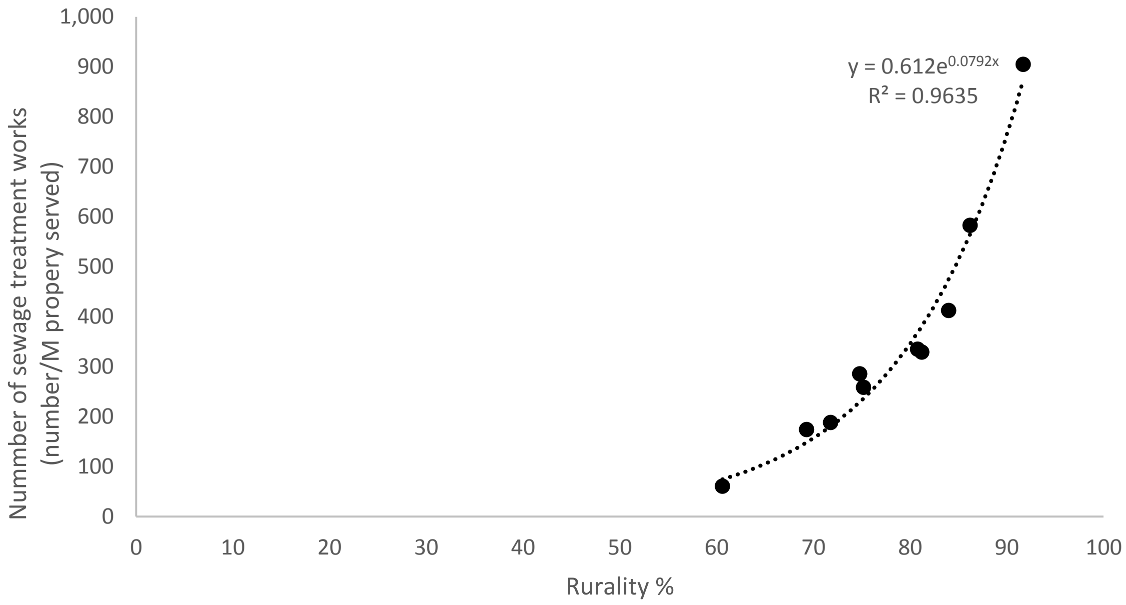

Figure 4. *The correlation between percentage of catchment being rural and the number of sewage treatment works normalised by million properties served for sewage, with an exponential trendline.*

A more minor potential impact that rurality induces on companies appeared to be an increase in the number of employees (R^2 0.407). The number of employees may actually be at least partially a result of the increased number of sewage treatment works too; further emphasizing the impact of rurality appears to be largely resulting from dispersed wastewater treatment.

The R^2 results for emissions that display relationships were carbon equivalent of sewage treatment (0.508), total company carbon equivalent (0.485), sewage sub-total carbon equivalent (0.466), carbon equivalent of sewage collection (0.460) and water sub-total carbon equivalent (0.427). These trends concur with the economic regressions to a lesser extent, which further shows how rurality leads to inefficiencies, particularly within sewage operations. This effect of rurality on efficiency matches that of Gibson's (2017) who presented the effect of remoteness, measured in "travel time to significant city", and correlated this with a "water service provider performance index". Their research stated, "remoteness from a commercial centre clearly has a significant impact on performance".

Our results emphasise the important exogenous influence of rurality on water company efficiency, which needs to be taken into consideration when benchmarking. Doing so would enable companies to more accurately ascertain their scope for improvement, and to identify priority aspects to drive this improvement (e.g. by clarifying best practice). NGOs could use these techniques to more reliably evaluate best and worst performers within the sector, whilst regulators could define more rigorous performance targets for urban water companies and adjust targets for rural companies to account for exogenous factors.

3.5.2. Methodology appraisal

In terms of methodology, the framework presented here provides a powerful tool to benchmark among companies where exogenous factors may influence spend or performance. Our approach may be preferential to methods that use clustering of similar company attributes where a decision has to be made whether to include borderline data in one or another cluster, this method instead provides a “sliding scale” to make individual benchmark cases.

The same methodology was also applied to the operating catchments of one water authority, and similar trends where found, although with fewer data points. That exercise highlighted another use for the method within companies, in aiding a more holistic approach to regional budgeting or how operational areas are drawn, especially concerning sewage treatment and collection.

The influence of topography was also studied within one operation catchment by means of the Melton Ruggedness Number and a 3D Analyst 2D area; however, no notable correlation was found for that study. However, the influence of topography on water company efficiency may merit further investigation.

4. Conclusions

The aims of this paper were to utilise a double-bootstrap Data Envelopment Analysis (DEA) method to compare unbiased environmental and economic efficiency across water companies, and to explore factors influencing these efficiencies, including the specific role of rurality. There are four main conclusions to draw from this work. Firstly, the results show that the average company could reduce their economic inputs by 19.4% and carbon emissions by

15.8% by stepping up to the efficiency frontier. Thus, we demonstrate that there is considerable scope for improvement in economic and environmental efficiency across water companies if they adopt the practises of the top performers. Secondly, bias-correction of DEA results using the double-bootstrap method changed performance rankings for nine companies in the economic evaluation and eight companies in the environmental evaluation. We propose that such bias correction is vital to undertake accurate benchmarking across water companies. Thirdly, the study identified important factors influencing efficiency. Surface water sourcing was significantly positively associated with economic and environmental efficiency (p-values 0.001, 0.013) as was population density (p-values 0.002, 0.001). These exogenous factors are beyond the control of water companies, and thus need to be corrected for when benchmarking. Water consumption per capita displayed a negative association with environmental efficiency (p-value 0.008); whilst leakage rate showed a negative effect on economic efficiency (p-value (0.000). These factors are at least somewhat within the control of water companies, and should be prioritised to improve efficiency. The fourth conclusion of this study is that the degree of catchment rurality significantly influences the efficiency of water service companies. More rural catchments are associated with higher water company total spend and higher greenhouse gas emissions per property connected is (R^2 of 0.633 and 0.485). Operational data correlations suggest that this is a consequence of a greater number of smaller decentralised sewage treatment works in more rural areas (R^2 of 0.823 for number of treatment works, R^2 of 0.792 for small treatment works). It is clear that exogenous factors such as rurality play a significant role in determining the apparent efficiency of water service company operations, and thus benchmarking should be adjusted to reflect this non-level playing field. Future research and development supporting more efficient water services should focus on how to mitigate the resource burdens associated with larger numbers of smaller sewage treatment plants in rural areas.

Acknowledgments

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