Benchmarking the Efficiency of Montenegro's Local Self-governments

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Abstract We examine the technical efficiency of Montenegro's local self-governments and determine the effect of tourism activity on Montenegro's local self-government efficiency. Due to the relatively small number of local self-governments in Montenegro, to conduct our analysis we combined principal component analysis (PCA) and Data Envelopment Analysis (DEA). We estimated the average technical efficiency of Montenegro's local self-government in 2011 to be between 60.3% and 67.3%, depending on the model. Furthermore, we confirm D'Inverno, et al., (2017) findings about the inverse relationship between tourism activity and efficiency. We estimated that on average tourism activity reduced Montenegro's coastal LSG technical efficiency by 30.4%.

Keywords: • Montenegro • local governments • efficiency • PCA-DEA • financial management

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1 Introduction

The Local Self-Governments (LSG) efficiency in providing local public goods and services is often used as an argument for further decentralization or increased centralization. Insistence on decentralization by entrusting additional competencies to LSGs that fail to provide services efficiently would provide little gain (Geys & Moesen, 2009a). The motivation for more efficient provision of public goods and services does not come just from policy goals but from financial constraints. LSGs could address these financial constraints without political costs by improving operational efficiency. The alternative is the reduction of public expenditures or an increase in fiscal burden, which could produce high political costs.

Montenegro is relatively a young state, as it gained its independence from the State Union of Serbia and Montenegro in 2006. The public governance system and territorial organization of Montenegro were inherited from the former Yugoslavia and the State Union. Montenegro has several distinctive characteristics concerning the role and financing of the local self-government. First, Montenegro has a relatively simple structure with only one level of sub-sovereign government – municipalities. Montenegro is currently divided into 24 municipalities (including two city municipalities). Since 2011, the year that is due to data availability used as the setting of this study, an additional two LSG were formed municipalities. Second, Montenegro is a highly centralized country. In particular, the central government oversaw education, health care, and social security, which was not always the case in neighbouring countries. As a result, the extent of local self-government competencies in Montenegro was substantially narrower than in neighbouring countries (NALAS, 2012). Third, LSGs are funded through four different channels: own revenues (fiscal and otherwise), allocated taxes and fees, the Equalization Fund, and state budget grants. As a consequence of no social sector responsibilities, Montenegrin LGS have a very high share of own revenues in total revenues. Increased LSG financial independence was provided with legislative changes in 2011. The new revenue structure increased municipalities' direct share in income from concession fees (70% vs. 30% previously) and real estate transfer tax (80% compared to the previous 50%). In addition, the new income structure provided additional funds for the Equalization Fund, namely 100% of revenues from passenger car, vessel, and aircraft taxes and 40% of revenues from concessions on games of chance.

To the best of our knowledge, there are no studies examining efficiency of Montenegrin LSGs. Therefore, in this paper, we examine the technical efficiency of Montenegrin's LSGs using an integrated approach by combining principal component analysis (PCA) and data envelopment analysis (DEA). Furthermore, Montenegro, and especially several municipalities are heavily dependent on tourism, and paper also assesses the effects of tourism on the efficiency of the provision of local public goods and services.

To this end this paper aims to make three main contributions. To begin, we hope to fill a gap in the empirical literature concerning the efficiency of Montenegrin LSGs. Second, we intend to create performance benchmarks for the present LSG system in Montenegro. Montenegro has previously completed territorial reforms by creating two new LSGs in 2013 and 2014. Any additional reforms would require evidence-based policy decisions based on efficiency criteria. Third, because Montenegro is highly dependent on tourism, we wish to provide Montenegrin policymakers with new insights on the effects of tourism on the efficiency of local public goods and services provision. Finally, the upcoming census could be used to assess the extent of changes in efficiency of LSGs having this study as a benchmark.

The remainder of the paper is structured as follows: in the next section, we review literature. First, we outline the DEA and PCA approach that will be employed. Next, we describe the data and limitations. Section 4 describes the empirical strategy and examines the findings. The paper is summarized and concluded in Section 5.

2 Literature overview

In the last 30 years, numerous empirical studies have been conducted concentrating on various perspectives and contexts of the efficiency in LSG. According to De Borger & Kerstens (1996), empirical research concerning the efficiency of LSG is either focused on the evaluation of a particular local service or on the performances of LSGs in providing a broad range of public services. Individual public services that were usually the focus of empirical research were water services (Garcıa-Sanchez, 2006a), waste management and street cleaning (Worthington & Dollery, 2000, 2001; Bosch, et al., 2000; Benito-Lopez, et al., 2011, 2015), street lighting (Lorenzo & Sanchez, 2007), road maintenance (Kalb, 2012), fire services (Garcıa-Sanchez, 2006b), and library services (Stevens, 2005) and other.

A significant body of empirical research was devoted to estimating the efficiency of LSGs in providing a broad range of public services. The subject of these researches was the cost efficiency of LSGs in Belgium (De Borger & Kerstens, 1996; Geys & Moesen, 2009a; Geys & Moesen, 2009b), Germany (Kalb, et al., 2012; Geys, et al., 2013), Finland (Loikkanen & Susiluoto, 2005), Italy (Barone & Mocetti, 2011; Boetti, et al., 2012), Portugal (Alfonso & Fernandes, 2006, 2008; Da Cruz & Marques, 2014), Czech Republic (Šťastná & Gregor, 2011, 2015), Spain (Balaguer-Coll, et al., 2010a, 2010b; Benito-Lopez, et al., 2015) United States (O'Loughlin & Wilson, 2021), from other countries as well.

In addition to the cost-efficiency of a broad range of public services, authors tended to analyse relationships between LSG's cost efficiency and some important determinants of efficiency. These determinants of efficiency usually included fiscal decentralization, the influence of the spatial closeness between municipalities, effects of political competition and other important factors (Narbón-Perpiñá & De Witte, 2018). In this context, the impact of tourism activity on the efficiency of LSGs was the subject of interest of several authors as well. Athanassopoulos & Triantis, (1998) stipulated that tourist activity in Greek 172 LSGs creates additional costs. Similarly, D'Inverno, et al., (2017) concluded in their research that Tuscan municipalities with a high level of tourism tend to be less efficient and that as the degree of tourism increases, the average level of efficiency declines. Furthermore, D'Inverno, et al., (2017) showed that LSGs with significant seasonality suffer greater costs than other LSGs.

The region of South-Eastern Europe was also represented in empirical publications concerning the efficiency of LSGs. Pevcin (2014, 2014b) estimated efficiency in 200 Slovenian LSGs in 2011 and concluded that their mean technical efficacy differs from 0.75 to 0.88. Slijepcevic, (2019) measured the efficiency of Croatian LSGs at the regional level and concluded that LSGs in the least efficient county could decrease their expenses on average by 55%. Soko & Zorič, (2018) found that the average municipal efficiency score of LSGs in Bosnia and Herzegovina is 0.71, while Lazović-Pita ans Ščeta (2021) found that LSGs total expenditures can be reduced by 46.8%. Radulovic & Dragutinovic, (2015) estimated that 143 Serbian LSG in 2012 delivered public services at costs that are between 21% and 23% higher than the 'best practice' peers. Nikolov & Hrovatin, (2013) have shown that the average efficiency score of North Macedonian's 74 LSGs is at the level of 0.59. Similar results were obtained by Athanassopoulos & Triantis, (1998) while estimating the mean efficiency of 172 Greek LSGs, ranging from 0.50 to 085. Doumpos & Cohen, (2014) estimated the mean efficiency of 2,017 Greek LSGs in the period from 2002 to 2009 in a similar range of between 0.65 and 0.75.

The literature uses a variety of methodologies to assess the efficiency of LSGs. There are two fundamental types of efficiency, technical and allocative efficiency. Technical efficiency considers achieving maximum outputs with the least inputs, while allocative efficiency answers how different inputs are combined to produce a set of diverse outputs. An overall efficiency represents the joint effect of technical and allocative efficiency (Radulovic & Dragutinovic, 2015). The primary focus of this paper is on the input-oriented technical efficiency, or how inputs may be reduced while keeping output levels constant.

The nonparametric and parametric methods are the two primary branches of the best-practice frontiers approach in determining efficiency. The most often used nonparametric methods in determining the efficiency of LSGs are Data Envelopment Analysis (DEA) and its nonconvex counterpart Free Disposal Hull (FDH). Some researchers utilized a dynamic technique to demonstrate how LSGs' efficiency varies over time. The Malmquist Productivity Index is the most often used dynamic technique in the nonparametric domain. The Stochastic Frontier Approach (SFA), on the other hand, is the most widely utilized parametric technique in determining LSG's efficiency. Because of the various approaches used to determine local government efficiency, variable selection, and sample sizes, the average LSG's efficiency scores varied significantly between the aforementioned studies, and even within studies covering the same country (Narbón-Perpiñá & De Witte, 2018).

3 Research

3.1 DEA Model

The DEA is a linear programming nonparametric method that measures the technical efficiency of DMUs relative to a deterministic best practice frontier based on empirical observations of inputs and outputs (Põldaru & Roots, 2014). The result of DEA is a relative efficiency score in the range between 0 and 1, where 1 refers to 100 per cent efficiency. The definition of DMU is generic and it could be used equally in the private and public sectors. In addition, standard DEA assumes the uniformity of all DMUs, or that all DMUs conduct the same activities with similar objectives, consumes similar inputs and produce similar outputs, and operate in similar operational environments (Syrjanen, 2004). In this paper, we observe Montenegrin's LSGs as DMUs in the process of determining their technical efficiency.

The Data envelopment analysis (DEA) is based on a convex production function frontier which derives its efficiency scores based on relative distances of inefficient observations from the best practice frontier (Afonso & Fernandes, 2006). The fact that the DEA measures DMUs' efficiency relative to the efficiency scores of the other DMUs in the sample (best practice frontier) means that the DEA calculates relative rather than absolute DMU's efficiency. This further implies that the real-life efficiency threshold could be higher compared to the efficiency threshold used in DEA to determine the most efficient DMU (Radulovic & Dragutinovic, 2015).

The DEA's non-parametric feature makes it the most suitable technique for measuring the efficiency of small samples of DMUs for which it would be a stretch to infer normal distribution according to the central limit theorem. Also, the combination of PCA and DEA is particularly useful when analysing small data sets (Adler & Yazhemsky, 2010). This is the case of Montenegro that had in total of 21 LSGs in 2011, which effectively prevents the implementation of parametric methods in determining LSGs efficiency. Furthermore, we assume that the convexity assumption holds true, or that consumers would prefer to use all public services in similar quantities (average) rather than certain local public services more than others (extreme).

DEA also has some disadvantages, of which the key one relates to measurement errors. Because of DEA's deterministic nature, every divergence from the best practice frontier is seen as inefficiency. This further implies the assumption that data are free of measurement errors and other noises coming from the real-life data and thus attributes all deviations from the frontier to inefficiencies (Põldaru & Roots, 2014). We employed principal component analysis (PCA) to address the measurement error problem. In this paper, we focused our intention on the year 2011, as currently, the last fully available data for Montenegrin's LSGs are from 2011.

DEA could be formulated with CCR or BCC specifications. *Charnes, et al., (1978)* proposed a CCR model that assumes a constant return to scale (CRS), or that any increase in input or output results in a proportional change in output or input respectively. Also, the CCR model assumes that there is no strong correlation between the scale of operation and efficiency, or it assumes that DMU is scale efficient. However, this assumption is only viable in instances where all DMUs are operating optimally. Otherwise, the technical efficiency measurements could be confounded by scale efficiencies (Coelli, et al., 2005). Therefore, when a CCR model is used, the resulting technical efficiency is a comprehensive technical efficiency that incorporates the scale efficiency component, rather than a pure technical efficiency (BRRC, 2009). *Banker, et al., (1984)* modified the CCR model by introducing variable return to scale (VRS) assumption instead, which relaxes the proportional change assumption of the CCR model. The BCC model permitted the measurement of pure technical efficiency (PTE) that is free of the scale efficiency effect (Young, 2014).

According to *Charnes, et al., (1978, p.430),* efficiency is defined as "the maximum of a ratio of weighted outputs to weighted inputs subject that the similar ratios for every DMU be less or equal to unity". Further, *Charnes, et al., (1978)* stipulates that the technical efficiency of DMU could be maximized under two constraints. First, the weights applied to DMU's outputs and inputs cannot generate an efficiency score greater than 1. Second, inputs and outputs weights are strictly positive and greater than zero. This represents a linear programming problem that must be solved for each DMU in the model. There are two different approaches for solving this problem, output or an input orientation of the model. The output-oriented efficiency holds input levels fixed and examines optimal output expansion, or the weighted sums of outputs are maximized holding inputs constant. On the other hand, the input-oriented efficiency estimates an optimal reduction of inputs without the change of outputs, or the weighted sums of inputs are minimized holding outputs constant (Huguenin, 2012). In other words, DEA estimates the extent to which output production could be increased without the addition of new inputs (Slijepcevic, 2019).

There is a significant consensus in the literature for utilizing input-oriented efficiency measures in policy settings. This is because policymakers are more likely to influence public expenditures (inputs) than the volume and quality of public goods and services (Radulovic & Dragutinovic, 2015). Thus, in this paper, we are focusing on CRS and VRS input-oriented models with slacks as the more appropriate orientation for determining the efficiency of the provision of local public goods and services.

The CRS input-oriented model can be expressed using the following linear programming envelopment form (Huguenin, 2012):

$$Minimize\ \theta_e - \varepsilon\left(\sum_{r=1}^{s} S_r + \sum_{i=1}^{m} S_i\right) \tag{1}$$

$$s.t.$$

$$Y_{re} - \sum_{j=1}^{n} \lambda_j Y_{rj} + S_r = 0, \quad r = 1, \dots, s \tag{2}$$

$$\theta_e X_{ie} - \sum_{j=1}^{n} \lambda_j X_{ij} - S_i = 0\ r = 1, \dots, m \tag{3}$$

$$\lambda_j, S_r, S_i \geq 0\ \forall_j = 1, \dots, n; r = 1, \dots, s; i = 1, \dots, m \tag{4}$$

Where, we assume there are (n) DMUs (DMU_j, $j = 1, \dots n$) that uses (m) inputs ($i = 1, \dots m$) to produce (s) outputs ($r = 1, \dots s$); DMU_e represents DMU under evaluation (DMU_e, $e = 1, \dots n$); (Y_{re}) is the quantity of output (r) produced by DMU (e); and; (X_{ie}) is the quantity of input (i) consumed by DMU (e); (Θe) represent the technical efficiency of DMU_e; (ε) represents the non-Archimedean value that is greater than zero and smaller than any positive real number; (S_r) represents output slacks; (Si) represents input slacks; (λ_j) represents the associated weighting of outputs and inputs of DMUs. In the VRS input-oriented model with slacks a measure of return to scale for DMUs is added to relax the CRS assumption:

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{5}$$

The optimal solution to the abovementioned linear problem (Θ^*) is known as the DMU's ratio (or radial) efficiency. The optimal solution, or technical efficiency of the DMU (Θ), exposes the presence, if any, of excess inputs and shortfalls in outputs known as slacks. CCR-efficient DMUs have maximum ratio efficiency ($\Theta = 1$), and no slacks in any optimal solution. Otherwise, the DMU has a disadvantage in its reference-set when compared to other DMUs. By removing the surplus input and increasing the output production, a DMU may become more efficient (Tone, 2001). The CCR model is a radial DEA model, which implies that in the input-oriented case with multiple inputs, the CCR is mainly focused on proportional reduction of input resources. In other words, the CCR model seeks the maximum proportional rate of reduction of inputs, i.e., a radial contraction of multiple inputs used in the production of existing outputs (Avkiran, et al., 2008).

The main advantage of DEA lies in its nonparametric nature. This allows DEA to include multiple inputs and outputs without any other specifications but quantities. DEA also doesn't require any functional specification and it allows implementation of both CRS and VRS assumptions (Hossain, et al., 2012). However, DEA also has some limitations. DMUs, usually do not operate at the optimal level due to different business environments and other constraints that prevent an optimal operational level (Young, 2014). As a result, applying the CRS assumption using real-life observations could produce technical efficiency measurements confounded by the scale efficiency (Coelli, et al., 2005). Scale efficiency could be defined as the amount by which production could be increased by moving to the most productive scale size. In other words, if a DMU is technically efficient but operates at a modest scale of operation, it is in the growing returns to scale section of the production frontier. This indicates that to reach the technically optimal productive scale, the DMU in question must expand its scale of operation. Otherwise, a DMU with decreasing returns must reduce its scale of operation to become more productive (Coelli, et al., 2005). In this paper, we will address this issue by isolating and quantifying scale inefficiency by implementing the BCC model with VRS assumption as well (Dyson, et al., 2001). The disparity in efficiency ratings between the CCR and BCC models in the radial model indicates that the DMU in question demonstrates scale inefficiency. The scale inefficiency could be derived by dividing CRS technical efficiency scores with the VRS technical efficiency scores (BRRC, 2009).

Though, the DEA's main limitations refer to its sensitivity to measurement errors and the total number of inputs and outputs used in the model. The sensitivity on measurement errors is pronounced due to the deterministic nature of DEA that assumes that all deviation from the best practice frontier could be attributed to inefficiency (Hossain, et al., 2012). Due to wrong model specification, the total number of DMUs located at the best practice frontier tend to increase with the higher number of input and output variables (Berg, 2010). This further implies that DEA in the presence of measurement errors and wrong model specifications produces biased estimates (Ruggiero J., 2007). This is also referred to as a discriminatory power problem or discrimination problem.

To overcome the measurement error problem, we reduced the dimensionality of the DEA model by implementing PCA analysis as suggested by *Põldaru & Roots, (2014) and Adler & Golany, (2001, 2002)*. The PCA contributes to solving this problem by reducing the total number of variables (dimensionality) and PCA components are less influenced by measurement errors (Põldaru & Roots, 2014). Further on we followed recommendations on the desired number of inputs and outputs in the model. *Golany & Roll, (1989)* stipulated that the total number of DMU should be at least twice the combined number of inputs and outputs. *Bowlin, (1998)* argued for the need that the total number of input and output variables should be less than one-third of the number of DMUs. *Dyson, et al., (2001)* suggested that the total number of DMUs should be at least equal to two times the product of the number of input and output variables. The total number of DMUs in our analysis satisfies all these recommendations.

Another DEA limitation is the inability to compute negative numbers and zeros. This DEA feature is sometimes referred to as a "positivity" requirement. One of the most common ways for dealing with non-positive values in DEA has been to add a suitably large positive constant to the non-positive input or output integer. This strategy would satisfy the "positivity" requirement, however, depending on the scale of altering constant value, it might impact the result of the analysis as well. This is one of the reasons why *Bowlin, (1998)* suggests converting negative or zero values into numbers with a smaller magnitude than the other numbers in the data set. Following the recommendation of *Bowlin, (1998)* and *Zhu & Cook, (2007*), *Huguenin, (2012)* proposed a method of dealing with the zero values for inputs and outputs in the dataset by substituting them with very low values such as 0.01.

3.2 PCA

The PCA decreases the total number of original variables used in the analysis by creating fewer principal components (PC) that represent linear combinations of the original variables. In this process, most of the variance of original data is attributed to the first few PC. These PC could be used instead of original input and output variables in the PCA-DEA model, with a minimal loss of information. The PCA complements the DEA analysis in two important ways. First, PC are modestly subject to the effects of measurement errors coming from the real-life data. Secondly, PC are reducing the dimensionality of the DEA model, by reducing the total number of variables in the model. In this paper, we implement PCA to combine multiple variables that represent outputs of Montenegrin's LSGs' provision of local public goods and services into PC used as output indicators in the PCA-DEA model. To secure a minimal loss of information, only a PC that can explain the most variance of the original data is used in a further input-oriented PCA-DEA model.

We standardized the data before performing the PCA by subtracting the column mean from the observations and then dividing the result by the column standard deviation. Data standardization was carried out for two reasons. First, hence the PCA tend to prefer variables with higher variance, the different variables measurement units tend to exaggerate this PCA feature and lead to biased PCA outputs (Kriegsman, 2016). By standardizing the data, we provided equal weight to all original variables that were included in the PCA. The second reason refers to the linearity assumption. This means that the original variables should have a Gaussian distribution, and if they don't, normalizing gets them closer to a normal or Gaussian distribution (Prykhodko, 2016).

The PCA scores for output variables are computed using the following formulas (Põldaru & Roots, 2014):

$$PC_r = l_{1r} * Y_1 + l_{2r} * Y_2 + \cdots., l_{sr} * Y_s \tag{6}$$

$$s.t.$$

$$Var\ (PC_r) = max, and\ \ \sum_{j=1}^{s} l_{js}^2 = 1 \tag{7}$$

Where, (PC_r) represents principal component of outputs ($r = 1, \dots s$); (l) represents normalized eigenvectors ($l_{1r}, l_{2r}, \dots l_{sr}$); ($Y$) is the quantity of output (r) produced by DMU;

Commonly, PCA is used to aggregate original variable's groups with a common theme. The first several PC usually contains most of the variance of original values' sample data.

These PC are uncorrelated and ranked by their variances in descending order (Adler & Golany, 2001). Some of the original data's explanatory power is lost in the process of producing PC in favour of the discriminatory strength of the PCA-DEA model (Põldaru & Roots, 2014). In the PCA-DEA model, the PC could be used as the substitute for inputs or outputs or simultaneously for both inputs and outputs. The properties of the DEA model are not affected using the PC. However, PC could contain negative values. Consequently, PC with negative signs must be transformed into PC with positive values. *Põldaru & Roots, (2014*), *Afonso & & St. Aubyn*, *(2011)* and *Ismail, et al.*, *(2018)* suggested a method for transformation of negative PC into the positive one by increasing PC values by the value of the most negative PC increased by the value of one:

$$Z_j = PC_j + Q \quad (8)$$

$$where\ Q = -\min\{PC_j\} + 1 \quad (9)$$

3.3 Inputs and Outputs

Narbón-Perpiñá & De Witte, (2018) have systematized commonly used variables as inputs and outputs in more than 80 empirical studies focusing on the efficiency of LSGs. They conclude that the selection of inputs and outputs could vary across countries due to the availability of data, specific accounting practices, different characteristics and jurisdictions of LSG and the research focus. Therefore, it is not feasible to establish uniform set variables across countries that could be used as a universal set of inputs and outputs. According to the same authors most research relied on input variables in cost terms because prices and physical units were not always easily available. They classified the inputs utilized in these studies into three categories: financial expenditures, financial resources, and non-financial inputs. Table 1 highlights the variables that are typically utilized as inputs.

Table 1: Input variables and description of input variables

Input variable	Output categories
- Total expenditures - Other variants of total expenditures - Current expenditures - Other variants of current expenditures - Personnel expenditures - Capital and financial expenditures - Other financial expenditures - Local revenues - Current transfers - Public health services - Area	- Total output indicator - Population - Area of municipality and built area - Administrative services - Infrastructures - Communal services - Parks, sports, culture, and recreational facilities - Health - Education

Source: Narbón-Perpiñá, I. & De Witte, K., 2018. Local governments' efficiency: a systematic literature review—part I. International transactions in operational research, Volume 25.

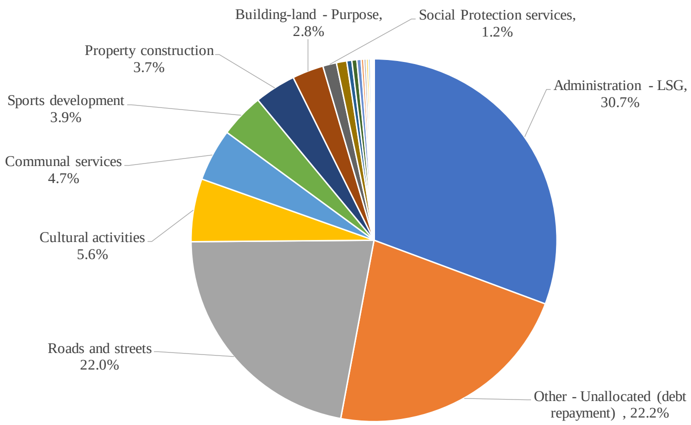
Different studies utilize different output metrics, even when analysing LSGs efficiency using the same country data. Furthermore, the number of output variables considered in the various research varies, since some studies aggregate diverse municipal services into a global index, whilst others analyse a collection of specialized local services. *Narbón-Perpiñá & De Witte, (2018*) identified 17 primary output categories used in empirical studies on LSGs' efficiency. Table 2 lists some of the most often utilized variables as outputs.

Other factors, in addition to the primary categories of output, were used to determine the efficiency of LSGs or some of their local public services as well. Tourism and tourism-related services variables were included in some of these studies as output variables as well. More precisely, researchers frequently utilized a share of non-residents, the number of tourists and overnights, the number of beds in tourism establishments as a proxy for services delivered to the non-resident population (Narbón-Perpiñá & De Witte, 2018). In their study, *D'Inverno, et al.,* (2017) used the resident population increased by average annual tourist presence as a proxy for higher demand for local public services. They also used a ratio of average annual tourist presence and the total population as output indicators in their analysis. On the other hand, *Wang & Kim, (2021)* stipulate the usage of tourist arrivals, tourism revenue and the number of nights spent as output variables. *Pavković, et al., (2021)* and *Ilić & Petrevska, (2018*) used a similar selection of output variables in their research of tourism efficiency.

3.4 Data

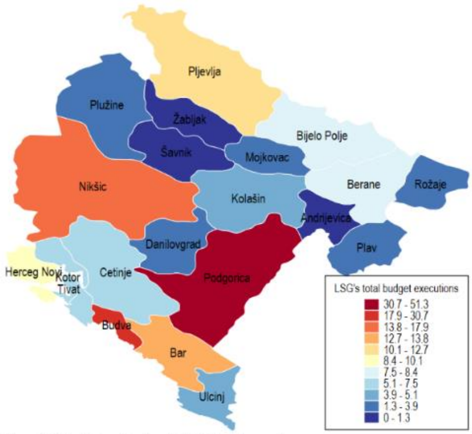
The most significant public expenditures of 21 Montenegrin LSGs in 2011, according to the LSGs' budget executions from final LSGs budget accounts, were costs of LSGs' administration (30.7%), road infrastructure and maintenance costs (22.0%), property construction and building-land related costs (6.4%), cultural activities costs (5.6%) and communal services costs (4.7%). Because of the limitation of data availability due to specific accounting practices, Authors couldn't accurately allocate costs to their specific purposes coming from LSGs' bank loans (22.2%). Figure 1 represents the structure of cumulative public expenditures of 21 Montenegrin LSGs in 2011, while Figure 2 geographical representation of cumulative budget executions in 2011.

Figure 1: Montenegrin LSGs cumulative budget executions structure in 2011



Source: Authors' calculations based on the data on LSGs' budget executions from Final LSGs budget accounts.

Figure 2: Montenegrin LSGs cumulative budget executions in 2011



Source: LSGs' budget executions from Final LSGs budget accounts

3.5 Selection of inputs and outputs

Primary sources for data regarding public expenditures were LSGs' budget executions from Final budget accounts from the year 2011 for each of 21 LSGs. Final budget accounts for Montenegrin LSGs are available on the Institute alternative website (Institut

Alternativa, 2021). Montenegro's population census from 2011 was used as a source for LSGs' population statistics (Monstat, 2021a), while Monstat's Statistical yearbooks for 2011 and 2012 (*Monstat, 2011; Monstat, 2012*) and Monstat's database (Monstat, 2021b) were used as sources for data on physical and other LSGs' characteristics (See Table 3).

From the economic standpoint land, labour and capital are seen as the basic factors of production, therefore the selection of input would belong to one of the basic factors of production. The choice of input and output variables is heavily influenced by Montenegro's Local Governance framework, LSGs' execution of public expenditures in 2011 and the focus of this research. In determining Montenegrin's LSG efficiency in providing a broad range of public services as input variable we selected:

- LSG' total expenditure executions

Hence, Montenegrin's LSG competencies were financed in a significant amount from borrowed funds, see Figure 1, we believe that the total expenditure as a proxy for the total cost of service provisions is the most appropriate choice for input in the PCA-DEA model.

Table 3: Summary statistics for input and output variables used in the PCA-DEA is presented

Variable	Obs	Mean	Std. Dev.	Min	Max
Total LSG's expend. executions	21	9496264.7	11840313	1041044.6	51222808
Population	21	29525.19	39652.66	2070	185937
Land area in km2	21	657.71	489.77	46	2065
Number of Local communities	21	17.52	11.43	6	57
Number of settlements	21	60.38	41.94	12	159
Local roads in km	21	217.72	178.09	26.5	828.5
Number of roads	21	41.52	44.39	5	221
Number of cars	21	9353.29	14513.18	349	68492
Water connections	21	9229.86	12615.45	380	58832
Heating connections	21	771.14	959.46	22	4207
Communal waste (t)	21	13287.65	14795.19	311.19	61537
Constructed areas (ha)	21	1548.76	1867.27	249	8677
Dwellings built	21	206.81	327.12	3	1489
Dwellings	21	14985.91	15917.90	2181	72688
Cultural institutions	21	10.86	15.97	1	71
Population 65+	21	3789.76	4358.66	411	19952
Children social *beneficiaries*	21	488.57	614.90	22	2363
Social services beneficiaries;	21	2465.10	4287.85	92.45	19145.73
Population + Tourist guests	21	94927.76	150571.69	2076	656796

Source: Authors' calculations.

In determining Montenegrin's LSG efficiency in providing a broad range of public services using the PCA-DEA model as output variables we selected *principal components (PC) that describes the following themes:* LSGs' administration, road infrastructure and maintenance, construction activity, cultural activities, communal services, social services, and tourism activity. The above-mentioned themes were chosen based on the most significant categories of cumulative public expenditures executions of 21 Montenegrin LSGs in 2011. The only exception to this criterion is tourism activity, due to its overall relevance to Montenegro and their LSGs.

4 Discussion

We began by running PCAs for the appropriate DEA-PCA models. We initially standardized the data to give the original variables equal priority due to the large disparities in original value magnitudes caused by different units of measurement. To assess the validity of the initial variables used to create PCs, we ran a set of diagnostic tests. The Bartlett test of sphericity rejected the null hypothesis that the original variables were not intercorrelated in each PCA at a significance level of less than 10% (See Table 5). The KMO test results in values ranging from 0.671 to 0.773, indicating adequate sampling adequacy of the initial variables used to create PCs (See Table 4). The eigenvalues of the first PCAs' components ranged between 2.6 and 3.1, significantly above Kaiser's rule that recommends using components with eigenvalues greater than 1 (See Table 5). Other components' Eigenvalues were less than 1 (See Tables 5-9).

Table 4: PCAs' diagnostic tests results

Tests	PCA Admin	PCA Roads	PCA Communal.	PCA Constr.	PCA Social
Bartlett test of sphericity	0.035	0.056	0.031	0.061	0.045
Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO)	0.728	0.672	0.671	0.773	0.767
The first PC's Eigenvalue	3.117	2.652	2.735	2.698	2.737
The first PC's Proportion of explained variance	0.779	0.884	0.911	0.899	0.912

Source: Authors' calculations using STATA version 15.

Furthermore, we used Horn's and Ender's parallel analysis to establish the exact number of components to keep in the PCA. Both tests showed that we should only include the first component in every PCA model. Additionally, a proportion of explained variance threshold for components selection is often set at the level between 70% and 90% *(Jolliffe, 2011)*. Proportion of the explained original variables variance of the first components in this paper ranged between 0.779 and 0.912 (See Table 4). Finally, we performed DEA analysis. Before doing the DEA analysis, we converted negative values in the data using the methods proposed by *Põldaru & Roots, (2014*), *Afonso & & St. Aubyn, (2011)* and *Ismail, et al., (2018)*. Furthermore, we mean-normalized the input employed in the DEA models to provide more trustworthy DEA results. We did this because high magnitude variables tend to dominate DEA calculation (*Sueyoshi & Mika Goto, 2013; Zhu & Cook, 2007*).

4.1 Principal Component Analysis (PCA)

We acquire the synthetic composite outputs after using PCA on the output variables. Tables 6-10 show the outcomes of five PCAs. The first column in Tables 6-10 displays the list of PCs for each PCA. The eigenvalues of the PCs are shown in the second column. The third column denotes the proportion of explained variation of the original variables regarding a single PC, and the fourth column denotes the cumulative explained variance of PCs. The coefficients of correlation between the PCs and the original output variables are shown in columns fifth to seventh (eight).

Table 5 shows the result of the PCA of variables use as proxy for LSGs' administration output. Output variables used in this PCA are population (Y1), land area in km2 (Y2), n*umber of local communities (Y3) and number of settlements (Y4). C*oefficients of correlations indicate that the first PC represents a measure of the size of each DMU in terms of population, land area and administrative organization. The first PC is characterized by a high correlation and its positive relationship with all original variables.

Table 5: PCA results of LSGs' administration output variables and coefficient of correlations.

Components	Eigen-analysis			Coefficient of correlations			
	Eigenvalue	Proportion	Cumulative	Y1	Y2	Y3	Y4
Comp 1	3.117	0.779	0.779	0.885	0.847	0.914	0.884
Comp 2	0.590	0.147	0.927	-0.413	0.445	-0.334	0.332
Comp 3	0.194	0.048	0.975	0.029	0.290	0.022	-0.323
Comp 4	0.098	0.025	1.000	0.212	0.013	-0.231	0.014

Source: Authors' calculations using STATA version 15.

Table 6 shows the result of the PCA of variables use as proxy for road infrastructure and maintenance output. Output variables used in this PCA are the length of local roads (Y1), number of roads (Y2) and number of cars (Y3). Correlation coefficients show that the first PC reflects a measure of size of road infrastructure and pool of vehicles. The first PC is distinguished by a high correlation between all original variables. Also, all the original variables are positively associated to PC1.

Table 6: PCA results of road infrastructure and maintenance output variables and coefficient of correlations.

Components	Eigen-analysis			Coefficient of correlations		
	Eigenvalue	Proportion	Cumulative	Y1	Y2	Y3
Comp 1	2.652	0.884	0.884	0.926	0.974	0.919
Comp 2	0.269	0.090	0.974	-0.354	-0.021	0.379
Comp 3	0.079	0.026	1.000	0.129	-0.224	0.108

Source: Authors' calculations using STATA version 15.

Table 7 shows the result of the PCA of variables use as proxy for communal services output. Output variables used in this PCA are the connections on the public water supply system (Y1), connections on the public heating system (Y2) and communal waste (Y3). According to the correlation coefficients, the first PC indicates a measure of size of public communal services systems. The first PC stands out due to a high correlation between all original variables and positively association with all original variables.

Table 7: PCA results of communal services output variables and coefficient of correlations

Components	Eigen-analysis			Coefficient of correlations		
	Eigenvalue	Proportion	Cumulative	Y1	Y2	Y3
Comp 1	2.735	0.911	0.911	0.982	0.945	0.936
Comp 2	0.212	0.070	0.982	-0.032	-0.306	0.343
Comp 3	0.053	0.017	1.000	-0.184	0.110	0.082

Source: Authors' calculations using STATA version 15.

Table 8 shows the result of the PCA of variables use as proxy for construction activity. Output variables used in this PCA are the constructed areas (Y1), number of dwellings built (Y2) and number of dwellings (Y3). *C*oefficients of correlations indicate that the first PC represents a measure of size of construction activity. The first PC stands out because of its high correlation with all original variables and its positive relationship with all original variables.

Table 8: PCA results of construction activity output variables and coefficient of correlations

Components	Eigen-analysis			Coefficient of correlations		
	Eigenvalue	Proportion	Cumulative	Y1	Y2	Y3
Comp 1	2.698	0.899	0.899	0.950	0.944	0.951
Comp 2	0.162	0.054	0.954	-0.166	0.330	-0.161
Comp 3	0.139	0.046	1.000	0.262	0.003	-0.265

Source: Authors' calculations using STATA version 15.

Table 9 shows the result of the PCA of variables use as proxy for social services activity. Output variables used in this PCA are population 65+ (Y1), number of children social *beneficiaries (Y2) and* number of *social services beneficiaries (Y3). Correlation coefficients show that the first PC reflects a measure of size of* social services activity. The first PC is distinguished by a high correlation between all original variables and positive relationship with all original variables.

Table 9: PCA results of social services output variables and coefficient of correlations

Components	Eigen-analysis			Coefficient of correlations		
	Eigenvalue	Proportion	Cumulative	Y1	Y2	Y3
Comp 1	2.737	0.912	0.912	0.953	0.947	0.965
Comp 2	0.160	0.053	0.966	-0.249	0.308	-0.057
Comp 3	0.103	0.034	1.000	0.170	0.090	-0.256

Source: Authors' calculations using STATA version 15.

4.2 Data Envelopment Analysis (PCA-DEA)

Table 10 shows the Pearson correlation coefficients between all the input and output variables. The results demonstrate a positive link between input and output variables, showing that they are isotonic and may be employed by the DEA model *(Golany & Roll, 1989)*. The isotonic relationship indicates that if the input increases while all other factors remain constant, the output quantity cannot decrease under the same conditions. The Pearson correlation coefficients also show a strong correlation between input and output variables, showing that the selected variables are highly relevant. Highly correlated variables, in general, would not have a large impact on DEA output, because weights may easily be moved from one component to another without having a substantial impact on the efficiency score. The exclusion of a highly correlated variable, on the other hand, might result in considerable changes in the efficiency of DMUs *(Dyson, et al., 2001*).

Table 10: The Pearson correlation coefficients of input and outputs

Variables	X1	Y1	Y2	Y3	Y4	Y5	Y6	Y7
(X1) Total LSG's expenditure executions	1.000							
(Y1) PC Administration	0.744	1.000						
(Y2) PC Roads	0.818	0.837	1.000					
(Y3) PC Communal	0.911	0.878	0.902	1.000				
(Y4) PC Construction	0.868	0.852	0.925	0.969	1.000			
(Y5) Cultural institutions	0.827	0.744	0.846	0.859	0.850	1.000		
(Y6) Population + Tourist	0.660	0.101	0.180	0.382	0.289	0.367	1.000	
(Y7) PC Social Services	0.794	0.879	0.895	0.935	0.938	0.781	0.167	1.000

Source: Authors' calculations.

In the current study, we use three PCA-DEA models with different specifications. The first two models included one input and six outputs variables, but with different selection of outputs. The role of the third model with one input and five outputs is to test and to isolate the effects of tourism activity on the DMUs (Montenegro's LSGs) technical efficiency (see Table 11).

Table 11: The Pearson correlation coefficients of input and outputs

Models' characteristics	Model 1	Model 2	Model 3
Number of input variables	1	1	1
Number of output variables	6	6	5
Input variables	X1	X1	X1
Output variables	Y1 Y2 Y3 Y4 Y5 Y6	Y1 Y2 Y3 Y4 Y5 Y7	Y1 Y2 Y3 Y4 Y5

Table 12 summaries results of the PCA-DEA analysis with constant return to scale (CRS). Each column displays the PCA-DEA analysis findings for a separate specification, and each row corresponds to a summary statistics of a separate model specification.

Table 12: Summary characteristics of PCA-DEA results for different specifications

Models' characteristics	Model 1 - CCR	Model 2 - CCR	Model 3 - CCR
Number of inputs and outputs	7	7	6
Number of technically efficient DMUs	6	4	4
Proportion of DMUs deemed technical inefficient	0.714	0.810	0.810
Average technical efficiency score	0.673	0.603	0.578
Minimum technical efficiency score	0.259	0.126	0.126
Standard deviation	0.263	0.284	0.280

Source: Authors' calculations.

The number of relative technically efficient DMUs estimated using DEA is presented in the third row of Table 12. Model 2 with one input and six outputs produced the same number of relative technical efficient DMUs as model 3 with one input and five outputs. This indicates that the dimensionality of the models (number of inputs and outputs) doesn't have a significant impact on the technical efficiency measure.

Hence, the first model has produced a higher number of relative technically efficient DMUs than Model 2 with the same specification, it further stipulates that the selection of outputs have a significant impact on the performance measure. In this case, it would be the inclusion of a proxy for touristic activity in the PCA-DEA model.

The proportion of DMUs found inefficient using DEA is shown in the fourth row of Table 12, and it ranges between 71.4 % and 81.0 %. Thus, Model 2 and Model 3 have estimated the same portion of relative technically inefficient DMUs it further argues in favour that the selection of output variables produces a higher impact on the efficiency measure than the dimensionality of the models. However, the average technical efficiency scores, represented in the fifth row of Table 12, tend to increase with the increasing number of inputs and outputs. Though, the effect of the increasing number of inputs and outputs on the average technical efficiency scores of the PCA-DEA models is relatively small. All the above indicates that the discrimination problem within the observed PCA-DEA models is relatively small due to proper models' specifications. Consequently, there is no pronounced trade-off between complete PCA-DEA information and the need to reduce the overestimation bias.

Table 12 compares the rankings of the DMUs for separate PCA-DEA model specifications. The rankings are assessed using the Spearman measure of correlation. The ranking correlation coefficients further confirms the hypothesis that the selection outputs, in this case, the inclusion of proxy for tourism activity in Model 1, has a profound impact on DMUs' efficiency scores. Model 1 DMUs' rankings are moderately correlated with the other two models, while DMUs' rankings of Models 2 and 3 are strongly correlated.

Table 13: Spearman correlation coefficients between DMUs' rankings for different PCA - DEA model specifications.

PCA -DEA model specifications	Model 1	Model 2	Model 3
Model 1 (DMUs – ranking)	1.000		
Model 2 (DMUs – ranking)	0.545	1.000	
Model 3 (DMUs – ranking)	0.408	0.771	1.000

Additionally, we tested rankings of models 1 and 2 against the rankings of the corresponding DEA models with ordinary variables instead of principal components. As a control for Model 1, we selected a model with the same input and land area in km2, local roads in km, connections on the public water supply system, number of dwellings built, population + tourist guests and number of cultural institutions as outputs. We found that the correlation of Model 1 DMU's ranking with the Control Model 1 DMU's ranking were somewhat lower ($\rho = 0.442$), but still moderate. Similarly, we selected a control model for Model 2 with a similar specification as Control Model 1. The only differences are that we selected population instead of land area in km2 and the number of *social services beneficiaries instead of* population + tourist guests. The correlation between Model 2 DMUs' rankings and the Control Model 2 DMU's ranking was weak ($\rho = 0.319$).

Similarly, we compared the Spearman correlation coefficients of Models 1 and 2 technical efficiency scores. We found a strong correlation between the technical efficiency score of Models 1 and 2, and a very strong correlation between the technical efficiency score of Models 2 and 3 (See Table 14). We also compared correlation between the technical efficiency score Models 1 and 2 and corresponding Control Models and found a very a very strong correlation of $\rho = 0.921$ and $\rho = 0.935$ respectively.

Table 14: Spearman correlation coefficients between DMUs' efficiency scores for different PCA - DEA model specifications

PCA -DEA model specifications	Model 1	Model 2	Model 3
Model 1 (DMUs – efficiency score)	1.000		
Model 2 (DMUs – efficiency score)	0.695	1.000	
Model 3 (DMUs – efficiency score)	0.777	0.948	1.000

Table 15: The technical efficiency scores for 21 Montenegro's LSGs for 2011

	Model 1 -CCR		Model 2 - CCR		Model 3 - CCR	
Rank	DMU	TE score	DMU	TE score	DMU	TE score
1	Andrijevica	1.000	Andrijevica	1.000	Andrijevica	1.000
2	Cetinje	1.000	Cetinje	1.000	Cetinje	1.000
3	Herceg Novi	1.000	Savnik	1.000	Savnik	1.000
4	Savnik	1.000	Zabljak	1.000	Zabljak	1.000
5	Ulcinj	1.000	Plav	0.865	Plav	0.833
6	Zabljak	1.000	Rozaje	0.846	Kotor	0.819
7	Kotor	0.890	Kotor	0.819	Herceg Novi	0.789
8	Plav	0.833	Herceg Novi	0.789	Danilovgrad	0.758
9	Danilovgrad	0.805	Danilovgrad	0.758	Pluzine	0.623
10	Budva	0.762	Pluzine	0.623	Mojkovac	0.564
11	Pluzine	0.623	Mojkovac	0.611	Bijelo Polje	0.468
12	Mojkovac	0.564	Bijelo Polje	0.475	Rozaje	0.421
13	Bar	0.519	Podgorica	0.418	Podgorica	0.418
14	Bijelo Polje	0.505	Kolasin	0.418	Kolasin	0.418
15	Podgorica	0.446	Ulcinj	0.386	Ulcinj	0.386
16	Kolasin	0.430	Berane	0.373	Berane	0.373
17	Rozaje	0.421	Pljevlja	0.354	Pljevlja	0.354
18	Berane	0.373	Bar	0.334	Bar	0.334
19	Pljevlja	0.373	Niksic	0.240	Niksic	0.231
20	Tivat	0.330	Tivat	0.222	Tivat	0.222
21	Niksic	0.259	Budva	0.126	Budva	0.126

Source: Authors' calculations using MaxDEA version 8.

Table 15 summarizes the PCA-DEA models' technical efficiency scores with a constant return to scale (CRS). As a result of the DEA producing measures of relative technical efficiency, technical efficient DMUs (Montenegro's LSGs) are only efficient when compared to other DMUs in the model. DEA does not generate an absolute efficiency measure or a universal efficiency threshold against which DMU efficiency is measured. This further implies that a DMU that is deemed to be technically efficient does not always imply that their operational methods are the most efficient, but merely in comparison to the practices of other DMUs in the model.

Availability of the resources and pronounced differences in tourism activity among DMUs are the most important factors that shaped the DMUs' ranking and the technical efficiency scores presented in Table 16. We compared the Spearman correlation coefficients of DMUs ranking in the availability of the resources, in terms of LSG' total expenditure executions, and DMUs ranking in technical efficiency scores in Models 1 and 2. We found a negative correlation in both models that diverged in the intensity while being weak in Model 1 ($\rho = -0.279$) and moderate in Model 2 ($\rho = -0.544$). This implies that DMUs (Montenegro's LSGs) that had more inputs or budget funds on their disposal tended to be less technically efficient. In other words, "wealthier" LSGs were more prone to inefficient allocation (squandering) of their budgetary funds. While, on the other hand, "less wealthy" LSGs had to apply stringier spending practices to be able to provide the required local public services and goods. This further indicate that, even if "less wealthy"

LSGs are generally deemed to be more efficient than "wealthier" LSGs, this does not necessarily imply that the "less wealthy" LSGs' operating practices are efficient. These findings could be explained by the insufficiently developed financial management and overall operational management skills among Montenegro's LSGs.

The other important factor relates to the hypothesis that tourism activity puts additional costs on LSGs in providing their local public services. To test this hypothesis, we compared the efficiency scores of coastal LSGs in Model 1, with a proxy for higher demand for local public services due to tourism activity, and Model 3 that has the same specification as Model 1 but without the effects of tourism activity. The results of comparisons show that the technical efficiency scores of six coastal LSGs are affected by the tourism activity disproportionally more compared to non-coastal LSGs (see Table 16).

The fact that the technical efficiency scores of six coastal Montenegro's LSGs depend heavily on tourism is not unexpected having in mind the distribution of tourist arrival. However, the intensity of the tourism impact of the LSGS on the six coastal Montenegro's LSGs compared to the non-coastal LSGs is somewhat surprising. By comparing PCA-DEA results from Models 1 and 3, we estimated that tourism activity reduced technical efficiency scores of Montenegro's coastal and non-coastal LSGs on average by 0.304 and 0.011 index points respectively. This corresponds to the 30.4% lower technical efficiency of Montenegro's coastal LSGs and 1.1% of non-coastal LSGs in Model 3 compared to Model 1. This disparity in six coastal LSGs' technical efficiency scores has translated into lower average overall DMUs' technical efficiency in Model 3 by 9.5% compared to Model 1 (see Table 17). Our findings on the impact of tourism activity on Montenegro's LSGs efficiency corresponds to the conclusions made by *Athanassopoulos & Triantis, (1998)* and *D'Inverno, et al.,* (2017) about the effect of tourist activity on Greek LSGs and Tuscan municipalities respectively. Both groups of authors argued that there is an inverse relationship between tourism and LSGs' efficiency. Also, *D'Inverno, et al.,* (2017) by combining DEA and Tobit regression analysis found that Tuscan municipalities with high tourism activity were on average 31.8% less efficient in 2011.

Table 16: The technical efficiency scores for 6 Montenegro's coastal LSGs for 2011

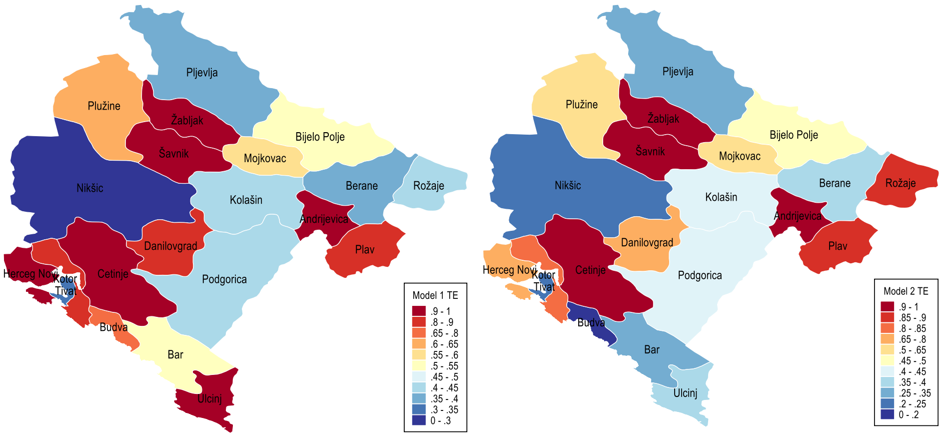
Model 3 -Without Tourism effect		Model 1 – With Tourism effect		Difference (Model 3 - Model 1)	
DMU	TE score	DMU	TE score	DMU	TE score
Bar	0.334	Bar	0.519	Bar	-0.185
Budva	0.126	Budva	0.761	Budva	-0.636
Herceg Novi	0.789	Herceg Novi	1.000	Herceg Novi	-0.211
Kotor	0.819	Kotor	0.890	Kotor	-0.071
Tivat	0.222	Tivat	0.330	Tivat	-0.108
Ulcinj	0.386	Ulcinj	1.000	Ulcinj	-0.614
Other LSGs (Average)	0.631	Other LSGs (Average)	0.642	Other LSGs (Average)	-0.011
Other LSGs (SD)	0.277	Other LSGs (SD)	0.270	Other LSGs (SD)	0.016
Average TE	0.578	Average TE	0.673	Average TE	-0.095

Source: Authors' calculations.

Having determined the impact of tourism on Montenegro's LSGs efficiency we believe that PCA-DEA Model 2 is biased against Montenegro's coastal LSGs. By not including the proxy for higher demand for local public services due to tourism activity Model 2 favours non-coastal LSGs in estimating technical efficiency. As a result of this and given the importance of tourism to Montenegro and its LSGs, we believe PCA-DEA model 1, which contains a proxy for tourist activity, to be more relevant in estimating Montenegro's LSGs efficiency.

Figure 3: Geographical distribution of Montenegrin LSGs technical efficiencies in 2011

A – Model 1 TE efficiency scores B– Model 2 TE efficiency scores



Source: Authors' calculations using MaxDEA version 8.

Tables 17 summarise the scale efficiency of the PCA-DEA Model 1. The third column refers to the technical efficiency score computed using the CCR model based on the constant return to scale (CRS). Similarly, the fourth column represents the pure technical efficiency score (PTE) calculated using the BCC model based on the variable return to scale (VRS). The fifth column lists scale efficiency scores (SE) and the sixth column represents the regions of return to scale (RTS) under which DMU is operating.

Table 17: PCA-DEA Model 1 - The scale efficiency for 21 Montenegro's LSGs for 2011

		Model 1 -CCR	Model 1 - BCC	Secale efficiency (SE)	RTS
Rank	DMU	TE score	PTE score	SE score	
1	Andrijevica	1.000	1	1	Constant
2	Cetinje	1.000	1	1	Constant
3	Herceg Novi	1.000	1	1	Constant
4	Savnik	1.000	1	1	Constant
5	Ulcinj	1.000	1	1	Constant
6	Zabljak	1.000	1	1	Constant
7	Kotor	0.890	1	0.890113	Decreasing
8	Plav	0.833	1	0.832679	Decreasing
9	Danilovgrad	0.805	1	0.805469	Decreasing
10	Budva	0.762	1	0.76198	Decreasing
11	Pluzine	0.623	0.964596	0.646221	Decreasing
12	Mojkovac	0.564	0.571692	0.98658	Increasing
13	Bar	0.519	1	0.519213	Decreasing
14	Bijelo Polje	0.505	1	0.50487	Decreasing
15	Podgorica	0.446	1	0.445746	Decreasing
16	Kolasin	0.430	1	0.430074	Decreasing
17	Rozaje	0.421	0.736541	0.571587	Decreasing
18	Berane	0.373	1	0.373012	Decreasing
19	Pljevlja	0.373	1	0.372839	Decreasing
20	Tivat	0.330	0.414933	0.795154	Decreasing
21	Niksic	0.259	1	0.258668	Decreasing

Source: Authors' calculations using MaxDEA version 8.

Under variable return to scale (VRS) assumption majority of Montenegro's LSG achieved pure technical efficiency (PTE) in both models (see Table 18). The differences between DMUs' TE and PTE estimation indicates the existence of scale inefficiency. For DMUs that scale efficiency score is below 1, it indicates that combination of their inputs and outputs is not scale-efficient. DMU is scale-inefficient when the size of its activities is suboptimal and modifications to its size are necessary to make DMU more efficient (*Coelli, et al., 2005*). This further indicate that technical efficiency scores cannot distinguish the effects of increased productivity due to DMU's shifting to a more productive scale size from the effects of cost reduction.

All technical inefficient DMUs in Model 1 (71.4%), are scale inefficient as well (see Tables 18). Furthermore, apart from LSG "Mojkovac", all scale inefficient DMUs operate with decreasing returns to scale. In other words, 66.6% of Montenegro's LSGs are beyond their optimal scale and may improve their technical efficiency by reducing either their size or scope of their responsibilities (local public goods and services). This indicates that any proportional increase in these LSG's inputs would result in a less than proportionate increase in its outputs. In other words, any increase in outputs by 1% would result in an increase of inputs by more than 1%. On the other hand, LSG "Mojkovac" operated in the region with increasing returns to scale. This implies that LSG "Mojkovac" could increase its technical efficiency by increasing the size or scope of its responsibilities. It further indicates that any increase in LSG "Mojkovac's" scale of operation would result in a greater than proportionate increase in its outputs.

Tables 18 depict input and output slacks of the PCA-DEA Model. The second column refers to the input slacks, while output slacks are represented from third to eight columns.

We chose slacks under the variable return to scale (VRS) assumption for PCA-DEA Model 1 as the more appropriate method for the computation of slacks. We believe the BCC model is far more relevant since the CCR model's technical efficiency is confounded by scale efficiencies. This has significant consequences for slacks calculation since DMUs' or LSGs' management do not have discretionary power to change the size of LSGs. As a result, in the case of LSG, calculating slacks (input excesses and output shortfalls) based on the pure technical efficiency free of the scale efficiency is more appropriate when analysing LSG's management performances.

Table 18: PCA-DEA Model 1 (BCC) – Slacks under variable return to scale (VRS) assumption

DMU	X1	Y1	Y2	Y3	Y4	Y5	Y6
Andrijevica	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Cetinje	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Herceg Novi	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Savnik	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Ulcinj	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Zabljak	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Kotor	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Plav	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Danilovgrad	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Budva	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Pluzine	**-0.009**	0.000	0.000	**0.311**	**0.350**	**0.025**	**0.194**
Mojkovac	**-0.091**	**0.159**	**0.612**	**0.030**	0.000	**0.032**	**0.121**
Bar	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bijelo Polje	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Podgorica	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Kolasin	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Rozaje	**-0.106**	**0.237**	0.000	0.000	0.000	0.000	**0.037**
Berane	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Pljevlja	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Tivat	**-0.454**	**0.960**	0.000	0.000	**0.053**	0.000	0.000
Niksic	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Source: Authors' calculations using MaxDEA version 8.

Input and output slacks are present in four DMUs in PCA-DEA Model 1. It stipulates that for these LSGs to be more efficient they need to reduce input and increase output production at the same time by making internal practices more efficient. After we transform DMUs' normalized input data into the original data and adjust it for input excesses, PCA-DEA Model 1 suggests input reduction for "Mojkovac" (-42.7%), "Pluzine" (-3.6%), "Rozaje" (-26.3%) and "Tivat" (-58.5%). In other words, data in PCA-DEA Model 1 show that with the achieved level of outputs in 2011 these four LSG on average have inefficiently allocated budgetary funds in the amount that correspond to 32.8% of their total expenditure execution. The fundamental disadvantage of PCA is the difficulty in interpreting PCs, as their interpretation is not straightforward. As a result, we could only identify areas in which output should be increased either through the increased reach of local public services or the scale of offered public goods.

However, because relatively few DMUs have slack issues, the main finding of the slack analysis is that scale inefficiency is a greater source of LSGs inefficiencies than internal practices. This suggests that to improve Montenegro's LSGs efficiency, it is necessary to re-evaluate the territorial organization of local self-governments in Montenegro, as well as the scope of responsibilities allocated to Montenegro's LSG.

5 Conclusions

Montenegro could develop a decentralized governance system based on the needs of its citizens. To do so, any further extensive reforms would require an evidence-based policy decision that will be based on the performance benchmarks for the overall efficiency of their local governance system. According to our findings, the range of technical efficiency of Montenegro's local governance system in 2011 was between 60.3% and 67.3%, depending on the observed model. Furthermore, we found evidence of an inverse relationship between tourism activity and the efficiency of Montenegro's LSGs. We found that on average tourism activity reduces Montenegro's coastal LSG technical efficiency by 30.4%. Inefficient internal practices and scale inefficiency were identified as the primary sources of technical inefficiency.

We found evidence of the insufficiently developed LSG's financial management and operational management skills as the main cause of the inefficient internal practices. However, a much greater generator of inefficiencies comes from scale inefficiency due to the suboptimal size of Montenegro's LSGs and/or the scale of delegated responsibility in terms of providing public services and goods. Therefore, to make Montenegro's LSGs more efficient it is necessary to improve the financial management and operational management know-how of Montenegro LSGs' management personnel. Though, the biggest impact on the improvement of the overall efficiency of Montenegro's local governance system would be achieved by re-evaluating the territorial organization of local self-governments in Montenegro, as well as the scope of responsibilities allocated to Montenegro's LSG. Given the influence of tourism on efficiency, we propose that any future analysis of LSG efficiency in Montenegro and any other country with pronounced tourism activity include a proxy for tourism activity. Also, any future evidence-based policy decision would require an updated efficiency analysis of Montenegro LSGs based on the most recent data.

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