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Ownership or procurement, which matters? exploring asymmetries in local public transportation in Italy through a semi-parametric approach

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ABSTRACT

The local public transportation (LPT) system is crucial for the growth and competitiveness of regions. The efficiency of service providers and the chosen procurement system significantly influence the LPT system's operational dynamics. This study combines an analysis of service contract determinants with a comprehensive examination of company ownership impacts and LPT service procurement dynamics in major Italian cities. Using a GAMLSS (Generalized Additive Models for Location, Shape, and Scale) approach, the study identifies key factors influencing contract outcomes. This study reveals the complex interplay of cost factors, ownership models, and geographical disparities, offering valuable insights for policymakers and public transportation professionals.

1. Introduction

Local public transport (LPT) plays a crucial role in shaping urban environments and providing sustainable mobility for residents. Efficient transportation systems are essential for the progress and development of an area (Debnath, 2022), particularly in addressing the needs of economically disadvantaged populations.

LPT services, classified as services of general economic interest, fall under network utilities and present regulatory challenges due to their nature as natural monopolies at the local level. These are economic activities deemed crucial by public authorities for citizens that would not be adequately provided, or would be offered under different conditions, without public intervention. In fact, the objective of delivering universal service in local public transport frequently results in low fares, leading to financial imbalances for service providers. This creates difficulties for authorities striving to balance the budgets while meeting the public service obligations (Polemis & Fafaliou, 2015). Consequently, funding allocation should reflect the costs borne by an efficient operator and employ a methodology that prevents regional inefficiency disparities. This study examines how these challenges are addressed within the Italian LPT context. Utilizing primary data from 2017–2019, it empirically analyzes the dynamics of LPT and government contracts in selected Italian municipalities.

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[1] The authors would like to express their gratitude to Biagio Martich for his invaluable assistance in providing key raw variables. Specifically, they are deeply indebted to him for his instrumental role in procuring the data for the following variables: per-capita contract, per-capita seat km bus, per-capita travelers, bidding process, and ownership. Additionally, the authors would like to extend their sincere thanks to the anonymous referees for their insightful comments and valuable suggestions, which have greatly contributed to improving the quality of the paper. Their thorough reviews and constructive feedback have been invaluable in refining the analysis and enhancing the overall clarity and impact of the findings The usual caveat applies.

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We aim to contribute to the literature on public transportation by addressing three key research questions.

Research question 1: *What factors influence the efficiency and performance of LPT services in Italian municipalities?*
The efficiency and performance of local public transport services in Italian municipalities are influenced by several factors, including ownership structures, competition, contracting models, incentives, political pressures, social capital, and benchmarking schemes. Each of these variables has been analyzed in the literature without reaching a general consensus. Bray and Mulley (2013) discuss for instance the lack of consensus on best practices in public transport contracting, while Hensher and Stanley (2008) question whether competitive tendering is better than negotiating with pre-selected operators. Yvrande-Billon (2006) argues that true competitive tendering is not possible due to the limited control powers of the public sector and the lack of transparency in the procurement process. Hart et al. state that private companies have strong incentives to reduce costs due to incomplete contracts, leading to weaker incentives for improving quality.

The relationship between ownership structures and the efficiency and performance of LPT is a topic of ongoing research and debate. Vickers and Yarrow (1991) suggest that state-owned companies can be inefficient due to political pressures. Hensher and Stanley (2008) discuss the importance of social capital in understanding LPT company operations, while Boitani, Nicolini, and Scarpa (2013) claim that public ownership (Dalen & Gómez-Lobo, 2003) suggest benchmarking schemes to improve firm performance and reduce regulatory costs, whereas Teodorovicz, Lazzarini, Cabral, and Nardi (2023) note that mixed systems can increase efficiency by mitigating constraints in public organizations. In addition to ownership structures, competition plays a significant role in driving efficiency and performance in local public transport services (Negrelli, Roukouni, & Chassy, 2017).

Boitani et al. (2013) highlight the positive impact of competition on productivity, while Ottoz, Fornengo, and Di Giacomo (2009) find that higher density and scale economies are more likely to occur in private companies (Negrelli et al., 2017). The choice of contracting model also affects the efficiency and performance of LPT services (Sheng & Meng, 2020). Some studies suggest that competitive tendering leads to better outcomes, while others argue that negotiating with pre-selected operators can be more effective (Negrelli et al., 2017). There is no consensus on best practices in public transport contracting, with some researchers questioning the effectiveness of competitive tendering and others emphasizing the importance of social capital and the role of the public sector in ensuring transparency in the procurement process. The literature on the relationship between ownership structures and the efficiency and performance of LPT services is multifaceted and presents differing perspectives on the topic (Ottoz et al., 2009; Sheng & Meng, 2020).

Building on this existing literature, we empirically test variables such as the bidding process to analyze the effect of procurement methods on LPT efficiency and funding allocation and the ownership structure that is crucial in determining efficiency and the quality of service, as noted in the literature. Our aim is to contribute to the literature on competitive tendering versus negotiated contracts, and ownership, facilitating the assessment of public vs. private ownership impacts on service provision and efficiency.

To offer a more comprehensive explanation of the determinants of Italian public service contracts and to answer the first research question, we also analyze traditional factors such as per-capita contract funding, which aligns with the financial aspects of service contracts. We also consider per-capita seat km for buses, indicating coverage and availability and assessing the efficiency of service provision relative to the population size ; usage rates for gauging operational efficiency and demand satisfaction; diesel prices as an operational cost factor impacting financial design and sustainability; and geographic size influencing complexity and cost-efficiency of service provision.

After gaining a general understanding of variable relevance, we explore specific factors unique to the Italian territory. These may help explain the divide between the northern and southern regions of the country and could also be applicable in other countries. This consideration gives rise to our subset of research questions.

Research question 2: *Does the mode of procurement (competitive bidding vs. non-competitive) and ownership structure (public vs. private) impact the efficiency and performance of LPT services?*

Hensher and Stanley (2008) raise the question of whether competitive tendering is better than negotiating with pre-selected operators. Boitani et al. (2013) suggest that competitive processes are linked to higher productivity, and mention that ownership changes from public to private increase TFP. Miranda and Lerner (1995) propose that a mixed public–private model allows for flexibility in pursuing different objectives and improves performance through benchmarking. Ballard and Warner (2000) advocate for expanding the pool of service providers to foster competition. Winston (2000) emphasizes the inefficiency and high subsidies associated with public monopolies, while Warner and Bel (2008) discusses how mixed systems can enhance efficiency by providing information about service costs and allowing government intervention in case of contract failure.

Hart, Shleifer, and Vishny (1997) and Vickers and Yarrow (1991) also addressed the topics of incentives and quality. According to Hart et al. (1997), private companies have a strong incentive to reduce costs, while public companies have less motivation to improve quality. Vickers and Yarrow (1991) highlight that political pressures can result in inefficiencies within state-owned companies.

According to Schmitz, public ownership may enable the government to ensure a higher level of service quality, although citizens' interests may diverge from the government's perspective. Warner and Bel (2008) propose that mixed systems can deter opportunistic behavior by incumbent service providers and maintain the government's intervention capability.

Bidding processes and ownership variables are critical themes in the literature, and are crucial for understanding the impact of governance structures on efficiency and service quality.

Research question 3: *How do geographical differences affect the allocation of public resources for LPT?*

The public sector is faced with the challenging decision of choosing between in-house provision and outsourcing, while also having the ultimate responsibility for defining the service area. Currently in Italy, service areas are defined by administrative boundaries without taking into account economies of scale or potential operator inefficiencies that may be present in different territories. To gain insights into regional and geographical factors that may affect service provision and efficiency, we categorized municipalities by region. This allows for an analysis of regional disparities in LPT efficiency and funding. Understanding these regional differences is crucial for comprehending variations in service contract efficiency and funding. Additionally, we incorporated altimetric bands to provide geographical context. This enables an understanding of how terrain and altitude might impact LPT services and costs. These variables can significantly influence operational costs as well as service efficiency, providing evidence of potential geographic bias in Italy or any common distinctions among Northern, Central, and Southern Italy.

The rest of the study is organized as follows. The next section, Section 2, examines the development of LPT financing and service allocation, providing background information on the Italian LPT. Section 3 describes the data and the empirical strategy. The regression results are presented in Section 3.2, which also includes a discussion of their implications. Section 4 concludes.

2. The reform process in Italy

The institutional and regulatory framework of the Italian LPT sector presents specific challenges, such as cost recovery due to increased operating expenses and reduced tariffs aimed at promoting universal access. A history-dependent cost-plus allocation of public funds to LPT subsidies has led to the accumulation of varying inefficiencies and cost inflation across regions and cities, resulting in an inequitable distribution of public funds among different areas (Avenali, Boitani, Catalano, D'Alfonso, & Matteucci, 2016).

In recent years, Italy, like many countries, has introduced various reforms and competitive tendering procedures to enhance productivity and reduce significant deficits. Specifically, Legislative Decree 50/2017 introduced new methods for allocating funds from the National Fund among different regions, replacing the historical expenditure method with the LPT Fund established by Law 228/2012. This Fund has shown stability recently, reaching €4,789.5 million in 2017 and €4,932.6 million in 2018. Ninety percent of the Fund's resources are allocated based on service levels, transport revenue, and standard costs, while the remaining 10% depends on achieving specific efficiency goals.

To enhance service efficiency and financial accountability of LPT providers, the decree encourages competitive bidding for contracts and links funding to traffic-derived revenue. Tariff setting considers service levels, European averages, and the relationship between tariffs and subscriptions. Despite initial plans for 2018, implementation has been postponed multiple times, with penalties for non-competitive assignments delayed until 2020.

The reform shifts subsidy management and service programming to regional authorities, who must now integrate funds for municipalities. Authorities and operators must enter formal agreements, known as "service contracts", delineating reimbursement policies and risk-sharing, whether tendering out concessions or making use of in-house provision. The different contract types have varying effects on the cost performance of LPT companies. In the Net Cost Contract, the operator assumes both industrial and commercial risks, incentivizing efficiency and higher passenger numbers. Conversely, in the Management Contract, the public sector bears all risks, and the operator receives a management fee, offering no incentives for efficiency or increased ridership. The most commonly used contract in Italy is the Gross Cost Contract, where the public sector assumes commercial risk, while the operator focuses on reducing costs.

It should be noted that, effective tendering is complex, requiring the determination of optimal tender area sizes to balance competition and economies of scale. Smaller service areas encourage competition but may not maximize economies of scale, while in large cities or metropolitan areas, service networks can become too large to manage efficiently. Unfortunately, in Italy, service areas are defined by administrative boundaries without taking into account economies of scale or potential operator inefficiencies that may be present in different territories.

Despite regulatory attempts, significant progress in separating controlling authorities from operators or increasing efficiency has been limited. Municipalities often prefer non-competitive procedures, such as direct awards and in-house contracting, to maintain public monopolies and therefore political benefits, limiting private sector involvement. Historically, the central government prevented LPT companies from going bankrupt, prioritizing the political benefits of maintaining monopolistic public companies over potential cost reductions from competition. These benefits included securing union support and providing career opportunities for politicians. More recently, Legislative Decree No. 201/2022 aimed to separate regulatory and managerial functions but remains largely advisory, allowing deviations in practice.

3. Data analysis

3.1. Description

Empirical research on public transport tends to focus on a single region often attributed to data limitations in the field. Our study stands out from others in this respect, as we conduct an investigation of the aforementioned hypotheses using an extensive database that encompasses Italian municipalities providing LPT services and situated within Ordinary Statute Regions (OSRs). Despite the differences between OSRs (in terms of size and political parties that govern them, extension, density, demographic age structure, and GDP *per-capita*), one of the benefits of limiting our empirical analysis to these regions is that we avoid to some extent the problem of omitted unobserved variables that explain heterogeneity in a multi-regional study. We focus on provincial capitals to have cities of a minimum size and companies with a certain degree of complexity, while some choice was driven by data availability. We collect data from 61 Italian provincial capitals for years 2017, 2018, and 2019 out of a total of 88 provincial capitals (Fig. 1). For the rest,

Fig. 1. Provincial capitals accounted.

it was not possible to obtain all the financial information on the companies providing public transportation, since only publicly owned ones are required to disclose their financial statements.[2]

Among the considered companies, only 13 operate in urban areas, while the remaining 48 are multi-service companies that also operate in non-urban areas. In addition, public transport in Italy is an interconnected system that includes both urban and extra-urban transport networks and is made up of different modes of transport. These include bus lines (which operate in both urban and suburban areas), tramways, subways, state-licensed or managed railroads that operate in suburban areas, and state railroads (FS) that are limited to local transit. This variety only partially illustrates the uniqueness of the LPT service in Italy and the challenges it poses for sector analysis.

The data used in this study come from a variety of sources, in part because of the complexity of the system. Financial information is sourced from the SOSE[3] questionnaires and the financial statements of the respective companies. Additionally, we have integrated data from authoritative sources such as ISTAT (Italian statistical institute) and the Ministry of Enterprises. The final dataset includes a total of nine variables, both quantitative and qualitative, which underwent raw data processing to render them suitable for this analysis. In particular, we compute the average values of all the continuous variables observed in the three years for each municipality. In Table 1, we present the comprehensive descriptive statistics of the quantitative variables, complemented by the empirical distribution illustrated in Fig. 2:

The first variable in Table 1, is the *average per-capita contract* which is the amount of the LPT contract per head of population as shown in the SOSE questionnaires and in the financial statements of the companies, the *average per-capita seat km bus* is the average kilometers *per-capita* per each seat in the bus, the *average travelers* expresses, on a *per-capita* basis, the annual number of passengers. The *average population* is calculated as the mean value of the population for each municipality. The *average per-capita value added*

[2] The exclusion of certain Municipalities was mainly due to private firms not disclosing their budgets and inconsistent or zero values in Sose's questionnaire regarding service contract costs and travel ticket revenues. This affected Municipalities such as Cremona, Lodi, and Varese, among others, totaling 15 out of the 27 exclusions, with a significant number from Southern Italy. Another reason for exclusion was the lack of detailed balance sheets from public transport companies, which often did not distinguish between revenues from service contracts and travel tickets. This made it challenging to separately analyze urban and extra-urban transport data, especially in cases where multi-utilities managed multiple municipal services alongside public transport. Municipalities like Alessandria and Asti fell into this category, making up 41% of the exclusions.

[3] SOSE SpA was an *in-house* company owned by the Italian Minister of Economy whose activities mainly concern data analysis and statistical modeling for public finance issues; the questionnaires collect information about services provided by municipalities, including waste collection, local police, nurseries, and others, to estimate a *standard needs*, which represent financial support from the central government to local authorities.

Table 1
Descriptive statistics.

	Mean	Median	Min	Max	Std. Dev	Skewness	Kurtosis	Shapiro wilk test
Average *per-capita* contract	70.00	54.70	6.00	497.30	72.90	3.88	21.49	.000
Average *per-capita* seat km bus	2167.70	1985.67	389.00	4989.33	1165.66	0.33	−.99	.020
Average *per-capita* travelers	95.94	66.67	6.00	504.33	98.39	1.91	3.83	.000
Average population	216949	102632	21487	2806671	408781.5	4.68	24.74	.000
Average *per-capita* value added	25989	26063	14652	49564	6497.80	.500	1.22	.026
Average provincial diesel price	1.48	1.48	1.41	1.52	.020	−.682	3.70	.240
Average Sqr. km area	190.04	124.53	30.55	1287.38	195.86	3.21	14.04	.000

serves as a proxy for the *per-capita income* at the provincial level. Other variables include the *average price of diesel*, which is the average price calculated at the provincial level, and the *area in square kilometers*, representing the average territorial size of the municipality. Most variables are highly scattered around the mean. Precisely, *average travelers*, *average per-capita contract*, *average population* and *average area in square kilometers* are highly right-skewed, while *average per-capita value added* and the *average per-capita seat km bus* have multiple modes. Moreover, *average per-capita contract*, which is our variable of interest, is strong leptocurtic. We test for normality using the Shapiro–Wilk test, which is appropriate for our sample (Shapiro & Wilk, 1965). This test allows to reject the null hypothesis of normality for all series at the 5% level, except for the *average diesel price*.

In Fig. 3 the bivariate graphs enable to visualize the relationships between the quantitative variables; in 3(b), 3(c), 3(d) 3(e) and 3(f) a linear relationship fits the data, while in 3(a) a non-linear relationship provides the best fit to the data.[4] These findings are helpful to better identify the relationships among the variables in the model (see Section 3.2).

To avoid bias from omitted variables and to account for geographic bias in the distribution of funds, the variable *Geo* is used to account for the North, South, and Center. In terms of geographical distribution, 14 (23%) of the municipalities in the sample are located in the south, 16 (26%) in central Italy, and 31 (51%) in the northern regions. In addition to *Geo*, the other qualitative variables in our dataset are *Bidding process* and *Ownership*. The variable *Bidding process* is a dummy variable that accounts for the award procedure of the service. It takes the value of 1 if the service is provided through a competitive bid and 0 otherwise.

To assess whether ownership influences the distribution of public resources, as emphasized in prior research (Aloulou & Ghannouchi, 2023; Boitani et al., 2013; Ottoz & Fornengo, 2006; Winston, 2000), an indicator variable, *Ownership*, is employed. This variable takes on a value of 1 if the company is owned by a public authority, and 0 otherwise, to test the impact of public ownership. Figs. 4, 5, and 6 display procurement methods, type of ownership and the interaction between the two dummy variables.

Ultimately, we utilized eight altimetric bands provided by ISTAT, indicating the percentage of territory within specific altitude levels. For simplification, we aggregated the percentages from the second to the eighth ranges into a single variable. Additionally, we incorporated both the first range (0–300 mt) and second range (above 300 mt) into our model, as detailed in Table 2.

3.2. Model estimation and results

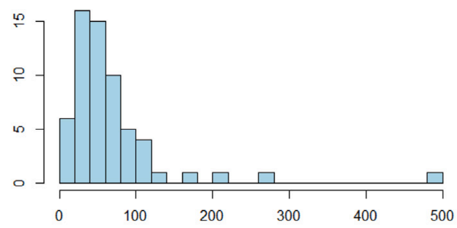
In literature focused on evidence-based policy evaluations, two main approaches are generally used: the classical linear regression model or, when data availability and conditions allow, a panel data model. However, the latter approach is not feasible in our case study due to the inability to observe the units over a sufficiently long period of time or over a sufficiently large cross-sectional dimension to capture any latent heterogeneity.

Moreover, we doubt the suitability of a conventional linear model. In the specific context of our study, a classical linear regression model may have limited predictive capacity, and the estimated coefficients may lack both economic and econometric significance due to the highly asymmetric and leptocurtic distribution of our dependent variable. Consequently, the conclusions drawn from such a model would be challenging to generalize and statistical inference would be invalidated. Alternative approaches include the use of generalized linear models (GLM) (Hardin & Hilbe, 2007; Nelder & Wedderburn, 1972) and generalized additive models (GAM) (Hastie & Tibshirani, 1990). These models offer the flexibility to move beyond the normal distribution while staying within the exponential family. However, these classes of models do not allow explicit modeling of skewness and kurtosis, which instead are typically determined by the location and scale parameters of the response variable.

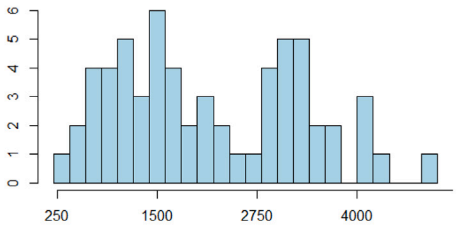
The need for a highly flexible approach to comprehensively model the conditional distribution of the dependent variable in relation to a set of covariates led us to the adoption of a specific method. This topic is discussed in Section 3.2, where the rationale behind selecting the Generalized Additive Models for Location, Shape and Scale (GAMLSS) approach is elucidated, given its ability to beyond the exponential family, to consider non-linear relationship, if any, and in particular to explicitly model the shape parameters.

In the context of the GAMLSS models a variety of distributions and highly adaptive data fitting techniques can be employed to accurately account for strong asymmetry, fat tails, and *anomalous* observations. Many contributions in the literature have explored the application of GAMLSS models for different types of data (among others, Coupé, 2018; Kneib, 2013; Marletta & Sciandra, 2020; Marmolejo-Ramos et al., 2023; Voudouris, Gilchrist, Rigby, Sedgwick, & Stasinopoulos, 2012; Zhang, Yan, Wang, Lu, & Liu, 2015).

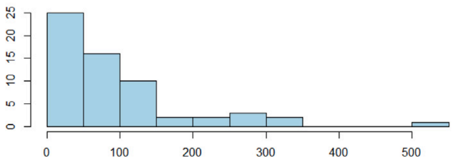
[4] In order to better visualize the plot, we use *value added* as average value added, *Kmq Surface* as area in square kilometers, *Target* as average euro *per-capita* contract, *Fuel* as average diesel price in euros and *Travelers* as average travelers. For clarity, we have excluded two observations, "Milan" and "Rome" in 3(b) and three observations, "Milan", "Rome" and "Brescia" in 3(e).



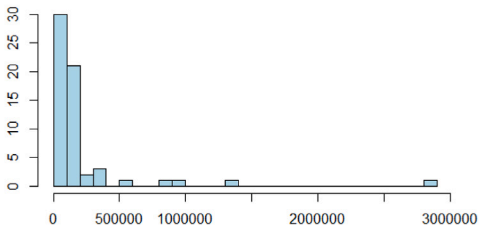
(a) Average Euro *per-capita* contract



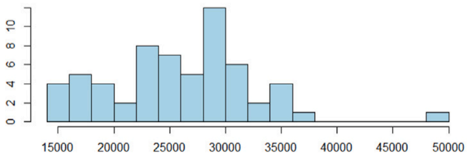
(b) Average *per-capita* seat km bus



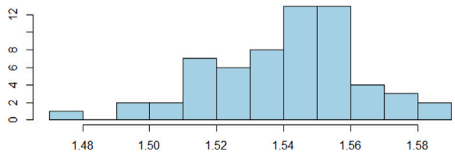
(c) Average *per-capita* travelers



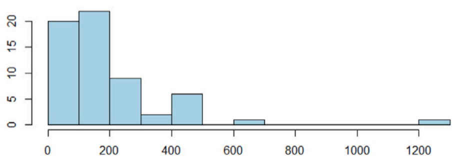
(d) Average population



(e) Average *per-capita* added value

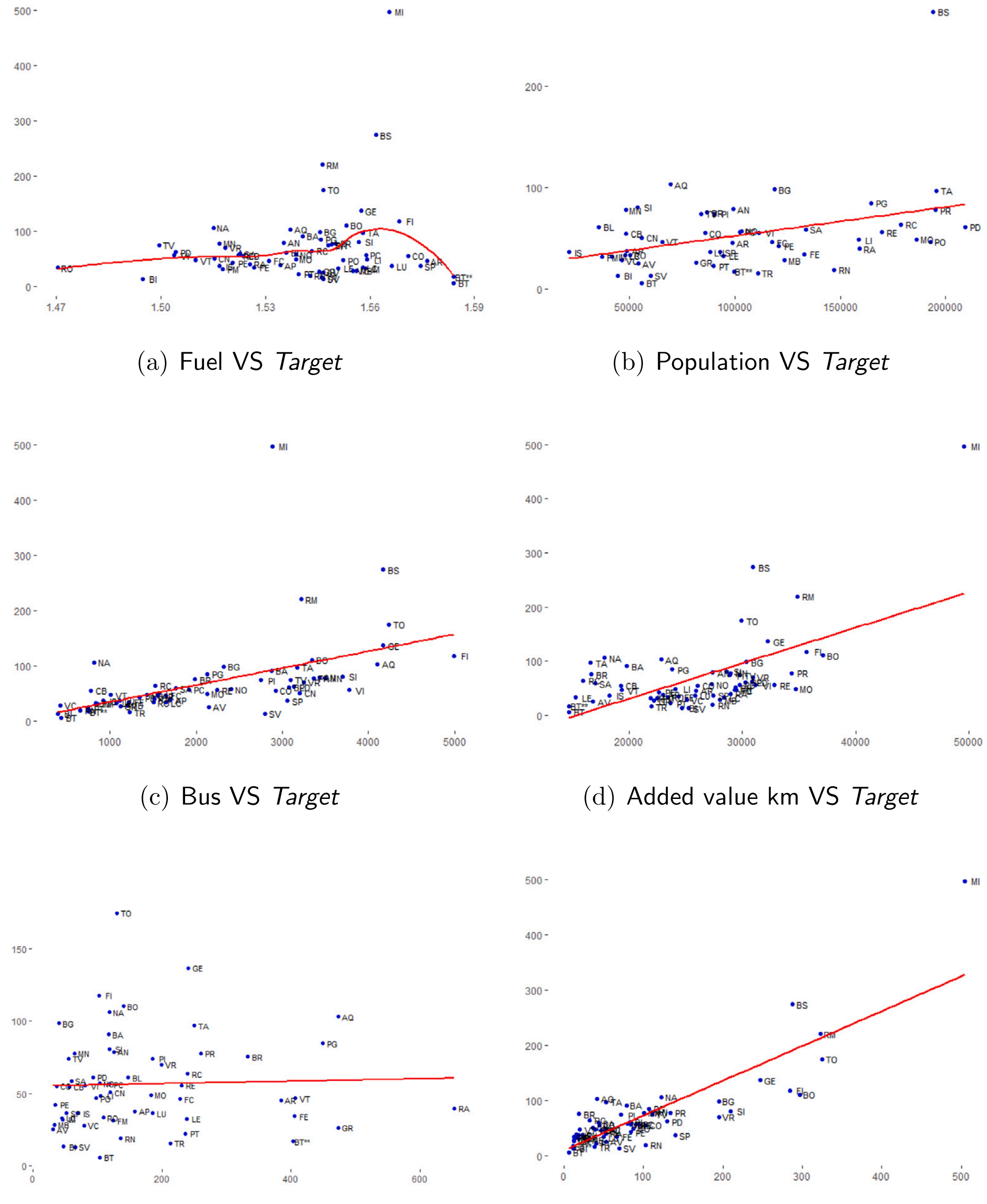


(f) Average diesel price



(g) Average squared km area

Fig. 2. Histograms of the continuos variables.



(a) Fuel VS *Target* (b) Population VS *Target*

(c) Bus VS *Target* (d) Added value km VS *Target*

(e) Square-km area VS *Target* (f) Travelers VS *Target*

Fig. 3. Bivariate scatterplots with fitted (smoothed) red lines. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2
Percentage altimetric bands.

Municipality	1st band	2nd band	Municipality	1st band	2nd band
Torino	84.9%	15.1%	Biella	0%	100%
Cuneo	0%	100%	Novara	100%	0%
Vercelli	100%	0%	Genova	61.7%	38.3%
Imperia	89.1%	10.9%	Savona	58.1%	41.9%
La Spezia	80.8%	19.2%	Milano	100%	0%
Bergamo	79.0%	21.0%	Brescia	88.7%	11.3%
Como	45.6%	54.4%	Lecco	26.6%	73.4%
Mantova	100%	0%	Monza	100%	0%
Belluno	0.2%	99.8%	Padova	100%	0%
Rovigo	100%	0%	Treviso	100%	0%
Verona	87.5%	12.5%	Vicenza	100%	0%
Bologna	99.4%	0.6%	Ferrara	100%	0%
Forlì	99.9%	0.1%	Modena	100%	0%
Parma	100%	0%	Piacenza	100%	0%
Ravenna	100%	0%	Reggio nell'Emilia	100%	0%
Rimini	100%	0%	Firenze	99.6%	0.4%
Arezzo	40.6%	59.4%	Grosseto	99.4%	0.6%
Livorno	97.1%	2.9%	Lucca	85.2%	14.8%
Pisa	100%	0%	Pistoia	45.4%	54.6%
Prato	87.3%	12.7%	Siena	75.3%	24.7%
Ancona	97.9%	2.1%	Ascoli Piceno	45.4%	54.6%
Fermo	99.9%	0.1%	Perugia	54.5%	45.6%
Terni	39.5%	60.5%	Roma	99.9%	0.1%
Viterbo	53.2%	46.8%	L'Aquila	0%	100%
Pescara	100%	0%	Campobasso	0%	100%
Isernia	0.1%	99.9%	Bari	100%	0%
Andria	60.3%	39.7%	Brindisi	100%	0%
Lecce	100%	0%	Taranto	100%	0%
Trani	100%	0%	Napoli	95.5%	4.5%
Avellino	5.7%	94.3%	Salerno	81.8%	18.2%
Reggio di Calabria	43.2%	56.8%	–	–	–

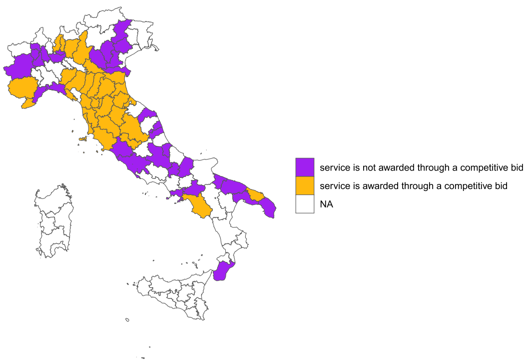


Fig. 4. Procurement methods.

The general formulation of the GAMLSS model is as follows: let $y^T = \{y_1, y_2, \dots, y_n\}$ be the vector of the response variable of length n and $g_k(\cdot)$ known monotonic link functions that relate the distribution parameters to the covariates through a semi-parametric additive models as follows:

$$g_k\left(\theta_k\right) = \eta_k = f_k\left(x_{ik}, \beta_k\right) + \sum_{j=1}^{J_k} f^*_{jk}\left(x_{ijk}\right) \tag{1}$$

where $i = 1, \dots, n$, $k = 1, 2, 3, 4$. $j = 1, 2, \dots, J_k$, θ is a vector of distribution parameters,[5] η_k is the predictor relating to the distribution parameters, β_k is the vector of unknown coefficients, x_{ik} a fixed known design vector, $f_k(\cdot)$ is a generic (non linear) function, f^*_{jk} is an additive non-parametric smoothing function of the covariates; if $f_k(\cdot) = \mathbf{x}^T_{ik}\beta_k$ and $J_k = 0$ then (1) reduces to a linear model.

We focus primarily on distributions with support on the positive real line, given that our target variable is bounded by $(0, \infty)$, and we aim to explicitly model shape parameters, such as asymmetry and kurtosis. In addition to the two-parameters

[5] Location, scale and shape parameters.

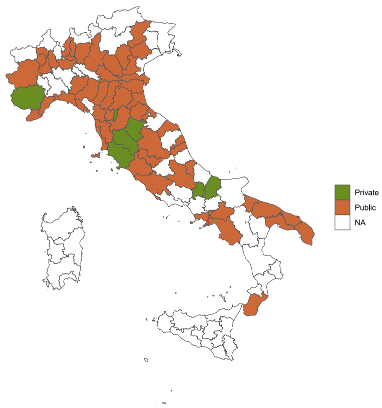


Fig. 5. Public control.

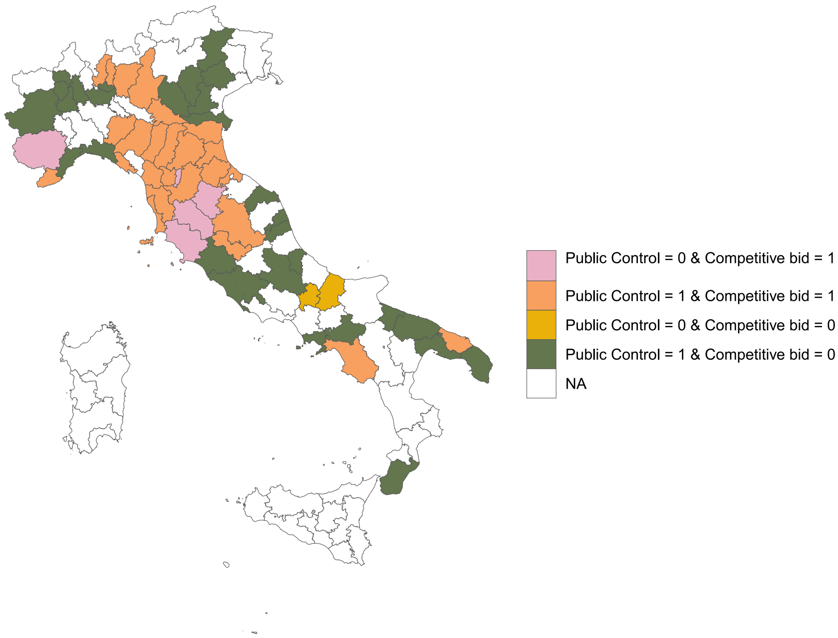


Fig. 6. Interaction between competitive bidding and ownership.

distributions in $\mathbb{R}_+$, including the Log-Normal distribution (LNO), Weibull (WEI3), the Inverse Gaussian (IG) (Johnson, Kotz, & Balakrishnan, 1994) and the Gamma distribution (GA), we consider three-parameters distributions such as the Box–Cox-Cole-Green distribution (BCCG) (Cole et al., 2009) and the Generalized Gamma distribution (GG) (Bourguignon et al., 2015), and four-parameters distributions, such as the Box–Cox-t distribution (BCT, Ferrari & Fumes, 2017; Rigby & Stasinopoulos, 2006), the Box–Cox-Power-Exponential distribution (BCPE, Olivier & Norberg, 2010; Rigby & Stasinopoulos, 2005) and the Generalized Beta type 2 distribution (GB2, McDonald & Ransom, 2008).

To find a suitable conditional distribution for the data, we leverage the capabilities of the package `gamlss` (Stasinopoulos & Rigby, 2008) within the `R` software environment (R Core Team, 2021). This package offers a wide range of distributions for modeling the dependent variable as well as considerable flexibility in specifying different regression models for the distribution parameters.

We first initialize the model for the location parameter using a Gaussian distribution and then search for a suitable conditional distribution based on `BIC`, (BIC, Schwarz, 1978). According to the `BIC` criterion, the five best identified distributions are BCPEo, GB2, BCCGo, BCTo[6] and WEI3.[7] We then fit the same regression model for each distribution, also setting adequate regression models

[6] In BCPEo, BCTo and BCCGo, the subscript "o" denotes the original version of the distribution, indicating that the link function for the location parameter is a log link.

[7] WEI3 identifies the parameterization of the Weibull distribution where μ is the mean.

Table 3
Best fitted distribution regression models according to BIC.

	linear par.	edf	df	BIC
GB2	30	9.474	39.474	582.5
BCTo	30	2.015	32.015	583.3
WEI3	18	5.716	23.716	591.8
BCCGo	24	2.000	26.000	733.7
BCPEo	32	–	–	–

Table 4
Estimation results for the location parameter.

	Estimate	Std. error	t-value	Pr (> |t|)
Intercept	1.116	1.488	.75	.457
Travelers	4.002	.397	10.07	.000
Population	.00005	.0005	.90	.374
pb(Diesel price)	484.3	938.4	.52	.610
Square km area	.5174	.0598	8.65	.000
Seat km bus	.3391	.0242	14.02	.000
Added value	−.0135	.0055	−2.47	.017
Center	−.1890	.046	−4.15	.000
South	.5140	.081	6.32	.000
First altimetric band	.2390	.033	7.28	.000
Bidding process = 1	1.094	.103	10.58	.000
Public control = 1	.7580	.080	9.52	.000
Bidding process = 1 × Public control = 1	−.9480	.112	−8.44	.000

for scale and shape parameters. As shown in Fig. 3(a), a non-linear relationship is observed between the *average diesel price* and the target variable; therefore, we use a smoothing function to model such a relationship. Specifically, we use the function `pb()`, which is a non-parametric P-spline smoothing function based on the penalized beta-spline (Eilers & Marx, 1996; Ferrara & Vidoli, 2017; Muggeo & Ferrara, 2008). This function is used for the explanatory variables to capture a plausible non-linear relationships with the dependent variable. Although alternative smoothing functions such as cubic splines or LOESS (Locally Estimated Scatterplot Smoothing) function are available, the clear advantage of using the function `pb()` is the automatic calibration of the smoothing parameters. In Table 3, the fitted models are displayed along with the number of estimated linear parameters for each distribution, the effective degrees of freedom for the additive terms, the total degrees of freedom and the value of the BIC.

According to BIC, the regression model using the GB2 distribution is the best among the five considered. However, it exhibits a very poor fit in terms of model assumptions,[8] additionally the regression model using the BCPEo distribution fails to converge. Therefore, we turn to the regression model whose considered distribution is BCTo, whose value of BIC is sufficiently close to that of the GB2 model. Then, given that $Y \sim \text{BCTo}(\mu, \sigma, \nu, \tau)$ the estimated Eq. (1) expands to[9]:

$$
\begin{aligned}
\log(\hat{\mu}) = {} & \hat{\beta}_{\hat{\mu};0} + \hat{\beta}_{\hat{\mu};1} \times x_1 + \text{pb}\left(x_2\right) + \hat{\beta}_{\hat{\mu};3} \times x_3 + \hat{\beta}_{\hat{\mu};4} \times x_4 + \hat{\beta}_{\hat{\mu};5} \times x_5 \quad + \\
& \hat{\beta}_{\hat{\mu};6} \times x_6 + \hat{\beta}^1_{\hat{\mu};7} \times x_7 + \hat{\beta}^2_{\hat{\mu};7} \times x_7 + \hat{\beta}_{\hat{\mu};8} \times x_8 + \hat{\beta}_{\hat{\mu};9} \times x_9 \quad + \\
& \hat{\beta}_{\hat{\mu};10} \times x_{10} + \hat{\beta}_{\hat{\mu};9,10} \times x_9 * x_{10} \\
\log(\hat{\sigma}) = {} & \hat{\beta}_{\hat{\sigma};0} + \hat{\beta}_{\hat{\sigma};1} \times x_1 + \hat{\beta}_{\hat{\sigma};3} \times x_3 + \hat{\beta}_{\hat{\sigma};6} \times x_6 + \hat{\beta}^1_{\hat{\sigma};7} \times x_7 + \hat{\beta}^2_{\hat{\sigma};7} \times x_7 \\
\hat{\nu} = {} & \hat{\beta}_{\hat{\nu};0} + \hat{\beta}_{\hat{\nu};1} \times x_1 + \hat{\beta}_{\hat{\nu};3} \times x_3 + \hat{\beta}_{\hat{\nu};6} \times x_6 + \hat{\beta}^1_{\hat{\nu};7} \times x_7 + \hat{\beta}^2_{\hat{\nu};7} \times x_7 \\
\log(\hat{\tau}) = {} & \hat{\beta}_{\hat{\tau};0} + \hat{\beta}_{\hat{\tau};1} \times x_1 + \hat{\beta}_{\hat{\tau};3} \times x_3 + \hat{\beta}_{\hat{\tau};6} \times x_6 + \hat{\beta}^1_{\hat{\tau};7} \times x_7 + \hat{\beta}^2_{\hat{\tau};7} \times x_7
\end{aligned}
$$

The estimates obtained, which are given in Table 4[10], provide valuable insights.

With respect to our third research question, there is a discernible trend indicating that LPT services contracts tend to be more expensive in southern Italy, with a remarkable increase in *per-capita* contract costs compared to the benchmark class. This observation may be an indication of higher operational efficiency in the northern regions and, in general, of a significant differentiation among italian macroregion.

In addition, the presence of a bidding process (*Bid*) in the award procedure correlates with an increase in the estimated *per-capita* target variable compared to the benchmark. This observation is consistent with the inherent nature of procurement procedures, which may contribute to cost escalation from the outset. Conversely, such stringent measures are essential for upholding European

[8] We also note that GB2 distribution is very sensible to model's specifications.

[9] For brevity, we used x_1 as *Average per-capita travelers*, x_2 as *Average diesel price*, x_3 as *Average squared Km area*, x_4 as *Average per-capita added value*, x_5 as *Average population*, x_6 as *Average seat km bus*, x_7 as *Geo*, x_8 as *Altimetric band*, x_9 as the bidding process, x_{10} as the ownership structure, $x_9 : x_{10}$ as a term to evaluate the interaction effect between the two dummy variables.

[10] We only provided the coefficients for the location parameter. In order to provide a better visualization of the estimates, we scaled covariates by a factor of .001

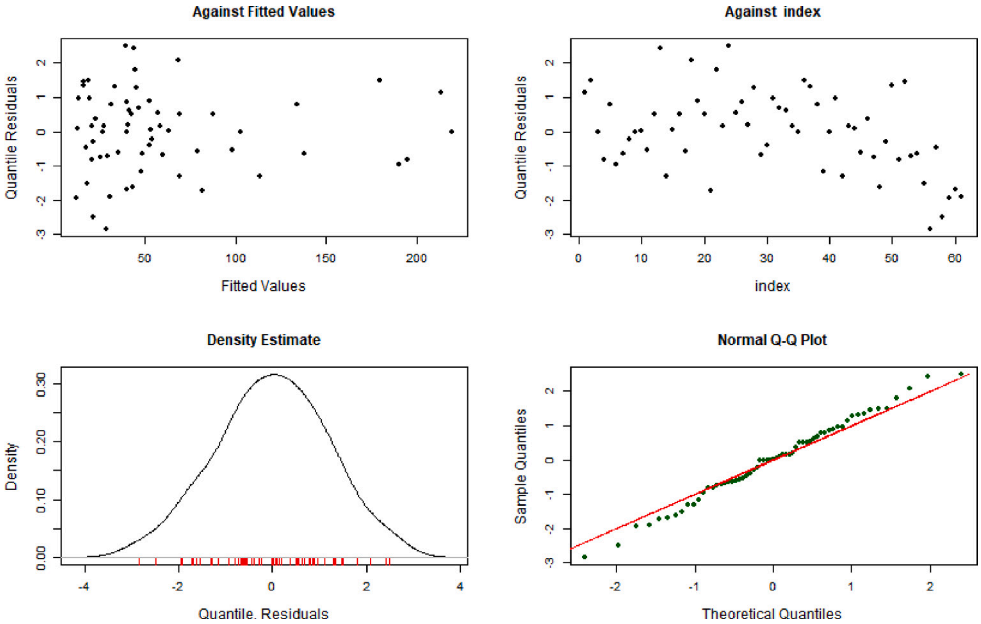


Fig. 7. Estimated residuals analysis: top-left: residuals vs. fitted values; top-right: residuals vs. index; bottom-left: estimated residuals density; bottom-right: Q-Q residuals plot.

competition principles and curbing possible infiltration by organized crime (such as the *mafia*), a concern that has manifested itself in Italy in the past. In contrast, if a public company provides LPT services, an increase in the *per-capita* contract costs and a statistically significant deviation from the benchmark can be observed. Considering all the estimated coefficients, the structure and ownership of the company providing the LPT service have a very large impact on costs and consequently on LPT contracts, more so than geographical size.

A plausible interpretation suggests considering a potential loss of efficiency if the service is managed by an *in-house* company, with the company's organizational structure and internal arrangements likely playing a crucial role.

Alternatively, it would be advisable to conduct a thorough business analysis to understand the differences between a *in-house* company and a private company that manages LPT. Such an analysis could uncover factors that may prove relevant in this context. This could be a spin-off of the present research unless the data on the companies were completely accessible. In addition, the coefficient for the interaction variable between *Biddin process* and *Public control* shows a less than an additive effect on the target variable, which essentially indicates that the most significant effects have already occurred in connection with the two dummy variables considered individually (Figs. 4, 5, and 6).

Furthermore, the estimated coefficients provide significant insights. The coefficient of *travelers* and that of *kmq area* have the largest impact on the (median) *per-capita* level of the service contract, followed by *Seat km bus*.

The impact of demand-indicative variables is found to be less significant. For instance, an increase in population seems to have no effect on the target variable. Consequently, *value added*, as an indicator of per-capita income, is found to have an effect on the target variable, suggesting that there is statistical evidence to support the notion that wealthier areas demand fewer public transport services. Lastly, there is no estimated statistical effect for a *supply* variable like *Diesel price*. In any case, if the coefficient were significant, its impact on the target variable could only be evaluated graphically, as it is estimated through a smoothing function.

The robustness of the estimates has been assessed through residual diagnostics, which indicate that the estimated model has strong performance. A Shapiro–Wilk normality test confirms the Gaussian distribution of the estimated residuals, with a test statistic of 0.99. These results are shown in Fig. 7, which reveals no discernible patterns, correlation, or latent heterogeneity.

In Fig. 8 the estimated density exhibits a very good fit to the observed data, particularly excelling at capturing the long right tail of the distribution and, in general, the pronounced asymmetry.

4. Conclusion

Many countries' regulatory frameworks for LPT typically include a provision for transferring funds from a regulatory authority to the transport company. This is because the latter often face universal service obligations whose commercial revenues are insufficient to cover operating costs, necessitating the payment of a subsidy to balance the budget. In countries such as Italy, this practice has resulted in a significant waste of public resources as public transport operators continue to face persistent financial deficits and crises. This study aimed to enhance understanding of the factors that influence the financial design of public transport service contracts

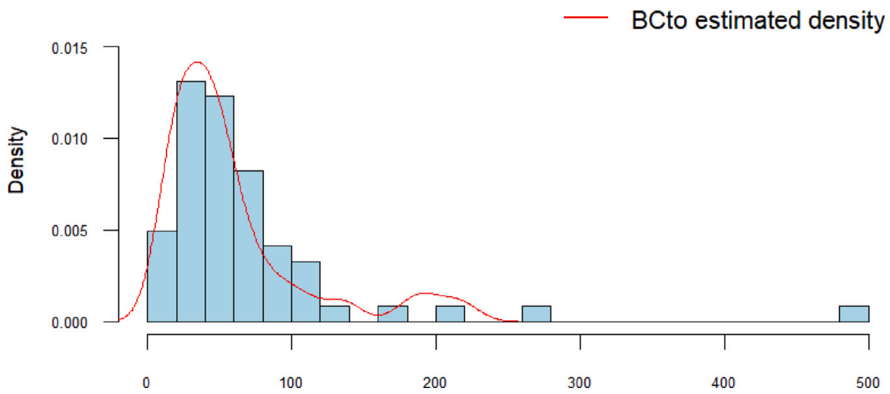


Fig. 8. Estimated density (in solid red line) on observed data. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

between the public sector and the transport operator. The objective is to provide insights for the reevaluation of traditional public interventions and the design of new regulatory measures, particularly with regard to contractual arrangements for subsidies.

Academic attention has increasingly focused on evaluating the performance, operational cost savings, and consumer satisfaction within LPT sector. Understanding these aspects is crucial for enhancing service efficiency. Given that the Italian LPT system comprises a diverse range of transport modes – including buses, tramways, subways, and state railroads – investigating the sector poses significant challenges due to the varied data sources required. This study utilizes an extensive database to analyze hypotheses related to LPT services in Italian municipalities using a Generalized Additive Model for Location, Scale, and Shape (GAMLSS) approach. The estimation and results emphasize the importance of including non-linear relationships and explicitly modeling the shape parameters to fully understand the dynamics of LPT contracts. The GAMLSS approach proves effective in capturing the intricate relationships within the data, providing a robust framework for policymakers to make evidence-based decisions regarding local public transportation contracts.

Key findings indicate that demand and supply variables significantly impact service contracts, with ownership structures playing a crucial role in cost implications. The study demonstrates that LPT contract costs increase when the service-providing company is publicly owned. Empirical evidence shows that the type of company operating LPT significantly affects the expected median value of the target variable, underscoring the importance of considering ownership structures in the analysis. Public companies are found to often lead to increased per-capita contract costs and deviations from benchmarks. This emphasizes the need to optimize economic strategies and reduce costs associated with tendering processes.

Moreover, regional differences in the Italian LPT system – particularly between Northern, Central, and Southern Italy – highlight the need to investigate geographical disparities. Such analysis can provide valuable insights into the regional aspects of public transport.

The interaction effect of variables such as the bidding process and public control further underscore the complexity of estimating contract costs. Although certain demand and supply variables may lack statistical significance in relation to the target variable, valuable insights can still be derived from factors such as the annual number of travelers or the size of the service area. In summary, this study emphasizes the importance of considering ownership structures, regional disparities, and performance metrics in formulating policies to improve LPT services in Italy. Conducting comprehensive business analyses and understanding the differences between public and private companies can enhance the efficiency and effectiveness of the LPT system, thereby driving improvements in public transportation services across various regions of the country.

Future research efforts could explore similar models that consider corporate aspects to identify possible internal organizational differences between *in-house* and private companies. This could be facilitated by access to more comprehensive data sets and additional information.

From a modeling perspective, extending the observed time series and including the remaining provinces not considered in the present analysis could pave the way for the transition to a panel data model. Such a model would account for latent heterogeneity, which may compensate for the lack of information on the corporate aspects mentioned above. An ambitious project could be to extend a similar analysis to a European context in order to capture the subtleties between the different countries that make up the European Union.

CRediT authorship contribution statement

Monica Auteri: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Conceptualization. **Alessandro Cremaschini:** Writing – original draft, Software, Investigation, Formal analysis, Data curation.

Declaration of competing interest

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

Appendix A. Probability density functions of the considered distributions

In our study, we considered several distributions to model the dependent variable in the GAMLSS framework. Here, we provide detailed descriptions of the five best probability density functions (PDFs) of the distributions we examined according to BIC.

As two parameters distribution;

1. **Weibull** (WEI3):
   This is a parameterization of the Weibull distribution where μ is the mean of the distribution. The pdf is:
   $$f_Y(y|\mu,\sigma) = \frac{\sigma}{\beta}\left(\frac{y}{\beta}\right)^{\sigma-1} \exp\left\{-\left(\frac{y}{\beta}\right)^{\sigma}\right\}$$
   for $y > 0,\ \mu > 0,\ \sigma > 0,\ \beta = \mu/\Gamma\left(\frac{1}{\sigma}+1\right)$.
   $\mathbb{E}(Y) = \mu$ and $\mathrm{Var}(Y) = \mu^2\left[\Gamma\left(\frac{2}{\sigma}+1\right)\left[\Gamma\left(\frac{1}{\sigma}+1\right)\right]^{-1} - 1\right]$

As three parameters distribution;

1. **Box–Cox-Cole-Green Distribution** (BCCG):
   The PDF of the BCCG distribution is given by:
   $$f(y|\mu,\sigma,\nu) = \frac{\nu}{\sigma y}\phi\left(\frac{\ln(y^{\nu}) - \mu}{\sigma}\right),$$
   where $\mu > 0$ is the location parameter, $\sigma > 0$ is the scale parameter, $-\infty < \nu < \infty$ is the shape parameter, and ϕ is the standard normal density function. This distribution generalizes the normal distribution to model skewed data.

As four parameters distribution;

1. **Box–Cox t distribution** (BCt):
   The BCt distribution is defined through the transformed random variable Z such that:
   $$Z = \begin{cases} \frac{1}{\sigma\nu}\left[\left(\frac{Y}{\mu}\right)^{\nu} - 1\right], & \text{if } \nu \neq 0 \\ \frac{1}{\sigma}\log\left[\frac{Y}{\mu}\right], & \text{if } \nu = 0. \end{cases} \tag{2}$$
   where Z is assumed to follow a truncated t distribution with degrees of freedom, $\tau > 0$ as a continuous parameter. The pdf is as follows:
   $$f_Y(y|\mu,\sigma,\nu,\tau) = \frac{y^{\nu-1} f_T(z)}{\mu^{\nu}\sigma F_T\left(\frac{1}{\sigma|\nu|}\right)} \tag{3}$$
   where $y > 0,\ \mu > 0,\ \sigma > 0,\ -\infty < \nu < \infty,\ f_T(t)$ and $F_T(t)$ are respectively the pdf and the CDF of the random variable T having a standard t distribution, with degrees of freedom $\tau > 0$, $T \sim t_{\tau} \equiv \mathbf{TF}$. If $F_T(t)$ approaches to 0 than Y has median equal to μ. This distribution is effective for modeling data with heavy tails and skewness.
2. **Box–Cox power exponential distribution** (BCPE):
   The BCPE is defined through (2), where the random variable Z is assumed to follow a truncated standard power exponential distribution (PE) with power parameter, $\tau > 0$ as a continuous parameter and it has the pdf as in (3) where $f_T(t)$ and $F_T(t)$ are respectively the pdf and the cdf of the random variable $T \sim \mathrm{PE}\,(0, 1, \tau)$
3. **Generalized Beta type 2 distribution** (GB2):
   This pdf of the generalized beta type 2 distribution, denoted by $GB2 \sim (\mu,\sigma,\nu,\tau)$ is:
   $$f_Y(y|\mu,\sigma,\nu,\tau) = \frac{\Gamma(\nu+\tau)\,\sigma\,(y/\mu)^{\sigma\nu}}{\Gamma(\nu)\,\Gamma(\tau)\,y\left[1 + (y/\mu)^{\sigma}\right]^{\nu+\tau}}$$
   for $y > 0,\ \mu > 0,\ \sigma > 0,\ \tau > 0,\ \Gamma(\cdot)$ is the gamma function.

Appendix B. Estimation method for regression parameters

We employed the Generalized Additive Models for Location, Scale, and Shape (GAMLSS) framework to estimate the regression parameters. The GAMLSS models allow for flexible modeling of the distribution parameters, including location, scale, and shape, using both parametric and non-parametric smoothing functions.

1. Estimation procedure

In this section briefly recall the estimation procedure of the regression parameters in GAMLSS:

1. **Initialization**: Initialize the model for the location parameter using the Gaussian distribution.
2. **Distribution Selection**: Identify suitable distributions for the response variable by comparing different distributions using BIC (Bayesian Information Criterion).
3. **Model Fitting**: Fit the selected distributions to the data by estimating the parameters for the location, scale, and shape using a penalized maximum likelihood estimation (PMLE).
4. **Diagnostics and Validation**: Perform diagnostic checks and validation to ensure the model's assumptions are satisfied and the fit is appropriate.

2. Penalized maximum likelihood estimation

Unlike a purely parametric GAMLSS model (i.e., without smoothing functions), which is estimated through the maximization of the likelihood function, a GAMLSS model employing non-parametric functions of the data, and in general, is estimated by maximizing a penalized likelihood function. Recall that $f^*_{jk}(\cdot)$ can be expressed as $\mathbf{Z}\gamma$, where $\mathbf{Z}$ is a matrix depending on the values of x, and γ is a set of coefficients subject to a quadratic penalty, $\gamma^T\mathbf{G}(\lambda)\gamma$; here, λ is a vector (or scalar) of hyperparameters. The penalized log-likelihood to be maximized is given by:

$$\ell_p = \ell - \frac{1}{2}\sum_{k=1}^{4}\sum_{j=1}^{J_k}\gamma^T\mathbf{G}_{kj}(\lambda_{kj})\gamma_{kj}$$

where ℓ is the log-likelihood function. The estimation is performed using two algorithms: CG algorithm, as a generalization of the Cole-Green algorithm (Cole & Green, 1992) and the RS algorithm which is a generalization of the Rigby–Stasinopoulos algorithm (Rigby & Stasinopoulos, 1996a, 1996b), with the latter employed in our case due to numerical issues encountered with the former algorithm.

3. Penalized splines (P-splines)

P-splines are used to add flexibility to the model by allowing for smooth non-linear relationships. The smoothing function f_{jk} is typically represented as:

$$f_{jk}(x_{ijk}) = \sum_{m=1}^{M} b_{jm}(x_{ijk})\gamma_{jm},$$

where $b_{jm}(x_{ijk})$ are B-spline basis functions and γ_{jm} are the coefficients to be estimated. The smoothness of the fit is controlled by a penalty on the coefficients γ_{jm}.

References

Aloulou, F., & Ghannouchi, I. (2023). The impact of ownership and contractual practice on the technical efficiency level of the public transport operators: An international comparison. *Research in Transportation Business and Management*, *46*, Article 100707.

Avenali, A., Boitani, A., Catalano, G., D'Alfonso, T., & Matteucci, G. (2016). Assessing standard costs in local public bus transport: Evidence from Italy. *Transport Policy*, *52*, 164–174.

Ballard, M. J., & Warner, M. E. (2000). *Taking the high road: local government restructuring and the quest for quality*. (Ph.D. thesis), Cornell University Ithaca, NY.

Boitani, A., Nicolini, M., & Scarpa, C. (2013). Do competition and ownership matter? Evidence from local public transport in Europe. *Applied Economics*, *45*(11), 1419–1434.

Bourguignon, M., Lima, M. d. C. S., Leão, J., Nascimento, A. D., Pinho, L. G. B., & Cordeiro, G. M. (2015). A new generalized gamma distribution with applications. *American Journal of Mathematical and Management Sciences*, *34*(4), 309–342.

Bray, D., & Mulley, C. (2013). Workshop 4: Designing contracts/concessions: What has worked and what has not and why?: 12th international conference series on competition and ownership in land passenger transport. *Research in Transportation Economics*, *39*(1), 226–231.

Cole, T. J., & Green, P. J. (1992). Smoothing reference centile curves: the LMS method and penalized likelihood. *Statistics in Medicine*, *11*(10), 1305–1319.

Cole, T., Stanojevic, S., Stocks, J., Coates, A., Hankinson, J., & Wade, A. (2009). Age -and size- related reference ranges: A case study of spirometry through childhood and adulthood. *Statistics in Medicine*, *28*(5), 880–898.

Coupé, C. (2018). Modeling linguistic variables with regression models: Addressing non-gaussian distributions, non-independent observations, and non-linear predictors with random effects and generalized additive models for location, scale, and shape. *Frontiers in Psychology*, *9*, 513.

Dalen, D. M., & Gómez-Lobo, A. (2003). Yardstick on the road: regulatory contracts and cost efficiency in the Norwegian bus industry. *Transportation*, *30*(4), 371–386.

Debnath, P. (2022). A QGIS-Based Road Network Analysis for Sustainable Road Network Infrastructure: An Application to the Cachar District in Assam, India. *Infrastructures*, *7*(9), 114.

Eilers, P. H., & Marx, B. D. (1996). Flexible smoothing with b-splines and penalties. *Statistical Science*, *11*(2), 89–121.

Ferrara, G., & Vidoli, F. (2017). Semiparametric stochastic frontier models: A generalized additive model approach. *European Journal of Operational Research*, *258*(2), 761–777.

Ferrari, S. L., & Fumes, G. (2017). Box–cox symmetric distributions and applications to nutritional data. *AStA. Advances in Statistical Analysis*, *101*, 321–344.

Hardin, J. W., & Hilbe, J. (2007). *Generalized linear models and extensions* (Second Ed.). A Stata Press publication. Taylor & Francis.

Hart, O., Shleifer, A., & Vishny, R. W. (1997). The proper scope of government: Theory and an application to prisons. *Quarterly Journal of Economics*, *112*(4), 1127–1161.

Hastie, T. J., & Tibshirani, R. J. (1990). *Generalized additive models*. London: Chapman & Hall.

Hensher, D. A., & Stanley, J. (2008). Transacting under a performance-based contract: The role of negotiation and competitive tendering. *Transportation Research Part A: Policy and Practice*, *42*(9), 1143–1151.

Johnson, N. L., Kotz, S., & Balakrishnan, N. (1994). Beta distributions. *Continuous Univariate Distributions*, *2*, 210–275.
Kneib, T. (2013). Beyond mean regression. *Statistical Modelling*, *13*(4), 275–303.
Marletta, A., & Sciandra, M. (2020). Gamlss for high-variability data: an application to liver fibrosis case. *International Journal of Biostatistics*, *16*(2), Article 20190113.
Marmolejo-Ramos, F., Tejo, M., Brabec, M., Kuzilek, J., Joksimovic, S., Kovanovic, V., et al. (2023). Distributional regression modeling via generalized additive models for location, scale, and shape: An overview through a data set from learning analytics. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *13*(1), Article e1479.
McDonald, J. B., & Ransom, M. (2008). The generalized beta distribution as a model for the distribution of income: estimation of related measures of inequality. In *Modeling income distributions and lorenz curves* (pp. 147–166). Springer.
Miranda, R., & Lerner, A. (1995). Bureaucracy, organizational redundancy, and the privatization of public services. *Public Administration Review*, *55*(2), 193–200.
Muggeo, V. M., & Ferrara, G. (2008). Fitting generalized linear models with unspecified link function: A p-spline approach. *Computational Statistics & Data Analysis*, *52*(5), 2529–2537.
Negrelli, A., Roukouni, A., & Chassy, A. (2017). Local public transport services: the efficiency of public enterprises competing with the private sector in the EU member states. In *The reform of network industries* (pp. 197–219). Edward Elgar Publishing, Chap 10.
Nelder, J. A., & Wedderburn, R. W. (1972). Generalized linear models. *Journal of the Royal Statistical Society, Series A, General*, *135*(3), 370–384.
Olivier, J., & Norberg, M. (2010). Positively skewed data: revisiting the box-cox power transformation. *International Journal of Psychological Research*, *3*(1), 69–78.
Ottoz, E., & Fornengo, G. (2006). La diversificazione delle imprese pubbliche e private nel trasporto pubblico locale: il caso del Piemonte. *Economia e Politica Industriale*, *1*, 73–95.
Ottoz, E., Fornengo, G., & Di Giacomo, M. (2009). The impact of ownership on the cost of bus service provision: an example from Italy. *Applied Economics*, *41*(3), 337–349.
Polemis, M. L., & Fafaliou, I. (2015). Electricity regulation and FDIs spillovers in the OECD: A panel data econometric approach. *The Journal of Economic Asymmetries*, *12*(2), 110–123.
R Core Team (2021). *R: a language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing.
Rigby, R. A., & Stasinopoulos, D. (1996a). A semi-parametric additive model for variance heterogeneity. *Statistics and Computing*, *6*, 57–65.
Rigby, R. A., & Stasinopoulos, M. D. (1996b). Mean and dispersion additive models. In W. Härdle, & M. G. Schimek (Eds.), *Statistical theory and computational aspects of smoothing* (pp. 215–230). Heidelberg. Physica-Verlag HD.
Rigby, R. A., & Stasinopoulos, D. M. (2005). Generalized additive models for location, scale and shape. *Journal of the Royal Statistical Society. Series C. Applied Statistics*, *54*(3), 507–554.
Rigby, R. A., & Stasinopoulos, D. M. (2006). Using the Box–Cox t distribution in GAMLSS to model skewness and kurtosis. *Statistical Modelling*, *6*(3), 209–229.
Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics*, 461–464.
Shapiro, S. S., & Wilk, M. B. (1965). An analysis of variance test for normality (complete samples). *Biometrika*, *52*, 591–611.
Sheng, D., & Meng, Q. (2020). Public bus service contracting: A critical review and future research opportunities. *Research in Transportation Economics*, *83*, Article 100938.
Stasinopoulos, D. M., & Rigby, R. A. (2008). Generalized additive models for location scale and shape (GAMLSS) in R. *Journal of Statistical Software*, *23*, 1–46.
Teodorovicz, T., Lazzarini, S., Cabral, S., & Nardi, L. (2023). Can public organizations perform like private firms? The role of heterogeneous resources and practices. *Organization Science*, *34*(4), 1527–1553.
Vickers, J., & Yarrow, G. (1991). Economic perspectives on privatization. *Journal of Economic Perspectives*, *5*(2), 111–132.
Voudouris, V., Gilchrist, R., Rigby, R., Sedgwick, J., & Stasinopoulos, D. (2012). Modelling skewness and kurtosis with the BCPE density in GAMLSS. *Journal of Applied Statistics*, *39*(6), 1279–1293.
Warner, M. E., & Bel, G. (2008). Competition or monopoly? Comparing privatization of local public services in the US and Spain. *Public Administration*, *86*(3), 723–735.
Winston, C. (2000). Government failure in urban transportation. *Fiscal Studies*, *21*(4), 403–425.
Yvrande-Billon, A. (2006). The attribution process of delegation contracts in the french urban public transport sector: why competitive tendering is a myth. *Annals of Public and Cooperative Economics*, *77*(4), 453–478.
Zhang, D.-d., Yan, D.-h., Wang, Y.-C., Lu, F., & Liu, S.-h. (2015). GAMLSS-based nonstationary modeling of extreme precipitation in Beijing–Tianjin–Hebei region of China. *Natural Hazards*, *77*, 1037–1053.