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Abstract

The provision of fundamental services by water and sewage companies (WaSCs) requires substantial energy and material inputs. A sustainability assessment of these companies requires a holistic evaluation of both performance and efficiency. The Hicks-Moorsteen productivity index was applied to 12 WaSCs in the United Kingdom (UK) over a 6-year period to benchmark their sustainability, based on eight approaches using different input and output variables for efficiency assessment. The choice of variables had a major influence on the ranking and perceived operational efficiency among WaSCs. Capital expenditure (utilised as part of *total expenditure*) for example, is an important input for tracking company operations however, potential associated efficiency benefits can lag investment, leading to apparent poor short-term performance following capital expenditure. Furthermore, *water supplied and wastewater treated* was deemed an unconstructive output from a sustainability perspective since it contradicts efforts to improve sustainability through reduced *leakage* and *consumption per capita*. *Customer satisfaction* and water quality measures are potential suitable alternatives. Despite these limitations, *total expenditure and water supplied and wastewater treated* were used alongside *customer satisfaction* and *self-generated renewable energy* for a holistic sustainability assessment within a small sample. They indicated the UK water sector has improved in productivity by 1.8% on average for 2014-18 and still had room for improvement, as a technical decline was evident for both the best and worst performers. Collectively the sample's production frontier was unchanged but on average companies moved 2.1% closer to it, and further decomposition of productivity revealed this was due to improvements in economies of scale and scope. Careful selection of appropriate input and output variables for efficiency benchmarking across water companies is critical to align with sustainability objectives and to target future investment and regulation within the water sector.

Keywords: Performance Evaluation; Water Companies; Total Factor Productivity; Data Envelopment Analysis; Sustainability assessment; Hicks-Moorsteen productivity index

List of Abbreviations

CAPEX	Capital Expenditure
CRS	Constant Returns to Scale
DEA	Data Envelopment Analysis
GWh	Gigawatt hours
HMPI	Hick-Moorsteen Productivity Index
IME	Input-oriented Mix Efficiency
ISE	Input-oriented Scale Efficiency
ITE	Input-oriented Technical Efficiency
Ml	Megalitre
MPI	Malmquist Productivity Index
OPEX	Operational Expenditure
RISE	Residual Input-oriented Scale Efficiency
RME	Residual Mix Efficiency
SFA	Stochastic Frontier Analysis
SIM	Service Incentive Mechanism
TECH	Technical Change
TFP	Total Factor Productivity
TFPE	Total Factor Productivity Efficiency Change
TOTEX	Total Expenditure
UK	United Kingdom
VRS	Variable Returns to Scale
WaSC	Water and Sewage Company

1. Introduction

A reliable and efficient supply of safe, treated water is fundamental to a prosperous society (Martínez-Santos, 2017) however, not all water networks are sustainable under current climate change projections (Zischg *et al*., 2017). When one measures the efficiency and sustainability of water systems they should consider a broad range of variables, including economic, social (e.g. sanitation) and environmental (e.g. carbon emission) impacts. Performance evaluation and benchmarking of water companies is vital to promote efficiency and protect the interest of customers (Zope *et al*., 2019). The number of studies on water company performance analysis has increased in recent years (Lombardi *et al*., 2019), and while this has covered many different locations and times, and applied numerous different methodologies, a more integrated assessment that includes environmental sustainability of water utilities is relatively rare compared to more focussed studies (de Witte and Marques, 2012; Cetrulo *et al*., 2019; Goh and See, 2020).

The majority of benchmarking and performance analysis of the water sector focuses on economic efficiency, as outlined by Abbot and Cohen (2009), Worthington (2014) and Lombardi *et al*. (2019). Amongst the financial indicators in these studies, labour and infrastructure often feature. Research with a focus on other factors are limited, except for a few notable works. Energy consumption is one of the most popular non-financial indicators utilised (although often used as a cost), as can be seen in the de Witte and Marques (2010a) and Krampe (2013) studies, which encompass water supply companies and treatment plants, respectively. More alternative assessments of efficiency include Tsargarakis (2018), who evaluated water company complaints against operational expenditure; Ananda and Pawsey (2019), where they analysed customer service and network reliability; and Haziq *et al*. (2019) that determined the satisfaction levels of customers against services provided. Although such studies have use on their own, a combination of the diversified subject matter outlined above for water companies within one sustainability assessment would offer unique insight, since only a handful of studies have taken this approach previously (e.g., Gill and Nema, 2016;

Molinos-Senante *et al*., 2016a; Murungi and Blokland, 2016; Villarreal and Lartigue, 2017, Pérez *et al*., 2019). Even within these studies, some split up their analyses into separate models, and still do not include energy within any of their approaches (Gill and Nema, 2016; Murungi and Blokland, 2016; Villarreal and Lartigue, 2017) however, prioritising service reliability, water quality, and customer satisfaction in their samples of developing countries is valuable. A holistic view would be particularly poignant considering the significant impact that water companies have on society. For example, the United Kingdom (UK) water industry employs 58,500 people, has an annual turnover of £11 billion (Energy and Utility Skills, 2020), and consumes 3% of national electricity (Majid *et al*., 2020). Furthermore, the array of approaches to analysing efficiency creates questions around the pitfalls and positives of the diverging variables. Selecting the appropriate variables is vital for a valid study as Villegas *et al.* (2019) and Molinos-Senante and Maziotis (2020a) displayed in their studies of England and Wales. Therefore understanding how the choice of variables relate to the study objective is imperative in order to draw meaningful conclusions.

Measuring efficiency can be an important aspect of complying with sustainability targets, which are often based on the aggregate impact of all consumption, such as fossil energy, resource use, and greenhouse gas emissions (Bonilla *et al*., 2018). Input-orientated efficiency is determined by assessing the levels of outputs relative to the levels of inputs, with the goal being to produce the most outputs with the fewest inputs. Naturally, efficiency results are affected by the choice of inputs and outputs used in the assessment. To investigate how to better evaluate the efficiency of water companies in a sustainability sense, an evaluation of the effects of using different variables that cover social, environmental and economic factors was undertaken. To conduct this, Total Factor Productivity (TFP) was used. In the context of this study, when benchmarking the efficiency of water and sewerage companies (WaSCs), productivity and efficiency are slightly different concepts. Productivity comprises of evaluating performance change over time, thus integrating a temporal element to sustainability analysis (Le *et al*., 2019). Goh and See (2020) reviewed 142 journal articles regarding water utility benchmarking between 2000-2019 and noted TFP was only used as a keyword in seven studies, whilst productivity growth appeared 12 times.

There is an array of indices that have been developed to compute TFP and have been utilised to evaluate water companies. They can be grouped into parametric and non-parametric methods, the former assuming a predefined technology function. The non-parametric approach can further be classified into frontier and non-frontier methods. One of the most common non-frontier methodologies is the Törnqvist productivity index (Berhera and Sharma, 2020; Oulmane *et al*., 2020), which measures the ratio of all the outputs, weighted by the corresponding revenues, to all the inputs, that are weighted by cost, in quantities by using the firms within the sample to be evaluated themselves (Simoes and Marques 2012). Many non-parametric frontier methods are used to compute TFP and have been applied to the water industry, such as the Färe-Primont productivity index (Molinos-Senante *et al.,* 2017a), Malmquist Productivity Index (MPI) (Molinos-Sennante *et al*., 2017b), Luenberger Productivity Index (Sala-Garrido *et al.,* 2018), Malmquist-Luenberger productivity indicator (Ananda, 2018; Sala-Garrido *et al*., 2019), and the Hicks-Moorsteen Productivity Index (HMPI) (Molinos-Senante *et al*., 2016b). The essential advantage of these non-parametric frontier methods over parametric methods is that they do not require a priori assumptions about the functional relationship between the variables, which can cause specification and estimation problems (Murillo-Zamorano and Vega-Cervera, 2001).

The MPI, which was introduced by Caves *et al*. (1982), is the most commonly applied method to analyse changes in TFP. The reason for its popularity is that it can be computed without price data, and can be broken down into measures of technical and efficiency changes (Shao and Lin, 2016). Despite the numerous positives of MPI, it does have some decisive limitations. O'Donnell (2014) comments that some of the distance functions within the index may be undefined and infeasibility problems might then ensue (Kerstens and Van De Woestyne, 2014). As an outcome, the results from MPI may not accurately express TFP change from scale effects. Moreover, MPI requires a choice of input or output orientation (Molinos-Senante *et al*., 2020), and is deemed inappropriate when the sample operates under variable returns to scale (VRS), as Grifell-Tatje and Lovell (1995) and O'Donnell (2008) demonstrated. VRS refers to a change in inputs that is not directly proportional to a change in outputs (Färe and Primont, 1995). MPI is thus not applicable to many situations.

The limitations that MPI encompasses are largely overcome by the HMPI. Defined as a ratio of the Malmquist input and output indices, while using the Shephard input and output distance functions, respectively (Bjurek, 1998), the HMPI does not require price data and satisfies all other index conditions, including multiplicative completeness and transitivity tests (O'Donnell, 2012). The HMPI thus functions within a simultaneous input and output orientation, and can be computed under both constant returns to scale (CRS) and VRS technologies, giving it a distinct advantage over similar TFP methods like MPI. Furthermore, HMPI makes no assumptions on behavioural aims such as maximising profit, or market settings like regulation and competition (Dhillon and Vachharajani, 2018). Briec and Kersten (2011) highlighted further advantages of HMPI, commenting that under strong input and output disposability, the determinateness axiom is satisfied so that infeasibility problems are avoided. Meaning that the index is well defined even when one or more of its arguments becomes zero or infinity. A feature of HMPI that makes it preferable to other TFP approaches is one it shares with MPI, which is that it can be decomposed into TFP change elements. These components are i) technical change, which measures movements in the production frontier, and ii) efficiency change, that measures unit movement relative to the frontier. Efficiency change can be further broken down into technical efficiency, mix efficiency, residual mix efficiency, scale efficiency, and residual scale efficiency, which collectively analyse movements around the frontier to capture economies of scale and scope (Laurenceson and O'Donnell, 2014). Such decomposition can be useful from the perspective of policy and regulation, with the effect of controls on WaSCs being identifiable through TFP decomposition analysis, enabling better decision-making (Wen *et al.,* 2018).

Although the HMPI has many positive attributes, it has thus far had limited use in applied research, particularly within the water sector, with just Molinos-Senante *et al*. (2016) using it to study wastewater treatment plants. Meanwhile, TFP has been assessed in the water sector with other methods. For example, Guerrini *et al*. (2018), Molinos-Senante *et al*. (2014), Molinos-Senante *et al*. (2019), Sala-Garrido *et al*. (2018) all utilise the Luenberger or Luenberger-Hicks-Moorsteen to analyse areas of the water sector from water companies directly to treatment plants. Even within other sectors such as banks, agriculture, manufacturing, energy and ports, the use of HMPI has not been common, as Medal-Bartual *et al*. (2016) and Mohammadian and Rezaee (2020) document.

The aims of this paper were three-fold. Firstly, to analyse the applicability of assorted HMPI variable configurations, then to assess how differing approaches affect results and identify the best variable approach for a comprehensive sustainability evaluation. Secondly, to investigate the productivity change on a sample of UK WaSCs over a six-year period using the variable configuration for sustainability analysis found in the first aim. Finally, to disaggregate results for individual companies and enable an investigation of areas in which they can improve – informed by TFP constituents. This study contributes to the current body of literature by utilising a method not widely applied in the water sector to assess the optimal routes to measure efficiency in a holistic sustainability context. Additionally, it provides an insight to TFP change and potential avenues for improvement for UK WaSCs and the sector as a whole. The findings and methods are of use to water company decision-makers and regulators, allowing identification of areas of improvement, effectiveness of their operations and potential collaborators for sharing of best practice.

2. **Methodology**

2.1. The Hicks-Moorsteen Productivity Index

The Hicks-Moorsteen Productivity Index is defined as a ratio of aggregate output quantity over aggregate input quantity index (Bjurek *et al*., 1998). A major advantage of HMPI over other productivity methods is that a choice between input or output orientation is not required since the approach conducts a simultaneous orientation of input and output. This is due to the combination of output and input quantity indices using the Shephard output and input distance functions (O'Donnell, 2011).

Under the assumption of each WaSC using a vector of *M* inputs x (x_1, x_2, …, x_M) to produce a vector of *S* outputs y = (y_1, y_2, …, y_S), the output and input distance functions are defined thus (Shephard, 1953):

$$D_t^o\,(x, y) = \min_{\delta}\{\delta > 0 : \left(x, {}^{y}/_{\delta}\right)\varepsilon T^t\} \tag{1}$$

$$D_t^i\,(x, y) = \min_{\rho}\{\rho > 0 : \left({}^{x}/_{\rho}, y\right)\varepsilon T^t\} \tag{2}$$

Where T^t denotes production possibilities set at period-t. D_t^o (x, y) symbolises the output distance function and evaluates the inverse of the largest radial expansion of the output vector, which is achievable, given the input vector. Conversely, D_t^i (x, y) denotes the input distance function and evaluates the largest radial contraction of the input vector attainable while fixing the output vector (Epure *et al*., 2011).

For a base period t, Bjurek et al. (1998) defined HMPI as:

$$HMPI_{T\,(t)}(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{[D_{T(t)}^o(x^t, y^t)/D_{T(t)}^o(x^t, y^{t+1})]}{[D_{T(t)}^i(x^t, y^t)/D_{T(t)}^i(x^{t+1}, y^t)]} \tag{3}$$

For a base period $t + 1$, HMPI is defined as:

$$HMPI_{T\,(t+1)}(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{[D_{T(t+1)}^o(x^{t+1}, y^t)/D_{T(t+1)}^o(x^{t+1}, y^{t+1})]}{[D_{T(t+1)}^i(x^t, y^{t+1})/D_{T(t+1)}^i(x^{t+1}, y^{t+1})]} \tag{4}$$

A geometric mean of the HMPI for base period t and $t + 1$ yields:

$$HMPI_{T(t),\ T(t+1)}\,(x^{t+1}, y^{t+1}, x^t, y^t) =$$
$$[HMPI_{T(t)}(x^{t+1}, y^{t+1}, x^t, y^t) \times [HMPI_{T(t+1)}(x^{t+1}, y^{t+1}, x^t, y^t)]^{1/2} \tag{5}$$

An asset of HMPI is its classification into technical potential (TECH) and relative efficiency (TFPE) change, along with breakdown of TFPE into various components. TECH indicates a shift in the efficiency production frontier, advancements of which illustrate expansion in production possibilities (Fare and Grosskopf, 1996). TFPE measures the movement of units (WaSCs) away or towards production frontier and is regarded as a catching up index (Maziotis *et al*., 2015). The indication being that TFPE involves the capacity of WaSCs to be managed with the best operational and corporate practices. TFP then, is the product of TECH and TFPE (O'Donnell, 2011):

$$TFP_{it} = TECH_{it} \times TFPE_{it} \tag{6}$$

O'Donnell (2008) devised the breakdown of TFPE into its drivers, using two production frontiers as references. The first, mix-restricted production frontier has the output or input sets held fixed. The second is the unrestricted production frontier, which has variable output and input sets. Established on these two frontiers, whilst under an input-orientation, the sub-indices for TFPE are defined by O'Donnell (2014) in Table 1.

Table 1. *Descriptions and explanations to the sub-indices of total factor productivity efficiency change, adapted from the works of O'Donnell (2008) and O'Donnell (2014).*

TFPE sub-indices	Description
Input-oriented Technical Efficiency (ITE)	Measures the difference between the observed and maximum TFP possible, while keeping the input mix, output mix and output level fixed. This concept is exhibited in Figure 1, where the curve passing through points B and D is the frontier of a mix-restricted production possibilities set. The production possibilities set is mix-restricted in the sense that it only contains input and output aggregate vectors that can be written as scalar multiples of the input and output vectors at point A. ITE is thus a measure of the difference in TFP at points A and B: $ITE_0 = \tan a / \tan b$.
Input-oriented Scale Efficiency (ISE)	Assesses the difference between TFP at a technically efficient point and maximum TFP possible while holding the input and output mixes fixed, but allowing the amounts to change. This measure of efficiency is represented in Figure 1 as a movement from point B to point D: $ISE_0 = \tan b / \tan d$.

Residual Mix Efficiency (RME)	Evaluates the contrast between TFP on a mix-restricted frontier point and maximum TFP possible when input and output mixes (and levels) can vary. This is illustrated in Figure 1 as a movement from point D to point E: $RME_0 = \tan d / \tan e$. The curve passing through E is the frontier of an unrestricted production possibilities set (unrestricted meaning there are no restrictions on input or output mix). The term "mix" refers to the movement from point D to E, where a movement from an optimal point on a mix-restricted frontier to an optimal point on a mix-unrestricted frontier occurs, therefore the difference in TFP is essentially a mix-effect. The term "residual" is used here because i) this movement may also involve a scale change ii) when comparing TFP at point A with TFP at the point of maximum productivity (point E), RME is the component that remains after accounting for pure technical and scale efficiency effects.
Input-oriented Mix Efficiency (IME)	Analyses the distance between TFP at a technically efficient point on the mix-restricted frontier and the maximum TFP possible, while the output level is fixed. This measure of efficiency is depicted in Figure 1 as a movement from point B to U: $IME_0 = \tan b / \tan u$.
Residual Input-oriented Scale Efficiency (RISE)	Determines the difference between TFP at a technically and mix-efficient point and TFP at the point of maximised productivity. The term "scale" is used to reflect the fact that any movement around an unrestricted production frontier is a movement from one mix-efficient point to another, so any improvement in TFP is essentially a scale effect. The term "residual" is also used since even though all the points on the unrestricted frontier are mix-efficient, they could still have different input and output mixes. Therefore, what is essentially a measure of scale efficiency may contain a residual mix effect. Residual is further appropriate as term here because when decomposing the difference between TFP at the observed point A and TFP at the point of maximum productivity E, the residual scale efficiency is the component that remains after accounting for pure technical and pure mix efficiency effects. RISE is exhibited in Figure 1 as a movement from point B to U: $RISE_0 = \tan u / \tan e$.

The TFPE is represented in Figure 1 as a movement all the way from point A to point E, measured as the difference between observed TFP and maximum TFP. The relationship with its components are simplified here:

$$TFPE_{it} = ITE_{it} \times IME_{it} \times RISE_{it} \tag{7}$$

$$TFPE_{it} = ITE_{it} \times ISE_{it} \times RME_{it} \tag{8}$$

A HMPI >1 indicates an increase in TFP, <1 illustrates a decline in TFP, a result of exactly 1 demonstrates there was no change in TFP.

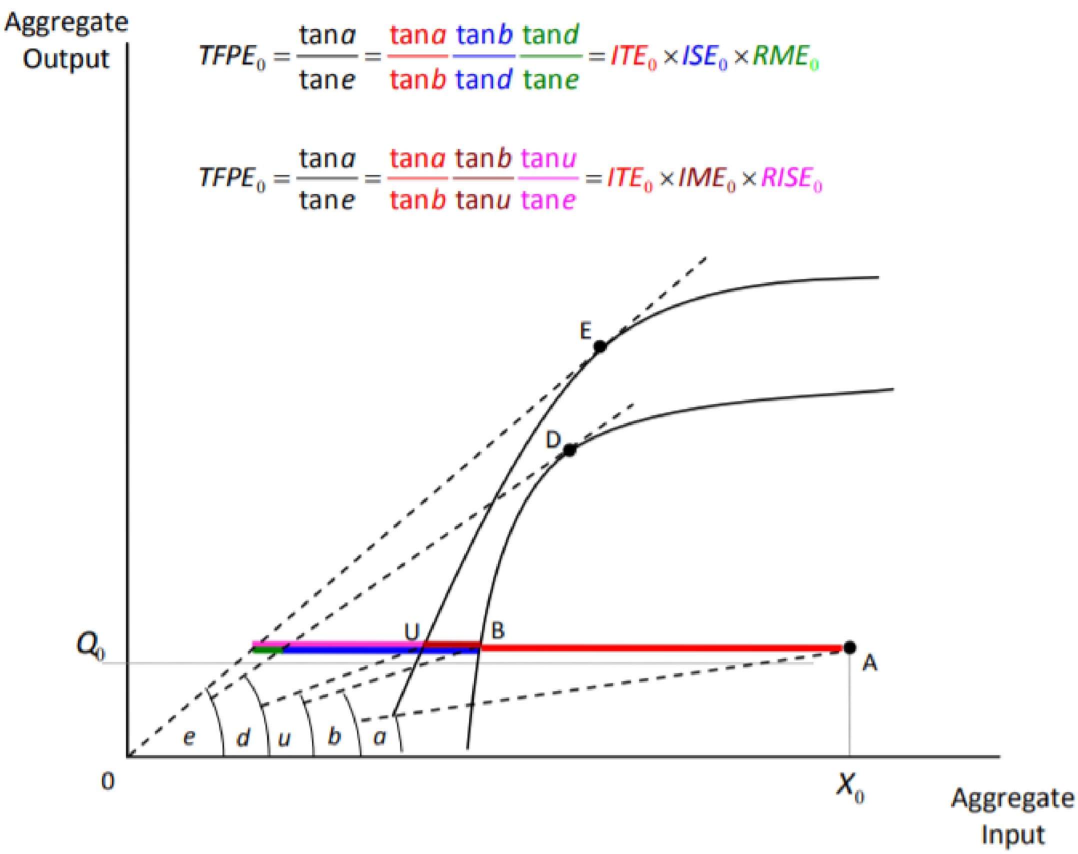

Figure 1. *An input-oriented decomposition of TFPE sourced from O'Donnell (2014). Q represents outputs, X depicts inputs, A is observed TFP point, E is maximum productivity, D is the optimal point on a mix-restricted frontier, B portrays the technically efficient point on the mix-restricted frontier, and U illustrates the maximum TFP possible when output levels are fixed. Further details are within Table 1.*

To compute output and input distance functions, and therefore HMPI, there are two approaches, parametric and non-parametric methods. Of the parametric methods, stochastic frontier analysis (SFA) is the most widely used. The advantage of SFA is that it explains random statistical noise and can account for the effects of errors in the data (Parmeter and Zelenyuk, 2019). The limitation is that parametric techniques require strong assumptions of the functional form (Moutinho *et al*., 2020). Conversely, non-parametric methods such as data envelopment analysis (DEA) use mathematical programming and thus do not need specification of the functional frontier (Silva *et al.,* 2017). This is the main advantage over SFA and outweighs DEA's limitations of assuming there are no atypical data observations, making it vulnerable to outliers and errors (Cooper *et al*., 2006). Due to the advantages DEA offers, and following O'Donnell (2011), Medal-Bartual *et al*. (2016), and Molinos-Senante *et al*., (2016), this study utilises DEA to compute HMPI. The input and output distance functions were computed in ‘R’, a statistical computing software with the package ‘productivity’ created by Dakpo *et al*. (2018).

2.2. Data description

The sample consisted of 12 WaSCs from across the UK, with annual data over the period 2013-2018. To justly represent the key operations of WaSCs, the choice of inputs and outputs is pivotal. To investigate the various approaches to analysing efficiency, different configurations of inputs and outputs were evaluated and the justifications for their use are outlined in Section 3.1. The inputs used were operational expenditure (*OPEX*) and total expenditure (*TOTEX*), whereas the diversified outputs were *water supplied and wastewater treated* (combined), *self-generated renewable energy*, *leakage reduction*, *consumption per capita reduction*, and *customer satisfaction*, which is measured by a service incentive mechanism (SIM) score out of 100, deployed by OFWAT. *Leakage reduction* and *consumption per capita reduction* were converted to non-negatives to allow the computation to proceed without errors; this was completed by bringing the largest negative up to a value of one, then adding the difference from the negative value to one, to all other values. All of the data was acquired from company annual reports and is summarised in Table 2.

The size of the sample, when using DEA, is required to satisfy a minimum size threshold to bypass relative efficiency discrimination issues. ‘Cooper’s rule’ is used to gauge this size threshold, and 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 maximum inputs and outputs used in any variable configuration in this study comprised of one input and three outputs, therefore Cooper’s rule was followed. Furthermore, one of the advantages of DEA is regarded to be its appropriateness with smaller sample sizes (Arjomandi *et al*., 2015).

Table 2. *Summary statistics for the six-year period (2013-2018) analysed for UK WaSCs.*

		Average	SD	Minimum	Maximum
Inputs	Total expenditure (million£)	863	506	288	2,724
	Operational expenditure (million£)	504	320	143	1,214
Outputs	Water supplied and wastewater treated (Ml/day)	2,613	1,763	725	7,102
	Self-generated renewable energy (GWh)	98	89	2	387
	Customer satisfaction (SIM score)	82	5	68	90
	Leakage reduction (Ml/day)	54	12	1	89
	Consumption per capita reduction (l/h/day)	11	4	1	22

3. **Results and discussion**

3.1. An enquiry into efficiency analysis

Evaluating the efficiency of water companies can take many forms, with hundreds of indicators available to choose from (Berg, 2013). However, in TFP analysis with frontier techniques like DEA and SFA, a limited core number of variables are often chosen, since including the majority of possible variables is not feasible (Worthington, 2014). Variations of core indicators are evaluated and their appropriateness is discussed relative to capturing the key operations and responsibilities of water companies in relation to wider sustainability objectives. This was conducted through eight repeats of the HMPI model, each with different configurations of variables, enabling the exploration of the importance of variable selection when assessing productivity. The breakdown of each individual model repeat, including all constituents of efficiency and individual company efficiency scores for each year are available in the Supplementary Information.

The most common variable approach to efficiency analysis of water companies in the literature comprises of including OPEX and capital expenditure (CAPEX) as inputs, and the volume of water supplied and wastewater treated as outputs, whether that is within a single year analysis or a multi-year evaluation within productivity (Zschille and Walter, 2014; Maiotis *et al*., 2015; See, 2015). This configuration of inputs and outputs therefore made up the first model run (T-W in Table 3), displaying an average increase in TFP of 0.86%, solely as a result of efficiency increase. This slight increase was anticipated as the mature UK market continues to optimise total spending, as supported by Portela *et al*. (2011) who showed significant productivity improvements between 1994-2005 using a meta-Malmquist index, before it dropped off until 2007. Molinos-Senante and Maziotis (2020b) published a similar result using a normalised quadratic function, illustrating that the sector increased its productivity annually by 6.1% within 1993-2016. The TFP increase however did contradict further TFP studies of the UK with similar indicators to T-W. Molinos-Senante *et al*. (2017a) used the Färe-Primont Productivity Index and concluded productivity declined by 7.2% during 2001-2008, whilst Molinos-Senante *et al*. (2014) showed the productivity of the UK water industry from 2001 to 2008 reduced by 11.5% and 12.9% when using the LPI and MPI, respectively. The disparity between studies is likely due to differing sample years, methodologies, and the sample itself, since some studies included the whole of the UK and others just England and Wales, some studies also contained water only companies and WaSCs, whilst others just WaSCs. Although this change in sample size is not large, it can be significant when the original sample size is small as is the case within the UK (Zhang and Bartels, 1998). The drawback to the T-W variable configuration is that it does not capture other elements that a water company provides and for which it is responsible.

Table 3. *Summarised TFP, TFPE and TECH* change of various variable configurations for UK water and sewage companies for 2014-18. Average changes are based on the mean percentage changes for all years and for all companies.*

Model	Inputs	Outputs	dTFP average	dTECH average	dTFPE average
T-W	TOTEX	Water supplied and wastewater treated	+0.86%	-0.39%	+1.37%
T-WRC	TOTEX	Water supplied and wastewater treated, renewable energy generation, customer satisfaction	+1.82%	-0.01%	+2.06%
T-RC	TOTEX	Renewable energy generation, customer satisfaction	+2.35%	-1.24%	+3.91%
T-LC	TOTEX	Leakage reduction, consumption per capita reduction	+4.86%	+0.29%	+5.14%
O-W	OPEX	Water supplied and wastewater treated	-3.15%	-3.85%	+0.79%
O-WRC	OPEX	Water supplied and wastewater treated, renewable energy generation, customer satisfaction	-1.15%	-2.43%	+2.06%
O-RC	OPEX	Renewable energy generation, customer satisfaction	-0.90%	-2.78%	+2.85%
O-LC	OPEX	Leakage reduction, consumption per capita reduction	+1.22%	-2.41%	+5.58%

**TFP is total factor productivity; TECH is technical change; TFPE is efficiency change*

Customer satisfaction and *self-generated renewable energy* were identified as key indicators to incorporate into the analysis, which along with the T-W variables (Table 3), make up T-WRC. *Customer satisfaction* was selected as it is the ultimate measure of success for a utility provider and, representing social aspects of sustainability, is a fundamental parameter for companies to prosper and avert regulatory sanctions. The more environmentally focussed *self-generated renewable energy* was chosen since water companies are a major consumer of energy, as noted in Section 1. Therefore, reducing their impact on the national grid supply and the associated greenhouse gas emissions is a responsibility that is incorporated into the second variable configuration. T-WRC resulted in a larger TFP increase of 1.82% between 2014 and 2018, compared to T-W, again due to the increases in TFPE. The progress relative to T-W was expected since *customer satisfaction* and *self-generated renewable energy* consistently increased throughout the sample period by 1.24% and 28% on average year-on-year, respectively. Although T-WRC does cover more operational outputs for water companies, it has a limitation in the form of the main service output indicator: *water supplied and wastewater treated*. Water companies have been tasked to reduce leakage in their supply network by 15% by 2025, and 50% by 2040 (EFRA, 2018) to help future-proof themselves against climate change, which could reduce the availability of abstraction water (Dallison *et al*., 2020; Gov.UK, 2020a), and to better manage water resources. Companies take active measures to do this by investing in leakage reduction and conducting education campaigns to reduce consumption; e.g., Manouseli *et al.* (2019) showed active users within such schemes reduced their consumption by approximately 15%. Therefore, having *water produced and wastewater treated* as outputs in a TFP model may mask efficiency by treating higher water consumption, and lower investment in consumption (leak) reduction, as efficient. This would inaccurately portray companies that have invested in leakage reduction and public campaigns to consume less water as being less efficient.

Thus, to avoid this potential distortion, the T-RC model consisted of *renewable energy self-generation* and *customer satisfaction* as the outputs, whilst keeping *TOTEX* as the input. This displayed a TFP increase of 2.35% between 2014 and 2018, with an increase of 3.91% for TFPE. To explore more areas that companies are prioritising and attempting to improve upon, T-LC has *leakage reduction* and *consumption per capita reduction* as outputs. Typically, *consumption per capita* is not considered an output within evaluations of water companies however, since it has been shown that companies can influence it, it is included here. This variable configuration resulted in the largest average TFP increase between 2014 and 2018 of 4.86%, which, along with showing how companies have improved more holistically, also exemplifies how efficiency analysis with *water supplied and wastewater treated* as an output could distort results with respect to sustainable business objectives. Collectively, models T-RC and T-LC demonstrate how much WaSCs in the UK have improved non-economic aspects of sustainability between 2013/14-2018/19.

The first four models were all calculated with *TOTEX* as an input, however, CAPEX being a part of this input had the potential to skew results as the benefits of capital investments are often not shown immediately (Abbott and Cohen, 2009). Model configurations O-W, O-WRC, O-RC and O-.LC therefore were all repeats of the first four variable configurations, but contained just *OPEX* as their inputs. As Table 3 illustrates, the *OPEX* versions of the models all resulted in the companies being less efficient compared to the *TOTEX* versions with O-W, O-WRC and O-RC actually presenting negative results, indicating that the sample has declined in efficiency. One possibility for these results is that CAPEX is more efficient than *OPEX* for companies within the sample and subsequently masked its inefficiency within *TOTEX*, however, reductions in CAPEX whilst also improving significantly in self-generated renewable production and leakage reduction seems unlikely. An alternative possibility is that CAPEX from the time preceding the sample period into the base year was higher to pay for infrastructure represented in outputs in these models such as *leakage reduction*, *renewable energy production* and *customer satisfaction* to a lesser extent. From then, a fall in CAPEX could have followed, so within *TOTEX* as an input, it was low compared to the now increasing outputs brought about by prior spending. If this is the case, then incorporating CAPEX essentially creates efficiency lags that must be accounted for, or at least acknowledged, when drawing conclusions from results. To evade this potential efficiency lag, studies with a sample over a longer period could adopt a five-year rolling average, since shorter periods could generate perverse incentives to cut investments in the short term if the efficiency lag is not considered in the research outputs. Some studies opt to include length of water mains as a proxy to represent capital (De Witte and Marques, 2010; Ananda, 2014; Molinos-Senante *et al.,* 2018), which negates the issue raised here however, that comes with its own issues of accuracy when acting as a proxy as demonstrated by Walker *et al*. (2020). Whilst these results have been attempted to be explained by the role of CAPEX, there are the direct ramifications of *OPEX* too. Inflation rate increased at an average of 1.7% per year over the sample period (Office for National Statistics, 2020a) and the energy price index also raised by an average of 3.19% per year for electricity and 8.44% for gas (Gov. UK, 2020b). Furthermore, the water retail price index increased by an average of 2.44% during the same period (Office for National Statistics, 2020b). These statistics combined likely had at least a small impact on the relatively lower productivity compared to *TOTEX* and further highlights the advantages of companies producing their own renewable energy.

The assorted inputs and outputs for the model variable configurations yielded changes in perceived productivity for the whole water sector. As Table 4 shows, company-level TFP also fluctuated. There was a disparity between the first four that used *TOTEX* as the input and the last four models that used *OPEX* as the input, which was seen in the overall sector trends in Table 3, too. For example, companies 7 and 8 were ranked 2nd and 1st in the majority of the *TOTEX* models, but dropped to below average and alternate between 4th and 5th in the *OPEX* models, respectively. Furthermore, company 12 went from generally below average rankings in the *TOTEX* models, with exception of model T-LC where it ranked 2nd, to ranking 1st in the latter four models. Company 9 appears to have fallen behind when the more sustainability-orientated indicators were introduced. It ranked 4th in T-W however, dropped to 10th-12th in models T-WRC, T-RC and T-LC when indicators such as *self-generated renewable energy*, *customer satisfaction*, *leakage reduction* and *consumption per capita reduction* were implemented. This trend was then replicated in the *OPEX* models, although to a lesser extent. Company 5 performed poorly throughout whether that was using *OPEX* or *TOTEX* as the input, suggesting that they have neglected all aspects of sustainability relative to the other companies and have held back the TFP progress for the whole sample. These results collectively show how choosing the correct variables to represent a specific desired objective is critical and how small variations in variable selection or definition could significantly skew benchmarking attempts. A larger sample would have enabled more indicators to be evaluated, giving a more holistic representation of sustainability however, with the limited indicators allowed by the sample, key sustainable parameters are included in this study.

Table 4. *Ranking 12 WaSCs for the eight model variable configurations, based on the TFP scores.*

Company	**Total Factor Productivity (TFP) Rankings**							
	T-W	**T-WRC**	**T-RC**	**T-LC**	**O-W**	**O-WRC**	**O-RC**	**O-LC**
1	8th	7th	8th	5th	11th	11th	11th	5th
2	12th	11th	10th	8th	6th	7th	8th	2nd
3	9th	5th	3rd	6th	8th	8th	3rd	6th
4	3rd	3rd	5th	4th	10th	10th	10th	3rd
5	11th	12th	11th	10th	12th	12th	12th	12th
6	6th	6th	6th	11th	7th	2nd	2nd	11th
7	2nd	2nd	2nd	3rd	9th	9th	7th	8th
8	1st	1st	1st	1st	4th	5th	5th	4th
9	4th	10th	12th	12th	2nd	4th	9th	10th
10	5th	4th	4th	7th	3rd	3rd	4th	7th
11	10th	9th	9th	9th	5th	6th	6th	9th
12	7th	8th	7th	2nd	1st	1st	1st	1st

3.2. Water market efficiency over time

The model variable configuration to analyse the TFP change of UK WaSCs in the following sections was model T-WRC in Table 3. T-WRC was selected because it included key indicators that cover all aspects of sustainability. *TOTEX* was incorporated as it was deemed that CAPEX should be represented because ultimately, it is an important component of company spending that can be associated with significant (lagged) technical efficiency and sustainability improvements. Furthermore, the UK water sector now actively reports under *TOTEX*, with the regulator OFWAT (2018) commenting that the switch to *TOTEX* has removed a regulatory barrier, enabling additional efficiencies and innovation. Any potential time lags in efficiency results are a limitation of the research in the upcoming sections but will be appreciated within the enquiry of the results. *Water supplied and wastewater treated* was chosen as it is the main service output of water companies, representing their whole reason for operating, therefore analysing efficiency without it cannot be considered holistic sustainability or otherwise.

Despite the limitations to some of the indicators discussed in Section 3.1, they are the most appropriate grouping considering the data available and sample size; furthermore, the results still give a good indication of how companies are performing within a more comprehensive sustainability efficiency assessment. Productivity change was deemed to increase when TFP and constituent scores were >1 and to decrease when estimates were <1.

The average TFP change was positive with a value of 1.018 over the sample period as shown in Table 5, which indicates an average increase in productivity of 1.8%, however, this was the consequence of 2015/16 having a large TFP estimate compared to other years of 1.23 (23%). The increase was large enough for the overall average productivity change to be positive, despite all other years displaying a decline in TFP. This was unexpected as 2015 was the beginning of the five-year cycle consisting of asset management plan 6, which was to be a period of increased investment (OFWAT, 2014), however, the year displayed a *TOTEX* decline of 13.17% compared to the previous year, whereas increased spending followed in the next four years. It is likely that the *TOTEX* decline in 2015 was a major driver of the increased efficiency, although *self-generated renewables* increased by 20.62%, whilst *customer satisfaction* improved by 1.02% and *water supplied and wastewater* treated declined by 1.95%. The limitation of confining productivity results to yearly values as opposed to extended blocks of time is exemplified here, but is applied in this research and many other pieces of work due to the limited temporal sample range. A larger increase in TFP was anticipated due to the inclusion of *self-generated renewable energy* as an output, since this increased dramatically in the sample period (28% average year-on-year). It is possible that the renewable energy increase masked some other inefficiency, which appears to be the case when examining model T-W within Table 3. This mix of variables displayed a TFP average increase of 0.86%, whilst containing *TOTEX* as the input and *water supplied and wastewater* *treated* as the output. This was approximately 1% lower compared to the more holistic model variable configuration used in this section, indicating *customer satisfaction* and *self-generated renewable energy production* attributed to increased TFP. Another reason the increase was not as large as anticipated appeared to be a result of *TOTEX* increasing nearly as much as their outputs during the sample period, with an average year-on-year increase of 3.01%. These combined with the limitations in using *water supplied and wastewater treated* as an output discussed in Section 3.1 likely limited larger TFP increases. Ultimately, there was a positive average TFP change and this should be viewed favourably, especially when companies are improving renewable energy generation and customer service, in addition to the core operations of providing high standards of drinking water and treating wastewater responsibly.

Table 5. *Summarised TFP change and its components* for UK water and sewage companies.*

Year	dTFP	dTECH	dTFPE	dITE	dISE	dRISE	dRME
2014/15	0.996	0.995	1.002	1.091	0.935	0.925	0.993
2015/16	1.230	1.057	1.176	0.987	1.036	1.194	1.158
2016/17	0.952	0.945	1.006	0.936	1.053	1.088	1.031
2017/18	0.945	0.958	0.987	1.026	1.004	0.968	0.965
2018/19	0.969	1.044	0.931	0.990	1.007	0.941	0.935
Average	1.018	1.000	1.021	1.006	1.007	1.023	1.017

**TFP is total factor productivity; TECH is technical change; TFPE is efficiency change; ITE is input-oriented technical efficiency; ISE is input-oriented scale efficiency; RISE is residual input-oriented scale efficiency; RME is residual mix efficiency.*

The main driver of the TFP positive change was TFPE, which averaged at 2.1%, whilst TECH remained at an unchanging 1. The indication being that from 2014-18, the production frontier remained at the same level, however, companies on average have moved 2.1% closer to the frontier. This was again largely due to 2015/16, which displayed an increase in TFPE of 17.6%, outweighing the decreases in the last two years of 1.3% and 6.9%, illustrated in Figure 2. The findings suggest that capital investment remained steady relative to increased outputs during the sample years, whereas management of infrastructure and resources improved marginally. Therefore, to improve TFP, WaSCs must invest more in impactful capital projects compared to their 9.15% year-on-year average reduction, if they are to improve the outputs used in the mode further; these solutions could be updated technologies at treatment plants, renewable energy installations, and extra customer-facing staff capacity. The extra capital enterprises may then allow the expert personnel that increased TFPE to propel efficiency on even more. Since the CAPEX decline at least partially drives positive efficiency here, it is possible that in future years there could be a negative legacy effect, where future efficiency evaluations show a decline because of their higher spending relative to the period covered in this study.

An advantage of the HMPI is that TFPE can be split up into component parts. A WaSC is deemed efficient if it has an ITE score of one as this indicates the company is on the efficient production frontier, less than one and it is under the frontier and inefficient. A company with an ITE score equal to one, whilst displaying a RISE of less than one, remains on the efficient production frontier however, it is considered relatively unproductive. Table 5 displays that ITE increased marginally by 0.6% on average, while RISE increased by 2.3%, showing both technical efficiency and scale efficiency components positively contributed to TFPE. Further constituents of TFPE namely, ISE and RME both on average increased by 0.7% and 1.7%. The scale efficiencies imply the UK water sector is moving closer to its technically optimal scale in regards to output. In 2015/16, the largest TFP and TFPE changes of +23.0% and +17.6% occurred, respectively, had a negative ITE score of 1.3%. Despite this, large productivity gains in RISE and RME of 19.4% and 15.0% ensured the year had such a large TFP increase. Collectively, these results suggest that economies of scale and scope contributed positively to the TFPE result, allowing WaSCs to move to closer the efficiency frontier by improving in diversified outputs and optimising treatment plant sizes relative distribution area.

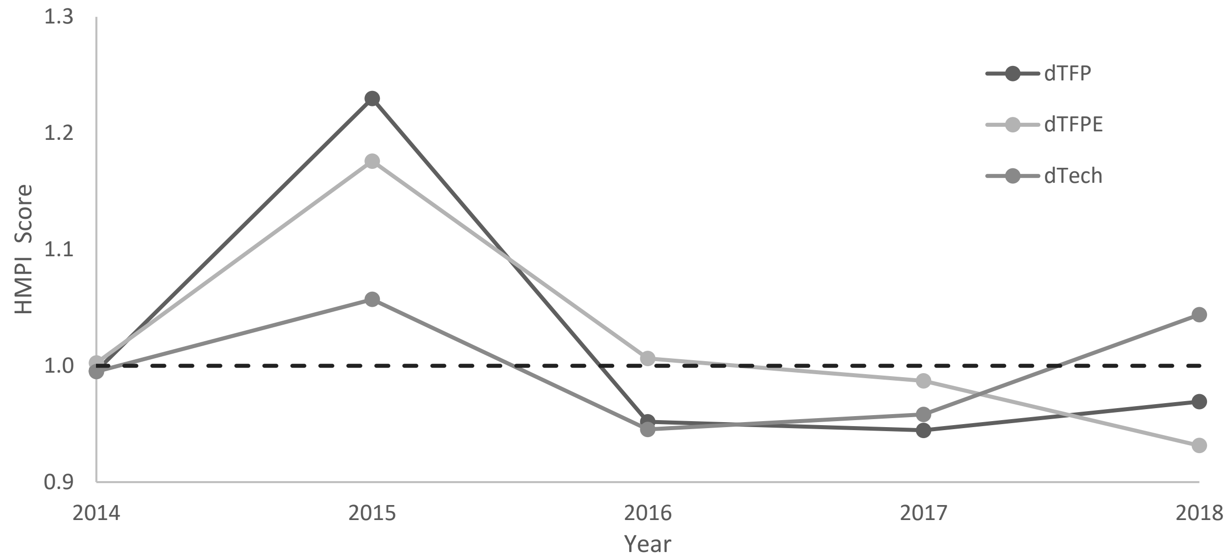

Figure 2. *The change in total factor productivity (TFP), TFP efficiency change (TFPE) and TFP technical change (TECH) for all UK water and sewage companies as a collective for 2014-2018.*

3.3. Company-level efficiency over time

Figure 3 displays that exactly half of the sample exhibited a positive TFP value, furthermore the TFP standard deviation was 0.043 (Table 6), indicating that the sample was relatively homogenous. This was expected to an extent since the UK has a mature water market, having been consolidated after the Second World War then eventually privatised in 1989 and regulated strictly ever since (OFWAT, 2020). The largest TFP gains were from company 8, which had increased productivity by 10.9%.

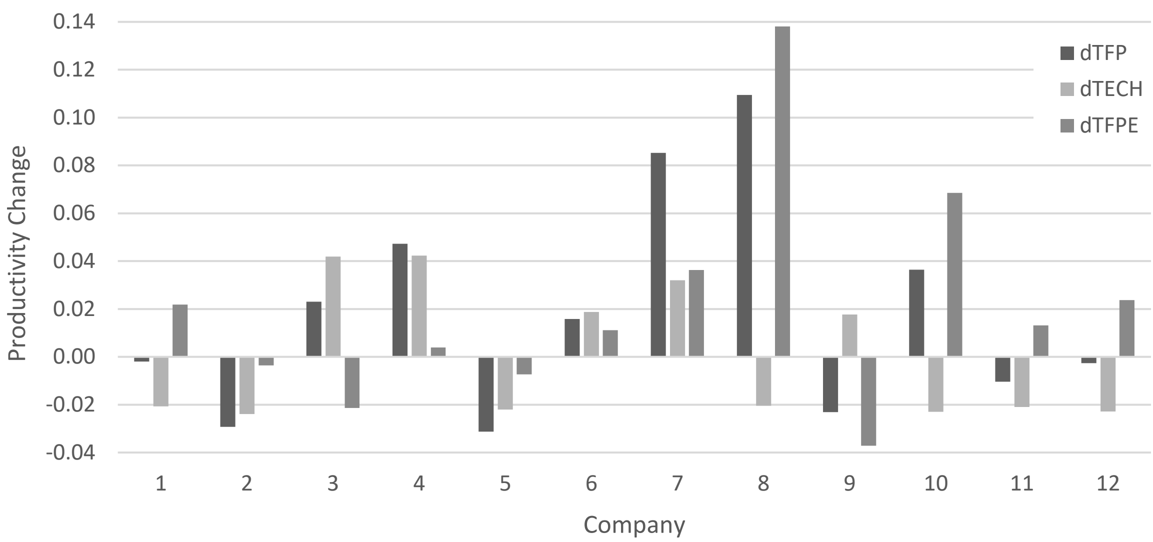

Figure 3. *The change in total factor productivity (TFP), TFP efficiency change (TFPE) and TFP technical change (TECH) for all individual UK water and sewage companies for 2014-2018.*

Table 6 shows that the increase was due to a large increase in TFPE of 13.8%, suggesting that the management of existing resources during this period significantly improved, although this is likely also due to capital projects from before the sample period coming online. Conversely, company 5 had the largest average decline in TFP during 2014-18 of -3.1%, struggling slightly more through optimising capital investment than through the management of resources. Companies 5 and 8 did have an almost identical average TECH decline, showing effective capital investment of the most improved company was as poor as the worst performing company. This conveys that company 8 can still considerably improve, despite being the top performer. It should be noted that not all companies necessarily operate in equal conditions, with exogenous factors such as rurality, water source and population density, to just name a few factors, all affecting their efficiencies (Walker *et al*., 2019). Although each company will have slightly different operational and corporate conditions, this exemplifies where communication and sharing of best practices can dramatically improve productivity. The current limitation to this is that the UK sector is privatised, and many efficiency gains are made through ‘commercially sensitive’ means.

The operational conditions within the UK are fairly uniform however, even minor variances in certain factors can affect renewable energy feasibility for companies, influencing their financial and energy payback times (Murphy and McDonnell, 2017). For example, wind speed averages and peaks are much higher in coastal areas and the north of the UK, ranging from an average 5-13 m/s in 1981-2010, whereas inland and in the south largely averages at 1.5-2.6 m/s (Met Office, 2020). A further example is in solar irradiance; Burnett *et al*. (2014) converted gridded sunshine duration to solar irradiance in order to map it for the UK within 1961-1990, which showed the south for average annual irradiance ranged from 90.9 to 126 Wm^{-2}, whilst the north had a range of 71.8-107.1. Additionally, topographical gradients vary throughout the whole of the UK (Topographic map, 2020), significantly altering the dynamics and viability of recovering energy from hydropower (McNabola *et al*., 2014). The one major renewable energy source that is uniform for all the companies in the sample is the production of biogas from wastewater, although the quantities will differ depending on populations, and transport distance (and associated costs) to centralised plants will vary with population densities (cities vs. rural, etc.). A further major barrier to renewable energy projects is land cost, which has disparities within the UK, generally being cheaper in the north and the south (Hall and Tewdwr-Jones, 2019). Collectively, this means generating renewable energy within the UK is not equal for each water company; therefore, future efficiency studies could enhance their analysis by considering this, perhaps integrating a 'percentage of possible renewable energy utilised' based on natural resources and economic thresholds.

Table 6. *Average TFP change and its components* for UK water and sewage companies 2014-18.*

Company	dTFP	dTECH	dTFPE	dITE	dISE	dRISE	dRME
1	0.998	0.979	1.022	1.012	1.019	1.045	1.038
2	0.971	0.976	0.996	0.978	1.004	1.029	1.023
3	1.023	1.042	0.979	1.000	1.000	0.979	0.979
4	1.047	1.042	1.004	1.000	1.000	1.004	1.004
5	0.969	0.978	0.993	0.956	0.995	1.037	1.047
6	1.016	1.019	1.011	1.000	1.000	1.011	1.010
7	1.085	1.032	1.036	1.000	1.033	1.036	1.003
8	1.109	0.980	1.138	1.080	1.027	1.077	1.046

9	0.977	1.018	0.963	0.997	0.999	0.966	0.967
10	1.036	0.977	1.068	1.033	1.005	1.025	1.017
11	0.990	0.979	1.013	0.994	0.998	1.029	1.028
12	0.997	0.977	1.024	1.025	1.005	1.041	1.037
Average	1.018	1.000	1.021	1.006	1.007	1.023	1.017
SD	0.043	0.027	0.044	0.029	0.012	0.029	0.024

TFP is total factor productivity; TECH is technical change; TFPE is efficiency change; ITE is input-oriented technical efficiency; ISE is input-oriented scale efficiency; RISE is residual input-oriented scale efficiency; RME is residual mix efficiency.

Technical change improved for five out of twelve WaSCs, with companies 3 and 4 leading with the way, improving by 4.2% each. This means that these companies have advanced regarding their technological condition, a probable result from long-term strategic planning and capital investment. However, when assessing the *TOTEX* year-on-year average, it was evident for these WaSCs that their change in spending was modest and comparable to their peers, increasing by 2.53% and 4.72%, respectively. This shows the difficulty in analysing the efficiency of capital expenditure as discussed in section 3.1. It should, however, be noted that the efficiency is in relevance to the outputs, and so it is probable that their capital spending was more optimised than other companies in the sample. Concerning efficiency change, eight out of twelve companies progressed their operational systems and procedures, with company 8 improving by 13.8%, the most of all the WaSCs.

The components of efficiency change, which are displayed in Table 6, can offer even more of an insight into productivity. As the previous section noted, an ITE score of 1 indicates the WaSC is on the production frontier, whilst a score of less than 1 for RISE categorises the WaSC as relatively unproductive. Eight companies (66%) displayed an ITE score of 1 or higher and therefore positively shifted the efficiency production frontier or remained on it. Although these improvements were observed, company 3 still reduced in TFPE due to it remaining relatively unproductive, as indicated by the decline in RISE. Only two companies, 3 and 9 did not match the overall positive trend for RISE and RME, whilst just companies 5, 9 and 11 presented negative results for ISE. This indicates that the majority of UK WaSCs had positive economies of scale and scope with TFP largely being driven by improved operational practices of existing infrastructure and resources. Although collectively the progress of TFP, TFPE and its constituents were small, continuing to improve in an already largely efficient sector is positive, especially within a framework evaluating more holistic sustainability outputs. Individual analysis at this scope further highlights how sharing best practice between the companies featured on different ends of the various components of TFP results could be advantageous, with lessons being relevant for companies outside of the region, too.

4. **Conclusions**

The objectives of this research were to utilise the Hicks-Moorsteen Productivity Index as a framework to evaluate the efficiency (as temporally applied TFP) of water service companies in the UK between 2013 and 2018, exploring the influence of input and output indicator selection on the representation of critical sustainability outcomes. In addition to more traditional indicators such as *TOTEX* and *Water supplied and wastewater treated,* the following indicators of sustainable performance were used: *self-generated renewable energy, customer satisfaction, leakage reduction, and per capita consumption reduction,* which were interchangeably utilised within eight model variable approaches. The study showed novelty by applying and comparing a mix of indicators across the sustainability spectrum, particularly poignant within the computation of the seldom-used HMPI on a UK sample of water companies. The choice of variables had a major influence on the ranking and perceived operational efficiency among WaSCs. CAPEX (used as part of *TOTEX*) for example, is an important input for tracking company operations however; possible associated efficiency benefits can lag investment, leading to apparent poor short-term performance following capital spending. A solution is to benchmark over longer periods where possible, implementing a 5-year rolling average or similar. Furthermore, *water supplied and wastewater treated* was deemed an unconstructive output from a sustainability perspective since it contradicts efforts to improve sustainability through reduced *leakage* and *consumption per capita*. Alternatives should be assessed in future research; possible options are *Customer satisfaction* and water quality measures. Despite these limitations, *TOTEX and water supplied and wastewater* *treated* were used alongside *customer satisfaction* and *self-generated renewable energy* for a holistic sustainability assessment that captures decisive company activities within a small sample. They indicated the UK water sector has improved in productivity by 1.8% on average for 2014-18 and still had room for improvement, as a technical decline was evident for both the best and worst performers. Collectively the sample's production frontier was unchanged but on average companies moved 2.1% closer to it, and further decomposition of productivity revealed this was due to improvements in economies of scale and scope with residual input-oriented scale efficiency and residual mix efficiency expressing increases of 2.3% and 1.7%, respectively. Careful selection of appropriate input and output variables, integrated within an appropriate productivity framework, is critical to align with sustainability objectives and to target future investment and regulation within the water sector. The largest limitation within this study was the small sample size, which restrained the quantity of indicators that could be used however, core sustainability indicators were still included and future studies can build upon this, particularly within the framework of the HMPI as was successfully applied here. Collectively, these outcomes can contribute to implications on policy, regulation, water management, and future research through displaying a process to assess the optimal routes to measure efficiency in a holistic sustainability context, enabling identification of areas of improvement, effectiveness of their operations, and potential collaborators for sharing of best practice.

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