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Water company productivity change: A disaggregated approach accounting for changes in inputs and outputs

Manuel Mocholi-Arce [a], Ramon Sala-Garrido [a], Maria Molinos-Senante [b,*], Alexandros Maziotis [b,c]

[a] Department of Mathematics for Economics, University of Valencia, Avd. Tarongers S/N, Valencia, Spain
[b] Departamento de Ingeniería Hidráulica y Ambiental, Pontificia Universidad Católica de Chile, Avda. Vicuña Mackenna, 4860, Santiago, Chile
[c] Department of Business, New York College, Athens, Greece

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ABSTRACT

The assessment of the productivity change of water utilities provides essential information to sector managers and regulators. This study uses the Luenberger-Hicks-Moorsteen Productivity Indicator (LHMPI) to evaluate productivity change as it can be further decomposed into three components namely technical change (TC), technical efficiency change (TEC), and scale efficiency change (SEC). This study evaluates the productivity of several water companies in England and Wales from 2001 to 2018. We found that productivity declined 1.2% per year due to the use of inputs that increased by 1.4% per year relative to outputs that increased by 0.2% per year.

1. Introduction

The assessment of productivity change is a crucial issue for improving water company performance and for regulatory policies that target the financial sustainability of companies, the affordability of customer bills, the protection of drinking water, and the environmental (Akimov and Simshauser, 2020). This type of assessment is very relevant in the water industry in England and Wales, where efficiency and productivity change is part of the price review process to set tariffs (Walker et al., 2019). Every five years Water and Sewerage Companies (WaSCs) and Water only Companies (WoCs) submit their business plans for approval to the water sector regulator, the Water Services Regulation Authority (Ofwat). Then, Ofwat reviews and challenges water company business plan and proposes final price determinations (Loftus et al., 2016; Portela et al., 2011).

From a methodological perspective, the estimation of productivity change can mainly be done using parametric (econometric) techniques and non-parametric techniques (Grifell-Tatjé et al., 2018). Parametric techniques require the specification of a functional form for the technology prior to estimation. Moreover, they require different assumptions regarding the distribution of the inefficiency term, such as half-normal, truncated normal or exponential (Coelli et al., 2005). In contrast, non-parametric techniques do not need the specification of a functional form and can easily accommodate multiple inputs and outputs (Suarez-Varela et al., 2017). Hence, as reviewed by Worthington (2014) and Berg and Marques (2011), in the context of water companies, several previous studies employed non-parametric techniques to estimate productivity change using either distance functions (e.g., data envelopment analysis, DEA) or index numbers (Ananda and Pawsey, 2019). Index techniques, however, are data-intensive, requiring price information for inputs and outputs (Maziotis et al., 2015). Distance functions do not have these constraints (Cooper et al., 2011; Nyathikala and Kulshrestha, 2017). Hence, this study focuses on the use of distance functions to estimate productivity change.

Within the distance function framework, the Malmquist Productivity Index (MPI) has been widely used to evaluate the determinants of productivity change in different industries (Wang and Lan, 2011) including water industry (e.g., Lin and Berg, 2008; De Witte and Marques, 2012; Saad and Harund, 2017). The MPI estimation is based on Shephard distance functions, which can be either input or output-oriented (Fare et al., 1995). The analyst needs to choose an orientation for the distance function as it does not allow for a simultaneous contraction of inputs and maximization of outputs. Moreover, Kerstens and Van De Woestyne (2014), O'Donnell (2014) and Ferreira and Marques (2016) noted that the computation of the MPI might suffer from infeasibility problems or total factor productivity (TFP) measures may not properly reflect changes due to scale effect.

To overcome the drawbacks of the MPI, Bjurek et al. (1998)

* Corresponding author.
E-mail address: mmolinos@uc.cl (M. Molinos-Senante).

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developed the Hicks-Moorsteen productivity index (HMPI), which is considered as the only multiplicatively-complete index computed without price data (O'Donnell, 2012; Molinos-Senante et al., 2016). Satisfying more properties than the MPI makes the HMPI a well-defined and more reliable productivity index (for more details see Briec and Kerstens, 2011; Briec et al., 2012). However, both MPI and HMPI are ratio-based indices, meaning that they cannot identify if the variables under assessment have a value of zero or are close to zero (Balk et al., 2008). Chambers et al. (1996) introduced a difference-based indicator known as the Luenberger Productivity Indicator (LPI) to deal with this limitation. It measures productivity change using differences (Diewert, 2005) and is estimated using directional distance functions, which allows for the simultaneous contraction of inputs and maximization of outputs (Molinos-Senante et al., 2019). However, the LPI is not "additively complete," meaning that it cannot be separated into changes in inputs and outputs. To overcome this limitation, Briec and Kerstens (2004) developed the Luenberger-Hicks-Moorsteen Productivity Indicator (LHMPI), which includes the best of the LPI and HMPI (Kerstens et al., 2018; Molinos-Senante et al., 2019). Thus, the LHMPI follows a difference-based approach and allows to identify the contribution of inputs and outputs to changes in productivity (Briec et al., 2012). Moreover, based on Ang and Kerstens's (2017) approach, the LHMPI decomposes into several factors of interest such as technical efficiency change (TEC), technical change (TC) and scale efficiency change (SEC).

Against this background, the main objective of this study is to estimate the productivity change and its components (TEC, TC and SEC) in the English and Welsh water industry. The LHMPI and its determinants are estimated for several WaSCs and WoCs in England and Wales over the period 2001–2018. Moreover, the impact of several environmental variables on water company productivity change has been assessed. To the best of our knowledge, in the context of water utilities, only Sala--Garrido et al. (2018) employed the LHMPI to evaluate the productivity change of a sample of Chilean water companies. However, their study focused on comparing LPI and LHMPI estimations and therefore, they simplified the decomposition of the LHMPI into TEC and TC drivers. Hence, this is the first study decomposing the LHMPI into.

TEC, TC and SEC for water companies.[1] Moreover, we also innovate by evaluating the impact of a set of environmental variables on the productivity change measured by the LHMPI. The productivity change results are finally linked to the regulatory cycle of the English and Welsh water industry to discuss the responsiveness of productivity from the regulator's price reviews and draw some policy implications.

The paper unfolds as follows. Section 2 presents the methodology employed in this study to estimate productivity change for water companies. It is followed by a discussion of the sample data in Section 3. Section 4 presents and discuss the main results, and the final section concludes.

2. Methodology

2.1. Productivity change assessment

This section describes the computation of the LHMPI and its decomposition into TEC, TC and SEC. Its derivation requires the definition of a production possibility set and directional distance functions, which refer to a simultaneous reduction in inputs and increase in outputs (Luenberger, 1992; Sala-Garrido et al., 2018). Assuming that at any time t, there are j units (or water companies) where $j = 1, \dots, J$ that use an input vector x_n where $n = 1, \dots, N$ to generate a set of outputs y_m where $m = 1, \dots, M$. The production possibility set, which shows the set of all outputs than can be produced based on the set of all inputs, can be defined as follows:

$$PPS^t = \{(x^t, y^t) | x^t \text{ can produce } y^t\} \quad \text{where } t = 1, \dots, T \tag{1}$$

The directional distance function at any time t, D^t is defined as follows:

$$D^t(x, y; \vec{g_x}, \vec{g_y}) = sup\{\phi : (x - \phi\vec{g_x}, y + \phi\vec{g_y}) \in PPS^t\} \tag{2}$$

where $\vec{g_x}$ and $\vec{g_y}$ represent the directional vectors for the inputs and outputs, respectively and decide the direction in which efficiency is estimated. In this study, assume that the water companies want to minimize their inputs and maximize their outputs (Marques et al., 2014). The directional distance function shows the distance between the observation (x, y) and the point $(x - \phi\vec{g_x}, y + \phi\vec{g_y})$ on the production frontier (Emrouznejad and Yang, 2016). Moreover, ϕ denotes the efficiency score and shows the maximum possible simultaneous reduction in inputs and increase in outputs (Molinos-Senante et al., 2019).

We now discuss the LHMPI as defined by Briec and Kerstens (2004). It is based on the input and output oriented versions of the LPI between time t and $t+1$, LI^t, LI^{t+1}, LO^t and LO^{t+1} respectively, as defined by Chambers (2002) (Briec and Kerstens, 2004). These take the following form:

$$LO^{t,t+1}\left(x^t, y^t, x^{t+1}, y^{t+1}; \vec{g_y^t}, \overrightarrow{g_y^{t+1}}\right) = \frac{1}{2}\left(LO^t + LO^{t+1}\right) \tag{3}$$

$$LI^{t,t+1}\left(x^t, y^t, x^{t+1}, y^{t+1}; \vec{g_x^t}, \overrightarrow{g_x^{t+1}}\right) = \frac{1}{2}\left(LI^t + LI^{t+1}\right) \tag{4}$$

where LO^t and LO^{t+1} were estimated using directional distance functions (Eq. (2)) as follows:

$$LO^t\left(x^t, y^t, y^{t+1}; \vec{g_y^t}, \overrightarrow{g_y^{t+1}}\right) = D^t\left(x^t, y^t; 0, \vec{g_y^t}\right) - D^t\left(x^t, y^{t+1}; 0, \overrightarrow{g_y^{t+1}}\right) \tag{5}$$

$$LO^{t+1}\left(x^{t+1}, y^t, y^{t+1}; \vec{g_y^t}, \overrightarrow{g_y^{t+1}}\right) = D^{t+1}\left(x^{t+1}, y^t; 0, \vec{g_y^t}\right) - D^{t+1}\left(x^{t+1}, y^{t+1}; 0, \overrightarrow{g_y^{t+1}}\right) \tag{6}$$

and LI^t and LI^{t+1} were estimated using directional distance functions (Eq. (2)) as follows:

$$LI^t\left(x^t, x^{t+1}, y^t; \vec{g_x^t}, \overrightarrow{g_x^{t+1}}\right) = D^t\left(x^{t+1}, y^t; \overrightarrow{g_x^{t+1}}, 0\right) - D^t\left(x^t, y^t; \vec{g_x^t}, 0\right) \tag{7}$$

$$LI^{t+1}\left(x^t, x^{t+1}, y^{t+1}; \vec{g_x^t}, \overrightarrow{g_x^{t+1}}\right) = D^{t+1}\left(x^{t+1}, y^{t+1}; \overrightarrow{g_y^{t+1}}, 0\right) - D^{t+1}\left(x^t, y^{t+1}; \vec{g_x^t}, 0\right) \tag{8}$$

Briec and Kerstens (2004) defined the LHMPI by taking the arithmetic mean of productivity change between time t and $t+1$ as follows:

$$LHMPI^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1}; g^t, g^{t+1}) = \frac{1}{2}\left(LHM^t + LHM^{t+1}\right) = \frac{1}{2}\left(LO^t - LI^t\right) + \frac{1}{2}\left(LO^{t+1} - LI^{t+1}\right) = \frac{1}{2}\left(LO^t + LO^{t+1}\right) - \frac{1}{2}\left(LI^t + LI^{t+1}\right) \equiv LO^{t,t+1} - LI^{t,t+1} \tag{9}$$

Thus, the LHMPI was defined as the difference between an output and input indicator. Following the approach of Diewert and Fox (2014; 2017) and Ang and Kerstens (2017), the LHMPI in Eq. (9) was decomposed into three components, namely: i) TEC; ii) TC and; iii) SEC.

$$LHMPI^{t,t+1} = TC^{t,t+1} + TEC^{t,t+1} + SEC^{t,t+1} \tag{10}$$

The TC component was calculated as follows:

$$TC^{t,t+1} = \left[\left(D^{t+1}\left(x^{t+1}, y^{t+1}; \overrightarrow{g_x^{t+1}}, 0\right) - D^t\left(x^{t+1}, y^{t+1}; \overrightarrow{g_x^{t+1}}\right) \times \left(D^{t+1}\left(x^{t+1}, y^{t+1}; 0, \overrightarrow{g_y^{t+1}}\right) - D^t\left(x^{t+1}, y^{t+1}; 0, \overrightarrow{g_y^{t+1}}\right)\right)\right)\right] \tag{11}$$

[1] The LHMPI has previously employed by Molinos-Senante et al. (2019) and Sala-Garrido et al. (2018) for the estimation of the productivity change of wastewater treatment plants in Spain and water and sewerage utilities in Chile. Moreover, the above studies decomposed the LHMPI into TEC and TC. Thus, the scale effect was not included in their analysis.

If $TC^{t,t+1}$ is positive, then technical progress exists, contributing positively to changes in productivity. If $TC^{t,t+1}$ is negative, then technical regress negatively impacts productivity change.

The TEC component was calculated as follows:

$$TEC^{t,t+1} = D^t\left(x^t, y^t; 0, \overrightarrow{g_y^t}\right) - D^{t+1}\left(x^{t+1}, y^{t+1}; 0, \overrightarrow{g_y^{t+1}}\right) \tag{12}$$

If $TEC^{t,t+1}$ is positive, then it means that less efficient water companies moved closer to the frontier (the most efficient companies). Thus, productivity improvements occur. If $TEC^{t,t+1}$ is negative, then efficiency losses lead to a deterioration in productivity.

The SEC component was calculated from the residual as follows (Ang and Kerstens, 2017):

$$\begin{aligned} SEC^{t,t+1} = LHMPI^{t,t+1} - TEC^{t,t+1} - TC^{t,t+1} = \left[D^t\left(x^{t+1}, y^{t+1}; 0, \overrightarrow{g_y^{t+1}}\right) - D^t\left(x^t, y^{t+1}; 0, \overrightarrow{g_y^{t+1}}\right)\right] \\ + \left[D^{t+1}\left(x^{t+1}, y^t; 0, \overrightarrow{g_y^t}\right) - D^{t+1}\left(x^t, y^t; 0, \overrightarrow{g_y^t}\right)\right] - \left\{ \begin{array}{l} \left[D^t\left(x^{t+1}, y^t; \overrightarrow{g_x^{t+1}}, 0\right) - D^t\left(x^t, y^t; \overrightarrow{g_x^t}, 0\right)\right] \\ + \left[D^{t+1}\left(x^{t+1}, y^{t+1}; \overrightarrow{g_x^{t+1}}, 0\right) - D^{t+1}\left(x^t, y^{t+1}; \overrightarrow{g_x^t}, 0\right)\right] \end{array} \right\} \end{aligned} \tag{13}$$

A positive value of $SEC^{t,t+1}$, i.e., increases in the scale of water company operations indicate improvements in productivity change, whereas a negative SEC deteriorates productivity change.

The computation of the LHMPI and its components required the estimation of several directional distance functions. Following the approach of Ang and Kerstens (2017) and Molinos-Senante et al. (2019) we estimated these directional distance functions using non-parametric (linear programming) approaches such as DEA.[2] Following past practice in water company performance assessment (Marques et al., 2014; D'Inverno et al., 2020), we ran DEA models assuming variable returns to scale. For more details on the optimization models, see supplemental material.

2.2. Identification of environmental variables affecting productivity change

We identify environmental variables affecting productivity change of water companies (Eq. (9)) by applying the following econometric model:

$$\mathrm{LHMPI}_j^{t,t+1} = a_o + \beta\, \mathrm{x_j} + \gamma_j + \mu_j,\ \mathrm{j} = 1, \ldots, \mathrm{N} \tag{14}$$

where x_j is a vector of environmental variables for a water company j that it is expected to be related to the water company's LHMPI, i.e., $\mathrm{LHMPI}_j^{t,t+1}$, through the vector of parameters β that we need to estimate, a_o denotes the constant term, γ_j captures firm-specific unobserved heterogeneity (e.g., managerial inability) and μ_j is an error term that follows the normal distribution. This firm-specific unobserved heterogeneity could be fixed or random (Greene, 2005). If unobserved heterogeneity is correlated with the explanatory variables (fixed), then the fixed effects (FE) model is estimated (Wooldridge, 2010). If it is uncorrelated with the explanatory variables (random), then the random effects (RE) model is estimated (Stock and Watson, 2020). I Hausman test is used to determine which model is appropriate (Greene, 2018). The final model is run with robust standard errors to control for heteroscedasticity (Kumbhakar et al., 2015; Greene, 2018).

3. Sample and data description

The LHMPI and its drivers were estimated for a sample of water companies in England and Wales over the period 2001–2018. The sample consisted of 10 WaSCs and 7 WoCs that provide water services. As WaSCs provide both water and sewerage services whereas WoCs just water services, the assessment focused on drinking water service excluding the sewerage service provided by WaSCs, which avoids bias due to the existence of economies of scope (Carvalho and Marques, 2014). The evaluation focused on the period 2001–2018 as the period prior to 2001 was widely studied in the past, and the impact of price-cap regulation on water company productivity has already been researched (e.g., Saal and Parker, 2001; Saal et al., 2007; Portela et al., 2011). Moreover, since several mergers and acquisitions among the water companies occurred over the years, we followed the approach of Molinos-Senante et al. (2017a), and we grouped the data from those water companies who followed the same pattern as mergers and acquisitions (Molinos-Senante et al., 2017a). The source of data was the Ofwat's website and water company annual financial reports.

The selection of inputs and outputs was based on studies conducted on this topic in the water industry in England and Wales and elsewhere. When selecting the number of inputs and outputs, we also had to satisfy the "Cooper's rule". This rule underlines that a DEA model will provide a solution (i.e., efficiency score) if the number of units (water companies in our case) is three times higher than the total number of selected inputs and outputs (Cooper et al., 2011). Thus, if it is assumed that the number of water companies is j, the total number of inputs is n, and the total number of outputs is m, then Cooper's rule requires that $j \geq max\{m \times n, 3(m+n)\}$. In this study, the "Cooper's rule" is met because the assessment involved two inputs and two outputs, whereas the total number of water companies was 17.

Following standard practice, the first input was the operating expenditure (OPEX) for water services expressed in millions of pounds per year (Saal and Parker, 2006; Molinos-Senante et al., 2014). The second input was the capital expenditure (CAPEX) for water services expressed in millions of pounds per year, to capture the capital invested for the maintenance of water infrastructure and non-infrastructure assets and network reinforcement (Saal et al., 2007; Molinos-Senante et al., 2017). We also selected the following two outputs for water services. The first one was the volume of water delivered, measured in megalitres per year, to capture abstracted water and sent to the network (Portela et al., 2011). The second output referred to water connected properties measured in thousands per year and reflects urbanization and size (Molinos-Senante et al., 2017).

Consistent with past studies that demonstrated the importance of evaluating the impact of environmental variables on company productivity (e.g. Berg and Marques, 2011; Marques et al., 2014; Pinto et al., 2017), we included the following variables in our analysis: i) percentage of water taken from boreholes (Villegas et al., 2019); ii) percentage of water taken from rivers (Brea-Solis et al., 2017); iii) percentage of water lost in the network (Molinos-Senante et al., 2017) and iv) population density defined as the ratio of water population to water area measured

[2] As it is reported in the introduction, an alternative approach could have been parametric (econometrics) methods such as SFA. In this study we use DEA (non-parametric) as it accommodates multiple inputs and outputs and doesn't need to specify a functional form for the technology or to assume a particular distributional form for the inefficiency as SFA does (Cooper et al., 2011).

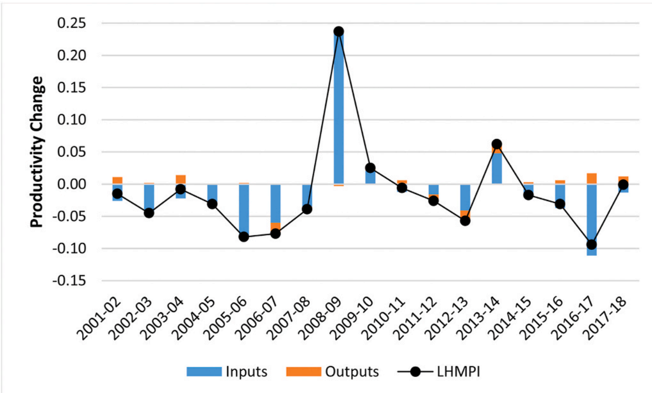

Fig. 1. Luenberger-Hicks-Moorsteen Productivity Index (LHMPI) and its decomposition into inputs and outputs change for all English and Welsh water companies evaluated.

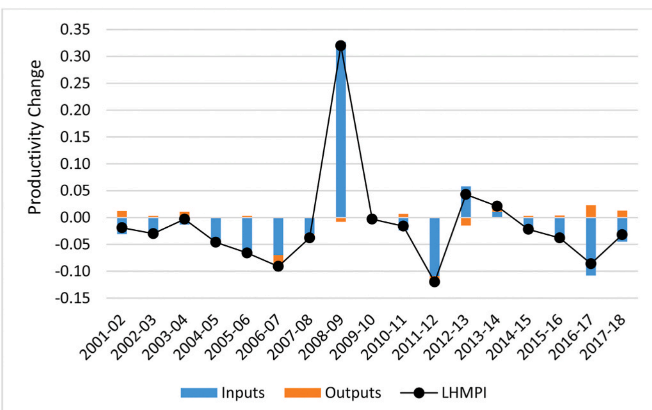

Fig. 2. Luenberger-Hicks-Moorsteen Productivity Index (LHMPI) and its decomposition into inputs and outputs change for the English and Welsh water and sewerage companies (WaSCs) evaluated.

in thousands per km^2 (Walker et al., 2019).

The descriptive statistics for the variables used in this study are reported in Table 1.

4. Results and discussion

4.1. Productivity change and its drivers

The LHMPI allows us to estimate the productivity change of the water companies and the contribution of inputs and outputs to this change. Figs. 1–3 show the results from the average estimates of the LHMPI and the contribution of inputs and outputs over time for all water companies evaluated, WaSCs and WoCs, respectively (see supplemental material for further details). Fig. 1 illustrates that during the period 2001–18, the average LHMPI for the English and Welsh water industry deteriorated at an annual rate of 1.2%. This trend was attributed to an average increase in inputs by 1.4% per annum, which outstripped a small positive change in outputs by 0.2% per year.

The average productivity of WaSCs (Fig. 2) and WoCs (Fig. 3) decreased by 1.3% and 1.0% per year, respectively, which was entirely attributed to an increase in inputs by 1.5% and 1.4% per year. In particular, it appears that increases in OPEX and CAPEX negatively influenced productivity for both WaSCs and WoCs during the years 2002–08. In this, period the water companies showed the highest increase in their use of inputs compared to the rest of the study period. The English and Welsh water companies continued to make substantial

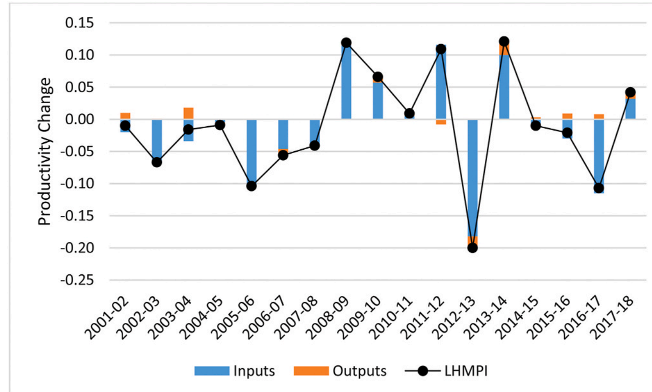

Fig. 3. Luenberger-Hicks-Moorsteen Productivity Index (LHMPI) and its decomposition into inputs and outputs change for the English and Welsh water only companies (WoCs) evaluated.

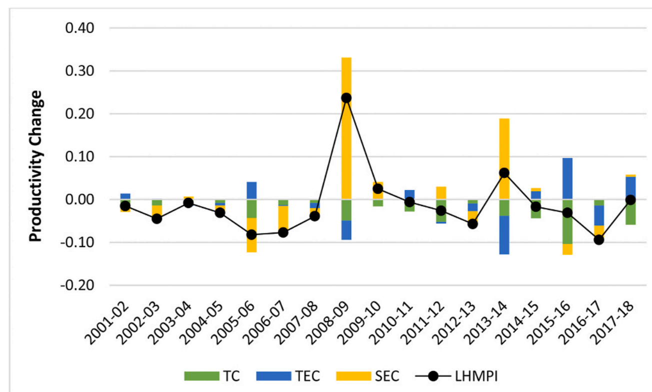

Fig. 4. Luenberger-Hicks-Moorsteen Productivity Index (LHMPI) and its drivers (technical change -TC-; technical efficiency change -TEC- and scale efficiency change -SEC-) for all English and Welsh water companies evaluated.

investments since privatization to improve their networks and improve operations.

Our finding corroborates the results from a previous study by Maziotis et al. (2014) who noted that significant increases in capital, labour, and other costs during the years 2001–05 negatively impacted WaSCs' productivity and profitability. We note that during the period 2002–08, which refers to the period entirely covered by the 1999 price review and part of the 2004 price review, OPEX and CAPEX increased by 6.0% and 3.7% on average per year, respectively. Thus, any small increases in the volume of water delivered and the number of water connected properties were outstripped by the increase in total costs leading, therefore to a decline in productivity. In particular, during the years 2002–08 WaSC and WoC's average productivity declined by almost 4.2% per year.

The downward trend in the English and Welsh water industry's productivity was interrupted in subsequent years. Decreases in OPEX for the years 2008–09 and in CAPEX for the years 2009–10, positively impacted productivity. However, productivity continued to deteriorate for the rest of the study period, except for the year 2013–14. Our results are consistent with a previous study by Molinos-Senante et al. (2014) where the authors reported a decline in the productivity of the English and Welsh water industry for the years 2002–08 using the LPI.

To better understand what drove water company productivity, Figs. 4–6 gather the decomposition of the LHMPI into TEC, TC and SEC. The results suggest that over the entire period, the deterioration in the water industry's productivity (Fig. 4) was attributed to a decrease in TC, which outstripped any gains in TEC and SEC. This finding is consistent

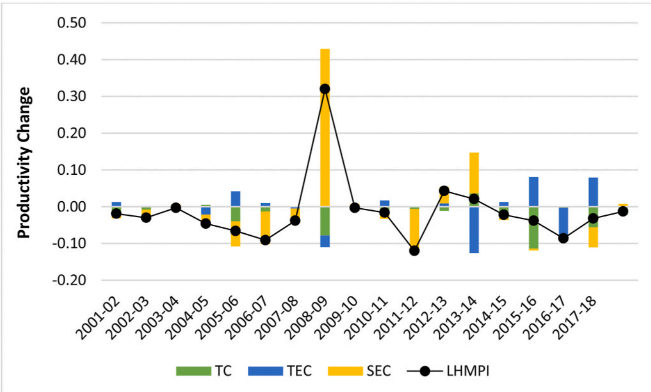

Fig. 5. Luenberger-Hicks-Moorsteen Productivity Index (LHMPI) and its drivers (technical change -TC-; technical efficiency change -TEC- and scale efficiency change -SEC-) for the English and Welsh water and sewerage companies (WaSCs) evaluated.

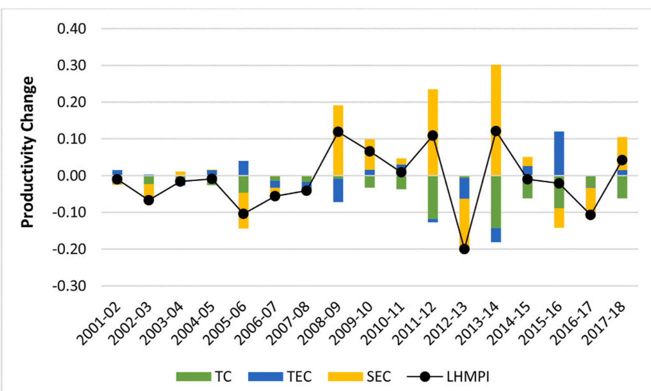

Fig. 6. Luenberger-Hicks-Moorsteen Productivity Index (LHMPI) and its drivers (technical change -TC-; technical efficiency change -TEC- and scale efficiency change -SEC-) for the English and Welsh water only companies (WoCs) evaluated.

with the study by Molinos-Senante et al. (2014), which found that the main factor influencing the deterioration in productivity was the negative TC. In our study, TC decreased by 3.1% on average per year, suggesting that the water industry experienced technical regress. Gains in TEC were small and at the level of 0.1% on average per year, suggesting that less efficient water companies made small improvements in their performance relative to the most efficient water company. SEC considerably increased by 1.7% on average per year, implying that adjustments in the operational scale of water companies positively impacted productivity.

The retardation in WaSC's average productivity (Fig. 5) was attributed to a technical (TC) regress of 2.2% per year, which outstripped any gains in SEC, which were at the level of 0.8% per year. Gains in TEC were negligible. WoC's average productivity (Fig. 6) decreased by 1.0% per year, mainly explained by a technical regress of 4.4% per year. Gains in SEC and TEC were at the level of 3.1% and 0.3% on average per year, respectively. Overall, the results suggest that WaSCs and WoCs could improve their productivity by investing resources in adopting best industries' practices.

Fig. 7 reports the average results of the LHMPI and its drivers at a water company level across all years (2001–2018). The results indicate that the most productive water company in the sample was WoC7, whose average productivity increased at an annual rate of 1.2%. An increase in TEC and SEC outstripped any losses in TC. By contrast, the worst-performing water company in terms of productivity was WaSC3,

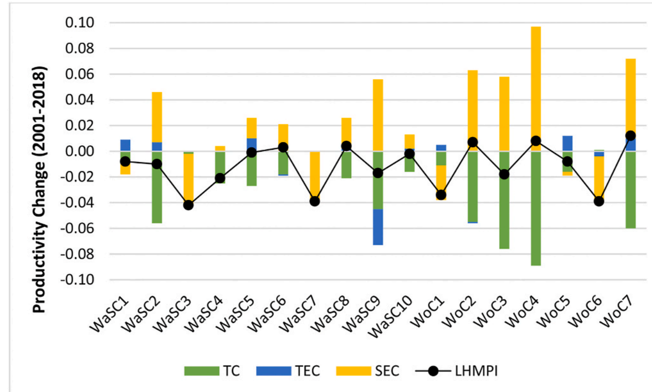

Fig. 7. Luenberger-Hicks-Moorsteen Productivity Index (LHMPI) and its drivers (technical change -TC-; technical efficiency change -TEC- and scale efficiency change -SEC-) over 2001–2018 for the English and Welsh water and sewerage (WaSCs) and water only companies (WoCs) evaluated.

which showed a considerable decline in its productivity at an annual rate of 4.2% on average and was entirely explained by the negative scale effect. All water companies except for WoC6 suffered a regression on TC. The range of technical regress varied from 0.2% to 8.9%, with WoC4 being the worst. In contrast, most of the water companies achieved gains in their efficiency. Only four companies did not improve their efficiency relative to the most efficient company. The water company with the highest efficiency gains was WoC5, whereas the water company with the highest efficiency losses was WaSC9. The scale effect was positive for most of the water companies. Among the WaSCs, three companies reported a negative value for SEC suggesting that the mergers with WoCs may not have lowered their costs. However, the rest of WaSCs reported positive rates for the SEC, thus contributing positively to productivity change. Most of WoCs reported high values of SEC (in excess of 5.8%), except for WoC1, WoC5 and WoC6 whose negative scale effect deteriorated productivity.

4.2. Impact of environmental variables on water company productivity

The final step of our analysis is to understand the influence of several operating characteristics on water company productivity. The final model that we estimate is the FE model with robust standard errors to control for heteroscedasticity (Greene, 2018). Supplemental material includes the preliminary results from the estimation of FE and RE models and the Hausman test to determine which model is suitable for our purposes. The results indicated that the percentage of water taken from rivers, the percentage of water leakage and population density had a statistically significant effect on productivity. Technical speaking and keeping other things equal, one unit increase in the percentage of water taken from rivers will decrease productivity. Abstracting water from rivers might require high pumping requirements, increasing overall costs and thus inefficiency. In contrast, dealing with water leakage could lead to higher service quality, lower production costs by better network management, and consequently, higher productivity. It is also found that as density increases, productivity could increase as well. Densely populated areas might be less costly to serve than less densely populated areas, which could lead to lower inefficiency and thus, higher productivity.

4.3. Productivity change and the regulatory cycle

As the period considered in this study involved several regulatory cycles, we also divided the productivity results into four sub-periods (see Table 3). It is shown that during the years 2002–05, which is the period covered by the 1999 price review, productivity declined for WaSCs and

Table 1
Descriptive statistics.

Variables	Units	Mean	Std. Dev.	Minimum	Maximum
Volume of water delivered	Ml/year	316,179.71	254,704.28	22,356.25	1,049,121.97
Water connected properties	000s	1448.53	1098.62	115.20	3826.42
Operating expenditure	£m/year	120.24	95.14	9.16	477.64
Capital expenditure	£m/year	117.37	116.37	4.70	608.72
Water taken from boreholes	%	40.9	30.3	5.0	92.2
Water taken from rivers	%	29.4	23.1	0.1	79.1
Water leakage	%	20.0	4.1	11.8	33.6
Population density	000 s/km^2	0.445	0.267	0.141	1.250

Note: operating expenditure and capital expenditure are in 2018 prices.

Table 2
Estimates of FE with robust standard errors.

	Coef.	Std. Err.	T-stat	P-value
Constant	−0.252	0.134	**−1.888**	0.077
% of water taken from rivers	−0.083	0.047	***−1.758***	0.098
% of water taken from boreholes	−0.112	0.074	−1.522	0.147
% of water leakage	1.490	0.567	**2.628**	0.018
Population density	0.285	0.101	**2.821**	0.000
F (4,268)	2.360			
P-value	***0.098***			
Obs	289			

Dependent variables = LHMPI.
Bold are statistically significant at a 5% significance level.
Bold italic are statistically significant at a 10% significance level.

Table 3
Average values of the Luenberger-Hicks-Moorsteen Productivity Index (LHMPI) and its drivers (technical change -TC-; technical efficiency change -TEC- and scale efficiency change -SEC-) during the sub-periods.

Sub-period	2001–05	2006–10	2011–15	2016–18
All water companies				
TC	−0.012	−0.026	−0.034	−0.059
TEC	0.001	−0.003	−0.014	0.034
SEC	−0.014	0.042	0.039	−0.018
LHMPI	−0.025	0.013	−0.009	−0.042
Water and sewerage companies				
TC	−0.007	−0.027	−0.007	−0.058
TEC	−0.001	0.002	−0.017	0.027
SEC	−0.017	0.049	0.005	−0.021
LHMPI	−0.024	0.024	−0.019	−0.052
Water only companies				
TC	−0.020	−0.024	−0.073	−0.061
TEC	0.004	−0.010	−0.010	0.044
SEC	−0.009	0.030	0.089	−0.013
LHMPI	−0.026	−0.003	0.006	−0.029

WoCs. Ofwat introduced several incentive schemes to encourage water companies to be more efficient. These include, for instance, the tightened cost reduction target levels and the implementation of an outperformance rolling incentive where the companies were permitted to keep efficiency savings for five years irrespective of the year occurred (Molinos-Senante et al., 2017). However, both WaSCs and WoCs experienced technical regress at a rate of 0.7% and 2%, respectively on average per year. This result is consistent with previous studies by Molinos-Senante et al. (2014; 2017) who demonstrated the negative impact of TC on water company productivity. Moreover, other studies by Bottasso and Conti (2009) and Portela et al. (2011) showed that TC significantly fell during the years 2001–05. SEC was also negative during that period for both WaSCs and WoCs, suggesting that the mergers among WaSCs and WoCs during the years 2000–01 may not have lowered water company costs. The negative impact of 2000–01 mergers on WaSC's productivity was also reported by Maziotis et al. (2014). Moreover, WaSCs showed small efficiency gains during the years 2002–04, but these were lost in 2004–05 (Fig. 5). In contrast, WoCs showed small efficiency gains at a rate of 0.4% on average per year for 2002–05 (Fig. 6). Overall, it seems that the introduction of price limits in 2000 did not positively impact on productivity, which is particularly evident for the most efficient water companies who did not continue to improve their productivity. Less efficient water companies appeared to have moved closer to the frontier, but gains in efficiency were small and only occurred among WoCs.

The introduction of new price limits in 2005 seemed to positively impact water company productivity, entirely attributed to the positive scale effect. However, there were not any improvements in TEC or TC. Ofwat kept the outperformance rolling incentive and introduced additional incentive schemes where water companies needed to share with customers any savings from outperformance in OPEX and CAPEX. However, the negative technical change found for the years 2006–2010 suggests that the production technology of both WaSCs and WoCs changed by incorporating and demanding more expenses related to the economic and environmental regulatory requirements. In contrast, adjustments in the scale of operations positively impacted both WaSC and WoC's productivity. Average WaSC showed considerable gains in technical efficiency during the years 2005–07, which were at the level of 2.6% per year, but these were lost in the subsequent years (Fig. 5). WoCs experienced significant efficiency losses during the years 2007–09, which were at the level of 3.5% on average per year, thus offsetting any efficiency gains during the years 2005–06 (Fig. 6). Less efficient WaSCs seemed to have made some gains in catching-up with the most efficient firm, but this was not the case for WoCs.

In the next sub-period (2011–16), average productivity slightly declined (Table 2). Any gains in scale efficiency were lost due to the negative TC and TEC. As part of the 2009 price review, Ofwat introduced other incentive schemes to increase company productivity. For instance, Ofwat introduced the Service Incentive Scheme (SIM) where the water companies were financially rewarded (penalized) if the customers are satisfied (or dissatisfied) with the way the water company cope with the quality of service incidents such as leakage, low pressure, or billing enquiries (Ofwat, 2012). Average WaSC's productivity declined at a rate of 1.9% per year, mainly attributed to TEC losses (Fig. 5). In contrast, average WoC's productivity remained positive for all years except for the periods 2011–12 and 2014–15 (Fig. 6). Thus, it showed a small increase at an annual rate of 0.6% on average. This increase was entirely attributed to the scale effect; the mergers that occurred among WoCs during the years 2012–13 might positively impact productivity.

As part of the 2014 price review, Ofwat introduced another financial incentive scheme to stimulate efficiency, called Outcome Delivery Incentives (ODIs), which consists of several performance indicators associated with quality of service and environmental standards. If the water companies meet the targets in those performance indicators, then they receive financial rewards; otherwise, penalties are imposed by the regulator (Frontier economics, 2017). However, in the last sub-period (2016–18), average productivity further declined, mainly attributed to the negative scale effect and technical regress. Average WaSC and WoC's productivity fell at an annual rate of 5.2% and 2.9% per year. Both less efficient WaSCs and WoCs achieved considerable gains in their efficiency, but these were lost due to the lack of adopting best industry's practices and adjustments in their scale of operations. As a result, their productivity declined.

The above analysis reveals several interesting policy implications. First, the methodology employed in this study estimates the productivity change the water industry over time. Moreover, the regulated water companies can identify the sources of productivity improvement or deterioration. It also showed that mergers among water companies might lead to lower costs. Finally, the methodological approach can help the water sector regulator determine if past and current incentive schemes have stimulated productivity improvements among water companies. This information is of great significance in introducing and designing new policies as part of future price reviews. The findings imply that water company productivity may have reacted to the regulator's price limits. Overall, savings in costs and improvements in productivity could benefit customers in several ways such as better service quality, more reliable network, and clean water and high quality of sewage discharged to the environment (Ofwat, 2004, 2006). In addition to this, Ofwat wants to ensure that customers receive the best quality of service at an affordable price while maintaining water companies' financial sustainability. Its price review methodologies reflect these goals (Ofwat, 2009, 2017). However, it should be noted that regulation is not the only factor that influences water company productivity. Other factors may include investments to improve service quality environmental variables, such as water leakage and bursts in mains (Molinos-Senante et al., 2014).

Moreover, since 2005 there was a significant increase in electricity prices, which was higher than the increase in the deflation index used to deflate expenditure (Portela et al., 2011; Molinos-Senante et al., 2014). Other factors that may influence water company costs could be related to climate change. For instance, the English and Welsh water industry experienced dry winters in 2005–05 and floods in 2006–07, which may have affected their costs. Our analysis showed that the percentage of water taken from rivers negatively impacted productivity. Other variables, such as water leakage and population density, could potentially lead to productivity improvement. Thus, managers of regulated water companies should include these variables in their decision-making process.

5. Conclusions

The evaluation of productivity change and its decomposition into several factors, such as TEC, TC, and SEC, is of great relevant to regulated industries when used in tariff setting. Studies in the past have evaluated productivity change using ratios or difference-based productivity indicators. In this study, we applied the LHMPI to evaluate productivity change of several WaSCs and WoCs in England and Wales over the years 2001–2018. Moreover, this indicator allowed us to identify the contribution of inputs and outputs to productivity.

The results indicate that during the study period, the English and Welsh water industry's productivity declined at an annual rate of 1.2%, which was explained by an average increase in inputs of 1.4% per year, which offset a small increase in outputs of 0.2% per year. In particular, average WaSC and WoC's productivity decreased at a rate of 1.3% and 1.0% per year, respectively, entirely attributed to an increase in inputs by 1.5% and 1.4% per year, respectively. A further decomposition of the LHMPI into TEC, TC, and SEC revealed that the industry experienced technical regress at an annual rate of 3.1% on average. Gains in scale and technical efficiency change average 1.7% and 0.1% per year. Less efficient WaSCs and WoCs appeared to have made small improvements in their efficiency relative to the most efficient water companies. Also, it seems that increases in the scale of operations might have lowered total costs. However, these gains were lost due to technical regress. The productivity of water companies seemed to have reacted to the regulator's price reviews. However, it should be noted that regulation is not the only factor influencing water company performance. Other factors may affect water company costs and productivity such as climatic events, quality of service and environmental variables. Our study showed that water taken from rivers negatively influenced productivity, whereas water leakage and population density could lead to productivity improvements.

From a policy perspective, the findings of our study underline the significance of evaluating the productivity change of regulated companies and identifying the sources of change. Water sector managers and regulators can identify the companies that are more or less efficient over time and understand how water companies respond to advancements in technology. It is evident that inputs, i.e., costs, contributed negatively to productivity change, whereas outputs did it positively. Water companies faced new regulatory and environmental requirements that increased their OPEX and CAPEX. Taking into account the regulatory model applied by the English and Welsh water regulator (Ofwat), these higher costs have been transferred to the water tariffs paid by customers. Hence, in the context of water utilities, the regulator should consider the trade-off between quality of service and water tariffs (especially in middle- and low-income countries). Another interesting result from this study with several policy implications is that the percentage of water leakage significantly impacts productivity change. Climate change and water scarcity have been accentuated in many countries generating significant conflicts among water users. In this context, as recognized by the Directive 2000/60/EC (Water Framework Directive), the principle of total cost recovery through tariffs suggests the inclusion of environmental and resources costs. Hence, when the regular considers productivity change values to set water tariffs, the percentage of water leakage of should be integrated into the analysis.

Although the methodology applied in this study and the empirical application conducted revealed several interesting results, it does not come without limitations. As the LHMPI was estimated using the DEA method, the number of inputs and outputs was limited by the number of available units (water companies). In this context, the study did not consider any variables related to the quality of service provided by the water companies, which might affect productivity change. Moreover, an extension of the assessment conducted might involve the inclusion of undesirable outputs, i.e., variables that water companies should minimize, such as the number of complaints, greenhouse gas emissions, and non-revenue water.

Data availability

Some of the data, models, and code that support the findings of this study are available from the corresponding author upon reasonable request.

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and materials

The datasets utilised and analysed during the current study are available from the corresponding author on reasonable request.

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Appendix A. Supplementary data

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