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Benchmarking technical efficiency of water utilities in Chile under heterogeneity: A latent class frontier approach

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ABSTRACT

Benchmarking the technical efficiency of water utilities is essential for informing evidence-based regulatory decisions. However, conventional performance assessment models often rely on the assumption of homogeneity among utilities. This study addresses this limitation by applying Latent Class Stochastic Frontier Analysis to 22 Chilean water utilities over the period from 2010 to 2017. The average technical efficiency scores for companies in Class 1 and Class 2 were 0.91 and 0.88, respectively. Companies in Class 1 exhibited stable performance over time, with efficiency scores ranging from 0.88 to 0.92. In contrast, companies in Class 2 demonstrated greater variability, with scores ranging between 0.85 and 0.93.

1. Introduction

Assessing the technical and economic performance, i.e., the technical performance, of firms is essential for identifying strengths and weaknesses, benchmarking against industry standards, and adjusting strategies to enhance long-term viability (Chai et al., 2022; Macedo et al., 2023). In the context of monopolistic industries, such as the provision of water and sanitation services, benchmarking technical performance becomes even more critical, as utilities often lack endogenous incentives to improve efficiency (Mocholi-Arce et al., 2025). Furthermore, in some regulatory frameworks, the results of technical efficiency assessments can serve as an input for tariff-setting processes, thereby linking performance outcomes with financial incentives and regulatory decisions (Carvalho et al., 2023; Walker et al., 2019).

Given the importance of benchmarking the performance of water utilities, the past twenty-five years have seen a significant increase in empirical studies assessing technical efficiency in the water sector (Goh and See, 2021; Cetrulo et al., 2019). In the majority of these studies, efficiency is estimated under the assumption that all water utilities within the sample are homogeneous, implying that they operate under the same production technology. However, this assumption may be unrealistic, as utilities often differ in key aspects such as ownership structure, scale of operations, and geographic location (De Witte and Marques, 2009). These sources of heterogeneity can significantly influence performance, and thus, efficiency estimates and the resulting benchmarking conclusions are sensitive to this fundamental assumption (Ananda and Oh, 2023).

To account for heterogeneity in the assessment of technical efficiency of water utilities, several studies have employed the metafrontier approach (Ananda and Oh, 2023; De Witte and Marques, 2009; Maziotis and Molinos-Senante, 2024; Molinos-Senante and Maziotis, 2019, 2025; Yin et al., 2024). This method involves partitioning the sample into distinct groups based on a priori information regarding observable factors contributing to heterogeneity, such as utility size or ownership structure (Delnava et al., 2023; Jin et al., 2024). Efficiency scores are then estimated separately for each group using group-specific frontiers, while a common technological frontier, i.e., the metafrontier, is estimated for the entire sample to facilitate cross-group comparisons (Du et al., 2023). However, a key limitation of this approach arises when the analyst lacks sufficient information to accurately identify the sources of heterogeneity, or when heterogeneity stems from unobservable factors, such as organizational culture, managerial practices, or variations in local regulatory environments. Additionally, water utilities are often simultaneously influenced by multiple heterogeneous dimensions, which further complicates their classification into mutually exclusive groups. These challenges undermine the validity of direct comparisons and underscore the need for advanced methodological approaches that can capture complex and multifaceted heterogeneity.

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Addressing the challenge of unobservable heterogeneity is essential for producing robust and meaningful technical efficiency assessments in the water sector. However, as reviewed by Ben Amor and Mellah (2023), econometric approaches to account for unobservable heterogeneity in the water sector are scarce. This study aims to overcome this limitation by incorporating unobservable sources of heterogeneity in the evaluation of the technical efficiency of water utilities. To illustrate the implications of ignoring utility heterogeneity, we compare the results of the proposed approach with those obtained using a conventional model that assumes all utilities are homogeneous. The case study focuses on the Chilean water sector, which is characterized by significant geographic diversity, varying ownership structures (including public, private, and mixed utilities), and institutional complexity. These structural features introduce meaningful heterogeneity across utilities, suggesting that a differentiated benchmarking approach may be more appropriate than uniform, "one-size-fits-all" comparisons under certain conditions. Applying latent class stochastic frontier analysis (LCSFA) in this context provides not only methodological value but also practical insights for regulators seeking to develop fair and credible performance evaluation frameworks.

Previous studies have assessed the technical efficiency of Chilean water utilities using both parametric and non-parametric approaches. Among non-parametric methods, data envelopment analysis (DEA) has been the most widely applied (Sala-Garrido et al., 2023a, 2023b; Mocholi-Arce et al., 2022; Molinos-Senante et al., 2016), primarily for comparing the performance of fully private versus concessionary companies. However, these approaches require a priori classification of utilities into predefined groups and, therefore, cannot capture unobserved heterogeneity across firms. In terms of parametric approaches, stochastic frontier analysis (SFA) is the most commonly used method for evaluating the efficiency of Chilean water utilities (Maziotis et al., 2023; Molinos-Senante and Maziotis, 2019). Like DEA, these studies estimate individual efficiency scores but assume a single frontier, thus overlooking potential unobserved structural differences among utilities. In contrast, the LCSFA applied in this study offers a novel contribution by explicitly modeling unobserved heterogeneity through the identification of latent groups, each with its own production frontier. This approach enables a more flexible and context-sensitive assessment of efficiency, better suited to the structural diversity of the Chilean water sector.

2. Methodology

To account for unobservable heterogeneity in the assessment of technical efficiency of utilities, a wide range of approaches has been developed. These include random parameters models (e.g., Greene, 2005a), which allow frontier parameters to vary continuously across units; true random effects (TRE) and true fixed effects (TFE) models (Greene, 2005b), which separate time-invariant heterogeneity from inefficiency; and latent class models, which capture unobserved heterogeneity by probabilistically grouping units into discrete segments with distinct frontiers (Orea and Kumbhakar, 2004). Other approaches include semi-parametric and non-parametric models, such as generalized additive models (GAMs) and local likelihood estimation, which relax assumptions about the functional form.

While all these approaches have positive features, LCSFA offers selveral advantages that are particularly relevant in the context of this study. First, interpretability: LCSFA assigns utilities to a small number of latent groups, each with its own estimated frontier and inefficiency structure, which regulators can interpret as representing distinct operational or structural regimes (e.g., by size, region, or ownership type). Second, empirical feasibility: Compared to fully flexible random coefficients models, LCSFA is less demanding in terms of sample size and computational complexity, which is critical when working with a relatively small and regulated utility sector such as Chile's. Third, and most importantly, policy relevance: the ability to benchmark performance within latent peer groups enhances the credibility and fairness of regulatory comparisons, thereby avoiding the pitfalls of applying a single benchmark to structurally different entities. Because of these positive features, the LCSFA approach was employed in this study (Orea and Kumbhakar, 2004).

Unlike the metafrontier approach, the LCSFA method does not require a predefined classification of utilities. Instead, group membership is determined endogenously based on utility-specific data, including inputs, outputs, and relevant environmental variables. In other words, LCSFA eliminates the need to impose any ex-ante assumptions regarding the classification of water utilities into homogeneous groups.

The latent class stochastic frontier production model is as follows (Lin and Du, 2014):

$$lny_{it}|_j = f(x_{it})|_j + \varepsilon_{it}|_j \tag{1}$$

where i denotes a water utility, t is time, and j captures the different classes. The vertical bar means that there is a different model for each class j (Ahimbisibwe et al., 2024).

It was assumed that each utility i belongs to one of the unobserved classes, indexed by j. Each class has its own stochastic frontier parameters $\left(\beta_j, \lambda_j, \sigma_j\right)$. The probability that unit i belongs to class j was modeled using a multinomial logit function:

$$\pi_{ij} = \Pr(C_i = j \,||z_i) = \frac{\exp(z_i\,\gamma_i)}{\sum_{m=1}^{J}\exp(z_i\,\gamma_m)} \tag{2}$$

where z_i is a vector of observed covariates affecting class membership, and the first class is used as a baseline with $\gamma_i = 0$ for identification. In the current study, z_i includes an intercept term only.

The likelihood function of each utility i at any time t, conditional on belonging to class j, can be expressed as follows:

$$LF_{itj} = f\left(y_{it}|x_{it}, \beta_j, \sigma_j, \lambda_j\right) = \frac{\Phi\left(\lambda_j\cdot\,\varepsilon_{it}|_j\big/\sigma_j\right)}{\Phi(0)}\;\cdot\;\frac{1}{\sigma_j}\cdot\varphi\left(\frac{\varepsilon_{it}|_j}{\sigma_j}\right) \tag{3}$$

where:

$$\varepsilon_{it}|_j = lny_{it} - \beta_j' x_{it}, \sigma_j = \left(\sigma_{uj}^2 + \sigma_{\nu j}^2\right)^{\frac{1}{2}} \tag{4}$$

$$\lambda_j = \frac{\sigma_{uj}}{\sigma_{\nu j}} \tag{5}$$

Φ and φ denote the cumulative distribution function and the probability density function of the standard normal distribution, respectively (Quiédeville et al., 2022). The overall likelihood function for each utility is derived as a weighted average of its class-specific likelihood functions, where the weights correspond to the prior probabilities of membership in each class j. Specifically, the unconditional likelihood for company i is given by:

$$LF_i = \sum_{j=1}^{J} P_{ij} LF_{ij}, 0 \le P_{ij} \le 1, \sum_j P_{ij} = 1 \tag{6}$$

The overall log-likelihood function is obtained by summing the logarithms of the individual likelihood functions across all observations, as follows (Barros, 2011):

$$logLF = \sum_{i=1}^{N} logLF_i = \sum_{i=1}^{N} log\sum_{j=1}^{J} P_{ij}\prod_{i=1}^{T} LF_{itj} \tag{7}$$

The log-likelihood function can be maximized with respect to the parameter vector $\left(\theta = \beta_j, \sigma_j, \lambda_j\right)$ using conventional maximum likelihood estimation techniques (Greene, 2005a). Once the parameters of the log-likelihood function are estimated, the posterior probabilities of class membership for each observation can be derived using Bayes' theorem

(Alvarez et al., 2012; Lin and Du, 2014), as follows:

$$P(j|i) = \frac{P_{ij}LF_{ij}}{\sum_{j=1}^{J} P_{ij}LF_{ij}} \tag{8}$$

Following prior research (Bokusheva et al., 2023; Dolšak et al., 2022; Yakath Ali and See, 2023), an input distance function is selected to represent the underlying production technology. The input distance function is particularly suitable for this context, as it assumes that firms seek to minimize input use for a given level of output. Moreover, it accommodates multiple inputs and outputs, making it appropriate for the complex nature of water company operations. Moreover, the input distance function does not require information on input prices, which is advantageous when price data are unavailable or unreliable (Liu et al., 2024; Mellah and Ben Amor, 2016).

The input distance function is defined in the input set $T(x)$, as follows:

$$d_I(x,y) = max\{\tau : (x/\tau) \epsilon T(x)\} \tag{9}$$

where $d_I(x,y)$ denotes the input distance function, which represents the maximum feasible proportional contraction of the input vector x using a scalar distance τ, while holding the output vector y constant.

If $d_I(x,y) = 1$, it indicates that the water utility under evaluation is operating on the frontier and therefore, is considered technically efficient. In contrast, a value of $d_I(x,y) > 1$ signifies inefficiency, implying that the utility could proportionally reduce its input usage while still producing the same level of output, thereby indicating room for improvement relative to its peers (Goh and See, 2023).

A translog functional form is selected to approximate the input distance function, as it is widely employed in empirical applications due to its flexibility and suitability for econometric estimation (Cullmann and Zloczysti, 2014; Saal et al., 2007; Molinos-Senante et al., 2018). To derive the frontier surface, also referred to as the transformation function, the input distance function is normalized such that $d_I = 1$ which corresponds to efficient production (Cullmann and Zloczysti, 2014).

By imposing the property of linear homogeneity in inputs (by dividing the inputs by the optimal input and rearranging), the translog input distance function for K inputs and M outputs can be expressed in the following form under the latent class stochastic frontier framework:

$$-\ln x_{Kit}|_j = \alpha_{0j} + \sum_{k=1}^{K-1} \beta_{kj} \ln(x_{kit}/x_{Kit}) + \frac{1}{2}\sum_{k=1}^{K-1}\sum_{l=1}^{K-1} \beta_{klj} \ln(x_{kit}/x_{Kit}) \ln(x_{lit}/x_{Kit}) + \sum_{m=1}^{M} \alpha_{mj} \ln y_{mit} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \alpha_{mnj} \ln y_{mit} \ln y_{nit} + \sum_{k=1}^{K-1}\sum_{m=1}^{M} \gamma_{mnj} \ln(x_{kit}/x_{Kit}) \ln y_{mit} + \sum_{m=1}^{M} \delta_{mj} \ln y_{mit} t + \sum_{k=1}^{K-1} \eta_{nj} \ln(x_{kit}/x_{Kit}) t + \pi_1 t + \frac{1}{2}\pi_2 t^2 + \sum_{p=1}^{P} \zeta_{pj}\xi_{pit} + v_{ijt} - u_{ijt} \tag{10}$$

where j denotes the latent class, ξ_{pit} represents a set of operating characteristics that may influence the input requirements of utility i at time t (Brea-Solis et al., 2017).

It should be noted that Eq. (10) assumes a composed error structure $\varepsilon_i = v_i - u_i$, where the noise term $v_i \sim \mathcal{N}(0, \sigma_v^2)$ and the non-negative inefficiency term $u_i \sim half \sim \mathcal{N}(0, \sigma_u^2)$ are independently distributed. Following standard practice in stochastic frontier analysis, the model was reparametrized in terms of:

$$\lambda = \frac{\sigma_u}{\sigma_v} \tag{11}$$

$$\sigma = \sqrt{\sigma_u^2 + \sigma_v^2} \tag{12}$$

This reparameterization is computationally convenient and allowed us to recover the original variances, which ensures both variance terms are positive:

$$\sigma_v = \frac{\sigma}{\sqrt{1+\lambda^2}} \tag{13}$$

$$\sigma_u = \frac{\lambda\,\sigma}{\sqrt{1+\lambda^2}} \tag{14}$$

The LCSFA model used in this study allows both the production frontier parameters and the distributional parameters (σ_v, σ_u) to vary across classes. This specification captures heterogeneity not only in technology but also in the stochastic structure of the composite error term, reflecting the possibility that utilities in different classes face distinct noise environments and inefficiency profiles. An alternative approach would constrain (σ_v, σ_u) to be equal across classes, attributing all heterogeneity to technological differences. However, this imposes a strong homogeneity assumption on inefficiency and noise that may not hold in practice, especially when comparing water utilities with divergent regulatory, geographic, or operational characteristics. For this reason, we opt for a fully flexible specification.

In latent class models, several approaches exist to compute efficiency scores. In this study, based on previous research (Sun et al., 2025), technical efficiency was calculated as the posterior-class-probability-weighted average of class-specific efficiency estimates, as shown in Equations (15) and (16). From a regulatory perspective, this approach is appropriate as it acknowledges classification uncertainty and avoids potentially significant misclassifications when posterior probabilities are diffuse (Johnes et al., 2022). Nevertheless, a class assignment, which assigns each unit to its most probable class or conditional mode, derives the mode of the full conditional distribution of u_i given data and estimated parameters rather than their means (Renner et al., 2021).

The technical efficiency of utility i at time t, relative to production technology associated with class j, can be estimated as:

$$TE_{it}|_j = E[exp(-u_{ijt})|\varepsilon_{ijt}] \tag{15}$$

Based on Equation (7), the technical efficiency of utility i at time t can be further estimated as (Lin and Du, 2014):

$$TE_{it} = \sum_{j=1}^{J} P(j|i) \times TE_{it}|_j \tag{16}$$

A critical step in applying the LCSFA approach is determining the optimal number of latent classes into which the full sample of companies should be partitioned (Greene, 2003; Orea and Kumbhakar, 2004). To this end, and following the methodology proposed by Barros (2011), model selection criteria are employed, specifically, the Akaike Information Criterion (AIC) and the Schwarz Bayesian Information Criterion (SBIC).

$$AIC = -2logLF(j) + 2\omega \tag{17}$$

$$SBIC = -2logLF(j) + log(\psi)^*\omega \tag{18}$$

where $logLF(j)$ denotes the value of the log-likelihood function for a model with j latent classes, ω represents the number of estimated parameters, and ψ is the number of observations (Barros, 2011). The model with the lowest AIC or SBIC value is considered the most appropriate specification, as it achieves the optimal balance between goodness of fit and model parsimony (Cullmann and Zloczysti, 2014).

We selected the number of latent classes using standard information criteria (AIC and BIC). Nevertheless, an alternative strategy would involve hypothesis testing, for instance, testing whether specific coefficients or distributional parameters are equal across classes. However, in latent class models, such tests often involve parameters on the boundary of the parameter space, which complicates the use of standard likelihood ratio or Wald tests (Gudicha et al., 2017). Moreover, joint testing of class invariance across multiple parameters is computationally intensive and can be sensitive to initial conditions. Recent methodological contributions have made advances in this area. In particular, Stead et al. (2023) discuss the distribution of likelihood ratio statistics in latent class and finite mixture stochastic frontier models and propose procedures to address these challenges. While these developments are highly relevant, in applied work, information criteria remain the most widely used and practical tool for class determination, and therefore, we followed this approach in the present study. Nevertheless, we acknowledge the value of hypothesis testing as a complementary approach for future research.

To assess the robustness of the class structure defined according to the AIC and BIC criteria, we estimated the average posterior probability for each class. After computing P_{ij}, each utility i was assigned to the class with the highest posterior probability. Subsequently, the average posterior probability for class j was estimated as follows:

$$\overline{P_j} = \frac{1}{N_j}\sum_{i\in C_j} P_{ij} \tag{19}$$

where N_j is the number of utilities assigned to class j; C_j is the set of utilities assigned to class j and; P_{ij} is the posterior probability of utility i belonging to class j.

For comparative purposes, a standard stochastic frontier (SF) model is also estimated under the assumption of a common production frontier (i.e., homogeneous technology) for all observations (Cullmann, 2012). Moreover, all continuous input and output variables were normalized around their mean. Specifically, for each variable x, we computed:

$$\widetilde{x_i} = \log x_i - \frac{1}{N}\sum_{i=1}^{N}\log x_i \tag{20}$$

This centring ensures that the first-order translog coefficients can be interpreted at the geometric sample mean, which is essential for the meaningful calculation of scale elasticities and marginal effects.

3. Data sample and selection

The empirical analysis focuses on a sample of water companies that provide water and sanitation services across all administrative regions of Chile. With a length of 4270 km and a width ranging from 445 km to just 90 km, Chile exhibits significant geographical diversity, leading to considerable variations in water resource availability. In the north, the Atacama Desert, recognized as the driest desert in the world, receives annual precipitation of less than 250 mm, whereas in the south, annual precipitation exceeds 4000 mm. These geographic disparities, combined with socio-demographic factors, result in substantial differences in water availability per capita, which range from 75 m^3/year to 1,000,000 m^3/year. Chile also displays significant socio-economic diversity, which influences drinking water consumption per capita, varying from 127.2 L per day to 611.5 L per day, with a national average of 170.7 L per day (SISS, 2017). Due to these divergences and other contextual factors, water companies in Chile exhibit significant heterogeneity.

The heterogeneity of Chilean water companies is explicitly recognized in the establishment of the regulatory model used to set maximum water tariffs (D.F.L. MOP N. 70/88). Unlike other approaches that compare the performance of different water companies, Chile's regulatory framework is based on the concept of an efficient water operator from both economic and technical perspectives (Maziotis et al., 2023). This approach involves monitoring the actual costs incurred by each water company and comparing them with those defined as efficient, which vary among companies. Given the multitude of factors contributing to the heterogeneity of Chilean water companies, identifying and isolating these factors remains a complex and challenging task. The application of the LCSFA methodology enables the incorporation of unobservable sources of heterogeneity in the efficiency assessment of Chilean water companies.

The sample of water companies evaluated consists of 22 entities that provide both water and sewerage services during the period 2010–2017. Hence, it embraces 176 observations. The 22 water companies under evaluation provide service to around 95 % of the urban Chilean population across all administrative regions of the country (SISS, 2017). The data used in this study is publicly available and was obtained from the website of the national water regulator, the "Superintendencia de Servicios Sanitarios" (SISS).

The selection of variables is guided by the study's aim, i.e., to assess the technical efficiency of water companies, the availability of statistical data, and the fact that the evaluated Chilean water companies provide both water supply and sanitation services. Consequently, two input and two output variables are incorporated into the assessment. The output variables represent the two primary functions of water companies: i) the volume of drinking water supplied, measured in thousands of cubic meters per year, and ii) the number of customers receiving wastewater treatment services. Regarding the input variables, the first input is the operating expenditure (OPEX) for water and sewerage services, expressed in Chilean pesos per year.[1] The second input is capital expenditure (CAPEX), which is proxied by financial investments made to maintain and upgrade the network, also expressed in Chilean pesos per year.

CAPEX was used as a proxy for capital stock due to the inherent difficulties in obtaining reliable, direct data on capital stock. For water utilities, which involve long-lived assets like pipes, treatment plants, and pumping stations, CAPEX represents the ongoing effort to maintain, replace, and expand this critical infrastructure. While CAPEX does not fully capture aspects such as asset depreciation, technological obsolescence, or the cumulative nature of capital accumulation, its use as a proxy is well established in the literature (Lin and Du, 2014; Molinos-Senante et al., 2017).

To enhance the assessment, two additional contextual variables are included in the model: i) Customer density, defined as the number of customers divided by the network length, and ii) non-revenue water, expressed as the percentage of water abstracted but not billed. NRW is calculated as the difference between abstracted water and the sum of unbilled authorized consumption, apparent losses, and real losses (IWA, 2000).

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

4. Results and discussion

4.1. Classes of water companies

According to the methodological approach employed in this study, the optimal number of classes was determined using the AIC and BIC. The results indicate that the two-class model provides the best fit. Spe-

[1] On 27th March 2025, the exchange rate was 1 *US\$* ≈ 924 *CLP*

Table 1
Descriptive statistics of the variables used in this study.

Variables	Notation	Unit of measurement	Mean	Std. Dev.	Minimum	Maximum
Volume of water delivered	y_1^*	10^3 m^3/year	49,460	91,878	635	458,025
Customers receiving wastewater treatment	y_2^*	nr	720,253	1,301,650	5835	6,451,025
Capital cost[a]	x_1^*	10^6 CLP/year	17,817,750	27,023,346	23,568	103,470,352
Operating cost[a]	x_2^*	10^3 CLP/year	31,481,820	41,966,256	799,873	201,122,273
Customer density	ζ_1^*	nr/km	58.20	15.59	19.41	104.69
Non-revenue water	ζ_2^*	%	30.40	11.68	1.00	51.20

[a] Costs are expressed in 2017 prices.

Table 2
Sample statistics of the two classes of water companies.

	Class of water company	Volume of water delivered (10^3 m^3/ year)	Customers receiving wastewater treatment (nr)	Operating expenditure (10^3 CLP/year)	Capital expenditure (10^6 CLP/year)	Customer density (nr/km)	Non-revenue water (%)
Average	Class 1	32,161	431,140	19,871,933	8,536,048	53.84	27.10
	Class 2	61,435	920,408	39,519,435	24,243,543	61.21	32.68
Std. Dev.	Class 1	43,856	730,032	30,517,235	16,414,118	17.45	10.82
	Class 2	111,903	1,544,047	46,484,785	30,681,396	13.27	11.62

cifically, the AIC and BIC values for the single-class model were −198.4 and −193.5, respectively. For the two-class model, they were −269.7 and −259.6, respectively. In exploratory estimation of a three-class model, we encountered convergence issues, including instability in the inefficiency variance. This finding is consistent with known challenges in finite mixture stochastic frontier models, where one class may exhibit near-zero inefficiency variance, often due to skewness that is inconsistent with the assumed inefficiency distribution. One alternative is to restrict distributional parameters (σ_u, σ_v.) to be constant across classes. This approach may improve model identifiability and aid convergence

Table 3
Estimation of the parameters for the LCSFA model.

Variable	Notation	Class 1				Class 2				Standard single class			
		Coeff	S. Error	T-stat	p-value	Coeff	S. Error	T-stat	p-value	Coeff	S. Error	T-stat	p-value
Constant	α	−7.001	0.425	**−16.465**	0.000	1.041	0.970	1.073	0.283	−1.759	0.992	***−1.773***	0.076
Volume of water delivered	$\tilde{y}_1$	−0.667	0.334	**−1.995**	0.013	−0.363	0.156	**−2.331**	0.021	−0.501	0.165	**−3.032**	0.002
Customers wastewater treatment	$\tilde{y}_2$	−0.200	0.113	***−1.774***	0.078	−0.545	0.240	**−2.272**	0.023	−0.360	0.177	**−2.038**	0.043
CAPEX	$\tilde{x}_1$	0.310	0.054	**5.781**	0.000	0.194	0.049	**3.987**	0.000	0.330	0.066	**4.971**	0.000
Time	t	−0.021	0.016	−1.272	0.203	−0.108	0.013	**−8.069**	0.000	−0.081	0.020	**−4.116**	0.000
CAPEX^2	$\tilde{x}_1 * \tilde{x}_1$	−0.014	0.045	−0.303	0.762	−0.188	0.049	**−3.860**	0.000	0.048	0.071	0.671	0.502
Volume of water delivered*CAPEX	$\tilde{y}_1 * \tilde{x}_1$	−0.009	0.106	−0.086	0.932	0.135	0.114	1.183	0.237	−0.027	0.083	−0.325	0.745
Customers wastewater treatment*CAPEX	$\tilde{y}_2 * \tilde{x}_1$	0.077	0.114	0.680	0.496	0.163	0.143	1.135	0.256	0.003	0.078	0.040	0.968
Volume of water delivered^2	$\tilde{y}_1 * \tilde{y}_1$	0.369	0.202	***1.828***	0.069	−0.418	0.233	***−1.797***	0.075	−0.440	0.286	−1.541	0.123
Customers wastewater treatment^2	$\tilde{y}_2 * \tilde{y}_2$	0.507	0.247	**2.058**	0.041	−0.480	0.272	***−1.768***	0.078	−0.852	0.243	**−3.502**	0.001
Volume of water delivered*customers with service of wastewater treatment	$\tilde{y}_1 * \tilde{y}_2$	−0.494	0.252	***−1.959***	0.051	0.410	0.202	**2.036**	0.043	0.682	0.264	**2.580**	0.010
CAPEX*Time	$\tilde{x}_1 * t$	0.017	0.005	**3.645**	0.000	−0.035	0.007	**−4.849**	0.000	−0.002	0.006	−0.270	0.787
Volumes of water delivered*Time	$\tilde{y}_1 * t$	−0.026	0.012	**−2.228**	0.026	0.083	0.015	**5.708**	0.000	0.026	0.012	**2.190**	0.029
Customers wastewater treatment*Time	$\tilde{y}_2 * t$	0.035	0.012	**2.892**	0.004	−0.055	0.011	**−4.859**	0.000	−0.023	0.010	**−2.264**	0.024
Time^2	$t * t$	0.003	0.003	1.003	0.316	0.020	0.003	**7.607**	0.000	0.011	0.004	**2.602**	0.009
Non-revenue water	$\tilde{\zeta}_2$	0.040	0.013	**3.009**	0.003	0.550	0.066	**8.355**	0.000	0.028	0.021	1.353	0.176
Customer Density	$\tilde{\zeta}_1$	2.983	0.162	**18.362**	0.000	−0.325	5.310	−0.061	0.951	0.957	0.396	**2.417**	0.016
Customer Density^2	$\tilde{\zeta}_1 * \tilde{\zeta}_1$	−0.281	0.015	**−19.346**	0.000	−0.084	0.640	−0.131	0.896	−0.125	0.037	**−3.386**	0.001
Lambda	λ	0.872	0.063	**13.832**	0.000	0.602	0.033	**18.182**	0.000	1.538	0.287	**5.366**	0.000
Sigma	σ	0.023	0.011	**1.987**	0.049	0.034	0.013	**2.575**	0.011	0.162	0.001	**194.451**	0.000
Class 1			Lambda	Sigma			Sigma (u)	Sigma (v)					
Class 2			0.87	0.023			0.015	0.017					
Log-likelihood			0.60	0.034			0.017	0.029					

Dependent variable is OPEX; Bold indicates that coefficients are statistically significant at 5 % significance level; Bold italic indicates that coefficients are statistically significant at 10 % significance level.
All variables were normalized around their mean (Eq. (19)). The specification is a standard translog distance function. Coefficients on first-order terms represent marginal elasticities at the sample mean.

when estimating more than two classes. While not pursued in this study, this approach represents a helpful direction for future work in contexts with strong noise but weak inefficiency signals.

Based on prior probabilities, Class 1 and Class 2 account for 49.7 % and 50.3 % of the observations, respectively, whose main characteristics are summarized in Table 2.

Beyond the information criteria (AIC and BIC), an additional robustness check was performed to ensure the validity of the latent class specification. As is proposed in the methodology section, the average posterior probability of class membership was estimated. It provides a measure of how clearly each utility is classified into a given class. Values above 0.7 are typically interpreted as evidence of reliable class assignment (Álvarez et al., 2012). The estimated results, presented as supplemental material, provide consistent results with those from AIC and BIC, reinforcing the categorization of the utilities evaluated into two classes. Finally, we acknowledge the relevance of hypothesis testing procedures for class determination, as recently discussed by Stead et al. (2023), although the practical challenges of boundary parameters and small sample sizes constrained their application in this study.

Class 1 comprises smaller water companies in terms of both the volume of drinking water supplied and the number of customers receiving wastewater treatment. This class is also characterized by lower customer density and a lower percentage of non-revenue water. In terms of OPEX and CAPEX at the annual level, and considering their smaller operational scale, the average values for companies in Class 1 are lower than those observed in Class 2. This pattern persists even when OPEX and CAPEX are normalized per cubic meter of drinking water supplied, with Class 1 exhibiting lower unit costs than the companies in Class 2. Conversely, Class 2 includes larger water companies that serve a greater number of customers receiving wastewater treatment and distribute higher volumes of drinking water. These companies typically operate in areas with higher customer density and are associated with a greater percentage of non-revenue water.

4.2. Estimated parameters of the latent class stochastic frontier analysis

To assess the technical efficiency of each water company, the parameters of the input distance function were estimated, as presented in Table 3.

The first-order coefficients of the input and output elasticities are statistically significant, yet they differ markedly between the two classes. In Class 1, the elasticity of the volume of water delivered is higher than that of customers receiving wastewater treatment, whereas the opposite is observed in Class 2. This pattern indicates that, for Class 1 companies, higher input requirements are needed to deliver water compared to Class 2 companies. Conversely, treating wastewater is more cost-intensive for Class 2 than for Class 1. Specifically, holding other factors constant, a 1 % average increase in the delivery of water and in treating wastewater is associated with increases in input requirements of 0.667 % and 0.200 %, respectively, for Class 1 companies, and 0.363 % and 0.545 %, respectively, for Class 2 companies.

The estimated coefficient for CAPEX is 0.310 in Class 1 and 0.194 in Class 2, while that for OPEX is 0.690 in Class 1 and 0.805 in Class 2, values derived using the homogeneity property (Stead et al., 2023). These results suggest that Class 2 companies, which deliver more water and serve a higher number of wastewater customers, incur higher operating costs in their day-to-day operations compared to Class 1 companies. Moreover, the inverse of the sum of output elasticities provides an indication of the returns to scale at which a company operates (Dakpo et al., 2024; Saal et al., 2007). At the sample mean, both classes operate under increasing economies of scale; however, the magnitude of this effect differs between the two classes. A 1 % increase in outputs is estimated to result in a 0.867 % increase in total costs for Class 1 and a 0.908 % increase for Class 2, suggesting that scaling operations in Class 1 companies may yield lower cost increments, thereby making them more efficient than those in Class 2 companies.

Regarding performance changes over time, the negative coefficient of the time trend indicates a technical regression for the average company, although this effect is statistically significant only for Class 2 companies. The second-order output coefficients provide further evidence of technological differences across companies. For Class 2 companies, the squared terms for both water and sewerage outputs are statistically significant and negative, indicating that these outputs increase at a decreasing rate. Additionally, the positive and statistically significant interaction term suggests the presence of cost complementarities between water and sewerage services. In contrast, for Class 1 companies, the negative interaction term between the volume of water delivered and the number of wastewater-treated customers implies cost discomplementarities between these two services.

Technological differences between the two classes are also evident when examining operating characteristics. For Class 1 companies, increases in customer density are associated with rising costs, as indicated by the first-order coefficient for customer density; however, this impact diminishes at higher levels of customer density. Similar findings regarding customer density in the Chilean water industry have been reported in previous studies (Maziotis et al., 2021). Notably, this effect is not statistically significant for Class 2 companies. Furthermore, non-revenue water affects the input requirements of water companies, with the magnitude of this impact differing between the two classes, posing a critical issue for companies in Class 2.

For comparative purposes, a standard stochastic frontier (SF) model, assuming a common technology across all observations, was also estimated. The results of this model are also shown in Table 3. Several notable differences emerge when comparing the standard SF model with the LCSFA model. At the aggregate level, the standard SF model indicates that delivering water to end users is more cost-intensive than treating wastewater; in the LCSFA model, this result was observed only for Class 1 companies. Furthermore, the standard SF model reports stronger economies of scale for the overall sample compared to those observed separately for Class 1 and Class 2. The interaction term between the volume of water delivered and the number of customers receiving wastewater treatment is positive and statistically significant in the standard SF model, suggesting the existence of cost complementarities between water and sewerage services. However, this effect was evident only for Class 2 companies in the LCSFA model. Finally, the standard SF model also reveals statistically significant economies of customer density for the entire sample. In contrast, within the LCSFA framework, this effect is present only for Class 1 companies. These comparisons highlight the importance of accounting for technological heterogeneity in technical efficiency assessments.

4.3. Technical efficiency assessment

The evolution of average technical efficiency scores for water

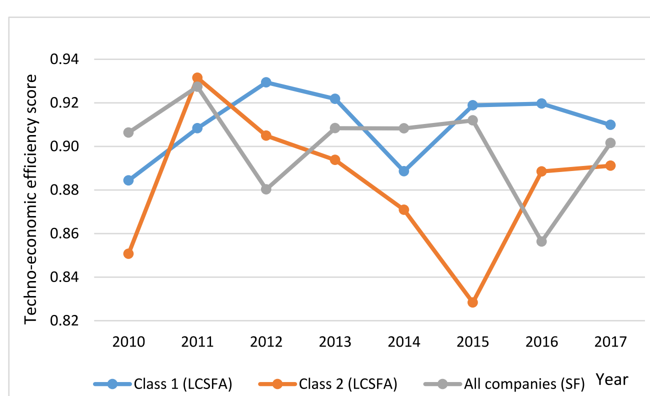

Fig. 1. Evolution of average technical efficiency of water companies.

companies classified into Class 1 and Class 2 using the LCSFA approach, along with those estimated for the entire sample using the standard SF model, is presented in Fig. 1. Although the average technical efficiency scores for the whole period (2010–2017) are relatively similar across the three groups, 0.91 for Class 1, 0.88 for Class 2, and 0.90 for the full sample based on the SF model, distinct trends emerge when examining their year-by-year evolution. For Class 1, technical efficiency scores remained relatively stable, ranging from 0.88 to 0.92. In contrast, Class 2 exhibited greater variability, with efficiency scores ranging from 0.85 to 0.93. Both classes experienced a notable increase in technical efficiency between 2010 and 2011. For Class 1, this upward trend continued, peaking in 2012, but was followed by a decline in 2013. From 2014 onwards, efficiency levels recovered and remained relatively stable throughout the study period. Conversely, Class 2 experienced a consistent decline in technical efficiency from 2012 onwards, with a brief recovery observed in 2016, approaching the levels of 2013. A potential explanation for the higher technical efficiency observed among Class 1 companies, compared to those in Class 2, lies in their greater returns to scale. This result suggests that Class 1 companies are better positioned to benefit from economies of scale. Consequently, mergers or consolidations among Class 1 companies may yield greater cost savings than similar strategies implemented among Class 2 companies. The trend observed for the full sample, as estimated using the standard SF model, diverges significantly from those of both Class 1 and Class 2. This finding suggests that ignoring heterogeneity among water companies and relying on a single average frontier may obscure important differences in efficiency dynamics.

Figs. 2 and 3 present the annual technical efficiency scores for each water company included in the analysis. Focusing on the companies classified within Class 1 (Fig. 2), WC7 stands out as the best-performing utility, with an average technical efficiency score of 0.964 over the period from 2010 to 2017. This finding implies that, on average, the potential for efficiency improvement was only 3.6 %. Notably, WC7 achieved a peak efficiency score of 0.996 in both 2012 and 2017, approaching the theoretical maximum of 1.000. WC7 is a relatively small utility, serving approximately 75,000 customers, but operates in a high-density area with 70 customers per kilometer of network, compared to the Class 1 average of 53 customers per kilometer. This finding suggests that the company's high level of technical efficiency may be attributed, in part, to economies of density. Conversely, WC15 recorded the lowest average technical efficiency score within Class 1, at 0.849. Unlike other companies such as WC11 and WC21, which exhibited considerable variability in their efficiency scores over time, WC15 consistently recorded relatively low scores, below 0.90, throughout the study period. WC15 is a moderately large utility, serving approximately 740,000 customers. A key factor contributing to its low efficiency performance is its persistently high level of non-revenue water, which ranged from 36.1 % to 45.4 % during the period under analysis. These substantial and sustained losses are likely a significant driver of the company's low technical efficiency.

Within the technical efficiency scores reported in Fig. 2, a significant decline is observed for WC11 in 2014, with its technical efficiency score dropping from 0.935 in 2013 to 0.623. Notably, the company recovered in the subsequent year, reaching a score of 0.907 in 2015. This temporary decline in performance was primarily due to a substantial increase in CAPEX during 2014, which coincided with a sharp rise in non-revenue water, from 13.3 % in 2013 to 34.7 % in 2014. In response, the utility undertook considerable investment aimed at reducing non-revenue water. While this investment temporarily reduced technical efficiency, it contributed to performance recovery in the following year. A similar pattern is evident for WC21 in 2017, when its technical efficiency score declined markedly from 0.995 in 2016 to 0.640. As with WC11, this regression in efficiency was driven by a significant increase in CAPEX. However, in this case, the additional investment was directed towards expanding wastewater treatment services, resulting in a 5.6 % increase in the population served compared to the previous year. These cases illustrate how short-term efficiency losses may result from strategic capital investments intended to improve service coverage or reduce operational inefficiencies, with potential long-term gains not immediately reflected in annual efficiency scores.

Analyzing the evolution of technical efficiency scores for water companies classified under Class 2 (Fig. 3), the average efficiency scores for the period 2010–2017 range from 0.746 to 0.967. This finding implies that the company with the lowest performance, WC16, has an average improvement potential of 25.4 %, whereas the best-performing company, WC13, shows an average improvement potential of only 3.3 %. WC16 consistently exhibited low efficiency scores throughout the assessment period, with a maximum value of 0.867 recorded in 2012.

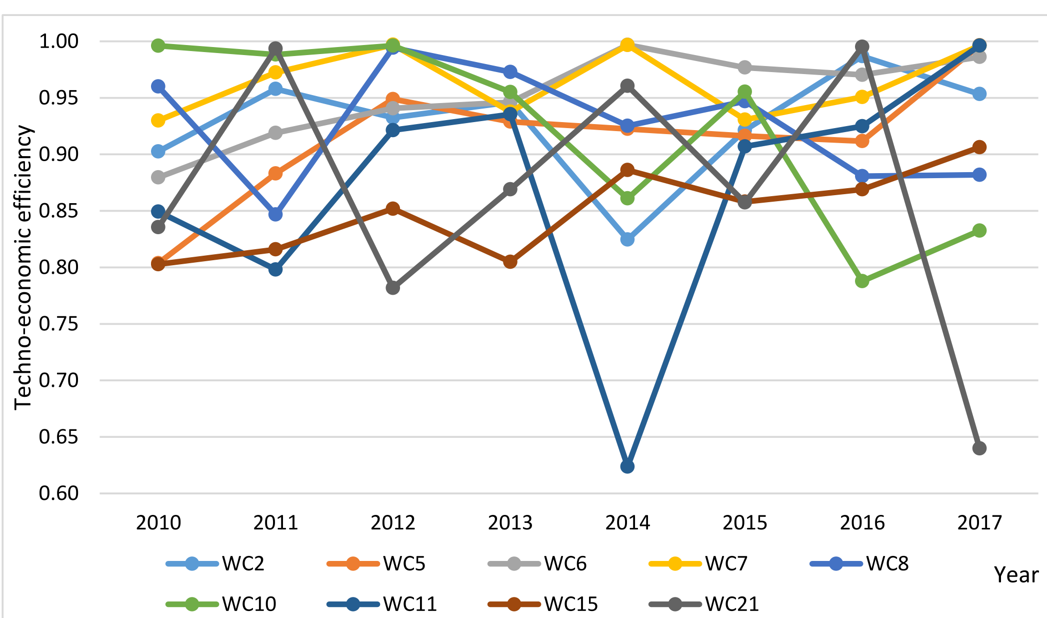

Fig. 2. Evolution of the technical efficiency of water companies embracing Class 1.

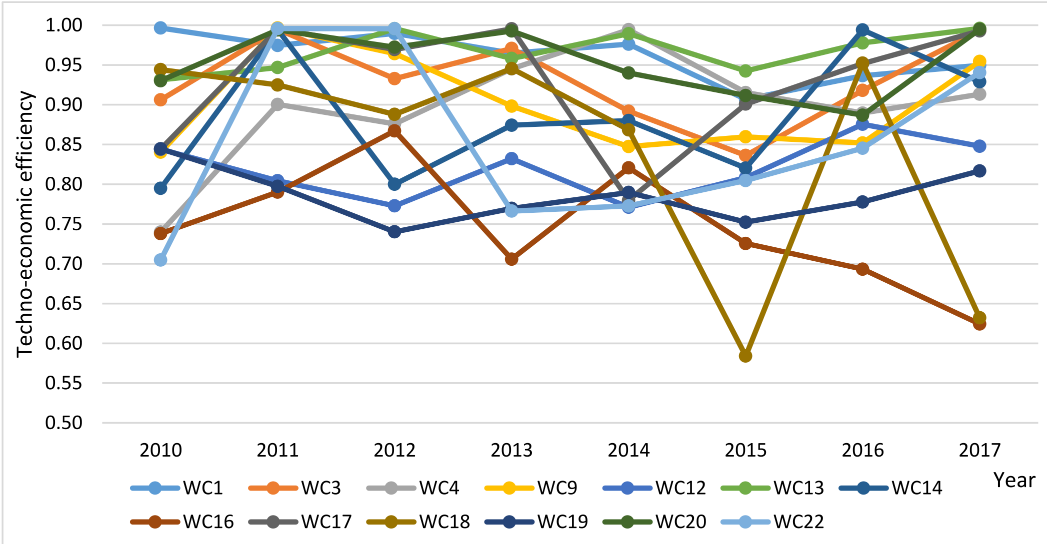

Fig. 3. Evolution of the technical efficiency of water companies embracing Class 2.

This company serves approximately 575,000 customers and is characterized by low water consumption per customer, averaging around five cubic meters per month. Water consumption is considered an output variable in the efficiency assessment and is inversely related to the company's performance. This issue is particularly relevant given the high fixed costs inherent in water utility operations (Marques et al., 2011).

In contrast, WC13 demonstrated consistently high technical efficiency scores over the study period, with a maximum value of 0.996 and a minimum of 0.931. A key driver of this strong performance is the company's low level of non-revenue water, which ranged between 24.1 % and 25.3 %, compared to the Class 2 average of 32.68 %. This result underscores the importance of incorporating operational variables, beyond conventional inputs and outputs, into efficiency assessments.

In terms of year-to-year variability in technical efficiency, WC18 presents a particularly notable case. Its efficiency score increased from a minimum of 0.584 in 2015 to a maximum of 0.952 in 2016, representing a remarkable 38.6 % improvement within a single year. This improvement was driven by favorable changes in both input and output variables. Specifically, the volume of drinking water supplied and the number of customers receiving wastewater treatment, both output variables, increased by 7.1 % and 3.6 %, respectively. Simultaneously, input variables experienced reductions, with OPEX and CAPEX decreasing by 9.1 % and 10.4 %, respectively.

In contrast, WC1 demonstrated a stable efficiency trajectory across the entire study period, with scores ranging from a minimum of 0.907 to a maximum of 0.996. This finding illustrates that while some water companies maintain consistently high performance, others experience significant fluctuations in efficiency. Such volatility can undermine economic sustainability and potentially affect the quality and reliability of service provision over time.

From a regulatory and policy perspective, the LCSFA model offers several key advantages over standard single-class approaches. Traditional models assume a common production frontier and a homogeneous distribution of inefficiencies across all utilities, which may not hold in settings where utilities differ in terms of scale, geography, regulatory environment, or infrastructure constraints. As a result, single-frontier models may produce biased or unfair efficiency benchmarks, penalizing some utilities simply because they operate under fundamentally different conditions. By contrast, the latent class approach identifies and estimates class-specific frontiers, grouping utilities into more comparable subsets. This approach enables regulators to benchmark performance within peer groups, thereby enhancing the credibility, fairness, and interpretability of efficiency assessments. In practice, this could inform the development of differentiated regulatory targets, tailored incentives, or context-specific support mechanisms. Furthermore, the model's probabilistic classification allows regulators to identify cases with uncertain group membership, flagging them for further review or sensitivity analysis. This built-in nuance enhances the transparency of performance evaluation and supports more evidence-based, equitable regulation, particularly in sectors marked by structural diversity.

The study further highlights the relevance of incorporating operational variables, such as non-revenue water, into the assessment of technical efficiency. Accordingly, performance benchmarking should be contextualized to reflect the specific operating environments in which individual water companies deliver water and sewerage services. A uniform evaluation framework that overlooks these contextual factors may produce misleading conclusions regarding efficiency. Moreover, the observed year-to-year variability in technical efficiency emphasizes the dynamic nature of company performance and the influence of capital investment cycles. Regulatory frameworks that rely exclusively on static efficiency indicators may misinterpret temporary declines in performance that are, in fact, linked to long-term strategic investments, such as network upgrades or expansions in wastewater treatment capacity. To address this, regulators are encouraged to adopt multi-year performance evaluation mechanisms that distinguish between short-term inefficiencies and forward-looking investments. Such an approach would help avoid disincentivizing necessary CAPEX that are critical to achieving long-term sustainability and service improvements.

Focusing on the specific results for Chilean water companies, the presence of increasing returns to scale across both latent classes suggests that technical efficiency gains may be achieved through scaling operations. Notably, the more pronounced scale economies observed in Class 1 indicate a greater potential for improving technical efficiency through strategic consolidation, the establishment of joint ventures, or the implementation of shared service arrangements among smaller utilities. In this context, policymakers should consider promoting incentives for voluntary mergers or the formation of regional consortia, particularly among Class 1 companies, to enhance cost-effectiveness while maintaining service quality. These collaborative strategies may also support infrastructure modernization and facilitate knowledge-sharing, without undermining local governance and accountability. Customer density has also emerged as a critical factor influencing cost structures, especially within Class 1 companies, where increasing density initially raises costs until a threshold is reached, beyond which economies of density begin to manifest. Consequently, regulatory benchmarking frameworks should incorporate customer density as a normalizing variable when evaluating efficiency performance. This adjustment would prevent the unintended penalization of utilities operating in sparsely populated or geographically complex areas, thereby enabling more accurate, equitable, and context-sensitive assessments of efficiency.

The findings of this study are consistent with a growing international literature emphasizing the critical role of heterogeneity in evaluating water utility performance. For instance, Ben Amor and Mellah (2023) employed a latent class approach to evaluate the cost efficiency of Tunisian water utilities, demonstrating that models assuming homogeneity underestimated inefficiency for firms operating in resource-scarce or complex environments. In the European context, Molinos-Senante and Maziotis (2019) also found that incorporating latent class or metafrontier structures significantly improved the reliability of benchmarking in heterogeneous systems such as the English and Welsh water industry. Notably, our finding that smaller Chilean utilities (Class 1) exhibit relatively stable and higher efficiency levels is consistent with those of Marques et al. (2011), who reported that decentralized utilities can outperform larger ones when economies of density and focused operational strategies are present. From a developing country perspective, Cetrulo et al. (2019) reviewed over 80 studies and emphasized that water utility performance in Latin America, Africa, and Asia is highly context-dependent, highlighting the importance of using heterogeneity-adjusted models, such as LCSFA or metafrontier frameworks, to inform policy. Moreover, recent studies from China (Yin et al., 2024), Malaysia (Goh and See, 2023), and Slovenia (Dolšak et al., 2022) have also highlighted the importance of incorporating environmental and institutional diversity into efficiency assessments.

The results of this study have direct relevance for the design and implementation of regulatory benchmarking frameworks. Traditional approaches to efficiency assessment often assume technological homogeneity, which can obscure structural differences among utilities and lead to biased benchmarks. By applying LCSFA, regulators can classify utilities into more comparable groups based on both observable and unobservable characteristics, enabling the development of class-specific performance frontiers. This refinement offers several practical advantages: it improves accuracy in tariff setting by ensuring that efficiency scores reflect the actual operating environment of each utility, allowing cost allowances in price reviews to be based on fair and achievable performance targets; it supports differentiated incentive schemes tailored to the technological and operational realities of each class, thus avoiding the penalization of utilities for factors beyond their control; it facilitates targeted performance improvement programs by guiding regulators toward interventions, such as leakage reduction or density-related infrastructure investments, where they are most likely to yield substantial efficiency gains; and it enables dynamic monitoring, with year-by-year class-specific efficiency trends helping to detect persistent inefficiencies and assess the impacts of regulatory changes over time. In the Chilean context, where the tariff-setting model already recognizes heterogeneity to some extent, the integration of LCSFA could enhance this process by replacing ex-ante classifications with empirically derived groupings, thereby strengthening the evidence base for regulatory decisions and ensuring that performance targets are both ambitious and realistic.

5. Conclusions

Assessing the technical efficiency of water utilities is essential for enhancing their overall performance. However, the presence of unobservable heterogeneity among utilities poses a significant challenge to the application of traditional benchmarking methodologies, which typically rely on the assumption of homogeneity across decision-making units. This study makes a novel contribution to the literature by explicitly accounting for unobservable heterogeneity through the application of LCSFA. Using data from the Chilean water industry, the findings reveal the existence of latent heterogeneity among the assessed utilities. Importantly, failure to account for such unobserved differences leads to biased estimates of technical efficiency, with potential implications for both regulatory and managerial decision-making.

The comparison between the results of the LCSFA and those of a conventional SF model, which assumes homogeneity among utilities, reveals significant discrepancies. The SF model tends to obscure class-specific dynamics, such as variations in output elasticities and the heterogeneous effects of contextual variables like customer density and non-revenue water on efficiency. Furthermore, while the SF model produces a smoothed temporal trend in average technical efficiency, the LCSFA identifies divergent efficiency trajectories across different latent classes of water utilities.

The analysis identified two latent classes of water utilities. Class 1 comprises smaller utilities characterized by lower customer density and reduced levels of non-revenue water, whereas Class 2 includes larger utilities operating in more densely populated areas and exhibiting higher leakage rates. The results reveal significant differences between these classes in terms of input-output elasticities, economies of scale, cost structures, and their responses to contextual variables. The average technical efficiency scores for utilities in Class 1 and Class 2 were 0.91 and 0.88, respectively. Regarding the temporal evolution of efficiency, companies in Class 1 exhibited relatively stable performance over time, with efficiency scores ranging from 0.88 to 0.92. In contrast, Class 2 exhibited greater variability, with scores ranging from 0.85 to 0.93. These findings highlight the importance of accounting for heterogeneity when evaluating efficiency dynamics and designing context-specific regulatory or managerial interventions.

From a policy perspective, the findings support the adoption of differentiated regulatory strategies that explicitly account for the heterogeneity among water utilities. Class-specific benchmarking and performance targets should be developed to ensure fair, accurate, and context-sensitive assessments. This approach would prevent the misinterpretation of technical efficiency outcomes and promote more equitable regulatory practices. Furthermore, incorporating key operational variables, such as non-revenue water and customer density, into benchmarking frameworks can significantly enhance the contextual relevance of performance evaluations, ultimately leading to more effective and targeted policy interventions.

This study has several limitations that should be acknowledged. First, the sample comprises only 22 Chilean water utilities over an eight-year period, which, although comprehensive within its national context, limits statistical power and generalizability to other settings. Second, although we explored a three-class model to test robustness, convergence issues arose, likely due to inconsistencies in skewness or vanishing inefficiency in one class, highlighting the known challenges in estimating finite mixture models with small samples. Third, the use of an input distance function enables multi-output modeling without requiring input price data; however, it precludes the analysis of allocative efficiency or cost minimization in an economic sense. Additionally, the use of annual CAPEX as a proxy for capital input represents a methodological limitation. While CAPEX captures investment flows in infrastructure, it does not fully reflect the accumulated stock of physical assets. As such, efficiency estimates may be influenced by short-term investment cycles rather than underlying changes in productivity. Future research should therefore explore the construction of capital stock series or alternative proxies to improve robustness. Finally, while the robustness checks included in this study are limited, the proposed LCSFA framework provides valuable insights. By capturing unobserved heterogeneity among Chilean water utilities, the approach yields informative and policy-relevant evidence to guide regulatory benchmarking and sectoral decision-making in Chile.

CRediT authorship contribution statement

Alexandros Maziotis: Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Maria Molinos-Senante:** Writing – review & editing, Software, Methodology, Conceptualization.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jup.2025.102076.

Data availability

Data will be made available on request.

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