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**Key performance indicators to explain energy & economic efficiency across water utilities, and identifying suitable proxies**

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**Abstract**

Water companies consume up to 8% of global energy demand, at billions of dollars' cost. Benchmarking of performance between utilities can facilitate improvements in efficiency; however, inconsistencies in benchmarking practices may obscure pathways to improvement. The aspiration was to conduct an unbiased efficiency comparison within a sample of 17 water only companies and water and sewerage companies in England and Wales, accounting for exogenous factors, whilst evaluating the accuracy of common proxies. Proxies were tested, and bias-corrected energy and economic efficiency scores with explanatory factors were analysed using a double-bootstrap data envelopment method. Bias correction altered the rankings of two companies for energy efficiency only. Results imply that on average, companies could reduce energy inputs by 91.7%, and economic inputs by 92.3%, which was symptomatic of the companies specialising in drinking water supply considerably out-performing combined water and sewerage companies. As exogenous influences were likely to be a factor in the disparity between the companies, five indicators were evaluated. The results varied but of note were *average pumping head height*, which displayed a significant negative effect for energy efficiency, and *proportion of water passing through the largest four treatment works,* that exhibited a significant negative effect on economic efficiency. Within proxy performance, *population served for drinking water* was an adequate replacement for *volume of water produced*, with results matching the core variable apart from two companies changing rank in the economic analysis. Conversely, *length of water mains* performed poorly when replacing *capital expenditure*, implying companies were on average 12.6% more efficient, resulting in ten companies changing their rank and causing explanatory variables to contradict direction of influence and significance. The findings contribute new insights for benchmarking, including how different types of water companies perform under bias-correcting methods, the degree to which factors affect efficiency and how appropriate some proxies are.

Key words: Performance Evaluation; Water Companies; Data Envelopment Analysis; Double-Bootstrap; Proxies; Explanatory Factors

1. Introduction

The water industry is a significant user of energy resources; with water companies spending billions of dollars per annum to ensure a high standard of cleanliness, whilst also protecting the environment through treatment of wastewater (Sedlak, 2014). Significant energy and economic costs are incurred by pumping, mixing and purification for contaminants such as heavy metals and inorganic salts (Yang *et al.,* 2019). Other resources consumed for the treatment of water include a variety of chemicals including algicides, chlorine, sodium hydroxide, and aluminium sulphate for a plethora of applications such as reducing algal blooms, disinfection, balancing pH, and coagulation-flocculation (Saleh, 2017). Moreover, contamination of drinking water sources with nutrients, in particular phosphorous and nitrogen, combined with regulatory requirements around acceptable concentrations is leading to increasing energy and economic costs for treatment. Biological nutrient removal and chemical precipitation are typically used to remove these elements, however, alternative lower-cost and effective methods are being investigated (Kuriqi, 2014; Saleh and Gupta, 2016; Li *et al.,* 2019).

The US Environmental Protection Agency (EPA, 2018) reported that for many municipal governments, drinking water and wastewater plants are often their largest energy consumers, typically accounting for 30-40% of municipality energy consumption. The EPA estimated that 2% of total energy use within the US is actually a result of drinking and wastewater systems. The US is not a particular area of high consumption either; 3% of all UK energy use is expended on drinking and wastewater systems (Fletcher, 2018). In fact, it is likely that these countries have low energy consumption from their water utilities relative to the rest of the world (Olsson, 2015). The United Nations stated that approximately 8% of global primary energy supply is used to deliver and treat water (UN Water, 2014; UNESCO, 2014). As well as the economic cost associated with such energy demand, it is responsible for considerable emissions of greenhouse gases (GHG), with the US and UK emitting 40 and 5 million tonnes $CO_2$ per year through the water sector, respectively (McNabola *et al.,* 2014; EPA, 2018). The imperative to reduce energy consumption and GHG emissions is a major driver for water companies to increase their efficiency (DEFRA, 2016).

Increasing energy efficiency would benefit companies' bottom line (profitability) and the climate, and enable a more reliable service, assuming that saved resources would at least partially be spent elsewhere such as on replacing leaky pipes or upgrading water treatment facilities. Benchmarking is viewed as a key mechanism to achieve improvements in efficiency by analysing performance, comparing results and identifying areas for improvement, and ultimately facilitating sharing of best practice (Alegre *et al.,* 2017). One of the most common methods in academic literature utilised to benchmark is production frontier analysis (Berg, 2013). A frontier can be computed with parametric methods like stochastic frontier analysis or non-parametric methods such as data envelopment analysis (DEA). DEA has three essential components that make it advantageous when evaluating water utilities. Firstly, the approach enables integration of numerous inputs and outputs for each company, providing a multi-criteria analysis. Secondly, weightings assigned to aggregate inputs and outputs are produced endogenously. Thirdly, DEA does not need *a priori* inferences regarding the functional exchange between the inputs and outputs (Cooper *et al.,* 2011).

To decipher variables that influence efficiency in water utilities, there are four key methodologies available for use in the second stage of analysis using DEA (Molinos-Senante and Guzmán, 2018). One method is to group the decision-making units (DMUs), which are water utility companies in this research, according to the explanatory variables and apply non-parametric statistical tests to verify if there are differences in the distribution of efficiency scores among groups of DMUs (Molinos-Senante *et al.,* 2014). This can be undertaken via several hypothesis tests such as analysis of variance, Kolmogorov-Smirnov distribution test or the Mann-Whitney test. This method however, does not allow isolation of the influence of the explanatory variables on the efficiency scores and therefore means causality cannot be determined (Molinos-Senante *et al.*, 2018). Secondly, a common approach is to conduct a regression analysis of the efficiency scores from the first stage results against the explanatory variables being investigated, the typical approach being the use of a Tobit regression analysis (Guerrini *et al.*, 2013; Guerrini *et al.*, 2015). However, conventional inference methods used in the second stage of the DEA method are based on efficiency values that are serially correlated; therefore, any inferences based on them may not be reliable (Daraio and Simar, 2007). The process is regarded to have shortcomings, with Simar and Wilson (2007) and Bădin *et al.,* (2014) proving that if the variables used in the original efficiency model are regressed against explanatory factors, then the second-stage estimates are inconsistent and biased. Due to these biases, the third main second-stage method 'order-m' was developed by Cazals *et al.,* (2002). Order-m is a partial frontier method that uses just a portion of the sample to determine the efficiency scores, and enables the inclusion of evaluating exogenous variables (Carvalho and Marques, 2011). The limitation to this method is in its uniqueness, by only taking a fraction of the original sample, it has issues around sample size requirements and the representativeness of the reduced 'm' sample from the original sample, which may greatly affect the efficiency scores (Da Cruz and Marques, 2014). The fourth method is a double-bootstrap procedure from Simar and Wilson (2007) that allows statistical inferences and hypothesis testing in DEA models, therefore facilitating the assessment of potential influencer variables on efficiency, whilst further contributing bias-correcting of the efficiency results generated from the original DEA computation (Yang and Zhang, 2018). This fourth second-stage approach is utilised in this research to overcome the limitations of the other methods outlined above, whilst delivering reliable results for benchmarking water companies and evaluating the factors that may influence their efficiency.

When conducting performance analysis, variable choices are vital for fair and validated results. However, the first choice variables are not always available, and in international benchmarking studies, issues around valuation and exchange rates need to be negated; therefore, proxies are often used to represent the first choice variables (de Witte and Marques, 2010). Though proxies can offer a useful alternative path to conducting benchmarking, it is not known how accurate some of them are in replacing the first-choice variables. This study therefore assesses the accuracy of two common proxies: population served for the service under review

(Molinos-Senante *et al.,* 2015; Molinos-Senante and Farías, 2018), which in this instance is drinking water, and water mains pipe network length (de Witte and Marques, 2010; Mbuvi *et al.,* 2012; Ananda, 2014). These proxies replace the first choice variables volume of water produced and capital expenditure, respectively.

Like many countries, England and Wales are serviced by a mixture of water only companies (WoCs) and water and sewage companies (WaSCs), which often prove difficult to analyse collectively due to their differing operations, although attempts have been made (Molinos-Senante *et al.,* 2015). An effective assessment of these companies together could enhance opportunities for sharing of best practices across a more diverse sample, leading to more improvements in economic and energy efficiency. This paper therefore uses a sample of WoCs and WaSCs, but only focusses on the water production side of the companies.

This study had three objectives. Firstly, to evaluate the naïve and bias-corrected energy and economic efficiency scores of all water utilities in England and Wales. Secondly, to appraise the role of an array of explanatory variables on the efficiency scores. Lastly, to assess the extent to which proxies may influence efficiency rankings and their influencing variables. These objectives collectively contribute valuable insights for academia and the water industry by attempting to fill gaps in the literature. Bias-corrected efficiency evaluation has not previously been undertaken across WaSCs and WoCs, and could offer unique insight into how WaSCs and WoCs compare in terms of efficiency. Furthermore, research of rare explanatory factors influencing energy and economic efficiency may contribute new knowledge to existing theories on how specific factors affect efficiency. Finally, the analysis of how proxy variables can influence efficiency and explanatory factor results could provide a new evidence base on the reliability of alternative metrics to analyse efficiency.

## 2. Methodology

To estimate the energy and economic efficiencies of WaSCs and WoCs in England and Wales, in addition to the elements influencing their efficiencies, the DEA double-bootstrap method incorporating a truncated regression was employed. The process allowed bias-corrected efficiencies to be ascertained and enabled evaluation of the indicators that affect these efficiencies. Broader benefits of the approach have been outlined in the previous section.

### 2.1. Original DEA model

DEA was initially created by Farrell (1957), then subsequently advanced by Charnes *et al.* (1978). It is a non-parametric procedure that applies linear programming to construct an efficient production frontier. The frontier establishes the comparative efficiency of the sample of units, by comparing their input and output relationships, relative to others in the sample (Charnes et al. 1978). Technical efficiency for the DMUs is then ascertained by appraising their distances from the frontier.

The DEA model can be input or output-orientated. Water utilities lack dominant control of their fundamental service output, that being volume of water delivered in this study. However, they do have more control over inputs; accordingly, this paper applied an input-orientated design. The variation of the DEA model used here was established on varying returns to scale, allowing for scale effects. This assumption was considered credible as the sample of water utilities vary in size and are therefore prone to producing different levels of outputs with similar levels of inputs. This judgement is supported by the majority of literature utilising similar methods within the water sector (Peda *et al.,* 2013; See, 2015).

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

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

$\theta_j$ is a scalar, which indicates the efficiency of the evaluated unit via the given value, which is deemed efficient when $\theta_j$ = 1 and inefficient when $\theta_j$ > 1. $M$ is the quantity of inputs, $S$ is the quantity of outputs generated, $N$ is the quantity of water companies analysed and $\lambda_j$ is a collection of intensity variables that represent the weighting of each unit $j$ within the composition of the frontier.

## 2.2. Double-bootstrap DEA method

The issue that arises with some second-stage DEA methods (discussed further in the Introduction) such as Tobit regression is that they can be inaccurate due to the nature of the standard DEA model. Since the efficiency scores are serially correlated when calculating this model, the efficiency estimates can be biased, and any inferences made about explanatory factors can be incorrect (Hoff, 2007; Simar and Wilson, 2007).

To calculate efficiency utilising DEA, but removing errors and potential biases, whilst enabling an analysis of the effect of explanatory factors, Simar and Wilson (2007) developed a double-bootstrap methodology. The model functions by simulating the distribution of the sample by mimicking the data-generation process (Chernick and LaBudde, 2011); the research in this paper generated 2,000 bootstrap samples. The efficiency results then are re-calculated using the new generated data, the divergence between the original values and the more robust values from the double-bootstrap approach reveals the extent of bias that could have distorted the results when using other methods. The full computational operation is defined beneath:

1. Estimate the DEA input-efficiency scores $\theta_j$ for all water utilities in the sample using equation 1.
2. Perform a truncated maximum likelihood estimation to regress $\theta$ against a group of explanatory variables $z_j$, $\theta_j = z_j\beta + \varepsilon_j$, and produce an estimate $\hat{\beta}$ of the coefficient vector $\beta$ and estimate $\widehat{\sigma_\varepsilon}$ of $\sigma_\varepsilon$, the standard deviation of the residual errors $\varepsilon_j$.
3. For each utility $j$ ($j$ = 1, …, $N$) repeat the succeeding steps (3.1-3.4) $B_1$ times to acquire a set of $B_1$ bootstrap estimates $\widehat{(\theta_{jb})}$ for $b$ = 1, …, $B_1$.

    3.1. Generate the residual error $\varepsilon_j$ 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. Compute the bias-corrected estimator $\widehat{\theta_j}$ for each unit $j$ $(j = 1, \ldots, N)$ 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 $\beta$ and an estimate $\widehat{\sigma^*}$ for $\sigma\varepsilon$.

6. Repeat the succeeding 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 $\varepsilon_j$ 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 $\beta$ and an estimate $\widehat{\sigma^{**}}$ for $\sigma_\varepsilon$.

7. Construct the estimated $(1-\alpha)\%$ confidence interval of the $n$-th element, $\beta_n$ of the vector $\beta$, that is $[Lower_{an}, Upper_{an}] = [\widehat{\beta_n^*} + \widehat{a_a}, \widehat{\beta_n^*} - \widehat{b_a}]$ with

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

The model was solved using ‘R’, a statistical computing software with the package ‘rDEA’ created by Simm and Besstremyannaya (2016).

## 2.3. Data description

The same sample of companies was used for both the energy and economic analyses, comprising a mix of ten WaSCs and seven WoCs from England and Wales. All data was for the year 2017-18 and was acquired through the ‘PR19’ data tables that must be submitted alongside business reports to the regional regulator, OFWAT (2020). Despite being secondary data, the quality was deemed sufficient due to the audits and controls implemented by the individual companies along with OFWAT. Thus, it is assumed that key data needed to run the model has been validated. The source files separated water production and wastewater operations, therefore enabling a fair comparison of just the water production side of all companies, whereas evaluation of the data via less granular sources may have led to errors. The resolution of the data is based on an entire year of operation, unless stated otherwise due to model requirements or the nature of specific indicators.

When utilising DEA, the sample size is required to satisfy a minimum size threshold in order to bypass relative efficiency discrimination problems. As the size of the sample was small in this study, 'Cooper's rule' was used in an attempt to avoid discrimination problems. 'Cooper's rule' specifies the quantity of units must be ≥ max$\{m\ x\ s; 3(m+s)\}$ where $m$ represents inputs and $s$ represents outputs (Cooper *et al*., 2007). The energy model used one input and one output, whilst the economic model used two inputs and one output; therefore, the minimum threshold was met. Moreover, a bootstrap approach within the DEA framework enables rigorous efficiency results despite a limited sample size (Molinos-Senante *et al*., 2018). Nonetheless, it should be noted that the constrained sample size could exaggerate results at either end of the efficiency spectrum. If the sample was large enough to enable more variables within one model, instead of requiring two separate models, results could differ. However, this limitation is difficult to overcome, given the limited number of water utilities in the UK.

The array of variables is critical for a DEA model to generate credible outcomes (Zhu, 2014). The energy model consisted of the sole input of *energy consumed*, which was the total amount of energy consumed in the year by water supply operations measured in kWh. The economic model encompassed *operational expenditure (OPEX)* and *capital expenditure (CAPEX)* as inputs; both models had *volume of water produced* as the only output. These variables were chosen because they represent the essential resources required for a water utility to function and the core operations and services that they provide. Furthermore, the indicators are concurrent with the literature (Peda *et al.,* 2013; Mardani *et al.,* 2017; Molinos-Senante and

Farías, 2018). Although the variables cover the essential activities of water companies, it should be noted that the approach is not as holistic as alternative methods of performance evaluation such as life cycle analysis or emergy accounting (Arden *et al.,* 2019), which would cover many different aspects of the water supply process in a narrower scope. *OPEX* and *CAPEX* data contained spending on third party services, and included wholesale and retail aspects of the companies. Using *CAPEX* over a single year has the potential misrepresent usual spending, therefore projected year-on-year capital expenditure change over the next four years was averaged for all companies, displaying an anticipated -5.43% average change. This was deemed an acceptable level of variation to validate the use of *CAPEX* over the 2017/18 year. Furthermore, *CAPEX* was used assuming that the utilities contribute enough capital to renew and maintain the distribution network long-term. As many studies have used proxies to replace key inputs and outputs, this paper reviewed how accurate the use of two common proxies are. The proxies were *population served for drinking water* and *length of water mains*, which replaced the output *volume of drinking water produced* and the input of *CAPEX*, respectively.

An elemental contributor of resource use for water companies is the quality of water they supply (Plappally and Lienhard, 2012). Utilities within efficiency analyses should not be penalised for contributing superior quality outputs than others; accordingly, this paper follows Saal *et al.,* (2007) and Walker *et al.*, (2019), and modifies the output variable that is used for both the energy and economic assessments according to water quality. The *volume of water produced* was amended by the quality of that water ($y_1$) as reported by the companies to the regulators Environment Agency and OFWAT. The indicator for water quality was reported as a percentage, with 100% expressing that all obligations are met; this was then converted to decimals and employed as a multiplier for the original output variable:

$$y_1 = WP \times DWQ \tag{2}$$

The *volume of water produced* is represented by $WP$ and $DWQ$ is drinking water quality. The resulting figure once adjusted then constituted the single output for the energy and economic DEA analyses.

In order to deduce reasons for the efficiency results and performances of companies, five explanatory variables were chosen for evaluation. The variables were *leakage*; *consumption per capita*; *number of abstraction sources*; *average pumping head height* (across raw water abstraction, treatment and transport); and *proportion of water passing through treatment plants sizes 5-8*, which are the largest treatment plants (total scale is measured from 1-8, OFWAT, 2019). These variables were chosen because they are deemed to affect efficiency, and in some cases, have not been studied before – e.g. *proportion of water passing through the largest treatment plants* and *average pumping head height*. Treatment plants are viewed to operate at economies of scale (Molinos-Senante and Sala-Garrido, 2017) but testing the limits to this within the context of other variables has seldom been done. Pumping head height is interesting to investigate, as a larger head would naturally cost more money to operate (Berg, 2013), however, the significance on cost and energy relative to the efficiency of a company is unknown. All the variables used in this research including inputs, outputs, proxies, explanatory variables and quality variables are summarised in Table 1.

***Table 1.*** *Summary of the 2017/18 data used in the DEA analyses displayed to three significant figures where possible. Data from the PR19 company reports available via OFWAT (2020).*

| | | **Average** | **SD** | **Minimum** | **Maximum** |
|---|---|---|---|---|---|
| **Inputs** | Energy (kWh) | 212,705.897 | 151,759.268 | 24,084.370 | 558,178.165 |
| | Operational expenditure (million£) | 210.757 | 172.782 | 21.543 | 638.661 |
| | Capital expenditure (million£) | 147.634 | 127.331 | 7.628 | 511.67 |
| **Output** | Volume of water produced (Ml/day) | 725.838 | 568.741 | 51.80 | 2,168.81 |
| **Proxies** | Length of water mains (km) | 12,015.72 | 13,710.524 | 2,627 | 46,540 |
| | Population with water service | 3,460,133 | 2,714,840 | 218,918 | 10,012,827 |
| **Explanatory variables** | Leakage (Ml/day) | 189.565 | 179.335 | 14.27 | 694.65 |
| | Consumption per capita (l/h/day) | 143.499 | 8.137 | 128.9 | 158.8 |
| | Number of abstraction sources | 102.294 | 67 | 9 | 235 |
| | Proportion of water passing through treatment works sizes 5-8 (%) | 74.071 | 18.138 | 31.58 | 97.50 |
| | Average pumping head height (m.hd) | 34.272 | 8.279 | 17.315 | 46.26 |
| **Quality variable** | Water quality compliance (%) | 99.96 | <0.001 | 99.93 | 99.98 |

3. Results and Discussion

3.1. Energy efficiency results

The results from the input-orientated distance function utilised in this study means scores of 1 are the most efficient, and those companies are operating at the frontier. Conversely, the more scores increase above 1, the further those companies are away from the frontier and thus the less efficient they are. The standard DEA model (equation 1) results represented as 'non-bias corrected scores' in Figure 1 estimated three of the 17 companies to be operating at the efficiency frontier with estimates of 1. The implication of this is that those companies cannot reduce their energy consumption any further, whilst also maintaining their drinking water delivery levels. The mean efficiency of the whole sample was 8.258 with a standard deviation of 6.462. Efficiency scores are based on all other aspects being equal, which is where exploring exogenous variables becomes important. A comprehensive display of the precise efficiency estimates, the rankings, and the confidence intervals for all the following sections are available in section one of Supplementary Information.

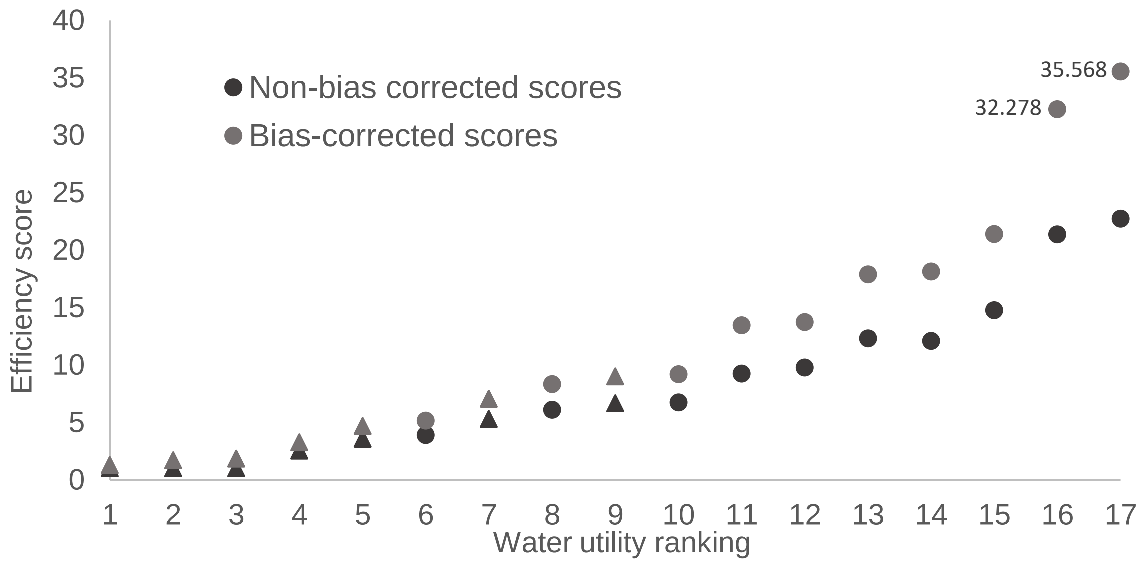


***Figure 1.*** *Rankings established from the original DEA model and bias-corrected DEA results produced with 2000 bootstrap iterations for the energy performance across 17 water companies in England and Wales. WoCs are featured as triangles and WaSCs are displayed as circles.*

Utilising the double-bootstrap method estimates that the whole sample was less efficient than the standard DEA model indicated (Fig. 1), which is an expected occurrence with this method.

The average bias taken out of the sample with the double-bootstrap method was -3.746, with a minimum value of -0.286 and maximum value of -12.8. Interestingly, although the bias taken out of the sample was large, it only changed the rank of two companies, swapping ranks 13 and 14 around. This result is rare and contrasts with other research (e.g., Ananda, 2014; Gómez *et al.*, 2017; Molinos-Senante *et al.*, 2018; Molinos-Senante and Sala-Garrido, 2019; Walker *et al.*, 2019) where their biases resulted in many rank changes. An explanation for this result could be that the sample is not large and does not lend itself to many rank changes naturally. Perhaps more importantly, the fact that there were broad efficiency distances between many companies within the sample meant that even large biases taken out did not affect ranking.

Since bootstrapping generates data from the original sample, there are slight variances in the estimates that are generated; therefore, three repeat tests were conducted to ensure that any variances were not large enough to make the study invalid and the following sections will comment on the variance of the results. Three repeats was chosen as this was enough to provide validity to results and could capture any significant variances. For energy bias-corrected results, the average difference in the results was 0.56%, with a range of -1.11%-1.56%. The bias-corrected efficiency scores had a mean average of 12.005, with a standard deviation of 9.996. This implies that the average water company in England and Wales could decrease inputs by 91.7% and maintain the same output standards of water delivery, if they were to perform at the same level as the best performers. The non-bias corrected scores indicated an average potential theoretical reduction of 87.8% (1-1/8.26), marginally lower in contrast to the bias-corrected average. The large average potential reduction is symptomatic of having a large spread in efficiency estimates using the DEA method, where some companies were perceived to be significantly less efficient than others, highlighted by the range of the sample being 1.286-35.568.

The reason for the large range of efficiency estimates appears to have been due to the sample including WaSCs and WoCs. Figure 2 shows that the top five performing companies are WoCs and only three WaSCs are amongst the WoCs altogether. Within the top ten performers, the efficiency estimates are relatively close (1.286-9.202) compared to the following seven companies (13.465-35.568), showing that there are clear efficiency disparities between companies that only deliver drinking water compared to the companies that deliver water and treat wastewater. This was a surprising result, since the study only focussed on the drinking water aspects of the businesses. One explanation could be that some companies are hindered by exogenous variables. A further potential explanation is that the WoCs only have the drinking water elements to focus on and thus have optimised their operations in this field, whereas the WaSCs also have the wastewater treatment components to provide, therefore optimisations such as replacement of inefficient pumps or leakage reduction measures are not prioritised. A further explanation could be that for WaSCs, there was inadequate separation of water treatment and water supply data. Following the results, further checks were conducted to ensure information was extracted correctly from the data sources; however, the sources could have incorrect data separation.

When conducting the energy efficiency analysis, *population served for water consumption* showed to be an appropriate proxy for *volume of water produced*. Figure 2 shows that the ranks of all the companies remained the same when the proxy was in use. The only impact the proxy variable had on energy efficiency analysis of the companies was that 14 of them displayed a reduction in their efficiency score, exhibiting an average of 0.172 reduction, equivalent to 1.01% compared to the results from the original variable of *volume of water produced*.

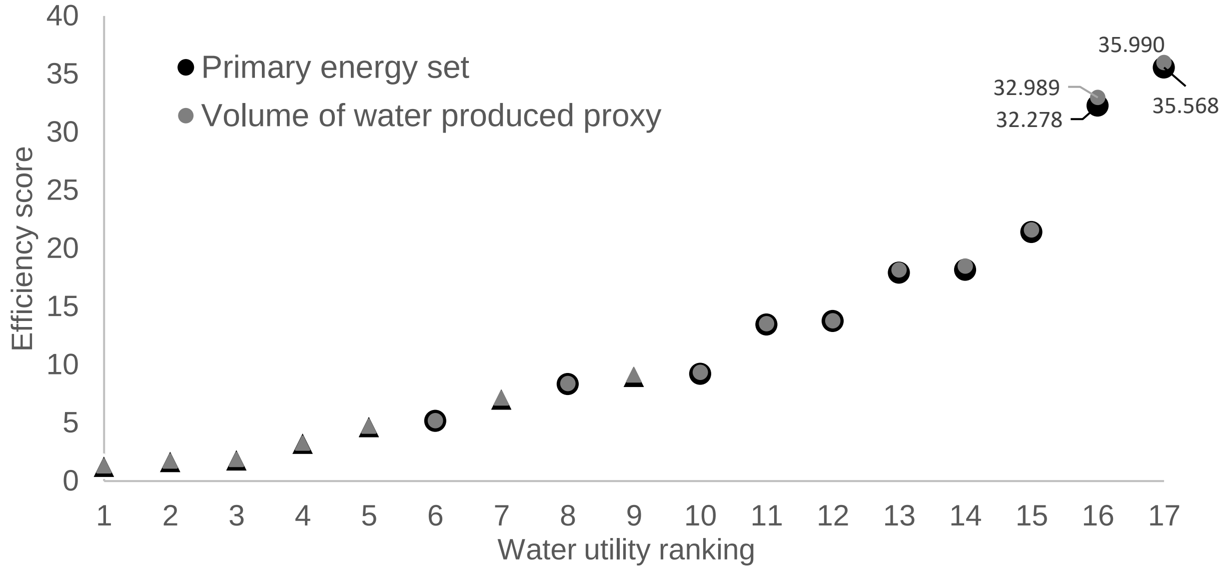


***Figure 2.*** *The bias-corrected (2000 bootstrap iterations) energy efficiency scores and ranking with the primary set of variables, and a volume of water produced proxy (population served for drinking water). WoCs are featured as triangles and WaSCs are displayed as circles.*

## 3.2. Role of explanatory factors on energy efficiency

An essential element of the double-bootstrap approach is the ability to appraise explanatory factors that may affect efficiency by employing a bootstrap truncated regression model. The explanatory factors analysed in this research were *leakage*, *per capita consumption*, *number of sources*, *proportion of water through size 5-8 water treatment plants* and *average pumping head height*; their influence on efficiency is presented in Table 2. A negative impact on efficiency is recognised if the bias-corrected coefficient value is positive and vice versa, and an asterisk is marked next to the coefficients to highlight significance to the 5% level. The variance average in the repeat tests for the bias-corrected coefficients was 1.03%, with a range of -2.03%-1.91%.

***Table 2.*** *Results of bootstrap truncated regression (bias-corrected) with 2000 iterations for energy efficiency assessment using the first choice variables and volume of water produced proxy: population served for water production.*

| | **Primary energy set** | | | **Energy WP replaced** | | |
|---|---|---|---|---|---|---|
| **Explanatory factor** | **Coefficient** | **Low** | **High** | **Coefficient** | **Low** | **High** |
| Leakage (Ml/day) | 0.045* | 0.031 | 0.059 | 0.046* | 0.032 | 0.060 |
| Number of sources | 0.053* | 0.008 | 0.097 | 0.053* | 0.011 | 0.097 |
| Average pumping head height (m.hd) | 0.423* | 0.136 | 0.736 | 0.426* | 0.136 | 0.729 |
| Proportion of water through size 5-8 treatment plants (%) | 0.142 | -0.033 | 0.323 | 0.140 | -0.029 | 0.318 |
| Per capita consumption (l/h/d) | -0.134 | -0.391 | 0.116 | -0.144 | -0.410 | 0.111 |

Note: *Statistically significant at the 5% level.

*Leakage* had a significant negative effect on energy efficiency, as to be expected since the more water that is lost, the more water needs abstracting, treating and delivering, which all require energy. Energy efficiency studies on water utilities that evaluate explanatory factors are rare. Walker *et al*., (2019) evaluated the environmental efficiency of water utilities in terms of carbon intensity, and found no significant link with leakage, although they did incorporate embodied carbon as well as operational carbon over just a one-year period, therefore one single significant capital project may have skewed the data depending on method of amortisation.

The variable *consumption per capita* had a positive relationship with energy efficiency to a non-significant extent. Although greater consumption overall would increase energy consumption due the requirements to pump and treat a larger volume, there are links to economies of customer density too, which can distort results (Byrnes *et al.*, 2010). When a pipe network is established, the volume of water actually flowing through it has nominal energy consumption and economic costs. In this instance, the insignificant relationship means inferences on reasoning are just speculative.

Results in Table 2 indicate that, as the *number of sources* increases, energy efficiency reduces. Although diversifying abstraction sources can be a positive attribute for companies to make their supply more resilient, it appears as though this is at the expense of a significantly increased energy consumption owing to more pumping being required through a larger network of piping. For benchmarking and regulation, this is a relationship to be aware of; however, water managers do not have much control over this factor, which is often determined by the magnitude of locally available supplies; therefore, any penalties on companies performing poorly on this metric need to carefully consider this context.

The *proportion of water passing through the largest four sizes of treatment works* was surprisingly associated with inefficiency, albeit insignificantly. The anticipated result was that economies of scale at the treatment level (Molinos-Senante and Sala-Garrido, 2017) would mean the more water being treated at larger treatment works, the more efficient energy use would be. An explanation of this could be that any economies of scale that are experienced are offset by the increase in the distribution of water to centralised treatment plants as Kim and Clark (1988) found, along with the increased leakages that occur over larger pipe network (<0.001 p-value using Pearson's r for relationship between leakage rates and network length found). Furthermore, scale economies are seen to be lost in treatment plants once they attain a certain size (Hernández-Chover *et al.,* 2018), therefore this would weaken any relationship in the data.

*Average pumping head height* showed a significant influence on energy inefficiency, meaning as the pumping head increases, so efficiency declines. This was anticipated, as pumping is a major consumer of energy for water utilities and the head is a pivotal facet of this consumption (Filion *et al.,* 2004; Díaz *et al.,* 2011). Water practitioners have no influence over pumping heads once infrastructure is in place, but this result does display how important it is for engineers and designers to minimise the head height when developing any part of the network to ensure long-term energy sustainability.

The *population supplied with water* also served as a useful proxy for the *volume of drinking water* produced in terms of evaluating the explanatory factors. The right half of Table 2 shows that the direction of the efficiency effect remained the same, as did the variables that showed significance.

### 3.3. Economic efficiency results

The non-bias corrected scores for economic efficiency results (Fig. 3) indicated that three of the 17 utilities are on the efficiency frontier, with a score of 1. The mean efficiency of these non-bias corrected estimates across the 17 companies was 9.321 with a standard deviation of 8.294, suggesting that an average UK water company can reduce their *OPEX* and *CAPEX* inputs by 89% and still produce their water production output to the same level.

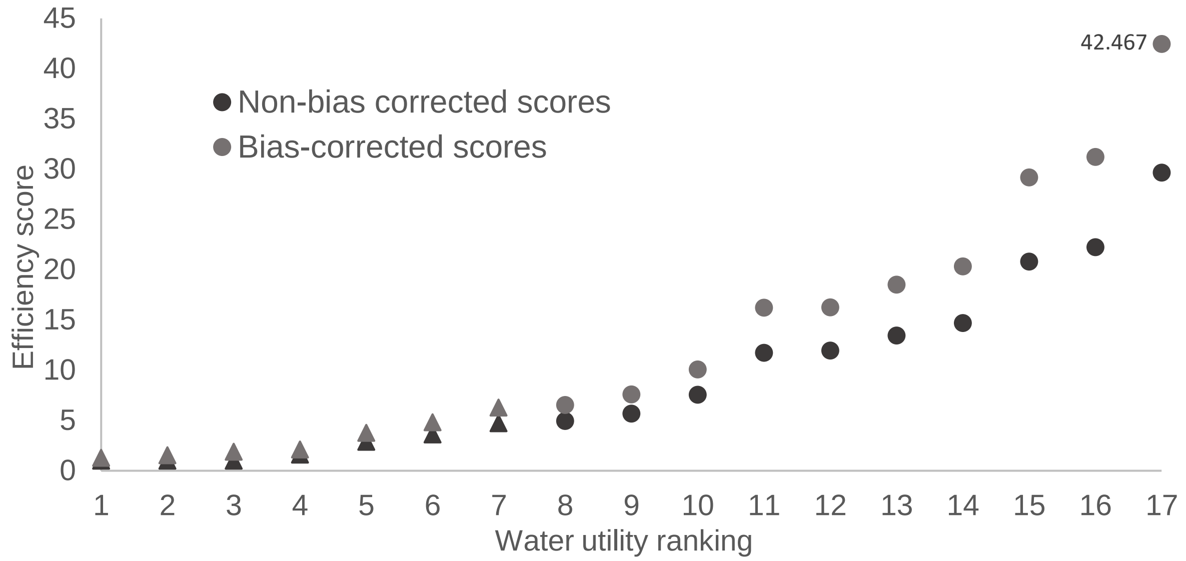


***Figure 3.*** *Rankings established from the original DEA model and bias-corrected DEA estimates produced with 2000 bootstrap iterations for the economic performance of 17 England and Wales water companies. WoCs are featured as triangles and WaSCs are displayed as circles.*

The bias taken out of the economic results ranged from -0.286 to -12.821, and averaged at -3.618. Despite the considerable bias taken out of the sample, it did not affect the rankings of the companies. This result contradicts other research (Ananda, 2014; See, 2015; Gómez *et al.*, 2017; Molinos-Senante and Sala-Garrido, 2019) where their biases altered the rankings of most of the sample. A potential justification for this is similar to that in the energy results in that the sizable efficiency spans between utilities proceeded to absorb biases taken off efficiency scores.

The bias-corrected efficiency results had a mean average of 12.94, with a standard deviation of 11.773. The variance in the three repeat tests was averaged at 0.78% with a range of -1.47%-2.01%. The average corrected efficiency scores indicated that an average water utility could scale down their collective *OPEX* and *CAPEX* by 92.3%, whilst producing the same amount of drinking water. This is particularly large compared to the Walker *et al*. (2019) study on UK and Irish water and sewerage utilities, where they calculated that the average utility could decrease their economic inputs by 19.4%. A possible reason for this was alluded to in Section 3.1, that having such a large theoretical drop in inputs is likely a result of the very considerable range in efficiency scores (1.286-42.467) brought about seemingly by the mixture of WaSC and WoCs in the sample. Figure 3 shows that all WoCs were ranked higher than the WaSC for economic efficiency, despite the data encompassing just the water production side of operations for all companies. An explanation explained earlier in Section 3.1 is that WaSCs may find it more difficult to disseminate and effectively utilise resources due to the extra operational strain of wastewater treatment compared to WoCs. Moreover, an array of exogenous can influence the efficiency results and cause the disparity between companies (main exogenous factor evaluation in Sections 3.2 and 3.4). For example, a justification appears to be linked to size; the bias-corrected coefficients were naively tested for correlation using Pearson's r against population with water service as an indicator to represent the size of the water utilities, and a positive correlation with a p-value value of <0.001 was found. This suggests that the larger companies are, the less efficient they are at producing water at lower costs. Since generally WoCs are smaller than WaSCs, with seven of the smallest eleven companies in this sample being WoCs (see Supplementary Information, Section 2 for breakdown), it appears size could at least partially explain the reason behind WoCs outperforming WaSCs. It is not clear why size has this correlation; population density was also correlated against coefficient values to test a reason behind the size result and this showed to have no impact (p-value of 0.153). It is possible that larger-scale operations are harder to manage efficiently, with the larger network, more abstraction and more sources of abstraction making companies more inefficient. The disparity of efficiency between WaSCs and WoCs is an area where future research could investigate; perhaps analysing factors such as precipitation, types of abstraction sources, topography and governance structures.

The proxies analysed for the economic analysis were *km of water mains* replacing *CAPEX* and *population served for drinking water*, which replaced *volume of water produced*. The latter appeared to be a satisfactory proxy, with only two companies (this ranks 11 and 12) exchanging places (Figure 4). If the sample were larger and closer in terms of efficiency range, then perhaps there would have been more ranking changes. The *CAPEX* proxy resulted in ten companies changing their rank compared to the original primary set of indicators, with 11 ranks moved (Figure 5). A further effect of the *CAPEX* proxy was the increased efficiency of the sample, implying companies were on average 12.63% more efficient. Some companies exhibited particularly large increases in efficiency, for example, ranks 16 and 17 went from 31.222 and 42.467 to 24.661 and 17.059 respectively. As more than half of the sample changed rank and some utilities experiencing such large changes, using the length of mains network does not appear be an apt proxy for *CAPEX*.

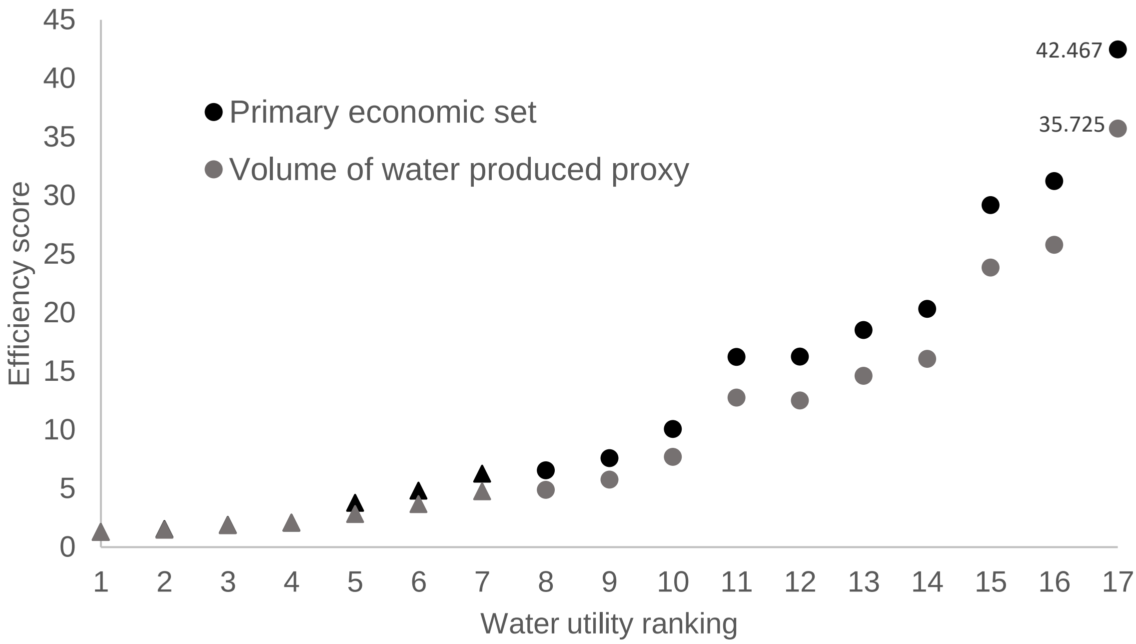


***Figure 4.*** *The double-bootstrap (2000 iterations) bias-corrected economic efficiency results with the primary set of economic variables, and a volume of water produced proxy (population served for drinking water). WoCs are featured as triangles and WaSCs are displayed as circles.*

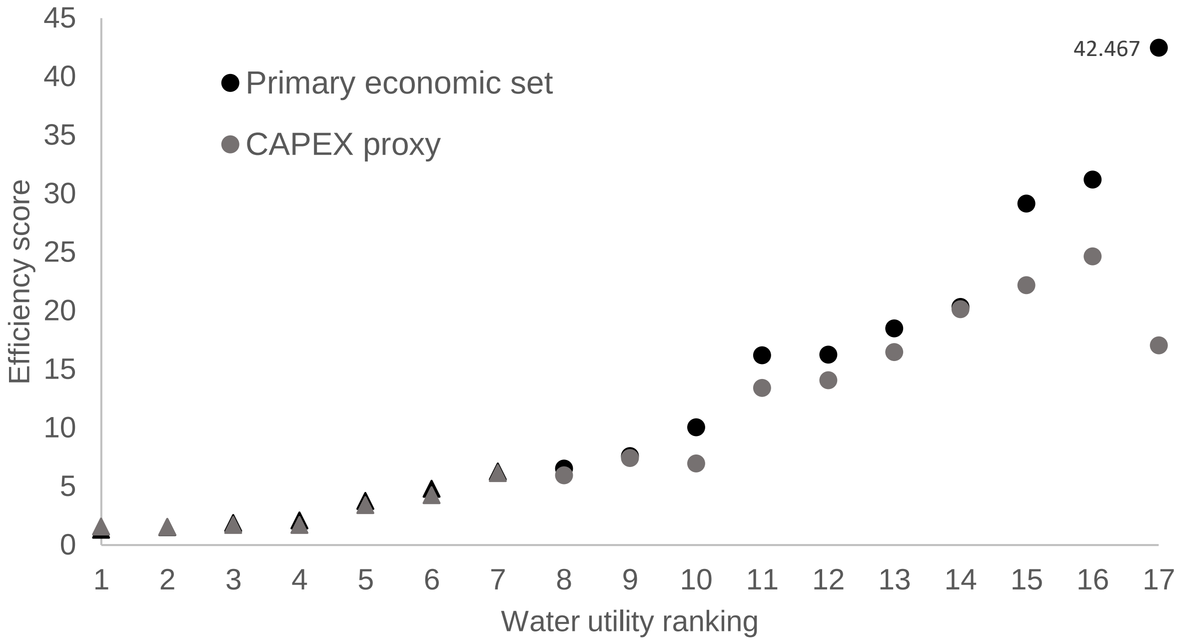


***Figure 5.*** *The double-bootstrap (2000 iterations) bias-corrected economic efficiency results with the primary set of economic variables, and a capital expenditure (CAPEX) proxy (kilometres of water mains network). WoCs are featured as triangles and WaSCs are displayed as circles.*

### 3.4. Role of explanatory factors on economic efficiency

The explanatory factors analysed in the economic assessment matched those analysed for energy efficiency; *leakage*, *per capita consumption*, *number of sources, proportion of water through size 5-8 water treatment plants* and *average pumping head height*. As mentioned in Section 3.2, the bias-corrected coefficients for the explanatory variables (Table 3) are regarded to adversely affect efficiency when their figures are of a positive value and positively influence efficiency if their figures are negative. The average variance in the three repeat tests was 1.08% (range of -2.47%-0.79%).

***Table 3.*** *Results of bootstrap truncated regression (bias-corrected) with 2000 iterations for economic efficiency analysis using the first choice variables, volume of water produced proxy: population served for water production, and CAPEX proxy: kilometres of water mains network.*

| | Primary economic set | | | Economic CAPEX replaced | | | Economic WP replaced | | |
|---|---|---|---|---|---|---|---|---|---|
| **Explanatory factor** | **Coefficient** | **Low** | **High** | **Coefficient** | **Low** | **High** | **Coefficient** | **Low** | **High** |
| Leakage (Ml/day) | 0.054* | 0.041 | 0.067 | 0.016 | -0.003 | 0.036 | 0.046* | 0.037 | 0.056 |
| Number of sources | 0.053* | 0.017 | 0.093 | 0.079* | 0.025 | 0.140 | 0.041* | 0.013 | 0.072 |
| Proportion of water through size 5-8 treatment plants (%) | 0.158* | 0.005 | 0.325 | 0.238* | 0.016 | 0.532 | 0.125* | 0.010 | 0.251 |
| Average pumping head height (m.hd) | 0.205 | -0.058 | 0.470 | -0.013 | -0.396 | 0.396 | 0.177 | -0.023 | 0.389 |
| Per capita consumption (l/h/d) | -0.121 | -0.343 | 0.103 | -0.358* | -0.763 | -0.001 | -0.076 | -0.249 | 0.095 |

Note: *Statistically significant at the 5% level.

The variable *leakage* mirrored the energy analysis and had a significant negative influence on economic efficiency. This result is concurrent with the majority of similar studies (Berg, 2013; See, 2015); however, this is not always the case. Some research shows the negative affect on efficiency to a non-significant extent (Marques *et al.,* 2014). Moreover, there are articles that demonstrate the opposite relationship, with *leakage* appearing to cause efficiency (de Witte and Marques, 2010; Ananda, 2014) albeit, to a non-significant degree. The leakage result in our research is a particularly interesting result for the UK since water companies operate under the 'sustainable economic level of leakage', where they are required by the regulator OFWAT (2019) to fix leaks, as long as the cost of doing so is less than the cost of not fixing the leak. The suggestion is therefore that leakage is less likely to be at such a rate that it significantly negatively affects economic efficiency however, due to other factors obscuring the time when replacement of pipes should occur, this may not be the case.

*Consumption per capita* displayed a positive relationship to a non-significant level, therefore also matching the energy explanatory factor results. As examined in Section 3.2, the contradiction in the expected result is likely to be from the links to economies of customer density that can relieve increased consumption per capita from having such a strong influence (Byrnes *et al.,* 2010; Carvalho *et al.,* 2012). The volume customers consume is not directly controllable by water managers, however, there have been awareness campaigns and water efficiency information and technology available to customers from companies to reduce user consumption that have had some affect. Manouseli *et al.,* (2019) evaluated the effectiveness of the water efficiency initiatives rolled out by water companies in England, and found that households that participated in the programme reduced their consumption by approximately 15%. Perversely, water conservation is bad for companies in terms of short-term profits, although it does provide benefits to wider society. The companies will however benefit in longer-term sustainability as water is expected to become scarcer in the UK due to climate change (Arnell and Delaney, 2006; Wade et al., 2013) and reduced consumption can reduce the frequency for requiring new infrastructure.

The *number of abstraction sources* was significantly associated with negative economic efficiency, again following the energy results. This was anticipated, as more materials are required such as pumps, piping and associated infrastructure to utilise more sources, thus increasing costs. This result shows that when increasing resilience of the water supply by increasing the number of sources, there is a trade-off, where efficiency lowers. Many companies may not have a choice of how many abstraction sources they utilise, furthermore the perfect balance of resilience and efficiency a company's number of sources is not yet known. Therefore, as noted in Section 3.2, any regulators conducting fines or punishments on companies for poor efficiency should consider such results.

The most unexpected result for variables that influence economic efficiency was the *proportion of water treated by size 5-8* (the largest) treatment plants. Table 3 indicates a significant negative influence on economic efficiency, deviating from the energy explanatory factor analysis. The economies of scale present at larger treatment plants was expected to result in a positive relationship with efficiency. Reasons for this are similar to those outlined for the role this variable had in energy efficiency (Section 3.2); greater pumping, maintenance and leakage costs from extended pipe networks and loss of scale economies at particular sizes (Hernández-Chover *et al.,* 2018), despite treatment plants being positively associated to economies of scale (Molinos-Senante and Sala-Garrido, 2017). For companies to take advantage of economies of scale in treatment plants to improve their economic and energy efficiency then, there is a need for better understanding of the multiple factors influencing efficiency across different sizes of plant, considering associated consequences for distribution effects.

The *pumping head average* was regarded to have a non-significant negative effect on economic efficiency, diverging from the energy results, which showed the same effect on efficiency, but with significance. Despite the higher energy demands that larger pumping heads create, the non-significant result indicates that energy costs are not the dominant factor in economic efficiency, which is supported by power (including climate change levy and carbon reduction commitments) representing an average of 10.8% of total *OPEX* for this sample.

Table 3 presents how the simple proxy of *population supplied with water* adequately replaced *the volume of water produced*, since the significance and direction of influence of explanatory factors on efficiency were the same. The satisfactory performance of the *volume of drinking water* proxy was expected to an extent, since the water produced is for the proxy of *population served for drinking water*. The proxy would theoretically match the original variable perfectly were it not for erroneous factors such as *leakage* and *per capita consumption*, which for this sample ranged from 15.8%-32% and 129-159 (l/h/d), respectively, which appeared to be not enough to skew the appropriateness of the proxy. The *CAPEX* proxy of *water mains network length* however, was less successful. It only directly matched two of the variables: *number of sources* and *proportion of water through size 5-8 water treatment plants*, for both direction of influence and significance. The proxy did match the direction of influence of the true *CAPEX* variable for *leakage* and *per capita consumption* however, significance of relationship was lost. Finally, for *average pumping head height*, the proxy misinterpreted the direction of efficiency affect, the result suggesting that larger pumping heads actually resulted in higher economic efficiencies.

## 4. Conclusions

The goals of this research were to implement a double-bootstrap DEA method to compare unbiased energy and economic efficiency between a mixture of water only companies and water and sewerage companies, to evaluate the effect of explanatory factors, and to analyse the accuracy of two common proxies. Results support four main conclusions. Firstly, that the average company could decrease their energy inputs by 91.7% and their economic inputs by 92.3%, if they were to perform at the efficiency frontier (in the absence of significant exogenous influences). Thus, we establish that there is substantial scope to improve energy and economic efficiency for water utilities in England and Wales, if the practices of best performers were widely adopted. There was a large variance in the potential reductions of inputs, which appeared to reflect the second main conclusion – that WoCs generally performed much more efficiently than WaSCs. All seven WoCs outperformed WaSCs in the economic analysis they were amongst the top nine performers in the energy analysis. Improper separation and reporting of operational data from companies into their reports may have been a reason for this, however exogenous factors likely played the major role. Size appeared to be a key determinant, displaying a positive relationship with efficiency and p-value of <0.001 when correlated with efficiency scores, but further research is recommended to investigate the complex influence of size. Thirdly, the paper determined factors that influence efficiency. Of the potential explanatory variables analysed, *leakage* and *number of abstraction sources* were concurrent in their negative effect and significance across both the energy and economic assessments. *Average pumping head height* displayed a significant negative affect for energy, whereas the variable *proportion of water passing through the largest four treatment works* was deemed to have a significant negative effect on economic efficiency. These exogenous factors therefore need to be corrected for in future benchmarking activities and have the potential to inform water companies about factors to prioritise in order to improve efficiency. The final conclusion was that the proxy *population served for drinking water* can adequately replace *the volume of water produced* as an input variable in efficiency benchmarking when *leakage* and *per capita consumption* are fairly uniform across the sample, since companies stayed at the same rank and explanatory factors displayed the same significance. Conversely, *length of water mains* performed poorly when replacing *CAPEX* as an economic input, implying companies were on average 12.6% more efficient, resulting in 10 companies changing their rank compared to the original variable and causing some explanatory variables to differ in direction of influence and significance. Further research is recommended on the energy and economic efficiency of WoCs and WaSCs, considering a wide range of exogenous variables and careful selection of (proxy) indicators.

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