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Development and application of the Hicks-Moorsteen productivity index for the total factor productivity assessment of wastewater treatment plants

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ABSTRACT

The assessment of the productivity change in wastewater treatment plants is essential to improve performance and reduce operational costs. Several indices are available to compute unit productivity, however some assessments are more reliable than others. In the absence of price data, the Malmquist productivity index is the most commonly applied; but it does not maintain total factor productivity properties under variable returns to scale technology. Hence, Malmquist productivity index is not a suitable index to compute total factor productivity change in wastewater treatment plants. The present study served to overcome such limitations by calculating, for the first time, total factor productivity changes in a sample of 204 Spanish wastewater treatment plants using the Hicks-Moorsteen productivity index. It is a multiplicatively-complete index, which can be decomposed as several sub-indices representing technical and efficiency changes. Therefore, this study also investigated the drivers of total factor productivity change in wastewater treatment plants. Results showed a 5.4% total factor productivity decline per year from 2003 to 2008 in the plants analysed. The primary driver in the reduction was efficiency change. Alternatively, technical change improved during the five years of study. The results of this study provide support for policymakers and managers in decision-making processes and contribute to the improvement of technical and economic wastewater treatment plants performance. In addition, it is evidenced that wastewater treatment plants current dependence on external energy sources should be reduced to improve productivity and reduce costs to citizens who pay for wastewater treatment services.

1. Introduction

Implementation of the Millennium Development Goals by the United Nations resulted in significant progress in access to sanitation. In particular, between 1990 and 2012, almost two billion people had improved sanitation accessible (UN, 2014). Moreover, many developed countries have adopted regulations regarding wastewater treatment, such as the EU Directive 91/271/EEC and the US Clean Water Act. Hence, in recent decades, the number of wastewater treatment plants (WWTPs) operating worldwide has increased substantially. The following main challenges are faced by (waste)water authorities and WWTP operators: (i) increasing environmental sustainability in the processes performed at WWTPs; and (ii) minimising the economic costs of operating WWTPs (Molinos-Senante et al., 2014a). In other words, it is essential to improve the productivity in wastewater treatment processes. Productivity is understood as an indicator, which describes the relationship between inputs and outputs, with the outcome of generating outputs over time (Färe et al., 2013). Thus, the assessment of the productivity change involves evaluate how

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the firms are doing over time, i.e., is a dynamic concept. Therefore, similar to other economic pursuits, an essential challenge for WWTPs is to produce more outputs using fewer inputs (Abbot and Cohen, 2010).

Typically, productivity change assessments are based on benchmarking procedures. Therefore, assessments assume strategic importance, because these evaluations allow WWTP operators and (waste)water authorities to deduce whether performance has improved or worsened over time (Epure et al., 2011). The information generated from these assessments is vital to the implementation of measures aimed at reducing WWTP operational costs and/or increasing efficiency in the removal of pollutants from wastewater. Moreover, productivity change assessments enable the identification of strengths and weaknesses in each company and therefore, identification of WWTPs that should be considered references for other sites. Due to its usefulness, evaluation of productivity growth has received heightened interest from regulators and water authorities. Therefore, in recent years, several studies have been conducted to assess the water industry's productivity changes in different countries, such as England and Wales (e.g., Maziotis et al., 2015; Molinos-Senante et al., 2014b; Portela et al., 2011), Portugal (Carvalho et al., 2012), Italy (Guerrini et al., 2013), and Australia (Worthington, 2014), among others. However, under the wastewater treatment framework, the number of studies evaluating productivity change in WWTPs, which have considered the plants as productivity units is much more limited. In fact, to the best of our knowledge, only Hernández-Sancho et al. (2011) evaluated productivity changes in a sample of WWTPs. In doing so, the Malmquist productivity index (MPI) was computed, which is based on a non-parametric method, such as data envelopment analysis (DEA). MPI applies the input or output distance function to evaluate different input–output combinations for productivity comparisons (Caves et al., 1982).

It should be emphasized that several alternative indices are available to compute productivity change in unit types (WWTPs in this case study). Therefore, evaluation of productivity change using a robust and reliable index is essential. Otherwise, results can be biased and policy and managerial conclusions derived from the results might not contribute towards improvements in WWTP performance. Under these conditions, there are two primary approaches to compute unit productivity change. The first approach requires price availability, i.e., input costs and output revenues must be known. The Törnqvist and Fisher indices are widely employed for this approach. However, in this case study, these indices could not be applied, because WWTP outputs are removed pollutants, which have no market value. Section 3 provides a more in depth description of the inputs and outputs used to compute WWTP productivity changes. Hence, the second approach, based on indices that do not require prices should be applied to assess WWTP productivity changes. This latter approach is the MPI and the most commonly used index to examine productivity changes. MPI is preferred due to the following three main factors (Lovell, 2003; O'Donnell, 2011): (i) MPI can be computed without price data; (ii) the index can be decomposed into measures of technical (TCH) and efficiency (ECH) changes; and (iii) DEA linear programs to compute MPI have been incorporated into some software packages.

Despite MPI's popularity, it presents some marked pitfalls. First, Grifell-Tatjé and Lovell (1999) and O'Donnell (2008) provided evidence that MPI was not a correct measure of TFP changes when the technology of the units analysed exhibited variable returns to scale (VRS). An assumption of constant returns to scale (CRS) technology indicated inputs and outputs respectively increased or decreased proportionally. Hence, technical inefficiency under CRS is a product of scale and pure technical inefficiencies (Charnes et al., 1978). Alternatively, VRS technology shows an increase (or decrease) in inputs does not result in a proportional change in outputs. Previous studies (Molinos-Senante et al., 2014a; Sala-Garrido et al., 2011; Tsagarakis, 2013) under the WWTP framework indicated these facilities operated under VRS technology. Hence, computation of TFP changes in WWTPs using MPI involves biased results, because CRS technology is assumed, when in reality WWTPs operate under VRS technology. Second, a choice between an output and an input orientation is required for MPI. In other words, it is necessary to determine whether units should minimise inputs to produce a certain output level, or whether the output generation given a set of inputs should be maximised. Third, some of the distance functions constituting this index may well be undefined, therefore infeasibility problems might occur (Kerstens and Van De Woestyne, 2014). Consequently, the resulting measures obtained by computing MPI do not properly reflect TFP change resulting from scale effects (O'Donnell, 2014).

Bjurek et al. (1998) proposed the Hicks-Moorsteen productivity index (HMPI) to overcome these limitations, which is recognised as the only multiplicatively-complete index computed without price data (O'Donnell, 2012). Some advantages of HMPI over MPI are summarised as follows: (i) HMPI maintains TFP properties under both CRS and VRS technologies; hence, TFP assessment by computing HMPI is more robust and reliable than when calculated by MPI (Grifell-Tatjé and Lovell, 1999); and (ii) under strong input and output disposability, the determinateness axiom is satisfied, and therefore infeasibility problems are avoided (Briec and Kerstens, 2011). HMPI is free from restrictive assumptions regarding the nature of the production technology, the firm's optimising behaviour, market structure, returns to scale, and/or price information. Moreover, HMPI satisfies all other index regulatory conditions, including multiplicative completeness and transitivity tests (O'Donnell, 2012). Consequently, compared with MPI, Hicks-Moorsteen is a more reliable index. Another HMPI characteristic, which makes it superior to other TFP indices is the index can be unambiguously decomposed into the following three productivity change components: (i) TCH (movements in the production frontier); (ii) ECH (unit movements towards or away from the production frontier); and (iii) scale and mix efficiency change (movements around the production frontier to capture scope and scale economies) (Laurenceson and O'Donnell, 2014). These forms of TFP delimitation are very useful in terms of policy. Different policies have different effects on various TFP components and decomposition analysis identifies the policy measures, which should be implemented to improve a firm's TFP (Widodo et al., 2014).

Despite its attractive properties, HMPI has scarcely been examined in applied research. The complete list of currently available empirical applications includes the assessment of TFP changes for the following: (i) manufacturers (Zaim, 2004); (ii) prefectures (Nemoto and Goto, 2005); (iii) financial institutions (Arjomandi et al., 2012, 2014; Arora and Arora, 2012, 2013; Epure et al., 2011; Maredza and Ikhide, 2013; Sharma and Dalip, 2014); (iv) agriculture (Hoang, 2011; Kerstens and Van De Woestyne, 2014; O'Donnell, 2010, 2012); (v) ports (Medal-Bartual et al., 2015); and (vi) airports (See and Li, 2015). It is found no record of HMPI applied to compute changes in TFP for the water industry, in general, and WWTPs, in particular.

Based on this foundation, the main objective of this study was to evaluate TFP changes in a sample of Spanish WWTPs from 2003 to 2008. In doing so, HMPI was computed, because it is a multiplicatively-complete index, which maintains TFP properties under VRS technology. Subsequently, TFP changes were decomposed into various components to provide enhanced understanding of the drivers of TFP change in the WWTPs analysed.

This study contributes to the current body of literature by applying HMPI in WWTP TFP assessment for the first time. Hence, this analysis is a pioneering and novel approach in the framework for evaluating WWTP productivity change, since HMPI, unlike MPI, maintains TFP properties under VRS. It should be emphasised that previous studies assumed WWTPs operate under CRS technology, which is incorrect.

Beyond its academic interests, the methods and findings of this study are very useful for policymakers and WWTP operators. Assessment of changes in WWTP TFP provides essential information to identify conditions and circumstances requiring corrective actions and facilitates the isolation of factors resulting in differences among companies. Consequently, (waste) water authorities can design and implement different measures to reduce operational costs of wastewater treatment, which are paid by citizen property taxes. Moreover, the assessment can identify the most efficient and innovative WWTPs, which can serve as models. Subsequently, the adoption of best practices determined from the most productive WWTPs can enhance corporate profits.

This paper is organised as follows: Section 2 provides the methods employed in this study; a discussion of the sample data is included in Section 3; the primary results are presented in Section 4; and the final Section 5 concludes the study.

2. Methods

HMPI is defined as a ratio of aggregate output-quantity over aggregate input-quantity index (Bjurek et al., 1998). One HMPI advantage over other productivity indices, such as MPI, is that a choice between an input or output orientation is not required; HMPI exhibits a simultaneous input and output orientation, because it combines output and input quantity indices using the Shephard output and input distance functions, respectively (O'Donnell, 2011).

Let us assume that each WWTP uses a vector of m inputs $x = (x_1, x_2, \ldots, x_m)$ to produce a vector of s outputs $y = (y_1, y_2, \ldots, y_s)$. The output and input distance functions are defined as follows (Shephard, 1953):

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

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

where T^t denotes production possibilities set at period-t. $D_t^o(x,y)$ represents the output distance function and measures the inverse of the largest radial expansion of the output vector, which is possible given the input vector. By contrast, $D_t^i(x,y)$ denotes the input distance function and measures the largest radial contraction of the input vector achievable while fixing the output vector (Epure et al., 2011).

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

$$HMPI_{T\ (t)}\left(x^{t+1}, y^{t+1}, x^t, y^t\right) = \left[D^o_{T(t)}\left(x^t, y^t\right) \Big/ D^o_{T(t)}\left(x^t, y^{t+1}\right) \right] \Big/ \times \left[D^i_{T(t)}\left(x^t, y^t\right) \Big/ D^i_{T(t)}\left(x^{t+1}, y^t\right) \right] \quad (3)$$

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

$$HMPI_{T\ (t+1)}\left(x^{t+1}, y^{t+1}, x^t, y^t\right) = \left[D^o_{T(t+1)}\left(x^{t+1}, y^t\right) \times \Big/ D^o_{T(t+1)}\left(x^{t+1}, y^{t+1}\right) \right] \Big/ \times \left[D^i_{T(t+1)}\left(x^t, y^{t+1}\right) \times \Big/ D^i_{T(t+1)}\left(x^{t+1}, y^{t+1}\right) \right] \quad (4)$$

HMPI can be defined as the HMPI geometric mean for base period t and $t + 1$ to avoid subjectivity and consider the selection of period t or $t + 1$ is not relevant:

$$HMPI_{T(t),\ T(t+1)}\left(x^{t+1}, y^{t+1}, x^t, y^t\right) = \left[HMPI_{T(t)}\left(x^{t+1}, y^{t+1}, x^t, y^t\right) \cdot HMPI_{T(t+1)}\left(x^{t+1}, y^{t+1}, x^t, y^t\right) \right]^{1/2} \quad (5)$$

For policy implementation, a notable HMPI advantage is its classification into technical (TCH) and several measures of efficiency (ECH) change. TCH refers to shifts into the efficient production frontier, and therefore, improvements in TCH involve expansion in production possibilities (Färe and Grosskopf, 1996). Molinos-Senante et al. (2014a) reported under the WWTP framework, TCH is primarily associated with implementation of technical innovations in facilities to increase pollutant removal efficiency and/or reduce consumption of resources and consequently, the overall operational costs. Alternatively, ECH is known as a catching-up index, and it measures unit movement (WWTPs) towards or away from the efficient production frontier (Maziotis et al., 2015). Consequently, ECH involves the capacity of WWTPs to be managed consistent with best operational practices.

A better understanding of the drivers of TFP change was obtained by O'Donnell (2008), who classified ECH into a series of sub-indices using two production frontiers as references. The first is the mix-restricted production frontier, which indicates the output or input sets are held fixed. The second is the unrestricted production frontier, with variable input and output sets. Based on these two production frontiers, and following an input-orientation, O'Donnell (2010, 2014) defined the following ECH sub-indices:

Input-oriented technical efficiency (ITE): ITE measures the difference between observed and maximum TFP possible, while maintaining set input, output, and fixed output levels.

Input-oriented scale efficiency (ISE): ISE measures the difference between TFP at a technically efficient point and maximum TFP possible, while maintaining fixed input and output, but allowing variable levels.

Input-oriented mix efficiency (IME): IME measures the difference between TFP at a technically efficient point on the mix-restricted frontier and the maximum TFP possible, while maintaining a fixed output level.

Residual Input-oriented scale efficiency (RISE): RISE measures the difference between TFP at a technically and mix-efficient point and TFP at maximum productivity level.

Residual Mix efficiency (RME): RME measures the difference between TFP on a mix-restricted frontier point and maximum TFP possible with variable input and output sets (and levels).

O'Donnell (2011) demonstrated TFP is the product of TCH and ECH [see Equation (6)]. Furthermore, the proportionate increase (for input orientation) in ECH can be reduced into the three component equations:

$$TFP_{it} = TCH_{it} \cdot ECH_{it} \quad (6)$$

$$ECH_{it} = ITE_{it} \cdot IME_{it} \cdot RISE_{it} \quad (7)$$

$$ECH_{it} = ITE_{it} \cdot ISE_{it} \cdot RME_{it} \quad (8)$$

HMPI and its components can be interpreted as follows: (i) HMPI > 1 shows an improvement in TFP; (ii) HMPI < 1 indicates a worsening in TFP; and (iii) HMPI = 1 represents no change in TFP.

Output and input distance functions, and therefore, HMPI, can be calculated using parametric and non-parametric approaches. Parametric methods rely on a predefined production function assumption; and a stochastic frontier analysis (SFA) is one technique more widely applied. SFA assumes any deviation from theoretical function is attributed, in part, to inefficiency and in part to measurement error. The advantage of the SFA approach is it explains random statistical noise and allows for assessing scale economies (Carvalho and Marques, 2015). However, parametric techniques require strong assumptions regarding the functional frontier form (Molinos-Senante et al., 2015). By contrast, DEA is a common non-parametric method, which uses mathematical programming to estimate the production frontier. DEA applies the productive process inputs and outputs (WWTPs in this case study) to compute the production frontier. Nevertheless, a drawback of DEA is that it assumes that there is no noise, nor atypical observations in the sample (Cooper et al., 2006). In other words, the efficiency scores obtained by applying DEA approach might be influenced by outlying observations (De Witte and Marques, 2010). Both approaches have pros and cons, but DEA does not require any *a priori* function assumptions representing the production frontier, which is DEA's main advantage over SFA. Based on these conditions, O'Donnell (2011) developed a DEA approach to compute and reduce HMPI. Hence, following Arjomandi et al. (2014) and Medal-Bartual et al. (2015), among others, it is adopted the DEA method to compute the input and output distance functions. Accordingly, eight linear programs are solved for each WWTP evaluated; four to estimate input and four to compute output distance functions.

3. Sample description

In this study, we assessed balanced panel productivity growth data in a sample of 204 Spanish WWTPs for the 2003–2008 period. A basic premise of applying the DEA technique is that the units to be evaluated should be as homogeneous as possible. Thus, all WWTPs assessed in this study carry out their wastewater treatment through the following processes: pretreatment; primary treatment; secondary treatment, based on an activated sludge system; secondary sedimentation. Therefore, the two primary pollutants removed during wastewater treatment were organic matter and suspended solids.

Selecting the output and input variables included in facility performance assessments is always a challenging task. Previous studies evaluating water company efficiency and productivity, including sewerage and wastewater treatment services, have chosen 'wastewater volume treated' as the output variable (e.g., Lannier and Porcher, 2014; Molinos-Senante and Sala-Garrido, 2015). However, this study specifically examined WWTPs. Therefore, it is determined that the operational costs of these facilities were affected by pollutant removal efficiencies (Rodriguez-Garcia et al., 2011). Hernández-Sancho et al. (2010) provided evidence that WWTPs were productive units, designed with the primary purpose of removing wastewater pollutants. Wastewater treatment required some inputs for the treatment functions to be completed, which were summarised as WWTP operational costs.

Two main pollutants constituted the outputs obtained from treatment processes, namely: (i) organic matter measured as chemical organic matter (COD); and (ii) suspended solids (SS). Both pollutants were expressed in kilograms per year. As Carvalho and Marques (2014) pointed out, to evaluate TFP change of facilities which remove pollutants it is important considering influent and effluent characteristics. Operation and maintenance costs were selected under input specification. Costs were delimited as follows: (i) energy costs, including fixed and variable parts (power term and energy consumption); (ii) staff costs; (iii) reagents costs; (iv) maintenance costs; (v) waste management costs; and (vi) other costs. Inputs were expressed in euros per year at constant prices. Following previous studies evaluating the efficiency and productivity change of WWTPs (Sala-Garrido et al., 2011, 2012; Molinos-Senante et al., 2014a), capital costs were not considered in the assessment.

Table 1 provides descriptive statistics for the variables used in this study. It indicated that on average, the volume of both pollutants (COD and SS) removed from wastewater increased from 2003 to 2008. This trend was also observed for inputs, i.e., all cost items increased over the time period examined. The rise in energy and staff costs, which exhibited about a 100% increase over the five years assessed was substantial.

4. Results and discussion

Results provided estimates of TFP change in the 204 WWTPs evaluated throughout 2003 to 2008 using HMPI. TFP and its components, i.e., TCH and ECH were calculated using DPIN version 3.0 (O'Donnell, 2015). In addition, the components of ECH, i.e., ITE, IME, RISE, ISE, and RME were also computed. Table 2 summarises the evaluation of productivity growth in WWTPs.

Average HMPI values showed that during the sample period, TFP decreased by 26.8%, i.e., 5.4% per year. This result was consistent with Hernández-Sancho et al. (2011), who also reported a decrease in productivity change for another sample of Spanish WWTPs. Nevertheless, they estimated an annual productivity retardation of 2.8% since they computed MPI productivity change, which does not

Table 1
Descriptive statistics of the inputs and outputs of the wastewater treatment plants.

		2003		2008	
		Average	Standard deviation	Average	Standard deviation
Outputs (Kg/year)	Chemical oxygen demand	246,174	657,267	296,812	1,011,528
	Suspended solids	130,193	368,357	150,402	548,756
Inputs (€/year)	Energy	16,877	35,733	32,200	77,684
	Staff	36,925	53,252	70,931	103,076
	Reagents	4678	19,189	6435	22,985
	Maintenance	8347	15,957	16,614	34,320
	Waste management	9699	38,209	22,734	94,588
	Other	5831	6532	11,916	13,618

Source. Entitat of Sanejament d'Aigues-EPSAR (Regional Government)

Table 2
Total factor productivity (TFP) change and its components[a] for 2003–2008 for the sample of wastewater treatment plants evaluated.

	dTFP	dTCH	dECH	dITE	dIME	dRISE	dISE	dRME
Average	0.732	1.187	0.617	1.068	0.750	0.768	0.705	0.817
Standard deviation	0.885	1.000	0.885	1.043	0.976	0.870	1.040	0.816

[a] TCH is technical change; ECH is efficiency change; ITE is input-oriented technical efficiency; IME is input oriented mix efficiency; RISE is residual input-oriented scale efficiency; ISE is input-oriented scale efficiency; RME is residual mix efficiency.

measure TFP, in contrast to HMPI. Therefore, the findings from this study were more reliable and accurate. A comparison of HMPI and MPI values at the WWTP level are provided in the Appendix. Results showed in 162 of 204 WWTPs (80%), HMPI determined larger TFP change values than MPI, i.e., overall MPI underestimated productivity change. Consequently, the use of MPI instead of HMPI as a TFP measure would penalize most WWTPs, since results showed a greater TFP change under HMPI than values reported by MPI.

Evidence indicated the drivers of TFP change, TCH and ECH, followed opposite trends (Table 2). TCH increased by 18.7% (i.e., 3.7% per year). Thus, from 2003 to 2008 a positive shift in the efficient production frontier was observed. This finding showed a significant capital investment was made in technical updates to WWTPs during this five year period. Alternatively, ECH estimates revealed from 2003 to 2008, on average, the WWTPs evaluated experienced a 38.4% (i.e., 7.7% per year) efficiency decline. This result suggested during the period assessed, WWTP management and consequently efficiency and productivity was poor and the analysed sites lost the capacity to be managed consistent with best operational practices. Hence, to improve efficiency, companies operating WWTPs must train professionals in the new technologies implemented. As more complex processes and systems are integrated in WWTPs, more expert knowledge is necessary in WWTP managers. It is essential to fulfil these criteria in management to improve the catching-up index, i.e., encourage WWTPs to reach the efficient production frontier.

One advantage of HMPI is that ECH may also be classified into component parts, including ITE, IME, and RISE. Thus, a WWTP is (relatively) efficient if its ITE score is one, because this means a WWTP is located on the efficient production frontier. If ITE is less than one, the WWTP is located under the frontier, and is therefore inefficient. A WWTP with an ITE equal to one, but displays an IME and RISE less than one, remains on the efficient production frontier, but is relatively unproductive. Results showed ITE exhibited positive behaviour in the WWTPs analysed because it increased by 6.7% (i.e., 1.3% per year), while IME and RISE decreased by 25.2% and 24.0%, respectively (Table 2). Therefore, IME was the foremost component of decline in the observed ECH level using the HMPI approach. The fact that IME decreased from 2003 to 2008 indicated the WWTPs operating near the unrestricted frontier were not operating at the most productive scale size.

WWTP oversizing primarily results from seasonality in wastewater volume treated and pollutant load. Twenty-five percent of the WWTPs evaluated are located in tourist areas and are therefore operated at full capacity during popular tourist months, while the WWTPs experience underuse problems during the remaining year. Productivity improvement of these WWTPs is necessary, which can be achieved by adoption of new management with technical advancements; summarized as WWTP modernisation. It involves adapting facility operating equipment to the flow of treated wastewater during each period (Sala-Garrido et al., 2012). By adopting these measures, energy consumption can be minimized. Another solution to seasonality challenges is construction of homogenisation tanks, which allows influent adjustment to the various elements that compose a WWTP. Hence, a better effluent quality is ensured, which also contributes to improve WWTP productivity, since pollutants removed from wastewater are an output of the productive process. Undersized WWTPs have a treatment capacity too small for efficient operation. Molinos-Senante et al. (2014a) reported larger WWTPs run more efficiently than smaller plants. Based on these results, (waste)water regulators should promote WWTP horizontal integration to achieve the advantages of economies of scale. Although these changes are difficult and expensive to implement, this information is fundamental to plan new WWTPs and provide service to small agglomerations.

From a managerial and policy perspective, it is essential to identify explanatory factors which inference with TFP change (Carvalho and Marques, 2011; Marques et al., 2014). In this study, the negative trend observed in the catching-up index was the main driver in decreased productivity experienced by the WWTPs. Important to policymakers and WWTP management, this finding showed technical innovation was implemented in the WWTPs evaluated, i.e., increased TCH during 2003–2008. However, on average, WWTPs notably diverged from efficient frontier of production, resulting in a TFP decline. In other words, WWTPs did not use the best operational practices to increase efficiency, thereby contributing to increased TFP. Hence, WWTPs can improve TFP by adopting better operational practices. Previous studies assessed productivity in water companies (Marques, 2008; Molinos-Senante et al., 2014b; Portela et al., 2011) and reported a primary cause that might explain TFP decline over time. Results indicated energy input costs increased notable from 2003 to 2008, which did not involve the same increase in energy consumption expressed in kWh/m^3 of treated water. The average energy consumption in the WWTPs analysed was 29.6 kWh/m^3 in 2003 and consumption increased to 33.8 kWh/m^3 in 2008, representing a 14.2% increase. However, marginal energy costs in Spain, where the WWTPs evaluated are located were subject to a different trend. In particular, from 2003 to 2008 in the EU-27, energy costs for industrial use increased, on average, by 35% (Eurostat, 2015). Hence, dissociation between energy consumption and energy costs occurred. Among other factors, energy prices increased more than RPI (the index used to deflate operational costs), which contributed to an explanation for decreased TFP between 2003 and 2008.

Results showed a reduction in energy consumption was a key factor to improve WWTP productivity. Therefore to enhance TFP, the primary recommendation to WWTP managers is to reduce dependence on external energy sources. Several compatible alternatives to achieve this objective are available. First, complex technologies, including pond systems and wetlands have smaller carbon footprints than conventional, such as activated sludge. In small WWTPs, where land availability is typically not a restriction, a plausible option to reduce energy consumption and consequently energy costs might be a change in secondary treatment. Second, interest in applying anaerobic digestion with co-digestion of other organic waste in sewage sludge treatment is on the rise. Koch et al. (2015) demonstrated the process increased CH_4 production, which can subsequently be applied to bioenergy production. Therefore, implementation of anaerobic digestion in WWTPs can generate free energy from organic waste treatment processes. Moreover, Meerburg et al. (2015) showed net energy-neutral or energy-

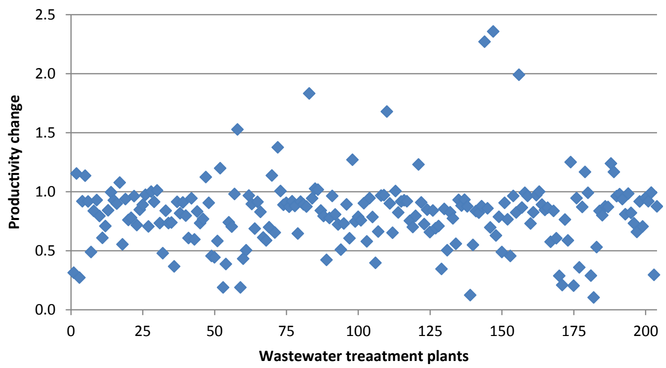

Fig. 1. Productivity change of wastewater treatment plants from 2003 to 2008.

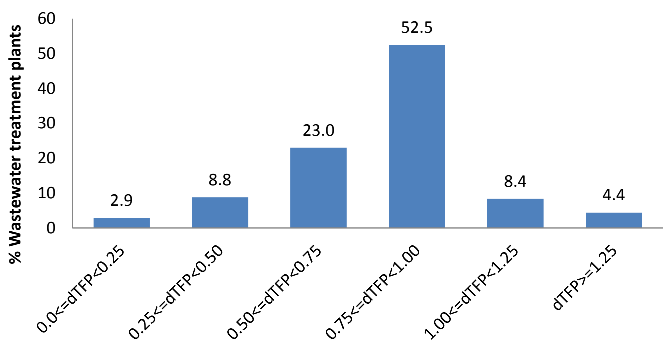

Fig. 2. Distribution of wastewater treatment plants according its total factor productivity change (dTFP).

positive wastewater treatment is feasible. These reports indicated several innovative technologies, such as microbial fuel cell or nitritation-anammox have been developed to achieve energy sustainability (Dai et al., 2015). Although implementation of these processes remains a challenge, water authorities should work to promote their practical application. Studies show these alternatives will contribute to improve WWTP sustainability and productivity.

Fig. 1 shows TFP change at the individual level. WWTP operators and water authorities can analyse management needs to improve TFP in each WWTP. This detailed information is essential to support the decision-making process. HMPI computation at the facility level showed the maximum increase in TFP was associated with WWTP 147. HMPI increased by 135% from 2003 to 2008 at this plant, which identified this site as exhibiting the best performance over the study period. It is recommended to WWTP operators analyse the managerial practices and technical innovations implemented at this WWTP, which so notably improved its TFP. The ECH of this facility remained almost constant, indicating the managerial capacity of the WWTP managers remained stable from 2003 to 2008. In addition, this WWTP experienced a significant improvement in the other TFP driver, i.e., TCH. This upturn was primarily due to the implementation of anaerobic digestion to treat sewage sludge. This observation confirmed the value of reducing energy consumption to improve TFP in WWTPs. A TFP decrease by 89.5% was determined in WWTP 182, resulting in the lowest performance level of all WWTPs analysed. Therefore, it is recommended the managerial practices at WWTP 182 should be avoided. There was no unique practice at the plant to explain the decline in TFP. Nevertheless, additional analyses during the study period provided evidence that the flow treated by this WWTP increased notable (around 40%), while the facility did not impose any technological improvements. This resulted in the loss of pollutant removal capacity and increased operational costs. The consequences of this negative trend were TFP reduction. This example clearly demonstrated WWTP processes must be updated consistent with the wastewater attributes (volume and pollutant load).

WWTP distribution congruent with productivity change is depicted in Fig. 2. It shows only 26 of 204 (12.8%) WWTPs improved productivity, while the remaining 87.2% showed a loss in TFP. It is notable that approximately one-half of the WWTPs evaluated suffered declines in productivity, between 0% and 25%. In contrast, 4.4% of the facilities improved their TFP by more than 25%. Table 3 shows the WWTP sample division into two groups, based on a decrease or increase in the TFP for 2003–2008. The cumulative productivity decline for the first group was 25.3% (around 5% per year). Both TFP drivers, i.e., ECH and TCH contributed to HMPI <1. However, TFP average growth was 31.7% (around 6% per year) in the group of WWTPs characterised by HMPI > 1. This TFP increase was explained exclusively by a positive shift in the efficient production frontier, i.e., TCH. In contrast, ECH contributed negatively to the TFP change, and showed the same trend in the entire WWTPs evaluated. Results showed HMPI decomposition into ECH and TCH were essential for management support in decision-making.

5. Conclusions

WWTP performance can be improved by implementing one essential element, an increase in productivity. Productivity under WWTP criteria is defined as the removal of more pollutants from wastewater with reduced operational costs. Several indices can be applied to compute productivity change. However, some are more reliable than others; therefore, the use of an inconsistent index to assess TFP change in WWTPs can likely result in biased results, in addition to poorly conceived policy and managerial conclusions. Therefore, HMPI is a multiplicatively-complete index that can be computed without price data. Unlike conventional MPI, HMPI maintains TFP properties under VRS technology, which was utilised in the WWTPs evaluated in this study.

This is the first study to calculate TFP change in a WWTP sample over time. Hence, this analysis is a pioneering and novel approach in the framework for evaluating WWTP productivity change, since HMPI, unlike MPI, maintains TFP properties under VRS. It should be emphasised that previous studies assumed WWTPs operate under CRS technology, which is incorrect.

The methods and results of this study are of considerable value to (waste)water authorities and WWTP operators, because the main drivers of TFP change, i.e., TCH and ECH were also identified. Moreover, the latter components were decomposed into several factors, i.e., ITE, IME, RISE, ISE, and RME. This information is

Table 3
Total factor productivity (TFP) and its components[a] by groups for 2003–2008 for the wastewater treatment plants evaluated.

	dTFP	dTCH	dECH	dITE	dIME	dRISE	dISE	dRME
Hicks-Moorsteen productivity index <1	0.746	0.986	0.756	1.032	0.807	0.907	0.834	0.878
Hicks-Moorsteen productivity index >1	1.317	1.418	0.929	1.109	0.920	0.911	0.879	0.953

[a] TCH is technical change; ECH is efficiency change; ITE is input-oriented technical efficiency; IME is input oriented mix efficiency; RISE is residual input-oriented scale efficiency; ISE is input-oriented scale efficiency; RME is residual mix efficiency.

essential for policymakers and managers in development and support of decision-making processes; and ultimately improves WWTP overall performance.

The main results of this study can be summarised as follows: (i) on average, TFP decreased over WWTPs and years analysed, primarily due to increased energy and staff costs; (ii) ECH was largely responsible for the decline in TFP, whilst TCH exhibited a positive trend; and (iii) TFP increased in 12.8% of the WWTPs assessed, indicating overall the facilities require substantial improvement in performance.

Important managerial and policy implications can be drawn from this study. First, WWTPs can improve TFP by implementing enhanced operational practices, which would move facilities closer to the efficient production frontier. Second, during the study time period, several technical innovations were implemented in WWTPs, which involved a positive shift toward the efficient production frontier. Accordingly, (waste)water authorities should provide incentives to WWTP companies to implement better operational practices to improve TFP in WWTPs. These practices have already shown positive effects, not only for WWTP operators, but also for the citizens who pay for wastewater treatment services.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jclepro.2015.10.114.

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