TECHNICAL EFFICIENCY OF TURKISH MUNICIPALITIES: EVIDENCE FROM DATA ENVELOPMENT ANALYSIS

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Abstract

This study investigates the technical efficiency of Turkish municipalities at the provincial level using Data Envelopment Analysis (DEA). Growing local responsibilities make efficiency assessment vital for policy, accountability, and transparent governance. Leveraging a novel dataset compiled from annual reports of the Turkish Court of Accounts (Sayıştay) spanning a 12-year period, this study contributes to the existing literature by estimating DEA models with alternative output measures. Two DEA models, focused respectively on service provision and treatment capacity, are applied separately to metropolitan and regular municipalities to reflect their distinct service mandates. The analysis highlights efficient benchmarks, underperformers, and slack-based inefficiencies in resource use. These findings offer actionable insights for municipal administrations, audit institutions, and policymakers. The study also offers a scalable framework for converting audit data into accessible performance metrics.

Keywords: Technical efficiency, local governments, municipalities, Data Envelopment Analysis (DEA), water, wastewater, water treatment, waste treatment, Turkey

JEL classification: H72, D24, R50

Türkiye'de Belediyelerin Teknik Etkinliği: Veri Zarflama Analizi (VZA) Bulguları

Özet

Bu çalışma, Türkiye'deki il düzeyindeki belediyelerin teknik etkinliklerini Veri Zarflama Analizi (VZA) ile incelemektedir. Yerel yönetimlerin artan görevleri, etkinlik değerlendirmesini politika tasarımı, hesap verebilirlik ve şeffaf yönetim için kritik hale getirmektedir. Sayıştay'ın 12 yıllık denetim raporlarından derlenen özgün veri setiyle farklı çıktılar içeren VZA modelleri tahmin edilmiştir. Temel hizmetler (su, kanalizasyon, atık yönetimi) ve arıtma kapasitesine odaklı iki model, büyükşehir ve il belediyelerine ayrı uygulanmıştır. Analiz, etkin belediyeler ile düşük performanslıları belirlemekte, artık kaynak (slack) temelli incelemeler kaynak kullanımındaki verimsizlikleri açığa çıkarmaktadır. Elde edilen bulgular, belediye yönetimleri, denetim kurumları ve politika yapıcılar için uygulanabilir öneriler sunmaktadır.

Anahtar Kelimeler: Teknik etkinlik, yerel yönetimler, belediyeler, Veri Zarflama Analizi (VZA), su, atıksur, su arıtma, atık yönetimi, Türkiye

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1. Introduction

In recent decades, local administrations have faced a notable increase in service demand, accompanied by a reallocation of responsibilities between the central and local governments. This transformation has elevated the economic and political significance of local governments, positioning them as key actors in governance and public service delivery. Consequently, issues related to the allocation of public resources, corruption, and the efficiency of local governments have gained increasing attention. Furthermore, the efficiency of public institutions has long been a subject of both theoretical and practical interest. Motivated by these arguments, this article examines the technical efficiency of Turkish province-level municipalities using Data Envelopment Analysis (DEA), aiming to establish concrete benchmarks and offer evidence-based policy recommendations.

Efficiency analysis of local governments offers several benefits to a wide range of stakeholders. From the citizen's perspective, enhanced transparency and accountability are among the primary benefits, as efficiency assessments provide clearer insights into administrative performance. This, in turn, contributes to more informed decision-making during elections and policy debates, fostering greater citizen engagement in local governance. Improved efficiency is also expected to enhance the quality of public service delivery, as the identification of inefficiencies can guide municipal administrators toward targeted improvements. Citizens may further benefit from increased cost-effectiveness in public spending, which may translate into reduced tax burdens or more affordable municipal services, such as public transportation. From a deeper and broader perspective, efficiency analysis can promote greater public participation. Given that most citizens may not be equipped to interpret detailed budget data or evaluate institutional performance directly, efficiency assessments can serve as a practical tool for making complex administrative information more accessible and actionable for the general public.

From the perspective of public officials, one of the primary advantages of efficiency analysis is its support for data-driven decision-making. Efficiency metrics provide valuable insights into departmental performance, enabling officials to make informed decisions regarding resource allocation, budget planning, and service delivery strategies. Data-driven decision-making fosters a more objective and evidence-based approach to governance. Comparing efficiency metrics across similar municipalities establishes a platform for benchmarking and knowledge exchange. Such comparative analysis enables officials to identify better performing units, adapt successful strategies, and continuously improve their strategies. Demonstrating a commitment to efficiency and transparency can significantly improve public perception of local government. Efforts to optimize resource utilization and deliver quality services can build trust and get support from citizens. In addition to local government officials, audit institutions can also benefit from the efficiency outcomes. Identified inefficiencies may serve as indicators of potential mismanagement, fraud and corruption, thereby aiding audit institutions in detecting and addressing such issues.

From a broader perspective, efficiency results also provide benefits for the general community. Increased efficiency frees up resources that can be redirected towards initiatives that attract businesses, stimulate economic growth, and create jobs within the community. This, in turn, fosters a thriving and sustainable local economy, benefiting both residents and businesses alike. Improved service delivery and cost-effectiveness resulting from efficiency efforts can contribute to better social outcomes for citizens. Depending on the framework of responsibility areas of local governments, this may include improved public health, access to quality education, better public transport, and enhanced infrastructure, thereby elevating the overall well-being of the community. Additionally, the efficient use of resources helps minimize waste and environmental impact. This contributes to a more sustainable future for the community, ensuring responsible stewardship of natural resources for generations to come.

To reliably achieve the aforementioned objectives, a comprehensive dataset is essential. However, in the Turkish context, data on local governments remain relatively limited, which has significantly hindered the growth of academic research in this area. Moreover, techniques used for measuring technical efficiencies such as DEA require a large number of observations to yield reliable results (Bowlin, 1998a). Recognizing this challenge, a key contribution of this study lies in its data collection strategy for obtaining the local government expenditures and budgets. Leveraging recent advancements in text analysis and data extraction methods, the study compiles a novel dataset of over 600 observations from annual reports published by the Turkish Court of Accounts (Sayıştay). This approach results in the first comprehensive dataset in the Turkish context, covering municipality-level data over a 12-year period. This broad span of data significantly improves the reliability of DEA results. Furthermore, it contributes to publicly available knowledge on municipalities, guiding the agents involved: public, audit and municipality administrations. In addition to identifying inefficient municipalities, the analysis highlights specific budget categories that contribute most to inefficiencies.

The structure of this article proceeds as follows: Section 2 reviews the existing literature, covering both global and Turkish studies on municipal efficiency and relevant datasets. Section 3 presents the data, beginning with a brief overview of the municipal structure in Turkey, followed by a detailed description of input and output variables used in the analysis. Section 4 outlines the methodological approach, while Section 5 reports the empirical findings. Sections 6 and 7 offer a discussion of the results and concluding remarks, respectively.

2. Literature Review

The assessment of public sector performance has long been a central concern in both economics and public administration. As governments and public institutions seek to improve service delivery and resource allocation, various analytical tools have been developed to measure efficiency. Among these, Data Envelopment Analysis (DEA) has become one of the most widely used non-parametric methods for evaluating the efficiency of decision-making units. Originally developed for non-profit and public organizations such as hospitals, schools, and military institutions, DEA has since been applied across a wide range of sectors, including banking and private industry (Bowlin, 1998b). In evaluating technical efficiency in non-profit contexts, where outputs typically consist of services rather than tangible goods, the choice of output variables becomes particularly important. An extensive review and comparative analysis of output variables used in measuring local government performance is provided by Narbón-Perpiñá & De Witte (2018).

In the efficiency analysis of local governments, one of the most frequently used output variables is the total population served, which is often interpreted as a proxy for the attractiveness or demand level of a given region. However, relying on population as an output requires caution. In the absence of balanced regional economic and industrial development, population figures may reflect migration driven by broader economic conditions rather than the actual performance or efficiency of local governments, a limitation that is particularly relevant in the Turkish context. As a result, many studies incorporate service and infrastructure indicators as more direct output measures. These typically include variables such as street lighting, municipal roads, waste collection, sewage systems, water supply, and electricity. In recent years, additional indicators, such as the provision of parks, sports, cultural amenities, and social services, have gained prominence, reflecting the evolving expectations of citizens from local administrations. Depending on the legal responsibilities assigned to local governments, education and healthcare services may also be considered as output variables. However, in Turkey, these domains are primarily managed by the central government, limiting their suitability as municipal-level outputs.

One of the pioneering applications of DEA to local governments was conducted by De Borger & Kerstens (1996). To measure the cost efficiency of local governments in Belgium, they employed both parametric and non-parametric methods to compare social, political and economic characteristics of municipalities. Prieto & Zofio (2001) utilized water, sewage, wastewater, roads and lighting services as output variables to measure the efficiencies of Spanish municipalities. The DEA results were used to propose recommendations for resource allocation by the central government to improve these services. Similar research with a broader temporal scope was carried out by Tupper & Resende (2004) for Brazilian municipalities.

A distinct approach was adopted by Woodbury & Dollery (2004) who emphasized the classification of output variables into qualitative and quantitative dimensions. In their study, the quality and sustainability of water supply were incorporated as quantitative outputs. Another notable DEA application on Brazilian municipalities was conducted by De Sousa et al. (2005), where a strong correlation on efficiency with the size of the municipality is identified. They also noted that natural, political, geographical, demographic, and socio-economic factors contributed to efficiency disparities. In the Portuguese context, Afonso & Fernandes (2008) measured the technical efficiency of 278 municipalities using a composite output indicator and concluded that considerable potential existed for enhancing municipal efficiencies.

Studies examining the efficiency of Turkish municipalities remain relatively scarce in the existing literature. Çağlar (2003) studied the efficiencies of 81 municipalities using DEA. The study relied on data from a specialized government initiative known as the "Local Municipalities Database Project" ("Yerel Yönetimler Bilgi Tabanı Projesi – YERELBİLGİ"), which covered only the year 2001 with an unbalanced data structure. Four different DEA models were constructed using varying combinations of input and output variables. The input variables included current expenditures, investment expenditures, transfer payments, total personnel, total vehicles, sewer network length, zoning staff, number of garbage trucks, number of garbage containers, number of garbage collection staff, tap water capacity, tap water network length, tap water storage capacity, and number of waterworks staff. The output variables included the surface area of municipal jurisdiction, tax revenues, non-tax revenues, grants and funds, the total number of building permits issued, garbage collected, number of households with water coverage, total household water consumption. The findings indicated, consistent with broader literature, that larger municipalities and regions predominantly consisting of large municipalities -such as Marmara region- exhibited higher efficiency scores.

Kaplan, Çelik and Tekeli (2006) conducted a study using data from 16 metropolitan municipalities covering the period from 2002 to 2004. They use a DEA model with the following input variables: personnel expenditures, investment expenditures, social grants, educational and cultural expenditures, and transfer payments. Output variables included population, total recreational area, daily water consumption, and passenger carrying capacity of public transport for peak hours. A study employing a similar analytical framework was conducted by Güneş and Akdoğan (2007), who utilized nearly identical input and output variables with the same set of metropolitan municipalities. They additionally implemented a model with security and well-being focus where they cover fire trucks and local security personnel ("zabıta").

İlkay & Doğan (2009) choose to focus the research on a narrow area of selected 14 district municipalities of Cappadocia Region for the years 2004 and 2008. They established four different models: garbage services model, zoning services model, financial model, and water services model. In the garbage services model the input variables included the number of garbage collecting personnel, number of garbage vehicles, population coverage while the output variables were municipal jurisdiction area and the total garbage collected. For the zoning services model, the input variables consisted of municipal jurisdiction area, zoning personnel, whereas the output variables were the total zoned area and the total number of building permits issued. In the financial model, the input variables included population coverage, municipal jurisdiction area, tax revenues, non-tax revenues with current expenditures and investment expenditures as output variables. Lastly the water services model employed total water supplied, water network length and water personnel as inputs and total water consumption and total households served as outputs.

Kutlar et al., (2012) analyzed the efficiency of 27 municipalities, including seven metropolitan municipalities, covering the period 2006 to 2008. They applied both DEA and Malmquist index methods to evaluate efficiencies. Personnel expenditures, social security expenditures, goods and services expenditures, current transfer expenditures, capital expenditures, capital transfers and total expenditures are the input variables used. Output variables included total population, proportion of 65+ population, number of pupils, the number of beds in tourism establishments, total number of beds in hospitals and the number of visitors. They used both input-oriented and output-oriented frameworks under constant and variable returns to scale assumptions. Their findings indicated a slight decrease in efficiency scores over the studied period (2006–2008). Contrary to prevailing literature, their results revealed no significant correlation between municipality size and efficiency.

Çelikkaya analyzed efficiency using data from 2015 for 30 metropolitan municipalities (Çelikkaya, 2016). Four different models employed in the research are financial model, infrastructure model, expenditures model and tax model. In the financial model, input variables consisted of personnel expenditures, transfer payments, purchases of goods and services, capital expenditures whereas output variables included tax revenues, non-tax revenues and grants and funds. For the infrastructure model, the input variables included total number of personnel, number of vehicles, total expenditures and output variables were the length of roads, length of sewer networks, length of water networks and municipal jurisdiction area.

For the expenditures model, the input variables consisted of personnel expenditures, social security expenditures, purchases of goods and services, interest payments, current expenditures, capital expenditures with output variables defined as municipality covered population, number of students, municipal jurisdiction area. Lastly for the tax model, the input variables were municipality covered population, municipal jurisdiction area with tax revenue as output variable.

Local literature on municipal efficiency in Turkey typically use short-span data and often focus on limited samples such as a selection of metropolitan municipalities, regional district municipalities or specific regions. The models developed employed range of output variables, such as water, waste, infrastructure, financials and zoning services. However, possibly due to data limitations, many analyses rely on small sample sizes and unbalanced datasets, frequently sourced from non-recurring projects or surveys. While the studies provide valuable insights over municipal administrations, their comparability and time scope are limited.

3. Data

3.1. Turkish Municipality Framework

Municipalities constitute one of the three[1] primary categories of local government bodies in the Republic of Turkey (Law No. 6360, 2013). There are four types of municipalities: metropolitan municipalities, provincial municipalities, district municipalities and town municipalities[2]. The legal definitions and regulations governing these entities are established under the Law of Municipalities (Law no. 5393). Metropolitan municipalities and metropolitan districts are also subject to a designated law, the Law of Metropolitan Municipalities (Law no. 5216). and **Table 1** present the overall distribution and population distribution of municipalities, respectively. As shown in **Table 2** there is a highly uneven distribution of population across municipalities, the four largest metropolitan cities account for 36.3% of the total population, with the top two cities alone comprising 26.8%. It is also noteworthy that, as of 2021, 78% of the total population resides within metropolitan municipality jurisdictions.

Table 1: Municipality types and numbers for 2022 (Source: YYGM, 2023)

Metropolitan	Metropolitan District	Province	District	Town	Total
30	519	51	403	388	1391

[1] The others are special administration of province ("İl Özel İdaresi"), and "village".

[2] Respectively: "Büyükşehir Belediyesi", "İl Belediyesi", "İlçe Belediyesi" and "Belde"

Table 2: Population distribution of municipalities (Source: TUIK ADNKS, 2023)

	Metrpol-itan	Province	Metropolitan District	District	Town	Total	Population
0 - 2.000			1	42	93	136	222.919
2.001 - 5.000			13	131	259	403	1.212.464
5.001 - 10.000			41	89	34	164	1.148.235
10.001 - 20.000			81	67	1	149	2.117.352
20.001 - 50.000		5	130	54	1	190	6.044.065
50.001 - 75.000		5	48	11		64	3.915.038
75.001 - 100.000		6	23	5		34	2.968.903
100.001 - 250.000		26	91	4		121	18.669.119
250.001 - 500.000		9	64			73	25.711.770
500.001 - 750.000	1		18			19	11.641.270
750.001 - 1.000.000	5		9			14	12.080.063
1.000.001 - 2.000.000	14					14	18.724.709
2.000.001 - 3.000.000	6					6	13.661.690
3.000.001 - 5.000.000	2					2	7.656.776
5.000.001 -	2					2	21.690.236
Total	30	51	519	403	388	1.391	80.810.660

Financial resources of the municipalities consist of several components, including allocations from the national tax revenues, resources within, central government transfers, debt resources. Resources within are fees, revenues from municipal subsidiaries as well as grants and funds.

Turkish Law of Municipalities grants the municipalities the ability to form municipal subsidiaries. Municipal subsidiaries function as semi-autonomous enterprises which are responsible and connected to municipality, yet exempted from the stricter labor laws of public sector. It is important to note that, although these subsidiaries have independent budgets, their financial accounts are consolidated into the annual municipality budget (Küçük, 2015). As of 2022, municipalities employed a total of 194.354 personnel representing 4.49% of total public sector employment. In contrast, municipality subsidiaries constitute 13.05% of all public employment with 564.354 employees. These figures are based on data from the 2022 General Activity Report of Local Governments (2022 Yılı Mahalli İdareler Genel Faaliyet Raporu, 2023), which reported a total public sector workforce of 4.328.197.

3.2. Input Variables

As required by the DEA framework, two sets of data are necessary: input and output variables. The input variables are derived from the expenditure titles of municipalities. However, in the Turkish case, there is a lack of available data covering a broad range of years and municipalities. This data limitation is also evident in prior research within the local literature, where studies typically have limited temporal and geographical coverage. Nevertheless, according to the Municipality Law, all municipalities are required to submit their annual balance sheets to central institutions, including the Ministry of Interior, the Ministry of Environment, Urbanization and Climate Change, and the Turkish Court of Accounts (pursuant to Law No. 5393 on Municipalities and Law No. 5216 on Metropolitan Municipalities). The Turkish Court of Accounts audits municipal budgets and reports any issues along with the balance sheet tables each year. Although these tables are publicly accessible, they are embedded within report documents rather than available as structured datasets. In this study, we employed text mining techniques to extract the relevant financial data from these embedded tables.

Turkish Court of Accounts selects municipalities for audit based on a set of criteria. These include risk assessment, budget size, recent audit results, public interests and expectations as well as claims and notifications. For instance, in 2022, 42% of district municipalities, 44% of municipalities, and 100% of metropolitan municipalities were audited and reported. As a result, the dataset is incomplete. Additionally, especially for the years before 2016, there are reports that are not suitable[3] for machine reading due to formatting and digitization limitations. The resulting data, number of balance sheets of municipalities extracted for each year is listed below in **Table 3**.

Table 3: The number of observations (extracted balance sheets) per year.

2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
47	65	73	80	64	54	47	67	51	47	44

Four categories of expenditures are used as input variables: personnel expenditures, goods and services expenditures, current transfers and a residual category labeled as other expenditures. All monetary values are deflated to account for inflation and are normalized by the population covered by each respective municipality, yielding real per capita expenditure figures. **Table 4** and **Table 5** shows the summary statistics of the input and output variables for two types of municipalities separately.

[3] Tables reported as pictures, in some cases even unreadable by human eye.

Table 4: Summary statistics of variables used for DEA of non-metropolitan municipalities.

Non-Metropolitan Municipality Data Summary Statistics

	Non-Empty Obs.	Mean	Standard Deviation	Min	Max
Outputs					
Sewage network coverage (%)	144	91.52	10.72	25.00	100.00
Sewage treatment volume	128	67.31	49.10	0.00	223.16
Waste collected	144	95.34	47.80	34.44	338.93
Water distributed	144	116.96	57.86	35.86	464.15
Water treatment volume	103	79.30	57.13	0.00	258.03
Inputs					
Current Transfers	144	12.89	13.81	0.02	92.90
Goods and Services Expenses	144	220.17	79.75	2.88	490.53
Other Expenses	144	117.60	114.98	1.15	891.37
Personnel Expenses	144	145.08	65.25	3.96	375.96

Table 4 shows that sewage network coverage variable exhibits the lowest standard deviation among the output variables, along with a relatively high value. This suggests that it is unlikely to emerge as a significant source of inefficiency in the analysis, given its consistent and widespread coverage across non-metropolitan municipalities. In terms of expenditure patterns, goods and services expenditures represent the largest per capita spending category for non-metropolitan municipalities, underlying their central role in resource allocation within this group.

Table 5: Summary statistics of variables used for DEA of metropolitan municipalities.

Metropolitan Municipality Data Summary Statistics					
	Non-Empty Obs.	Mean	Standard Deviation	Min	Max
Outputs					
Sewage network coverage (%)	133	85.65	10.63	60.00	100.00
Sewage treatment volume	132	49.36	23.74	3.75	169.93
Water distributed	133	50.69	13.17	17.96	100.57
Water treatment volume	118	47.24	26.74	0.00	105.46
Inputs					
Current Transfers	133	11.28	14.63	0.40	76.62
Goods and Services Expenses	133	99.59	51.63	1.07	305.86
Other Expenses	133	92.68	68.12	3.76	399.08
Personnel Expenses	133	65.20	46.84	9.90	396.75

For the metropolitan counterparts, sewage network coverage also exhibits low variation, however with an average coverage of 85.65% of municipal population, there remains room for improvement in achieving full service access (**Table 5**). The summary statistics further show that, treatment variables have higher variability compared to service variables. On the expenditure side, goods and services remain the largest spending category. Although the average expenditure levels are relatively close across categories, the within variation is notably higher in metropolitan municipalities.

3.3. Output Variables

Data availability on municipality service areas are highly limited for Turkish municipalities. The Turkish Statistical Institute (TÜİK) publishes core service indicators such as water supply, sewerage, waste collection on a biannual basis covering even years. These indicators are often reported in multiple forms, including total service volume (e.g., total water supplied), service coverage (e.g., percentage of the population served), and per capita metrics (e.g., water supplied per person). Coverage variables represent the percentage of the municipal population, as defined by the municipal jurisdiction, that is served by each core service.

In this study, two base models are employed. The first, referred to as the **service supply model**, includes the following output variables: volume of distributed water (measured in cubic meters per person), sewerage network coverage (percentage of population served), and waste collected (kilograms per person). It is important to note that waste collection and management responsibilities are structured differently in metropolitan municipalities, where district municipalities are responsible for collection and metropolitan municipalities manage subsequent processing. Due to this division of labor and the resulting ambiguity in data attribution, the waste collection variable is excluded from the metropolitan models.

The second model, referred to as the **treatment services model**, focuses on wastewater and water treatment services. This model uses two output variables: sewage treatment volume and water treatment volume, both measured in m^3 per person.

Summary statistics for the output variables in metropolitan and non-metropolitan municipalities are presented in tables **Table 4** and **Table 5**, respectively. A time series overview of these variables is provided in **Table 6** and **Table 7**.

Table 6: Yearly statistics for output and input variables – non-metropolitan municipalities.

Yearly Statistics - Non-Metropolitan Municipalities

Mean and Standard Deviation by Year

	2012		2014		2016		2018		2020		2022	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Outputs												
Sewage network coverage (%)	88.75	11.65	89.11	13.28	88.93	13.95	93.44	5.54	95.82	3.32	95.55	2.94
Sewage treatment volume	73.35	61.01	55.94	42.40	61.21	48.75	60.83	55.13	80.13	42.67	79.42	52.94
Waste collected	118.56	49.98	92.14	37.98	98.64	53.62	101.19	63.91	80.19	38.69	90.34	45.94
Water distributed	108.03	35.80	115.03	73.00	114.16	60.98	123.81	67.42	110.42	41.18	132.17	44.84
Water treatment volume	95.51	63.29	75.84	54.69	86.43	61.53	80.08	58.00	56.97	46.42	87.44	61.08
Inputs												
Current Transfers	16.66	22.68	11.80	9.26	18.65	20.22	10.98	7.98	11.24	6.90	7.20	4.79
Goods and Services Expenses	206.80	50.05	205.97	71.75	245.50	112.14	241.82	104.17	236.95	52.88	187.37	36.66
Other Expenses	90.02	98.77	109.01	90.61	156.83	182.71	161.75	112.63	104.77	77.36	79.75	37.03
Personnel Expenses	164.50	48.80	157.70	68.79	165.26	71.94	167.36	66.48	124.01	49.43	86.51	24.78

All service output indicators show an improving trend over time with the exception of water treatment volume, which demonstrates fluctuating average values and a high degree of variation among non-metropolitan municipalities within each year, as shown in **Table 6**. On the expenditure side, all categories peaked in 2016, followed by a consistent decline in spending levels through 2022.

Table 7: Yearly statistics for output and input variables – metropolitan municipalities.

Yearly Statistics - Metropolitan Municipalities

Mean and Standard Deviation by Year

	2012		2014		2016		2018		2020		2022	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Outputs												
Sewage network coverage (%)	85.56	9.45	84.39	11.83	82.35	11.92	85.20	12.74	85.57	10.62	89.27	7.73
Sewage treatment volume	50.93	51.39	41.47	23.52	46.27	22.09	47.59	21.54	50.55	18.15	57.29	19.39
Water distributed	52.33	21.12	44.11	16.12	49.63	10.91	50.47	10.76	52.23	11.59	55.31	11.29
Water treatment volume	49.66	15.01	45.17	24.38	41.86	28.42	47.41	25.34	51.75	28.52	47.76	29.91
Inputs												
Current Transfers	10.40	13.30	8.25	9.80	10.66	12.92	11.17	13.13	10.29	13.38	16.06	22.58
Goods and Services Expenses	98.42	79.31	69.78	46.82	131.47	71.05	106.98	45.22	95.58	24.42	85.48	29.07
Other Expenses	37.66	37.58	68.76	83.47	102.00	60.90	123.98	81.19	103.40	60.63	70.63	35.26
Personnel Expenses	50.91	20.60	57.40	34.34	66.18	28.32	74.73	54.86	70.44	70.26	57.32	31.91

For the metropolitan counterparts of output variables, 2014 and 2016 represent the periods of lowest service performance, followed by a gradual upward trend extending to 2022, as illustrated in **Table 7**. When analyzed in conjunction with expenditure data, 2016 emerges as a particularly inefficient year, marked by elevated spending levels alongside weaker service outcomes.

4. Methodology

There are two main approaches used to measure technical efficiencies of local governments: parametric and non-parametric. The most common non-parametric method used is the Data Envelopment Analysis (DEA). It has different sub-versions such as (nonconvex) Free Disposal Hull, super-efficiency DEA, etc. DEA assumes that there is a set of "efficient" decision making units (DMUs – local governments in our case) that represent the best practices through DMUs. The performance of each DMU is evaluated by comparing it to the efficient frontier, which is the set of DMUs that achieve the maximum output for a given set of inputs. DEA evaluates the efficiency of each DMU by constructing a linear programming model that maximizes the weighted sum of outputs relative to the weighted sum of inputs, subject to the constraint that the DMU cannot be more efficient than any of the efficient DMUs. For the interpretation, DEA estimates the relative efficiency of each DMU, which measures how well each DMU uses its inputs to produce outputs relative to the best practice (i.e., the efficient frontier). DEA can also identify the most efficient DMUs and the sources of inefficiency for each DMU.

Stochastic Frontier Analysis (SFA) is the parametric approach to analyze efficiency in organizations. SFA determines the frontier by using a functional form derived from econometric techniques. SFA assumes that there are two components to the observed output: a stochastic error term and a deterministic component. The error term represents the random variation in the data, while the deterministic component represents the maximum output that could be achieved given the inputs. SFA estimates a production function that relates the observed inputs to the observed outputs, while accounting for the random error term. The efficiency score is then calculated as the ratio of the observed output to the predicted output based on the estimated production function. SFA estimates the technical efficiency of each DMU, which measures how well each DMU uses its inputs to produce outputs relative to the best practice (i.e., the maximum achievable output). SFA can also decompose the efficiency score into two components: pure technical efficiency, which measures how well the DMU uses its inputs to produce outputs, and scale efficiency, which measures how well the DMU uses its inputs to produce outputs relative to its size.

For comprehensive and practical efficiency assessments, DEA models offer greater flexibility and impose fewer assumptions than the parametric models, such as SFA. One of the primary advantages of DEA is its ability to accommodate multiple inputs and multiple outputs without requiring a predefined functional form. This makes DEA particularly suitable for evaluating complex public organizations like municipalities, where diverse services are delivered using heterogeneous resources.

However, DEA is not without limitations. Its deterministic nature means that all deviations from the frontier are attributed to inefficiency, making the model highly sensitive to outliers and measurement errors. This sensitivity can affect the robustness of efficiency scores, particularly in datasets with noise or irregularities.

Additionally, a simpler method occasionally referenced is the ratio index approach, which involves calculating efficiency as the ratio of total outputs to total inputs (Borge et al., 2008). While this method offers ease of implementation and interpretability, it lacks the ability to account for multiple inputs and outputs or provide relative efficiency scores.

This study adopts DEA as the primary method for evaluating municipal efficiency. First, as public service providers, municipalities do not produce a single, quantifiable output as is often the case for private firms. DEA offers the flexibility to incorporate multiple output variables, enabling the analysis of technical efficiency from various service dimensions. Second, the multi-service, socially oriented and politically influenced nature of municipal production scheme makes it unsuitable to be captured by a specific functional form which is necessary to impose Stochastic Frontier Analysis. Finally, the large number of DMUs included in this study presents additional challenges for SFA, particularly in terms of model complexity and estimation feasibility, further supporting a non-parametric approach.

We evaluate technical efficiency in separate, cross-sectional DEA problems for each calendar year in 2012–2022. Within a given year, let there be n province-level municipalities (DMUs), indexed by $\mathrm{j} = 1, \dots, \mathrm{n}$. For each DMU j, let $\mathrm{x_{kj}}$ denote the quantity of input k for $\mathrm{k} = 1, \dots, \mathrm{K}$, and $\mathrm{y_{rj}}$ denote the quantity of service output r for $\mathrm{r} = 1, \dots, \mathrm{R}$. Because the model is solved year by year, the year index is suppressed in all expressions below. The services specification uses the service-output variables defined in the data subsection; the treatment services specification is obtained by replacing the output vector y with the treatment outputs (same program forms).

CCR/CRS, output-oriented (envelopment form):

For a focal municipality i, the constant-returns, output-oriented problem is (Charnes et al., 1978; Farrell, 1957):

$$\max \varphi$$

subject to

$$\begin{aligned} \sum_{j=1}^{n} \lambda_j \, y_{rj} \; &\geq \; \varphi \, y_{ri} \quad (r = 1, \dots, R), \\ \sum_{j=1}^{n} \lambda_j \, x_{kj} \; &\leq \; x_{ki} \quad (k = 1, \dots, K), \\ \lambda_j \; &\geq \; 0 \quad (j = 1, \dots, n). \end{aligned} \tag{1}$$

The expansion factor $\varphi \geq 1$ yields output-oriented technical efficiency $\mathrm{TE_i} = 1/\varphi \in (0,1]$.

The vector λ selects and weights observed municipalities to form a reference (benchmark) point on the efficient frontier for the focal municipality. Under VRS, the convexity constraint $\sum_j \lambda_j = 1$ ensures the benchmark is a convex combination of observed DMUs. Any $\lambda_j > 0$ identifies municipality j as a peer; its magnitude is the share that municipality contributes to the benchmark mix. Geometrically, the DEA projection moves the focal bundle (x_0, y_0)

radially inward by φ (and then along slacks which will be discussed) to a point on the convex hull of feasible production points; λ gives the coordinates of that hull point. Because multiple convex combinations can lie on the same supporting facet, λ need not be unique.

In practice, λ serves three purposes: (i) peer identification (which municipalities set the standard), (ii) construction of target inputs/outputs via the weighted sums above (consistent with the φ and slack targets), and (iii) returns-to-scale diagnosis through the chosen convexity restriction (CRS vs. VRS vs. NIRS/NDRS).

BCC/VRS, output-oriented (envelopment form)

Variable returns are imposed by the convexity constraint (Banker et al., 1984; Farrell, 1957):

$$\max \varphi$$

subject to

$$\begin{aligned} &\sum_{j=1}^{n} \lambda_j \, y_{rj} \ \geq \ \varphi \, y_{ri} \quad (r = 1, \dots, R), \\ &\sum_{j=1}^{n} \lambda_j \, x_{kj} \ \leq \ x_{ki} \quad (k = 1, \dots, K), \\ &\sum_{j=1}^{n} \lambda_j \ = \ 1, \quad \lambda_j \ \geq \ 0 \ (j = 1, \dots, n). \end{aligned} \tag{2}$$

This program delivers pure technical efficiency under VRS; scale efficiency can be inferred by comparing CCR and BCC scores.

Slack-refined variants

To rule out residual input excesses or output shortfalls after the radial step, we use the standard ε refinement. Let $s_k^- \geq 0$ be input slacks and $s_r^+ \geq 0$ be output slacks; pick a small $\varepsilon > 0(\text{e.g.}, 10^{-6})$ and we get CCR/CRS with slacks (Cooper et al., 2007):

$$\max \varphi - \varepsilon \left(\sum_{k=1}^{K} s_k^- + \sum_{r=1}^{R} s_r^+ \right) \tag{3}$$

subject to

$$\sum_{j=1}^{n} \lambda_j \, x_{kj} + s_k^- = x_{ki} \quad (k = 1, \dots, K),$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = \theta \, y_{r0}, \quad (r = 1, \dots, R), \tag{4}$$

$$\lambda_j \geq 0, \, s_k^- \geq 0, \, s_r^+ \geq 0.$$

And BCC/VRS with slacks:

$$\max \varphi - \varepsilon \left(\sum_{k=1}^{K} s_k^- + \sum_{r=1}^{R} s_r^+ \right) \tag{5}$$

subject to the two equalities above and

$$\sum_{j=1}^{n} \lambda_j = 1, \quad \lambda_j \geq 0, \, s_k^- \geq 0, \, s_r^+ \geq 0 \tag{6}$$

The interpretation outline is as follows:

- Orientation: Output-oriented in the Farrell (1957) sense: φ scales the focal DMU's outputs while holding inputs fixed.
- Returns to scale: CCR assumes CRS; BCC imposes VRS via $\sum_j \lambda_j = 1$. NIRS adoption is via: $\sum_j \lambda_j \leq 1$.
- Efficiencies: Report ($TE_i = 1/\varphi^*$). Comparing CCR vs. BCC identifies scale effects.
- Model scope. Programs are solved separately for each year; all peer weights \lambda reference municipalities in the same year. The treatment services model is obtained by substituting the treatment outputs for y; inputs remain as in the services specification.

By introducing the slack ($s_k^- \geq 0$ and $s_r^+ \geq 0$) variables, equation (3) clarifies two aspects of DEA. Slacks capture the distances from the efficient frontier, quantifying the input excesses and output shortfalls of each DMU relative to the efficient frontier. This enables both an envelopment of the production possibility set and the identification of specific sources of inefficiencies. After estimating the DEA model on municipal data, these inefficiency measures can inform targeted policy recommendations for individual municipalities.

In our analysis, input variables are selected from expenditure titles of municipalities. In theory, municipal efficiency involves two decision layers: resource generation and resource allocation. In a local governance framework where tax revenue forms one of the main sources of revenue for a municipality, we can claim a meaningful involvement of the municipality administration on both resource generating and allocation. However, as previously discussed, Turkish municipalities derive approximately 70% of their funding from central government transfers (2022 figure, consistent with past averages). Given this structural characteristic, applying an input-oriented DEA model—which assumes discretion over input levels—would misrepresent the decision space of Turkish municipalities. Therefore, an output-oriented model is more appropriate, as it focuses on assessing the capacity of municipalities to maximize service provision with largely predetermined input levels.

As outlined in the Turkish Municipality Framework section, Turkish municipalities are classified into two main subgroups. For the purposes of this study, these two categories differ significantly in two key aspects: the scope of their responsibilities and the scale of their operations in terms of population and budget size. The divergence in service mandates and resource capacities results in substantial structural differences between the subgroups. These imbalances necessitate a disaggregated approach in the DEA analysis to ensure methodological soundness and to allow for meaningful efficiency comparisons within each group.

Furthermore, disaggregation is also methodologically justified by a fundamental data requirement of DEA models: the number of decision-making units (DMUs) must be at least three times the maximum of the number of input or output variables—formally expressed as:

$$n_{\{DMUs\}} \geq 3 \times \max\left(n_{\{inputs\}}, n_{\{outputs\}}\right)$$

This condition helps to prevent overfitting and ensures that the efficiency frontier is constructed on a statistically meaningful basis (Banker et al., 1984).

Another important variant within DEA modeling concerns the assumption regarding returns to scale. In the context of local governments, factors such as budgetary limitations, geographical constraints, and operational complexities often restrict the ability to proportionally scale inputs and outputs. These real-world limitations justify the use of non-increasing returns to scale (NIRS) in the efficiency models applied in this study. The appropriateness of this specification is further supported by the statistical test developed by Simar & Wilson (2002), which provides empirical validation for selecting the NIRS assumption over constant returns to scale.

5. Results

Based on the selection of the output variables, two primary DEA models are constructed – service supply and treatment services models. To enhance the reliability of the DEA results, each model was applied separately to metropolitan and non-metropolitan municipalities. This disaggregation is in line with best practices in DEA, which emphasize that greater homogeneity among DMUs improves the robustness of efficiency comparisons. The structure of the model output sets is summarized in **Table 8**, which presents the matrix of output variable combinations for different scenarios.

Table 8: Output scenarios of DEA models matrix. (M: metropolitan, N-M: non-metropolitan)

	Service M	Service N-M	Treatment M	Treatment N-M
Water Supply	*	*	-	-
Waste Collected	-	*	-	-
Sewage Network Coverage	*	*	-	-
Water Treatment	-	-	*	*
Sewage Treatment Volume	-	-	*	*

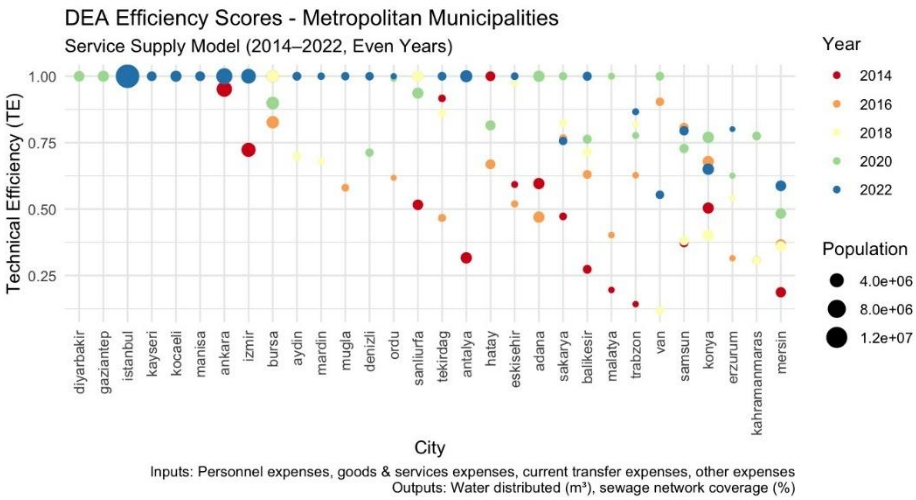
5.1. Service Supply Models

All results of the service supply model along with yearly and city averages are presented in appendix (**Table A1** and **Table A3**). It is important to note that, DEA evaluates relative efficiencies and produces scores ranging from 0 to 1. An efficiency score of 1.00 does not indicate a perfect or absolute performance; rather, it indicates that the corresponding DMU lies on or close to the estimated efficient frontier. The results for the year 2012 are omitted due to the insufficient number of observations that do not meet DEA requirements. The missing observations in the tables are mostly not audited for that year or have non-readable balance sheet reports.

For an overall picture of results, **Figure 1** presents the annual efficiency scores alongside population sizes for metropolitan municipalities, ordered by decreasing average efficiency. The yearly average results in the bottom row of metropolitan table of **Table A1** suggest a gradual improvement in efficiency over time, a trend that is also supported by **Figure 1**. As the largest city of Turkey, accounting nearly 20% of the national population, İstanbul appears as a notable outlier in the service supply model, likely due to its scale. Municipalities such as Adana, Malatya and Trabzon exhibit greater variability in efficiency scores across years, while Ankara, İzmir and Bursa show more stable and consistent results.

The municipalities with higher and stable results are benchmark examples, studying their governance structures and policy practices may yield valuable insights for municipalities with persistently low scores. Conversely, the underperforming municipalities have to be deeper analyzed for the root causes of inefficiency. To this end, a more detailed discussion of slack variables is provided in the following sections to support diagnostic interpretation.

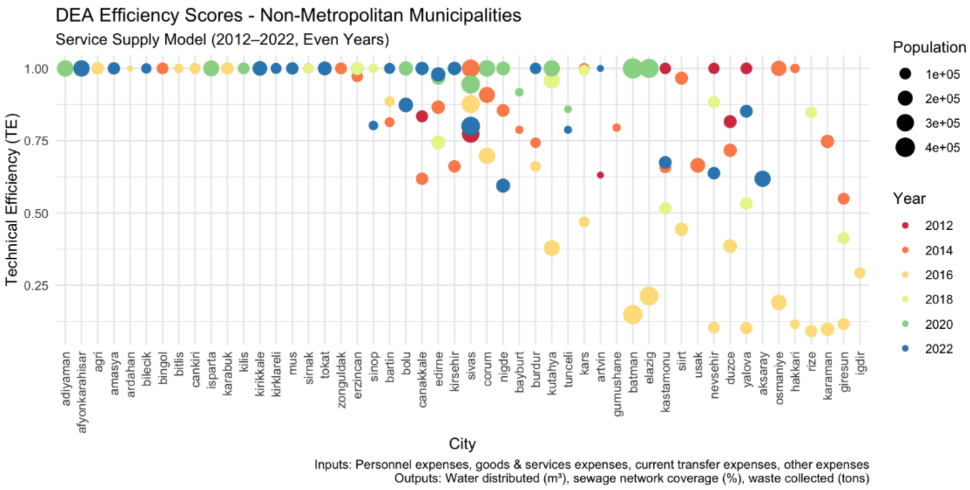
Figure 1: Yearly results for service supply model, metropolitan municipalities.



For the non-metropolitan pool of the services model, 2012 data have sufficient number of observations. Notably, 36% of the non-metropolitan municipalities in the sample achieve an efficiency score of 1.00, positioning them as benchmark units. Moreover, the overall average efficiency in the non-metropolitan group exceeds that of their metropolitan counterparts. This disparity can be attributed to the greater structural complexity, significantly more service areas and higher volume of service transactions in metropolitan municipalities, which tend to increase operational challenges and contribute to relatively lower efficiency levels.

It is important to emphasize that DEA models were estimated separately for each year. The relatively weak performance of non-metropolitan municipalities in 2016 is evident from the average efficiency scores presented in the bottom row of **Table A2** and visualized in **Figure 2.** Municipalities with consistently low or volatile efficiency scores -such as Karaman, Rize, Giresun- should conduct a detailed analysis of their slack values to identify the sources of inefficiency and establish targeted areas for improvement.

Figure 2: Yearly results for service supply model, non-metropolitan municipalities.



The results discussed above have identified the inefficient DMU's. By utilizing the slack values computed within the DEA framework, we are able to address the specific sources of inefficiency for each of the DMU. Slacks values represent the distance of a specific variable of a DMU from the efficient border, thereby allowing for the identification of the input or output components that contribute most significantly to inefficiency.

Table 9 reports the slack values of metropolitan municipalities in the service supply model, focusing on the three lowest performing DMUs in each year. For a cross-check, the table also includes the within group deviations of each variable from its annual mean.

To illustrate, consider 2014 results for Malatya Metropolitan Municipality. The slack analysis reveals that the primary sources of inefficiency are goods and services expenditures and sewage network coverage. The deviation values also support the findings of the DEA with an 37% more than group average of goods and services expenditures and a 12% lower sewage network coverage from the average coverage value. In simplified terms, this municipality spend higher than average but delivered services lower than average. These results suggest the municipality should review the efficiency and allocation of its goods and services expenditures and prioritize expanding its sewage infrastructure, rather than focusing on water supply, which appears less relevant to its inefficiency profile.

Table 9: Slack and deviation table for metropolitan municipalities, service model.

Slack & Deviation Matrix

Bottom 3 Inefficient Municipalities Per Year

		Personnel Expenses		Goods and Services Expenses		Current Transfers		Other Expenses		Water distributed		Sewage network coverage (%)	
		% Dev	Slack	% Dev	Slack	% Dev	Slack	% Dev	Slack	% Dev	Slack	% Dev	Slack
2014	malatya	5%	0.0	37%	17.8	−15%	1.1	−74%	0.4	−42%	0.0	−12%	14.5
	mersin	46%	1.7	−47%	0.0	−49%	0.4	−72%	0.1	−25%	0.0	−4%	5.7
	trabzon	76%	2.3	−37%	0.0	−44%	0.2	−37%	3.9	−38%	0.0	−6%	9.1
2016	erzurum	69%	0.0	186%	28.5	−18%	0.0	141%	28.6	7%	0.0	−6%	8.7
	kahramanmaras	86%	0.0	23%	0.0	−60%	0.3	57%	9.8	12%	0.0	−24%	24.7
	mersin	43%	0.0	59%	0.0	−26%	0.5	23%	2.8	−9%	3.1	−4%	0.0
2018	kahramanmaras	8%	0.0	11%	0.7	−30%	0.3	51%	22.5	12%	0.0	−20%	0.0
	mersin	42%	6.4	77%	7.6	−46%	0.0	64%	0.0	−3%	0.0	−12%	0.0
	van	1%	0.0	38%	12.1	220%	1.8	51%	3.5	−32%	12.1	−20%	0.0
2020	denizli	513%	233.6	29%	4.2	−56%	0.0	−5%	0.0	12%	0.0	6%	0.0
	erzurum	35%	13.0	23%	0.0	−64%	0.0	233%	154.4	20%	7.1	−6%	0.0
	mersin	−6%	0.0	40%	0.0	−30%	0.0	117%	54.3	2%	0.0	−11%	4.7
2022	konya	9%	0.0	41%	0.0	41%	0.0	63%	29.7	26%	0.0	7%	0.0
	mersin	−32%	0.0	22%	11.8	−61%	0.0	6%	32.3	3%	0.0	−6%	5.0
	van	−18%	0.0	3%	0.0	−58%	0.0	−31%	3.3	−20%	13.1	0%	0.0

Slack values are calculated for all DMUs, enabling the aggregation of annual average slack scores. These averages provide valuable insights into overall trends in inefficiency, as summarized in **Table 10.** Moreover, when contrasted with the results presented in **Table 12**, they allow for a comparative analysis between metropolitan and non-metropolitan municipalities.

The findings indicate that water service variables are not major contributors to inefficiency in metropolitan municipalities, suggesting a relatively saturated development in this area. In contrast, non-metropolitan municipalities continue to exhibit potential for improvement in water service provision. Sewage network coverage, on the other hand, appears to be well-established across both municipal types, showing relatively low slack values.

In terms of expenditure related inefficiencies, goods and services expenditures and other expenditures emerge as the most significant contributors. Notably, the pattern of inefficiency related to personnel expenses shows asymmetrical fluctuations over time between the two municipal subgroups, indicating differing dynamics in human resource allocation and efficiency management.

Table 10: Yearly slack analysis for metropolitan service supply model.

Average Slack Values by Year

Mean inefficiencies per input/output variable

Year	Personnel Expenses	Goods and Services Expenses	Current Transfers	Other Expenses	Water distributed	Sewage network coverage (%)
2014	6.5	10.1	2.1	18.3	0.6	5.4
2016	1.3	20.0	1.6	9.2	4.2	4.2
2018	3.1	8.1	0.2	11.3	1.4	0.0
2020	11.7	2.9	0.3	14.9	1.4	1.6
2022	0.0	1.9	0.5	6.2	1.1	0.2

Table 11 presents the slack values for non-metropolitan municipalities under the services model, highlighting the three lowest-performing municipalities for each year. The table allows for the identification of specific sources of inefficiency in these poorly performing cases. In contrast to the metropolitan results in **Table 9**, output slacks are considerably higher among non-metropolitan municipalities. This suggests that basic service provision is more adequately achieved by metropolitan municipalities, whereas non-metropolitan counterparts exhibit greater shortfalls. In other words, there remains significantly more room for improvement in the service delivery performance of non-metropolitan municipalities.

Table 11: Slack and deviation table for non-metropolitan municipalities, service model.

Slack & Deviation Matrix

Bottom 3 Inefficient Municipalities Per Year

		Personnel Expenses		Goods and Services Expenses		Current Transfers		Other Expenses		Water distributed		Sewage network coverage (%)		Waste collected	
		% Dev	Slack	% Dev	Slack	% Dev	Slack	% Dev	Slack	% Dev	Slack	% Dev	Slack	% Dev	Slack
2012	artvin	60%	7.4	5%	0.0	−26%	1.5	−9%	7.1	5%	0.0	−5%	6.8	31%	60.7
	duzce	−24%	0.0	4%	0.0	14%	2.3	−23%	0.0	−46%	60.4	−1%	0.0	0%	41.4
	sivas	23%	0.0	23%	56.4	−46%	3.1	12%	0.0	−33%	51.5	5%	0.0	−31%	103.1
2014	canakkale	100%	0.0	0%	0.0	34%	0.0	177%	61.5	11%	36.6	3%	0.0	53%	0.0
	giresun	44%	0.0	6%	0.0	246%	18.7	−2%	0.0	−11%	25.2	−13%	0.0	12%	0.0
	kastamonu	40%	0.0	−6%	0.0	5%	0.0	50%	26.1	−12%	38.3	1%	0.0	31%	0.0
2016	karaman	9%	11.5	−16%	15.2	79%	0.0	15%	5.4	−59%	65.8	−3%	7.0	−47%	41.0
	rize	−18%	6.8	94%	36.1	92%	0.0	387%	44.3	−35%	37.4	−11%	15.0	−11%	6.8
	yalova	66%	0.0	73%	13.3	488%	4.8	252%	29.0	13%	0.0	4%	0.0	−16%	14.1
2018	giresun	46%	0.0	71%	11.3	46%	0.1	42%	0.0	−8%	11.2	−9%	16.0	10%	5.7
	kastamonu	69%	0.0	14%	0.0	42%	2.5	55%	0.0	−12%	14.7	3%	4.1	−20%	31.7
	yalova	32%	0.0	39%	22.8	119%	7.4	17%	0.0	13%	0.0	5%	2.2	−16%	43.0
2020	bayburt	22%	62.3	−21%	0.0	39%	7.2	−25%	0.0	−35%	18.1	5%	0.0	−49%	14.9
	sivas	−45%	0.0	22%	59.1	−16%	0.0	32%	43.6	−5%	0.0	6%	0.0	−41%	16.8
	tunceli	47%	75.8	1%	0.0	−42%	4.2	−8%	0.0	25%	0.0	2%	2.0	−25%	26.5
2022	aksaray	−32%	22.1	−29%	0.0	−55%	0.6	−57%	4.5	−38%	106.4	−1%	1.0	−59%	30.3
	nevsehir	−25%	3.0	−16%	0.0	−71%	0.3	−20%	7.3	25%	26.3	3%	0.0	−26%	14.0
	nigde	−52%	2.6	−26%	0.0	−57%	0.3	−31%	21.7	−16%	80.5	−3%	3.0	−36%	9.0

Table 12: Yearly slack analysis for non-metropolitan service supply model.

Average Slack Values by Year

Mean inefficiencies per input/output variable

Year	Personnel Expenses	Goods and Services Expenses	Current Transfers	Other Expenses	Water distributed	Sewage network coverage (%)	Waste collected
2012	3.1	3.5	2.5	2.0	7.0	0.5	15.0
2014	7.2	10.0	2.1	13.3	14.8	0.5	2.5
2016	9.7	23.1	1.7	13.8	19.4	5.4	10.3
2018	0.0	34.1	1.2	30.5	7.0	2.7	16.8
2020	6.3	2.7	0.5	10.6	2.4	0.1	2.6
2022	6.8	3.3	1.5	9.1	20.1	0.2	4.5

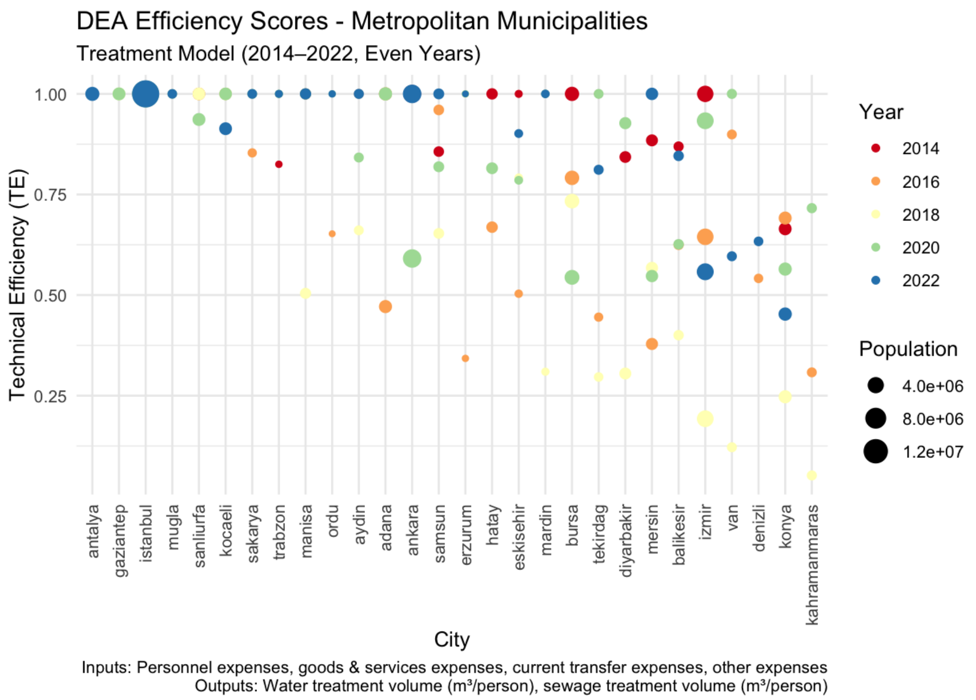
5.2. Treatment Services Models

The treatment services model utilizes two variables from TÜİK: water treatment volume and sewage treatment volume. Similar to the service supply model, metropolitan observations for year 2012 were insufficient to meet DEA requirements, thus no model estimated for that year.

Figure 3 and **Figure A3** present the efficiency results of treatment models for metropolitan municipalities. The cities of İstanbul, Muğla, and Gaziantep consistently appear as benchmark units, maintaining efficiency scores of 1.00 across all annual models. However, a notable decline in overall efficiency is observed in 2018, warranting further investigation into potential structural or operational disruptions during that period.

A comparison between İzmir and İstanbul reveals divergent efficiency trajectories among the most populous municipalities, indicating that scale alone does not determine treatment service performance. Furthermore, Denizli, Konya, Kahramanmaraş and Van exhibit substantial inefficiency gaps, highlighting the need for targeted improvements in treatment service infrastructure and management.

Figure 3: Efficiency scores of treatment model for metropolitan municipalities.



The slack values reported in **Table 13** offer valuable insights into underlying sources of inefficiency in the treatment services model. For instance, 2018 data for İzmir indicate that the the municipality performs relatively well in terms of service provision, as reflected by high treatment volumes. However, its overall efficiency score is weakened due to cost efficiency, suggesting a disproportionate level of expenditure relative to outputs. In contrast, municipalities such as Kahramanmaraş (2016), Bursa (2020), and Van (2018) exhibit low efficiency scores primarily due to insufficient service provision, rather than excessive spending. These cases illustrate the importance of distinguishing between input-driven and output-driven inefficiencies when interpreting DEA results.

The average slack values presented in **Table 14** offer a broader perspective on efficiency gaps across all DMUs. In terms of input variables, goods and services expenditures and other expenditures emerge as the primary contributors to inefficiency, indicating potential misallocation or excess spending in these categories. On the output side, water treatment volume consistently appears as the most significant source of inefficiency, suggesting that many municipalities underperform in delivering this service relative to their resource levels. These findings highlight key areas for targeted efficiency improvements in both expenditure management and service provision.

Table 13: Slack and deviation table for metropolitan municipalities, treatment model.

Slack & Deviation Matrix

Bottom 3 Inefficient Municipalities Per Year

		Personnel Expenses		Goods and Services Expenses		Current Transfers		Other Expenses		Water treatment volume		Sewage treatment volume	
		% Dev	Slack	% Dev	Slack	% Dev	Slack	% Dev	Slack	% Dev	Slack	% Dev	Slack
2014	diyarbakir	−37%	0.0	−44%	3.9	−67%	0.0	−74%	0.0	−14%	0.0	−51%	0.9
	konya	−33%	0.0	18%	36.2	−38%	0.0	44%	69.3	−86%	5.5	−33%	0.0
	trabzon	76%	49.6	−37%	0.0	−44%	0.0	−37%	0.0	41%	0.0	−63%	21.5
2016	erzurum	69%	0.0	186%	56.1	−18%	2.2	141%	42.7	62%	0.0	−30%	30.8
	kahramanmaras	86%	0.0	23%	0.0	−60%	0.8	57%	13.8	−98%	73.3	−87%	51.4
	mersin	43%	0.0	59%	0.0	−26%	0.3	23%	1.5	27%	0.0	−5%	1.6
2018	izmir	180%	13.0	10%	0.0	368%	3.8	86%	0.0	20%	0.3	29%	0.0
	kahramanmaras	8%	0.0	11%	0.3	−30%	0.0	51%	3.7	−62%	23.6	−76%	0.0
	van	1%	0.0	38%	12.4	220%	1.9	51%	3.6	−72%	32.8	−43%	0.0
2020	bursa	18%	13.0	13%	0.0	21%	3.1	47%	38.5	−29%	45.1	3%	0.0
	konya	−34%	0.0	4%	1.6	66%	5.6	96%	64.2	8%	40.4	−17%	4.7
	mersin	−6%	0.0	40%	2.7	−30%	0.0	117%	69.5	33%	9.4	19%	0.0
2022	izmir	45%	2.4	−5%	0.0	547%	30.2	21%	0.0	21%	0.0	36%	0.0
	konya	9%	0.0	41%	5.2	41%	0.0	63%	42.2	9%	0.0	−16%	26.4
	van	−18%	0.0	3%	9.9	−58%	0.0	−31%	14.1	−74%	27.2	36%	0.0

Table 14: Yearly slack analysis for metropolitan cities, treatment model.

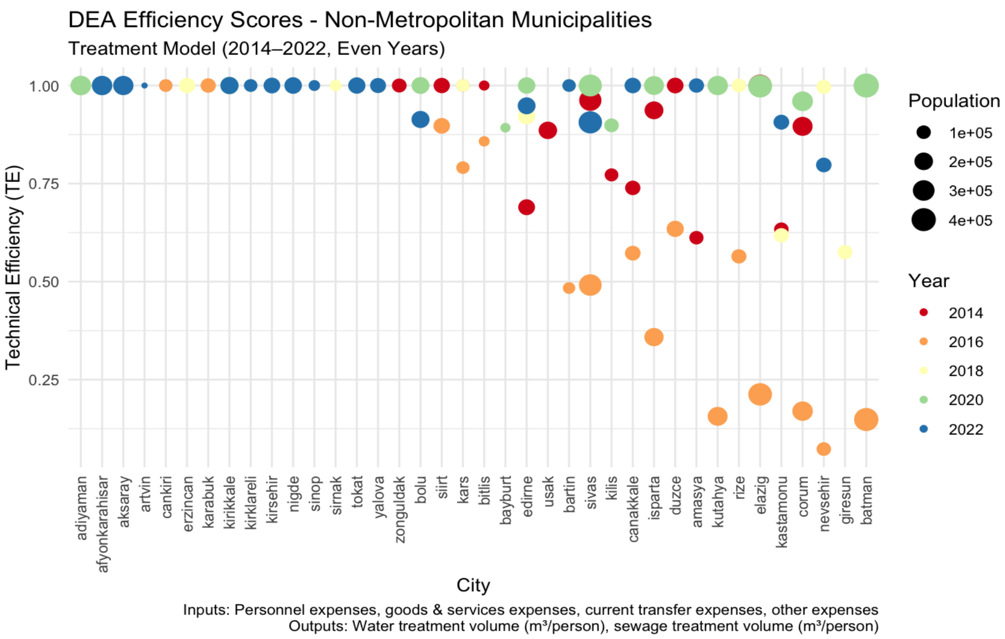
Average Slack Values by Year

Mean inefficiencies per input/output variable

Year	Personnel Expenses	Goods and Services Expenses	Current Transfers	Other Expenses	Water treatment volume	Sewage treatment volume
2014	5.7	4.6	0.1	4.9	0.3	2.1
2016	1.5	30.0	3.5	17.4	17.5	5.6
2018	2.0	7.1	0.2	15.4	7.4	0.1
2020	7.1	1.2	1.9	18.3	10.8	3.4
2022	0.1	5.0	2.6	8.3	3.0	2.8

In the treatment model for the non-metropolitan subgroup, 2012 data has insufficient number of observations to meet DEA requirements. As shown in **Table A4** and **Figure 4,** the year 2016 exhibits a noticeably lower average efficiency score compared to other years, which remain relatively stable around 0.95. Among the non-metropolitan municipalities, Afyonkarahisar, Sinop and Yalova demonstrate consistently high efficiency levels across the evaluated period, positioning them as benchmark performers within this subgroup.

Figure 4: Efficiency scores of treatment model, non-metropolitan subgroup.



Bayburt (2020) with a slack value 54.5 for personnel expenditure combined with a below average treatment values, indicate substantial inefficiency in personnel management, potentially addressing overstaffing. In contrast, Amasya (2014) exhibits a relatively balanced expenditure profile, yet underperforms in converting these expenditures into treatment service outputs, suggesting inefficiencies in operational effectiveness (**Table 15**).

Yearly slack analysis presented in **Table 16** further highlights 2016 as a notable outlier, with pronounced inefficiencies across multiple variables. If we omit the 2016 as an outlier, the remaining period reveals more balanced slack values and indicates a general improvement trend or at least a convergence among municipalities.

Table 15: Slack and deviation table for non-metropolitan municipalities, treatment model.

Slack & Deviation Matrix

Bottom 3 Inefficient Municipalities Per Year

		Personnel Expenses		Goods and Services Expenses		Current Transfers		Other Expenses		Water treatment volume		Sewage treatment volume	
		% Dev	Slack	% Dev	Slack	% Dev	Slack	% Dev	Slack	% Dev	Slack	% Dev	Slack
2014	amasya	31%	0.0	7%	0.0	−30%	0.0	−9%	1.7	−98%	90.6	−100%	29.9
	edirne	−18%	0.0	53%	38.1	22%	2.1	19%	0.0	23%	0.0	−96%	29.6
	kastamonu	40%	0.0	−6%	0.0	5%	5.1	50%	45.3	−34%	52.8	−84%	8.4
2016	batman	−4%	16.6	−12%	25.8	18%	0.0	131%	32.4	−86%	36.1	−41%	61.3
	kutahya	−8%	17.0	−5%	29.9	12%	0.0	22%	14.6	−64%	18.4	44%	4.4
	nevsehir	70%	0.0	19%	0.0	240%	0.0	658%	54.5	−31%	0.0	22%	13.5
2018	edirne	−19%	0.0	37%	0.0	16%	6.2	62%	36.1	44%	0.0	−64%	0.0
	giresun	46%	0.0	71%	0.0	46%	5.2	42%	0.0	−98%	75.4	−26%	18.2
	kastamonu	69%	0.0	14%	0.0	42%	4.9	55%	0.0	−1%	21.7	−67%	0.0
2020	bayburt	22%	54.5	−21%	0.0	39%	7.8	−25%	8.9	−96%	9.5	−10%	0.0
	corum	−45%	0.0	8%	0.0	3%	0.0	100%	94.5	−23%	0.0	38%	0.0
	kilis	−31%	0.0	82%	102.5	−11%	0.0	−10%	0.0	15%	0.0	−46%	45.1
2022	kastamonu	−29%	0.0	−21%	0.0	−8%	6.9	−38%	0.0	−10%	0.0	38%	0.0
	nevsehir	−25%	0.0	−16%	0.0	−71%	0.4	−20%	0.0	−76%	12.9	−1%	18.8
	sivas	−50%	0.0	2%	0.0	−34%	2.3	−6%	14.7	−2%	0.0	15%	0.0

Table 16: Yearly slack analysis for non-metropolitan municipailties, treatment model.

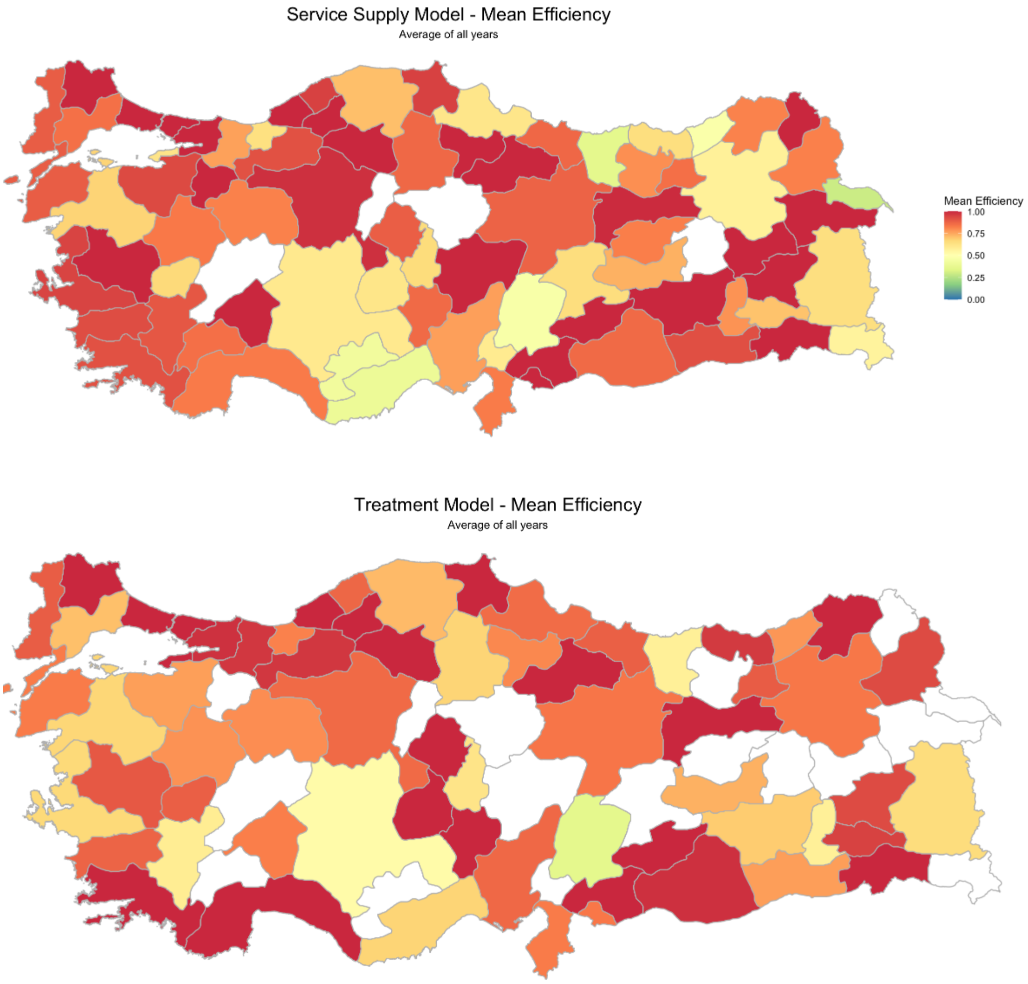
Average Slack Values by Year

Mean inefficiencies per input/output variable

Year	Personnel Expenses	Goods and Services Expenses	Current Transfers	Other Expenses	Water treatment volume	Sewage treatment volume
2014	2.1	5.6	2.6	25.3	21.8	4.3
2016	21.2	48.4	2.7	33.1	8.2	20.1
2018	0.0	0.0	1.2	2.6	8.3	1.3
2020	3.0	9.4	0.4	5.7	0.5	2.8
2022	0.0	1.9	0.7	6.1	0.7	2.0

Figure 5 presents a visual representation of the mean efficiency scores of municipalities over the period 2012-2022, mapped geographically across Turkey. While Turkish municipalities exhibit considerable heterogeneity in terms of economic activity, population, geography, climate, demography, the spatial distribution of efficiency scores does not reveal a strong pattern of regional dependence. This observation holds for both the service supply and treatment services models, suggesting that efficiency performance is influenced more by local administrative and operational factors than by broad regional characteristics.

Figure 5: Services and treatment models, mean efficiency scores 2012-2022 illustrated on map. (Empty regions represent lack of data.)



6. Discussion

The findings of this study both align with and extend the existing literature on municipal efficiency in Turkey, offering important methodological and empirical advancements. Earlier studies, such as Kutlar et al. (2012) and Çelikkaya (2016), have documented persistent inefficiencies among Turkish municipalities, with a particular emphasis on the gap between spending and service outcomes. Our findings confirm this pattern, particularly through the use of slack analysis, which reveals specific spending categories (e.g., goods and services) that frequently exceed group norms without corresponding service output. This adds a diagnostic layer absent from prior work, which typically reported only composite efficiency scores.

Studies like Kaplan et al. (2006) and Güneş & Akdoğan (2007) suggested that metropolitan municipalities may benefit from economies of scale, though efficiency varied by service type. Our findings provide more nuanced evidence: while some large municipalities such as Istanbul maintain consistently high efficiency, others such as İzmir and Ankara display more volatile performance, particularly in treatment-related services. This supports the conclusion that scale alone does not guarantee efficiency, a claim previously noted but now reinforced by multi-year, multi-model evidence.

İlkay & Doğan (2009) emphasized the importance of modeling efficiency by service domain, a principle that this study adopts through its dual-model structure (Service Supply and Treatment Services). By disaggregating models and treating metropolitan and non-metropolitan municipalities separately, this study provides a more nuanced understanding of performance variation, especially in light of differences in functional responsibilities, resource levels, and data availability.

Moreover, unlike previous studies that largely relied on short time frames (usually 1–3 years) and static datasets, this research utilizes a longitudinal dataset spanning 12 years and derived through computational text analysis from Turkish Court of Accounts audit reports. This methodological innovation overcomes longstanding data limitations in the literature and establishes a scalable, replicable framework for future research.

By transforming technical accounting and financial data into accessible and interpretable efficiency metrics, this methodology contributes meaningfully to transparency and accountability in local governance. As shown in prior literature (e.g. Narbón-Perpiñá & De Witte, 2018), the use of efficiency indicators derived from non-parametric methods such as DEA can be instrumental in evaluating and comparing municipal performance. In well-functioning democracies, such transparency may even support more informed and conscious electoral behavior, empowering citizens to evaluate local administrations beyond political narratives.

The service categories used in the models, such as water distribution, sewage coverage, and treatment volume, remain foundational for small and mid-sized municipalities, and continue to align with standard efficiency measurement frameworks used internationally (e.g., Afonso & Fernandes, 2008; Prieto & Zofio, 2001). However, in metropolitan municipalities, the role of these basic services is increasingly supplanted by broader social service demands. These include urban transportation, poverty alleviation programs, childcare and elder care services, public health, and recreational infrastructure, which now constitute a growing share of local government responsibilities. Consequently, future analyses would benefit from incorporating a wider array of service indicators to capture the full complexity of urban governance, as also suggested in the extended DEA applications of Woodbury & Dollery (2004) and De Sousa et al. (2005).

Recent international studies, such as Rella et al. (2025), apply multi-stage DEA frameworks to evaluate efficiency in Italian municipalities, often integrating socio-economic or governance-related contextual variables to explain variations in performance. These approaches emphasize not only the technical aspects of waste services but also broader accountability and policy factors. In contrast, the Turkish case presents a distinct landscape shaped by rapid urbanization, strong central government transfers, and evolving legal frameworks, as discussed by Rahmani & Özçelik (2024). Although similar in methodological application, Turkish municipalities often operate under tighter fiscal and institutional constraints and face structural differences in service mandates—especially between metropolitan and non-metropolitan municipalities. These distinctions may partly explain the relatively larger slack values and inefficiency margins observed in Turkish wastewater and waste services. Overall, while Türkiye shares common analytical ground with international literature in terms of DEA methodology, its unique administrative and financial context necessitates a more localized interpretation of efficiency results.

Moreover, the rising fiscal importance of local governments relative to central administrations, as observed over the last two decades, underscores the need for greater data transparency and performance monitoring. This trend is mirrored globally in developed and developing economies alike, where municipal-level decision-making increasingly influences public service quality and citizen well-being. With access to more and diversified data on municipal services, the DEA framework applied in this study could be easily expanded to generate more reliable and actionable results.

Importantly, this method provides an antidote to information bias and distortion, which are common in politically polarized environments. Publicly available data, including satisfaction surveys, are often subject to interpretive manipulation, whether intentional or unintentional, by competing political actors. In contrast, the method proposed in this research relies on objectively measurable service outputs and audited financial data, producing results through transparent and replicable algorithms. As such, the framework offers a rare avenue for evidence-based evaluation, independent of political alignment or subjective perception.

7. Conclusion

This study evaluates the technical efficiency of Turkish municipalities at the provincial level using a novel and comprehensive dataset extracted from Sayıştay (Turkish Court of Accounts) reports. By applying two DEA models, one focused on service provision and the other on treatment capacity, we offer new insights into efficiency patterns across both metropolitan and regular municipalities over a 12-year period. The research identifies benchmark municipalities across different years and subgroups, captures regional and temporal variation, and generates evidence-based insights for municipal administrations, audit institutions, and the general public.

The results highlight several key areas for policy attention. First, the identification of resource-intensive municipalities with relatively low service outputs suggests the need for a more performance-oriented budgeting process. Municipalities should integrate output-based performance metrics into their budgetary decision-making to ensure that increased expenditures translate into tangible service improvements. Second, municipalities that consistently demonstrate high efficiency can serve as benchmarks for others. Their best practices in budget management, service delivery strategies, and governance structures should be documented, shared, and adapted to local contexts. Third, given the structural and functional differences between metropolitan and regular municipalities, a one-size-fits-all model of performance evaluation may be inadequate. Tailored performance criteria and service expectations should be developed to reflect the distinct mandates and capacities of each municipality type. Finally, the methodology developed in this study provides not only a tool for academic analysis but also a practical framework for public sector auditing and oversight. Efficiency analysis can complement traditional financial audits by flagging potential areas of mismanagement or underperformance, thereby strengthening accountability mechanisms.

The primary limitation of the study lies in the limited availability of output variables, particularly for metropolitan municipalities. In addition, the irregular auditing schedule and incomplete coverage by the Turkish Court of Accounts create data discontinuities, undermining the application of panel-based methods. Future research may build on this foundation by integrating additional service dimensions such as social care, education, or urban resilience, especially for metropolitan municipalities with expanding mandates. Extending the analysis to include district-level municipalities and municipal subsidiaries as distinct decision-making units would provide a more granular understanding of local government performance. Moreover, by identifying subsets of municipalities with consistent annual data, future studies may apply panel-based methods such as the Malmquist Productivity Index to trace changes in efficiency over time.

Appendix

A Supplementary Graphs and Tables

Table A1: Services model efficiency results – all metropolitan municipalities.

City	2014	2016	2018	2020	2022	Average
diyarbakir	1.00		1.00	1.00		1.00
istanbul	1.00	1.00	1.00	1.00	1.00	1.00
kayseri	1.00	1.00	1.00	1.00	1.00	1.00
kocaeli	1.00	1.00	1.00	1.00	1.00	1.00
manisa	1.00	1.00	1.00	1.00	1.00	1.00
gaziantep			1.00	1.00		1.00
ankara	0.95			1.00	1.00	0.98
izmir	0.72	1.00	1.00	1.00	1.00	0.94
bursa	1.00	0.83	1.00	0.90		0.93
aydin		1.00	0.70	1.00	1.00	0.92
mardin	1.00		0.68	1.00	1.00	0.92
mugla	1.00	0.58	1.00	1.00	1.00	0.92
denizli		1.00		0.71	1.00	0.90
ordu		0.62		0.99	1.00	0.87
sanliurfa	0.52	1.00	1.00	0.94		0.86
tekirdag	0.92	0.47	0.86	1.00	1.00	0.85
antalya	0.32	1.00		1.00	1.00	0.83
hatay	1.00	0.67		0.82		0.83
eskisehir	0.59	0.52	0.98	1.00	1.00	0.82
adana	0.60	0.47	1.00	1.00		0.77
sakarya	0.47	0.77	0.82	1.00	0.76	0.76

Table A2: Services model efficiency results – all metropolitan municipalities. (Continue)

City	2014	2016	2018	2020	2022	Average
balikesir	0.27	0.63	0.72	0.76	1.00	0.68
malatya	0.20	0.40	1.00	1.00		0.65
trabzon	0.14	0.63	0.82	0.78	0.87	0.65
van		0.90	0.12	1.00	0.55	0.64
samsun	0.37	0.81	0.38	0.73	0.79	0.62
konya	0.50	0.68	0.40	0.77	0.65	0.60
erzurum		0.31	0.54	0.63	0.80	0.57
kahramanmaras		0.31	0.31	0.77		0.46
mersin	0.19	0.37	0.36	0.48	0.59	0.40
Average	**0.69**	**0.73**	**0.79**	**0.91**	**0.91**	**0.81**

Table A3: Services model efficiency results – all non-metropolitan municipalities.

City	2012	2014	2016	2018	2020	2022	Average
afyonkarahisar	1.00	1.00	1.00		1.00	1.00	1.00
ardahan	1.00	1.00	1.00				1.00
kirklareli	1.00				1.00	1.00	1.00
mus	1.00	1.00			1.00	1.00	1.00
sirnak	1.00	1.00	1.00	1.00			1.00
tokat	1.00				1.00	1.00	1.00
agri		1.00	1.00				1.00
amasya		1.00			1.00	1.00	1.00
bilecik		1.00	1.00	1.00		1.00	1.00
bingol		1.00					1.00
bitlis		1.00	1.00				1.00

Table A4: Services model efficiency results – all non-metropolitan municipalities.(Continue)

City	2012	2014	2016	2018	2020	2022	Average
cankiri		1.00	1.00				1.00
isparta		1.00	1.00	1.00	1.00		1.00
kilis		1.00			1.00		1.00
zonguldak		1.00					1.00
karabuk			1.00				1.00
adiyaman					1.00		1.00
kirikkale					1.00	1.00	1.00
erzincan	1.00	0.97	1.00	1.00			0.99
sinop		1.00	1.00	1.00		0.80	0.95
bartin	1.00	0.81	0.89	1.00	1.00	1.00	0.95
bolu		0.88			1.00	0.87	0.92
canakkale	0.83	0.62	1.00		1.00	1.00	0.89
edirne		0.87		0.74	0.97	0.98	0.89
kirsehir		0.66		1.00		1.00	0.89
sivas	0.77	1.00	0.88		0.94	0.80	0.88
corum		0.91	0.70		1.00		0.87
nigde		0.85		1.00	1.00	0.59	0.86
bayburt		0.79			0.92		0.85
burdur		0.74	0.66		1.00	1.00	0.85
kutahya		1.00	0.38	0.96	1.00		0.83
tunceli					0.86	0.79	0.82
kars		1.00	0.47	0.99			0.82
artvin	0.63					1.00	0.82

Table A5: Services model efficiency results – all non-metropolitan municipalities.(Continue)

City	2012	2014	2016	2018	2020	2022	Average
gumushane		0.80					0.80
batman	1.00	1.00	0.15		1.00		0.79
elazig		1.00	0.21		1.00		0.74
kastamonu	1.00	0.66		0.52		0.67	0.71
siirt		0.97	0.44				0.71
usak		0.66					0.66
nevsehir	1.00		0.10	0.88		0.64	0.66
duzce	0.82	0.72	0.39				0.64
yalova	1.00		0.10	0.53		0.85	0.62
aksaray						0.62	0.62
osmaniye		1.00	0.19				0.60
hakkari		1.00	0.11				0.56
rize			0.09	0.85			0.47
karaman		0.75	0.10				0.42
giresun		0.55	0.12	0.41			0.36
igdir			0.29				0.29
Average	**0.94**	**0.90**	**0.61**	**0.87**	**0.99**	**0.89**	**0.83**

Table A6: Treatment model efficiency results – all metropolitan municipalities.

City	2014	2016	2018	2020	2022	Average
istanbul	1.00	1.00	1.00	1.00	1.00	1.00
mugla	1.00	1.00	1.00	1.00	1.00	1.00
gaziantep			1.00	1.00		1.00
antalya					1.00	1.00

Table A7: Treatment model efficiency results – all metropolitan municipalities. (Continue)

City	2014	2016	2018	2020	2022	Average
sanliurfa	1.00	1.00	1.00	0.94		0.98
kocaeli	1.00	1.00	1.00	1.00	0.91	0.98
sakarya	1.00	0.85	1.00	1.00	1.00	0.97
trabzon	0.83	1.00	1.00	1.00	1.00	0.97
manisa	1.00	1.00	0.50	1.00	1.00	0.90
ordu		0.65		1.00	1.00	0.88
aydin		1.00	0.66	0.84	1.00	0.88
adana	1.00	0.47	1.00	1.00		0.87
ankara	1.00			0.59	1.00	0.86
samsun	0.86	0.96	0.65	0.82	1.00	0.86
erzurum		0.34	1.00	1.00	1.00	0.84
hatay	1.00	0.67		0.82		0.83
eskisehir	1.00	0.50	0.79	0.79	0.90	0.80
mardin			0.31	1.00	1.00	0.77
bursa	1.00	0.79	0.73	0.54		0.77
tekirdag	1.00	0.45	0.30	1.00	0.81	0.71
diyarbakir	0.84		0.31	0.93		0.69
mersin	0.88	0.38	0.57	0.55	1.00	0.68
balikesir	0.87	0.62	0.40	0.63	0.85	0.67
izmir	1.00	0.64	0.19	0.93	0.56	0.67
van		0.90	0.12	1.00	0.60	0.65
denizli		0.54			0.63	0.59
konya	0.66	0.69	0.25	0.56	0.45	0.52
kahramanmaras		0.31	0.05	0.72		0.36
Average	**0.94**	**0.73**	**0.65**	**0.87**	**0.89**	**0.81**

Table A8: Treatment model efficiency results – all non-metropolitan municipalities.

City	2014	2016	2018	2020	2022	Average
afyon-karahisar	1.00	1.00		1.00	1.00	1.00
cankiri	1.00	1.00				1.00
sinop	1.00	1.00	1.00		1.00	1.00
zonguldak	1.00					1.00
karabuk		1.00				1.00
yalova		1.00	1.00		1.00	1.00
erzincan			1.00			1.00
nigde			1.00	1.00	1.00	1.00
sirnak			1.00			1.00
adiyaman				1.00		1.00
kirikkale				1.00	1.00	1.00
kirklareli				1.00	1.00	1.00
tokat				1.00	1.00	1.00
aksaray					1.00	1.00
artvin					1.00	1.00
kirsehir					1.00	1.00
bolu	1.00			1.00	0.91	0.97
siirt	1.00	0.90				0.95
kars	1.00	0.79	1.00			0.93
bitlis	1.00	0.86				0.93
bayburt				0.89		0.89
edirne	0.69		0.92	1.00	0.95	0.89
usak	0.89					0.89

Table A9: Treatment model efficiency results – all non-metropolitan municipalities. (Continue)

City	**2014**	**2016**	**2018**	**2020**	**2022**	**Average**
bartin		0.48	1.00	1.00	1.00	0.87
sivas	0.96	0.49		1.00	0.91	0.84
kilis	0.77			0.90		0.84
canakkale	0.74	0.57		1.00	1.00	0.83
isparta	0.94	0.36	1.00	1.00		0.82
duzce	1.00	0.63				0.82
amasya	0.61				1.00	0.81
kutahya	1.00	0.16	1.00	1.00		0.79
rize		0.56	1.00			0.78
elazig	1.00	0.21		1.00		0.74
kastamonu	0.63		0.62		0.91	0.72
corum	0.90	0.17		0.96		0.68
nevsehir		0.07	1.00		0.80	0.62
giresun			0.57			0.57
batman		0.15		1.00		0.57
Average	**0.91**	**0.60**	**0.94**	**0.99**	**0.97**	**0.89**

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