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RESEARCH ARTICLE OPEN ACCESS

Assessing Eco-Efficiency in Municipal Solid Waste Management Integrating Heterogeneity: A Latent Class Stochastic Frontier Analysis

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Received: 12 November 2024 | **Revised:** 22 October 2025 | **Accepted:** 20 January 2026

Keywords: circular economy | eco-efficiency | latent class analysis | stochastic frontier analysis | technological heterogeneity | waste management

ABSTRACT

The measurement of eco-efficiency in the municipal solid waste (MSW) sector has garnered significant attention due to the substantial environmental impacts of unsustainable MSW management and the high operational costs associated with public service provision. Given the heterogeneous nature of municipalities providing MSW services, a robust method is necessary to account for technological differences when assessing eco-efficiency. This allows for consistent comparisons and reliable policy recommendations. In this study, we applied a latent class Stochastic Frontier Analysis (SFA) model that accommodates technological heterogeneity without requiring predefined groups of municipalities. A case study of 297 Chilean municipalities that collect, dispose of, and recycle MSW was conducted. The analysis identified two distinct groups of municipalities based on operational scale and waste management patterns. Group 1, composed of larger municipalities, exhibited lower eco-efficiency scores, with an average eco-efficiency score of 0.595. In contrast, Group 2, consisting of smaller municipalities, achieved a higher eco-efficiency score of 0.862. While population density influenced eco-efficiency in both groups, its effect was more pronounced in smaller municipalities. These findings underscore the need for targeted policies aimed at improving eco-efficiency in the MSW sector.

1 | Introduction

Municipal solid waste (MSW) generation is projected to increase from 2.1 billion tonnes in 2023 to 3.8 billion tonnes by 2050. The unsustainable management of MSW contributes significantly to the triple planetary crisis of climate change, biodiversity loss, and pollution (United Nations 2024). Additionally, MSW generation not only poses potential environmental risks but also imposes substantial direct costs on society. According to the United Nations (2024), the global cost of MSW management was estimated at US\$252.3 billion in 2020. In this context, achieving cost savings in the MSW sector could enable reinvestment into improving the quality and capacity of waste management services, and potentially lead to lower tariffs for citizens (Romano et al. 2020).

Policymakers have established the necessary legislation and regulatory frameworks to improve the economic and environmental management of MSW. For example, the European Union promotes the concept of a circular economy, which aims to minimize waste production and encourage the reuse of products within the economy (European Commission 2015). Similarly, Goal 11 (Sustainable Cities and Communities) of the United Nations' Sustainable Development Goals advocates for the efficient management of the waste sector (Llanquileo-Melgarejo and Molinos-Senante 2021). What becomes clear from these and other international policies is that the efficient management of MSW services must address both the economic and environmental aspects of waste management, commonly referred to as eco-efficiency (EE) (Romano and Molinos-Senante 2020). This approach not only focuses on reducing costs but also emphasizes minimizing the environmental impacts of waste management practices.

EE is defined as the production of more goods (outputs) and services using fewer resources (inputs) and with a lower environmental impact (Beltrán-Esteve et al. 2017). The prefix “eco” represents both environmental and economic dimensions, with EE assessments offering valuable insights from these two perspectives (Lo Storto 2021). Due to the growing importance of improving EE in the management of MSW, the body of literature on this topic has expanded significantly over the past 20 years. Since 2015, more than 50 research papers assessing the EE of MSW service providers have been published, reflecting the increasing attention to sustainable and efficient waste management practices.

From a methodological perspective, both parametric and non-paramdetric approaches have been employed to assess the EE of MSW service providers. The most commonly used non-parametric method in this context is Data Envelopment Analysis (DEA) (Simoes et al. 2012; Sarra et al. 2017; Guerrini et al. 2017; Exposito and Velasco 2018; Castillo-Giménez et al. 2019; Romano and Molinos-Senante 2020; Delgado-Antequera et al. 2021; Amaral et al. 2022; Chioatto et al. 2023; Alizadeh et al. 2023; Molinos-Senante et al. 2023, 2024; Lin and Rijal 2024; Sala-Garrido et al. 2024; Lo Storto 2024a, 2024b). DEA is a multi-factor productivity analysis model used for estimating the relative efficiencies of a homogeneous set of units. It is a deterministic approach, which means that any deviations from the efficient frontier are due to inefficiency only (Suárez-Varela et al. 2017). Therefore, it is sensitive to outliers. Conversely, stochastic frontier analysis (SFA) is the preferred parametric method to assess EE in the context of MSW (Vishwakarma et al. 2012; Sulemana et al. 2020; Fan et al. 2020; Doussoulin and Colther 2022). SFA also allows for the integration of multiple inputs and outputs in EE assessment. However, unlike DEA, SFA assumes a functional form for the underlying production technology. A key advantage of SFA is that it distinguishes between noise (random errors) and inefficiency, enabling more accurate estimates of EE for each unit by accounting for the potential influence of external, uncontrollable factors in the performance evaluation (Du et al. 2024).

Both studies using DEA and SFA to assess the EE of municipalities in the provision of MSW services share a common limitation. They assumed that all municipalities are homogeneous, which involves that they operate under the same technology. However, it is well known that municipalities have structural differences, such as population size, density, and geographical location, which can significantly influence their EE in providing MSW services. For a robust EE assessment and to ensure meaningful comparisons, it is crucial to account for the heterogeneity among municipalities. To address this limitation, pioneering studies such as Pérez-López et al. (2016) and Zafra-Gómez et al. (2023) applied the metafrontier approach to assess the cost efficiency of Spanish municipalities with different management models. In terms of EE, Romano and Molinos-Senante (2020) were the only ones to account for municipal heterogeneity. They compared the EE of Tuscan municipalities where MSW services were provided by public, mixed, and private firms. The metafrontier approach effectively integrates heterogeneity in efficiency assessments by allowing municipalities with different characteristics to be compared under a common framework (Ananda and Oh 2023). However, the metafrontier approach requires the sample of municipalities to be split a priori based on characteristics that are evident to the analyst, such as ownership structure (Lin and Du 2014). In the context of MSW services, municipalities may exhibit heterogeneity based on characteristics that are less easily observable, making it more challenging to group them appropriately.

An alternative to the metafrontier approach for integrating heterogeneity in efficiency assessments is the latent class SFA model, introduced by Greene (2002) and further developed by Orea and Kumbhakar (2004). Unlike the metafrontier method, the latent class SFA model does not require the sample to be pre-classified into groups before estimation (Dakpo et al. 2024), thus reducing the likelihood of misclassifying the sample and avoiding a poorly specified grouping (Renner et al. 2021). The latent class SFA model automatically classifies the sample into distinct groups, each with its own set of technologies and efficiency distributions (Orea 2020). Furthermore, the estimation of technological heterogeneity is performed in a single step, simplifying the process (Chang and Tovar 2017). By applying the latent class SFA model, policymakers can design more targeted, group-oriented policies, which can significantly enhance the decision-making process (Stetter et al. 2023). Despite the advantages of the latent class SFA approach, particularly in supporting more nuanced and effective policy-making for MSW service providers, to the best of our knowledge, this method has not yet been applied in this context.

The main objective of this study is to evaluate the EE of a sample of municipalities providing MSW management services, while incorporating municipality heterogeneity without the use of predefined groups. To achieve this, we apply the latent class SFA approach, which does not require any prior class specification. This study represents a novel approach by integrating EE assessment with parametric techniques and heterogeneous technologies, specifically in the context of the solid waste sector.

2 | Methodology

In this section we outline the methodology that was used to estimate the EE of several municipalities providing MSW services. The methodological approach used based on the latent class SFA model involves four main stages, as illustrated in Figure 1, which are described in detail as follows:

2.1 | Stage 1: Definition of the Input Distance Function

The first stage involves defining the production technology which is represented based on the input distance function

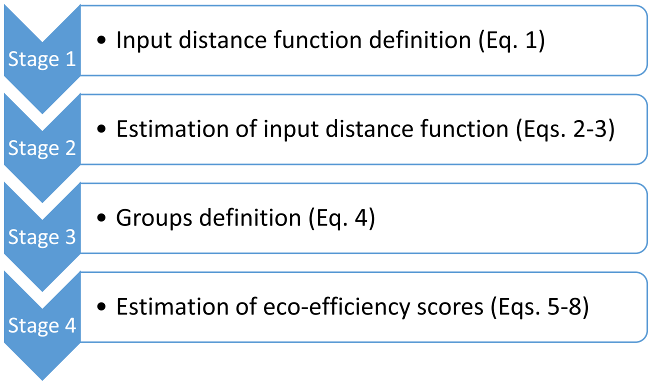

FIGURE 1 | Main methodological stages to estimate EE scores of municipalities accounting for heterogeneity.

framework. Distance functions provide a natural representation of multiple-output and multiple-input technologies (Aparicio and Pastor 2011). In the context of MSW management services, municipalities aim to minimize their operational costs and unsorted waste (inputs) for a given level of waste produced and recycled (outputs) (Lo Storto 2024a). Therefore, the input distance function is used to model the production technology for each group j. The input distance function measures the largest radial contraction of the input vector while ensuring that the production remains technically feasible, effectively capturing how much input can be reduced without compromising the production of outputs.

The input distance function is well-suited for EE analysis because it focuses on minimizing resource use (inputs) while holding service output levels constant. In the context of MSW management, this means assessing how much a municipality could reduce its operational costs and unsorted waste generation without decreasing the amount of waste it recycles. This aligns directly with the EE principle of "doing more with less"—delivering environmental services while using fewer financial and material resources (Barbosa et al. 2025).

The input distance function is defined as follows:

$$D_I(x,y)\big|_j = \max\left\{\varphi : \left(\frac{x}{\varphi}, y\right) \in PT\Big|_j\right\} \tag{1}$$

where $D_I(x,y)\big|_j$ is the input distance function for each group j, φ is the maximal contraction of inputs to produce the same level of output and $PT|_j$ is the production technology for each group j. It shows the set of all inputs, x, that are used to produce a set of outputs, y.

2.2 | Stage 2: Estimation of the Input Distance Function

The next stage in assessing the EE of municipalities is to specify and estimate the functional form of the input distance function defined in Equation (1). Consistent with previous studies (Doussoulin and Colther 2022), the translog input distance function was chosen due to its flexibility, which allows for variations in homogeneity among inputs and economies of scale across different units (Cullmann and Zloczysti 2014). The translog input distance function for each group of municipalities j under the latent class SFA framework is defined as follows:

$$\begin{aligned} \ln D_I(x,y)\big|_j = {} & \alpha_{oj} + \sum_{k=1}^{K} \beta_{kj} \ln x_{ki} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{klj} \ln x_{ki} \ln x_{li} \\ & + \sum_{m=1}^{M} \alpha_{mj} \ln y_{mi} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{N} \alpha_{mnj} \ln y_{mi} \ln y_{ni} \\ & + \sum_{k=1}^{K}\sum_{m=1}^{M} \gamma_{kmj} \ln x_{ki} \ln y_{mi} + \sum_{p=1}^{P} \zeta_{pj}\xi_{pi} + v_{ij} \end{aligned} \tag{2}$$

where $i$denotes municipality, k is the number of inputs, m is total number of outputs, ξ is a set of environmental variables that could impact inefficiency and v captures the error term which follows the normal distribution, $v_{ij} \sim N\left(0, \sigma^2_{vj}\right)$ (Kumbhakar et al. 2015).

After imposing homogeneity in inputs (Coelli and Perelman 1999), the estimable form of the translog input distance function under latent class is defined as follows:

$$\begin{aligned} \ln\left(\frac{1}{x_{Ki}}\right)\Big|_j = {} & -\ln\left(x_{Ki}\right)\Big|_j = \alpha_{oj} + \sum_{k=1}^{K-1} \beta_{kj} \ln x^*_{ki} \\ & + \frac{1}{2}\sum_{k=1}^{K-1}\sum_{l=1}^{K-1} \beta_{klj} \ln x^*_{ki} \ln x^*_{li} + \sum_{m=1}^{M} \alpha_{mj} \ln y_{mi} \\ & + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{N} \alpha_{mnj} \ln y_{mi} \ln y_{ni} \\ & + \sum_{k=1}^{K-1}\sum_{m=1}^{M} \gamma_{kmj} \ln x^*_{ki} \ln y_{mi} + \sum_{p=1}^{P} \zeta_{pj}\xi_{pi} + v_{ij} - u_{ij} \end{aligned} \tag{3}$$

where $x^*_{ki} = \frac{x_{ki}}{x_{Ki}}$ and u_{ij} denotes the eco-inefficiency of each municipality i in each group j. Eco-inefficiency (u_{ij}) is assumed to follow the half-normal distribution, $u_{ij} \sim N^+\left(0, \sigma^2_{uj}\right)$ (Orea and Kumbhakar 2004).

Since the assessment involves j groups of municipalities, the coefficients of the variables in Equation (3) vary for each group, thereby capturing the differences in technology among the different groups of municipalities, i.e., reflecting heterogeneous technologies (Cullmann and Zloczysti 2014).

2.3 | Stage 3: Definition of Groups Municipalities

The latent class SFA model in Equation (3) automatically classifies the sample into distinct groups taking into account heterogeneity. To determine the optimal number of groups the Akaike Information Criterion (AIC) is employed. The AIC represents the relative amount of information lost by a given model with a particular set of independent variables (Praveen Kumar et al. 2024). Lower values of AIC indicate that less information is lost when considering the set of independent variables (Ayadi and Hammami 2015). This implies that the model is capable of providing a better fit between the dependent and the independent variable (Zanini and Woodbury 2016):

$$AIC = -2 \log LF(j) + 2\theta \tag{4}$$

where AIC stands for the Akaike Information Criterion, $\log LF(j)$ is the value of the estimated log-likelihood function and θ denotes the number of variables (Barros 2011).

2.4 | Stage 4. Estimation of EE Scores

The computation of the EE scores for each municipality i and for each group j ($EE_i|_j$) as it is shown in Equation (3) involves estimating the parameters of the likelihood function using maximum likelihood estimation techniques (Orea and Kumbhakar 2004) whose main methodological steps are presenting on Equations (5–8):

$$EE_i|_j = E\left[\exp\left(-u_{ij}\right) | \varepsilon_{ij}\right] \tag{5}$$

The log-likelihood function for each municipality i for each group j is expressed as follows (Alvarez et al. 2012):

$$LF_{ij} = \frac{\Phi\left(\lambda_j \cdot \varepsilon_i|_j / \sigma_j\right)}{\Phi(0)} \cdot \frac{1}{\sigma_j} \cdot \varphi\left(\frac{\varepsilon_i|_j}{\sigma_j}\right) \tag{6}$$

where $\varepsilon_i|_j = -u_{ij} + v_{ij}, \sigma_j = \left(\sigma_{uj}^2 + \sigma_{vj}^2\right)^{\frac{1}{2}}, \lambda_j = \frac{\sigma_{uj}}{\sigma_{vj}}$. Moreover, in Equation (6) Φ and φ define the cumulative distribution function and standard normal density, respectively. Under the latent class SFA framework, the prior probabilities of group j membership can be used as weights to derive the unconditional likelihood of each municipality of each group (Lin and Du 2014):

$$LF_i = \sum_{j=1}^{J} P_{ij} LF_{ij}, 0 \leq P_{ij} \leq 1, \ \sum_j P_{ij} = 1 \tag{7}$$

Assuming that there are S total number of municipalities in the sample, then the overall likelihood can be defined as follows:

$$LF = \sum_{i=1}^{S} LF_i \tag{8}$$

Despite its strengths, the latent class SFA model for assessing the EE of municipalities in MSW management is not without limitations. First, the classification of municipalities into latent groups is sensitive to the chosen functional form, the specification of variables, and the assumed distribution of the error terms. Although the AIC was used to select the optimal number of classes, alternative model specifications could lead to different groupings. Second, the model does not explicitly account for potential endogeneity between certain inputs and outputs, nor does it capture dynamic effects that may evolve over time.

3 | Case Study Description

The sample consists of 297 municipalities that collected, disposed of, and recycled MSW in Chile in 2018. The total number of municipalities in Chile is 345, which corresponds to a population of 18,729,160 inhabitants (Censo 2017). Our dataset includes 14,711,119 inhabitants, representing more than 78% of the total population. Therefore, the sample can be considered both representative and sufficient for measuring the EE of the solid waste sector in Chile. Of the 48 Chilean municipalities excluded from the analysis, 25 were omitted due to a lack of statistical data, while 23 were categorized as outliers based on average and standard deviation values, following the methodology outlined by Tukey (1977). To assess the sensitivity of our results to the exclusion of these outliers, a robustness check was performed by re-estimating the latent class SFA model using the full sample of 320 municipalities, including the 23 outliers. The results confirmed the relevance of identifying and removing outliers to avoid biased EE estimation. These results are presented in Supporting Information S1.

Chile is a middle-income country with a gross domestic product (GDP) of 15,820 USD per capita in 2018 (World Bank 2018). The per capita generation of MSW increased from 294.6 kg in 2000 to 436.1 kg in 2018 (OECD 2004). This rise in waste generation has occurred within a regulatory framework where the adoption of the waste management hierarchy and circular economy principles is still in its early stages. It was not until 2016 that Chile implemented the Extended Producer Responsibility (REP) and Recycling Promotion Law. This law aims to reduce waste generation and promote recycling by holding producers and importers accountable for financing the proper management of waste generated from their marketed products. The law sets collection targets for six priority products, with targets starting to apply in 2023 (Law N° 20.920, 2016). However, the law is still in its early stages of implementation, as the necessary regulations have yet to be published (Sala-Garrido et al. 2024).

The lack of sustainable MSW management in Chile is also reflected in waste disposal practices, with landfilling being the dominant method, accounting for 80% of solid waste disposal (SINIA 2021). In contrast, recycling and other recovery alternatives remain limited, with rates below 5% (Araya-Córdova et al. 2021). The collection, transport, valorization, and final disposal of MSW in Chile are the responsibility of local authorities. However, in many municipalities, these activities are outsourced to private companies. MSW is primarily collected through door-to-door services (Valenzuela-Levi 2021). Recycling programs have emerged as independent local initiatives, depending largely on the available municipal budget (Valenzuela-Levi 2019). Approximately 25% of local authorities incorporate informal recyclers into their recycling policies. These informal recyclers, especially in poorer communities, often view recycling as a potential source of income (Valenzuela-Levi 2021).

To estimate the EE of municipalities, outputs and inputs were selected based on data availability and previous research (e.g., Simoes et al. 2010; Guerrini et al. 2017; Romano and Molinos-Senante 2020; Llanquileo-Melgarejo and Molinos-Senante 2021; Amaral et al. 2022; Lo Storto 2024b). In line with MSW recycling rates, two recyclable waste outputs, which are variables to be maximized, were included. The first output was the amount of glass collected and recycled, expressed in tons per year. The second output was the amount of organic waste collected and recycled, also measured in tons per year. These outputs—glass

TABLE 1 | Descriptive statistics of the variables used for estimating EE scores.

Variables	Unit of measurement	Mean	Standard deviation	Minimum	Maximum
Total costs	CLP/year	1,175,056	2,055,146	98	14,765,504
Glass recycled	Tons/year	89	302	0.0001	2759
Organic waste recycled	Tons/year	3053	45,078	0.0001	775,267
Unsorted waste	Tons/year	29,340	61,994	3.00	778,893
Population density	Inhabitants/km^2	1006	2965	0.11	18,386

TABLE 2 | Main characteristics of the two groups of municipalities.

Group of municipalities	Total cost (CLP/year)	Glass recycled (Tonnes/ year)	Organic waste (Tonnes/year)	Unsorted waste (Tonnes/year)	Population density (inhabitants/ km^2)
Group 1	1,254,942	95	3322	31,459	1039
Group 2	288,790	31	2	5265	623

and organic waste—were selected due to their representativeness and data availability. Organic waste comprises the largest portion of MSW in Chile and presents major environmental challenges due to its potential for greenhouse gas emissions if not properly managed. Glass, on the other hand, is widely recycled and benefits from relatively well-developed collection systems. Most importantly, these two waste streams are the most consistently and reliably reported across municipalities in Chile's National Waste Declaration System (SINADER). Although other recyclable fractions such as plastics or paper are also relevant, they were excluded from the analysis due to incomplete or inconsistent reporting across the sample. We acknowledge that the exclusion of other waste types could influence EE scores. However, we prioritized data integrity and reliability in our variable selection, which ultimately supports more robust EE estimation.

Two inputs were defined as variables to be minimized to improve EE. The first input was the total operating cost of providing collection and recycling services, expressed in Chilean pesos per year (Table 1). The second input was the amount of unsorted waste, measured in tons per year. Data sources for these variables were the National Waste Declaration System (SINADER) and the National System of Municipal Information (SINIM). Consistent with previous studies, population density was included in the assessment as an exogenous (contextual) variable (Agovino et al. 2020; Molinos-Senante et al. 2023). It was defined as the number of inhabitants divided by the area of the municipality. Table 1 provides the descriptive statistics of the variables used in the case study conducted.

4 | Results and Discussion

4.1 | Groups of Municipalities Defined

Before analyzing the results from the latent class SFA model based on group heterogeneity (please see Table 3 in Section 4.2), it is worth discussing first the groups that are defined when estimating the model. According to the AIC results, two groups of municipalities are defined (AIC = 664.4), as the AIC value for one group was larger (AIC = 688.2). Overall, it appears that the latent class SFA model splits the municipalities into small and large ones based on the volumes of recyclable and unsorted waste (see Table 2). The first group includes municipalities characterized by high operating costs and the collection and recycling of large amounts of glass and organic waste. However, a significant amount of waste remains unsorted. These municipalities tend to operate in densely populated areas, with an average population density of 1039 inhabitants per km^2. In contrast, the second group consists of smaller municipalities that collect and recycle relatively lower amounts of recyclable waste. These municipalities have lower operating costs and are located in areas with a lower population density, averaging 623 inhabitants per km^2.

4.2 | Parameters of the Input Distance Function

According to the methodological approach presented in Figure 1, the derivation of the EE of municipalities involves estimating the input distance function, whose estimated parameters are shown in Table 3. Regarding the significance of the parameters, the results indicate that the estimated coefficients for both output and input elasticities are statistically significant from zero. Additionally, they display the expected signs, with negative coefficients for outputs and inputs, indicating a proper relationship as expected. Thus, the input distance function appears to fit the observed data well (Cullmann and Zloczysti 2014). The prior probabilities for each group of municipalities indicate that 85.5% of the observations are classified in group 1, while 14.5% are in group 2, and this classification is statistically significant from zero.

The estimated coefficients of output elasticities differ between the two groups of municipalities and are all negative, as expected under the input distance function framework used in

TABLE 3 | Estimation of the input distance function parameters for both groups of municipalities.

	Group 1 of municipalities				Group 2 of municipalities			
Variables	**Coeff**	**St. Error**	***T*-stat**	***p*-Value**	**Coeff.**	**St. Error**	***T*-stat**	***p*-Value**
Constant	−7.470	0.594	**−12.568**	0.000	−9.837	0.207	**−47.461**	0.000
Glass recycled	−0.158	0.045	**−3.527**	0.000	−0.224	0.005	**−46.129**	0.000
Organic waste recycled	−0.112	0.033	**−3.373**	0.001	−0.098	0.005	**−20.260**	0.000
Unsorted waste	0.662	0.138	**4.808**	0.000	0.513	0.027	**19.144**	0.000
Glass recycled^2	−0.040	0.010	**−4.214**	0.000	−0.031	0.004	**−7.495**	0.000
Organic waste recycled^2	−0.018	0.007	**−2.718**	0.007	0.038	0.003	**12.102**	0.000
Unsorted waste^2	0.009	0.023	0.405	0.686	0.114	0.001	**135.044**	0.000
Glass*Organic waste	0.001	0.001	0.911	0.362	−0.004	0.001	**−5.045**	0.000
Glass*unsorted waste	−0.008	0.010	−0.750	0.453	−0.024	0.001	**−26.319**	0.000
Organic waste*unsorted waste	−0.021	0.009	**−2.237**	0.025	−0.024	0.003	**−8.859**	0.000
Population density	−0.318	0.026	**−12.137**	0.000	−0.497	0.014	**−35.245**	0.000
Sigma	1.227	0.082	**14.898**	0.000	0.320	0.069	**4.652**	0.000
Lambda	3.477	0.916	**3.796**	0.000	1.695	0.379	**4.473**	0.000

	Prior probabilities for each group membership			
Groups of municipalities	**Coeff**	**St. Error**	***T*-stat**	***p*-Value**
Group 1	0.855	0.032	**26.385**	0.001
Group 2	0.145	0.032	**4.462**	0.000
Log-likelihood	−322.2			

Note: Total cost is the dependent variable. Bold indicates that coefficients are statistically significant at 5% significance level.

this study. In group 1, a 10% increase in the collection and recycling of glass and organic waste is estimated to raise operating costs by 15.8% and 11.2% on average, respectively, indicating that both glass and organic waste contribute similarly to the costs of these municipalities. In contrast, in group 2 of municipalities, glass appears to be the major driver of costs. Specifically, a 10% increase in the collection and recycling of glass could lead to a 22.4% increase in operating costs. While organic waste recycling also plays a significant role in influencing costs for group 2 municipalities, its impact is relatively smaller. A 10% increase in the recycling of organic waste is estimated to increase operating costs by 9.8%, as indicated by the estimated coefficient (−0.098).

The estimated coefficients of the input elasticities vary between the two groups of municipalities. In group 1, the elasticity of unsorted waste is 0.662, indicating that the collection of unsorted waste is a significant driver of costs for large municipalities. This suggests that a 10% increase in the amount of unsorted waste could lead to a 66.2% increase in operating costs on average for these municipalities. For small municipalities (group 2), while unsorted waste still influences costs, its impact is smaller, with an elasticity of 0.513. This implies that for small municipalities, a 10% increase in unsorted waste could raise costs by 51.3%. In group 2 of municipalities, as the volume of unsorted waste grows, its elasticity also increases, as reflected by the positive sign of the squared terms in the coefficient. Additionally, for small municipalities, an increase in recycled glass and organic waste could reduce the amount of unsorted waste, potentially alleviating some of the pressure on operating costs. Although managing recyclable waste could slightly increase costs, it would bring significant environmental and public health benefits. This relationship was also significant for large municipalities but was primarily observed between organic waste and unsorted waste.

The stronger effect of population density on the EE in smaller municipalities may be attributed to infrastructure limitations and logistical challenges. In these areas, modest increases in population density can lead to disproportionately higher operational burdens due to the lack of scalable waste management infrastructure, such as transfer stations or local recycling hubs. Furthermore, service delivery routes in small municipalities tend to be less optimized, and staff or equipment may be insufficiently scaled to handle denser populations. These conditions can reduce collection efficiency and increase the volume of unsorted waste, thereby lowering EE. In contrast, larger municipalities often benefit from more developed infrastructure and professionalized waste management systems that mitigate the marginal cost impact of higher population density.

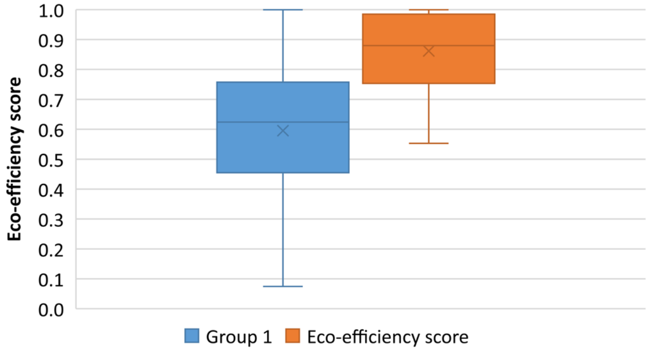

FIGURE 2 | Statistics of the EE scores for groups 1 and 2 of municipalities.

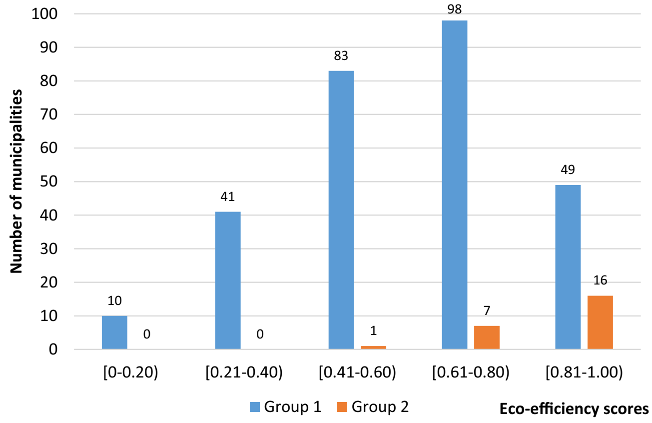

FIGURE 3 | Histogram with distribution of EE scores.

4.3 | Eco-Efficiency Scores of Municipalities

Figure 2 presents the key statistics of the estimated EE scores for the two groups of municipalities. The findings indicate that the average EE of municipalities in group 1 was significantly lower than that of group 2, suggesting that larger municipalities are less eco-efficient than smaller ones. Specifically, the mean EE for group 1 municipalities was 0.595, implying that large municipalities could reduce their operating costs and the amount of unsorted waste by nearly 40% while maintaining the same levels of glass and organic waste recycling. In contrast, the average EE for group 2 municipalities was 0.862, indicating that small municipalities have the potential to save approximately 13.8% in operational costs and unsorted waste.

Focusing on the best and worst municipalities, notable differences are observed between the two groups. Thus, Figure 2 shows that municipalities in group 1 exhibit greater heterogeneity in terms of EE, while municipalities in group 2 are more homogenous in their EE performance. In group 1, the municipality with the worst economic and environmental performance has a significant gap to close in order to catch up with the most efficient municipalities in the group. On average, the worst performer in group 1 reported an EE score of 0.075, indicating substantial room for improvement. The highest EE score in this group was 0.999, meaning it is close to the maximum possible value (1.0), but still not fully eco-efficient. In contrast, the EE scores for municipalities in group 2 ranged from 0.553 to 1.000. This suggests that the worst-performing municipality in group 2 faces far fewer potential economic savings and reductions in unsorted waste generation compared to those in group 1.

Figure 3 presents the distribution of municipalities across different EE score ranges for two groups, "group 1" and "group 2," represented by blue and orange bars, respectively. The majority of municipalities in group 1 are distributed in the middle EE score intervals. Most municipalities are concentrated in the score ranges [0.61–0.80] (98 municipalities) and [0.41–0.60] (83 municipalities). A relatively smaller number of municipalities fall in the highest score interval, with 49 municipalities in the [0.81–1.00] range. Most municipalities in group 2 are concentrated in the highest EE score range [0.81–1.00] (16 municipalities), while 7 municipalities fall within the [0.61–0.80] range. The [0.41–0.60] range has just 1 municipality, and there are no municipalities in the lowest two score intervals [0–0.20] and [0.21–0.40]. In general, group 1 has a wider distribution of municipalities across all EE score ranges, with a notable concentration in the middle intervals. In contrast, group 2 has fewer municipalities overall but shows a higher concentration in the upper score ranges, indicating higher economic and environmental performance.

The methodological approach used in this study also enabled the ranking of municipalities based on their EE. Table 4 presents the performance of the ten most eco-efficient municipalities from both group 1 and group 2. In group 1, "Viña del Mar" was identified as the best performer. This medium-sized municipality, with a population of 334,248 inhabitants (Censo 2017), is the most populous city in the Valparaíso Region. In terms of MSW management, "Viña del Mar" stands out for recycling a significant percentage of glass (around 5% of total MSW generated) compared to its peers. Additionally, it operates with lower-than-average operating costs, estimated at 25,023 CLP/ton, compared to the sample average of 40,097 CLP/ton. This combination of strong economic performance and higher rates of glass recycling contributed to its top EE score within group 1. In group 2, "Empedrado" was identified as the best performer. This small municipality, with a population of 4142 inhabitants (Censo 2017), is located in the Maule Region in central Chile. Despite its small size, since 2014, "Empedrado" has adopted a local environmental ordinance aimed at enhancing sustainable MSW management. This ordinance promotes educational campaigns and recycling initiatives in schools and neighborhood organizations. As a result of these efforts, "Empedrado" demonstrated the best economic and environmental performance among the municipalities in group 2, achieving the highest EE score in its group.

The results from the assessment of EE scores across the two groups of municipalities have several important policy implications, discussed as follows:

Lack of economies of scale: The findings indicate that larger municipalities (group 1) have significantly lower EE scores (average 0.595) compared to smaller municipalities (group 2, average 0.862). This suggests that the assessed municipalities do not benefit from economies of scale in MSW management. The literature on this topic is mixed, with some studies (Pérez-López et al., 2018; Delgado-Antequera et al. 2021; Lo Storto 2024b) showing evidence of economies of scale, while others (Guerrini

TABLE 4 | Best performers in groups 1 and 2.

Group 1			Group 2		
Municipality	Eco-efficiency score	Population density (inh/km^2)	Municipality	Eco-efficiency score	Population density (inh/km^2)
Viña del Mar	0.999	2740	Empedrado	1.000	5.32
Negrete	0.930	39	Galvarino	0.999	7.30
Olivar	0.917	206	Perquenco	0.999	10.77
Curacautín	0.899	8	Río Negro	0.999	5.52
Panquehue	0.899	31	Independencia	0.999	14,326
Contulmo	0.891	3	Futaleufú	0.989	1.45
Quilaco	0.889	2	San Rosendo	0.972	31.60
San Miguel	0.889	10,795	Codegua	0.967	24.46
Providencia	0.886	10,149	Curarrehue	0.966	1.94
Lo Prado	0.884	13,750	Algarrobo	0.934	61.93

et al. 2017; Expósito and Velasco 2018) found the opposite. The results from this study suggest that larger municipalities could benefit from targeted policies aimed at improving their EE, such as the adoption of technical measures to reduce operating costs given the large volumes of MSW that need to be collected and disposed of.

Variability in EE scores among larger municipalities: Group 1 municipalities show considerable variability in EE scores. Therefore, policy frameworks should be flexible and adaptable to the specific needs of different municipalities within this group. Low-performing municipalities could benefit from more direct support, such as technical assistance or financial incentives to adopt best practices from high-performing municipalities. Scaling successful strategies from high performers to other municipalities could be an effective option. Educational campaigns and localized environmental ordinances that promote recycling can also serve as models for replication in other municipalities.

Promoting regional cooperation: The results suggest that municipalities could benefit from regional cooperation, where high-performing municipalities support others through knowledge sharing and collaboration on waste management solutions. Policies that encourage inter-municipality partnerships could help lower-performing areas adopt proven techniques and improve their EE. Such cooperation could include sharing resources, strategies, and best practices in MSW management, which would help bridge the performance gap between municipalities (Molinos-Senante et al. 2024).

5 | Conclusions

Given the significant potential environmental impacts of unsustainable MSW management and the high operational costs associated with its public provision, assessing the EE of MSW service providers is crucial. The heterogeneous nature of the MSW sector necessitates accounting for differences in technologies to ensure consistent and meaningful comparisons. A latent class SFA model was applied to measure the EE of municipalities, acknowledging the diverse technologies they employ.

The case study focuses on the collection, recycling, and disposal services of several municipalities in Chile. The main results are summarized as follows: First, the sample was divided into two groups, highlighting the heterogeneity of the municipalities evaluated. The first group consists of municipalities that collect large amounts of recyclable and unsorted waste in densely populated areas. The second group includes municipalities with lower operational costs that handle smaller amounts of waste in relatively densely populated areas. The econometric results revealed that, for municipalities in group 1, the collection and recycling of glass and unsorted waste contribute equally to costs. In contrast, in group 2, the collection of glass significantly influences costs more than other factors. Unsorted waste has a greater impact on the costs of large municipalities compared to small ones. Additionally, while population density influences costs in both groups, its effect is more pronounced in small municipalities than in large ones. Regarding EE scores, substantial inefficiency was observed among municipalities in group 1. The average EE score of 0.595 indicates that large municipalities need to reduce costs and unsorted waste by 40.5% to achieve the same level of output. In contrast, small municipalities in group 2 had an average EE score of 0.862, suggesting that potential input savings in this group could reach 13.8%.

The methodological approach proposed in this study and estimated results could be of significant value to policymakers. This study demonstrates an approach that enables consistent comparisons and produces reliable EE scores by accounting for the heterogeneous nature of the units under evaluation. The findings indicate that policymakers should prioritize actions aimed at improving the EE of larger municipalities. Nevertheless, small municipalities also present room for improving their EE. Specific measures could include the implementation of source separation at origin to reduce unsorted waste volumes, the adoption of pay-as-you-throw (PAYT) schemes to incentivize waste minimization at the household level, and the introduction of decentralized composting initiatives to manage organic waste more sustainably. Furthermore, investing in digital technologies for real-time monitoring of waste collection and recycling processes can help optimize logistics and resource allocation. Finally, establishing municipal benchmarking systems and fostering structured inter-municipal cooperation—where low-performing municipalities learn from high performers—can accelerate the adoption of proven strategies.

These recommendations provide strategies that policymakers can use to improve both the economic and environmental performance of MSW services across Chilean municipalities.

Conflicts of Interest

The authors declare no conflicts of interest.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Table S1:** Eco-efficiency scores of Chilean municipalities considering the full sample, i.e., 320 municipalities, and removing outliers, i.e., 297 municipalities.