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RESEARCH ARTICLE

# Evaluating trends in the performance of Chilean water companies: impact of quality of service and environmental variables

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**Abstract**
In monopoly services that provide drinking water, it is of paramount importance to evaluate the total factor productivity (TFP) change of water companies. Most of the previous studies have computed the Malmquist productivity index (MPI) by applying non-parametric methods. By contrast, following a pioneering approach, in this study, we estimated the MPI using a parametric method that allows us to decompose TFP change into a larger number of drivers, including exogenous and quality of service variables. An empirical application for the Chilean water industry over 2007–2015 was conducted. We found that productivity change estimates were variable across years, differentiating a first period (2007/11) in which productivity declined and a second period (2011/15) in which TFP notably improved. In both periods, scale efficiency change and input mixed effect were the main drivers of productivity change, illustrating the importance of operation scale in water companies' performance. The decomposition of the TFP change in a large number of drivers is essential to propose incentives and measures to promote productivity across time.

**Keywords** Total factor productivity · Environmental variables · Malmquist productivity index · Water companies · Chile

## Introduction

Access to water and sanitation have been recognized by the United Nations (UN) as human rights, and the Sustainable Development Goals include achieving universal and equitable access to safe water and sanitation for all by 2030 as goal 6 (UN 2015). Although water and sewerage services are essential for citizens, they are provided by water companies through monopoly regimes. Thus, benchmarking the performance of water companies carries paramount importance to protect customers' interest and promote efficiency and innovation of water companies by water regulators (Zope et al. 2019; Marques et al. 2014). In recent years, performance assessment in the water industry has attracted notable attention among researchers (Cetrulo et al. 2019; See 2015). In the framework of water utility benchmarking, efficiency and productivity are different concepts. Productivity involves assessing the performance change over time and, therefore, integrates a temporal component into efficiency assessment (Gandhi and Sharma 2018).

From a methodological point of view, several indexes have been developed and applied to compute the total factor productivity (TFP) change of water companies, such as the Malmquist productivity index (MPI) (e.g., Portela et al. 2011; De Witte and Marques 2012; Ali and Klein 2014; Nyathikala and Kulshrestha 2017); Luenberger productivity indicator (Molinos-Senante and Sala-Garrido 2015; Sala-Garrido et al. 2018); Malmquist-Luenberger productivity indicator (e.g., Maziotis et al. 2017; Song et al. 2018; Ananda 2018); and Färe-Primont productivity index (Molinos-Senante et al. 2017a, b). Nevertheless, a literature review revealed that after the influential work of Färe et al. (1992), the majority of empirical applications evaluating the productivity

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change of water companies have computed the MPI using the data envelopment analysis (DEA) technique, which is a non-parametric method. The main advantage of this approach is the capacity of modeling production technology without imposing a particular functional form (Mavi and Mavi 2019). However, when MPI is estimated using non-parametric methods, it is not a correct measure for TFP change when variable returns to scale is assumed (Grifell-Tatjé and Lovell 1997). To overcome this limitation, other studies (e.g., Balk 2001; Fuentes et al. 2001; Yu-Ying Lin et al. 2013) have used parametric techniques to estimate the MPI. The main advantages of this approach can be summarized as follows: (i) it does not require the estimation of constant returns to scale production technology (Mirza et al. 2017); (ii) it allows consideration of measurement errors and random noise; (iii) it permits formal statistical hypothesis testing (Pantzios et al. 2011); and (iv) it allows the integration of exogenous and quality of service variables, which can impact on input requirements (Walker et al. 2019).

Improvements in TFP involve using lower inputs and generating higher outputs over time from the application of technology and better utilization of resources (Saal et al. 2007). In this context, for developing policies and measures aimed to improve the performance of water companies, it is essential to identify the drivers of performance change (Guan et al. 2018). Previous studies on this topic (e.g. Saal et al. 2007; Portela et al. 2011; Molinos-Senante et al. 2018; Molinos-Senante and Maziotis 2019a) have decomposed TFP change into three components or drivers: (i) technical change (TC); (ii) technical efficiency change (TEC); and (iii) scale efficiency change (SEC). However, Balk (2001) revealed that there is no unique way of decomposing TFP change. In a pioneering work, Pantzios et al. (2011) extended the framework of Fuentes et al. (2001) and, based on parametric techniques, provided an alternative decomposition of the MPI, which not only considers TC, TEC, and SEC as drivers of TFP change, but also the input mix effect (IME). Also, the TC was decomposed into three sub-drivers: (i) technical change index; (ii) output bias index; and (iii) input bias index. Such a detailed decomposition of the TFP change of firms (water companies in this study) is of great interest for water regulators and managers since it allows for identifying the sources of productivity change and can inform the development of water industry regulatory framework. Despite these positive features, in the framework of water and sewerage companies, to our knowledge, there are no previous studies parametrically decomposing the MPI based on the Pantzios et al. (2011) approach.

The prime objective of this study is to assess the TFP change and its drivers for a sample of water companies. In doing so, the methodological approach proposed by Pantzios et al. (2011) was used since it allows decomposing TFP estimates into a larger number of drivers than non-parametric MPI estimations. This decomposition provides a better understanding of the relative importance of various drivers (TEC, TC, SEC, IME) over the study period. Moreover, the parametric estimation of the MPI, which is a novel issue in the framework of water utilities, allows us to integrate exogenous and quality of service variables into TFP change estimations. To our knowledge, there are no prior studies decomposing TFP change in such a large number of drivers. The empirical application focused on a sample of 22 Chilean water and sewerage companies over 2007–2015. The Chilean water industry is a paradigmatic case in Latin America since, after its privatization, it has achieved almost universal coverage in both drinking water and wastewater treatment services. The Chilean water and sewerage industry were privatized from 1998 to 2004, leading to the creation of two types of private water companies: full private water companies (FPWCs) and concessionary water companies (CWCs). In the case of FPWCs, ownership including infrastructure was privatized for an indefinite period of time. By contrast, for CWCs, water and sewerage services were privatized for 30 years. Thus, our study also provides insights into the ownership of water companies and productivity change over time.

## Methodology

### Decomposition of the Malmquist productivity index

The Malmquist productivity index, $M_{t,\,t+1}$, between time $t$ and $t+1$ is decomposed into several components based on Balk (2001) and Pantzios et al. (2011) approach following an input orientation. Assuming that $x$ and $y$ are inputs and outputs, respectively; the Malmquist productivity index is defined as follows:

$$\begin{aligned} M_{t,t+1}\left(x_t, y_t, x_{t+1}, y_{t+1}\right) = {} & \mathrm{TC}_{t,t+1}\left(x_{t+1}, y_{t+1}\right) \\ & \times \mathrm{TEC}_t\left(x_t, y_t, x_{t+1}, y_{t+1}\right) \\ & \times \mathrm{SEC}_t\left(x_t, y_t, y_{t+1}\right) \\ & \times \quad \mathrm{IME}_t\left(x_t, x_{t+1}, y_{t+1}\right) \end{aligned} \tag{1}$$

The elements of the input-oriented MPI in Eq. (1) are denoted as follows:

$$\mathrm{TC}_{t,t+1} = \frac{D_{It+1}\left(, x_{t+1}, y_{t+1}\right)}{D_{It}\left(x_{t+1}, y_{t+1}\right)} \tag{2a}$$

$$\mathrm{TEC}_t = \frac{D_{It}\left(x_t, y_t\right)}{D_{It+1}\left(, x_{t+1}, y_{t+1}\right)} \tag{2b}$$

$$\mathrm{SEC}_t = \frac{ISEFCH_t\left(x_t, , y_{t+1}\right)}{ISEFCH_t\left(x_t, y_t\right)} \tag{2c}$$

$$\mathrm{IME}_t = \frac{ISEFCH_t(x_{t+1},,y_{t+1})}{ISEFCH_t(x_t,y_{t+1})} \tag{2d}$$

where $D_{It}$ and $D_{It+1}$ are the input distance function at time $t$ and $t+1$, respectively. According to previous studies (e.g., Molinos-Senante et al. 2019; Molinos-Senante and Maziotis 2019a, b), an input orientation was chosen since the objective of the water companies, in terms of productivity, is to minimize their operational and maintenance costs satisfying the demand of drinking water by customers. ISEFCH$_t$ in Eq. (2c) is defined as the input-oriented scale efficiency change which measures the productivity of an actual input and output vector regarding the most productive scale (Pantzios et al. 2011). TC is defined as technical change and captures the shift in technology between two periods evaluated at two different observed output and input vectors. If TC is greater than one, then, technological progress occurs. Following the Fare et al. (1997) and Pantzios et al. (2011) approaches, technical change in Eq. (2a) can be further decomposed as follows:

$$\mathrm{TC}(x_{t+1},y_{t+1}) = \mathrm{TCM}(x_t,y_t)\times \mathrm{OBI}(y_t,x_{t+1},y_{t+1}) \times \mathrm{IBI}(x_t,x_{t+1},y_{t+1}) \tag{3}$$

The term TCM is defined as a technical change magnitude index and measures the movement in the frontier between period $t$ and $t+1$ measured at the period $t$ observation (i.e., the rate of TC locally). OBI is the output bias index and includes the input vector from period $t+1$ and the output vectors from periods $t$ and $t+1$. IBI is the input bias index and includes the input vectors from periods $t$ and $t+1$ and the output vector from period $t$. The output and input bias indices compare the scale of TC along a ray employing inputs and outputs of time $t+1$ and the scale of TC along a ray employing inputs and outputs of time $t$ (Pantzios et al. 2011). The output (input) bias index equals one and does not contribute to productivity when implicit Hicks output (input)-neutral technical change and constant returns to scale prevail (Pantzios et al. 2011; Jan et al. 2012; Shen and Lin 2017).

For the other terms of Eq. (1), TEC measures changes in 1technical efficiency from one period to the next. If TEC is greater than one, then, technical efficiency improves. The other two elements, SEC and IME, are calculated based on the input-oriented scale efficiency change component (ISEFCH). Thus, SEC shows the impact of scale efficiency to productivity growth. If SEC is greater than one, then, the output vector at period $t+1$ is closer to the point of technical optimal scale than the output vector of period $t$ does; thus, scale efficiency improves (Pantzios et al. 2011; Shen and Lin 2017). Moreover, IME captures the input mix effect and shows the effect of changes in the mix of inputs on productivity growth. This estimates how the distance of a frontier-point to the frontier of the technology changes when there is a change in the mix of inputs (Pantzios et al. 2011; Singbo and Larue 2016). If IME is greater than one, then, there is a positive contribution of the input mix effect to productivity growth. Thus, the overall scale effect on productivity change is given by the product of SEC and IME (i.e., the combined effect of scale efficiency and input mix) (Pantzios et al. 2011; Yu et al. 2014).

## Parametric estimation

The estimation of the MPI in Eq. (1) is done using parametric techniques that require a pre-defined functional form of the distance function for estimation. Following past practice (see Coelli et al. 2003; Saal et al. 2007; Molinos-Senante et al. 2018, 2019), we define the following translog input distance function for $N\,(i:1,\ldots,N)$ water companies observed in $T\,(t:1,\ldots,T)$ time periods and $M\,(m:1,\ldots,M)$ outputs and $K\,(k:1,\ldots,K)$ inputs:

$$\begin{aligned}\ln D_I(X_{it},Y_{it},t) = {} & \alpha_i + \sum_{k=1}^{K}\rho_k \ln x_{kit} + \frac{1}{2} \\ & \times \sum_{k=1}^{K}\sum_{n=1}^{K}\delta_{kn} ln x_{kit}\ln x_{nit} + \sum_{m=1}^{M}\mu_k \ln y_{mit} \\ & + \frac{1}{2}\sum_{m=1}^{M}\sum_{l=1}^{L}\beta_{ml} ln y_{mit}\ln y_{lit} \\ & + \sum_{k=1}^{K}\sum_{m=1}^{M}\theta_{km}\ln x_{kit} ln y_{mit} \\ & + \sum_{m=1}^{M}\lambda_m \ln y_{mit} t + \sum_{k=1}^{K}\tau_k \ln x_{kit} t + \omega_1 t \\ & + \frac{1}{2}\omega_2 t^2 + \varepsilon_{it}\end{aligned} \tag{4}$$

The properties of the distance function are fulfilled in Eq.(4). Let $\ln D_I = u_{it}$ then $TE_{it} = e^{-u_{it}}$ which varies between 0 and 1 with a value of 1 meaning that the company is efficient; and $u_{it}$ is an inefficiency index (Molinos-Senante et al. 2017a, b).

We write an estimable distance function specification of Eq. (4) by using the assumption of homogeneity of degree 1 in inputs:

$$\sum_{k=1}^{K}\rho_k + \sum_{k=1}^{K}\sum_{n=1}^{K}\delta_{kn} ln x_{nit} + \sum_{k=1}^{K}\sum_{m=1}^{M}\theta_{km} ln y_{mit} + \sum_{k=1}^{K}\tau_k \mathrm{t} = 1$$

It will be satisfied if $\sum_{k=1}^{K}\rho_k = 1$ and $\sum_{k=1}^{K}\delta_{kn} = \sum_{k=1}^{K}\theta_{km} = \sum_{k=1}^{K}\tau_k = 0$.

By including these restrictions in Eq. (4), then, we can estimate the following input distance function:

$$
\begin{aligned}
&-\ln x_{Kit} = \\
&\alpha_i + \sum_{k=1}^{K-1} \rho_k \ln \tilde{x}_{kit} + \frac{1}{2}\sum_{k=1}^{K-1}\sum_{n=1}^{K-1} \delta_{kn} \ln \tilde{x}_{kit} \ln \tilde{x}_{nit} + \sum_{m=1}^{M-1} \mu_m \ln y_{mit} + \\
&\frac{1}{2}\sum_{m=1}^{M-1}\sum_{l=1}^{M-1} \beta_{ml} \ln y_{mit} \ln y_{lit} + \sum_{k=1}^{K-1}\sum_{m=1}^{M-1} \theta_{km} \ln \tilde{x}_{kit} \ln y_{mit} + \sum_{k=1}^{K-1} \tau_k \ln \tilde{x}_{kit} t + \\
&\sum_{m=1}^{M} \lambda_m \ln y_{mit}\, t + \omega_1 t + \frac{1}{2}\omega_2 t^2 + \sum_{p=1}^{P} \chi_p \mathfrak{z}_{pit} + v_{it} - u_{it}
\end{aligned} \tag{5}
$$

where $\tilde{x}_{mit} = \frac{x_{mit}}{x_{Mit}}$ and $\varepsilon_{it} = v_{it} - \ln d_{it} = v_{it} - u_{it}$. The error term in Eq. (5) consists of two elements, the random error $v_{it}$, which is assumed to be independently and identically distributed and the inefficiency error term $u_{it}$ which is drawn from a half-normal distribution.

Following past practice (Saal et al. 2007; Molinos-Senante et al. 2018, 2019), we included $\chi$ exogenous variables in our model which are represented by the term $\sum_{p=1}^{P} \chi_p \mathfrak{z}_{pit}$. Intercept parameter $\alpha_i$ accounts for heterogeneity of the analyzed companies. We use the true fixed effect method suggested by Greene (2005) as it controls for other factors impacting inputs and inefficiency that have not been specifically controlled in the model (Saal et al. 2007; Molinos-Senante et al. 2018; Molinos-Senante and Maziotis 2018a, b). Previous studies (Balk 2001; Fuentes et al. 2001; Pantzios et al. 2011) noted that the components of the MPI in Eq. (1) can be calculated based on the estimated parameters of the translog input distance function and the observed input and output vectors. Thus, the technical change magnitude index, the output bias index, and input bias index in Eq. (3) can be calculated as follows:

$$
\mathrm{TCM}(x_t, y_t) = exp\left[\omega_1 + \omega_2\left(t + \frac{1}{2}\right) + \sum_{m=1}^{M} \lambda_m \ln y_{mit} + \sum_{k=1}^{K-1} \tau_k \ln x_{kit}\right] \tag{6}
$$

$$
\mathrm{OBI}(y_t, x_{t+1}, y_{t+1}) = exp\left[\sum_{m=1}^{M} \lambda_m\left(\ln y_{mit+1} - \ln y_{mit}\right)\right] \tag{7}
$$

$$
\mathrm{IBI}(x_t, y_t, x_{t+1}) = exp\left[\sum_{k=1}^{K-1} \tau_k\left(\ln x_{kit+1} - \ln x_{kit}\right)\right] \tag{8}
$$

Hence, the TC component in Eq. (2a) of the MPI in Eq. (1) can be derived as the product of Eqs. (6)–(8).

Moreover, the TEC in Eq. (1) is calculated as follows:

$$
\mathrm{TEC} = exp\left[\ln D_t(x_t, y_t) - \ln D_{t+1}(x_{t+1}, y_{t+1})\right] \tag{9}
$$

The remaining two elements of the MPI, SEC and IME, are calculated in terms of the input-oriented scale efficiency measure (ISEFCH). For the translog input distance function, the SEC term can be estimated as follows:

$$
\mathrm{ISEFCH}(\bar{x}, \bar{y}) = exp\left[\frac{1}{2\beta}\left(\frac{1 - \varepsilon^t(\bar{x}, \bar{y})}{\epsilon^t(\bar{x}, \bar{y})}\right)^2\right] \tag{10}
$$

where

$$
\beta = \sum_{m=1}^{M-1}\sum_{l=1}^{M-1} \beta_{ml} \tag{11}
$$

$$
\begin{aligned}
\epsilon^t(\bar{x}, \bar{y}) &= -\left(\sum_{m=1}^{M-1} \frac{\vartheta \ln d_I(\bar{x}, \bar{y})}{\vartheta \ln y_m}\right)^{-1} \\
&= \left(\sum_{m=1}^{M-1}\left[\mu_m + \sum_{k=1}^{K-1} \theta_k \ln \bar{x}_k + \sum_{l=1}^{M-1} \beta_l \ln \bar{y}_l + \lambda_k t\right]\right)^{-1}
\end{aligned} \tag{12}
$$

Based on Eqs. (2c) and (12), the SEC component and the input mix effect can be calculated as follows:

$$
\mathrm{SEC}(x_t, y_t, y_{t+1}) = \exp\left\{\frac{1}{2\beta}\left[\left(\frac{1}{\varepsilon^t(x^t, y^{t+1})} - 1\right)^2 - \left(\frac{1}{\varepsilon^t(x^t, y^t)} - 1\right)^2\right]\right\} \tag{13}
$$

$$
\mathrm{IME}(x_t, x_{t+1}, y_{t+1}) = \exp\left\{\frac{1}{2\beta}\left[\left(\frac{1}{\varepsilon^t(x^{t+1}, y^{t+1})} - 1\right)^2 - \left(\frac{1}{\varepsilon^t(x^t, y^{t+1})} - 1\right)^2\right]\right\} \tag{14}
$$

## Sample and data description

The empirical application carried out in this study focuses on 22 private water companies in Chile over the period 2007–2015. These companies provide water and sewerage services to more 85% of the Chilean urban population. Thus, results are representative of the Chilean water and sewerage industry. The same number of FPWCs and CWCs (i.e., 11 of each type) were evaluated over the period 2007–2015. The regulator, the "Superintendencia de ServiciosSanitarios" (SISS), was set up, whose duties are to regulate the industry and set tariffs based on the definition of a hypothetical efficient firm (Sala-Garrido et al. 2018). The data used in this study come from the management reports of the water and wastewater services published annually by SISS.

The selection of inputs and outputs to estimate the TFP and its drivers in the Chilean water and sewerage industry was based on previous studies from Chile and other countries (Berg and Marques 2011; See 2015; Romano et al. 2016; Molinos-Senante and Maziotis 2018a, b). Therefore, the outputs used in this study reflect both the water and sewerage services and they are (i) drinking water delivered expressed in cubic meters per year and (ii) customers with access to wastewater treatment (Molinos-Senante et al. 2018, 2019; Sala-Garrido et al. 2018). Three inputs are considered (i) length mains defined as the sum of the water and sewer networks (in km), which was used as a proxy for capital costs (Ferro and Mercadier 2016); (ii) operation expenditure (opex) (Chilean pesos/year), defined as the total operating costs of the water and sewerage companies, deflated by the consumer price index taken from national statistics; and (iii) the number of employees, which represents the labor input. The number of employees is used as the normalized variable in the distance function. We also included a set of exogenous and quality of service variables that can influence the productivity change of the Chilean water and sewerage companies: (i) customer density, defined as the number of customers per length pipe (customers/km); (ii) non-revenue water, defined as the percentage of water that was produced and not charged due to real and apparent losses (Neamtu 2011); (iii) drinking water quality; and (iv) wastewater treatment quality. The last two variables are measured by the water regulator (SISS) as quality synthetic indices between 0 and 1, with a value of 1 indicating that the water company met all legal requirements regarding the quality of drinking water and wastewater treated (e.g., concentrations of pollutants) and sampling. Table 1 shows the descriptive statistics of the variables used in this study.

## Empirical results and discussion

### Parameter estimation of the translog input distance function

The estimated parameters of the translog input distance function are reported in Table 2. The monotonicity and curvature conditions are satisfied by all observations in our sample. We normalized all variables around their means so that we can interpret the first-order coefficients of the outputs and inputs as output and input elasticities, respectively, for the average firm (Molinos-Senante et al. 2018). The estimated firm-specific effects in the input distance function, which are not reported for spacious reasons, range from 3.629 to 3.952. The range of 0.322 means that there is still some unobserved heterogeneity among the companies even if we control for several exogenous factors (Molinos-Senante and Maziotis 2018b).

As expected, the elasticities of the water delivered and the customers receiving wastewater treatment are negative and statistically significant from zero. This suggests that the input distance function is non-increasing in outputs. The estimated elasticities of the network length, opex, and labor are at the level of 0.614, 0.299, and 0.087, respectively. This implies that the industry is capital-intensive which is consistent with previous studies by Ferro and Mercadier (2016) and Molinos-Senante et al. (2018). Furthermore, the interaction term between the two outputs is positive which imply that water delivered and wastewater treatment services may not be complementary. The estimated second-order coefficients of water delivered and customers receiving wastewater treatment are negative and statistically significant from zero which suggests that the elasticities of these outputs increase at an increasing rate (Molinos-Senante et al. 2018).

Network length and opex elasticities over time are negative and statistically significant, which means that improving the network and increasing the operational costs over time

**Table 1** Summary statistics of the variables. Source: own elaboration from SISS data

| Variables | Unit | Mean | Standard deviation | Minimum | Maximum |
|---|---|---|---|---|---|
| Water distributed | $10^3$ $m^3$/year | 28,059 | 33,427 | 635 | 145,020 |
| Customers receiving wastewater treatment | Nr | 415,587 | 529,794 | 3563 | 2,421,954 |
| Network length | Km | 2207 | 2782 | 36 | 12,477 |
| Labor | Nr | 441 | 516 | 22 | 2.081,00 |
| Opex* | $10^6$ CLP/year | 18,491,629 | 21,856,189 | 541,395 | 105,976,893 |
| Density | km/customer | 90.663 | 178.873 | 18.430 | 10,467 |
| Non-revenue water | % | 30.250 | 13.246 | 0.010 | 52.100 |
| Drinking water quality | Index | 0.959 | 0.067 | 0.650 | 1.000 |
| Wastewater treatment quality | Index | 0.972 | 0.052 | 0.670 | 1.000 |
| Total number of observations is 198 | | | | | |

*Note that operational costs were adjusted to nominal CLP by the Chilean Consumer Price Index

**Table 2** Estimated parameters of the translog input distance function

| Variables | Parameter | Coeff | St. error | *T* stat | *p* value |
|---|---|---|---|---|---|
| Water distributed | $\mu_1$ | −0.253 | 0.035 | *−7.163* | 0.000 |
| Wastewater customers treated | $\mu_2$ | −0.813 | 0.043 | *−19.056* | 0.000 |
| Network length | $\rho_1$ | 0.614 | 0.036 | *17.186* | 0.000 |
| Opex | $\rho_2$ | 0.299 | 0.040 | *7.482* | 0.000 |
| Time | $\omega_1$ | −0.016 | 0.009 | **−1.813** | 0.070 |
| Network length$^2$ | $_{1,1}$ | −0.638 | 0.044 | *−14.416* | 0.000 |
| Network Length × opex | $_{1,2}$ | 0.094 | 0.036 | *2.604* | 0.009 |
| Opex$^2$ | $_{2,2}$ | 0.159 | 0.086 | **1.853** | 0.064 |
| Water distributed × network length | $\theta_{1,1}$ | −0.147 | 0.085 | **−1.722** | 0.085 |
| Wastewater customers treated × network length | $\theta_{2,1}$ | 0.278 | 0.083 | *3.330* | 0.001 |
| Water distributed × opex | $\theta_{1,2}$ | 0.472 | 0.078 | *6.062* | 0.000 |
| Wastewater customers treated × opex | $\theta_{2,2}$ | −0.520 | 0.068 | *−7.684* | 0.000 |
| Water distributed$^2$ | $_{1,1}$ | −0.433 | 0.065 | *−6.681* | 0.000 |
| Wastewater customers treated$^2$ | $_{2,2}$ | −0.339 | 0.053 | *−6.420* | 0.000 |
| Water distributed × wastewater customers treated | $_{1,2}$ | 0.351 | 0.056 | *6.278* | 0.000 |
| Network length × time | $\tau_1$ | −0.011 | 0.004 | *−3.031* | 0.002 |
| Opex × time | $\tau_2$ | −0.018 | 0.006 | *−2.891* | 0.004 |
| Water distributed × time | $\lambda_1$ | −0.001 | 0.005 | −0.295 | 0.768 |
| Wastewater customers treated × time | $\lambda_2$ | 0.010 | 0.004 | *2.284* | 0.022 |
| Time$^2$ | $\omega_2$ | −0.002 | 0.002 | −0.990 | 0.322 |
| Customer density | $\zeta_1$ | −2.543 | 0.039 | *−64.880* | 0.000 |
| Customer density$^2$ | $\zeta_2$ | 0.412 | 0.009 | *43.476* | 0.000 |
| Wastewater treatment quality | $\zeta_3$ | −0.214 | 0.088 | *−2.418* | 0.016 |
| Drinking water quality | $\zeta_4$ | −0.093 | 0.076 | −1.236 | 0.216 |
| Non-revenue water | $\zeta_5$ | −0.021 | 0.013 | −1.595 | 0.111 |
| Sigma | | 0.1433 | 0.0047 | *30.471* | 0.000 |
| Lambda | | 2.172 | 0.2512 | *8.646* | 0.000 |
| Log likelihood | 223.847 | | | | |
| Average technical efficiency | 0.914 | | | | |

Labor input is the dependent variable

Italic coefficients are statistically significant from zero at the 5% level

Bold coefficients are statistically significant from zero at the 10% level

increased the inefficiency for the average firm in the sample. It should be noted that the coverage of wastewater collection and treatment in Chilean urban settings increased from 20% in 2000 to 97.2% in 2017 (SISS 2017). Moreover, it seems that the industry has undergone technological regress as denoted by the estimated coefficient of the time variable which is negative and statistically significant from zero. Looking at the results on the control variables we conclude that the density variable is negative whereas and the density squared variable is positive. This result suggested that increases in customer density led to increases in input requirements and therefore inefficiency. However, this effect eventually may not exist at high levels of customer density. The existence of economies of density in the water industry in Chile and elsewhere was also reported in previous studies (Kirkpatrick et al. 2006; Mellah and Ben Amor 2016; Molinos-Senante et al. 2017a, b; Guerrini et al. 2018). The elasticity regarding the wastewater treatment quality was negative and statistically significant from zero which suggests that investments to improve the wastewater treatment quality resulted in higher inputs and thus inefficiency. This finding is consistent with previous studies analyzing the economics of wastewater treatment (Haslinger et al. 2016; Tarpani and Azapagic 2018; Awad et al. 2019). Results about drinking water quality and non-revenue water are not statistically significant which means that these variables do not have an impact on the performance of the water companies from a statistical point of view. Finally, the high level of average technical efficiency indicates that on average the Chilean water and sewerage industry is a mature industry, which is consistent with previous studies by Ferro and Mercadier (2016) and Molinos-Senante et al. (2018).

## Total factor productivity estimation at the water industry level

The estimation of the translog input distance function allowed us to compute the MPI and its components for each Chilean water company. Table 3 shows the average TFP and its drivers over the period 2007–2015. It is found that during the years 2007–2015, on average, the industry increased its productivity with an annual rate of 6.8%. The rate of productivity growth per annum was considerably higher during the years 2011–2015 than 2007–2010. This finding is consistent with Sala-Garrido et al. (2018) who also reported positive productivity growth in the Chilean water and sewerage industry over the years 2011–2016. As shown in Table 3, productivity change was not constant over time. During a first period, from 2007 to 2011 (except 2008/09), productivity decreased annually by 12.7%, being remarkable the dramatic productivity regression suffered on overage by Chilean water companies in 2007/08 (productivity declined by 33.3%). During these years, the water companies made notable efforts to improve the coverage of wastewater collection and treatment, which impacted significantly on their productivity. By contrast, the annual growth rate was substantially higher during the second half of the period under consideration (2011/15), where the productivity improved annually by 26.1%.

Looking at the sources of the productivity growth, on average from 2007 to 2015, TEC, SEC, and IME contributed positively to productivity growth, whereas the temporal changes of TC hurt productivity. This finding implies that it will be wiser for water companies to not base productivity plans only on technical efficiency and scale effect, but to focus further on technological progress. In particular, the results in Table 3 indicate that the Chilean water and sewerage companies slightly improved their efficiency towards the frontier company at an average annual rate of 0.3%. The TEC reflects the capacity of water companies to be managed on the efficient frontier. Hence, the average value of 0.3% for this driver suggests that the position of the Chilean water companies regarding the efficient frontier has remained almost constant. The temporal changes of TC were the major source of deterioration in productivity as it decreased at an annual rate of 8.3%. This implies that the Chilean water and sewerage industry experienced technical regress, which was more evident in the second half of the period examined (2012/15). The TC is not Hicks-neutral and emerges from an output-biased technical regress, which amounts to 6.3%. This implies that water companies should make technological improvements that can positively influence the mix of outputs and, thus, productivity. The input bias is close to one, which implies that Hicks input-neutral TC prevails.

For the full-time period analyzed, SEC slightly contributed to improving productivity over time. In particular, this driver contributed negatively to productivity until 2010/11, whereas it significantly improved productivity during the other years evaluated. The scale efficiency associated with the output from two successive years showed an increase at an annual average rate of 3.9%. This implies that Chile's water industry is now moving closer to its technically optimal scale in terms of output. IME is the most important source of TFP growth during the period examined. The average value of the IME indicates that the scale efficiency associated with the input combinations used over two successive years increased at an annual rate of 13.1%. This implies that the Chilean water and sewerage industry has adopted an efficient cost allocation of resources by for instance substituting operating expenses with capital. Finally, the overall scale effect, that is, the combined effect of radial scale efficiency changes and SEC associated with temporal changes in the input mix, increased the TFP by 17.0%.

## Total factor productivity estimation for full private and concessionary water companies

As reported in "Sample and data description," the 22 Chilean water companies evaluated present two types of ownership, FPWCs and CWCs. Table 4 depicts the decomposition of the

**Table 3** Average total factor productivity (TFP) change and its drivers for Chilean water and sewerage companies

| | TFP | Technical efficiency change | Technical change | Technical change index | Output bias index | Input bias index | Scale efficiency change | Input mix effect |
|---|---|---|---|---|---|---|---|---|
| 2007/08 | 0.667 | 1.022 | 0.875 | 0.947 | 0.950 | 0.976 | 0.854 | 0.890 |
| 2008/09 | 1.103 | 0.968 | 1.104 | 0.949 | 0.956 | 1.215 | 0.901 | 1.159 |
| 2009/10 | 0.887 | 1.037 | 0.866 | 0.950 | 0.894 | 1.014 | 0.954 | 1.059 |
| 2010/11 | 0.836 | 0.993 | 0.909 | 0.954 | 0.911 | 1.041 | 0.990 | 0.966 |
| 2011/12 | 1.067 | 0.994 | 0.943 | 0.956 | 1.006 | 0.979 | 1.042 | 1.097 |
| 2012/13 | 1.162 | 1.010 | 0.877 | 0.959 | 0.904 | 1.014 | 1.124 | 1.185 |
| 2013/14 | 1.356 | 0.999 | 0.897 | 0.962 | 0.951 | 0.979 | 1.188 | 1.328 |
| 2014/15 | 1.462 | 1.001 | 0.865 | 0.966 | 0.922 | 0.970 | 1.260 | 1.362 |
| Average | 1.068 | 1.003 | 0.917 | 0.956 | 0.937 | 1.023 | 1.039 | 1.131 |

**Table 4** Average total factor productivity (TFP) change and its drivers for Chilean water and sewerage companies by ownership type

| | TFP | Technical efficiency change | Technical change | Technical change index | Output bias index | Input bias index | Scale efficiency change | Input mix effect |
|---|---|---|---|---|---|---|---|---|
| Full private water companies | | | | | | | | |
| 2007/08 | 0.682 | 1.026 | 0.846 | 0.942 | 0.959 | 0.938 | 0.866 | 0.945 |
| 2008/09 | 1.050 | 0.968 | 1.091 | 0.944 | 0.964 | 1.195 | 0.915 | 1.106 |
| 2009/10 | 0.929 | 1.061 | 0.859 | 0.946 | 0.873 | 1.026 | 0.961 | 1.103 |
| 2010/11 | 0.779 | 1.002 | 0.894 | 0.950 | 0.871 | 1.069 | 0.985 | 0.943 |
| 2011/12 | 1.067 | 0.988 | 0.932 | 0.953 | 1.015 | 0.965 | 1.044 | 1.111 |
| 2012/13 | 1.089 | 1.005 | 0.838 | 0.956 | 0.853 | 1.032 | 1.118 | 1.177 |
| 2013/14 | 1.325 | 0.980 | 0.870 | 0.960 | 0.931 | 0.971 | 1.175 | 1.405 |
| 2014/15 | 1.446 | 1.008 | 0.812 | 0.964 | 0.894 | 0.941 | 1.245 | 1.439 |
| Average | 1.046 | 1.005 | 0.893 | 0.952 | 0.920 | 1.017 | 1.039 | 1.153 |
| Concessionary water companies | | | | | | | | |
| 2007/08 | 0.652 | 1.019 | 0.905 | 0.953 | 0.942 | 1.014 | 0.841 | 0.834 |
| 2008/09 | 1.156 | 0.968 | 1.118 | 0.953 | 0.948 | 1.236 | 0.886 | 1.211 |
| 2009/10 | 0.846 | 1.014 | 0.874 | 0.954 | 0.915 | 1.002 | 0.947 | 1.015 |
| 2010/11 | 0.892 | 0.984 | 0.924 | 0.958 | 0.951 | 1.014 | 0.995 | 0.990 |
| 2011/12 | 1.067 | 0.999 | 0.953 | 0.960 | 0.998 | 0.992 | 1.040 | 1.082 |
| 2012/13 | 1.234 | 1.015 | 0.916 | 0.962 | 0.955 | 0.997 | 1.130 | 1.193 |
| 2013/14 | 1.387 | 1.017 | 0.923 | 0.965 | 0.970 | 0.986 | 1.202 | 1.251 |
| 2014/15 | 1.478 | 0.995 | 0.919 | 0.969 | 0.951 | 0.998 | 1.274 | 1.285 |
| Average | 1.089 | 1.001 | 0.941 | 0.959 | 0.954 | 1.030 | 1.040 | 1.108 |

TFP during the years 2007–2015 by ownership type. The results indicate that during the period examined, the TFP of FPWCs and CWCs increased with an annual rate of 4.6% and 8.9%, respectively. These results demonstrate that CWCs exhibited better performance over time than FPWCs. This finding is consistent with the estimations by Sala-Garrido et al. (2018) who estimated the productivity change of Chilean water companies, including undesirable outputs. Of the four drivers of TFP, TC was the only one that contributed negatively to productivity change for both types of companies. In particular, the average estimated annual rates of technical regress were10.7% and 5.9% per year for FPWCs and CWCs, respectively. Molinos-Senante and Sala-Garrido (2015) and Molinos-Senante et al. (2018) also concluded that TC led to a decline in the productivity for FPWC and CWCs in Chile over time. By contrast, the IME was the driver that contributed the most to productivity rose of both FPWCs and CWCs since it increased annually by 45.3% and 10.8%, respectively. The average annual rate of SEC contributed to 3.9% of growth for FPWCs and 4.0% of growth for CWCs, indicating that both types of water companies have benefited by improving its scale of operating. This effect happened incrementally since 2011, when wastewater collection and treatment achieved almost universal coverage (SISS 2017). The average technical efficiency changed little from 2007 to 2015 for both types of water companies. Moreover, TEC exhibited great variability across years, contributing positively and negatively to TFPC. Given that positive values of TEC are mainly attributed to managerial improvements (Ananda 2018), results of TEC suggest that neither Chilean FPWCs nor CWCs have implemented specific plans for improving management issues in the long term.

## Total factor productivity estimation at the water companies level

Given the relevance of assessing TFP change to regulate water companies and to promote efficiency improvement, Table 5 shows the average MPI during the years 2007–2015, as well as its sources of growth at the company level. We found that seven out of 11 FPWCs improved their productivity, with the IME and SEC drivers contributing most to this improvement. By contrast, in the three out of four FPWCs whose productivity declined, this was due to the negative contribution of SEC. This finding illustrates the importance of operating on an optimal scale to provide efficient water and sewerage services. Regarding TC, only the FPWC4 exhibited a positive evolution, while the remaining FPWCs suffered a negative shift of the efficient frontier. The same pattern is observed for the CWCs since TC contributed negatively to TFP change of all water companies. This result evidences that the Chilean water regulator should introduce policies or incentive-based regulation to improve the TC (i.e., to promote the positive shift of the efficient frontier, of both FPWCs and CWCs).

**Table 5** Average total factor productivity (TFP) change and its drivers for at water company level during the years 2007–2015

| | TFP | Technical efficiency change | Technical change | Technical change index | Output bias index | Input bias index | Scale efficiency change | Input mix effect |
|---|---|---|---|---|---|---|---|---|
| Full private water companies (FPWCs) | | | | | | | | |
| FPWC1 | 0.854 | 1.001 | 1.009 | 0.996 | 0.947 | 1.069 | 0.882 | 0.948 |
| FPWC2 | 0.915 | 0.996 | 0.967 | 0.990 | 0.959 | 1.018 | 0.902 | 1.036 |
| FPWC3 | 0.950 | 1.002 | 0.959 | 0.971 | 0.947 | 1.043 | 0.946 | 1.037 |
| FPWC4 | 1.018 | 0.985 | 1.025 | 0.977 | 0.962 | 1.091 | 0.986 | 1.011 |
| FPWC5 | 1.187 | 0.999 | 0.983 | 0.958 | 0.952 | 1.073 | 1.036 | 1.138 |
| FPWC6 | 1.256 | 1.022 | 0.886 | 0.961 | 0.948 | 0.975 | 1.071 | 1.420 |
| FPWC7 | 0.886 | 1.006 | 0.713 | 0.908 | 0.846 | 0.922 | 1.067 | 1.169 |
| FPWC8 | 1.011 | 0.989 | 0.739 | 0.913 | 0.863 | 0.940 | 1.104 | 1.319 |
| FPWC9 | 1.059 | 1.021 | 0.834 | 0.944 | 0.854 | 1.036 | 1.098 | 1.134 |
| FPWC10 | 1.256 | 1.028 | 0.831 | 0.934 | 0.894 | 0.998 | 1.162 | 1.331 |
| FPWC11 | 1.116 | 1.002 | 0.874 | 0.917 | 0.949 | 1.022 | 1.172 | 1.143 |
| Concessionary water companies (CWCs) | | | | | | | | |
| CWC1 | 0.904 | 1.007 | 0.966 | 0.966 | 0.955 | 1.048 | 0.944 | 0.977 |
| CWC2 | 1.070 | 0.995 | 0.942 | 0.972 | 0.935 | 1.037 | 0.954 | 1.176 |
| CWC3 | 1.025 | 1.001 | 0.961 | 0.973 | 0.959 | 1.030 | 0.949 | 1.097 |
| CWC4 | 1.135 | 1.001 | 0.976 | 0.966 | 0.934 | 1.082 | 0.948 | 1.178 |
| CWC5 | 1.008 | 1.014 | 0.919 | 0.978 | 0.943 | 0.998 | 0.957 | 1.122 |
| CWC6 | 1.210 | 0.993 | 0.995 | 0.956 | 0.952 | 1.093 | 1.003 | 1.212 |
| CWC7 | 1.253 | 0.995 | 0.983 | 0.952 | 0.973 | 1.062 | 1.037 | 1.230 |
| CWC8 | 1.047 | 1.003 | 0.867 | 0.936 | 0.944 | 0.980 | 1.068 | 1.109 |
| CWC9 | 1.354 | 0.995 | 0.908 | 0.914 | 0.918 | 1.085 | 1.274 | 1.184 |
| CWC10 | 1.050 | 1.008 | 0.894 | 0.951 | 1.009 | 0.931 | 1.355 | 0.860 |
| CWC11 | 0.922 | 1.004 | 0.942 | 0.989 | 0.969 | 0.984 | 0.946 | 1.040 |

Focusing on the productivity change over time of CWCs, Table 5 reveals that nine of 11 CWCs improved their productivity from 2007 to 2015 in average terms. However, unlike FPWCs, there is no predominant driver, but for each CWC, the productivity increase was determined by a different combination of determinants. Thus, for example, SEC contributed positively only for five of nine CWCs whose productivity increased. For the remaining CWCs, the most determinant factors to productivity increase were IME and TEC. This indicates that a set of CWCs have improved their managerial practices, and, therefore, their input-output combination has approached to the efficient frontier.

Beyond the specific results for each FPWC and CWC, the novel way in which TFP change is decomposed in this study allows water regulators and water companies to identify the main drivers contributing for changes (positive or negative) in productivity over time. This information is essential to identify and propose specific policies and measures to improve the performance of water companies over time, which is of great interest for water regulators, water companies, and citizens.

## Conclusions

Assessing the TFP change of water companies is of paramount importance to protect customers' interest and promote efficiency and innovation of water companies. In doing so, several indexes can be used, among which the MPI is the most applied. However, previous studies used the DEA technique to estimate the MPI for water companies. By contrast, following a pioneering methodological approach, in this study, MPI was computed using a parametric technique that allowed us to decompose TFP change into seven drivers, namely TEC, TC, SEC, IME, technical magnitude change index, output bias index, and input bias index. To illustrate the usefulness of decomposing TFP change into such a large number of components, an empirical application for the Chilean water and sewerage industry was conducted.

The main findings of the empirical application are summarized as follows. First, the Chilean water industry is capital-intensive and this feature has been accentuated over time as the coverage of wastewater collection and treatment increased. Second, the improvement of productivity of the Chilean water companies was not constant over time. On the one hand, from 2007 to 2011, productivity decreased mainly due to the fact that the operation scale of the water companies was not optimal. On the other hand, from 2011 to 2015, productivity notably improved thanks to the positive contribution of SEC and IME. Third, the average TC contributed negatively to TFP change for all years analyzed. This shows efficient production has shifted negatively over time. This finding suggests that, from a regulatory perspective, it is required to introduce policies to improve the performance of water companies. Fourth, while on average both FPWCs and CWCs improved their productivity from 2007 to 2015, CWCs exhibited better performance over time than FPWCs.

From policy and management points of view, this study evidences the importance of not just assessing TFP change but also to decompose it in a large number of components. This approach allows identifying the drivers that have contributed positively and negatively to productivity change of the water companies. Such detailed decomposition is fundamental to support the decision-making of water regulators and water companies to define the more adequate policies, incentives, and measures to promote productivity growth in water utilities.

**Data availability statement** All data, models, or code generated or used during the study are available from the corresponding author by request.

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