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Cost and quality of service performance in the Chilean water industry: A comparison of stochastic approaches

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ABSTRACT

The evaluation of efficiency can be of great value to water companies and regulators to adopt policies and design incentives to enhance performance. This study delves into the implications of employing distinct methodologies, namely the classical Stochastic Frontier Analysis (SFA), Bayesian SFA, and Stochastic non-parametric Envelopment of Data (StoNED), to evaluate cost and quality of service efficiency within the water industry. Chilean water companies reported average efficiencies of 0.623, 0.583, and 0.522 using the SFA, BSFA, and StoNED approaches, respectively. Furthermore, the SFA analysis suggested that the performance of water companies experienced a decline of −0.59% per year from 2010 to 2018. In contrast, the BSFA and StoNED estimations indicated an opposite trend, with annual performance improvements of 0.51% and 0.17% respectively, over the same period. These findings underscore the critical role of selecting appropriate methodologies when interpreting and comparing efficiency results for making informed long-term decisions.

1. Introduction

Improving sustainability in the provision of water and sanitation services involves an efficient use of economic resources by water companies and at the same time, ensuring quality of services to customers (Goh and See, 2021). Efficiency is defined as a ratio between observed (actual) outputs (or costs) and some optimal (frontier) values (Li et al., 2016). Efficiency assessment allows the identification of best and worst performers (e.g. water companies) and therefore, allows policy makers to understand the production process, how resources are converted to outputs, and consequently, to explore strategies to improve performance.

Improving efficiency in water companies can lead to a wide range of long-term benefits that positively impact the environment, customers, and the overall sustainability of water resources (Marques, 2011). Enhanced efficiency can lead to reduced operational costs. This, in turn, can lead to lower expenses for water companies and potentially lower water bills for customers (Ngobeni and Breitenbach, 2021). Improving efficiency often involves upgrading and modernizing infrastructure. This investment in infrastructure can lead to a more reliable and robust water supply system, reducing the frequency of leaks, bursts, and disruptions (Amaral et al., 2023). Water treatment and distribution require significant energy input. By becoming more efficient, water companies can reduce their energy consumption, leading to lower greenhouse gas emissions and a smaller environmental footprint (Cetrulo et al., 2019). By reducing costs, optimizing operations, and investing in modern infrastructure, water companies can enhance their long-term economic viability. Financial stability enables them to make further improvements, invest in research and development, and respond effectively to future challenges (Thanassoulis et al., 2022; Heesche and Bogetoft, 2022).

To contribute to the ongoing debate about the influence of benchmarking techniques on efficiency scores in the water industry, in this study we assess the cost and quality of service (CQoS) efficiency of a sample of water companies using three different stochastic frontier methods. The first approach is the standard SFA method originally introduced by Aigner et al. (1977) and Meeusen and van den Broeck (1977). Following Battese and Coelli's (1992) approach we assume that

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inefficiency is varying over time. The second approach is the Bayesian Stochastic Frontier Analysis (BSFA) originally introduced by van den Broeck et al. (1994), further developed by Koop et al. (1995, 1997) and Griffin and Steel (2007) with significant further contributions from several authors (see for instance Tsionas and Kumbhakar, 2014; Assaf et al., 2016; Carvalho and Marques, 2016). Compared to the standard SFA techniques, the main advantage of the BSFA approach is that it uses both observed data and a priori information about the estimated parameters (coefficients and inefficiency) of the model (Arbelo et al., 2018). The third stochastic frontier approach used is the StoNED method developed by Kuosmanen (2008). StoNED incorporates convexity, monotonicity and returns to scale in its analysis.

Against this background, the main objective of this study is to evaluate and compare the CQoS efficiency of the urban water sector in Chile using three different stochastic frontier techniques, i.e., SFA, BSFA and StoNED. These stochastic frontier techniques are chosen because including both noise and inefficiency in the estimation process is relevant (Guerrini et al., 2018). To make the three methodological approaches comparable, we assume that inefficiency is varying over time.

To the best of the authors' knowledge, there is a lack of existing studies within the water industry that have specifically measured and compared the level of inefficiency across different stochastic frontier techniques, such as SFA, BSFA, and StoNED. Therefore, this study makes a valuable contribution to the current literature by filling this gap and providing a measurement and comparison of water company performance using these distinct stochastic frontier techniques. By conducting such a comparative analysis, this study adds to our understanding of the different methodologies employed in assessing efficiency within the water industry. It offers insights into the variations and potential strengths of each technique, thus advancing the knowledge and discussion within this field of research.

The remainder of this paper is organized as follows. Section 1 describes the introduction; Section 2 presents a brief literature review on the topic; Section 3 discusses the three parametric methods used in the study; Section 4 shows the sample and data used to conduct the empirical application following by Section 5 which presents and discusses the results. Finally, Section 6 presents the conclusions of the study.

2. Literature review

Based on the bibliographic reviews conducted by Abbott and Cohen (2009), Walter et al. (2009), Berg and Marques (2011), Carvalho et al. (2012), Worthington (2014), Cetrulo et al. (2019) and Goh and See (2021), two main approaches have been used to assess the efficiency in the provision of water and sanitation services: i) non-parametric methods such as Data Envelopment Analysis (DEA) and; ii) parametric methods such as Stochastic Frontier Analysis (SFA). The main limitation of DEA techniques is that it is deterministic. This means that deviations from the efficient frontier are due to inefficiency only and no statistical noise is incorporated (Stolp, 1990; Hossain et al., 2022). Moreover, DEA cannot deal effectively with the presence of measurement error in the data (Khan et al., 2021; Bibi et al., 2021). In contrast, parametric techniques take into account both inefficiency and noise (Rasheed et al., 2022). However, they require the specification of a functional form (e.g., Cobb–Douglas) for the estimation of production technology (Lannier and Porcher, 2014; Khan et al., 2023).

Moreover, it is important to consider that the use of the SFA approach may have limitations when the number of observations is small. These limitations include: i) reduced statistical power: with a small number of observations, the statistical power of the analysis is diminished, and the models may encounter convergence issues (Campos et al., 2022); ii) overfitting: there is a risk of overfitting when employing a model that is excessively complex compared to the available data. This can lead to unreliable results (Corrigan and Zhang, 2020); iii) model identification: the identification of the model can become more challenging with a small number of observations, leading to a higher degree of uncertainty in estimating efficiency levels (Silva et al., 2019). These limitations should be taken into account when interpreting the results obtained through the SFA approach in studies with a small sample size. To overcome these limitations, past studies combining DEA and SFA techniques to estimate efficiency scores following different approaches. For example, Tsionas (2003) used DEA scores for crafting a prior for stochastic frontier models. This innovative approach was later extended by Tsionas (2023), who combined stochastic frontier models and DEA using the least absolute shrinkage and selection operator. An alternative approach was developed by Silva et al. (2019) who proposed a stochastic frontier approach with maximum entropy estimation.

Focusing on the water sector, Molinos-Senante and Maziotis (2021), Molinos-Senante et al. (2022) and Maziotis et al. (2023) used Stochastic non-parametric Envelopment of Data (StoNED) method to benchmark the efficiency of water companies. Like SFA, StoNED incorporates both inefficiency and noise and like DEA, it does not assume a priori a functional form for the underlying technology. Nevertheless, the StoNED approach also presents some limitations: i) the statistical properties of the multivariate convex nonparametric least squares estimator are not well-established and ii) the composite error term assumptions borrowed from SFA can be overly restrictive and may not be suitable for the given context (Silva et al., 2019). Another limitation of the StoNED approach is its computation burden. As indicated by Kuosmanen and Kortelainen (2012) and Lee et al. (2013) traditional quadratic programming algorithms are limited by the number of constraints. Therefore, the computational burden when employing quadratic programming to run CNLS is challenging even when the size of the sample is relatively small. Moreover, Kuosmanen and Kortelainen (2012) indicated that because of the non-parametric orientation of the StoNED method, it may be vulnerable to the curse of dimensionality. This suggests that the size of the sample must be large when the number of input variables is high.

Focusing on the countries studied by past research, the number of studies assessing the performance of water companies operating in developed countries is much higher than those focusing on developing countries which present specific features (Cetrulo et al., 2019). Hence, as Cetrulo et al. (2019) stated more research evidence on the performance of the water sector from developing countries is needed. Consequently, our study focuses on the water industry in Chile which underwent its privatization process during the years 1998–2004 (Molinos-Senante et al., 2018). Moreover, in terms of quality of service, current regulation does not financially penalize water companies when they do not reduce the level of non-revenue water. Hence, it remains at constant across years around 33% (Sala-Garrido et al., 2019; SISS, 2023). Customers are not economically compensated when water is cut off due to company's malfunction in the network. Therefore, our study aims to explore the inefficiency in the Chilean industry incorporating these undesirable outputs in the analysis.

Because Chilean water industry presents several differentiating features in terms of ownership, levels of coverage and water tariffs regulation (see Section 3 for additional details), several past studies have evaluated the efficiency of water companies operating in Chile with mixed results (e.g., Sala-Garrido et al., 2018; Molinos-Senante and Maziotis, 2020, 2022, 2023). In this context, Molinos-Senante and Maziotis (2019) compared efficiency changes across time of Chilean water companies employing DEA and SFA methods. Subsequently, Molinos-Senante et al. (2022) also integrated the StoNED method in the comparison of efficiency techniques. They evidenced the influence of benchmarking methods on efficiency results.

The literature review conducted for this study reveals a notable gap in the existing research within the water industry framework. Specifically, no previous studies have been identified that estimate and compare the CQoS efficiency using three different parametric approaches: SFA, BSFA and StoNED. This research contributes to the current body of literature by addressing this gap and providing a comparative analysis of CQoS efficiency across these three parametric methods.

3. Methodology

In this section we present the methodologies used to estimate the CQoS efficiency of several Chilean water companies, i.e., SFA, BSFA and StoNED.

3.1. Traditional Stochastic Frontier Analysis (SFA)

Unlike non-parametric approaches the SFA technique assumes that firms (water companies) deviate from the efficient frontier due to both inefficiency and statistical noise. The cost frontier model based on SFA has the following form:

$$C_{it} = f(y_{it}; \beta_{it})\exp(v_{it} + u_{it}) \tag{1}$$

where C_{it} denotes the production costs of any firm i at any time t, y_{it} is the set of output vectors and β_{it} is its estimated parameters. In Eq. (1), statistical noise is captured by the term v_{it} which assumes to follow the normal distribution, $v_{it} \sim N(0, \sigma_v^2)$ and inefficiency denoted as u_{it} is assumed to follow the half-normal distribution $u_{it} \sim N^+(0, \sigma_u^2)$. Alternatively, other distributions such as exponential, gamma, lognormal and truncated normal could be assumed (Smith, 2008). Following Battese and Coelli (1992) we assume that cost inefficiency is time-varying and is defined as $u_{it} = \gamma(t)u_i$. The time-dependence of inefficiency, $\gamma(t)$ takes the following form:

$$\gamma(t) = \exp(-\eta(t - T)) \tag{2}$$

where t denotes time and T is total number of time periods.

In Eq. (2), inefficiency is assumed to be decreasing, increasing or remain constant. In our study we estimate the following stochastic frontier model, which assumes that takes the Cobb–Douglas function. We use this specification because the sample of our study is small and therefore, does not require many degrees of freedom compared to the translog functional form (Cullmann, 2012; Ferro and Mercadier, 2016). Moreover, translog form was not used to avoid the potential risk of collinearity among second order terms (Silva et al., 2019). The cost function employed is as follows:

$$C_{it} = a_0 + f(y_{it}, z_{it}, t; \beta_{it}) + v_{it} + u_{it} \tag{3}$$

where $v_{it} \sim N(0, \sigma_v^2)$, $u_{it} = \exp(-\eta(t - T))u_i$, $u_i \sim N^+(\mu, \sigma_u^2)$ i.e., noise and inefficiency are distributed independently of each other and the explanatory variables of the model.

In the above model specification, a set of environmental variables, z_{it}, are included. They capture quality of service variables i.e., non-revenue water and unplanned interruptions. Time trend is also included to capture technical change in our analysis. Moreover, based on the sign of η, inefficiency could be decreasing, increasing or remain unchanged.

3.2. Bayesian Stochastic Frontier Analysis (BSFA)

Unlike the traditional SFA, which relies on observed (actual) data to estimate inefficiencies, the BSFA techniques employs information from two foundations. The first source relies on prior information, which presents the researcher's beliefs about the parameters of interest such as outputs and efficiencies, and the second source relies on observed (actual) data (Vu and Turnell, 2010). Using the Bayes ́ theorem, the researcher combines the prior information and observed data to derive posterior distribution of the parameters of interest such as outputs and efficiencies and make statistical inferences on them (Arbelo et al., 2018). Thus, the main advantages of the BSFA over traditional SFA techniques are exact finite sample inference in stochastic frontier models such as estimated parameters of inputs, outputs and efficiencies, easy inclusion of prior ideas, and determine the formal specification of parameters and model uncertainty (Griffin and Steel, 2007; Vu and Turnell, 2010).

Following Griffin and Steel (2007) we specify the following BSFA model:

$$C_{it} = a_0 + f(y_{it}, z_{it}, t; \beta_{it}) + v_{it} + u_{it} \tag{4}$$

where costs are assumed to follow a normal distribution with mean μ and variance σ^2. Following Fernandez et al. (2002), Griffin and Steel (2007), Li et al. (2016), Arbelo et al. (2018) and Deng et al. (2019) we assume the following prior distributions for the estimated parameters:

$$a_o \sim N(0, 10^{-6}) \tag{5}$$

$$\beta \sim N(0, 10^{-16}) \tag{6}$$

$$\sigma^2 \sim Ga(10^{-3}, 10^{-3}) \tag{7}$$

As for the inefficiency, following Griffin and Steel (2007) we assume that it follows the half-normal distribution, so that $u_{it} \sim N^+(0, \lambda)$. The prior distribution $\lambda \sim Ga(1, 1/37.5)$ gives a prior median efficiency of 0.875 which is consistent with previous studies such as Ehlers (2011), Li et al. (2016), Brea-Solis et al. (2017) and Deng et al. (2019).

To make comparable with the traditional SFA model, we assume that inefficiency is time-varying and takes the following form, $u_{it} = \gamma(t)u_i$, where $\gamma(t) = \exp(-\eta(t - T))$. We define a prior distribution for η to have a zero mean normal distribution with variance 0.4, $\eta \sim N(0, 0.4)$ (Griffin and Steel, 2007; Li et al., 2016).

The Bayesian Stochastic Frontier model was run using Monte Carlo Markov Chain algorithm for sampling from the posterior distribution (Kumbhakar and Tsionas, 2005; Arbelo et al., 2018). A total of 200,000 interactions were generated, 4000 of which were ignored to avoid the sensitivity of initial values and guarantee convergence (Arbelo et al., 2018).

3.3. Stochastic non-parametric Envelopment of Data (StoNED)

This methodology combines the qualities of SFA and DEA (Kuosmanen and Kortelainen, 2012). Like SFA, it takes into account both inefficiency and statistical noise. Inefficiency is assumed to follow the half-normal distribution and noise is assumed to follow the normal distribution. In contrast to SFA, it does not assume a priori a functional form for the underlying production technology. Like DEA, the StoNED approach takes into account convexity, monotonicity and returns to scale (Johnson and Kuosmanen, 2011, 2012).

There is a two-step process to estimate the cost frontier with the StoNED approach (Kuosmanen et al., 2013). The first approach estimates the parameters of the cost frontier function using convex nonparametric least squares (Kuosmanen, 2008). The second step estimates the expected value of inefficiency, the variances of inefficiency and noise, and the firm-specific efficiencies (Johnson and Kuosmanen, 2011, 2012). Hence, the first step of the StoNED approach solves the following non-linear programming by minimizing the sum of the squared residuals, ε_{it}, where $\varepsilon_{it} = v_{it} + u_{it}$:

$$\min \sum_{i=1}^{I} \sum_{t=1}^{T} \varepsilon_{i,t}^2 \tag{8}$$

subject to :

$$lnC_{i,t} = ln(\alpha_{i,t} + \beta_{i,t}y_{i,t}) + \delta_{i,t}z_{i,t} + trend(t) + \varepsilon_{i,t} \qquad i = 1, .., I; t = 1, \ldots, T$$

$$a_{i,t} + \beta_{i,t}y_{i,t} \geq \alpha_{j,w} + \beta_{j,w}y_{j,w} \qquad i, j = 1, \ldots, I; t, w = 1, \ldots, T$$

$\beta_{i,t} \geq 0 \qquad i=1,..,I; t=1,\ldots,T$

Consistent with the SFA models, the StoNED frontier model includes a set of outputs for each firm over time, a set of environmental variables (non-revenue water and unplanned interruptions) and a time trend to capture technical change (Li et al., 2016). The term a_{it} captures returns to scale. In this study, we set $a_{i,t}=0$ as we assume that the firms operate under constant returns to scale (Ferro and Mercadier, 2016; Sala-Garrido et al., 2018; 2019). The first inequality ensures that the cost function is convex and the second inequality guarantees that monotonicity in outputs is satisfied.

In the second step of the StoNED approach, we use the Method of Moments (MoM) approach to estimate the expected value of inefficiency and variances of inefficiency and statistical error (see Kuosmanen and Kortelainen, 2012; Kuosmanen et al., 2013, 2015 for more details). Firm-specific inefficiency estimates are derived using the Jondrow et al. (1982) approach and under the half-normal distribution (Li et al., 2016). Thus, cost inefficiencies obtained from all three models are comparable.

4. Data and sample selection

4.1. Water industry in Chile

Our empirical approach is applied to several water companies in Chile during the years 2010–18. The Chilean water industry presents several features that make it an interesting case for other middle-income countries. The Chilean water industry was privatized during the years 1998–2004. Two types of water companies operate in the industry, i.e., full private and concessionary companies. Full private companies are responsible for the operation and upgrade of the infrastructure for an infinite time period (Molinos-Senante et al., 2018). Concessionary companies are in charge of providing water and sanitation services for a limited time period, i.e., 30 years. There is also one public water company that provides water services to less than 2% of total customers (Molinos-Senante et al. 2019).

In the last twenty years, the coverage levels on wastewater treatment have significantly increased. Thus, in 2000 the coverages of drinking water supply, wastewater collection and wastewater treatment were 99.69%, 93.19% and 20.9%, respectively. However, since 2020, the coverage levels have improved up to 99.9%, 96.8% and 99.8% for drinking water supply, wastewater collection and wastewater treatment, respectively (SISS, 2020).

Water companies in Chile are regulated by a national urban water regulator, i.e., Superintendencia de Servicios Sanitarios (SISS), who is in charge of setting the maximum water and wastewater tariffs. The process to set water tariffs is based on the definition of a hypothetical efficient water company, i.e., an "ideal firm" (Marques, 2011). Under this approach the performance of the "real" water company is compared with a virtual, efficient company known as the "model" company, which is considered to be the benchmark. It is a theoretical water company created by the regulator which satisfies the demand in an optimal manner. Under this approach, the maximum level of non-revenue water to a water company be considered efficient is 15% (SISS, 2020). However, the average non-revenue water in the Chilean water industry has remained almost constant at 33% during the last 10 years (SISS, 2020). The performance of water companies in terms of quality of service is not regulated (not considered) in the process to set water tariffs (Marques, 2011). Hence, it is relevant to include some quality of service variables in the performance of water companies in Chile.

4.2. Data for efficiency estimation

Our sample includes 10 full private, 9 concessionary and 1 public water company providing both drinking water and wastewater services in urban areas in Chile. The total number of water companies operating in Chile is 54. Nevertheless, the 20 assessed water companies in this study provide services to around 90% of total urban Chilean population. The data used in our analysis was retrieved from the website of the national water regulator.

We selected the following inputs, outputs and quality of service variables based on previous studies in water industry (see for instance, Berg and Marques, 2011; Carvalho and Marques, 2011; Pinto et al., 2017; Cetrulo et al., 2019; Goh and See, 2021), data availability and main features of the Chilean water industry. As input, we used the total expenditure of water and wastewater services measured in thousands of Chilean pesos (CLP) per year. It is defined as the sum of operating and capital expenditure, the annual expenditure required to maintain and upgrade the infrastructure. We used total expenditure as the dependent variable in all three models. We used three outputs in model specification. The first output was the network length measured in kilometers (km) because it captures the size of the service area (Thanassoulis, 2000, 2002; Jamasb et al., 2012; Guerrini et al., 2018). The second output was the volume of drinking water delivered measured in thousands of cubic meters per year (Brea-Solis et al., 2017). The third output was the number of customers receiving wastewater treatment (Sala-Garrido et al., 2018). The last two outputs were adjusted to reflect changes in quality over time. Following past practice (e.g., Saal et al., 2007; Sala-Garrido et al., 2019), we multiplied the volume of water delivered with the drinking water quality indicator reported by the water regulator, SISS. In an analogous manner, we multiplied the number of wastewater treatment customers with the wastewater treatment quality indicator reported by SISS. Both quality indicators take a value between zero and one with one meaning that the companies met drinking water and wastewater treatment standards defined by the SISS (SISS, 2020). The two quality of service variables included in our assessment are: i) volume of non-revenue water measured in thousands of cubic meters per year and; ii) number of water supply unplanned interruptions measured in hours per year. Table 1 depicts the descriptive statistics of the variables used in our study.

5. Results and discussion

5.1. Cost function estimations

Estimated parameters of cost functions of the three methodological approaches employed in this study to assess CQoS efficiency of water companies (SFA, BSFA, StoNED) Eqs. (3), ((4) and (8)) are shown in Table 2. In all models, variables have the same sign but the magnitude of their estimated coefficients differ. We first discuss the results obtained from the standard SFA model. As expected, the coefficients of the three outputs have a positive sign and are statistically significant from zero. This implies that when these outputs increase, costs increase as well. A 1% increase in the length of network would lead to an increase in production costs by 0.345% keeping other variables constant. Moreover, a 1% increase in the volume of water delivered and the number of wastewater treatment customers could result in an increase in costs by 0.319% and 0.164%, respectively. This finding suggests that network length and volume of water delivered are the major cost drivers in the Chilean water industry. As for the quality of service variables, the coefficient of the variable water supply unplanned interruptions had a statistically significant impact on inefficiency. A 1% increase in the frequency of unplanned interruptions could increase production costs and inefficiency by 0.013% keeping other variables constant. The time trend captures technical change. A positive sign means that companies' costs increased over time. An annual rate of 1.7% of technical regress was evident for the Chilean industry. The variable η takes a negative value which is statistically significant from zero. This means that efficiency has been decreasing at a small rate of 0.7% per year on average.

Like the standard SFA model, in the BSFA approach, the coefficient sign of the outputs is positive. Both network length and volume of water delivered are the major drivers of costs as indicated by the magnitude of their estimated coefficient. Compared to the standard SFA model, the

Table 1
Descriptive variables of Chilean water companies to assess their CQoS efficiency.

Variables	Unit of measurement	Average	Std. Dev.	Minimum	Maximum
Total expenditure	000s CLP/year	42,002,519	46,407,202	1,441,502	188,199,088
Quality adjusted volumes of water delivered	000s m^3/year	32,408	35,556	895	152,266
Quality adjusted wastewater treatment customers	nr/year	482,970	587,020	5800	2,589,669
Non-revenue water	000s m^3/year	11,142	13,328	104	52,380
Water supply interruptions	h/year	4222	7157	3	34,051

Observations: 180; Total costs are expressed in 2018 prices.

Table 2
Estimates of SFA, BSFA and StoNED frontier models.

	Standard SFA				BSFA		StoNED			
	Coef.	Std. Err.	z	*P>z*	Mean	Std.Dev	Coef.	Std. Err.	z	*P>z*
Constant	8.884	0.267	**33.220**	<0.001	8.573	0.481				
Network length	0.345	0.101	**3.430**	0.001	0.378	0.105	0.343	0.022	**15.310**	<0.001
Qual. adj. volume of water	0.319	0.066	**4.840**	<0.001	0.295	0.074	0.691	0.021	**32.465**	<0.001
Qual. adj. wastewater treatment customers	0.164	0.055	**3.000**	0.003	0.179	0.064	0.651	0.019	**34.421**	<0.001
Non-revenue water	−0.050	0.035	−1.450	0.147	−0.035	0.037	−0.035	0.019	***−1.819***	0.070
Unplanned interruptions	0.013	0.008	***1.680***	0.093	0.012	0.009	0.006	0.001	**4.114**	<0.001
Time	0.017	0.004	**4.370**	<0.001	0.017	0.004	0.056	0.001	**49.339**	<0.001
μ	−0.233	0.024	**−9.694**	<0.001						
η	−0.007	0.004	***−1.830***	0.068						
λ					2.000	0.758				
η					0.006	0.006				
σ^2					0.006	0.053				
R^2							0.940			
Log-likelihood	155.111									
Observations	180									
Wald $X^2(6)$	**873.63**									
Prob>X^2	<0.001									

Dependent variable is total expenditure.
Bold statistics are statistically significant at 5% significance level.
Bold and italic statistics are statistically significant at 10% significance level.

coefficients of network length and wastewater treatment customers are slightly higher meaning that their impact on production costs is slightly bigger. As for the quality of service variables, the impact of non-revenue water on costs is considerably lower. Under standard SFA and BSFA, the impact of unplanned interruptions on companies' costs is similar. The annual rate of technical regress under standard SFA and BSFA is also similar, 1.7% on average. Unlike standard SFA, the variable η takes a positive value which means that efficiency has been increasing at a small rate of 0.6% per year on average.

Focusing on the results from the StoNED frontier model, like the SFA models, the coefficients of all outputs are positive and statistically significant from zero. The magnitude of the estimated coefficients differs from the SFA models for several variables. This is attributed to the fact that the StoNED frontier is a combination of parametric and non-parametric approaches. Unlike SFA and BSFA models, the quality adjusted volume of water delivered and the number of customers receiving wastewater treatment are the major cost drivers. Ceteris paribus, a 1% increase in the volume of water delivered and wastewater treatment customers could increase production costs by 0.691% and 0.651%, respectively on average. Network length is also a significant cost driver and its impact on costs is similar to the SFA models. As for the quality of service variables, the coefficient of the non-revenue water has a negative sign and is statistically significant from zero. This means that non-revenue water could reduce cost inefficiency and good quality of service could come at an affordable cost. In contrast, a 1% increase in the unplanned supply interruptions could slightly increase costs by 0.006% on average keeping other things equal. Like the SFA models, the StoNED frontier model indicates that the Chilean water industry experienced technical regress. Its rate was at the level of 5.6% on average per year which was higher than the SFA models.

Results from the three frontier models used in this study (SFA, BSFA and StoNED) evidence that the three outputs (network length, volume of water delivered and number of customers receiving wastewater treatment) had a statistically significant impact on costs and inefficiency on Chilean water companies. Under standard SFA and BSFA models, network length and volume of water delivered had the major impact on costs. On the contrary, quality adjusted volume of water delivered and the number of customers receiving wastewater treatment are the major cost drivers in StoNED model. According to the three methodological approaches, unplanned water supply interruptions significantly influenced costs. The rate of technical regress differs depending on the frontier technique used to estimate cost function. In the case of the SFA approach (standard SFA and BSFA), the estimated technical regress is 1.7% whereas for StoNED approach increases up to 5.6%.

5.2. Estimation of cost and quality of service (CQoS) efficiency of water companies

Average CQoS efficiency estimations over the years 2010–18 for the three frontier models are shown in Fig. 1. As different assumptions are imposed by the models, it is reasonable that efficiency scores would differ. The standard SFA model reports higher efficiency scores than the BSFA and the StoNED models. In particular, average CQoS efficiency score under standard SFA is 0.623 which means that on average water companies need to reduce costs and improve quality of service by 37.7% to generate the same level of outputs. Lower efficiency scores are reported under BSFA and the StoNED frontier models, 0.583 and 0.522, respectively. This means that under these models, on average water companies need to reduce costs, non-revenue water and unplanned interruptions by 41.7% and 47.8%, respectively. Thus, the findings from the different frontier models suggest that CQoS inefficiency in the Chilean water industry exists.

The trend of efficiency scores across years also differs based on the methodology used for its estimation (Fig. 1). The results from the

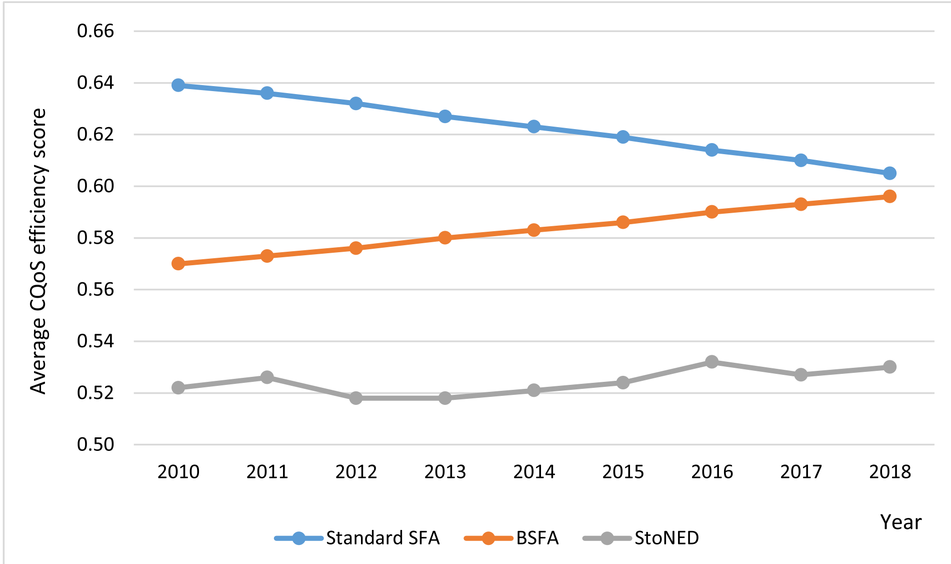

Fig. 1. Average cost and quality of service (CQoS) efficiency of Chilean water companies across years.

standard SFA model demonstrated that CQoS efficiency follows a downward trend over time suggesting that performance of Chilean water companies had been decreasing over time. CQoS efficiency decreased by −5.39% on average from 2010 to 2018. This implies that efficiency had been decreasing by a small rate of 0.60% per year on average. In contrast, the BSFA model showed that CQoS efficiency had been increasing by 0.51% on average per year. However, its CQoS efficiency estimates were considerably lower than the ones reported by the standard SFA.

The CQoS efficiency estimates from the StoNED frontier model were considerably lower than the ones by the SFA models. As shown in Table 2, the magnitude of the output elasticities and technical regress in the case of StoNED was higher than the SFA models, implying more pressure on production costs. This might have led to lower efficiency scores. Moreover, more volatility is shown for the efficiency scores under the StoNED frontier model. CQoS efficiency scores slightly decreased during the years 2012–13 but this was interrupted the following years. We note that during the years 2014–16, CQoS efficiency has been increasing by 0.91% on average per year. However, efficiency decreased the subsequent years. In 2018, on average water companies still needed to reduce costs, non-revenue water and unplanned water supply interruptions by approximately 47.7% to become more efficient.

A correlation analysis among the CQoS efficiency scores of the different models reveals a high correlation, which is statistically significant from zero (Table 3). This finding suggests that the efficiency scores obtained from the different models are consistent. However, as the level of CQoS efficiency scores matters for benchmark analysis the regulator needs to be cautious which approach it should use.

The CQoS efficiency estimates obtained in our study align with findings from previous studies conducted in the Chilean water industry. For example, Molinos-Senante et al. (2018) found that, on average, Chilean water companies would need to reduce their inputs by 39% to achieve the same level of output since its average efficiency score was 0.61. The authors employed a double bootstrap DEA approach to estimate bias-corrected technical efficiency scores. Another study by Molinos-Senante and Sala-Garrido (2015) also identified a slowdown in productivity within the water industry during the period of 1997–2013. This deceleration was attributed to technical regress, which is consistent with the findings in our study. Furthermore, these studies reported efficiency losses within the industry. Sala-Garrido et al. (2019) conducted another study using DEA techniques to assess the impact of undesirable outputs, such as water leakage and unplanned interruptions, on the productivity of Chilean water companies. Their findings indicated that fully private companies exhibited a decline in productivity from 2010 to 2015, while concessionary companies experienced the opposite trend. Both types of companies, however, encountered efficiency losses. Specifically, the average annual change in efficiency was −0.04% for fully private companies and −1.03% for concessionary companies. The consistency between our study and these previous findings further reinforces the understanding of efficiency and productivity dynamics within the Chilean water industry.

Table 3
Pearson correlation matrix among cost and quality of service efficiency estimations.

	Standard SFA	BSFA	StoNED
Standard SFA	1.000		
BSFA	0.987	1.000	
StoNED	0.906	0.916	1.000

All estimates are statistically significant from zero at 1% confidence level.

Fig. 2 reports the CQoS efficiency estimates under the different models by ownership type. Full private and public water companies were more efficient than concessionary ones. The BSFA and StoNED frontier models showed that the public water company slightly performed better than full private ones, whereas the opposite was true if we look at the CQoS efficiency scores from the standard SFA model. Our results are consistent with Molinos-Senante and Sala-Garrido (2015) and Molinos-Senante et al. (2018) who found that full private companies performed slightly better than concessionary companies. However, considerable cost inefficiencies exist for all companies. We note that across the different frontier models, full private water companies should reduce costs, non-revenue water and unplanned water supply interruptions between 31.7% and 46.6%.

According to Fig. 2 estimations, the CQoS efficiency scores obtained from the standard SFA follow a downward trend over time, whereas the ones obtained from the BSFA and the StoNED models followed a small but stable upward trend. These models showed an annual increase in efficiency of 0.51% and 0.18% on average, respectively for full private water companies. In contrast, efficiency decreased by 0.58% per year on average based on the standard SFA model. As for concessionary water companies, the results showed that they should considerably improve their daily operations. This could be done by moving to a more efficient allocation of resources and adopting best industry's practices. Concessionary could catch-up with the most efficient companies in the sample

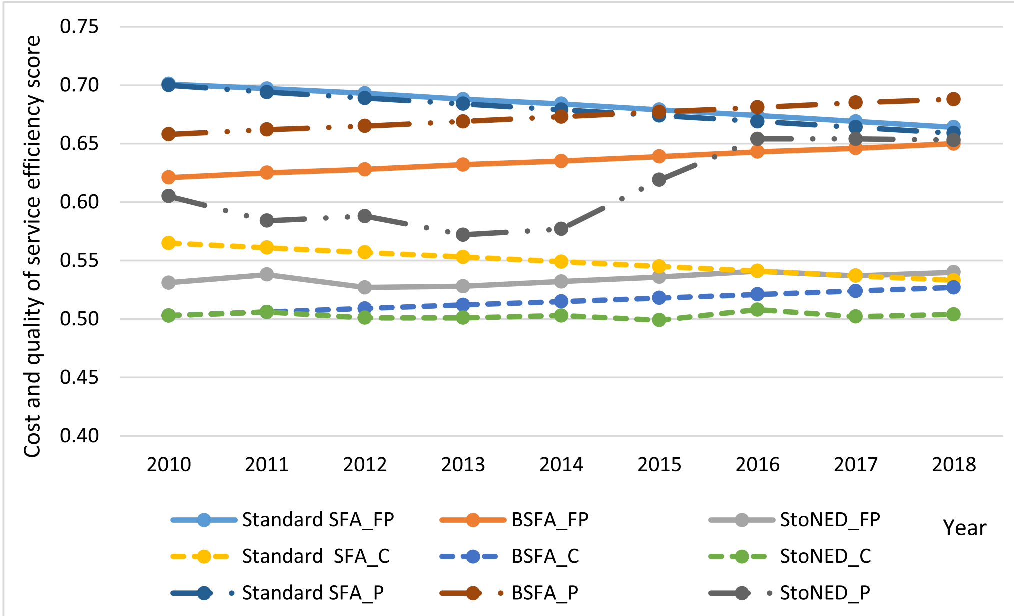

Fig. 2. Average cost and quality of service efficiency scores by ownership type (FP: full private; C: concessionary and; P: public).

by reducing costs between 45.1% and 49.7% according to different models. The BSFA model showed a small increase in efficiency which was at the level of 0.51% per year on average. In contrast, the StoNED model showed an immaterial change in efficiency. As far as the efficiency scores of the public is concerned, it ranged from 0.586 to 0.679. This means that the potential for cost savings for the public water companies varied between 32.1% and 38.8%. Based on the Bayesian SFA and StoNED models, its efficiency slightly increased at a rate of 0.51% and 0.89%, respectively per year on average.

Table 4 reports the average CQoS efficiency scores for each company over the years 2010–18 and their related ranking. We highlight the main points as follows. First, the same company is found as the most efficient one in the industry across the three methods employed to estimate CQoS efficiency scores. The same is evident with respect to the worst performing company. Thus, these findings corroborate the consistency and robustness of the three frontier methods. In general, the ranking of the companies is consistent across the models. However, there are some cases where the ranking differs. While the rankings between the standard SFA and BSFA are very similar, there are some differences between these models and the StoNED model. For instance, WaSC1 is ranked 14th based on its SFA scores but ranked 19th based on the StoNED model. Under the standard SFA the worst performing company (concessionary) reported an average efficiency score of 0.189, whereas the most efficient company needed to reduce its costs by almost 0.7% on average (full private). The potential cost savings for the most efficient concessionary company were at the level of 2.1% on average. These savings increase at the level of 17.44% and 28.40% on average under the BSFA and StoNED methods, respectively. Similarly, under these methods the reduction in costs required for the most efficient company to produce the same level of output were at the level of 7.6% and 24.5%, respectively.

In addition to ownership, there are various other factors that can influence the CQoS efficiency of water companies. Some of these factors are external to the operations and management of the companies, such as customer density, the main source of water, and seasonality in water

Table 4
Cost and quality of service efficiency estimations and ranking at company level: 2010–18.

Water company	Type of water company	Cost and quality of service efficiency scores			Ranking of water companies		
		Standard SFA	Bayesian SFA	StoNED	Standard SFA	Bayesian SFA	StoNED
WaSC1	Full private	0.415	0.439	0.230	14	14	19
WaSC2	Full private	0.390	0.405	0.313	18	15	17
WaSC3	Concessionary	0.601	0.604	0.620	10	10	7
WaSC4	Full private	0.539	0.540	0.581	12	12	11
WaSC5	Concessionary	0.525	0.521	0.594	13	13	9
WaSC6	Concessionary	0.189	0.190	0.194	20	20	20
WaSC7	Public	0.679	0.673	0.612	9	8	8
WaSC8	Concessionary	0.217	0.213	0.308	19	19	18
WaSC9	Concessionary	0.405	0.396	0.365	15	16	15
WaSC10	Full private	0.585	0.562	0.468	11	11	13
WaSC11	Concessionary	0.395	0.378	0.405	17	17	14
WaSC12	Concessionary	0.797	0.739	0.586	7	7	10
WaSC13	Full private	0.993	0.924	0.755	1	1	1
WaSC14	Concessionary	0.836	0.768	0.738	6	6	4
WaSC15	Full private	0.893	0.802	0.740	4	4	3
WaSC16	Full private	0.862	0.785	0.628	5	5	6
WaSC17	Full private	0.980	0.874	0.751	2	2	2
WaSC18	Full private	0.404	0.360	0.363	16	18	16
WaSC19	Full private	0.774	0.664	0.516	8	9	12
WaSC20	Concessionary	0.979	0.826	0.716	3	3	5

demand (Molinos-Senante et al., 2018; Sala-Garrido et al., 2022). Furthermore, there may be variables that are related to the lack of investment by water companies in improving the quality of service to customers. This could include issues such as aging infrastructure, insufficient maintenance, or inadequate technology adoption. These factors can have a significant impact on the overall efficiency and quality of service provided by water companies. It is important to note that the performance assessment conducted in this study goes beyond solely considering economic variables. It also incorporates measures of quality of service, such as non-revenue water and unplanned water supply interruptions. By integrating these aspects into the analysis, a more comprehensive evaluation of CQoS efficiency is achieved, capturing both economic and service-related dimensions of performance.

6. Conclusions and policy implications

Getting an insight of how efficient water and sanitation industry is could be of great value for regulated companies to provide services to their customers in an economic and environmentally sustainable way. This could be of great significance for the regulator when comparing costs and quality of service across companies to determine tariffs. Evaluating CQoS efficiency not only benefits the water company itself by identifying areas for improvement but also fosters a positive relationship with the water regulator. By demonstrating transparency, compliance, cost-effectiveness, and a commitment to service quality, efficient water companies can gain the trust and support of the regulator, leading to a more cooperative and collaborative regulatory environment.

Over the years, several approaches have been used to evaluate water companies' efficiency. These are mainly split between non-parametric approaches which include inefficiency only (deterministic) and parametric ones which incorporate both inefficiency and noise (stochastic). In this study, we, for first time, evaluate the CQoS efficiency of several water companies in Chile using three stochastic frontier approaches; the traditional SFA, the BSFA and the StoNED method. The main points can be summarized as follows. First, according to the three frontier models used in this study, an expansion of network, delivering more water to customers and treating more wastewater considerably could pressure on costs. Water companies are faced with higher costs when unplanned interruptions are frequent. In contrast, water leakage could potentially lead to lower costs suggesting that there is a positive relationship between cost efficiency and service quality. Moreover, technical regress is evident in the Chilean water industry. This means that the companies need to adopt new technologies which could help them reduce the costs of production.

According to this study, the three methodologies produce different scores. Thus, it is unreasonable to state that the regulator should use classical, BSFA or the StoNED approach to compare companies' costs when setting tariffs. The choice of the method needs the consent of both researchers, regulators and regulated companies. The common ground of these methodologies is that the water industry is characterized by technical regress and cost inefficiencies and thus, there is still room for efficiency improvements. Our study finally wants to highlight that any benchmark methodology requires a good knowledge of the industry, its inputs, outputs and quality of service before it is used by researchers and policy makers for benchmarking purposes.

The sensitivity of the CQoS efficiency scores to the model specifications is consistent with expectations and indicates that different methodologies can yield varying results. However, despite the differences in the absolute values of efficiency scores, a high correlation is observed among the scores obtained from the different models. This suggests that the rankings of the companies remain consistent across the models, highlighting the credibility and robustness of the employed methodologies. The water regulator plays a critical role in driving efficiency improvements. Designing and implementing policies that incentivize companies to become more efficient is essential. For example, the regulator could introduce financial rewards for companies that meet their performance targets in terms of operational costs and service quality, while imposing financial penalties on those that fail to meet these targets. Such measures would encourage companies to optimize their operations, reduce costs, and enhance the quality of service provided to customers. By actively promoting and enforcing efficiency-enhancing policies, the regulator can contribute to the overall improvement of the water industry, benefitting both the companies and the customers they serve.

This study not only contributes to the ongoing debate on selecting the most appropriate method for assessing the performance of water companies but also raises new research questions and policy-oriented considerations. Some of these questions include: i) How can parametric methods effectively integrate uncertainty? Uncertainty is inherent in many performance assessment models, and addressing this uncertainty is crucial for obtaining reliable and robust results. Future research could explore techniques or methodologies that explicitly incorporate uncertainty; ii) Which methods are most suitable when the number of observations is limited? Small sample sizes pose challenges for performance assessment models. Future research could explore alternative approaches, such as hybrid models that combine different techniques, to address the limitations associated with small sample sizes; iii) How can regulators effectively incorporate exogenous variables into the regulation of water company performance? The inclusion of external factors can provide a more comprehensive understanding of the determinants of performance and enable regulators to design more targeted and effective regulatory frameworks. Addressing these research questions will contribute to advancing the understanding of water company performance assessment and inform policy-making in the water industry.

CRediT authorship contribution statement

Alexandros Maziotis: Methodology, Writing – original draft. **Ramon Sala-Garrido:** Resources, Validation. **Manuel Mocholi-Arce:** Resources, Validation. **Maria Molinos-Senante:** Investigation, Writing – review & editing.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.strueco.2023.07.011.

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