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How environmental factors impact tax service efficiency in Castilla y León

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Abstract: This paper analyses the tax administration of the nine delegations in Castilla y León, Spain, for the period 2004 to 2016. A three-stage model is used, combining nonparametric data envelopment analysis with Logit regression with bootstrap. We thus provide a feasible solution to draw inferences using a robust regression model on efficiency, which determines those environmental factors that prove to be relevant; namely, population and GDP. With these, we adjust inputs to achieve environmentally adjusted efficiency, which was comparable among delegations.

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PALABRAS CLAVE:
Eficiencia técnica, Gestión tributaria autonómica, Análisis envolvente de datos (DEA), Regresión logística, Prueba U de Mann-Whitney.

Resumen: En este trabajo se analiza la gestión tributaria de las nueve delegaciones de Castilla y León para el 2004-2016. Se utiliza un modelo de tres etapas, que combina la metodología no paramétrica del Análisis envolvente de datos con la regresión Logit con bootstrap. De esta forma, se proporciona una solución factible para realizar inferencia, mediante la utilización de un modelo de regresión robusto con el que se determinan los factores influyentes del contexto, que son la población y el PIB. Con estos, se ajustan los inputs para obtener la eficiencia ajustada al entorno, que es comparable entre las delegaciones.

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1. Introduction

Controlling the management of resources is a primary goal of all governments, regardless of the level of decentralization involved. Efficiency in obtaining these resources is essential since they serve to subsequently fund regions (autonomous communities: Spanish acronym - CCAA) for the provision of the key public services under their control: health, education, and public social services.

As a result, the tax administration strives to ensure the sustainability of public funds, which is by no means a trivial task. Tax offices –as must all the entities that make up the public administration– must therefore maximise their objectives without wasting the means at their disposal used to obtain such funds.

In the specific case of the Spanish regional tax administration, one of the controlling bodies is the General Inspectorate of the Ministry of Finance who, in order to inspect the regional tax authorities, draws up an annual report in which it publishes data reflecting the efficiency levels achieved, the quality of the services provided and the cooperation between regional administrations in terms of tax management. In addition, the cited report also publishes data on the means used and results obtained in the application of the taxes under the control of regional administrations[1]. These input and output data enable tax administration efficiency to be measured and, thereby, to ensure effective control in the management of such essential resources.

Transfer of tax management from central government to the regions has also been accompanied by the handover of legislative power and decision-making to the regional level, which has led to enormous diversity therein. For this reason, analysis of regional tax management proves problematic and should be interpreted with caution when carried out amongst the various regions. Nevertheless, analysis of regional finance ministries does prove plausible internally, given the uniformity of the provinces that make up the regions. Moreover, analysis is necessary in view of the fact that regions are directly charged with the tax management under their jurisdiction; in other words, they are responsible for their income and expenditure.

This work thus seeks to gauge efficiency in the management of territorial tax services in the region of Castilla y León. This autonomous community is made up of nine provinces, such that it has the largest number of delegations in Spain. Moreover, these territorial services in Castilla y León enjoy the same powers of taxation as assumed by the State delegation vis-à-vis the taxes ceded. This parity in interprovincial tax legislation enables a comparative analysis to be made in regional tax management.

This analysis aims to measure the level of technical efficiency in tax administration in Castilla y León and to ascertain possible differences in the management carried out in the territorial delegations of which it is comprised. For this purpose, data envelopment analysis (DEA) – Charnes, Cooper and Rhodes (1978)– emerges as the most widely used technique in the academic field to approximate efficiency. This method applies a mathematical optimisation program that maximises efficiency, perceived as: the ratio whose numerator contains the weighted sum of the outputs achieved by the tax administration, and whose denominator is the weighted sum of the inputs used to obtain the previous ones.

In addition, when calculating efficiency, the analysis takes account of the impact of contextual factors. The efficiency calculated for each province can therefore be compared to the efficiency of the others, since the analysis places all the tax office services in equal conditions in terms of contextual factors and statistical noise. The efficiency determined in this research thus reflects the management efforts of the tax delegations in Castilla y León once the effect of the conditioning environmental factors has been removed, these being the economic and sociodemographic context in which tax functions are performed.

2. Literature review

Studies into tax management efficiency are summed up in this section. These studies show how the most frequently used technique in multi-stage methods is the combination of non-parametric and parametric procedures. Such techniques seek to examine efficiency in tax management and to explore the possible factors underlying these outcomes.

A look at previous studies reveals the scarcity of research addressing the decentralised tax management levels into which Spanish public tax administration is split: regional and local. Spanish references –such as Esteller (2003) and Cordero *et al.* (2020)– are some examples of studies which examine regional public finances, and where comparative studies are carried out between the various regional tax administrations. Far fewer studies deal with the local level, with one prominent study being that of Fuentes and Lillo-Bañuls (2015), whose work addresses local tax administration offices in Alicante.

We now look at the main results to emerge from the leading works carried out overseas. Thirtle *et al.* (2000) in India report a link between management efficiency and GDP, agriculture and poverty, when applying DEA and with MPI – the Malmquist Productivity Index (1953). In Belgium, Moesen and Persoons (2002) use Free Disposal Hull (FDH) by Deprins, Simar and Tulkens (1984) and DEA with a second stage through the Tobit truncated regression model (Tobin, 1958), with which they determine that the efficiency of tax offices is related to the existence of a central administration. In the case of Portugal, prominent is the study by Barros (2005), applying SFA –*Stochastic frontier analysis*– with which the author obtains a significant relation between the efficiency of tax offices and labour inflexibility. Using MPI, Barros (2006) finds an improvement in tax management production of 19.2% for the period 1999-2002. In the following work, Barros (2007) estimates

[1] The taxes traditionally ceded are inheritance and gift tax, personal wealth tax, property transfer and documented legal acts tax and stamp duties, and gambling tax.

a mean efficiency of 81.6% when applying DEA. In the second stage of the research, a Tobit regression is applied and determines a link between efficiency and GDP, public spending and the location of urban tax offices. Using SFA, Lewis (2006) establishes for Indonesia that the efficiency of local tax offices –measured with revenue generated and administration costs– is inversely related to central transfers. In Greece, Katharaki and Tsakas (2010) apply a DEA-*window* by Charnes *et al.* (1985) to determine trends. Using a Tobit regression, they also establish that efficiency is related to population and GDP. In the same country and for the same period –2001-2006– Tsakas and Katharaki (2014) determine through the use of DEA and Tobit regression with *bootstrap* that the efficiency of Greek tax offices is related to poor resource management, the number of legal entities, and tax evasion in the area. In Norway, Forsund *et al.* (2015) estimate the change in productivity by applying MPI with a *bootstrap* over the period 2002-2004, and find a positive production variation of 4% during the three years analysed. Mattos *et al.* (2011) study the Brazilian tax administration using FDH and a Tobit regression and find an inverse relation between efficiency and subsidies.

Another group of studies examines the efficiency of tax administrations in various countries compared to one another. Prominent amongst such works is that of Alm and Duncan (2014) who apply three-stage DEA to SFA with which they determine a mean efficiency of 83-90% for 28 Organisation for Economic Cooperation and Development (OECD) countries. Using DEA and regression analysis, Savić *et al.* (2015) later report a link between the submerged economy and independent variables –employment, efficiency and tax workers– for a sample of 13 OECD countries.

Finally, we now mention the results of some of the leading works that deal with the Spanish tax administration. González and Miles (2000) use DEA with *bootstrap* and obtain a mean efficiency of 81% for 1995. The regional inspection units that proved to be inefficient are Andalucía and the Canaries. Using SFA in 1992 and for the period 1995-1998, Esteller (2003) obtains a mean efficiency of 83%, which is inversely related with transfers and directly related to deficit. The study by Fuentes and Lillo-Bañuls (2015) is one of the few works to examine local public finance offices. Their study specifically looks at tax offices in Alicante in 2004-2006 using MPI with *bootstrap* and applying the Mann Whitney U test, and finds a link between efficiency and investment in infrastructure. Using DEA, Barrilao and Villar (2013) examine the efficiency of special delegations in 2008, where the most efficient are seen to be Andalusia, Castilla La-Mancha, Cataluña, and la Rioja. Villar *et al.* (2017) again apply a DEA, with which they determine that tax efficiency in 2012 could improve by 21%, which in economic terms would translate to a potential increase of 1,023 million euros.

One key recent work is that of Cordero *et al.* (2020) where they estimate the tax efficiency of Spanish regions over the period 2005-2014 by applying a robust conditional model. They conclude that differences in efficiency are reduced when taking into account the context, measured with GDP pc, inhabitants, over 65-year-olds, property, public deficit in relation to regional GDP, and time.

3. Methodology

3.1. Analysis units

The study sample consists of the nine territorial economy and finance services that make up the Castilla y León regional tax administration; namely the services in Ávila, Burgos, León, Palencia, Salamanca, Segovia, Soria, Valladolid, and Zamora. These territorial services are directly related to taxpayers when exercising tax management, such that the analysis focuses on these services. They are responsible for dealing with taxes, carrying out inspections and tax evaluations, providing cash service, tax collection, dealing with general treasury issues, as well as provincial tasks not assigned to central services.

The uniform nature of these delegations in terms of the tax duties they perform, as well as the regulatory powers ceded by the central administration in tax matters, makes the present an ideal study sample to conduct a comparative analysis.

3.2. Methodology

Tax administrations have limited control over the operating environment, which is defined with their fiscal capacity (Alm and Duncan, 2014). The variables that measure the environment do not form part of the production function because the tax authority has no control over them, even though do impact efficiency levels. As a result, in order to study the efficiency of the delegations and make comparisons between them, the contextual or environmental conditions in which they operate must be taken into account. To achieve this, the present research uses the Alm and Duncan (2014) three-stage technique which consists of estimating efficiency using DEA with inputs and outputs observed empirically. The observed inputs are later adjusted to the environmental factors. Finally, efficiency is estimated through DEA using the inputs adjusted in the second stage.

We therefore first estimate the levels of relative technical efficiency, θ^*, using DEA, which is a mathematical non-parametric optimisation technique that enables the construction of an efficient production frontier[2] based on best practices for the data available from a set of units analysed –known as *Decision Making Units* (DMU). The units that determine the frontier are the efficient ones, with the ones that are not at the frontier being inefficient. We thus obtain the relative technical efficiency measures of each unit analysed as its distance to the efficient frontier. Specifically, we use DEA by Banker, Charnes and Cooper (1984), (DEA-BCC), which involves variable returns to scale

[2] Since the production technology is not known, the efficient production frontier is built based on the combinations of the observed inputs and outputs.

so as to take into account the different size of the entities analysed. This kind of returns to scale refers to the proportion in which the volume of product increases vis-à-vis the increase in the production factors.

Given that the output of the tax administration depends on the fiscal capacity thereof, we opted for an *input* orientation, which has been used, among others, by Bendodo *et al*. (2019), Díaz and De Jorge (2018), Alm and Duncan (2014) and Cordero *et al*. (2020). This orientation seeks the maximum contraction of inputs within the set of feasible production possibilities. Put differently –and given the level of output– this model seeks the maximum proportional reduction in the vector of inputs whilst remaining at the frontier of production possibilities. A unit that is able to reduce its inputs without altering its level of output will not be efficient. The same number of DEA programs must be executed as analysis units there are, such that the formulation of the DEA model applied is the following:

$$
\begin{aligned}
& mín_{\theta,\ \lambda,s^+,s^-}\ \theta_0-\varepsilon(Is^+ + Is^-) \\
& s.a.: \\
& \lambda Y = y_0 + s^+ \\
& \lambda X = \theta^* x_0 - s^- \\
& \vec{1}\lambda = 1 \\
& \lambda, s^+, s^- \geq 0
\end{aligned}
\qquad [1]
$$

In expression [1] the parameter θ^* represents the efficiency obtained by the DMU_0. As a result, the unit will be classified as efficient if, and only if, the model solution is θ^* = 100, and the output and input slacks, respectively, are all null s^+, s^-= 0. Therefore, in order to be efficient, units should reduce inputs radially up to the efficient frontier, in a percentage of (100 - θ^*) and should reduce slacks individually through additional movement on the efficient frontier. Y_0 represents the output vector and X_0 represents the input vector.

Parameter I represents the identity matrix, which is required for the matricial formulation of the model. In turn, the intensity parameter is λ which identifies, for the DMU_0 evaluated, the units that provide the benchmark, since they envelop it and are taken as a reference to build the efficient frontier. The epsilon parameter is an infinitesimal of small value $\varepsilon = 1 \times 10^{-6}$ = 0.000001 units, which is required to introduce the restrictions to the weights of the input and output variables and which are added in this research so that efficiency is not oversized and to ensure that the model is more discriminant. As a result, the DMUs will use all the input and output variables considered in the model, without allowing the weight of any of them to take the value 0.

Having obtained the levels of efficiency, θ^* , in the second stage of the research we adjust the inputs observed empirically to introduce the environmental effects into the efficiency measures, which must be recalculated with the new values of the adjusted inputs through another DEA. In other words, a regression is performed to estimate the relation between efficiency, θ^* , and the environmental variables, z_d. For this task, we estimate the impact of the contextual factors and statistical noise on efficiency through the following stochastic frontier analysis:

$$\theta_{dj} = f(z_d;\beta) + v_{dj} \quad d = 1, \dots, D \qquad [2]$$

where, θ_{dj} is the estimated efficiency at the first stage, which has been modified so as to convert it into a binary variable that takes the value 1: efficient when θ^* = 100 and the value 0: inefficient when θ^* < 100. The function $f(z_d;\beta)$ is the stochastic frontier that captures the environmental factors, z_d. The error term is v_{dj}. In conclusion, the β parameters estimated at this second stage are used to make the adjustments in the inputs.

Several methodological options exist to estimate the β. Most of these require the separability assumption of Daraio *et al*. (2018) between the space of the inputs-outputs and that of the exogenous variables (Cordero *et al*., 2016), which proves difficult to accomplish in practice. As a solution to this, in this study we apply *bootstrap resampling*[3] (Simar and Wilson, 2007), formalised by Efron (1979). This technique serves to perform statistical inference for cases in which traditional parametric methods are not appropriate (Gil, 2005).

In addition, the second stage regression must comply with the assumption of error independence, which in this study is fulfilled because the efficiency indices are not dependent from one another because we apply an isolated and transversal DEA for each of the years involved in the analysis.

Another possible problem is that the dependent variable is censored by the numerous efficient DMUs located at the frontier. To correct this censoring, some studies –such as Fried *et al*. (2002)– opt to apply a Tobit regression. Other studies –such as Martínez and Pérez (2013)– apply Logit regression to examine which factors impact efficiency.

Based on the above, in order to estimate the parameters of the β regression and to avoid suffering from problems of bias and inconsistency that might be caused by the above-mentioned problems, the Logit model with *Bootstrap* techniques is used. Logit is a discrete choice model that is used when the dependent variable is binomial, in this research: efficient and non-efficient; which predicts the probability of an event happening based on the values of the independent variables, which has the following functional form:

$$P_i = F(z_i, \beta) + v_i \qquad [3]$$

where the β coefficients express the change in the logarithm of the probabilities, when one of the explanatory variables changes in a unit. F is the logistic function:

[3] *Bootstrap* is the most typical and widely used method and involves generating a high number of random samples with replacement, built directly based on observed data, as the grounding to study certain statistics. For each resulting sample, the value of the statistic is calculated. This gives an approximation to the distribution of statistical sampling (Ledesma, 2008). In addition, *bootstrap* is combined with other statistical techniques such as hypothesis testing, classification, principal component analysis, regression, correlation coefficients, factor analysis, time series or structural equation models, amongst others.

$$F(logit) = \frac{1}{1+e^{-logit}} \quad [4]$$

The Logit is thus:

$$\ln\left(\frac{p(efficient)}{p(non-efficient)}\right) = \beta_0 + \beta_1 x_1 + \cdots + \beta_1 x_n \quad [5]$$

such that the odds ratio is:

$$\frac{p(efficient)}{p(non-efficient)} = \frac{p(efficient)}{1-p(efficient)} = e^{logit} = e^{\beta_0+\beta_1 x_1+\cdots+\beta_1 x_n} \quad [6]$$

with the probability of efficiency therefore being:

$$p(efficient) = \frac{e^{logit}}{1+e^{logit}} = \frac{e^{\beta_0+\beta_1 x_1+\cdots+\beta_1 x_n}}{1+e^{\beta_0+\beta_1 x_1+\cdots+\beta_1 x_n}} = \frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\cdots+\beta_1 x_n)}} \quad [7]$$

Possible multicollinearity between the independent variables may lead to biased estimations and to inflated standard errors. To overcome this in the research, we need to avoid introducing highly correlated independent variables, such that we performed a Pearson correlation analysis.

To measure the model fit, we use the Hosmer-Lemeshow criterion, which is a widely used test in logistic regression to verify that the proposed model is able to explain what is observed. This method involves comparing the expected model values with the values actually observed. Both distributions –expected and observed– are compared using a Chi-squared test, where the null hypothesis is that there are no differences between the observed values and the anticipated values; in other words, that the model adjusts to the reality. As a result, for a p-value of less than 0.05 points, rejection of the null hypothesis would indicate that the model does not evidence a good fit.

To estimate the model coefficients, we use the maximum likelihood method, given that the least square method is not suitable because the regression function is not linear in the ß parameters, such that obtaining the estimators that minimise the sum of the squares of the differences between the values observed and their mean values does not lead to a system of easily solvable linear equations. In addition, the distribution of the dependent variable is not normal but Bernoulli, which can only give rise to two mutually exclusive events, such that minimising the sum of squares would not give statistically optimal estimators.

In addition to the above, at this stage of the research in order to identify the possible environmental factors z_d, which will be used in the logistic regression, we carry out the Mann-Whitney U test, which has been applied, amongst others, by Fernández, Martínez and Fernández (2013), and Fuentes and Lillo-Bañuls (2015) to determine the link between efficiency and other variables. The Mann-Whitney U test serves to observe the link between the dichotomous variables obtained in the first stage –the efficiency indicators– and the environmental variables. It is therefore used to ascertain whether there are statistically significant differences between two groups that are independent from one another –the group of efficient DMUS and the group of inefficient DMUS. Independence indicates that the same DMU analysed cannot belong to both groups at the same time. The contrast statistic is U, defined as the lower between U_1 and U_2 which is:

$$U_1 = n_1 n_2 + n_1(n_1+1)/2 - \sum R_1$$
$$U_2 = n_1 n_2 + n_2(n_2+1)/2 - \sum R_2 \quad [8]$$

where n_1 and n_2 are the respective sizes of each sample. The sum of the ranges of the observations of group 1 and 2 are $\sum R_1$ and $\sum R_2$, respectively. The null hypothesis is homogeneity in the medians of the two samples; in other words, the absence of differences between groups, with the alternative hypothesis being heterogeneity in the medians. As a result, when the p-value is greater at the level of significance α (0.05 points) the null hypothesis is accepted and there is no association between the variables analysed and efficiency, since the medians of the two groups are equal at the population level.

Having obtained the variables that have proved to be influential in terms of efficiency, in the third stage of the research we again perform DEA with the inputs adjusted to environmental factors and statistical noise, expressed by $x_{dj}^{adjusted}$. Following Alm and Duncan (2014), the adjustment carried out on the inputs observed is as follows:

$$x_{dj}^{adjusted} = x_{dj}^{observed} + [max_d\{z_d\hat{\beta}\} - z_d\hat{\beta}] + [max_d\{\hat{v}_d\} - \hat{v}_d] \quad [9]$$

These adjustments increase the inputs of each DMU proportionally to their favourable environment, measured with the variables and the statistical noise, which is vd. DMUs that operate in favourable environments and which perform better are more penalised as a result of seeing their inputs increased. In contrast, DMUs which find themselves in more adverse environments will see their levels of efficiency improved because of the reduction in their inputs.

3.3. Input and output variables

The Castilla y Leon tax administration manages two kinds taxes –its own[4] and those taxes ceded to it[5]. The latter are the most important in terms of manageable revenue, since

[4] Own taxes are: 1) tax on environmental impact caused by certain uses of reservoir water, by wind farms and by high tension electrical energy transport facilities, and 2) tax on the elimination of waste in landfills and dumps.

[5] The taxes ceded to the region of Castilla y Leon are: 1) property transfer and documented legal acts tax and stamp duties (ITPAJD), 2) inheritance and gift tax (ISD), 3) personal wealth tax (IP), 4) gambling taxes, 5) 50% VAT, 6) 50% income tax, 7) tax on certain means of transport (IDMT), 8) 58% of special manufacturing taxes: 8.1) beer tax, 8.2) tax on wine and fermented beverages, 8.3) tax on intermediate products, 8.4) tax on alcohol and derived beverages, 8.5) mineral oil tax, and 8.6) tax on tobacco products; 9) 100% of special manufacturing taxes: electricity tax, and 10) tax on the retail sale of certain mineral oil products which, as of 1 January 2013, are included in the special mineral oil tax.

they represent the largest source of funding with legislative powers assumed by the State delegation.

This research aims to carry out a management analysis, such that we only use data relating to ceded taxes that are managed directly and in full by the region of Castilla y León, and which are[6]:

1) Property transfer and documented legal acts tax and stamp duties (ITPAJD).
2) Inheritance tax (ISD).
3) Gambling tax.

In line with the above, the input indicator used in this research is:

- The staff charged with managing the ceded taxes, measured by the number of workers at the end of the year, obtained from the General State Budget (PGE), for the period 2004-2016. This variable represents the number of equivalent full-time personnel estimated proportionally vis-à-vis dedication in the management of the ceded taxes [7]. Studies that use personnel as an indicator of input include Fuentes and Lillo-Bañuls (2015) and Mattos *et al*. (2011).

In addition to staff, tax management also involves the use of material means such as premises and computer equipment. These are not included in the research due to a lack of the statistical sources that provide them. Furthermore, including quality in the study did not prove possible because data concerning complaints and suggestions –an indicator of quality– is not disaggregated at the territorial service level.

Moreover, given that the principal objective of the tax administration is to collect revenue, in this research we use the following as output indicators:

- Net applied revenue, measured in thousand euros, obtained from the PGE, for the period 2004-2016. This is calculated as the amount collected minus the amounts returned. As a result, we include the part of the revenue obtained by the Castilla y León tax administration. This variable has been deflated by the 2016 CPI so as to make comparisons over time.

  Tax revenue collection tends to be the most widely used measure of *output* by researchers in analyses aimed at studying tax administration efficiency; for example, in Alm and Duncan (2014), Thirtle *et al*. (2000) and Katharaki and Tsakas (2010).

- Inspection reports carried out, measured in the number of units, obtained from the PGE, for the period 2004-2016. Another study that uses inspection reports as a measure of *output* is Gonzalez and Miles (2000).

For the results of the analysis to be accurate and reliable, DEA requires homogeneity in the sample as well as a correct relation between the number of entities to be analysed and the number of input and output variables used in the model. Following the recommendation of Banker *et al*. (1989), the sum of the inputs and outputs should not exceed one third the number of units evaluated. This means that in order to analyse the nine territorial delegations of Castilla y León, the sum of the inputs and outputs should be three at most. The relation between the variables and delegations is three to nine which, added to the weight restrictions, means that the model achieves an adequate degree of discrimination. As a result, we use one input and two outputs, previously described, whose descriptive statistics are shown in Table 1.

[6] The IDMT and mineral oil tax are managed transitorily by the national tax administration (AEAT) because the region lacks the means to do so. Management of IP is shared jointly with the AEAT. There is also cooperation with AEAT for managing income tax (IRPF).

[7] The 2016 management report –the latest available– issued by the General Inspectorate of the Ministry of Finance states that Castilla y León continues to suffer from a greater relative lack of human resources to carry out tasks in the areas of inspection and evaluation. The report also sets out that, broadly speaking, the staff are well qualified. The lack of staff in the taxpayer service centre in Segovia led to it being the service that received most complaints in 2016, due to poor information, failure to attend the public, and because of queues, with the subsequent low standards in the quality of the service provided.

Table 1: Descriptive statistics of the input and output variables used in the DEA

	INPUTS	OUTPUTS	
	STAFF -mean- (Persons /Million inhabitants)	REVENUE APPLIED -mean- (thousand € /Million inhabitants)	INSPECTION REPORTS -mean- (Units /Million inhabitants))
AVILA	692	791,661	668
BURGOS	406	658,377	525
LEON	622	903,786	465
PALENCIA	541	503,006	1123
SALAMANCA	375	618,040	464
SEGOVIA	772	845,824	599
SORIA	857	604,291	1318
VALLADOLID	247	547,521	122
ZAMORA	645	613,705	1098
Mean	**573**	**676,246**	**709**
Minimum	232	321,730	0
Maximum	947	1,535,420	4,301
Standard deviation	193	295,079	727

Source: own, with SPSS.

The territorial distribution of the input and output values used to estimate efficiency are shown in maps of Castilla y León in Figures 1, 2 and 3, below.

Figure 1: Input: staff. Mean 2004-2016 (persons per million inhabitants)

Source: own.

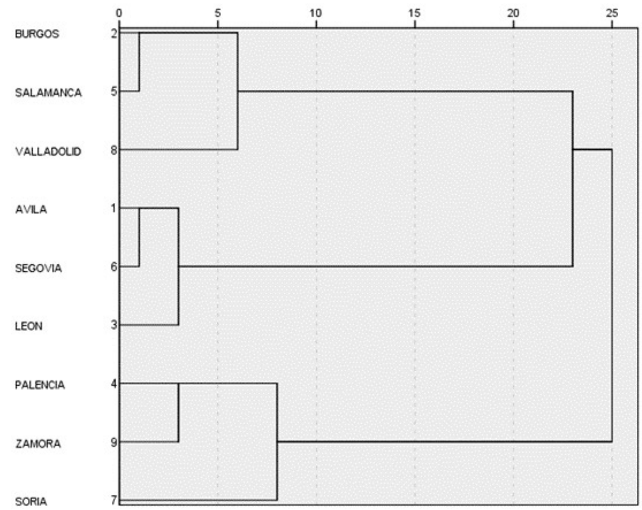
Figure 2: Output: reports issued. Mean 2004-2016 (units per million inhabitants)

Source: own.

Figure 3: Output: revenue. Mean 2004-2016 (euros per inhabitant)

Source: own.

Figure 4: Dendrogram of the Castilla y León territorial tax services. Mean 2004-2016



Source: own, with SPSS.

The previous input and output variables are prepared before applying DEA so as to add robustness to the model using hierarchical *cluster* analysis, which is a multivariate technique used to sort a set of individuals into homogeneous groups. The analysis aims to group individuals such that, if this agglomeration process is successively carried out, a distance is minimised or a measure of similitude is maximised. These measures are based on the variables used in the production process and are: staff, number of reports issued, and typified net collected amount of revenue.

As a result, hierarchical cluster analysis allows a classification tree –known as a dendrogram– to be constructed, shown in Figure 4. This shows the iterations that occur until a single conglomerate is formed based on the nine initial groups. In other words, reading the dendrogram from left to right offers a graphic representation of the unification procedure followed, showing the groups that are gradually formed. The x-axis shows the real distances re-scaled to values between 0-25 points. The y-axis shows the nine territorial tax services, represented by a numerical code.

Specifically, the first clusters of the dendrogram show how the greatest homogeneity can be seen in Burgos, Salamanca, and Valladolid. Another cluster is initially made up of Avila, Segovia, and León. Likewise, Palencia, Zamora, and Soria display similarity to one another. Later, in the following iterations, the first two groups join, such that finally all the territorial services cluster together in the final process. In conclusion, the initial hypothesis of homogeneity in the tax management functions performed by the territorial services can be seen.

3.4. Exogenous variables

The criteria followed to select the exogenous variables of the second stage of this work are the availability of statistical sources for the period 2004-2016, disaggregated by provinces. We also examined the variables used in previous studies into tax management, and also considered variables that might impact the taxable event of the taxes studied, and which are the ITPAJD, the ISD and gambling taxes.

The variables analysed as possible factors of the social, demographic and economic context of Castilla y León are as follows:

1) Population, measured in units of persons, obtained from the National Statistics Institute (INE).
2) Population growth, measured as a percentage, obtained from the INE.
3) GDP per capita, measured in euros per inhabitant at constant prices deflated with 2016 CPI, obtained from the INE.
4) Municipalities of less than 101 inhabitants, measured in units, obtained from the INE.
5) Municipalities of 1,001 to 2,000 inhabitants, measured in units, obtained from the INE.
6) Municipalities of 5,001 to 10,000 inhabitants, measured in units, obtained from the INE.
7) Municipalities of 10,001 to 20,000 inhabitants, measured in units, obtained from the INE.
8) Activity rate, measured as a percentage, obtained from the INE.
9) Unemployment rate, measured as a percentage, obtained from the INE.
10) Employment rate, measured as a percentage, obtained from the INE.
11) A binary dummy variable representing the regional financing systems that existed during the analysis period. The variable is 0 for the system applied in the

period 2004-2009[8]; its value is 1 for the period 2010-2016[9].

12) Life expectancy at birth, measured in years, obtained from the INE.
13) Life expectancy at 65-69 years of age, measured in years, obtained from the INE
14) Mortality rate at birth, measured per thousand, obtained from the INE.
15) Mortality rate at 65-69 years of age, measured per thousand, obtained from the INE.
16) Births, measured in units per 10,000 inhabitants, obtained from the INE.
17) Deaths, measured in units per 10,000 inhabitants, obtained from the INE.
18) Marriages, measured in units per 10,000 inhabitants, obtained from the INE.

The descriptive statistics of these variables are shown in Table 2.

Table 2: Descriptive statistics of the exogenous variables

VARIABLES	MINIMUM	MAXIMUM	MEAN	DEVIATION
1) Population	90,040	534,874	280,131	149,671
2) Population growth	-1.74	2.87	-0.16	0.88
3) GDP pc	16,994	29,317	21,926	3,085
4) Municipalities of less than 101 inhabitants	2	158	62.75	40.41
5) Number of municipalities from 1,001 to 2,000 inhabitants	3	42	15.13	8.67
6) Number of municipalities from 5,001 to 10,000 inhabitants	1	9	3.62	1.93
7) Municipalities from 10,001 to 20,000 inhabitants	0	5	1.00	1.53
8) Activity rate	44.95	61.12	54.19	3.89
9) Unemployment rate	2.87	26.62	14.19	5.84
10) Employment rate	34.03	54.94	46.50	4.60
11) Regional financing systems (binary variable)	0	1	-	-
12) Life expectancy at birth	80.74	84.58	82.72	0.98
13) Life expectancy at 65-69 years of age	19.65	22.61	21.19	0.61
14) Mortality rate	0.00	8.24	2.97	1.60
15) Mortality rate at 65-69 years of age	7.09	13.28	10.25	1.27
16) Births	52.00	96.00	74.93	10.29
17) Deaths	86.00	156.00	113.38	14.53
18) Marriages	21.00	51.00	32.51	5.78

The units in which the variables are expressed are detailed in the list preceding this table.

Source: own, with SPSS.

[8] This system is regulated by Organic Law 7/2001, of 27 December, amending Organic Law 8/1980, of 22 September, on the funding of the autonomous communities.

[9] This system is regulated by Organic Law 3/2009, of 18 December, amending Organic Law 8/1980, of 22 September, on the funding of the autonomous communities.

The previous exogenous variables are evaluated using the Mann-Whitney U test in order to determine whether or not they are linked to efficiency. This test requires the variables to be freely distributed[10], which is verified with the Kolmogorov-Smirnov normality tests when there is a p-value < 0.05 points and the normality hypothesis is rejected. In contrast, a T test for independent samples is applied for variables that follow a normal distribution[11] in order to ascertain whether or not they are associated to efficiency.

4. Results

4.1. Results of the Mann-Whitney U test

The variables which are related to efficiency according to the Mann-Whitney U test shown in Table 3 are:

1) Population.
2) GDP pc.
3) Municipalities of less than 101 inhabitants.
4) Municipalities of 1,001 to 2,000 inhabitants.
5) Municipalities from 10,001 to 20,000 inhabitants.

In contrast, for the remaining variables we see an asymptotic bilateral significance of p-value > 0.05 points, such that the null hypothesis is accepted, with the medians of the two groups being equal, indicating that there is no link between the efficiency levels and these variables.

Table 3: Mann-Whitney U Test

VARIABLES	MANN-WHITNEY U TEST	ASYMPTOTIC SIG. (BILATERAL)
1) Population	1,270	**0.020***
2) GDP pc	1,291	**0.027***
3) Municipalities of less than 101 inhabitants	960	**0.000***
4) Municipalities of 1,001 to 2,000 inhabitants	1,139	**0.002***
5) Municipalities of 5,001 to 10,000 inhabitants	1,500	0.274
6) Municipalities of 10,001 to 20,000 inhabitants	1,232	**0.004***
7) Activity rate	1,432	0.148
8) Applied regional financing systems	1,610	0.588
9) Number of marriages	1,571	0.495

Cluster variable: efficiency. * Significant at 95% confidence level.

Source: own, with SPSS.

The link between efficiency and exogenous variables that follow a normal distribution is studied with the T test for independent samples. This determines there are significant differences between the efficient and the inefficient group vis-à-vis the mortality rate at birth, given that the level of significance shows a p-value = 0.043 < 0.05 points. As a result, efficiency in tax management is conditioned by the mortality rate of the province. No link to efficiency was found in the rest of the variables analysed. Having identified which variables impacted efficiency –and in order to avoid problems of multicollinearity– when applying the

[10] Free distribution occurs in the following variables: 1) population, 2) GDP pc, 3) municipalities of less than 101 inhabitants, 4) municipalities of 1,001 to 2,000 inhabitants, 5) municipalities of 5,001 to 10,000 inhabitants, 6) municipalities of 10,001 to 20,000 inhabitants, 7) the activity rate, 8) the applied system of regional financing, and 9) the number of marriages.

[11] Variables that follow a normal distribution are: 1) population growth, 2) unemployment rate, 3) employment rate, 4) life expectancy at birth, 5) life expectancy at 65-69 years old, 6) mortality rate at birth, 7) mortality rate at 65-69 years old, 8) number of births, and 9) number of deaths.

Logit regression, we carry out a Pearson correlation analysis[12].

Based on the above, the factors which impacted efficiency and which are initially included in the Logit regression are the following four:

1) Population.
2) GDP pc.
3) Number of municipalities between 10,001 and 20,000 inhabitants.
4) Mortality rate at birth.

4.2. Results of the Logit regression

The Logit model chosen –shown in Table 4– is the one which presents the best overall and individual fit[13]. This conclusion was arrived at after having carried out several Logit estimations with *bootstrap* for a simulation of 2,000 samples, combining the four variables that impact efficiency established in the previous section. The final Logit model thus includes as explanatory variables of efficiency: 1) population, and 2) GDP pc. As a result, the size of the municipality and the mortality rate are excluded since individually they do not prove to be significant within the regression.

The statistics obtained in column B reveal whether the independent variables – population and GDP pc– are good predictors of the level of efficiency obtained. The results of the Logit regression show how those delegations in Castilla y León with a higher GDP pc are more likely to be efficient. Likewise, the analysis determines that provinces with a greater volume of population for whom to manage taxes are less likely to be efficient.

Table 4: Logit model: sampling simulation for the variables in the equation

	B	SAMPLING SIMULATION*				
		BIAS	STD. ERROR	SIG. (BILATERAL)	CONFIDENCE INTERVAL AT 95% BCA (BIAS CORRECTED AND ACCELERATED)	
					Inferior	Superior
Population	-0.000003	-9.9931E-8	0.000001	0.019490	-0.000006	-5.8838E-7
GPB pc	0.000178	0.000004	0.000071	0.008496	0.000043	0.000328
Constant	-3.234236	-0.055909	1.492952	0.021489	-6.102368	-0.586536

* Unless otherwise stated, the results of the sampling simulation are based on 2,000 samples.

Source: own, with SPSS.

The territorial distribution of the GDP and population variables that impact efficiency are shown in the Castilla y León maps in Figures 5 and 6 below. Provinces with a more intense colour in the GDP variable are wealthier and therefore operate in more favourable environments. Based on this –according to the Logit– they are more likely to be efficient.

[12] According to the Pearson analysis carried out, the variables measuring the size of the municipalities are highly correlated with one another. As a result, we only maintain in the study the number of municipalities between 10,001 and 20,000 inhabitants; amongst the variables measuring the size of municipalities, this is the one that most weakly correlates with population.

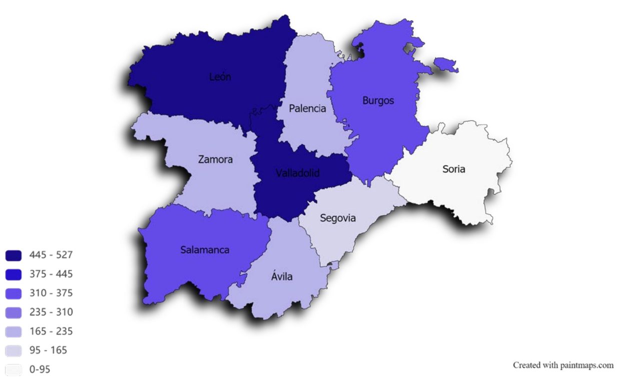
[13] In order to determine individual and overall goodness of fit of the Logit model, we conducted the omnibus test of model coefficients, with a significance level of 0.002 points, and the Hosmer and Lemeshow test, which showed a good fit, with a p-value of 0.836 points. The goodness of fit analysed in the classification table reveals how the model is suited to predicting why the percentage of cases classified correctly for the sample of known data is 65.8%.

Figure 5: Mean GDP 2004-2016 (thousands of euros per inhabitant)

Source: own.

Less intense colour on the population map implies a lower volume of inhabitants and a greater likelihood of being efficient in tax management.

Figure 6: Mean population 2004-2016 (thousands of people)



Source: own.

The next step in the analysis is to adjust the inputs taking into account that the provinces in Castilla y León with the highest GDP pc and the lowest population operate in more favourable environments than those which are less wealthy but that have a higher population. Adjustment entails a greater increase in the inputs of those delegations where the environment is more favourable, such that we ensure that all the territorial tax services in Castilla y León operate in equal conditions.

The adjustments made to the inputs have meant variations in staff input in the range [-1.57; +1.95] units of persons. Specifically, the territorial service of Valladolid in 2008 – the province with the best scenario in terms of population and GDP pc– needs to increase staff by 1.95 units, from 80 to 82 people involved in handling taxes. At the opposite end of the scale is Avila for 2015, where input should be reduced by 1.57 units in order to reach parity with the rest of the provinces in Castilla y León over the period 2004-2016. Its input thus goes from 40 to 38.4 people working in tax administration functions.

4.3. Levels of efficiency

The levels of efficiency observed without the influence of the environment and adjusted thereto and obtained when using DEA for each territorial service of Castilla y León over the period 2004-2016 are shown in Table 5. This also shows the mean for each province and year, the maximum and minimum values, adjustment to efficiency due to the environment, and the ranking of the delegations vis-à-vis their efficiency in tax management.

Mean efficiency adjusted to the environment is 88.11%, which means that, broadly speaking, delegations should reduce the number of staff working in tax management by 11.89% in order to achieve optimal performance.

Table 5: Efficiency observed without environmental influence (Efficiency estimated with environmental influence) -in %-

	Ávila	Burgos	León	Palencia	Salamanca	Segovia	Soria	Valladolid	Zamora	Media
2004	83.78 (84.04)	100 (100)	65.74 (65.06)	79.97 (76.1)	97.87 (96.2)	94.39 (88.94)	100 (100)	76.02 (74.86)	100 (100)	88.64 (87.24)
2005	100 (100)	100 (100)	65.19 (64.64)	93.75 (91.88)	100 (100)	73.17 (70.54)	100 (100)	51.05 (49.77)	81.68 (80.51)	84.98 (84.15)
2006	100 (100)	100 (100)	64.55 (62.87)	73.63 (70.16)	100 (100)	67.31 (63.55)	100 (100)	47.41 (45.41)	100 (100)	83.66 (82.44)
2007	100 (100)	100 (100)	65.59 (64.45)	71.43 (67.46)	95.88 (95.02)	77.15 (67.38)	97.22 (92.21)	100 (100)	100 (100)	89.70 (87.39)
2008	83.72 (83.41)	100 (100)	69 (67.61)	100 (100)	100 (100)	83.94 (82.61)	100 (100)	52.31 (51.11)	95.24 (95.11)	87.13 (86.65)
2009	93.71 (93.43)	100 (100)	47.72 (47.17)	100 (100)	72.78 (72.47)	82.47 (81.14)	100 (100)	45.88 (44.56)	83.79 (83.56)	80.71 (80.26)
2010	96.73 (96.29)	100 (100)	47.17 (46.53)	100 (100)	100 (100)	90.2 (88.21)	100 (100)	89.97 (89.13)	81.69 (81.28)	89.53 (89.05)
2011	97.27 (97.48)	100 (100)	75.41 (75.78)	100 (100)	89.69 (89.89)	89.86 (88.81)	100 (100)	91.96 (91.13)	92.93 (92.57)	93.01 (92.85)
2012	72.78 (71.76)	70.65 (68.73)	100 (100)	100 (100)	88.63 (88.27)	81.37 (79.62)	100 (100)	100 (100)	84.85 (83.56)	88.70 (87.99)
2013	75.56 (74.78)	86.23 (84.26)	100 (100)	100 (100)	78.73 (78)	100 (100)	100 (100)	80.62 (78.39)	89.23 (88.03)	90.04 (89.27)
2014	88.07 (87.53)	100 (100)	75.52 (75.77)	100 (100)	93.44 (94.13)	100 (100)	100 (100)	98.93 (97.5)	89.03 (86.31)	93.89 (93.47)
2015	100 (100)	78.25 (76.49)	100 (100)	100 (100)	84.74 (83.45)	100 (100)	100 (100)	100 (100)	82.5 (80.83)	93.94 (93.42)
2016	100 (100)	77.3 (74.31)	78.18 (76.93)	100 (100)	100 (100)	91.2 (88.22)	100 (100)	100 (100)	82.42 (81.73)	92.12 (91.24)
Mean 2004-2016	**91.66 (91.44)**	**93.26 (92.60)**	**73.39 (72.83)**	**93.75 (92.74)**	**92.44 (92.11)**	**87.00 (84.54)**	**99.79 (99.40)**	**79.55 (78.60)**	**89.49 (88.73)**	**88.93 (88.11)**
Ranking	**5º**	**3º**	**9º**	**2º**	**4º**	**7º**	**1º**	**8º**	**6º**	**-**
Influence of the environment *	-0.22	-0.66	-0.56	-1.01	-0.33	-2.46	-0.39	-0.95	-0.76	-0.82
No. of times efficient	5	9	3	9	5	3	12	4	3	-
Max.; Min.	100; 71.76	100; 68.73	100; 46.53	100; 67.46	100; 72.47	100; 63.55	100; 92.21	100; 44.56	100; 80.51	100; 80.26

* Influence = Observed Efficiency – estimated efficiency.

Source: own, with Frontier Analyst version 4.4.0.

The efficiency results obtained in this work are also displayed in Figure 7, which shows the territorial distribution of mean technical efficiency. The greater the colour intensity of the province, the higher the level of efficiency in administering ceded taxes. In mean terms, the best results are found in Soria, which is very close to 100% efficiency during the years of the study. This delegation employs more staff than others and collects below mean revenue, despite which it tops the ranking. As a result, sound tax management in Soria might mainly be due to the fact that it processes more reports per million inhabitants than the rest. Added to this is the fact that Soria is the province with the lowest number of inhabitants and has an above average level of wealth: in other words, its environment lends itself to good tax management.

Figure 7: Mean technical efficiency Castilla y León 2004-2016 (%)

Source: own.

For their part, the delegations in León, Valladolid, and Segovia show below average levels of efficiency. In the case of León –and after seeing the data– the explanation for its low efficiency lies in the fact that its operating environment is less propitious than the rest, given its high population and below average level of wealth. This is because it issues approximately the same number of tax reports as the mean, collects an amount of revenue that is also around the mean and has a similar average number of staff. The low tax management efficiency results in Valladolid might be explained by its high volume of population and small amount of staff, since its delegation employs the lowest mean number of workers. This leads to the number of reports and revenue being below the average. At the delegation in Segovia, there is an above average number of staff, which leads to lower than mean levels of relative efficiency. This province achieves results superior to the mean, but using a higher average number of staff.

The remaining five delegations –Zamora, Ávila, Palencia, Salamanca, and Burgos– are above mean efficiency for the period analysed. Zamora presents efficiency levels close to the mean, which may fundamentally be due to the high number of reports issued in the province. In the case of Avila, it is the high volume of revenue collected that explains its high efficiency levels in tax management. In the case of Palencia, the operating environment is ideal for executing good tax management, since it has less population and more GDP on average than the rest. Palencia's high level of efficiency might be due to the large number of reports issued, since the revenue collected is the lowest of all. In addition, these results are obtained with fewer staff than the average. The efficiency results for Salamanca are very similar to those of Palencia, with the difference being that the environment in the former does not favour tax management. The number of reports issued and the revenue obtained are below the mean, such that this delegation's high efficiency is down to the fact that it employs fewer than average staff. Finally, the Burgos delegation –which has the highest mean GDP pc– obtains high levels of efficiency, which might be because, in addition to having the highest mean GDP, it employs a below average number of staff. This is because its output results –the revenue collected and the reports issued– are around the mean.

In addition to the previous results, the study also shows that the contextual impact triggers an adjustment in inputs that reduces mean tax management efficiency by 0.82 percentage points. Put differently, efficiency goes from 88.93% to 88.11% when considering exogenous variables: population and GDP pc, and statistical noise. This result is consistent with the initial hypothesis of study sample homogeneity, such that in the event of strong similitude between the delegations studied, any input adjustments should be small since they are calculated as distances to the most unfavourable environment. In this latter situation of the worst scenario for the province, the variation in inputs is null when the contextual variable displays an inverse relation to efficiency, such that there would be no variation between observed efficiency and context adjusted efficiency. In this research, this situation occurs in the adjustments caused by the population variable, such that the highest adjustment in input takes place in those delegations with the smallest population; in other words, in the provinces with the most favourable environment. In these provinces, the smaller the population the greater the increase in their input. Put differently, those with more population are favoured and those with least population lose out because of variations in the levels of input for putting all the provinces on an equal standing.

Adjustments caused by the GDP variable that are directly linked to direct efficiency function in the opposite way to that described for population. In this case, the best scenario that should be penalised is the highest level of GDP. As a result –and in accordance with the formula[14] for adjusting inputs– the greatest GDP has a zero adjustment while for the rest the further their GDP is the from the maximum GDP the more their inputs will be reduced.

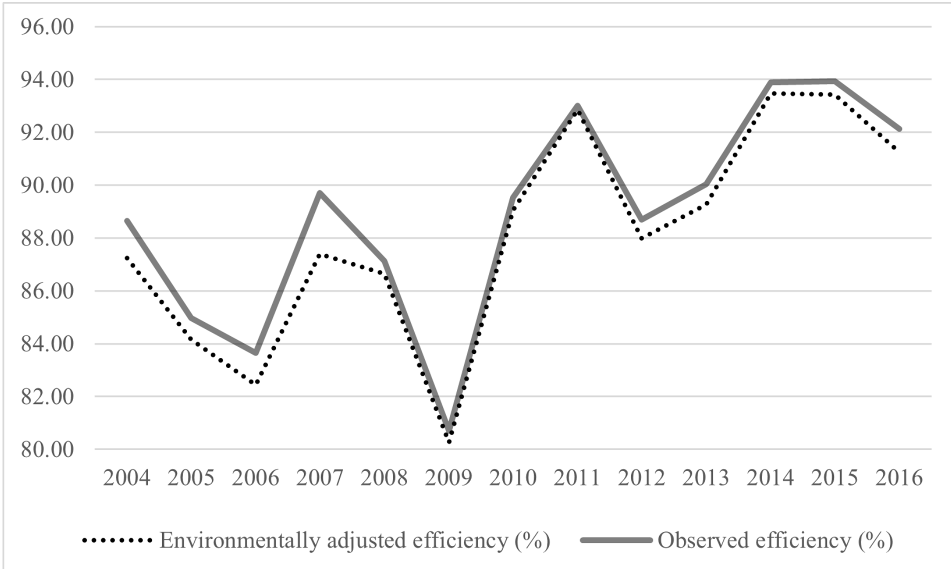
Finally, Figure 8 shows the efficiency time pattern over the period 2004-2016, where a slight increasing trend can be seen. Moreover, environmentally adjusted efficiency is, on average, below the efficiency observed prior to adjustment. This highlights how, broadly speaking, provinces do their work in a favourable environment, such that their efficiency results prior to being corrected by social and economic conditions are over-dimensioned.

[14] As mentioned earlier in the method section, according to equation [9] the adjustment carried out on the observed inputs is as follows:

$$x_{dj}^{adjusted} = x_{dj}^{observed} + [max_d\{z_d\hat{\beta}\} - z_d\hat{\beta}] + [max_d\{\hat{v}_d\} - \hat{v}_d]$$

such that, for a maximum level of population the adjustment would be [maximum {PBβ} - maximum PBβ]= 0. Likewise, for a level of maximum GDP the adjustment would also be null.

Figure 8: Progression of technical efficiency of territorial services in Castilla y León



Source: own.

In line with the above, another enlightening result is that the environmental effect proves to be less influential during the years in which the economic crisis hit hardest –from 2008 to 2011– where the variation in efficiency due to environmental circumstances is virtually zero, such that the curves for observed efficiency and adjusted efficiency coincide. As is obvious in these years of crisis, the environment was more unfavourable in relative terms than in the rest of the years analysed, where there were greater adjustments caused by the higher level of wealth.

5. Conclusions and discussion

- This study measures the tax management efficiency of territorial tax services in the nine provincial delegations in Castilla y León over the period 2004-2016 vis-à-vis the taxes usually ceded and which are handled in full by the region: the ITPAJD, ISD, and gambling taxes.
- An analysis of previous studies would seem to confirm that this field of research in regional finance has thus far received no attention, despite its importance, given that the Castilla y Leon regional tax administration –as do the rest of the regions– have their own tax management system. Moreover, this region's tax efficiency does not depend on nor is conditioned by the actions of its neighbouring regions, whose performance might be attributable to their own particular characteristics and guidelines when applying tax legislation.

  Studies examining the regions in comparative terms with one another might show that one region collects more revenue –for example for the ISD tax– not because it is more efficient but because it applies tax legislation that offers fewer tax breaks for taxpayers for that specific tax. However, it should be pointed out that we do not believe that studies which analyse regions with one another should not be deemed valid, since they all provide fresh complementary findings, but that they should be interpreted with caution and taking into account their own specifications and particularities.
- For this research, we applied the three-stage DEA model, proposed amongst others by Alm and Duncan (2014). This mixed method combines a non-parametric model with a parametric method with *bootstrap* in various stages.
  - In the first stage of the research, we proxy efficiency with inputs and outputs observed empirically through DEA.
  - In the second stage, we offer possible causes for the previous results, which provide arguments to account for interprovincial differences, and which respond to demographic and economic factors. For this, we estimate coefficients and statistical noise through a binary logistic regression with *bootstrap* in order to avoid errors of bias and inconsistency.
  - Finally, in the third stage, we modify the inputs so as to adjust them to the variables which were shown to impact efficiency in the previous stage. These proportional adjustments modify the inputs, penalising tax delegations that find themselves in favourable environments with an increase therein, whilst those delegations in Castilla y León that suffer adverse environments vis-à-vis efficiency are favoured through a reduction in their inputs.
  - In line with this, the efficiency measures obtained in this work incorporate the effect of the representative variables of the socioeconomic context and the luck factor, such that all the delegations are in equal conditions prior to proxying their levels of efficiency in tax management.
- This type of method applied to the specific field of the Castilla y Leon administration has borne out the homogeneity of the sample, the usefulness of the

technique used, and the apparent consistency in the results to emerge.

- The mean efficiency obtained by the Castilla y Leon tax administration is 88.11%. This implies that the same levels of production – reports issued and applied revenue– could have been obtained with 11.89% fewer staff. Broadly speaking, this infers a slight waste of resources. As a result, achieving full efficiency or maximisation of resources –on average– for the nine delegations over the period studied would entail a reduction of 68 tax administration workers for each one million inhabitants.

- The study reveals significant differences amongst the delegations in Castilla y León vis-à-vis the management of the taxes ceded. In 2016, efficiency in Avila, Palencia, Salamanca, Soria, and Valladolid is 100%, while in Burgos it is 74.31%, which represents the lowest value for that year. The lowest value for the period is found in the province of Valladolid in 2009, which reached a level of 44.56%. Nevertheless, the average for this delegation is 78.60% in the 13-year period studied. In addition, mean efficiency levels in Castilla y León improved over the period studied, rising from 87.24% in 2004 to 91.24% in 2016.

- The operating environment proved to have an impact on efficiency levels. The factors which condition tax management obtained in this study seem to concur with those reported in some previous studies. In other words, we found a direct link between tax efficiency and GDP that concurs with the results obtained in Thirtle *et al.* (2000), Barros (2007), and Katharaki and Tsakas (2010).

  In addition, territorial services that have a greater volume of total population for whom they manage taxes are less likely to be efficient. In line with the above – and in view of the fact that Castilla y León has an ageing population compared to the rest of Spain– this result might be considered to be in line with that reported by Cordero *et al.* (2020) who find that efficiency is inversely related to a population that is over 65 years of age.

- As a result of the above, based on the information provided by this research, it might be believed that in order to achieve enhanced tax management efficiency economic growth (GDP) should be encouraged and that an effort should be made to secure smaller production scale economies for tax delegations, given that tax management is seen to improve in provinces with fewer inhabitants.

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