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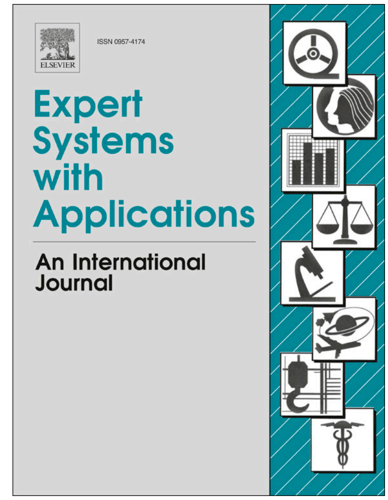


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# ASSESING THE INFLUENCE OF ENVIRONMENTAL VARIABLES ON THE PERFORMANCE OF WATER COMPANIES: AN EFFICIENCY ANALYSIS TREE APPROACH

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**Abstract**

Efficiency assessment is a valuable tool for industries that are regulated, such as the provision of drinking water. Hence, past research on this topic is wide. However, current, widely used approaches such as parametric, non-parametric and partial frontier methods present several limitations and pitfalls. Thus, here, the Efficiency Analysis Tree (EAT) method was trialled on a sample of water companies. This method overcomes overfitting issues, because it employs a combination of classification, regression tree methods, and non-parametric analyses. For comparative purposes, efficiency was also estimated using Data Envelopment Analysis (DEA) and Free Disposal Hull (FDH) non-parametric methods. The approach was applied empirically using a sample of English and Welsh water companies during 1991–2020. Average efficiency was estimated at 0.489, showing that water companies could save 51.1% of their costs if efficient. Except for the 2011–2015 period, efficiency increased over time, indicating that price reviews by the English and Welsh water regulator contributed to improving water company performance. The application of bootstrap regression analysis techniques showed that the main source of raw water, percentage of metered properties, population density, and percentage of water leakage represented environmental variables that significantly influenced the efficiency scores of water companies. The approach introduced here could be of use to water regulators, as it overcomes the existing limitations of traditional approaches employed to assess the performance of water companies, facilitating sound decision-making.

**Keywords:** regression trees; efficiency analysis; performance; water utilities; environmental variables; water services.

## 1. INTRODUCTION

Measuring the efficiency of production processes is valuable for decision making units (DMUs). Such measurements show how inputs are used to generate outputs “i.e.” production technology, and evaluate the efficiency of processes. Efficiency measures the maximal (minimal) contraction of inputs (outputs) to generate the same level of output (input) (Farrell et al., 1957). The concept of efficiency has been widely used for monitoring the performance of several sectors of the economy such as education, health services, airports, e-commerce enterprises and banking (Iyer and Jain, 2019; Zakowska and Godycki-Cwirko, 2020; Pratap et al., 2022). Assessing efficiency in regulated industries (such as water, gas, and electricity) is of particular interest to researchers and policy makers (Berg and Marques, 2011; Daraio et al., 2020; Mergoni and De Witte, 2022), as it allows the impact of regulatory reforms and policies to be evaluated. Furthermore, it can be used to determine future cost allowances and tariffs for customers (Cetrulo et al., 2019; Goh and See, 2021).

Efficiency has been traditionally measured using parametric and non-parametric techniques. Parametric techniques use econometrics, such as Stochastic Frontier Analysis (SFA), to compare the inputs and outputs of units. SFA incorporates both noise and inefficiency “i.e.” it is stochastic. To do this, a functional form must be specified for the production technology “e.g.” Cobb-Douglas, translog, which makes different assumptions regarding the distribution of inefficiency “e.g.” half-normal, exponential (Wang et al., 2017). In contrast, non-parametric techniques do not have these requirements. Non-parametric methods build on linear programming models, such as Data Envelopment Analysis (DEA) and Free Disposal Hull (FDH). In this case, the production frontier is not estimated econometrically, but is constructed using observed data on inputs and outputs. The production frontier under DEA is piecewise linear and convex, whereas under FDH the frontier is a step function (O´Donnell, 2018). Non-parametric approaches assume that any deviation from the efficient frontier is only caused by inefficiency “i.e.” they are deterministic (Dyckhoff, 2018). To overcome the deterministic nature of this approach, other techniques have been proposed, such as the bootstrap DEA procedure and partial frontier techniques “e.g.” order-*m*(Simar and Wilson, 2007; Ferreira and Marques, 2017). However, it is challenging to select the number of bootstrap replications and optimal number of *m* (Villegas et al., 2019). Consequently, Esteve et al. (2020, 2021a) developed a new technique, called Efficiency Analysis Trees (EAT). This technique combines the Classification and Regression Trees (CART) proposed by Breiman et al. (1984) with non-parametric analysis to measure efficiency. By using regression trees, DMUs are separated into several regions using a set of different thresholds (Esteve et al., 2021b). The EAT approach adjusts the regression tree to estimate production frontiers and efficiency. Specifically, the free disposability assumption is imposed where the estimated value of the response (output) variable refers to its maximum (value), and not the average value. As a result, the estimated frontier utilizes a step function that allows efficiency scores to be measured. Esteve et al. (2020, 2021a) demonstrated that the EAT technique outperformed other non-parametric techniques (such as DEA and FDH), and improved the accuracy of efficiency measurements, because values are not overfitted.

Thus, this study aimed to evaluate the efficiency of water utilities using EAT, the newly developed technique. The regression tree allowed the maximum (frontier) expenditure required to provide water services to be visualised at different thresholds (rules). EAT allows the efficiency scores for each water utility to be estimated. To allow comparison, our study also estimated efficiency using non-parametric techniques (such as DEA and FDH). In parallel, we explored how several environmental variables (operational characteristics) influenced the efficiency of water utilities. Bootstrap regression analysis techniques were used, in which the EAT efficiency score was regressed against a set of factors associated with network quality, source of raw water, and population density.

Literature reviews conducted by Cetrulo et al. (2019) and Goh and See (2021) demonstrated that many studies have evaluated the efficiency of water companies. The bibliometric analysis conducted by Goh and See (2021) identified 142 articles on benchmarking the performance of water companies during the years 2000-2019. Moreover, Cetrulo et al. (2019) identified that DEA was the most commonly used method to evaluate the efficiency of water companies. The aim of these previous studies was diverse. Some studies focused on comparing the efficiency of public and private companies (Estache and Trujillo, 2003; Molinos-Senante et al., 2016). It is also possible to observe benchmarking studies linked to the implementation of regulation processes (Berg and Lin, 2008; Drusiani et al., 2013). Other studies explored the impact of economies of scale, scope and density on the performance of water companies (Guerrini et al., 2015; Lo Storto, 2020). Several studies (Marques et al., 2014; Pinto et al., 2017) examined the influence of exogenous variables on the performance of water companies. However, all previous studies on this topic used traditional parametric and non-parametric methods. Despite the advantages of EAT, it has not been previously used to assess the efficiency of water companies. Hence, this study extends the literature on this subject by employing a newly developed technique that combines decision tree analysis and production economics to improve the accuracy in evaluating the efficiency of water utilities.

The paper unfolds as follows. Section 2 presents the methodologies employed in this study to estimate efficiency scores and the impact of environmental variables on efficiency. Section 3 describes the case study and sample data. Section 4 presents and discusses the main findings, whereas the final section concludes.

## 2. METHODOLOGY

### 2.1 Efficiency methods

Efficiency scores for a sample of water utilities were estimated using EAT, in which the predicted values of the response (output) variable were visualised through a decision tree. DMUs were split into several non-overlapping regions based on a set of thresholds of predictor (input) variables (James et al., 2013; Rebai et al., 2019). With EAT, the efficient frontier was estimated using step functions that satisfied the basic properties of microeconomics, such as free disposability.

Let us consider $n$ water companies to be evaluated. Assuming that the set of predictor variables is denoted as $x_1$,...,$x_m$ with $\boldsymbol{x_j} \in R^+$, $j = 1$,...,$m$ is used to predict a set of response variables denoted as $y_1$,...,$y_s$ with $\boldsymbol{y} \in R^+$. The EAT algorithm selects predictor variable $j$and threshold $\boldsymbol{s_j} \in S_j$, in which $\boldsymbol{S_j}$ denotes the set of likely thresholds for variable $j$to separate the data into two nodes, $t_R$ and $t_L$ (Esteve et al., 2021a). The split is achieved by minimising the sum of the mean squared of error

(MSE); namely, the difference between the actual and response variables derived in that particular node. Mathematically, this is done as follows:

$$R(t_L) + R(t_R) = \frac{1}{n}\sum_{(x_i,y_i)\,\in\, t_L}(y_i - y(t_L))^2 + \frac{1}{n}\sum_{(x_i,y_i)\,\in\, t_R}(y_i - y(t_R))^2 \qquad (1)$$

where $t$ presents the node of the tree, $R(t)$ is the MSE of each node $t$, $n$ denotes the sample size, and $\boldsymbol{y}(\boldsymbol{t_L})$ and $\boldsymbol{y}(\boldsymbol{t_R})$ represent the predicted value of the response variable, which is derived based on the data that belongs to nodes, $t_L$ and$t_R$, respectively. Nodes $t_L$ and $t_R$ denote the left and right nodes of the tree, respectively. A regression tree is visualised graphically as shown in Figure 1.

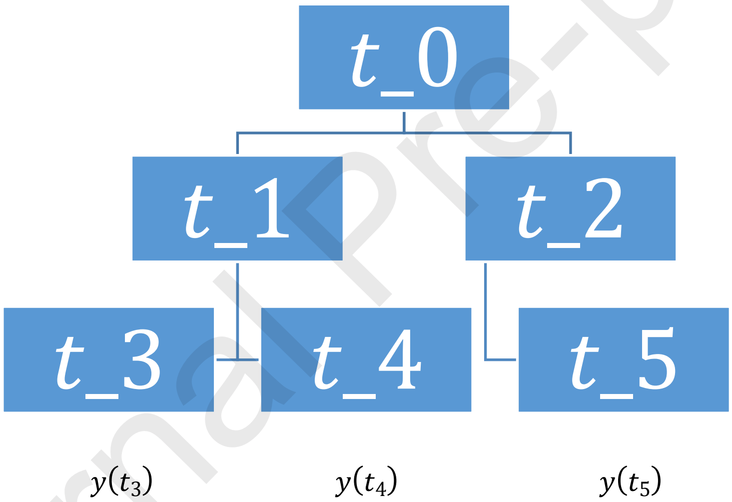


Figure 1. Example of a regression tree

The regression tree obtained using the EAT algorithm terminates when further meaningful splits of data are not feasible. This arises when $n(t) \leq n_{min} = 5$ (Breiman et al., 1984; Breiman et al., 2001; Esteve et al., 2020). EAT extends the CART approach by allowing the inclusion of two characteristics of production economics. First, it allows the frontier (maximum) variable to be estimated, rather than the average of the response variable. Second, the data from each node are split in a way that the free disposability assumption is satisfied, while minimising Eq. (1). Both characteristics are accomplished by introducing the concept of Pareto-dominant nodes (for more details, see Esteve et al., 2020; 2021a; 2022).

Consequently, the predicted (estimated) values of the response variable for a given node $t$, $y(t)$, must be equal to, or higher (or equivalently, must not be smaller), than the those belonging to the Pareto-dominant node. Mathematically, the fulfilment of the free disposability assumption in the regression tree that is built based on the EAT algorithm is expressed as follows:

$$y(t_L) = max\{max\{y_i{:}(x_i{,}y_i) \in t_L\}{,}y(I_{T(k|t^* \to t_L,t_R)}(t_L))\}$$

$$y(t_R) = y\ (t) \quad (2)$$

where $T$ denotes the sub-tree that is produced from applying the EAT algorithm, $k$ is the number of splits, $y(I_{T(k|t^* \to t_L,t_R)}(t_L))$, and $y(I_{T(k|t^* \to t_L,t_R)}(t_R))$ presents the highest estimate of variable $y$ at Pareto-dominance nodes of $t_L$ and $t_R$, respectively (Esteve et al., 2020). Thus, the predictor function is non-decreasing, and the estimated production frontier looks like a step function (Aparicio et al., 2021; Esteve et al., 2021a). Thus, the production technology estimated using EAT is defined as follows:

$$\widehat{PT}_{T_k} = \{(x{,}y) \in R_+^{m+1}{:}y \le d_{T_k}(x)\} \quad (3)$$

where $d_{T_k}(x)$ denotes the predictor estimator related to sub-tree $T_k$.

Cross-validation techniques could be used to obtain the best regression tree, such as the optimal number of leaf nodes or the minimum number of DMUs in a node for a split to arise (Green et al., 2021; Elbeltagi et al., 2022). Overall, the tree constructed using the EAT algorithm uses a vector of inputs and outputs, and each node of the tree uses a sub-matrix of these data. Each node uses a predictor and a set of thresholds to produce a predicted value of the response variable. Each split is determined by minimising the MSE. The EAT algorithm applies the free disposability assumption, so the estimated frontier looks like a step function, and the predicted (estimated) value of the response variable is the frontier, not the average. Given that the EAT algorithm produces a size increasing sequence of trees, i.e., $\{t_0\} < T_1 < T_2 < \ldots < T_K = T_{max}$, ensuring that each tree $T_K$ fulfils free disposability. Thus, according to Esteve et al. (2021), the opposite sequence ($T_{max} > T_{K-1} > T_{K-2} > \ldots > \{t_0\}$) was used for the pruning process as a sequence of subtrees. Hence, we note that the following relationship among the estimated outputs of the pruned EAT, DEA and FDH approaches exist as indicated by Esteve et al. (2021) $d_{T*}(x) \geq d_{T_{max}}(x) \geq f'_{FDH}(x)$. The efficiency score when using EAT is derived by solving the following linear equation:

$$\theta^{EAT}(x_k,y_k) = \min \theta \qquad (4)$$

$$subject\ to:$$

$$\sum_{t \in \tilde{T^*}} \lambda_t a_j^t \leq \theta x_{jk}, \qquad j = 1,\ldots,m$$

$$\sum_{t \in \tilde{T^*}} \lambda_t d_{rT^*}^t(a^t) \geq y_{rk}, \quad r = 1,\ldots,s$$

$$\sum_{t \in \tilde{T^*}} \lambda_t = 1$$

$$\lambda_t \in \{0,1\}, \qquad i = 1,\ldots,n$$

where $\theta$ is the efficiency score, $\left(a^t, d_{T^*}(a^t)\right)$ are points in the input-output space for all $t \in T^*$, in which * denotes the final sub-tree, and $\lambda$ are intensity variables used to construct the efficient frontier. A value of one indicates that the unit under evaluation (water utility in this study) is fully efficient.

Finally, to allow comparison, we estimate the efficiency scores of two alternative non-parametric approaches, DEA and FDH. DEA constructs a piecewise convex efficient frontier, whereas FDH estimates an efficient frontier that looks like a step function[1]. Under DEA, efficiency is measured by assuming that the variable returns to scale, and requires the solution of the following linear equation:

$$\theta^{DEA}(x_k,y_k) = \min \theta \qquad (5)$$

$subject\ to$:

$$\sum_{i=1}^{n} \lambda_i x_{ji} \le \theta x_{jk}, \qquad j = 1,\ldots,m$$

$$\sum_{i=1}^{n} \lambda_i y_{ri} \ge y_{rk}, \qquad r = 1,\ldots,s$$

$$\sum_{i=1}^{n} \lambda_i = 1$$

$$\lambda_i \ge 0, \qquad i = 1,\ldots,n$$

To calculate the efficiency scores under FDH, the following linear equation is used:

$$\theta^{FDH}(x_k,y_k) = \min \theta \qquad (6)$$

$subject\ to$:

$$\sum_{i=1}^{n} \lambda_i x_{ji} \le \theta x_{jk}, \qquad j = 1,\ldots,m$$

$$\sum_{i=1}^{n} \lambda_i y_{ri} \ge y_{rk}, \qquad r = 1,\ldots,s$$

$$\sum_{i=1}^{n} \lambda_i = 1$$

$$\lambda_i \in \{0,1\}, \qquad i = 1,\ldots,n$$

To assess the relationship between the efficiency scores estimated using EAT, DEA, and FDH, Spearman´s rank-correlation coefficient is used. It is a non-parametric

[1]More details on DEA and FDH are available in Cooper et al. (2011).

approach that was appropriate for our case study, because the efficiency scores are non-normally distributed.

For a more in-depth examination of efficiency scores estimated using the EAT, DEA and FDH methods, kernel density analysis is conducted. Kernel density provides valuable information about the distribution of efficiency scores computed across the 682 observations (water companies). According to Henderson and Parmeter (2015), in our case study, the density function is defined as follows:

$$\hat{f}(\theta) = \frac{1}{682h}\sum_{k=1}^{682} K\left[\frac{1}{h}(\theta - \theta_k)\right] \quad (7)$$

where $\theta_k$ is the efficiency score for the water company $k$; $K$ is a kernel function and, $h$ is a smoothing bandwidth parameter. Based on past research (Castillo-Gimenez et al., 2019; Ding et al., 2020), a *Gaussian* function is used for the kernel function which is as follows:

$$K(\theta) = (\sqrt{2\pi})^{-1} \exp\left(-\frac{1}{2}\theta^2\right) \quad (8)$$

The kernel density analysis is conducted for the efficiency scores estimated using the EAT, DEA and FDH methods.

**2.2. Environmental variables influencing efficiency**

Potential factors influencing the efficiency scores estimated in Section 2.1 are investigated. The potential impact of certain operating characteristics on company efficiency is explored, such as population density and source of water collection. We perform truncated regression using the efficiency score (values between zero and 1) as a dependent variable and the vector of operating characteristics as independent variables (Ananda, 2018; Wang et al., 2020; Sala-Garrido et al., 2021a). Typically used Tobit regression might generate biased estimates, due to serial correlation among efficiency scores, error terms, and explanatory variables (Simar and Wilson, 2007). Therefore, bootstrap truncated regression developed by Simar and Wilson (2007) is used. The regression model is defined as follows:

$$\theta_i = \beta_0 + \beta_i \eta_i' + year_i + \varepsilon_i \tag{9}$$

where $\theta_i$ captures the efficiency score obtained from the previous stage, $\beta_0$ is the constant term, $\boldsymbol{\eta_i'}$ is the set of operating characteristics of any water company $i$, and $\beta_i$ is the parameters that must be estimated. We also includes dummies for each year observed in the sample, captured by the term$year_i$. $\varepsilon_i$ denotes the error (noise) term, and follows the standard normal distribution.

The truncated maximum likelihood is maximised with respect to the estimated parameters and variance of the error (Badunenko and Tauchmann, 2019). A parametric bootstrap of the truncated regression is employed to obtain unbiased beta coefficients and valid confidence intervals (Simar and Wilson, 2007).

## 3. CASE STUDY DESCRIPTION

The empirical application conducted focused on measuring the efficiency in the provision of water services by several water utilities in England and Wales during 1991–2020. The water utilities that were evaluated included both water and sewerage companies (WaSCs) and water only companies (WoCs). Being natural monopolies, an economic regulator, the Water Services Regulation Authority (Ofwat), was set up to monitor the performance of utilities. Every five years, the regulator evaluates the efficiency of the water utilities to delineate a baseline future cost allowance (Molinos-Senante et al., 2017). The results of this performance assessment are translated into revenue allowance and price limits, including allowed charges to customers (price review).

Predictors and response variables were selected based on past research on this topic (see review by See, 2015; Cetrulo et al., 2019; Goh and See, 2021). The response variable was defined as the annual total expenditure of water services measured in millions of ₤ (Saal et al., 2007; Bottasso et al., 2011; Sala-Garrido et al., 2021b). Total expenditure was defined as the sum of operating and capital expenditure from the provision of water services. Three predictor variables were selected. The first variable was the volume of drinking water delivered, which was measured in megalitres per year (De Witte and Marques, 2010; Molinos-Senante et al., 2017). The second predictor variable was the number of water connected properties, which was measured in thousands per year (Bottasso and Conti, 2009; Molinos-Senante et al., 2014). The third predictor variable the length of water mains, which was measured in thousands of kilometres (km).

Past studies that benchmarked the efficiency of water companies (Ananda, 2018; Cetrulo et al., 2019; D´Inverno et al., 2020; Goh and See, 2021) showed that several operating characteristics (or environmental variables) impact performance, and should be part of the assessment exercise. Hence, we included several operating characteristics that we were related to the quality of the network, source of raw water, and density of the areas served by water utilities. The percentage of water leakage was used to reflect the quality of network (Brea-Solis et al., 2017). The percentage of raw water collected from rivers and reservoirs was used to indicate the source of raw water. The average pumping head was used as a proxy for the energy required to extract, treat, and deliver water to end users (Molinos-Senante and Maziotis, 2018). The percentage of metered properties was used as an indicator of efficiency (Brea-Solis et al., 2017). Population density was defined as population divided by the area supplied by the water company as an environmental variable (Sala-Garrido et al., 2021a; 2021b). Table 1 presents the descriptive statistics of the variables used in the analysis.

Table 1. Descriptive statisticts of the English and Welsh water companies

| Variables | Units | Mean | St.Dev. | Min | Max |
|---|---|---|---|---|---|
| Volume of water delivered | Ml/year | 244105 | 258269 | 10216 | 1049122 |
| Water connected properties | 000s | 1057 | 1083 | 37 | 4047 |
| Length of mains | km | 14560 | 13754 | 480 | 47151 |
| Total expenditure | Millions of £ | 159 | 170 | 5 | 866 |
| Water leakage | % | 15 | 5 | 5 | 36 |
| Water taken from rivers | % | 23 | 24 | 0 | 87 |
| Water taken from reservoirs | % | 32 | 27 | 0 | 100 |
| Water metered properties | % | 30 | 20 | 3 | 87 |
| Average pumping head | nr | 128 | 36 | 52 | 224 |
| Water population density | 000s/km$^2$ | 0.475 | 0.327 | 0.134 | 2.810 |

*Number of DMUs: 682*

## 4. RESULTS AND DISCUSSION

### 4.1 Efficiency estimation

Figure 3 presents the regression tree from implementing the EAT algorithm. Each node shows the identification number, MSE, number of DMUs, predictor that the split was based on, and predicted value of the response variable, which is the frontier value. All variables "i.e." water connected properties, length of water mains, and volume of drinking water delivered) contributed towards predicting total expenditure (Figure 2). Water connected properties (wcprop) and length of mains (mainskm) had a major impact on costs, as shown in the regression tree (Figure 3). Different levels of frontier expenditure were required, as shown by the different set of thresholds for predictor variables.

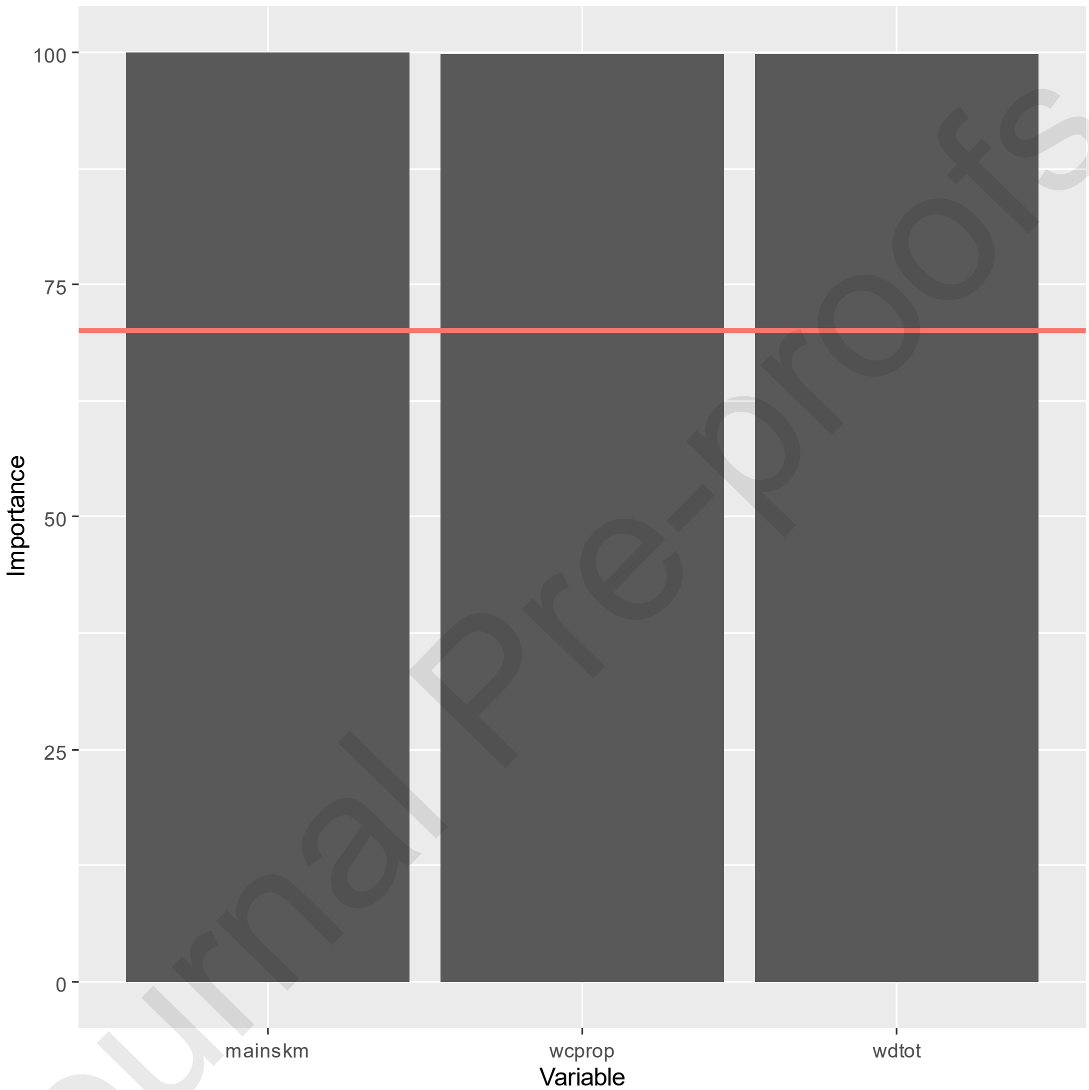


Figure 2. Variable importance for the EAT regression tree

Delivering water to more than 2,000,000 connected properties per year could require an operating expenditure of £865 million, representing the maximum (frontier) expenditure. For connected properties of less than 2,000,000 and a network of pipes of 11,645 thousands of kilometres, maximum expenditure could reach £335 million. However, for smaller networks "i.e." 2,824–11,645 thousands of kilometres, the predicted required efficient total expenditure was £143.5 million. Lower expenditure was needed "i.e." £34.3 million when the length of mains did not exceed 2,824 thousands of kilometres. Thus, the higher the number of connected properties, the higher the number of pipes that must be laid to deliver drinking water, raising company costs.

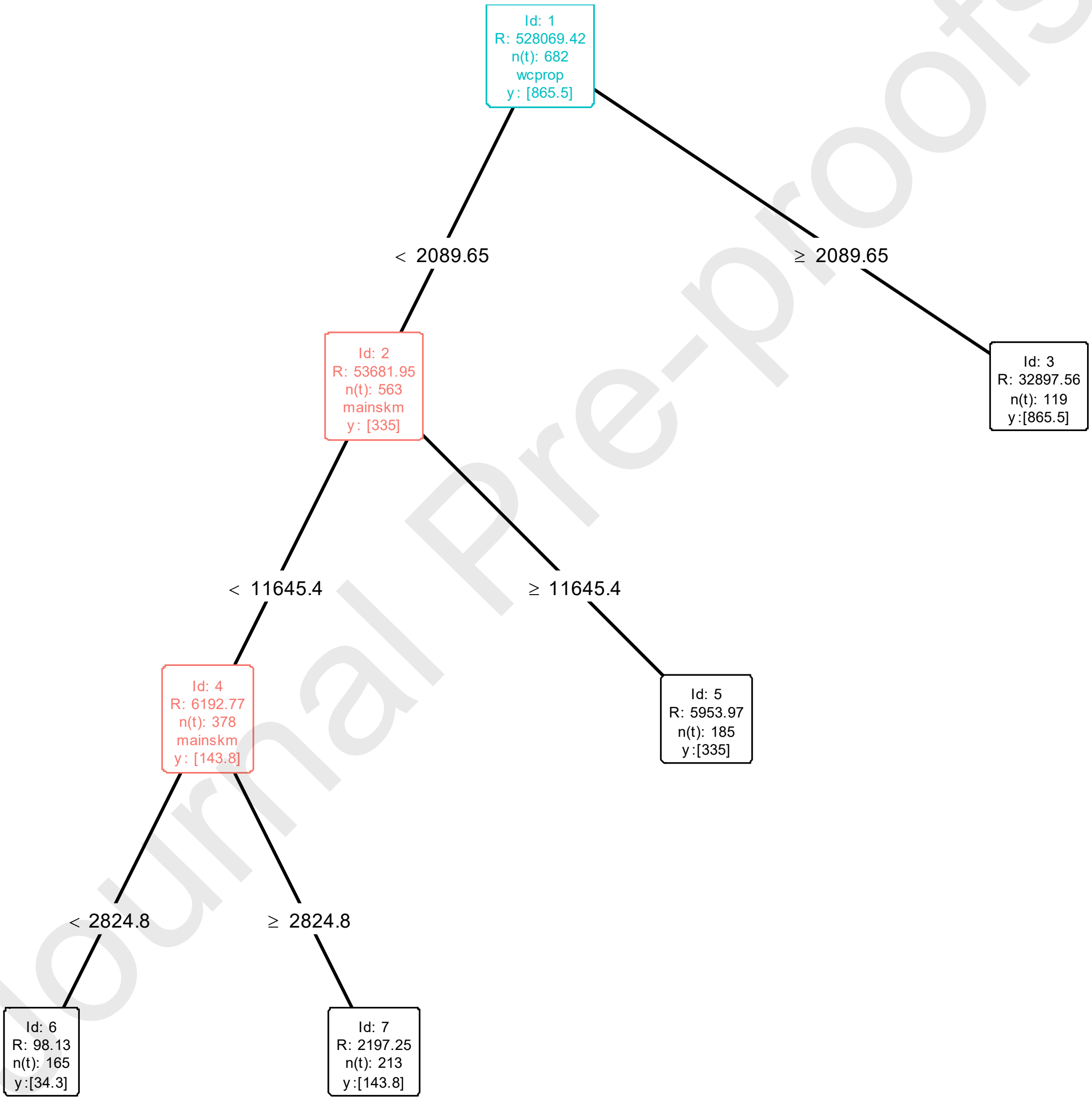


Figure 3. Regression Tree for English and Welsh water companies from EAT algorithm

Table 2 summarizes the efficiency scores obtained from the EAT algorithm, DEA methods and FDH methods. The efficiency scores were larger for DEA and FDH compared to EAT. Several water companies had an efficiency score of 1 for FDH and

DEA. In particular, 25% and 5% of the total number of DMUs under FDH and DEA, respectively, were fully efficient, and constructed the efficient frontier. Under EAT, six out of 682 DMUs (0.9%) had an efficiency score of 1. Thus, there is a risk of overfitting when estimating efficiency frontiers under FDH and DEA. This result is consistent with past research (Pereira et al., 2021).

Table 2. Summary statistics of efficiency scores for English and Welsh water companies

| | Method | Mean | St.Dev. | Minimum | Maximum | Number of efficient DMUs |
|---|---|---|---|---|---|---|
| FDH | | 0.789 | 0.211 | 0.252 | 1.000 | 171 |
| DEA | | 0.715 | 0.153 | 0.159 | 1.000 | 34 |
| EAT | All | 0.489 | 0.236 | 0.139 | 1.000 | 6 |
| | WoCs | 0.500 | 0.252 | 0.139 | 1.000 | 4 |
| | WaSCs | 0.476 | 0.214 | 0.154 | 1.000 | 2 |

The average efficiency score under FDH and DEA was estimated to be 0.789 and 0.715, respectively. Thus, the potential savings in costs among English and Welsh water companies under FDH and DEA were 21.1% and 28.5%, respectively. In contrast, the average efficiency score based on EAT was 0.489, meaning water companies could save 51.1% of costs if they operated like the efficient ones. Spearman's rank-order correlation (Table 3) showed that there the efficiency scores of EAT and FDH were more correlated than DEA. This difference was attributed to EAT and FDH estimates being generated via a step function efficient frontier, whereas DEA constructs a convex piecewise frontier. Nevertheless, differences among average efficiency scores computed using DEA, FDH and EAT demonstrated the importance of selecting an adequate method to estimate the performance of utilities (Valero-Carreras et al., 2021). This issue is even more relevant when efficiency scores are used for benchmarking purposes. For instance, the English and Welsh water industry are regulated via price caps, in the form of RPI+K, where RPI is Retail Price Index and K consists of two parts, Q and X. The former represents the price increase to finance environmental improvements, while X is the offset in productivity (Helm, 2020). Recent price reviews showed that the efficiency of water utilities is evaluated through benchmarking. This information is used to set a cost baseline scenario for each utility, which is then compared with the forecast costs of a utility submitted in business plans. This information is used to set cost and revenue allowances, which are translated into price limits for five years (Ofwat, 2020). In this context, using a reliable and robust method, such as EAT, is extremely relevant.

Table3. Spearman's rank-order correlation among efficiency scores

| | EAT | FDH | DEA |
|---|---|---|---|
| EAT | 1.000 | 0.519 | 0.221 |
| FDH | 0.519 | 1.000 | 0.194 |
| DEA | 0.221 | 0.194 | 1.000 |

The computation of kernel densities for efficiency scores estimated using the EAT, DEA and FDH approaches allowed us to analyze the potential impact of each method used on the distribution of performance for the water companies evaluated. It also offered evidence of the concentration of efficiency around given scores. Figure 4 shows the kernel distributions of efficiency scores estimated using the EAT, DEA and FDH methods. It is illustrated that the mode of the distribution of efficiency scores estimated using the FDH and DEA methods is broadly similar whereas a different distribution was observed for efficiency scores based on the EAT approach.

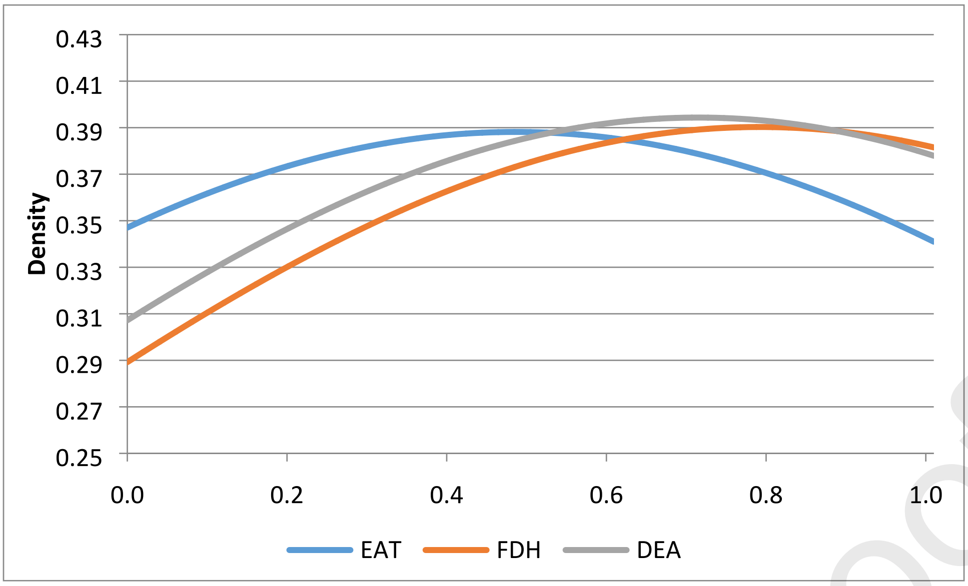


Figure 4. Kernel densities of the efficiency scores estimated using Efficiency Analysis Tree (EAT), Free Disposal Hull (FDH) and Data Envelopment Analysis (DEA) methods.

The results based on EAT estimations showed that the mean efficiency of the English and Welsh water industry was 0.489. Non-relevant differences among WoCs and WaSCs were reported in terms of average efficiency scores. On average, WoCs and WaSCs could reduce their costs by 50% and 52.4%, respectively, to provide the same level of water services. Our results indicate that the water industry was characterised by high levels of inefficiency, with capacity to improve the managerial practices of companies to become more efficient, supporting previous studies (Portela et al., 2011; Byatt, 2017; Walker et al., 2020; Mocholi-Arce et al., 2021).

Evaluating the distribution of efficiency scores across companies, based on EAT algorithm method, provided insights on variation in the levels of inefficiency scores (Figure 5). Most DMUs associated with both WoCs and WaSCs reported an average efficiency score ranging between 0.21 and 0.60. Thus, over the entire study period, the potential savings in costs for most English and Welsh water companies varied between 40% and 80%, on average. This finding corroborates the low efficiency levels that characterised the water industry. However, the average efficiency score was lower for WoCs compared to WaSCs on occasion. Specifically, 66 out of the 382 DMUs (17.3%) related to WoCs were considerably inefficient, as their mean efficiency score did not exceed 0.20 during the study period. In contrast, this value was 9.0% for WaSCs, as 27 out of 300 DMUs had efficiency scores lower than 0.20. DMUs with the highest efficiency scores “i.e.” higher than 0.8 were mostly WoSCs. Overall, 75 out of 382 (19.6%) DMUs with average efficiency scores higher than 0.80 were WoCs. Not many WaSCs (30 out of 300; 10.0%) were within that efficiency range during the study period. Thus, while WoCs performed very well in terms of efficiency on several occasions in 1991–2020, efficiency, in most cases, did not exceed 0.60. Therefore, the management practices of WoCs must be considerably improved to reduce costs. WaSCs rarely showed high levels of efficiency.

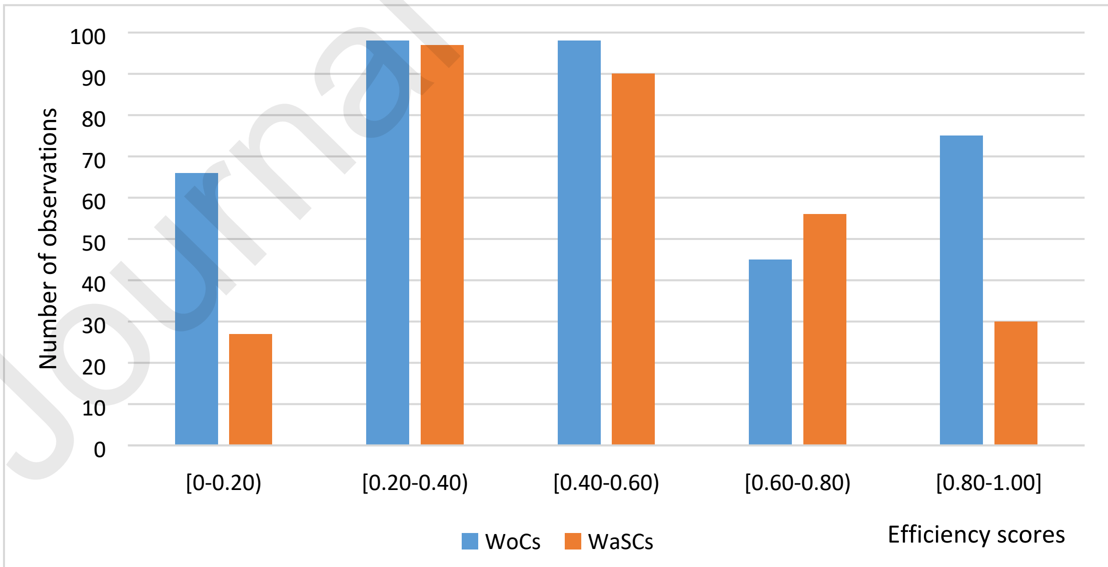


Figure 5. Histogram with the distribution of efficiency scores for English and Welsh water companies.

As the study period covered several price reviews, the average efficiency scores of WaSCs and WoCs, estimated using the EAT approach, were split in several sub-periods to link them with the regulatory cycle of the English and Welsh water industry (Figure 6). There was an upward trend in average efficiency for both WoCs and WaSCs over the study period. Thus, the efficiency of the English and Welsh water industry improved over time. On average, the efficiency of water companies improved by 39.5% between 1991–1995 and 2016–2020 (from 0.412 to 0.575, respectively). WaSCs achieved higher efficiency gains compared to WoCs. The efficiency of WaSCs improved by 57.5% on average over the same period (from 0.364 to 0.573). The improvement in the efficiency of WoCs was also considerable over the same period, but at a lower magnitude (25.2%; from 0.461 to 0.577, respectively). Although the efficiency scores of average WaSCs were lower compared to average WoCs in the first period (1991–1995), they caught up with the most efficient WoCs and, in some cases, became more efficient than WoCs, on average. Therefore, the efficiency scores of WoCs and WaSCs converged over time.

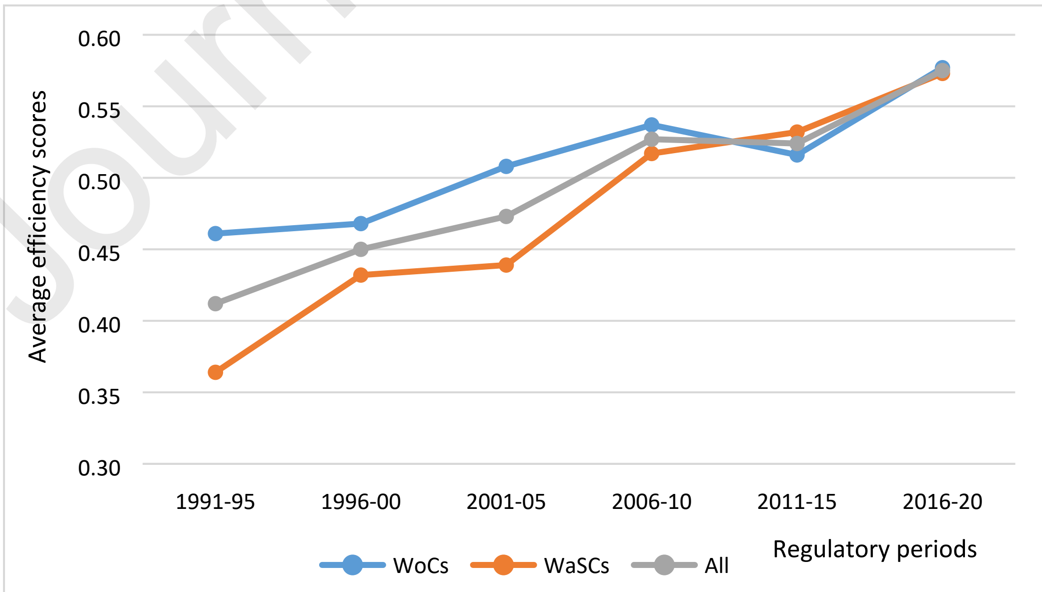

Figure 6. Average efficiency scores by regulatory period for English and Welsh water companies

During the 1991-95 period, the average efficiency score for WoCs and WaSCs remained low (0.461 and 0.364, respectively). Thus, the potential savings in costs among WoCs and WaSCs could have been of 53.9% and 63.6%, respectively. Therefore, the transition period from public to private ownership had no substantial impact on cost savings, supporting previous studies. For instance, Erbetta and Cave (2007) showed that the years after privatisation had no a major impact on the efficiency of companies. An upward trend in industry efficiency was observed in 1996–2000. This trend was mainly driven by the gains in efficiency for average WaSCs, which improved from 0.364 to 0.432, on average. In contrast, the efficiency of WoCs remained constant. The 1994 price review introduced two main policies to boost industry performance. The first policy was related to higher allowed increases in customer tariffs (and more lax cost reduction targets) to invest in maintaining and upgrading the network (Molinos-Senante and Maziotis, 2018). The second policy was associated with promoting mergers among companies. These reforms might have explained improved company efficiency. Moreover, the 1999 price review was the first in which water companies were forced to reduce the prices charged to customers. The regulator wanted to ensure that any cost savings gained in previous years were passed to customers in terms of lower prices. This price review did not appear to affect the efficiency of water companies. Further cost savings were reported that might have allowed companies to regain any losses in their profits that occurred due to reduced revenue. Cost savings were higher for WoCs compared to WaSCs, supporting previous studies. For instance, Bottasso and Conti (2009) and Portela et al. (2011) observed that improving industry efficiency resulted in less efficient companies moving closer to the frontier. However, there was potential for further cost savings in daily operations and the management of assets.

The efficiency of the English and Welsh water industry improved considerably during the 2006-2010 period. Regulatory incentives might positively impact efficiency, such as sharing any outperformance in expenditure with customers and financial rewards and penalties when network quality improves (Villegas et al., 2019). The efficiency of WaSCs substantially improved (from 0.439 to 0.517, on average), whereas the mean efficiency of WoCs increased slightly (from 0.508 to 0.537). Therefore, less efficient WaSCs appeared to be trying to catch-up with the most efficient WoCs in the industry. In the 2011-2016 period, where cost reduction targets were tightened, efficiency slightly reduced. The 2009 price review might have been challenging for WoCs; in contrast, the mean efficiency of WaSCs exceeded that reported by WoCs. In the last period (2017–2020), the situation was reversed. During this period, the regulator introduced several incentives for companies to improve efficiency. For instance, it introduced a set of common and bespoke performance targets to monitor economic and environmental performance, and imposed financial rewards/penalties when these targets were met/not met (Villegas et al., 2019). The average efficiency of both WoCs and WaSCs became similar; however, considerable inefficiency remained, with the potential for improvement.

**4.2 Influence of environmental variables on efficiency scores**

To analyse the influence of environmental variables on the efficiency of English and Welsh water companies, bootstrap regression analysis was conducted (Table 4). The year dummies were statistically significant from zero (data not presented due to length restrictions). The percentage of water taken from rivers, average pumping head and percentage of water leakage had a statistically significant and negative impact on efficiency. In contrast, the percentage of metered properties and population positively affected efficiency.

Specifically, the higher the percentage of raw water taken from rivers, the lower the efficiency, on average. This finding might be attributed to water taken from rivers requiring higher treatment compared to groundwater and, therefore, higher production costs. A similar result was obtained for average pumping head. Higher pumping requirements to abstract, treat and distribute water from different sources could increase energy costs and overall costs. Thus, water companies could reduce production costs by investing in more energy efficient pumps or by using renewable energy when abstracting and treating water. This approach could benefit people and the environment, as less carbon might be emitted to the atmosphere from the provision of water services.

Higher levels of water leakage were related to lower efficiency levels (Table 4). This phenomenon might be attributed to the need for resources to deal with network incidents. Moreover, the lost water is drinking water that had already incurred economic costs through being abstracted and treated; however, these costs cannot be recovered through tariffs. Reducing the level of water leakage could enhance environmental sustainability, because more water would be available for people and the environment. The more metered properties that a water company has, the higher the level of efficiency. This phenomenon might be explained by the fact that metres allow companies to better understand water use and costs, providing an opportunity to set costs that reflect tariffs.

Population density positively impacted efficiency. As the population increased in an area, the costs to serve the people in this area could decline, indicating the existence of economies of density. Thus, densely populated areas could be less costly to serve than less densely populated areas, supporting previous studies on the water industry in other countries, including Portugal (Carvalho and Marques, 2016), Spain (Alvarez et al., 2014), Slovenia (Filippini et al., 2008), Italy (Guerrini et al., 2018), United States of America (Torres and Morrison-Paul, 2006) and Canada (Renzetti and Dupont, 2009).

Table 4. Influence of environmental variables on efficiency. Bootstrap regression analysis

| Variables | Coeff. | Std. Err. | z-stat | p-value |
|---|---|---|---|---|
| Constant | 0.317 | 0.121 | **2.619** | 0.008 |
| % water taken from rivers | -0.101 | 0.021 | **-4.809** | 0.000 |
| % water taken from reservoirs | -0.015 | 0.020 | -0.750 | 0.453 |
| % of metered properties | 0.215 | 0.073 | **2.945** | 0.003 |
| Average pumping head | -0.051 | 0.030 | ***-1.701*** | 0.088 |
| Population density | 0.175 | 0.028 | **6.250** | 0.000 |
| % of water leakage | -0.314 | 0.033 | **-9.515** | 0.000 |
| $X^2(35)$ | 64.12 | | | |

DMUs: 682
EAT efficiency is the dependent variable
Bold indicates that coefficients are statistically significant at 5% significance level
Bold italic indicates that coefficients are statistically significant at 10% significance level

## 5. CONCLUSIONS

Measuring efficiency and its determinants in the water industry is valuable for managers and regulators. This information can have both backward- and forward-looking impacts. The efficiency of water companies in past years could be used to determine a future cost allowance and tariffs to customers. Traditionally, non-parametric techniques “e.g.” DEA and FDH are used to measure efficiency. To overcome overfitting issues, this study trialled a newly developed technique, called EAT, which combines decision tree and non-parametric analysis to estimate the efficient frontier and derive the efficiency of water companies. We also used bootstrap regression techniques to investigate the impact of several environmental variables on the efficiency of utilities.

Through empirically applying the new approach to the English and Welsh water industry, we showed that the higher the number of connected properties, the higher the number of mains must be laid to deliver water, raising the total expenditure of companies. Considerable inefficiency was reported for the water industry in England and Wales during 1991–2020. Efficiency was 0.489 on average, indicating that the potential cost savings among water utilities were 51.1% to produce the same level of output. Moreover, WoCs were slightly more efficient compared to WaSCs (0.500 versus 0.476 average efficiency, respectively). During the study period, most the efficiency score of most WoCs and WaSCs ranged between 0.21 and 0.60. On several occasions, WoCs achieved higher efficiency scores compared to WaSCs, on average. The industry's efficiency improved over time, indicating that regulatory reforms and policies might contribute towards boosting the performance of utilities. Higher efficiency gains were achieved for average WaSCs compared to WoC; however, efficiency scores converged after 2006, indicating that the performance of WaSCs improved towards the most efficient companies in the industry, moving closer to the efficient frontier. However, industry performance could improve further, as efficiency levels remain low. Of note, the percentage of water taken from rivers and average pumping head raised costs and reduced efficiency. Water leakage also increased costs, because fixing leaks might require higher operational costs. In contrast, metered properties and population density positively impacted efficiency.

The findings of our study have several policy implications. We provided and implemented a robust methodology to improve accuracy and overcome the shortcomings of past approaches, allowing the efficiency of decision-making units to be evaluated. Managers could visualise the maximum expenditure required to provide water services based on different regulations. For instance, costs of companies might be considerably high when water services must be provided to more than two million connected properties. The approach developed here also allows policy makers to understand the level of inefficiency in the industry and, importantly, the most and least efficient companies. This information allows managers to ascertain how efficiency evolves over time, and whether gains or losses exist in the efficiency of different companies. Consequently, policy makers could quantify the savings in costs that companies could potentially achieve to improve performance. Our method also allows policy makers to assess the impact of regulatory reforms and policies on the efficiency of companies.

The current study also explored how different operating characteristics affect efficiency. For instance, higher costs are associated with water that is taken from rivers and higher pumping. Thus, abstracting water from rivers might have high energy requirements to pump it into the network. Therefore, a more energy efficient use of pumps might be required to reduce costs. Moreover, the need to treat water from rivers might increase energy costs. Therefore, more energy efficient technologies, such as using energy from renewable sources, might represent potential solutions for reducing cost. Fixing leaks might require the use of more resources, which could raise costs. In contrast, densely populated areas might be less costly to serve than urban areas. These factors could contribute to the costs and efficiency of companies, and should be included in the decision-making process of businesses. Dealing with other operating characteristics (such as water leakage and the use of less energy intensive activities) when producing water could have wider environmental impacts that are considered crucial in light of climate change. Consequently, utilities should focus on evaluating economic performance and improving environmental sustainability.

This study focused on estimating efficiency scores for water companies. This means that quality of service variables were not directly integrated in performance assessment. Future research could assess the "eco-efficiency" of water companies by integrating some relevant quality of service variables as undesirable outputs. Moreover, uncertainty in data is always an issue to be considered when efficiency scores are computed using non-parametric methods. In this study, an outlier identification analysis was conducted before estimating efficiency scores using the EAT, DEA and FDH methods. Nevertheless, as part of future research development on this topic, parametric approaches could also be employed to better identify outliers.

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**Declaration of interests**

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

**HIGHLIGHTS**

Overfitting issues were overcome in efficiency assessment by using efficiency analysis trees.

Average efficiency of water companies over 1991 – 2000 was 0.489

Environmental variables influencing performance of water companies were identified.

MMS: Conceptualization; Visualization; Writing – Review & Editing

AM: Methodology; Sofware; Writing – Original Draft

RSG: Data curation; Writing – Review & Editing

MMA: Writing – Review & Editing; Supervision