Efficiency in regional connectivity: an empirical analysis about the impact of intergovernmental capital transfers in Uruguay

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Abstract

In this paper, we empirically analyze the efficiency of sub-national governments in Uruguay to improve the connectivity of the local population through investments in rural roads. To do this, we have constructed a novel database of intergovernmental capital transfers during the period 2016-2019 and then applied the Data Envelopment Analysis methodology in two stages. The results of the first stage indicate that sub-national governments in Uruguay could increase the kilometers of rural roads intervened by 29% while maintaining the same level of expenditure. The results of the second stage reveal that efficiency increases the smaller the size and the wealth of the region are, and the higher the quality of the local bureaucracy is.

Keywords: Efficiency in regional connectivity, Data Envelopment Analysis, Truncated regression analysis, Uruguay.

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1. Introduction

An important aspect of fiscal federalism literature refers to the role of intergovernmental transfers in improving the provision of local public services. In this context, the main concern of scholars could refer to the efficiency of local governments in the administration of public funds.

Several scholars point to a positive effect of decentralization on the efficiency of public policies. In this sense, some studies have indicated that a certain degree of decentralization increases efficiency by greater electoral control and yardstick competition among competing jurisdictions (see, for example, Adam et al. 2014). In this same vein, Christl et al. (2020) has argued that revenue decentralization increases information about the preferences and needs of the communities as well as accountability thus reducing incentives for overspending of sub-national governments and therefore improving public sector efficiency. Besley and Smart (2007) also argue that decentralization enhances the public interest to compare the public services and taxes across their jurisdictions contributing to a reduction in the “bad” use of the resources by politicians. Additionally, inter-jurisdictional competition might be observed in terms of the provision of public goods and taxation to keep their tax bases or attract new taxpayers from other jurisdictions (Sepúlveda and Martinez-Vazquez 2011).

In recent years, in developing countries like Uruguay, regional public policies have become increasingly important. Both the design and implementation of these policies are of central relevance in the agenda of scholars and policymakers (Martinez-Vazquez et al. 2017). However, in contrast to the considerable growth in the literature for developed countries;[1] in developing economies these debates have not focused on the evaluation of the efficiency of fiscal performance at the sub-national level. One of the main reasons is due to the limitations imposed by the scarce availability of information at a local level in these developing countries.

Sub-national public investment has been proven to be of substantial relevance for boosting infrastructure investment at the national level (OECD 2019). In this sense, in this article by using a novel database, we empirically analyze the efficiency of regional public spending in Uruguay by considering a specific series of conditional intergovernmental capital transfers of the "Departmental Roads Program" (DPR) during the period 2016-2019.[2] The DPR represents

[1] For a complete survey, see García and Suárez (2019).
[2] See, https://www.opp.gub.uy/es/camineria-rural.

an annual budget of 13% of the total annual investment in infrastructures of local governments in Uruguay. The program finances two types of public interventions: (i) maintenance of the rural road network and, (ii) rehabilitation, improvement, and new interventions of rural roads. Our analysis includes both types of interventions and considers all the years for which such information is available for the 19 Departmental Governments (DGs) of Uruguay.[3]

The empirical strategy is based on a two-stage non-parametric method. In the first stage, by using the Data Envelopment Analysis (DEA), a relative efficiency score is estimated for each DG of Uruguay. At this stage, each observation is considered for every DG in a given year (DG-year) as a Decision-Making Unit (DMU) and the performance of these decision units are evaluated through an efficiency frontier analysis. In this context, the frontier concept evaluates the extent to which a DMU (in our case DG) is achieving the maximum production (output) with the lowest consumption of resources (inputs). In addition, it is assumed that the results achieved in terms of efficiency are conditioned by contextual variables that cannot be directly controlled by the executing units (DMUs). Therefore, in the second stage, we analyze the influence of these contextual factors on the relative efficiency scores estimated in the first stage of the analysis (Simar and Wilson 2007 and 2011).

The empirical results obtained in the first stage suggest that the DGs in Uruguay could increase, on average, 29% of the kilometres of rural road network intervened while maintaining the same level of expenditure, However, behind this average, we find that the levels of inefficiency are heterogeneous, which implies that, for those DGs that have been relatively more inefficient, the improvement target varies significantly concerning the average. In addition, the results of the second stage reveal that efficiency increases the smaller the size and the wealth of the region are, and the higher the quality of the local bureaucracy is.

The remainder of this paper is structured as follows. Section 2 presents the theoretical framework related to the concept of efficiency. Section 3 discusses those specific empirical studies that constitute the background of the present analysis. Section 4 analyzes the different types of intergovernmental transfers in place in Uruguay. Section 5 details the methodology and section 6 the data to be used. Section 7 presents the empirical results. Finally, section 8 details some conclusions.

[3] Uruguay is divided into 19 departments (regions) which are the second level of government, after central government. For details of the administrative composition of Uruguay see Figure A.1 in Appendix 1.

2. Economic efficiency analysis

The efficiency analysis is related to the relative comparison of different DMUs that generate similar products (outputs) by using some specific resources (inputs). In this context, the concept of efficiency incorporates the idea of the "production possibilities frontier" which indicates the feasible levels of production given the available scale of production of the DMUs analyzed. Thus, efficiency gains are a movement towards this frontier which represents the "best practices" (Mandl et al. 2008). Furthermore, within the specialized literature, there are two main methodological approaches to analyze economic efficiency: (i) parametric methods, and (ii) non-parametric methods.

Parametric approaches require determining a specific functional form of the production function that presupposes the form of the efficient frontier (Aigner et al. 1977). Among the employed methods, those based on Ordinary Least Squares (OLS) or Corrected Ordinary Least Squares (COLS), interpret the total deviation from the frontier as inefficiency. Within these approaches, those methods based on the stochastic frontier (SFA) decompose the deviation of the frontier between the effect of random events beyond the control of the DMU being evaluated (statistical noise) and the inefficiency of this DMU (Battese and Broca 1997, Greene 2005).

Within the non-parametric approaches, the most commonly used method is the Data Envelopment Analysis (DEA). The DEA method has the advantage of being less restrictive and more flexible than parametric methods. In this type of analysis, it is not necessary to know the form of the production function and allows the handling of multiple input and output variables. However, it has the disadvantage of its deterministic nature, which means that all deviations from the frontier are considered as inefficiency. Some new statistical techniques attempt to mitigate this last limitation. Among them, bootstrap methods based on sub-sampling have been used to correct possible biases in the calculation of the DEA method and to make statistical inferences (i.e. consistency analysis, bias correction, confidence interval, etc.).[4]

Farrell's (1957) pioneering work proposed the DEA method for measuring production efficiency by taking into account several production factors. Its formulation is based on estimating an efficient frontier from a cloud of points (DMUs) and measuring the efficiency of these different units based on two key assumptions: (i) convexity: if two points are

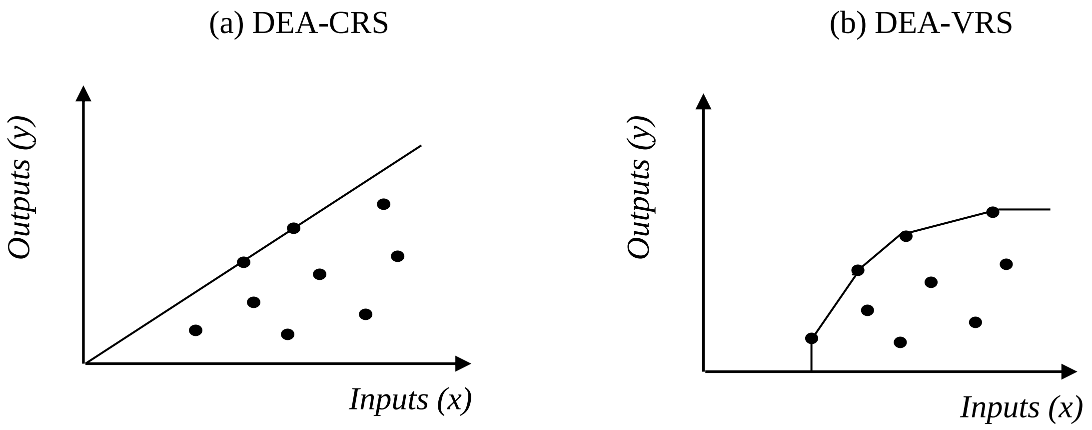
[4] See, for example, Simar and Wilson (2007 and 2011) and Bogetoft and Otto (2011).

achievable, then any weighted average of them is also achievable; and (ii) existence of negative slope in the input isoquant: an expansion of inputs cannot result in a reduction of outputs. In this context, the input-oriented efficiency scores measure how much we can proportionally reduce inputs to obtain the same output. Analogously, output-oriented efficiency scores measure how much we can proportionally increase the outputs for a given amount of inputs.

Farrell's ideas were popularized by Charnes et al. (1978) which provided the mathematical foundations for frontier analysis based on linear programming techniques. The original model proposed by Charnes et al. is input-oriented and assumes constant returns to scale (DEA-CRS) of the production function. Later, Banker et al. (1984) proposed an alternative to this DEA-CRS model, by assuming variable returns to scale (DEA-VRS model). The DEA-VRS model requires the incorporation of the DEA-CCR an additional convexity constraint. As a consequence, this DEA-VRS model takes into account the variation of efficiency concerning the scale of operation. In this sense, the DEA-VRS model considers that some units may not be able to achieve the productivity of the most efficient ones; therefore, the study is carried out by using "pure technical efficiency" measures and referring each DMU to the highest productivity among those of its size.

Figure 1 shows the DEA models, with CRS and VRS, by considering the case of one input and one output, where the points observed are the DMUs.

Figure 1 - DEA-CRS and DEA-VRS technologies (one input and one output)



Source: Own elaboration

While in DEA-CRS the efficient frontier is linear (figure 1, panel a), in the case of DEA-VRS (figure 1, panel b) a convex hull built up around the DMUs analyzed. This convex hull has two implications; on the one hand, the efficiency scores under DEA-VRS turn out to be higher or equal to the efficiency scores under DEA-CRS (higher efficiency levels are achievable) and, on the other hand, a larger number of DMUs turn out to be efficient (points on the frontier).

Finally, within these DEA-CRS and DEA-VRS approaches, the two-stage analysis allows adjusting the efficiency estimations to the consideration of "exogenous" or contextual factors not directly controlled by the DMUs. This type of analysis assumes a separability condition where the operating environment does not influence the levels of inputs and outputs, but only the efficiency. Such an approach involves estimating relative efficiency scores in the first stage through the DEA method, and including a set of determinants (contextual factors) of these estimated scores of efficiency in a second stage through the use of techniques such as the Tobit censored regression model, ordinary least squares (OLS) or truncated regression methods (Simar and Wilson 2007).

3. Empirical literature review

The analyses of the efficiency of regional public policies have advanced considerably for developed countries. According to their object, we can divide these empirical studies into two broad categories: (i) those works which evaluate the performance of local government from a "global point of view", and (ii) those analysis which evaluate a particular local service.

Regarding the "global approach", the results in terms of average efficiency scores per country, measured as the average between the maximum and minimum scores found in the literature, vary considerably due to differences in the samples, methodologies, and the included variables. But, in general, Germany has the highest average efficiency scores (0.90), followed by Japan, the United States, and Finland with averages scores above 0.8. In turn, Spain, Belgium, Portugal, and Australia have scores between 0.8 and 0.6. [5]

Meanwhile, those works which evaluate a particular local service are scarcer. Table 1 summarizes the main output and input variables that have been used in this kind of analysis.

[5] A systematic review of this literature can be found in Narbón-Perpiñá and De Witte (2018a and b).

Table 1 - Output and input variables applied in efficiency studies of local governments considering a particular local service

OUTPUT variables	INPUT variables
• Number of light points • Surface area of: - road infrastructure - public parks - public buildings • Volume of waste (domestic, industrial and commercial) • Number of dwellings with daily garbage collection services • Length of roads in kilometres • Number of vehicles as a proxy for the surface area of public roads • Infrastructure quality • Urban area	• Expenditure: a. total b. current c. salaries d. financial and capital • Revenues: a. total b. current

Source: own elaboration

The visual inspection of Table 1 allows us to observe that s that the majority of this works has been focused on evaluating the garbage collection and street cleaning (Bosch et al. 2000; Worthington and Dollery 2000 and 2001; Benito et al. 2015); or, in some cases, in street lighting (Lorenzo and Sánchez 2007).

In general, the review of the specialized literature shows that, to date, few empirical studies have explicitly addressed the analysis of efficiency in fiscal performance at the sub-national level for developing countries. This is our objective in this study. We examine the efficiency of the regional governments of Uruguay to improve the connectivity of the local population through investments in rural roads.

4. Local public finances in Uruguay: the role of intergovernmental transfers

The new system of intergovernmental transfers in Uruguay was established in the Constitutional Reform of 1996 with the purpose to promote fiscal decentralization in this unitary country. Since then, successive five-year National Budget Laws have determined the amounts, their components, and the distribution by DG. Within this framework, the intergovernmental transfers are channelled through four main instruments:

- *Article number 214 of the National Constitution* states that 3.33% of the total annual General Government (GG) revenues will be transferred to the DGs. This is the main source of unconditional intergovernmental transfers in Uruguay.
- The *Interior Development Fund* was established by Article number 298 of the National Constitution. The Law establishes that 66.65% of this fund will be used for decentralization policies executed by the Central Government (CG) and 33.35% to finance projects executed by the DGs.
- The *Incentive Fund for the Management of Municipalities* was established by Article number 19 of the National Constitution. These amounts are divided into literal A (10%) which is distributed without conditionality; literal B (75%) destined to projects, programs, and operating expenses and; literal C (15%) to finance projects and programs according to the fulfilment of goals arising from management commitments.
- The *Departmental Roads Program (DRP*) was established in Budget Law No. 19.355. These are the main source of capital intergovernmental transfers in Uruguay.

Table 2 shows the weight of total intergovernmental transfers over the total revenues of DGs.

Table 2: Share of intergovernmental transfers in total DG revenues (2016 – 2019)

DG	2016	2017	2018	2019
Artigas	60%	55%	59%	58%
Canelones	26%	26%	28%	28%
Cerro Largo	61%	57%	58%	58%
Colonia	30%	29%	30%	30%
Durazno	49%	47%	49%	49%
Flores	45%	40%	44%	43%
Florida	48%	40%	44%	44%
Lavalleja	53%	50%	52%	52%
Maldonado	20%	17%	16%	14%
Montevideo	10%	10%	10%	11%
Paysandú	43%	43%	46%	47%
Río Negro	50%	50%	49%	52%
Rivera	53%	48%	52%	52%
Rocha	40%	38%	39%	40%
Salto	48%	42%	44%	44%
San José	43%	38%	37%	40%
Soriano	46%	44%	46%	44%
Tacuarembó	45%	45%	47%	48%
Treinta y Tres	64%	60%	60%	66%
Total	**29%**	**27%**	**28%**	**28%**

Source: Own elaboration.

The inspection of Table 2 allows us to observe that intergovernmental transfers represent, on average, 28% of the annual revenues of DGs over the period considered (2016-2019). However, for some of the DGs, these transfers explain more than 40% of their revenues, and in a few cases exceeding 50%.

The Departmental Roads Program

Within the different existing intergovernmental transfers programs, the "Departmental Roads Program" (DRP), which is the main source of capital intergovernmental transfers in Uruguay, arose from an agreement between the Central Government (CG) and each DG of Uruguay. Law 19.355 established for this program a total amount of US$ 950 million (2015 values), assigned to three projects:

- Number 999: Maintenance of the Departmental Road Network
- Number 998: Maintenance of the Sub-national (various GDs together) Road Network
- Number 994: Complement of Departmental and Sub-national Roads

The distribution of resources by the project has been as follows: U$350 million (37% of the total) corresponds to project 999, U$150 million (16% of the total) to project 998, and U$450 million (47%) to project 994. In addition, in 2016 were fixed the aliquots by DG for the distribution of their resources. These aliquots are presented in Table 3. These aliquots remain fixed for all years analyzed in this article (2016 to 2019) and were based on the distribution criterion which was agreed between the CG and each DG.

Table 3: Aliquots for the distribution of DRP funds

DG	Aliquot (%)
Artigas	5.55
Canelones	11.70
Cerro Largo	6.49
Colonia	5.39
Durazno	5.38
Flores	2.88
Florida	4.66
Lavalleja	5.40
Maldonado	4.03
Montevideo	3.21
Paysandú	6.06
Río Negro	4.00
Rivera	4.48
Rocha	4.52
Salto	6.16
San José	4.40
Soriano	4.51
Tacuarembó	7.13
Treinta y Tres	4.05
Total	**100.00**

Source: National Congress of DGs

A key component of the DRP is the diagnosis of rural roads in Uruguay. In this context, a series of actions were established between the CG and each DG of Uruguay in order to improve the administration strategies for rehabilitating the infrastructure and ensuring its conservation. This process has involved the elaboration of the National Departmental Road Plan (NDRP), which is part of the DRP and has been carried out with the support of the Inter-American Development Bank (IADB). The NDRP was prepared under a participatory and technical methodology through which the demands for intervention and/or expansion of the existing rural network were identified. It considers the prioritization of interventions according to their relative importance in the departmental economic development. In the process of elaborating the plan, the entire rural road network was identified, codified, and categorized according to different dimensions (spatial and economic). In this sense, the categorization of the rural road network determined that approximately 10% were prioritized as "high" importance, 16% as "medium" importance, and the remaining 74% as "low" importance (Oficina de Planeamiento y Presupuesto 2018). Specifically, were differentiated five types of interventions:

a. *Ordinary maintenance*: activities aimed at the permanent maintenance of pavements, drainage infrastructures, signalling, and public strips.

b. *Extraordinary maintenance*: activities aimed at recovering deterioration of the road surface caused by traffic and climatic phenomena.

c. *Rehabilitation*: activities aimed at reconstructing or recovering the initial conditions of the road, so that it fulfils the technical specifications for which it was designed.

d. *Improvement*: change of specifications and dimensions of the road or drainage infrastructure, which allow an adaptation to the levels of service required by the current and projected traffic.

e. *New projects*: construction of previously non-existent infrastructure, in particular the construction of new rural roads.

Finally, it is important to point out that the conditional capital transfers corresponding to the DRP represented between 2016 and 2019, the 5% of intergovernmental transfers in Uruguay. In addition, these types of transfers were exclusively earmarked for public investment projects. The latter highlights the importance of this kind of capital transfer since most of the DGs of Uruguay show a low rate of investment throughout the period considered (around 15% annual average). These transfers also contribute, on average, to the 13% of the total investment expenditure of the DGs of Uruguay.

5. Empirical methodology

5.1 Stage One: Data Envelopment Analysis (DEA)

The DEA methodology is based on a multidimensional linear program that solves "multiple nature production function" problems. In this context, the concept of efficiency mostly used to evaluate the performance of the DMUs refers to the ratio between total outputs and inputs (in physical or monetary units). Therefore, a basic efficiency measure is expressed by:

$$Efficiency = \frac{Output}{Input} \qquad (1)$$

It is important to note that the measure of equation (1) is of relative efficiency to the sample of DMUs analyzed. In this sense, the estimate of efficiency is based on the ratio of each DMU to the best-performing DMU (or DMUs). This method allows identifying and quantifying the inefficiencies in inputs and outputs, giving some guidelines for the improvement of the different units analyzed. To the best performing DMUs are assigned the value of 1 and the performance of the others varies between 0 and 1 about this best performance DMU (Ramanathan 2003).

To compare n units (or DMUs), the DEA model adopts the following fractional expression, where m is the reference unit for which efficiency is to be maximized:

$$\begin{cases} \max E_m = \dfrac{\sum_{j=1}^{J} v_{jm} y_{jm}}{\sum_{i=1}^{I} u_{im} x_{im}} & (2) \\ \text{subject to:} & \\ 0 \leq \dfrac{\sum_{j=1}^{J} v_{jm} y_{jn}}{\sum_{i=1}^{I} u_{im} x_{in}} \leq 1;\, n = 1, 2, \ldots, N\,;\, v_{jm}, u_{im} \geq 0;\, i = 1, 2, \ldots, I;\, j = 1, 2, \ldots, J & (3) \end{cases}$$

where:

E_m is the efficiency of the m-th *DMU*

y_{jm} is the j-th output of m-th *DMU*

v_{jm} is the weight of each output

x_{im} is the i-th input of m-th *DMU*

u_{im} is the weight of each input

y_{jn} and x_{in} are the jth output and i-th input, respectively, of the nth *DMU*, n=1, 2, …N

n includes m.

As we can see, the DEA model consists in solving "n" maximization problems, corresponding to each of the n units whose efficiency is evaluated. The objective function chooses the weights (u_i, v_j) that maximize the efficiency of each DMU. There is one constraint for each existing unit, which implies that all DMUs must have an efficiency score between 0 and 1. In addition, once the "n" problems have been solved, a subset of DMUs is formed by the units that have proved to be efficient when solving the model. To them corresponds a value equal to 1. If the DMU analyzed does not meet this condition, it will be considered inefficient concerning the previous subset and will have an efficiency score between 0 and 1. Thus, the efficiency calculation allows obtaining an ordered ranking of indicators that express how close or far are the different DMUs from the efficiency frontier.

In the DEA model with input orientation, the objective function is the weighted sum of inputs and the weighted sum of outputs is restricted to be equal to 1. Similarly, a linear program can be formulated to maximize the weighted sum of outputs by setting the weighted sum of inputs equal to 1, which is called the output-oriented DEA program. In fact, given the nature of the formulations, the optimal value of the input-oriented DEA program will be the reciprocal of the optimal value of the output-oriented DEA program (Table 4).

Table 4 – The DEA model

DEA of minimization of inputs	DEA of maximization of outputs
$\min \theta_m$ θ, λ Subject to: $Y\lambda \geq Y_m$ $X\lambda \leq \theta_m X_m$ $\lambda \geq 0;\ \theta_m\ free$ where: λ is a vector m x1 with the weights of all DMUs. **$\theta_m \leq 1$ is the efficiency score of unit m (indicates the maximum output shrinkage the inputs).** if θ=1 then the DMU is technically efficient (Farrell's definition)	$\max\ \theta_m$ θ, λ Subject to: $Y\lambda \geq \theta_m Y_m$ $X\lambda \leq\ X_m$ $\lambda \geq 0;\ \theta_m\ free$ where: λ is a vector m x1 with the weights of all DMUs. **$\theta_m \geq 1$ is the inverse of Farrell's output efficiency measure.** $\theta_m - 1$ indicates the maximum proportional expansion in all outputs for unit m to reach the frontier. if θ_m=1 then the DMU is technically efficient

Source: Own elaboration.

In this context, the efficiency estimation is usually performed by applying the dual form of the linear program, where the estimated efficiency scores of the output-oriented DEA model for each DMU analyzed (θ_m), satisfy that:

- $\theta_m \geq 1$ is the inverse of Farrell's output efficiency measure (i.e., 1/ θ_m varies between 0 and 1).
- $\theta_m - 1$ indicates the maximum proportional expansion of all outputs of unit m to reach the efficient frontier.
- If $\theta_m = 1$ the unit *m* is efficient.

In this paper, we estimate both the DEA-CRS and DEA-VRS models to analyze different types of efficiency. Moreover, we compute the bootstrapping DEA method (Simar and Wilson 2007 and 2011; Bogetoft and Otto 2011) that is based on the numerical simulation of the original dataset calculating the efficiency of the simulated sample through DEA to generate bias-corrected efficiency and confidence intervals (Efron 1979; Simar and Wilson 199 and 2000). Then, to determine which model is the most appropriate for the DMUs analyzed, a test of returns to scale of Simar and Wilson (2015) will be applied.

5.2 Second stage: truncated regression

The performance of a given public action in terms of efficiency may be affected by contextual conditions (see, for example, Kyriacou et al. 2018). In this sense, we can examine the extent to which the efficiency scores estimated in the first stage of our analysis are influenced by contextual variables not directly controllable by the DMUs (in our case, DGs). For this purpose, the estimated relative efficiency scores ($\hat{\theta}_i$) of the first stage are considered as the dependent variable in a regression model that considers a group of contextual factors as explanatory variables. *(Z)*.

Most studies that perform this two-stage analysis employ a censored regression model (i.e. Tobit model). These kinds of analysts argue that the efficiency estimates in DEA are censored since there are usually numerous estimates of efficiency scores equal to one (see, for example, Hoff 2007). However, Simar and Wilson (2007 and 2011) argue that the regression should be truncated rather than censored because the efficiency scores are truncated (by one) by construction and not by censoring.

In addition, a problem arise since true DEA efficiency scores are unobserved and replaced by the previously estimated $\hat{\theta}_i$, which in turn are serially correlated to the non-discretionary explanatory variables in an unknown way (Fernandes et al. 2018). Therefore, a bootstrap procedure is implemented to overcome the correlation problem and obtain unbiased coefficients and valid confidence intervals. Thus, following Simar and Wilson (2007 and 2011), a double bootstrap method will be used, in which DEA scores are bootstrapped in the first stage of the analysis to obtain bias-corrected efficiency scores, and then the second stage is performed, consisting of regressing the bias-corrected efficiency scores on a set of potential explanatory factors using a bootstrap truncated regression.

Thus, in the second stage, the regression equation takes the form:

$$\hat{\theta}_i = f(Z_i \hat{\beta}_i, \varepsilon_i) \qquad (4)$$

Where,

$\hat{\theta}_i$ is the latent or dependent variable represented by the bootstrap-corrected efficiency value of the DMUi obtained in the first stage;
Z_i is the vector of the explanatory variables;
β is the vector of parameters to be estimated;
ε_i is the error term.

6. Data and information sources[6]

The DMUs to be analyzed are the 19 DGs in Uruguay during the period 2016-2019. The study is based on a database built from administrative records related to the execution of the DPR. For this purpose, it was necessary to consult more than one source of information and to

[6] See Appendix 2 Table A.2.1 for variables definitions and data sources and Table A.2.2 for summary statistics.

work with project management software and documentation contained in administrative file folders. In this way, it was possible to validate the data and verify their consistency. Likewise, both for the construction of the database and for making methodological decisions regarding the construction of the output and input variables were consulted qualified informants, such as technicians associated with the PCR (for example, civil engineers).

Input and output variables

The only input variable used was the total annual expenditure incurred by each DG using the DPR allocations. The construction of this variable involves the sum for each DG-year of the total annual expenditure in constant 2010 Uruguayan pesos.

For the consideration of variables related to outputs, were consider two issues. On the one hand, interventions included in category (i) refer to road segments (measured in kilometers) where investments are made to maintain a minimum standard of connectivity service to the local population. On the other hand, the interventions included in category (ii) refer to road segments (measured in kilometres) where investments are made to provide a significant improvement in the connectivity service. Considering these two categories, we have defined two output variables:

- *Output 1: Kilometres of roads maintenance*. Administrative registers are available for the three main types of maintenance interventions: ordinary, ordinary with contribution, and extraordinary. To aggregate all interventions homogeneously, the ratio between the average annual costs paid per kilometre for the three maintenance items in each year is taken into account.

- *Output 2: Kilometres of roads that have been rehabilitated, improved, and/or with new constructions*. For rural roads rehabilitation, improvement, and new roads, the DGs present projects that can be executed in terms that exceed one year. In other words, for a given number of kilometres to be intervened on a road, the DGs may present expenditure records in two or more years (which are sometimes the result of delays in the work schedule). Therefore, associated with the annual expenditures of that project, a criterion for measuring the number of kilometres executed per year is to prorate the total amount of investment and the total kilometres to be intervened on that road according to the annual expenditure.

The input and output variables are summarized in Table 5.

Table 5: Selection of input and output variables

INPUT Variables	OUTPUT Variables
Input: total annual expenditure of PCR in constant 2010 Uruguayan pesos.	***Output 1:*** Kilometres of roads maintenance.
	Output 2: Kilometres of roads that have been rehabilitated, improved and/or with new construction.

Source: Own elaboration.

Contextual variables

For the second stage of the analysis, and in agreement with the international literature priory reviewed (see section 3), and the disposable information at regional level for Uruguay, we have considered the following contextual variables:

- *GDP per cápita of the department:* this variable reflects the richness of the department and, therefore, is an adequate indicator of the state of the rural road network in the region.
- *Total population of the department:* on the one hand, one could intuitively think that economies of scale and externalities of agglomeration determine that larger DGs are more efficient; on the other hand, having a larger population can also have negative effects linked to scale inefficiencies (see, for example, Dollery and Fleming 2006).
- *Percentage of professionals in each DG*: ratio of professional staff to total employees of each DG. This variable is taken as a proxy for the quality of the local bureaucracy. The hypothesis to be tested is that the higher the proportion of qualified personnel, the better the administration of resources, and the effect on efficiency should be positive.

- *Year of execution of funds:* These dummies variables try to capture possible changes that affect all the DGs in a similar way, associated with events common to them that may have had a positive or negative influence on efficiency.
- *Political alignment*: dummy variable that takes the value 1 if the DG's governing political party coincides with the CG political party and 0 otherwise. According to the political economy literature,[7] a positive relationship should be expected between political factors, such as political alignment between CG and DGs, and the magnitude and coordination in the execution of intergovernmental transfers. Therefore we have included a dummy variable that tries to capture the political alignment criteria in the allocation and use of intergovernmental transfers.
- *Fiscal result of the DG*: dummy variable that takes the value 1 if the annual fiscal result is positive and 0 otherwise. The main hypothesis is that the DGs that have higher surpluses have better financial performance and therefore, it is expected that they present greater efficiency in resources management. Although, a negative and significant correlation between surplus and efficiency has also been found, affirming that local bureaucrats tend to maximize the size of the budget to create opportunities to take advantage of local budgets freely according to their interests.

7. Results

Stage 1: Data Envelopment Analysis

Given the methodology to be used, the main data limitation lies in the number of DMUs considered (the 19 GDs of Uruguay). For this reason, for the first stage of the empirical analysis (DEA), the whole period for which DPR information is disposable is considered as a single cross-section database. In this way, it is possible to obtain a total of 74 observations-years.[8] Also, the methodological decision to take the four years (2016 to 2019) as if they were a single moment in time is based on the fact that during this period both the resources allocated to this program and their distribution aliquots remain fixed.

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[7] See, for example, Lindbeck and Weibull (1987); Dixit and Londregan (1998).

[8] Since there is no information recorded for any type of rural road maintenance (Output 1), it was not possible to collect information for two DGs in two years: Maldonado-2019 and San José-2017.

The estimates for the DEA model were made with an output orientation and with DEA-CRS and DEA-VRS.[9] From these estimates were possible to extract the following data: Pure Technical Efficiency (PTE) obtained by the estimation with DEA-VRS, Overall Technical Efficiency (OTE) determined by the computation of DEA-CRS, and from the ratio of the efficiency scores under the DEA-CRS and DEA-VRS models, it was obtained the Scale Efficiency (SE), which allows analyzing whether the evaluated DMU produces below or above its productive capacity. Finally, we present an approximation to non-increasing returns to scale measure (NIRS).

Since DEA models are sensitive to the presence of outliers that can distort efficiency calculations, outlier detection is performed to purify the database following two methods: (i) box plots and (ii) Wilson's (1993) method.[10] According to both methods, the following DG-year outliers were detected: Lavalleja-2019, Río Negro-2017, Colonia-2017, and Cerro Largo-2016. Therefore, the final sample is composed of 70 DGs-years or DMUs.

Table 6 shows the estimated ranking efficiency scores computed. In all cases, the indicators show the position of each DG-year concerning efficiency, ordered from the most efficient to the least efficient considering de DEA-VRS (PTE) estimation. Therefore, DMUs with efficiency technical scores equal to unity are efficient. For those units with scores above 1, the pure technical inefficiency comes from the own resource management performed by each unit (DG). On the other hand, scale inefficiency is determined because the DG is operating at a sub-optimal scale.

[9] To obtain the DEA efficiency scores, we use the “Benchmarking” package (function DEA.boot) in R software and the bootstrap truncated regression analysis was performed in STATA. All code is available from the authors upon request.

[10] Details about these procedures and the corresponding results are presented in Appendix 3 and 4, respectively.

Table 6 - DEA estimation results

DMU	ID	VRS (PTE)	CRS (OTG)	EE	NIRS	DMU	ID	VRS (PTE)	CRS (OTG)	EE	NIRS
1	Artigas-2019	1,00	1,00	1,00	1,00	36	Río Negro-2019	1,23	1,23	1,00	1,23
2	Canelones-2019	1,00	1,54	1,54	1,00	37	Treinta y Tres-2019	1,24	1,25	1,00	1,24
3	Cerro Largo-2019	1,00	1,06	1,06	1,00	38	Lavalleja-2017	1,25	1,40	1,11	1,25
4	Flores-2019	1,00	1,08	1,08	1,08	39	Durazno-2018	1,27	1,33	1,05	1,27
5	Florida-2017	1,00	1,00	1,00	1,00	40	Soriano-2017	1,30	1,31	1,00	1,30
6	Florida-2019	1,00	1,01	1,01	1,00	41	Rocha-2018	1,30	1,33	1,02	1,30
7	Montevideo-2019	1,00	1,58	1,58	1,58	42	Treinta y Tres-2016	1,33	1,33	1,00	1,33
8	Río Negro-2016	1,00	1,00	1,00	1,00	43	Treinta y Tres-2017	1,33	1,35	1,01	1,35
9	Tacuarembó-2016	1,00	1,21	1,21	1,00	44	Florida-2018	1,35	1,38	1,03	1,35
10	Tacuarembó-2017	1,00	1,17	1,17	1,00	45	Maldonado-2018	1,39	1,39	1,00	1,39
11	Tacuarembó-2018	1,00	1,30	1,30	1,00	46	Colonia-2018	1,39	1,41	1,02	1,39
12	Tacuarembó-2019	1,00	1,01	1,01	1,00	47	Soriano-2016	1,39	1,40	1,00	1,39
13	Colonia-2016	1,01	1,07	1,07	1,01	48	San José-2018	1,41	1,43	1,01	1,41
14	Soriano-2019	1,01	1,04	1,02	1,04	49	Soriano-2018	1,43	1,46	1,02	1,43
15	Paysandú-2019	1,01	1,20	1,18	1,01	50	Colonia-2019	1,44	1,45	1,01	1,44
16	Rocha-2016	1,01	1,02	1,01	1,01	51	Rivera-2017	1,46	1,90	1,30	1,46
17	Flores-2016	1,02	1,07	1,05	1,02	52	San José-2019	1,46	1,47	1,00	1,46
18	Lavalleja-2018	1,03	1,19	1,15	1,03	53	Flores-2018	1,48	1,51	1,02	1,51
19	Canelones-2016	1,03	1,64	1,58	1,03	54	Rocha-2017	1,48	1,48	1,00	1,48
20	Canelones-2017	1,05	1,56	1,49	1,05	55	Durazno-2019	1,51	1,53	1,02	1,51
21	Rivera-2019	1,06	1,09	1,03	1,06	56	Treinta y Tres-2018	1,54	1,54	1,00	1,54
22	Canelones-2018	1,07	1,63	1,52	1,07	57	Rocha-2019	1,56	1,76	1,13	1,56
23	Artigas-2017	1,10	1,22	1,11	1,10	58	Flores-2017	1,61	1,63	1,01	1,63
24	Salto-2019	1,12	1,16	1,04	1,12	59	Durazno-2017	1,62	1,78	1,10	1,62
25	Cerro Largo-2018	1,13	1,35	1,19	1,13	60	Durazno-2016	1,65	1,72	1,04	1,65
26	Río Negro-2018	1,13	1,13	1,00	1,13	61	Montevideo-2018	1,66	1,67	1,01	1,67
27	Salto-2016	1,14	1,36	1,20	1,14	62	Lavalleja-2016	1,66	1,78	1,07	1,66
28	Paysandú-2016	1,15	1,46	1,27	1,15	63	Montevideo-2016	1,68	1,75	1,04	1,75
29	Paysandú-2017	1,16	1,32	1,13	1,16	64	Rivera-2016	1,69	1,81	1,07	1,69
30	San José-2016	1,16	1,18	1,02	1,16	65	Maldonado-2016	1,71	1,73	1,02	1,73
31	Rivera-2018	1,17	1,33	1,14	1,17	66	Salto-2018	1,71	1,79	1,04	1,79
32	Artigas-2016	1,17	1,21	1,04	1,17	67	Maldonado-2017	1,72	1,73	1,00	1,73
33	Paysandú-2018	1,17	1,41	1,20	1,17	68	Flores-2016	1,74	1,82	1,04	1,82
34	Artigas-2018	1,22	1,23	1,01	1,22	69	Salto-2017	1,82	1,83	1,01	1,83
35	Cerro Largo-2017	1,23	1,59	1,30	1,23	70	Montevideo-2017	1,90	1,94	1,02	1,94

Source: Own elaboration

From the visual inspection of table 6, we can observe that if the results are analyzed under DEA-CRS (OTG indicator), the number of efficient DMUs under DEA-CRS are three (Artigas-2019, Florida-2017, and Río Negro-2016), i.e. 4.3% of the units analyzed. The average efficiency score is 1.40, which implies that DMUs could increase, on average, 40% of their outputs while maintaining the level of inputs employed. The range of inefficiencies also shows that in 46% of the DG-years, the overall technical inefficiency level is above the average.

However, if the results are analyzed under DEA-VRS where the variation of efficiency concerning the scale of operation is taken into account, the efficient DMUs increase to 12 (17.1% of the unit-years analyzed). The average efficiency index of this model (PTE) is 1.29, which implies that the DMUs could increase, on average, 29% of their outputs (kilometres of rural road network intervened) while maintaining the level of inputs used (monetary resources of the RCP). In this case, 44% of the observed DG-years present a level of pure technical inefficiency above the average. The inefficiency comes from the excessive consumption of available resources by the unit analyzed for the level of production it performs.

Afterward, the Simar and Wilson (2011) scaling test was performed to determine which model (DEA-CRS or DEA-VRS) is the most appropriate for the DMUs analyzed in this research. According to their results, the null hypothesis RTS=CRS at 95% confidence is rejected (p-value=0.003). Therefore, the evidence indicates that DGs operate under variable returns to scale. As a consequence, the analysis that follows will be conducted with the DEA-VRS model. Table 7 summarizes the overall values and their distribution for our sample of 70 DGs-year.

Table 7: Descriptive Summary of Efficiencies under DEA-*VRS*

Returns	Min.	1st Quartile	Median	Mean	3rd Quartile	4th Quartile
VRS	1.00	1.03	1.23	**1.29**	1.47	1.90

Source: Own elaboration

According to the data in Table 7, 50% of the DGs-years operate with the inefficiency of up to 23% (the median of the distribution corresponds to the value 1.23). Also, we can see that the maximum inefficiency for a quarter of the analyzed DMUs is up to 90% (i.e., for a considerable part of the sample, given the resources, the outputs obtained could be almost doubled).

Stage 2: Truncated regression

This section presents the results of the analysis about the influence of contextual variables on the efficiency scores estimated by DEA-VRS in the first stage. To this end, a bootstrap technique was applied to a regression model with a truncated dependent variable (Simar and

Wilson 2007 and 2011). In the first stage DEA-VRS model, units are efficient when they present efficiency scores equal to unity; and the higher the score (>1) this means higher levels of inefficiency. Therefore, a positive sign of the estimated regression parameter indicates that ceteris paribus, an increase in this variable contributes to increasing the inefficiency obtained (or reducing efficiency). On the other hand, a negative sign of the estimated parameter indicates its contribution to reduce inefficiency (or to increase the efficiency ratio).

Table 8 shows the results of the model as a function of the context variables outlined in the section 6. In panel (A) results correspond to 200 replications in the bootstrap process. Panel (B) presents the results estimated for 1000 replicates as a robustness exercise.

The four models correspond to the following specifications: in model 1, we test the relevance of the year; the size of the department (approximated to its population); the GDP per capita; and finally, the percentage of professionals in the staff of local government bureaucrats, as an approximation to the quality of the local bureaucracy. In model 2, the positive fiscal result is added to the previous variables, as an indicator of fiscal performance. In model 3, the government political party of CG and each DG is added to capture the importance of the political alignment.

Table 8: Second stage: Truncated regressions results

Panel A

Variables	(1) Robust coefficients	Confidence interval Lower	Confidence interval Upper	(2) Robust coefficients	Confidence interval Lower	Confidence interval Upper	(3) Robust coefficients	Confidence interval Lower	Confidence interval Upper
Year	-0,0691 **	-0,1339	-0,0060	-0,0683 **	-0,1359	-0,0037	-0,0701 **	-0,1385	-0,0037
log of total department population	0,2543 **	0,0180	0,4855	0,2487 **	0,0361	0,4883	0,2728 **	0,0180	0,5625
Professional percentage	-0,2978 **	-1,5299	0,6838	-0,2846 **	-1,5796	0,7122	-0,3189 **	-1,8049	0,6963
log of GDP pc	0,2621 **	0,1515	0,5456	0,2914 **	0,2536	0,5520	0,4008 **	0,3250	0,6481
Fiscal result (positive)				-0,0124	-0,1547	0,1342	-0,0121	-0,1515	0,1276
Political alignment							-0,0293	-0,2129	0,1410

Confidence intervals are obtained with 200 bootstrap replicates in the second cycle of the Simar and Wilson (2007) algorithm

*Zero value does not fall within the 90% confidence interval, **Zero value does not fall within the 95% confidence interval, ***Zero value does not fall within the 99% confidence interval.

Panel B

Variables	(1) Robust coefficients	Confidence interval Lower	Confidence interval Upper	(2) Robust coefficients	Confidence interval Lower	Confidence interval Upper	(3) Robust coefficients	Confidence interval Lower	Confidence interval Upper
Year	-0,0701 **	-0,1380	-0,0042	-0,0712 **	-0,1382	-0,0094	-0,0727 **	-0,1411	-0,0112
log of total department population	0,2559 **	0,0290	0,5066	0,2516 **	0,0323	0,4810	0,2796 **	0,0229	0,5892
Professional percentage	-0,3215 **	-1,7255	0,6701	-0,2838 **	-1,5922	0,6459	-0,3489 **	-1,8592	0,6987
log of GDP pc	0,3134 **	0,1150	0,8400	0,3086 **	0,1944	0,6958	0,4414 **	0,2985	0,7272
Fiscal result (positive)				-0,0097	-0,1580	0,1294	-0,0103	-0,1522	0,1435
Political alignment							-0,0288	-0,2199	0,1357

Confidence intervals are obtained with 1000 bootstrap replicates in the second cycle of the Simar and Wilson (2007) algorithm

*Zero value does not fall within the 90% confidence interval, **Zero value does not fall within the 95% confidence interval, ***Zero value does not fall within the 99% confidence interval.

The estimation results for model 1 show that the coefficient associated with the year is statistically significant and negative, i.e., the higher the year, the more efficient the DMUs analyzed are. This result suggests that there has been a learning-by-doing process in the administration of DRP funds by the different DGs in Uruguay. In addition, the coefficient associated with the total population variable is significant and positive, which shows that efficiency is reduced in departments with larger populations. In this sense, this result suggests that neither economy of scale nor agglomeration externalities were observed in Uruguay. The coefficient associated with GDP per cápita is significant and positive. The latter is evidence that PCR investments, as stipulated (see section 4), were mostly oriented to less rich departments where there were fewer rural roads. Finally, the last variable incorporated in this base model, the percentage of professionals, has the expected effect of improving efficiency (coefficient with a negative sign) and is significant. This shows the importance of local bureaucracy in improving the efficiency of local investments in rural roads.

In the following two models (models 2 and 3), the variables fiscal result and government political party are added successively as a robustness exercise of the base model. Although the results of the base model are maintained, in none of these models do these new variables turn out to be significant. Finally, in the case of the results of the estimations carried out for 1000 replications, the same results detailed above are obtained.

8. Conclusions

The present research was focused on the analysis of the relative efficiency of Uruguayan DGs in the use of resources received through the DRP during the period 2016-2019 to "produce" kilometres of rural roads that provide a certain standard of connectivity service to the local population.

The empirical analysis provides evidence that suggests that the DGs of Uruguay could make better use of the resources allocated through the DRP and achieve a greater intervention in the rural road network by an average of 29%. However, behind this average, we find that the levels of inefficiency are heterogeneous, which implies that, for those DGs that have been relatively more inefficient, the improvement target varies significantly about the average.

In addition, it was possible to determine that the efficiency of the DGs increases when the department decreases in terms of population, which evidences the existence of diseconomies of scale at the regional level; the efficiency also increases when the regional richness decreases, which implies a correct allocation of PCR funds according to the degree of regional development. In addition, there is also an improvement in efficiency with an increase in the quality of local bureaucracy, which implies better management of the funds transferred by the central government. Finally, regarding the year variable, the findings are consistent with the results of the first stage, given that the coefficient suggests that as time has passed, the DGs have improved the economic management of their resources. This could be explained by the effect of an improvement in their internal administration, the actions taken by the CG towards the DGs to favour better results, or a combination of both.

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Appendix 1

Figure A.1. - Administrative division of the República Oriental del Uruguay

Source: National Civil Service Office of the Presidency of the Republic, Uruguay.

Appendix 2

Table A.2.1 - Data definitions and sources

Variable	*Definition*	*Source*
Input total	*Input:* total annual expenditure of PCR in constant 2010 Uruguayan pesos.	Planning and Budget Office Presidency of the Republic - Uruguay
Output 1	Kilometres of roads maintenance	Planning and Budget Office Presidency of the Republic - Uruguay
Output 2	Kilometres rehabilitated, improved, and/or with new constructions	Planning and Budget Office Presidency of the Republic - Uruguay
Department Population	Department population (in thousands)	Continuous Household Survey of the National Institute of Statistics of Uruguay
Department GDP per cápita	GDP pc of the department in constant pesos of 2010	Central Bank of Uruguay and Planning and Budget Office Presidency of the Republic - Uruguay
Professional percentage	Professional percentage of the total staff of each DG	Planning and Budget Office Presidency of the Republic - Uruguay
Fiscal result	Dummy variable that takes the value 1 if the DG's fiscal result is positive and 0 otherwise.	Office of Planning and Budget - Presidency of the Republic - Uruguay
Political Alignment	Dummy variable that takes the value 1 if the political party of RG department at time t is the same as the political party that governs the central state and 0 otherwise	Electoral Court of the República Oriental del Uruguay

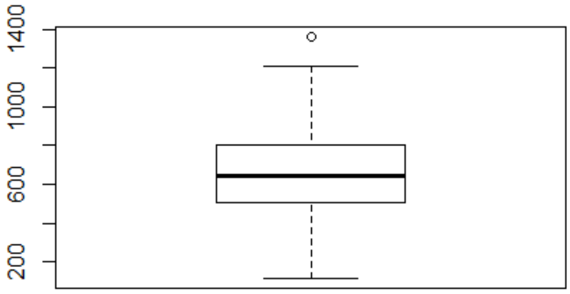
Table A.2.2 Data description

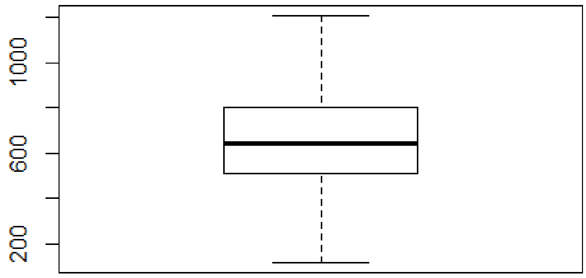
Variable	Observations	Mean	Std Dev	Min	Max.
Input total *(Uruguayan constant pesos of 2010)*	70	25.136	9.589	6.974	49.918
Output 1*(kilometres maintained)*	70	659.486	264.548	116.700	1207.706
Output 2*(kilometres rehabilitated, improved, and/or with new constructions)*	70	10.288	7.267	0.085	26.000
Total population *(in thousands)*	70	179302.400	302015.700	25050	1319108
GDP per cápita (*millions of constant Uruguayan pesos of 2010*)	70	36338.21	74662.36	4885.985	348675.6
Professional percentage	70	6.710	9.000	0.029	57.878
Fiscal result	70	0.571	0.498	0	1
Political alignment	70	0.328	0.473	0	1

Appendix 3 - Detection of outliers through box plot analysis

Output 1: kilometers maintained

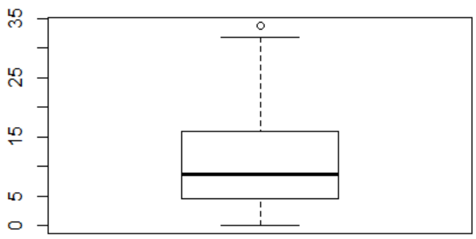
For output 1, through the analysis of the box plot, Lavalleja-2019 is detected as an outlier. The second graph is made in addition to the elimination of this value.

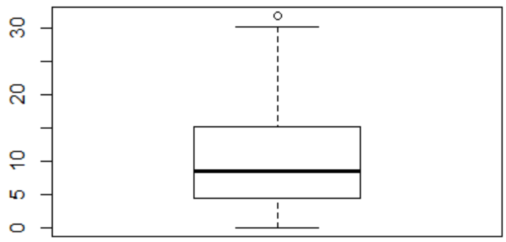


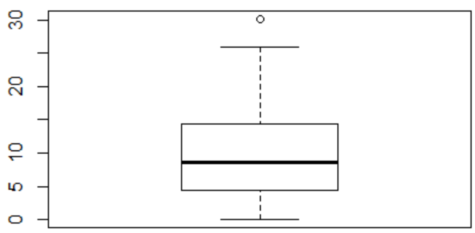


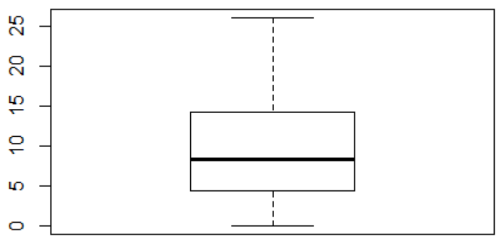
Output 2: kilometers rehabilitated, upgraded and/or with new works

The succession of box plots shows that the first outlier detected is Rio Negro-2017. In addition, once this unit is eliminated from the sample, Colonia-2017 and Cerro Largo-2016 emerge as outliers.







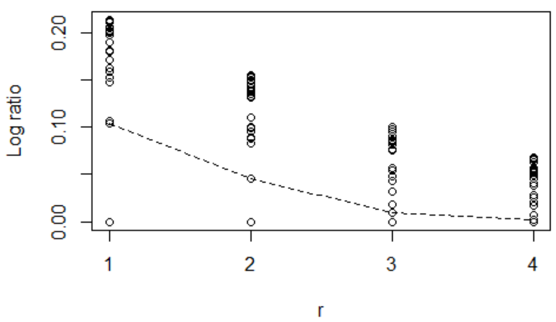


Appendix 4 - Detection of outliers through Wilson (1993) method.

In order to contrast the previous procedure, the method of Wilson (1993) is applied. This test involves taking a combined matrix of inputs (x) and outputs (y) (of dimension m*n) of the DMUs to be analyzed. The rows of this matrix can be seen as a cloud of points in the plane $R_+^M \text{x} R_+^n$, where each point represents one DMU. The cloud volume is represented as D(X, Y). To find one or more outliers, we can observe how the cloud volume changes when we remove one or more observations. Let $D^{(i)}$ the determinant after eliminating unit i, and considering the ratio of the new volume of the data cloud over the previous volume, we have the following ratio:

$$R^{(i)} = \frac{D^{(i)}}{D}$$

If the unit to be eliminated is an outlier then values of this ratio less than 1 are obtained. This approach is not restricted to eliminating only one observation, but several units can be eliminated in addition. For ratio values close to zero, this means that probably all outliers have been eliminated. In graphical terms this involves constructing and analyzing the graph of the logarithm of ratios, as shown below:



I					$R^{(i)}$
1	45				0,7707562
2	14	45			0,6293661
3	14	32	45		0,5380669
4	9	14	32	45	0,4640177

Since in the box plot method four outliers were detected, in this method we also took that number as the maximum number of units to be considered as a group of outliers, in order to verify the previous results. On the other hand, the software function of the R software *"outlier.ap"*, works well for eliminating between 1 and 4 units; for larger values it is too slow and may not yield results. In the table above, each row shows the numbers corresponding to the unit detected by this method as a candidate for elimination and they correspond to the units detected in the previous method: 45 (Rio Negro-2017), 14 (Colonia-2017), 32 (Lavalleja-2019) and 9 (Cerro Largo-2016). Likewise, given that the value of $R^{(i)}$ in row four of the table, which implies eliminating the four units, is not small enough (very close to zero), which implies that these four units can be considered as outliers.